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Additionality, common practice and incentive schemes for the uptake of innovations

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ABSTRACT

Crucial components of carbon offset trading schemes are the determination of whether a technology or practice is innovative (i.e. not common practice), and whether the practice is adopted as a result of incentives (termed additional). Under schemes such as the Clean Development Mechanism (CDM), early adopters of carbon reducing technologies receive tradable carbon credits that can be sold to businesses to offset their emissions. However, frameworks for distinguishing early adopters are inconsistent, and the effect of incentive schemes on uptake is poorly understood. In this study we: 1) review measures of common practice taken from the literature with the purpose of informing a standardised approach; and 2) using the Bass model we explore the effects of incentive schemes on adoption with the purpose of establishing the proportion of uptake attributable to the scheme. We found that a fixed common practice threshold of approximately 20% adoption is well supported by a wide range of approaches, and that 85–95% (approximately) of early adoption can be attributed to incentives, such as offset schemes. Although we focussed on carbon reducing technologies, our results have broad implications for general practice and product diffusion, and the effect of promotions on adoption.
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1. Introduction

Incentive schemes have been recently established to reduce greenhouse gas emissions including the Alberta-based Offset Credit System, the Clean Development Mechanism (CDM) and the Carbon Farming Initiative (CFI, Australia). In general terms, these schemes issue credits for practices or activities that lead to greenhouse gas abatement, which can then be sold to individuals, businesses or governments to offset their emissions. These markets in tradable credits have defined the need to develop consistent and robust measures to determine which activities are eligible. A core criterion for eligibility is whether the abatement is additional. For example, the Kyoto Protocol (1998) mandates that tradable credits should be 'real, measurable and additional'. Here, we define additionality as abatement that would not have occurred in the absence of a specific incentive scheme that promotes it – that is, it would not have occurred under business-as-usual (BAU) (Anon., 2011; Climate Action Reserve, 2010).

Assessing additionality is one of the most controversial and debated concepts in the environmental policy literature (Muller, 2009; Schneider, 2009; Shrestha and Timilsina, 2002; Streck, 2010). In general, approaches to additionality determination are considered lengthy and unpredictable (Streck, 2010), and clear, consistent and objective methodologies are required to reduce policy uncertainty, increase investment and thereby reduce emissions more effectively (Michaelowa, 2012; Shrestha and Timilsina, 2002; Streck, 2007, 2010; Trexler et al., 2006). Recent schemes, such as the Australian CFI have proposed a more objective and consistent approach to additionality assessments – they suggest that if an activity is not a common practice then it should qualify as additional. Common practice infers that the practice is well established

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and no longer in its early stages of adoption. It is called a standardised approach to additionality as it is based on uniformly applicable criteria such as activity adoption-level data. Standardised approaches are understood to have several advantages over project-specific approaches that examine projects on a case-by-case basis (e.g. legal, regulatory or financial tests). Generally, they reduce delays associated with case-by-case evaluations, are administratively easier to apply, improve consistency across determinations, and alleviate uncertainties for investors (Climate Action Reserve, 2010).

Thus, within the framework of additionality assessments, two distinct criteria emerge: whether the adoption of a practice is directly attributable to an incentive (that is would not have occurred under a business-as-usual scenario); and whether the practice is within the early stages of adoption and thus is not a common practice. For effective policy implementation, these two criteria require an unambiguous means of evaluation. Concerning the first criterion of additionality, we are unaware of any standardised quantitative approaches to assessing whether practice adoption is directly attributable to an incentive scheme. However, for the second criterion of common practice, two general approaches have been proposed in the literature: market penetration levels (Kartha et al., 2005), and adoption based on the diffusion of innovations theory (Mathur et al., 2007). Each defines a threshold adoption level beyond which the activity is deemed common practice and credits are not tradable.

Our motivation for this paper is to establish how innovation diffusion theory can contribute to a standardised determination of these two assessment criteria for offset schemes, although the results also have broader implications for general incentive schemes, practice diffusion and product promotions.

A substantial body of literature exists that addresses the impact of advertising and marketing on the uptake of particular technologies or products, as well as, more recently, the effect of government incentive schemes on practice adoption and the reduction of emissions (Greene et al., 2005; Guidolin and Mortarino, 2010; Heinz et al., 2013; Higgins and Foliente, 2013; Higgins et al., 2011, 2012, 2014; Islam, 2014; Kalish and Lilien, 1983; Koeppel and Urge-Vorsatz, 2007; Lund, 2006; Newell et al., 2006; Tang et al., 2013). However, accurate predictions of how such schemes impact on adoption numbers is complex, is not well understood, and is not consistent across the literature. Complex approaches are available (for example, Refs. (Higgins et al., 2011; Kuehne et al., 2011)), but in those cases considerable data are required for predictions. In specific cases, where data are available, such models have advantages; however, for new innovations, and early in the adoption process when additionality decisions are required, it is likely that data are few. To our knowledge, there is no previous study that compares and tests a variety of thresholds for common practice determination, or provides general measures that distinguish additional adoption from business as usual (BAU). This work aims to address these issues. Using models that are appropriate when data are few, we reveal generic trends relevant to a large class of different practices, which are highly relevant for robust and standardised policy formulation concerning the two criteria.

The purpose of this study is threefold. First, we review measures of common practice reported in the literature, and compare distinct approaches for determining common practice thresholds. We consider market penetration and two innovation diffusion approaches, and how they can inform a standardised approach to a general definition of common practice and threshold evaluation. Our preliminary threshold analysis was provided to, and informs, Australia's CFI (Woodhams et al., 2012), which considers the adoption of emission reducing land management practices. Second, we explore the effects of incentive schemes on uptake using the Bass model. We do not distinguish between specific incentives in this paper (they may be financial incentives, loaded taxes, marketing, promotions, advertising, carbon price, or the like) and herewith refer to them collectively as promotions or incentives. Rather we analyse the general impact of such incentives on measures of additionality by estimating the proportion of adoption directly attributable to the incentive (adoption which would not have occurred under business as usual), and consider a broad range of possibilities to provide information under uncertainty. We focus on robustness and commonality in such measures, which can inform and validate additionality determination in an objective and consistent way. The third objective is to estimate the relative increase in adoption over a longer target period, which follows as a direct result of the scheme, and to establish the reduction in time until penetration targets are achieved. The purpose is to gain insight into how government incentives for emission reductions could contribute to meeting long-term targets.

For each of the above objectives we do not develop new models. Rather, we establish how results from the literature, and the Bass model in particular (which is widely accepted as the best predictor of adoption under uncertainty), can expose general adoption characteristics to inform robust policy concerning additionality assessments.

The paper is organised as follows. We first review the literature on common practice thresholds and diffusion theory in Section 2, introducing the Bass model for innovation uptake. In Section 3 we present our analysis. We determine an appropriate common practice threshold, based on commonalities between a wide range of quantitative and qualitative approaches (Section 1), and conjecture how promotional schemes might impact on uptake to determine the proportion of adoption due to an incentive scheme and that due to BAU (Sections 2 and 3). In Section 4 we extend these results to consider how schemes can contribute to long-term targets, in terms of adoption numbers and time frames. In Section 4 we summarise our results, and then interpret their meaning within a policy context in Section 5. Finally, we provide concluding remarks in Section 6.

2. Background

2.1. Thresholds for common practice

The concept of a common practice threshold is not straightforward to quantify – whether a practice is common or not, is, in reality, an arbitrary definition. Thus we draw on the literature for a general view of how early adoption has been defined. Our findings are discussed below and summarised in Table 1.

In the literature, comparable thresholds are also referred to as 'tipping' points, or 'takeoff' points, or defining a 'critical mass', with the understanding that at this point adoption of a particular practice becomes self-sustaining (Phillips, 2007). A number of approaches can be used to inform the establishment

Table 1
Summary of a literature review for common practice thresholds. Note that $\mathcal{T}$ here refers to the point of maximum acceleration in uptake, and is thus equivalent to the inflection point calculated by Ref. (Mahajan et al., 1995) to be 19% (on average). Thresholds I and III vary with the product, and their general characteristics will be explored further in Section 1 and compared with Threshold II.

Value	Method of determination	Reference
16%	Divisions based on a normal distribution with 1 or 2 standard deviations from the mean (average across products)	Refs. (Garber et al., 2004; Goldenberg et al., 2001; Moore, 1991; Rogers, 1983)
$\mathcal{T}=19\%$	Divisions based on the Bass model points of inflection (average across products)	Refs. (Mahajan et al., 1990, 1995)
21%	Division based on adoption incubation times (average across products)	Ref. (Kohli et al., 1999)
$\approx\mathcal{T}=19\%$	Division based on resistance to change (average across products)	Ref. (Phillips, 2007)
2–10%	Fixed market penetration	Ref. (Kartha et al., 2005)
20% (threshold II)	Fixed market penetration	Ref. (Anon., 2011)
T (threshold I)	Division based on maximum acceleration in uptake (uniquely calculated for each product)	Refs. (Mathur et al., 2007; Stremersch and Tellis, 2004; Tellis et al., 2003)
Threshold III	Division based on when imitators exceed innovators (uniquely calculated for each product)	Ref. (Phillips, 2007)

of such a threshold in terms of innovators, early-adopters and the nature of the diffusion process, and we discuss them below.

Ref. (Rogers, 1983) divides the population (or market potential) into groups associated with the adoption sequence, as illustrated in Fig. 1. These results are based on an assumption that adoption over time follows a normal distribution, and the categories are then defined by one or two standard deviations from the mean. Refs. (Mahajan et al., 1990, 1995) estimate ranges with innovators between 0.2% and 2.8% of final adoption numbers, and early adopters from 12.3% to 20.2%. These divisions use the Bass model, and assume the points of inflection determine the divisions. Combining the first two divisions in each case, Ref. (Rogers, 1983) estimates an early adoption threshold at 16% of adoption, while Ref. (Mahajan et al., 1995) has this figure at 19% (approximately).

Refs. (Garber et al., 2004; Goldenberg et al., 2001) apply a threshold of 16% (division between 'early informed' and 'middle

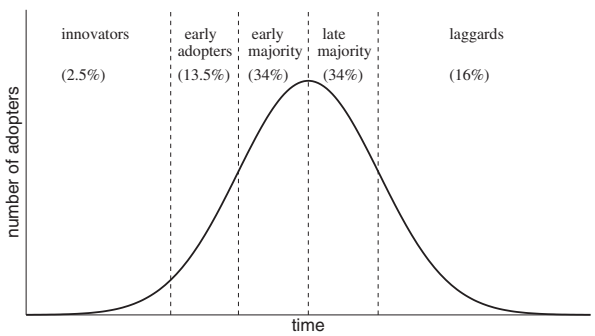

Fig. 1. Categories of adoption according to Ref. (Rogers, 1983), assuming the number of adopters (y-axis) over time (x-axis) follows a normal distribution. The five categories (innovators, early adopters, early majority, late majority and laggards) are defined by one or two standard deviations from the mean (dashed lines).

informed', or adoption proportion at peak sales, respectively) following Ref. (Rogers, 1983). Ref. (Moore, 1991) identifies a 'chasm' between the early adopters of new technologies (visionaries) and the early majority (pragmatists), differentiating between the adoption of technologies and products, but with a division between early adopters and an early majority equivalent to that of Ref. (Rogers, 1983) (that is, 16%). Ref. (Kohli et al., 1999) discusses incubation times before takeoff and adoption slowdowns. Based on data from a number of distinct product types, they approximate an average takeoff at 21% of market potential adoption (if an approximately symmetric diffusion curve is assumed). Ref. (Phillips, 2007) deals specifically with resistance to change in behaviour (and thus to product adoption), based on the Bass model. This results in a 'tipping point' which is typically close, but not necessary equal, to the maximum change in adoption numbers in a time interval.

Alternatively, Ref. (Mathur et al., 2007) proposes a threshold at the point of maximum acceleration in adoption for a particular process, with a similar approach taken in Refs. (Stremersch and Tellis, 2004; Tellis et al., 2003). We note that this is the same division as Ref. (Mahajan et al., 1990) proposed, although their division was generally applicable across all adoption curves, while Ref. (Mathur et al., 2007) considers this should be calculated uniquely for each process. Ref. (Kartha et al., 2005) focuses on carbon reducing innovations with thresholds determined by the proportion of the potential population (the market) that has adopted a practice. An example of this approach is the recently developed stepwise approach of the Clean Development Mechanism (Anon., 2011) for common practice assessments, which includes a 20% threshold adoption level that was defined during the signing of the Marrakesh Accords in 2001 (pers. comm. Axel Michaelowa). However, no clear analysis was found in the documentation to underpin this 20% threshold. In contrast, Ref. (Kartha et al., 2005) suggests a generic threshold of 2–10%, which is considerably

lower than the proposed divisions of Refs. (Mahajan et al., 1995; Rogers, 1983) and the Clean Development Mechanism (CDM).

Ref. (Phillips, 2007) suggests a different approach to defining a threshold, based on distinct mechanisms of adoption. He proposes that the point at which the group who adopt through word-of-mouth (or imitation) equals and then exceeds the pioneer group (that is the group who adopt through innovation) is an appropriate common practice threshold. This is quantifiable (Mahajan et al., 1990), provided the probabilities of adoption are known or relevant data are available on adoption mechanisms.

Broadly, two approaches to common practice threshold definition emerge: the first is a threshold based on a fixed market penetration, or proportion of adoption; and the second is calculated from an assumed adoption curve, or a data series, and is unique to a practice. The former requires an estimate of market potential and a defined fixed threshold – it is simple to calculate with few data. Alternatively, the latter may not require a market potential, but would require data sufficient to predict the threshold. The latter has the advantage of being specific to a practice, but, with few data, parameter and/or threshold estimation can be uncertain.

Clearly, there are many other possible threshold definitions, including those based on the number of producers of the technology/product (Agarwal and Bayus, 2002; Gort and Klepper, 1982), or culture and/or economics could determine adoption patterns (Higgins et al., 2011; Stremersch and Tellis, 2004). However, these have extensive data requirements, and are thus less appropriate for standardised approaches and not considered further here.

To assess approaches to common practice threshold determination in our analysis below, we draw on this review and compare results from a variety of models to establish commonalities.

2.2. Diffusion processes and the Bass model

Numerous modelling approaches have been applied to practice or product diffusion processes, leading to a plethora of models, each with a different purpose. Ref. (Rogers, 1983) provides an extensive description of the general theory, and for a comprehensive review of models see, for example, Refs. (Mahajan et al., 1995, 2000; Meade, 1984; Meade and Islam, 1995, 2006; Peres et al., 2010; Usha Rao and Kishore, 2010). Models are based on the premise that new products are not adopted by all individuals at the same time, but that over an extended period individuals adopt them for a number of reasons including financial, social and political. For a general process overview see Ref. (Dosi, 1991).

Following decades of research, the main modifications since the 1970s include economic marketing variables, international diffusion processes and successive generations of technologies (Meade and Islam, 2006), as well as social structures, networks and spatial characteristics (Emmanouilides and Davies, 2007). However, forecasting remains complex and uncertain.

The most widely applied models are based on the Bass model (Bass, 1969) (Appendix A):

$$\frac{dY(t)}{dt} = \left(p + \frac{q}{m}Y(t)\right)(m - Y(t)), \tag{1}$$

where $Y(t)$ is a cumulative representation of those who have adopted a practice at time t, m is the total population who could adopt the practice (the market potential), and p and q are parameters associated with distinct adoption mechanisms (described below). This model has been shown to provide a very good empirical generalisation for the diffusion of new products (Bass et al., 1994; Mahajan et al., 1995; Meade and Islam, 1995; van den Bulte and Lilien, 1997), and is the most widely used underlying model in diffusion research (Higgins et al., 2011, 2012, 2014; Meade and Islam, 2006; Park et al., 2011; Tsai et al., 2010; Usha Rao and Kishore, 2010). The cumulative proportion of the population that has adopted a practice or product follows the standard S-curve (consistent across innovations (Dosi, 1991)), but explicitly includes two mechanisms for adoption that have been shown to be the key adoption drivers (Emmanouilides and Davies, 2007): that of innovation, or adoption caused by external factors such as research and promotion (parameter p), and that of imitation, or adoption caused by internal factors such as the number who have already adopted the practice (parameter q).

The generalised Bass model introduces a further time-dependent marketing effect that includes price and advertising (Bass et al., 1994; Meade and Islam, 2006; Park et al., 2011) (Appendix A). While this provides greater flexibility, it also introduces further parameters as well as time-dependent functions defining price and marketing effort rates of change. Its effect is to modify the diffusion structure in time, incorporating time-dependent delays in adoption. Since the standard Bass model works well without market-effects, the generalised model is formulated such that, when price and effort rates of change are approximately constant over the appropriate time period, it simplifies to the standard Bass model (Bass et al., 1994).

Our focus here is on general diffusion characteristics for the adoption of new practices, with few data from which to forecast. Thus, while acknowledging the standard Bass model is relatively simple, it nevertheless underlies the majority of more complex models (Heinz et al., 2013; Higgins et al., 2011, 2012, 2014; Meade and Islam, 2006; Park et al., 2011; Tang et al., 2013; Tsai et al., 2010; Usha Rao and Kishore, 2010), it incorporates explicitly the key adoption drivers (Emmanouilides and Davies, 2007), it has been shown to provide a good fit to a wide variety of diffusion processes (Bass et al., 1994; Meade and Islam, 1995), and has been found to be one of the most accurate for forecasting (Meade and Islam, 1995). Ref. (Meade and Islam, 1995) considered 17 different diffusion models and found that, in general, model complexity did not improve forecasting performance, with the Bass model superior to all others in this regard. We note that this level of performance occurs even though prices may vary with time, as is likely in many applications.

For these reasons we have undertaken our analysis concerning additionality (determining the proportion of adoption attributable to an incentive scheme) using the Bass model, with the aim of establishing general characteristics relevant for policy. However, we note that similar analytical methods could be applied to any other model if deemed more appropriate than the Bass model.

3. Methods and results

Our purpose is the determination of appropriate and practical tools to establish common practice and additionality that can be applied across a wide range of practices and thus

inform standardised assessments. The analyses we undertake to achieve this are as follows. First we establish a reasonable means of determining whether a practice may be deemed 'common practice' (Section 1). We do not develop a new mathematical measure, but assess quantitative and qualitative approaches from the literature and suggest a practical measure, showing that it embodies many of these more complex methods and provides very similar results. Second we establish a reasonable means of determining additionality – that is, an estimate for the proportion of practice adoption under an incentive scheme that could be attributed to that scheme (Sections 2 and 3). In this case we use sensitivity analysis to propose a new quantitative approach. Our motivation is a standardised measure, so we consider a number of different modelling approaches to including incentive schemes and identify commonalities. Such commonalities are clearly evident, and suggest a practical means of assessing additionality that is valid for a very broad range of practices. And third we establish a reasonable means of determining how incentive schemes can contribute to meeting long-term emission reduction targets within fixed timeframes (Section 4). These results follow naturally from the former two analyses.

3.1. Common practice threshold determination

Our purpose is to determine an appropriate common practice threshold by comparing methods proposed in the literature (Section 1). This is not necessarily a threshold beyond which the innovation 'takes off' without doubt. Rather, we seek a standardised means of distinguishing early or innovative adoption from common practice based on approaches in the literature, which is reasonably robust across practices, and which is practical to implement.

Section 1, summarised in Table 1, identifies methods for calculating thresholds that are unique to an application, and thus without specific values (Table 1 Thresholds I and III). We now use models and a sensitivity analysis to determine how these methods compare with the others listed in the table. Using the Bass model (Eq. (1)), we compare three approaches for determining a threshold: the point of maximum rate of adoption increase (Threshold I), a constant threshold based on the proportion of the market potential that has adopted a practice (Threshold II), and the point at which 'imitators' (that is, those who adopt as a result of internal influences such as word-of-mouth) exceed 'innovators' (that is, those who adopt as a result of external influences such as research and promotion) (Threshold III).

Fig. 2(a) illustrates an example adoption curve for the Bass model with the three thresholds, while (b), for the same example, distinguishes between adoption curves for innovators and imitators. The parameter values used are the average values calculated from an extensive range of product adoption processes (Sultan et al., 1990). We note that these parameter values derive from 213 different innovations adopted over a 40 year period, and they serve to illustrate the dynamics. However, throughout this paper we consider full plausible ranges for each value, based on a far wider review of the literature, to expose the nonlinear interactions and general dynamics.

Fig. 3(a) illustrates how parameter variation in the Bass model affects the thresholds illustrated in Fig. 2, where plausible parameter ranges are taken from the literature with $0 < p \leq 0.03$ and $0.1 < q < 1$ (Heinz et al., 2013; Higgins et al., 2011; Mahajan et al., 1995; Park et al., 2011; Sultan et al., 1990). This figure provides an understanding of how parameters interact and impact on the 3 thresholds, and thus the appropriateness of each threshold is more easily assessed. We note that Thresholds I and III are not always defined within plausible parameter intervals (e.g. for $q < p$).

Although Threshold III (for which innovators are exceeded by imitators) is mooted in Ref. (Phillips, 2007) as an option for a common practice threshold, its high variability within these parameter intervals, together with the range of plausible parameters for which it is not defined, suggests that this threshold is not robust across innovations and is not a reliable candidate for standardised threshold determination. It would be possible to use it in conjunction with other thresholds, but it is not considered further in this paper.

For Threshold I, these results (for the Bass model) expose an upper bound – that is, as $q \leq 1$ increases and $p \geq 0$ decreases, the threshold approaches 21%. To provide further generality concerning this upper bound, Fig. 3(b) compares Threshold I (maximum acceleration in adoption increase) across a number of alternative models that have been applied to agricultural and energy efficiency practices in the literature (that is, the logistic, Stanford and Gompertz models, with equations provided in, for example, Ref. (Mahajan et al., 1990)). What is notable, and can be shown theoretically, is that for a number of appropriate diffusion models, Threshold I is bounded above by the threshold for the logistic equation – adoption proportion $(2-\sqrt{3})/(3-\sqrt{3}) \approx 0.21$. It is clear that, for considerable parameter ranges, an adoption proportion of between 0.15 and 0.2 is a reasonable approximation to this threshold, and when the innovation parameter is small (p of the order 10^{-3}), the threshold approaches 0.2, approximately, for the full range of imitation parameter values (q) in the Bass model.

The Gompertz model has a maximum rate of adoption increase (Threshold I) of below 10 %, which agrees (approximately) with Ref. (Kartha et al., 2005), although this model is more appropriate for demand forecasting of technologies than practice diffusion (Usha Rao and Kishore, 2010). Models such as the von Bertalanffy and Nelder models (Mahajan et al., 1990; Nelder, 1962; Richards, 1959; von Bertalanffy, 1957), are flexible in that parameters are not necessarily mechanistic, but determine symmetries and inflection points directly, and thus they would not be expected to converge over parameter ranges (Usha Rao and Kishore, 2010). For these models, the threshold can exceed 0.21. Thus we note that not all parameter combinations and models have this threshold in the 15–20% range. However, the mechanistic models (Bass, logistic and Stanford), do conform to this interval.

In summary, Fig. 3 illustrates that for considerable parameter ranges (not just the 'average' case), and for a number of fundamental diffusion models with mechanistic parameters, this threshold measure (Threshold I) lies between 0.15 and 0.2. In particular, for the Bass model with parameter values averaged across many innovations ($p = 0.03$ and $q = 0.38$ (Sultan et al., 1990)), the proportion who have adopted is close to 15 %, while for smaller values of p as are very common in the literature (Higgins et al., 2011; Horsky and Simon, 1983; Kohli et al., 1999; Norton and Bass, 1987; Teng et al., 2002; Woodhams et al., 2012), this threshold approaches 20 % (approximately). This

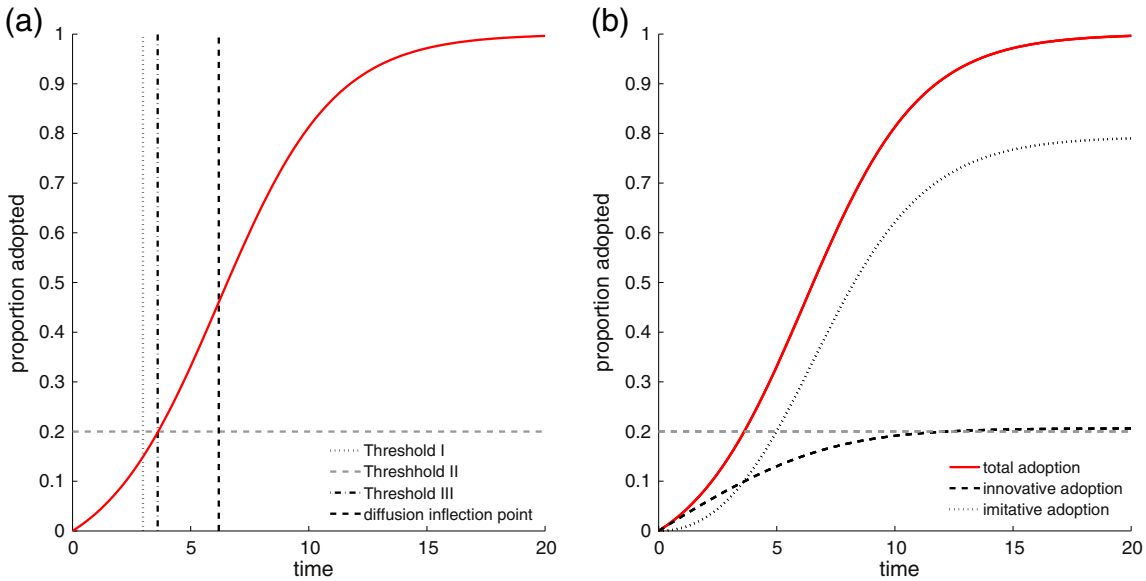

Fig. 2. The red curves illustrate the diffusion curve for the standard Bass model (Eq. (1)) with parameter values $p = 0.03$, $q = 0.38$, and $m = 1$, which are average estimates from numerous diffusion curves (Sultan et al., 1990). Plot (a) illustrates the 3 thresholds considered: Threshold I is the point of maximum acceleration in adoption, Threshold II is a fixed penetration proportion of 20 %, and Threshold III is the point at which innovators are exceeded by imitators. Plot (b) illustrates the fraction of total adoption attributable to innovators and imitators in this example.

general result, based on a sensitivity analysis of the method proposed in Refs. (Mathur et al., 2007) for individual products, agrees with many of the thresholds proposed in the literature, such as Refs. (Kohli et al., 1999; Mahajan et al., 1990; Phillips, 2007; Rogers, 1983; Stremersch and Tellis, 2004; Tellis et al., 2003) and the CDM (see Table 1 and Section 1). Our results provide quantitative support for a fixed penetration proportion of, approximately, 0.2. This approximation is supported by empirical work by Ref. (Kohli et al., 1999), in an average sense by the resistance modelling work of Ref. (Phillips, 2007), the statistical approach of Ref. (Rogers, 1983), and the average of modelling work carried out by Ref. (Mahajan et al., 1990).

We note that, if a common practice threshold estimate is required in real time, that is, early in the adoption process before data are available, parameter estimation for any chosen model is likely to be uncertain and, consequently, the threshold

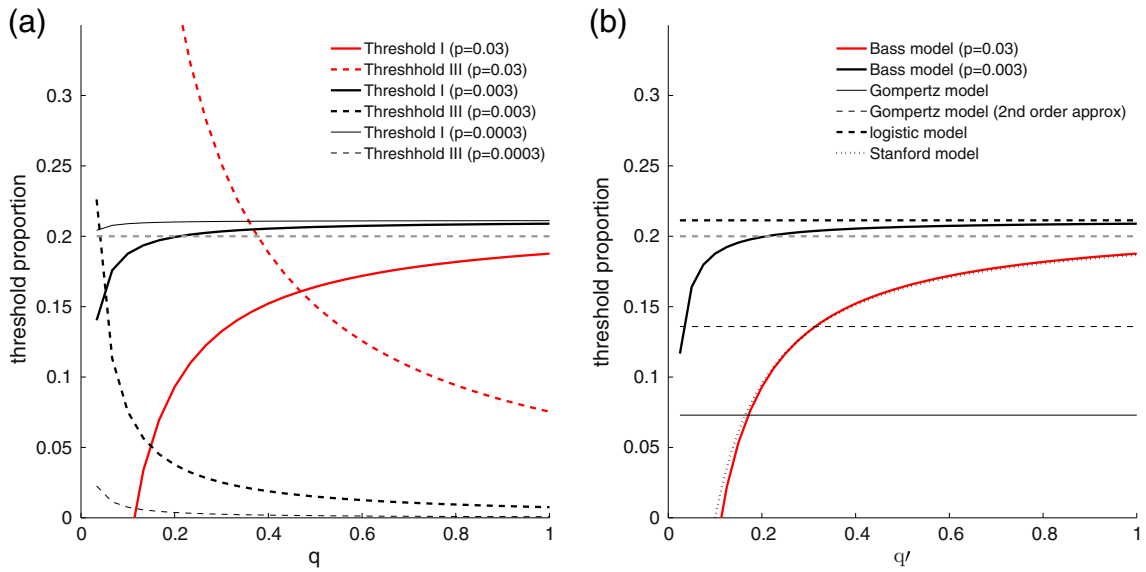

Fig. 3. (a) This figure compares the full range of Threshold I (solid curves) and Threshold III (dashed curves) for the Bass model (Eq. (1) with $m = 1$) as q varies between 0 and 1, and for p decreasing by two orders of magnitude. The grey dashed line is at adoption proportion 20%. (b) Threshold I for a number of different diffusion models are compared as the driving parameter (q') increases. The parameters are scaled for comparison purposes: for the Bass model $q = q'$, for the Gompertz model $q = q'$, for the logistic model $r = q'$, and for the Stanford model $q = 20q'$, relative to the model definitions in, for example, Ref. (Mahajan et al., 1990). The grey dashed line is at adoption proportion 20%.

will also be highly uncertain (Heeler and Hustad, 1980; Kamakura and Balasubramanian, 1987; Kohli et al., 1999; Mahajan et al., 1986; Meade and Islam, 2006; Srinivasan and Mason, 1986; Woodhams et al., 2012). Several studies of the sensitivity of the parameters in the Bass model indicate that estimates using data early in the adoption process can be unstable unless the period over which estimates are made extends past the maximum rate of increase in number of adopters (Srinivasan and Mason, 1986). Fig. 4 provides an illustration of this uncertainty in parameter estimation for three case studies, all of which have uncertain values well beyond the point of maximum rate of acceleration in adoption. Similar uncertainties were observed when estimating Threshold I using the method from Ref. (Mathur et al., 2007).

For the remainder of this paper, where a threshold for common practice is applied, we will apply a 20% threshold. However, the same methods could be applied with any alternative threshold where that is considered more appropriate.

3.2. Incentive schemes and additionality

We now turn our attention to the assessment criterion of additionality as defined in Section 1. Additionality assessments require the determination of adoption that can be attributed to an incentive scheme, and would not have occurred under BAU. Our purpose is to expose generic properties concerning the impact of incentive schemes on adoption, that are robust across innovations and enable a general understanding. The aim is to estimate the proportion of BAU abatement since, for offset schemes with this criterion of additionality, adoption that is additional to BAU is eligible for tradable credits. We achieve this through a sensitivity analysis of the Bass model, drawing on the literature to establish how incentive schemes are likely to alter the model parameters.

The impact of promotional schemes on diffusion may be considerable (Greene et al., 2005; Guidolin and Mortarino, 2010; Higgins and Foliente, 2013; Higgins et al., 2011, 2014; Islam, 2014; Kalish and Lilien, 1983; Tang et al., 2013), and there are many examples for which advertising, promotion and government incentives have been incorporated into the Bass model. Which approach best incorporates an incentive scheme, however, is unclear and the resulting dynamics difficult to quantify precisely (Higgins and Foliente, 2013; Higgins et al., 2011; Horsky and Mate, 1988; Islam, 2014; Kamakura and Balasubramanian, 1988). Thus we compare a number of approaches that have been taken in the literature, and define measures with the purpose of distinguishing (as far as possible) the proportion of adoption due to the incentive. We acknowledge that it is possible that adoption *only* occurs with an incentive, in which case there is no adoption under BAU and all adoption is attributable to the scheme.

The literature suggests that incentives/costs may affect innovative adoption through an increase in p (Dockner and Jørgensen, 1988; Fleming et al.; Heinz et al., 2013; Horsky and Mate, 1988; Horsky and Simon, 1983; Islam, 2014; Kalish, 1985; Kamakura and Balasubramanian, 1988; Norton and Bass, 1987; Phillips, 2007; Simon and Sebastian, 1987), they may impact on both innovative and imitative adoption through variation in p *and* q (Bass et al., 1994; Dalla Valle and Furlan, 2011; Dockner and Jørgensen, 1988; Islam, 2014; Kalish, 1985; Kalish and Lilien, 1983; Kamakura and Balasubramanian, 1988; Robinson and Lakhani, 1975; Simon and Sebastian, 1987), and/or increase the potential market m (Bass et al., 1994; Dockner and Jørgensen, 1988; Higgins et al., 2011; Higgins et al., 2014; Horsky, 1990; Islam, 2014; Jain and Rao, 1990; Kalish, 1985; Kamakura and Balasubramanian, 1988; Mahajan and Peterson, 1995; Talukdar et al., 2002). Motivation in many of the above cited papers was to model the impact of precise mechanisms

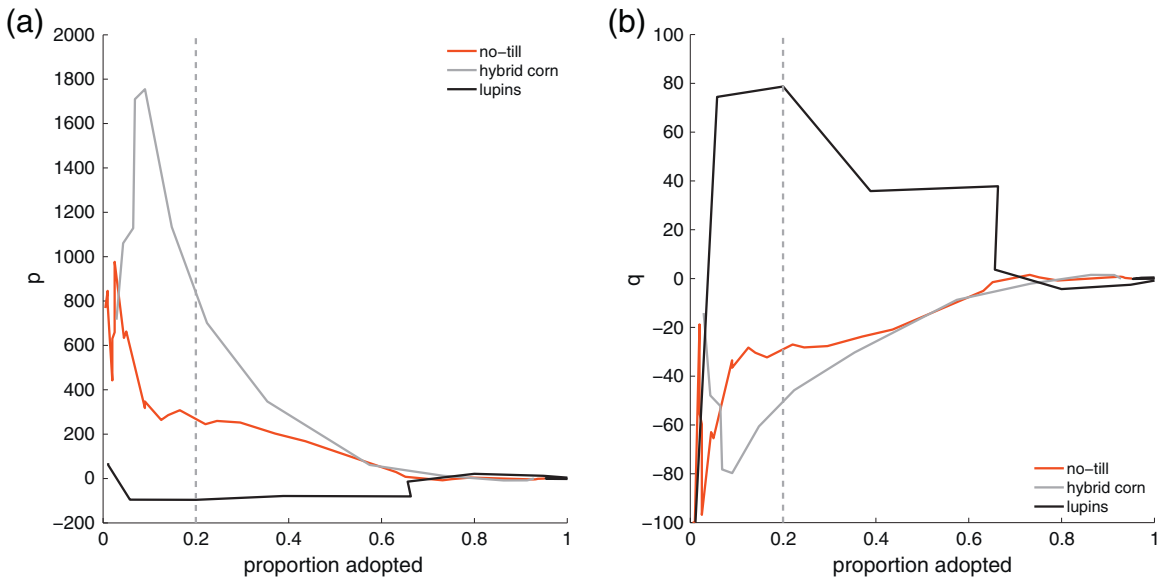

Fig. 4. The error in Bass model parameter estimates of p (plot (a)) and q (plot (b)) as the proportion adopted (and thus available data) increases (x-axis). Errors (y-axis) are expressed as the percent deviation relative to estimates with the full dataset. Model parameters are fitted to three adoption datasets; no-till cultivation practices in Western Australia Marsh et al., 2000, hybrid corn uptake in America (Rogers, 1983), and farming lupins in Western Australia (Llewellyn and D'emDen, 2010), using the non-linear least squares parameter estimation method. The dashed vertical lines show when 0.2 of the population have adopted the innovation. (Results are for the standard Bass model.)

for specific applications. However, our motivation differs. We are interested in how measures of additionality and practice adoption might change in a general sense as these parameters vary. Fig. 5 illustrates general characteristics of the impact of variation in each of these parameters (p, q and m) on the diffusion curve, and will be discussed below. Although provided for a single example, these results illustrate the general qualitative changes. In summary, for the Bass model, if incentives increase the market potential (m) alone, then early adoption increases only marginally. Alternatively, if innovative adoption (p) increases due to promotion, then early adoption increases, amplifying the effect of early imitative adoption and/or increased market potential. Innovative adoption is the driver of early adoption while imitative adoption and increased market potential have greater impact during the intermediate and later stages of the diffusion process, respectively (Eqs. (A.1) and (A.3), and Fig. 5). We consider it likely that with an incentive all three parameters vary to some degree.

The academic literature and the advertising business are testament to the claim that promotions and/or cost reductions can increase the rate of adoption of new technologies, products and practices in a significant way. However, as discussed above the precise formulation for incentive inclusion is uncertain and inconsistent. Government incentives are often financial with promotions through advertising and direct household communication (external influences), but may also include social events where consumers can interact, such as field days in rural settings (internal influences). Thus it is plausible that p (and m) are increased most from these types of promotional schemes, but that q (and m) are also affected. Since others disagree with this view (Refs. (Higgins et al., 2011; Jain and Rao, 1990) for example), and since all products/practices are not necessarily suited to one paradigm, sensitivity analyses for a number of distinct formulations for including the impact of incentives into the Bass model have been provided below for comparison.

3.3. Additionality determination

We examine the distinct modelling approaches to including the effect of incentives discussed above, with the purpose of revealing general characteristics that can contribute to standardised additionality assessments. For assessment purposes, we consider the impact of incentives on adoption before a common practice threshold is reached to estimate adoption that is additional to BAU in this interval. To this end we define a measure for the increase in total adoption of a practice relative to BAU, *during the period for which an incentive is in place* (similar to that suggested, but not implemented, in Ref. (Simon and Sebastian, 1987)). Fig. 6 provides an illustrative example of the characteristic differences between diffusion curves with and without incentives, and with an imposed fixed threshold of 20% adoption at which point the incentive ceases. This example assumes that an incentive increases innovative adoption (p), and we use the areas between these curves as a basis for defining a measure of increased adoption, in an average sense and over the specified time period, and we 'remove' the effect of time by examining changes relative to BAU (Appendix B). It is uncertain how the probability of adoption might vary when the incentive is removed, although the 'true' curve is likely to lie between the red (parameters revert to BAU) and dashed black lines (parameters remain increased). Fig. 6(c) illustrates an interesting, although predictable, scenario. With these parameters, even though the parameter reverts to the BAU case, the diffusion curve has sufficient 'momentum' and tracks the case for which parameters are unchanged (dashed line).

We now compare the distinct modelling approaches in terms of a determination of adoption proportion attributable to

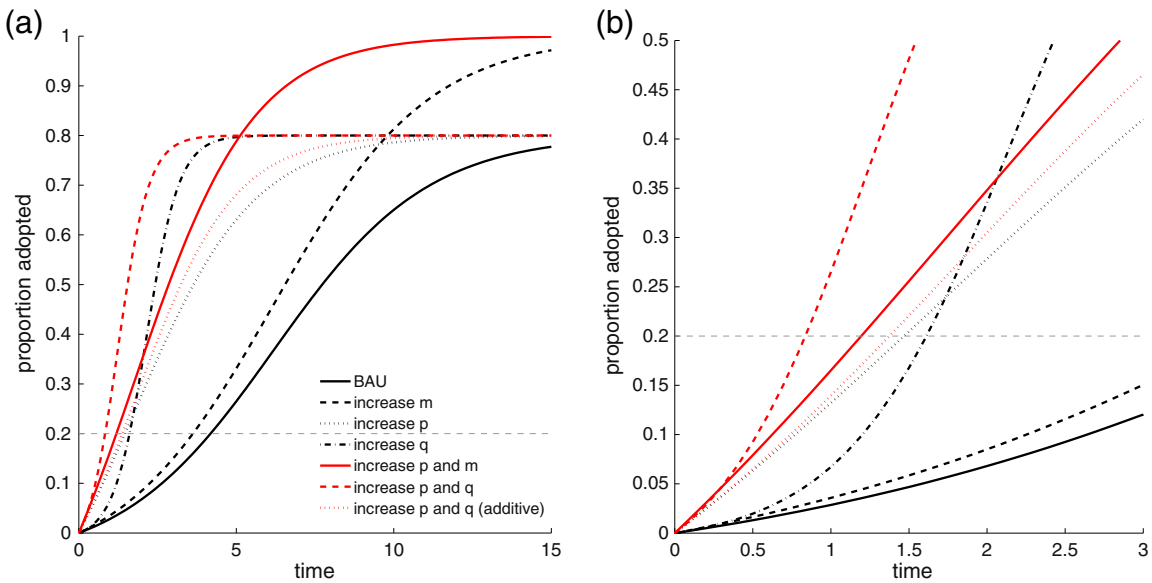

Fig. 5. (a) The impacts of increasing m, p and/or q on the diffusion curve are illustrated using the underlying BAU parameter values of $p = 0.03$ and $q = 0.38$ (average values from Ref. (Sultan et al., 1990)). Increases in p and q are by a factor of 5 (or by a fixed amount in the 'additive' case), and in the case m increases it is by 25 %. The plot in (b) provides a detail from (a). (Results are for the standard Bass model.)

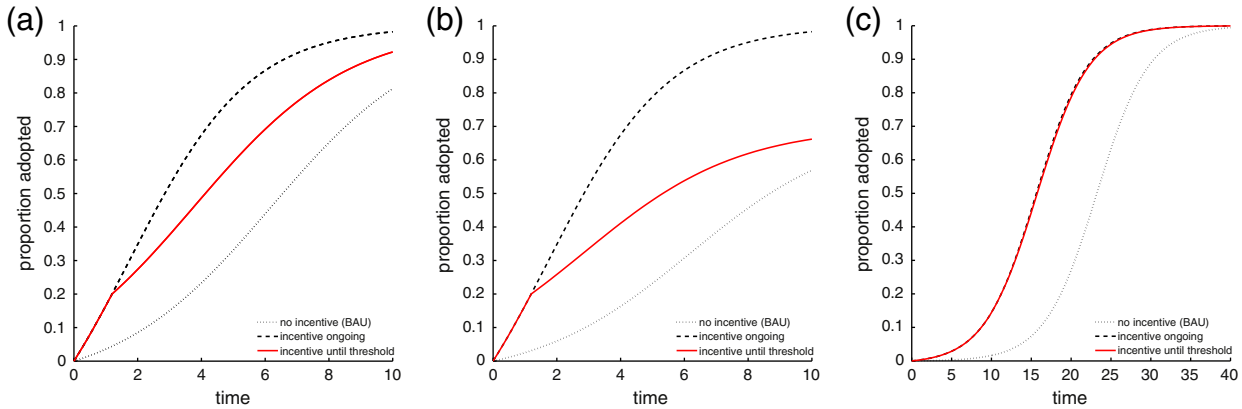

Fig. 6. Illustrative examples of the impact of an incentive, implemented for a fixed period, on the diffusion curve. The black dashed line is the case in which the incentive (and increased parameter values) continues through time; the red curve illustrates the case where the incentive ceases at the threshold, and the parameter values revert to those of BAU; and the black dotted line represents BAU. For (a) $q = 0.38$, $p = 0.03$ for the BAU case (Sultan et al., 1990), an incentive increases p by a factor of 5, and the common practice threshold is at 20 %. The plot in (b) is as for (a), but with m reduced by 30 % in the BAU case. And (c) is as for (a), but with BAU parameters $q = 0.306$, $p = 0.000249$ and with the incentive increasing p by a factor of 10. (Results are for the standard Bass model.)

an incentive as distinct from BAU, with a view to exposing common characteristics.

3.3.1. Incentives increase innovative adoption (p)

First we consider the case in which promotion, through advertising and/or incentive, affects only rates of innovative adoption – that is, parameter p. This model is likely to be most valid in the early stages of the adoption process, when innovators affect diffusion most, and is particularly relevant when adoption is of new (innovative) technologies (Dockner and Jørgensen, 1988; Simon and Sebastian, 1987). This can be deduced from the conditional adoption probability (Appendix A), which also determines how increases in p amplify the effect of q (and m). Fig. 5 clearly illustrates the impact of increasing innovative adoption on early uptake (before the threshold is reached), relative to variation in other parameter values. Ref. (Kamakura and Balasubramanian, 1988) argues that if promotion with financial incentives focusses on advertising, communication, household drops and presentations, then innovative adoption rates vary most.

Fig. 7 illustrates the proportion of adoption due to the promotion alone, in an average sense and within the period of promotion, when p increases (through increased promotional effort) by the factor given on the x–axis (measure Appendix B (1)). With total potential adoption (m) unchanged with the incentive (solid line), the proportion due to promotion alone is approximately constant for a factor above 5. Our results demonstrate that small changes in incentives can be effective in increasing adoption in a significant way – although once increased, further promotional effort has relatively little effect. But what is particularly notable is that the results in Fig. 7 are independent, approximately, of the BAU values for p and q within their respective plausible ranges, and therefore robust across all practices (measure Appendix B(1) simplifies to $\approx (1 - 1/\text{factor})$).

These results suggest that, if an incentive increases parameter p by a factor greater than 5, then regardless of the underlying (BAU) values for p and q, approximately 10–15% of adoption before the threshold is reached is attributable to the BAU scenario. And, the greater the increase in market potential due to the incentive (equivalently, smaller m for BAU), the proportion attributable to BAU declines (dashed and dotted curves in Fig. (7)).

To validate factors above 5 (approximately) for increases in p caused by an incentive, plausible values have been estimated from the literature, although clear data are scarce. Ref. (Horsky and Simon, 1983) formulates p directly as a function of advertising effort, $p \approx a + b\ ln(A)$, where a and b are parameters established empirically and A is expenditure or,

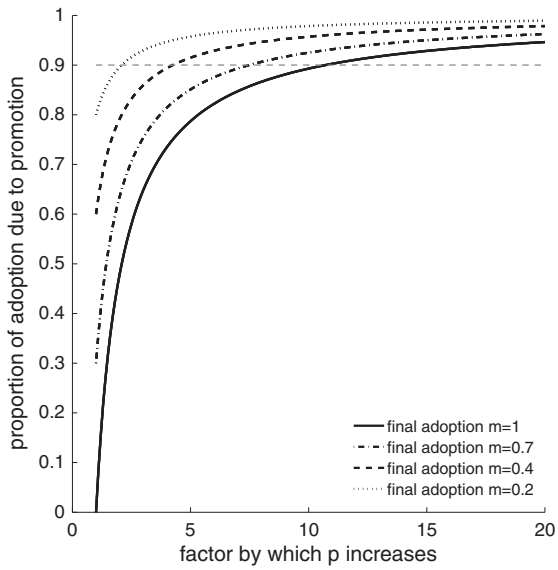

Fig. 7. The curves (Appendix B(1)) illustrate the proportion of total adoption, over the period before the common practice threshold is reached, that is attributable to the incentive as p increases by the factor given on the x-axis. The solid curve has no change in market potential, while the other 3 curves show results for which both p and m increase with the incentive. The horizontal line (grey dashed) at 0.9 is given for comparison. (Results are for the standard Bass model.)

equivalently, promotional effort. On average, for the 5 examples in that paper, advertising increases p by a factor of 9, approximately. Ref. (Horsky and Mate, 1988) reports expenditure increases that, when substituted into the model of Ref. (Horsky and Simon, 1983), lead to an average factor above 10. Ref. (Bass et al., 1994) considers a model in which both p and q vary with price reduction and advertising. Using 'back of the envelope' estimates, p increases by a factor far greater than 5 early in the adoption process (although incorrect positive and negative signs make estimation uncertain). Ref. (Jain and Rao, 1990) reports increases in the total probability of adoption of 40 % to 100 % (approximately); if these results are interpreted as predominantly variation in p this would equate to factors well above 5. Ref. (Dalla Valle and Furlan, 2011) applies pulse functions to model finite length incentive schemes, which increase both p and q by a factor of at least 5 in their 6 applications. When considered as an increase in p alone, these factors would be considerably larger. We acknowledge that these examples do not provide proof for increases in p of a factor above 5, however, they suggest it is reasonable.

The consequence of these results (Fig. 7) and the plausible parameter ranges from the literature discussed above, is that an assumption of 10–15% total adoption due to BAU within the 'early adoption' interval is reasonable for a diverse range of practices and promotion effort levels. Thus this estimation is especially appropriate when there is uncertainty around parameter values associated with both the BAU case and the precise impact of promotion.

3.3.2. Incentives increase the market potential (m)

Final adoption rates (market potential m) are likely to increase through government incentives and the cost of adopting a practice (Greene et al., 2005; Higgins et al., 2011; Jain and Rao, 1990; Kalish, 1985). A number of authors consider incentives and cost reductions to impact *only* on the market potential, and not on the innovation and imitation parameters (Higgins et al., 2011; Jain and Rao, 1990). We note that adoption at any time t increases in the same proportion as the market potential m (Eq. (A.2)), and Fig. 5 illustrates, for increased m, only marginal increases in adoption during the early stages of diffusion when compared with later adoption.

From the literature, we estimate plausible changes in market potential as a result of an incentive. Ref. (Higgins et al., 2011) proposes a time dependent function for variation in m, based on costs and rebate benefits, as well as demographics, for the adoption of emission reducing technologies (solar panels and hot water heaters). They estimate that government incentives (promotion) increased the market potential for solar panels by close to 60% and solar hot-water heaters by close to 75% (although their values vary with time), while, with an alternative approach, these increases are approximately 100% and 500%, respectively, over a 10 year period (Higgins and Foliente, 2013). We note that these figures do not necessarily reflect total final adoption, which is likely to be lower. For the adoption of electric cars, Ref. (Higgins et al., 2012) projects market share increases of between 10% and 80%, depending on vehicle type and promotion/rebate strategy, and Ref. (Greene et al., 2005) reports increases in vehicle energy efficiency of up to 60% with 'Feebates and Rebates'. For a variety of standard products, Ref. Jain and Rao, 1990 reports increases in total adoption of 25–50% (approximately) as a result of promotion, relative to BAU. The Bass models applied in our analysis do not include time dependence in market potential, thus we use the ranges cited above to estimate a plausible interval for m (the proportion of final BAU adoption relative to the case with an incentive) of $0.5 \leq m \leq 1$.

We have considered two scenarios for increases in market potential due to incentives: the case in which both innovative adoption and market potential (p and m) are altered through promotion, and the case in which *only* the market potential (m) varies. The former scenario is illustrated in Fig. 7 where the dashed lines are provided for three alternative BAU market populations. As before, the results are the same for all underlying BAU values of p and q (within the ranges considered).

Alternatively, the latter scenario is illustrated in Fig. 8. The case in which *only* market potential (m) varies with the promotion, measure Appendix B(1) simplifies to *1-m* and is illustrated with a solid line. If incentives vary the probability of innovative adoption (p), *as well as* the market potential, then the increase in adoption attributable to the scheme is considerably increased (dashed and dotted lines), relative to the case when only market potential varies (solid line).

It follows that if the implementation of an incentive increases the market potential alone, the proportion of adoption attributable to the scheme increases linearly, but is likely to be below 40% for a 50% increase in market potential (Fig. 8). However, from the literature (Ref. (Higgins and Foliente, 2013) and Fig. 5), this case is unlikely – it is more likely that the conditional probability of adoption also increases. In this case, if the probability of innovative adoption (parameter p) increases, even by marginal amounts (factors below 2), an estimate of 5–10% of adoption attributable to BAU is very reasonable for a diverse range of practices and promotion effort levels (Fig. 7), it remains constant (approximately) for higher factors, and it declines as the effect of the incentive on market potential increases.

3.3.3. Incentives increase innovative and imitative adoption (p and q)

Promotional schemes could impact on both innovative and imitative adoption rates, or, equivalently, increase the effect of the conditional adoption probability. Ref. (Dalla Valle and Furlan, 2011), for example, uses this approach with the Bass model to establish the impact of government incentives on the adoption of wind power technologies, while Ref. (Heinz et al., 2013) examines the promotion of the hydrogen economy. Ref. (Kamakura and Balasubramanian, 1988) reports (for 6 products and 12 models), that the best fit to price reduction effects did not include increased market potential but, consistently, the impact was only on the probability of adoption (that is, on the conditional probability $p + qy(t)$, Appendix A). Refs. (Dockner and Jørgensen, 1988; Simon and Sebastian, 1987) suggest that variation in q best describes innovations/practices in their intermediate stages of adoption, as illustrated in Fig. 5. Ref. (Islam, 2014) establishes ideological, social and economic drivers that impact imitative adoption for solar cells; however, Ref. (van den Bulte, 2004) highlights that the mechanisms underlying 'contagion' are difficult to define, that there is skepticism about its importance, and that heterogeneity in propensity to adopt can underlie the diffusion S-curve. He concludes that higher income distribution leads to increased

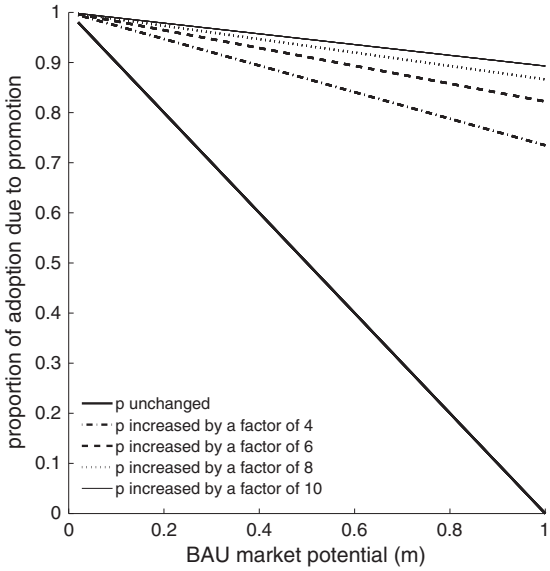

Fig. 8. The lines illustrate the proportion of total adoption, over the period before the common practice threshold is reached, that is attributable to an incentive (Appendix B(1)) as the effect on market potential increases. Each line has $p = 0.03 \times$ factor and $q = 0.4$ fixed, and m for the BAU case increasing from zero to one on the x-axis. The solid line illustrates the case for which only m increases – when the measure reduces to 1-m. Other lines have p increased by the factor given in the legend. (Results are for the standard Bass model.)

q/p, and a steeper diffusion curve , so that an incentive, which effectively increases the income distribution for that product, is likely to 'increase' q.

We apply the Generalised Bass model (Appendix A). Note that, although the market-effect ($\gamma(t)$ in Eq. (4)) can be viewed as a means of shifting the hazard function (that is, the conditional probability of adoption at time t) (Bass et al., 1994), and not *changing* p and q but rather the shape and temporal structure of diffusion (Guidolin and Mortarino, 2010), it is also plausible that the probability an individual adopts a practice (or buys a product) is increased directly with a rebate (or sale) – with p and q the associated parameters. Nevertheless, mathematically the two concepts are equivalent and thus the results below hold regardless of the interpretation. It is important to note that for the latter view the conditional probability must, by definition, remain less than one.

For specific products or practices, price and advertising variations may be available; however, we consider here a constant value for $\gamma(t)$, with $\gamma(t) = c$ and c dependent on an, approximately, fixed price change (rebate or tax penalty) and an, approximately, fixed promotional effort. The rationale for a constant term is that, in general, incentives or government promotions offer a fixed rebate, reduced price, or extra cost for non-compliance, for a fixed period, while also widely promoting the scheme. While not inclusive of time-dependent processes, our results provide bounds on measures for the proportion of adoption attributable to BAU that are appropriate for cases in which price and advertising effort may be highly variable.

Fig. 9(a) shows the proportion of adoption attributable to a promotional scheme (measure Appendix B(2)) as c increases (solid lines), and how this varies with changes in the underlying BAU value for q, with p for the BAU case unchanged. It is evident that the results are marginally dependent on this variation. Fig. 9(b) is as for Fig. 9(a), except that variation in BAU values for p is examined, with q for the BAU case unchanged. In this case, as p decreases, so the proportion attributable to BAU declines, with the greatest difference for smaller factors of c ($c < 5$, approximately). These results illustrate that there is little change as the underlying BAU value of q varies (in the plausible range), but much greater change as the BAU value of p varies (in its plausible range). Nevertheless, the results remain similar qualitatively, and estimates of 10% or less for the proportion of adoption attributable to BAU remain reasonable for $c > 5$.

Plausible values for $\gamma(t) = c$ have been calculated in Ref. (Bass et al., 1994) for three products, with estimates of $c \approx 2.1$, $c \approx 26.6$ and $c \approx 8.6$, with price reductions of 37%, 17% and 13%, respectively, and considerable effort in product promotion. Although these values are rough estimates at best, since fitting procedures were not constrained, they provide an indication as to plausible values for c and, consequently, plausible values for the proportion of adoption attributable to BAU.

Finally, we consider the case when including an incentive increases p and q by *different* factors (Fig. 5, red dotted line). Ref. (Bass et al., 1994) considered a model with price reductions (incentives) influencing the innovative and imitative adoption parameters differently. In their exploration of 7 models, this formulation provided the best fit (outperforming, or equivalent to, other models in all three of their case studies). We illustrate the general characteristics in Fig. 9(c), where we assume that both p and q increase with an incentive, but at different rates. Clearly, when variation in q is very small, results converge to those of Fig. 7; while, as variation in q increases, results approach those of Fig. 9(a) and (b). What Fig. 9(c) provides, is some understanding of the nonlinear manner in which this change occurs when there is variation in the underlying BAU value for p. In the case of variation in the underlying BAU value for q, the differences are very small and are thus not illustrated.

Three main results emerge from the above approach: if the factor by which innovative adoption (p) increases is above 5 (approximately), regardless of changes in q, then attributing 10–15% of adoption over the period of incentives to BAU is reasonable, or is an overestimate when p is particularly small (Fig. 9(b)); for very small values of p in the BAU case, small changes in incentives can produce considerable increases in adoption, relative to BAU (Fig. 9(b)); and if the effect of incentives on q is small relative to the impact on p (by an order of magnitude), then Fig. 7 provides a reasonable estimate of the proportion of adoption attributable to the promotion (Fig. 9(c)).

3.4. Incentive schemes and long-term targets

Above we have examined the impact of schemes prior to the common practice threshold, while the incentive is in place. However, governments have made commitments for emission reductions within particular time periods, and incentive schemes contribute to these goals and could be specifically designed and timed to achieve required outcomes. Motivated by this, we compare long-term differences in adoption between

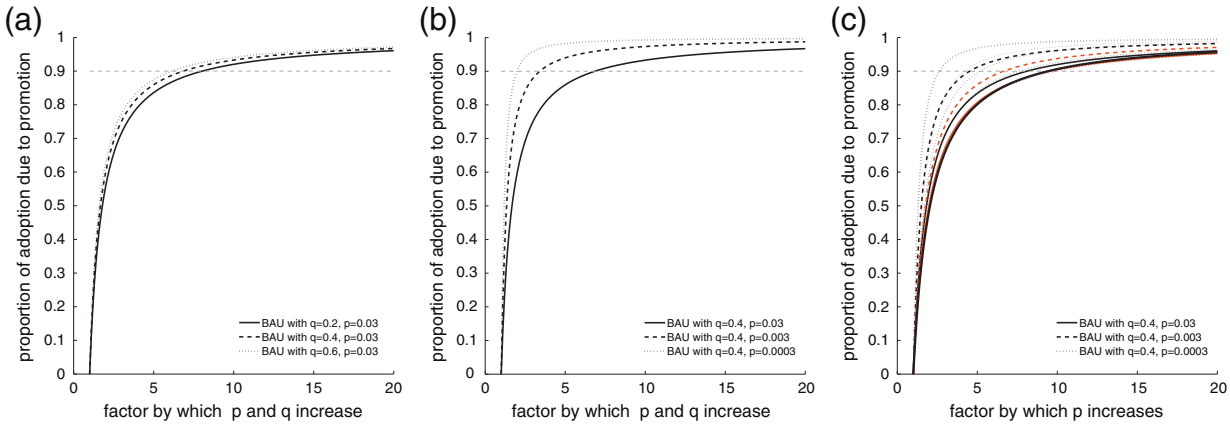

Fig. 9. The curves (Appendix B(2)) illustrate the proportion of total adoption, before the threshold is reached, that is attributable to an incentive with $m = 1$, and $\gamma(t) = c$ for the Generalised Bass model. (a) In this case the underlying BAU value of p is fixed, while q varies, although *both* p and q vary by the same factor with the incentive; (b) In this case the underlying BAU value of q is fixed, while p varies, although *both* p and q vary by the same factor with the incentive; (c) In this case the underlying BAU value of q is fixed, while p varies, but p and q are influenced *differently* by the incentive. The heavy, solid black curve represents no change in q, while the other black curves have $p \to cp$ and $q \to q(1 + (c - 1)/2)$, red curves have $p \to cp$ and $q \to q(1 + (c - 1)/6)$, and the fine curves have $p \to cp$ and $q \to q(1 + q(c - 1)/10)$. The dashed grey line at 0.9 is provided for comparison.

BAU, the implementation of an incentive scheme that ends at a common practice threshold, and the case of an on-going incentive.

Fig. 10 illustrates the proportion of total adoption until 50% adoption in the BAU case (t = 0 to $t = T_{BAU50}$), that is attributable to a promotion with a 20% common practice threshold (solid curves), and with an ongoing incentive (dashed curves) (measure Appendix B(3)). Results are given for three distinct examples that provide an informative range of values for p and q – one example uses averages across a vast range of product adoptions, one is for a farming practice, and one is for the adoption of solar water heaters. For Fig. 10(a) and (b) we assume the incentive increases the probability of innovative adoption, and does not change imitative adoption rates, while for (c) and (d) we assume both innovative and imitative adoption rates increase with the incentive. And in (a) and (d) we assume that the incentive does not alter the potential number of adopters, while in (b) and (d) we assume this number is increased by ≈ 40 % (equivalently, $m \approx 0.7$). Note that the water heater example does not appear in (a) and (c) because the model used for parameter estimation assumes an increase in market potential (Higgins et al., 2011). For each example, the likely adoption curve lies between the solid and dashed curves since it is unknown how parameters might vary when an incentive ends.

We note that regardless of how an incentive affects the parameters of the Bass model, the proportion of adoption attributable to the scheme is above 70%, and this increases when the incentive increases market potential. However, the results are clearly dependent on the parameter values of the underlying BAU case, except when the process becomes self-sustaining with only the innovative adoption rate increased due to the incentive (dashed lines in Fig. 10(a) and (b)). (This result can be deduced similarly to that for Fig. 7.)

The range of estimates encountered for p in the literature, and particularly those that relate to agricultural and energy reducing practices, are typically well below 0.01 with the difference between p and q *at least* one order of magnitude (Dalla Valle and Furlan, 2011; Guidolin and Mortarino, 2010; Heinz et al., 2013; Higgins and Foliente, 2013; Higgins et al., 2011; Higgins et al., 2012; Lund, 2006; Marsh et al., 2000; Norton and Bass, 1987; Park et al., 2011; Talukdar et al., 2002; Teng et al., 2002; Woodhams et al., 2012). Thus we consider the above results likely to be robust for a wide range of practices.

Finally, since government targets relate directly to time ('by 2020', for example), we examine the proportional reduction in *time* for half the potential population to adopt a practice, relative to BAU. Ref. (Phillips, 2007) mentions this issue, although does not derive any general conclusions, and Ref. (van den Bulte, 2000) considers an alternative approach using diffusion speed given by the slope coefficient of the logistic model.

Fig. 11, for the same four scenarios and examples as Fig. 10, illustrates how the time taken until 50% have adopted a practice is reduced by promotion (measure Appendix B(4)). For clarity, a value of 0.6 on the y-axis implies that the time until 50% of the market potential have adopted a practice is reduced by 60%, relative to BAU. We note that, for the three examples in Fig. 11, and when the process becomes self-sustaining with both innovative and imitative adoption rates increased due to the incentive (dashed lines in Fig. 11(c) and (d)), the results are independent of the underlying parameters of the BAU case (measure simplifies to $(1 - 1/c)$).

Although these results vary quantitatively, depending on the underlying BAU parameters and model, they nevertheless illustrate that an incentive scheme is very likely to lead to considerable time reductions, of 50% or more, for adoption by half the potential population. Depending on government targets, and the time scales for the adoption of particular practices, the generic characteristics of these results (both Figs. 10 and 11) provide a means of assessing the impact of incentive schemes on emission reduction (through an increased proportion of adopters) and the achievement of targets (through the reduction in time for 50% adoption).

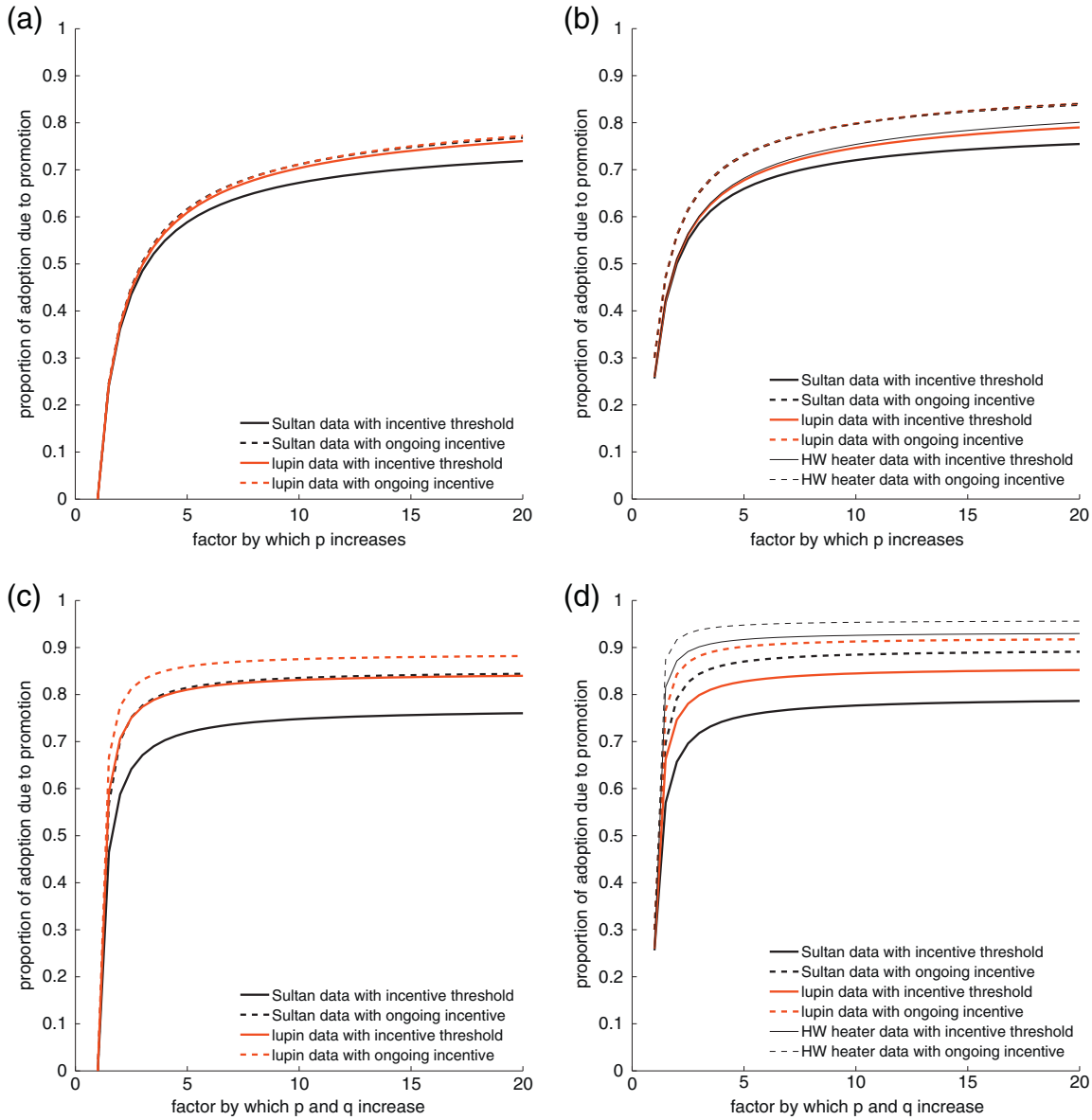

Fig. 10. The curves (Appendix B(3)) compare, for three distinct datasets, the proportion of adoption attributable to the incentive scheme for time interval $t = 0$ to $t = T_{BAU50}$ – with a threshold at 20% (solid curves) and with an ongoing incentive (dashed curves), and where the incentive impacts on p, q and/or m of the Bass model. The first dataset (heavy black), is similar to that from Ref. (Sultan et al., 1990) ($p = 0.005$ and $q = 0.38$) for an extensive range of adoption processes, the second (red), is for lupin data ($p = 0.00184$ and $q = 0.789$, see Ref. (Marsh et al., 2000)), and the third (fine black), is for solar water heaters data ($p = 0.000249$ and $q = 0.306$, see Ref. (Higgins et al., 2011)). The four plots differ as follows: (a) only p changes with an incentive, and $m = 1$; (b) both p and m change with the incentive, with $m = 0.7$ in the BAU case; (c) both p and q change with the incentive, but $m = 1$ is fixed; and (d) all of p, q and m change with the incentive, with $m = 0.7$ in the BAU case. Note that the solar water heater parameters assume an increase in m, and thus do not appear in (a) and (c). (Results are for the Bass model.)

4. Discussion

We now summarise our results, which have broad implications for incentive schemes and product adoption, and provide an explicit interpretation for policy concerning emission reducing schemes in the next section.

To establish a standardised threshold for common practice we considered a number of approaches from the literature. Although this determination is a matter of definition (and thus arbitrary in some sense), our results suggest that the threshold determined by Ref. (Rogers, 1983), Ref. (Mahajan et al., 1990), the CDM, as well as the approach of Ref. (Mathur et al., 2007) for the logistic, Bass and Stanford models (the mechanistic models with plausible parameter ranges), all agree, approximately, with a threshold of close to 20% (16–21%). From the literature, for emission reducing practices, the reported values of p are less than 10^{-3}, implying the threshold suggested by Ref. (Mathur et al., 2007) (the maximum acceleration in adoption) is closer to 20% than to 16%. Further, we demonstrated that the approach of Ref. (Mathur et al., 2007) can be

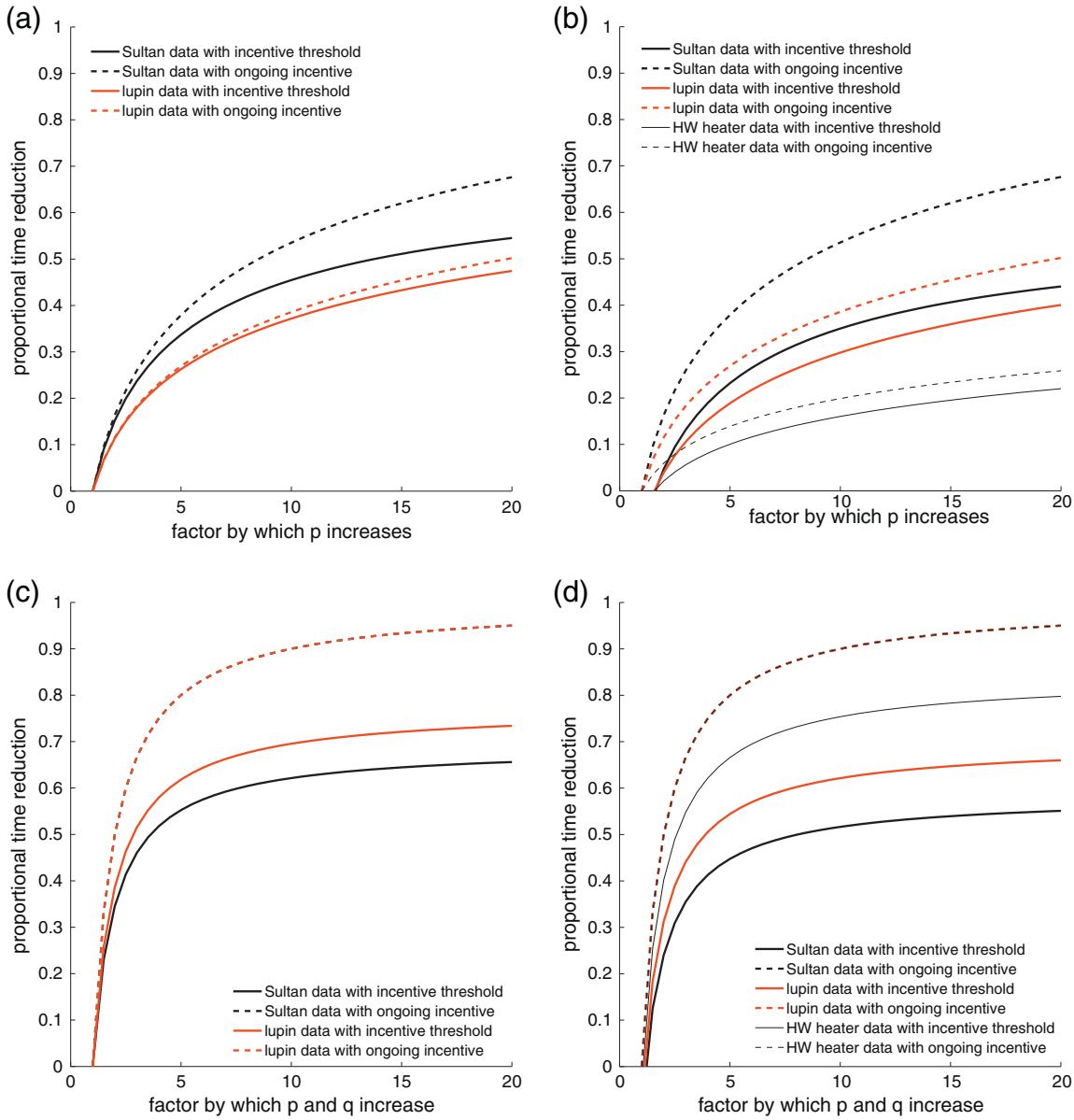

Fig. 11. The curves (Appendix B(4)) compare, for three distinct datasets, the proportion by which time to reach 50% adoption is reduced by an incentive ('proportional time reduction'). Solid curves include a threshold at 20%, dashed curves include an ongoing incentive, and the incentive impacts on p, q and/or m of the Bass model. The first dataset (heavy black), is similar to that from Ref. (Sultan et al., 1990) ($p = 0.005$ and $q = 0.38$) for an extensive range of adoption processes, the second (red), is for the lupin data ($p = 0.00184$ and $q = 0.789$, see Ref. (Marsh et al., 2000)), and the third (fine black), is for the solar water heaters data ($p = 0.000249$ and $q = 0.306$, see Ref. (Higgins et al., 2011)). The four plots differ as follows: (a) only p changes with an incentive, and $m = 1$; (b) both p and m change with the incentive, with $m = 0.7$ in the BAU case; (c) both p and q change with the incentive, but $m = 1$ is fixed; and (d) all of p, q and m change with the incentive, with $m = 0.7$ in the BAU case. Note that the solar water heater parameters assume an increase in m, and thus do not appear in (a) and (c). (Results are for the Bass model.)

difficult to determine with few data, and thus a fixed threshold (that we have shown is close to this maximum rate of adoption increase threshold) is likely to offer robustness for a diversity of practices and under uncertainty. If a general and practical approach is required to determine a common practice threshold, these results provide quantitative and qualitative support for a threshold of, approximately, 20%.

The determination of additionality over BAU is complex. If a model is assumed to describe diffusion, the model is uncertain before the event, the parameters are uncertain with few data, and the precise impact of an incentive scheme on these parameters is unknown. Therefore our analysis, using a sensitivity analysis of the Bass model, considered a number of approaches to include the effect of incentives on diffusion, and looked for general trends that provide approximations that are consistent across practices. Further, we assumed that incentive schemes, in terms of financial rewards and promotion, are approximately constant over the period of their implementation and occur early in the process. Our results show that, if an incentive increases the probability of adoption through innovation, or

through both innovation and imitation, by more than 5 fold (shown as likely from the literature but not proven), then a reasonable estimation of the proportion of adoption due to BAU is between 10% and 15%. And these percentages reduce in the case that the number of potential adopters increases with the incentive. We thus deduce that an assumption of 7–10% of total adoption being due to BAU becomes reasonable for all practices, since the standard Bass model that we have used is widely accepted as an appropriate model for practice adoption (Bass et al., 1994; Meade and Islam, 1995; Phillips, 2007), an increase in the probability of adoption though innovation of greater than 5 fold is reasonable from the literature (Bass et al., 1994; Horsky and Simon, 1983), and the number of potential adopters is likely to increase by up to 50% (approximately) (Higgins et al., 2011; Jain and Rao, 1990). This inference is also independent (approximately) of the parameter values (p and q) associated with BAU. Consequently, if a standardised approach is required to establish the proportion of adoption that is due to an incentive, and not attributable to BAU, then an estimate of 90–93% is reasonable.

Promotional incentives for practice adoption also affect long-term targets for emission reductions, where we assume that the units of adoption are directly proportional (approximately) to ensuing emission reductions. Once the threshold has been reached, and the incentive ceased, it is unknown whether model parameters return to those of BAU (worst-case scenario) or whether adoption maintains the momentum it had under the scheme. Our results indicate that, in the time taken until 50% of the potential population would have adopted the practice in the BAU case, approximately 70–90% of adoption can be attributable to the incentive. This represents a considerable increase in adoption relative to BAU and an increase in associated emission reductions of comparable proportions, approximately. As above, these results are valid for a wide range of parameter values for the BAU case, including an increase in potential market of up to 40%. Thus, even for the worst-case scenario (in which adoption rates revert to those of BAU when the incentive ends), an incentive can lead to large percentage increases in the reduction of emissions over this specified time interval, relative to BAU. Although such reductions may have occurred without an incentive, but over much longer time periods, there are clear advantages for government targets within committed time frames. We note, however, that it is possible that a practice is never adopted without an incentive, in which case adoption ceases when an incentive scheme ends.

Finally, considering the above results in a different way, the time until 50% adoption is reached can be reduced considerably through incentive schemes, thus facilitating the attainment of government targets within specified time frames. We found that reductions in time were more dependent on underlying parameters of the BAU case and the impact of incentives on diffusion than previous results (that is, adoption proportions). However, for the worst-case scenario and with an incentive, the time until 50% adoption was reached was reduced by between 20% and 70% (approximately) relative to BAU, with well over 80% possible when the incentive extended beyond the threshold or the process became self-sustaining. The implication is that practices with long expected time-scales for adoption can be strategically chosen and promoted so as to contribute optimally to an upcoming target year.

5. Relevance for policy

It is not the purpose of this analysis to formulate policy. Rather, the intention is to provide evidence that supports approaches to determining standardised thresholds and additionality criteria associated with incentive schemes, or offset schemes. We now provide a brief summary of the relevance of the main findings to policy questions.

Certain offset schemes (including the CDM and Australia's CFI) use a common practice test as a measure for additionality. However, thresholds for common practice to establish whether a practice is eligible for credits can be determined in a number of ways, and different approaches can be practice-dependent or have uncertain thresholds with few data available during the early stages of adoption, and are thus not practical to implement. Here we have shown that an adoption threshold between 16% and 20% agrees with many of the quantitative and qualitative approaches proposed in the literature, and with data across a wide range of practice adoption studies. The implications are that, while acknowledging some uncertainty, a threshold within this range is appropriate across a broad range of practices, is underpinned by a variety of quantitative and qualitative methodologies, as well as being simple and practical to implement. Thus, our results suggest that offset schemes that use common practice tests as a basis for determining additionality have quantitative evidence to support a fixed threshold between 16% and 20%.

The explicit determination of additionality is difficult. However, our analysis suggests that 90–93% (approximately) of total adoption can be attributed to an incentive scheme, where the incentive is fixed over time and is adequate to promote uptake. From the literature there is considerable uncertainty around how incentives should be incorporated into models, and thus we considered a range of approaches. While acknowledging uncertainties, general and consistent characteristics were clear across a range of models and different practices, with 7–10% (approximately) of uptake attributable to BAU. This leads to an easily implementable additionality assessment, underpinned by a range of modelling approaches and remarkably consistent over a wide range of practices.

Globally, many governments and councils have committed to emission reduction targets within fixed times. We applied the above thresholds and incentives to determine their likely contributions to meeting targets. We found that, in a fixed time period (the time taken to reach 50% adoption without any incentive), an incentive scheme is likely to at least double the number of adopters. Further, the same results considered in an alternative way, suggest that the time taken to reach 50% adoption levels can be reduced by between 20% and 70% (approximately) when an incentive is offered. From a policy perspective these results indicate how effective incentive schemes can be, and how they can be chosen strategically to contribute in an optimal way to achieving targets. Moreover, we acknowledge that reduced time frames and/or increased target reductions are likely to influence price and demand in any trading scheme, which operate as incentives within the system. These feed-back and time-dependent effects are not included here, where we have included only fixed incentive schemes.

We note that the Kyoto Protocol CDM originally mandated a conservative BAU baseline, suggesting a preference for over-estimating BAU rather than under-estimating its proportional contribution to adoption (Streck, 2007; Streck, 2010). This has implications for trading schemes and target attainment, both nationally and internationally. Taking this into consideration indicates a preference for the upper bounds of the BAU intervals given here (or lower bounds for the intervals for adoption attributable to the scheme). The interpretation is straightforward to infer from the analysis provided. Further, Ref. (Trexler et al., 2006) provides a discussion of statistically derived false positives and negatives for additionality tests relevant to specific projects. We have not adapted any such tests to our approach here. However, we consider a statistical application of this nature, used in conjunction our results and the CDM preference for a conservative baseline, would contribute to the robustness of policy in the area.

Furthermore, while our results are relevant at any scale (for example, individual, farm, industry, unit of surface area), it is important to ensure that each unit of adoption within the population leads to an equivalent (approximately) reduction in emissions, for each practice, if the assessment purpose is to encourage emission reductions. This is an essential aspect for policy consideration before implementation.

6. Conclusion

To conclude, we reiterate that the diffusion process of new practices and technologies is complex. However, its characteristics are important for the successful implementation of emission trading schemes. Here we provide the first study that examines the relative advantages and disadvantages of a subset of common practice thresholds, with particular relevance to situations with few data. Further, to our knowledge, there is no study that provides a general quantitative measure for the effect of an incentive scheme on adoption, relative to BAU – a criterion for determining additionality. This work defines and analyses one such a measure, and by examining full plausible ranges for model parameters the results for any particular set of values (regardless of the mechanisms that drive them) can be interpreted. Our focus is on exposing common trends, rather than specific details for a particular practice, to inform standardised assessment approaches. In particular, our analysis, while considering part of a much broader framework, exposes some simple, robust and defensible practice adoption characteristics that could contribute to assessment tools for a wide range of technological initiatives and incentive schemes.

The standard Bass model without any marketing term has been shown in the literature to be amongst the most reliable approaches to describing and forecasting diffusion processes, even when all such processes are subject to marketing variations in price and promotional effort (Bass et al., 1994; Meade and Islam, 1995). This suggests that our results provide reasonable diffusion estimates for incentives with near constant rebates or penalties over the period of implementation, providing validation to our approach. Further, by considering relative measures, the impact of alternative formulations (we considered a number of approaches to including the impact of incentives) is dampened, resulting in the exposure of general characteristics that are reasonably consistent across models. All the measures applied above assume that an incentive increases one or more of the parameters of the Bass model. We acknowledge that it may require an incentive of a particular size to change probabilities for adoption and/or the market potential. We have not explored the size of incentives required to initiate a changed diffusion process, but, as reported in the literature (Kamakura and Balasubramanian, 1988), financial incentives only affect the diffusion of high-cost items, Ref. (Phillips, 2007) proposes that a 20% to 30% reduction in price is required to initiate adoption take-off, and Refs. (Greene et al., 2005; Higgins and Foliente, 2013; Higgins et al., 2011; Higgins et al., 2014; Tang et al., 2013) discuss the incentive size, type and/or timing to optimize adoption for specific applications. Nevertheless, our analysis indicates that once an incentive does alter the parameters, the general results discussed above are valid almost immediately and are, approximately, independent of further promotional effort.

Finally, every model application is based on assumptions, and we mention a few as they are important for interpretation. Our analysis assumes a smooth adoption curve as applied in the literature, although in reality adoption is likely to be sporadic and plateau (Peres et al., 2010; Steffens and Murphy, 1992), for the potential pool of adopters to vary (Higgins et al., 2011; Higgins et al., 2012), and for some 'adoptees' to 'dis-adopt'. Further, we have assumed a homogeneous population. Spatial aspects and other heterogeneous or time-dependent effects, including environmental changes and economic effects, have not been considered here although they may affect the system (Garber et al., 2004; Heinz et al., 2013; Higgins et al., 2011; Meade and Islam, 2006; Park et al., 2011). Nevertheless, based on the data sets and findings in the literature, and the success of the Bass model across a wide range of distinct adoption processes that would be subject to time-dependent effects, we argue that our results and conclusions remain relevant, particularly in large populations.

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Appendix A

A.1. Bass and Generalised Bass model equations

For $Y(t)$, the cumulative number who have adopted a practice at time t in a market of size m, the standard Bass model and solution are,

$$\frac{dY(t)}{dt} = \left(p + \frac{q}{m}Y(t)\right)(m - Y(t)) \quad \text{and} \quad Y(t) = \frac{m\left(1 - e^{-(p+q)t}\right)}{1 + \frac{q}{p}e^{-(p+q)t}}, \tag{A.1}$$

where $Y(0) = 0$ is assumed, and the conditional probability of adoption at time t is $p + \frac{q}{m}Y(t)$. The general solution with initial

condition $Y(t_0) = Y_0$ is,

$$Y(t) = \frac{m\left(1 - p\frac{m-Y_0}{pm+qY_0}e^{-(t-t_0)(p+q)}\right)}{1 + q\frac{m-Y_0}{pm+qY_0}e^{-(t-t_0)(p+q)}}. \quad \text{A.2}$$

(A derivation is given in Ref. (Bass, 1969).)

The generalised Bass model and solution are,

$$\frac{dY(t)}{dt} = \left(p + \frac{q}{m}Y(t)\right)(m - Y(t))\gamma(t) \quad \text{and} \quad Y(t) = \frac{m\left(1 - e^{-(p+q)\int_0^t \gamma(s)ds}\right)}{1 + \frac{q}{p}e^{-(p+q)\int_0^t \gamma(s)ds}}, \quad \text{(A.3)}$$

where, $Y(0) = 0$ is assumed and,

$$\gamma(t) = 1 + \beta_P \frac{dP(t)}{dt}\frac{1}{P(t)} + \beta_A \frac{dA(t)}{dt}\frac{1}{A(t)},$$

with P representing price, A advertising expenditure or effort, and β_P and β_A associated weightings (Bass et al., 1994). Note that if $(p + qF(t))\gamma(t)$ is interpreted as the conditional probability, then $\gamma(t) \leq (p + qF(t))^{-1}$ (see text for discussion). (A derivation is given in Ref. (Bass et al., 1994).)

A.2. Equations used for measures

We note that the proportion measures (1), (2) and (3) provided below are based on 'average' increases in adoption with an incentive, relative to BAU, over a specified time interval (see areas between curves in Fig. 6). These measures are thus a ratio of averages. (We acknowledge that many alternative measures could be defined, if deemed more appropriate, and applied similarly.)

1. The measure illustrated in Fig. 7 is given by,

$$\frac{\int_0^T y_f(s)ds - \int_0^T y(s)ds}{\int_0^T y_f(s)ds},$$

where $y(t)$ is the solution to the Bass model (Eq. (2)), $y_f(t)$ is this solution but with parameter p increased through promotion, and T is the time at which the adoption threshold is reached under this promotional scheme. Further, $y(0) = 0 = y_f(0)$. Assuming a threshold of adoption proportion Y_T, and p increased by a factor f, the time at which this threshold is reached with the incentive in place is given by,

$$T = \frac{\ln\left(\frac{fpm + Y_T q}{fp(m - Y_T)}\right)}{fp + q}.$$

2. The measure illustrated in Fig. 9 is given by,

$$\frac{\int_0^T y_\gamma(s)ds - \int_0^T y(s)ds}{\int_0^T y_\gamma(s)ds},$$

where $y(t)$ is the solution to the Generalised Bass model (Eq. (A.3)), $y_\gamma(t)$ is this solution but with the conditional probability multiplied by the function $\gamma(t)$ through promotion, and T is the time at which the adoption threshold is reached under this promotional scheme. Further, $y(0) = 0 = y_\gamma(0)$. Assuming a threshold of adoption proportion Y_T, and constant $\gamma(t)$=c, then the time at which this threshold is reached, with the incentive in place, is given by,

$$T = \frac{\ln\left(\frac{pm + Y_T q}{p(m - Y_T)}\right)}{c(p + q)}.$$

3. The measure for the solid curves illustrated in Fig. 10 is given by,

$$\frac{\left(\int_0^T y_f(s)ds + \int_T^{T_{BAU50}} y_1(s)ds\right) - \int_0^{T_{BAU50}} y(s)ds}{\left(\int_0^T y_f(s)ds + \int_T^{T_{BAU50}} y_1(s)ds\right)},$$

where $y(t)$ is the solution to the Bass model (Eq. (A.1)) and subscript f denotes that parameter p (or the conditional probability) has been increased by the factor given on the x-axis. Further, $y(0) = 0 = y_f(0)$. Integration limit T is the time at which the adoption threshold Y_T is reached under this promotional scheme, T_{BAU50} is the time at which there is 50% adoption in the BAU case, and $y_1(s)$ has the same parameter values as $y(s)$, but with changed initial condition $y_1(T) = Y_T$ (see Eq. (A.2)).

For the dashed curves, the measure is,

$$\frac{\int_0^{T_{BAU50}} y_f(s)ds - \int_0^{T_{BAU50}} y(s)ds}{\int_0^{T_{BAU50}} y_f(s)ds},$$

where the notation is as above.

4. The measure for the solid lines illustrated in Fig. 11 is given by,

$$1 - \frac{\text{time of 50\% adoption with promotion before threshold}}{\text{time of 50\% adoption without promotion (BAU)}} = 1 - \frac{\hat{T}_{50}}{T_{BAU50}},$$

where T_{BAU50} is the time at which 50% adoption is reached in the BAU case, while for the case with promotion ($\hat{T}_{50}$), parameter p (or the conditional probability) has been increased by the factor given on the x-axis until the threshold is reached, and beyond the threshold parameters revert to BAU values. Further, we assume no adoption at $t = 0$.

For the dashed curves, the measure is,

$$1 - \frac{\text{time of 50\% adoption with promotion ongoing}}{\text{time of 50\% adoption without promotion (BAU)}} = 1 - \frac{T_{50}}{T_{BAU50}},$$

where, for the case with promotion ongoing (T_{50}), parameter p (or the conditional probability) has been increased by the factor given on the x-axis, and *does not* revert to the BAU value after the threshold has-been reached. Further, we assume no adoption at $t = 0$.

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