The Carbon Farming Initiative

A proposed common practice framework for assessing additionality

Felicity Woodhams, Darren Southwell, Sarah Bruce, Belinda Barnes, Helen Appleton, Jasmine Rickards, James Walcott, Beau Hug, Linden Whittle and Helal Ahammad

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<th>Description</th>
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<tbody>
<tr>
<td>AAE</td>
<td>Australian Agricultural Environments</td>
</tr>
<tr>
<td>ABARES</td>
<td>Australian Bureau of Agricultural and Resource Economics and Sciences</td>
</tr>
<tr>
<td>ABS</td>
<td>Australian Bureau of Statistics</td>
</tr>
<tr>
<td>ANZSIC</td>
<td>Australian and New Zealand Standard Industrial Classification</td>
</tr>
<tr>
<td>ASGC</td>
<td>Australian Standard Geographical Classification</td>
</tr>
<tr>
<td>BAU</td>
<td>Business-as-usual</td>
</tr>
<tr>
<td>CCX</td>
<td>Chicago Climate Exchange</td>
</tr>
<tr>
<td>CDM</td>
<td>Clean Development Mechanism</td>
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<tr>
<td>CFI</td>
<td>Carbon Farming Initiative</td>
</tr>
<tr>
<td>DAFF</td>
<td>Australian Government Department of Agriculture, Fisheries and Forestry</td>
</tr>
<tr>
<td>DCCEE</td>
<td>Australian Government Department of Climate Change and Energy Efficiency</td>
</tr>
<tr>
<td>DOIC</td>
<td>Domestic Offsets Integrity Committee</td>
</tr>
<tr>
<td>IBRA</td>
<td>Interim Biogeographic Regionalisation of Australia</td>
</tr>
<tr>
<td>LaMP survey</td>
<td>Land Management Practices survey</td>
</tr>
<tr>
<td>MLE</td>
<td>Maximum likelihood estimation</td>
</tr>
<tr>
<td>NLS</td>
<td>Non-linear least squares</td>
</tr>
<tr>
<td>OLS</td>
<td>Ordinary least squares</td>
</tr>
<tr>
<td>SA2</td>
<td>Statistical Area 2</td>
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Executive summary

Commencing in December 2011, the Carbon Farming Initiative (CFI) is an important component of the Australian Government’s Clean Energy Future plan, designed to reduce emissions from land sector activities. It is a long-term policy mechanism that will help the land sector sell carbon credits in domestic and international markets.

Policy rationale

The CFI is expected to encourage farmers and landholders to adopt or more rapidly adopt technologies or practices that have a carbon benefit but that would otherwise have financial or other barriers to adoption. In other words, relative to other innovations and practices, it will provide commercial advantage to innovations not yet widely adopted that reduce greenhouse gas emissions or increase carbon sequestration. Adoption of new technologies or practices is also supported by improved access to information delivered through the research, demonstration and extension programs of the Land Sector Package (a complementary activity to the CFI within the Clean Energy Future plan). The CFI is expected to result in environmental benefits through the reduction of greenhouse gas concentrations in the atmosphere.

Additionality requirements for the CFI

Like all carbon offset schemes, the CFI should meet internationally recognised integrity standards, including the standard for additionality. Meeting the CFI integrity standards, such as the one for additionality, is important because it gives buyers of CFI credits the confidence that each CFI credit they buy amounts to a guaranteed tonne of emissions offset.

The CFI involves a two part additionality requirement: (1) offset projects must not be required by law; and (2) project activities must go beyond common practice. This report is centred on the second requirement. According to the Explanatory Memorandum to the CFI Bill (2011), ‘Abatement activities that are not common practice within an industry or region would be included on a ‘positive list’ and recognised as additional.’

The ‘positive list’ is only one part of the policy process that makes a project eligible for CFI crediting. Among other checks, the project must adhere to one of the approved CFI ‘methodologies’ that establish a project baseline of ‘usual’ emissions against which abatement is measured.

Additionality assessment frameworks

In this report a proposed framework for the CFI common practice assessment is described. The framework draws on lessons learned from other schemes, academic literature and the results of ABARES mathematical analyses. This framework will inform policy development and, if adopted, will support CFI integrity by using a streamlined approach while ensuring a transparent and systematic approach to common practice assessments.

While there are a range of practices that result in a reduction of emissions from agriculture, the proposed framework is designed to cover only those that can be assessed for inclusion in the ‘positive list’ for the CFI.

There is growing recognition of the merits of common practice additionality tests in various international schemes and academic forums. The common practice test is a standardised approach and represents a move away from project-specific assessments adopted in other offset schemes in the past (for example, the Clean Development Mechanism of the Kyoto Protocol).
Standardised approaches, such as common practice tests, with clearly defined thresholds for adoption are considered to be more streamlined, transparent and objective than case-by-case (project-specific) assessments. According to the Explanatory Memorandum to the CFI Bill (2011), project-level additionality tests were removed to reduce complexity and address concerns that these would limit scheme opportunities. However, common practice tests do have limitations as they can be less flexible than project-specific approaches to additionality, with reduced capacity to take into account project-specific conditions. Proposed requirements under the approved ‘methodologies’ can address some of these concerns.

**Common practice tests**

Common practice tests measure the extent to which an abatement activity has already occurred in a ‘comparison group’ or ‘population’. A threshold is estimated for each abatement activity. If the estimated adoption level for an activity is below the threshold it may be considered ‘additional’; if the estimated adoption level is above the threshold the activity may be considered non-‘additional’. In this report some challenges in estimating this threshold, particularly with limited data, are highlighted and possible options to address these are suggested.

**ABARES analysis**

The mathematical analysis underpinning the proposed framework is based on the diffusion of innovations theory. The theory describes the adoption of a practice or technology in a specified ‘comparison group’ or ‘population’, which typically follows an S-shaped diffusion path over time. The S-shaped diffusion path reflects a slow uptake in the early stage of adoption, followed by rapid acceleration in uptake as the diffusion proceeds over time. The analysis presented in this report examines the diffusion path's sensitivity to key parameter values (parameters influence the shape and position of the curve) and diffusion paths estimated by ABARES for several farm practices. The analysis also identifies potential common practice thresholds, advantages and disadvantages of each threshold, and methods for estimating the threshold using limited data.

Two potential threshold options could be used for the common practice test. The first, often referred to as the take-off point, represents the maximum increase in the rate of practice diffusion. However, calculating the take-off point is problematic with limited data. For this reason, a second, default threshold is recommended in most cases. The default threshold is a fixed proportion of the ‘population’.

ABARES recommends using the fixed proportion threshold for the common practice test because:

- accurate prediction of the take-off point is not possible with a limited data series
- fixed proportion thresholds can provide a valid approximation for the take-off point for a broad range of model parameter values and modelling approaches
- fixed proportion thresholds provide a simpler approach that circumvent a number of implementation problems discussed in the report.

An adoption level of 20 per cent for the fixed proportion threshold is identified, as this approximates the upper bound for the empirical estimates of the take-off point. In many cases it is also close to the ‘true’ value. The 20 per cent threshold can be adjusted depending on the maximum number of potential adopters for the practice. A lower bound of 5 per cent for the take-off point is also identified, drawn from the literature.
Applications of the proposed common practice framework

The proposed common practice framework can be seen in Figure S1. The framework can be implemented with one year (and/or one collection) of survey data or additional information for each practice. If the number of adopters of a practice falls below 5 per cent of the target ‘population’, the practice may be deemed ‘additional’. If the number of adopters is above 20 per cent of the target ‘population’, the practice may be deemed non-‘additional’. A more rigorous threshold analysis may be conducted for any practice that has an adoption level between 5 and 20 per cent, or even above 20 per cent in certain circumstances.

The boundaries used in the framework can be supported and explained as follows:

- 5 per cent lower bound for the threshold is supported by Rogers (2003), following research on the adoption of innovations across a range of industries. Practices that have an adoption level below 5 per cent are likely to go straight on the ‘positive list’

- 20 per cent upper bound for the threshold is supported by ABARES analysis of adoption of agriculture practices, literature and the thresholds proposed by other offset schemes. Practices that fall between 5 and 20 per cent will also likely go on the ‘positive list’, depending on additional threshold analysis

- practices above the 20 per cent upper bound for the threshold may not go on the ‘positive list’ unless there are other factors taken into account beyond the adoption test proposed here.

An appropriate ‘comparison group’ needs to be identified for applying the framework. The ‘comparison group’ may consider regional and non-regional factors, depending on the industry and the practice defined in the ‘positive list’ assessment.

The framework can be applied using data from the Australian Bureau of Statistics (ABS) Land Management Practice (LaMP) survey and/or other sources, including other ABS surveys and censuses, ABARES surveys and industry data collections, published literature and expert opinion. ABARES is currently exploring the practical application of the proposed framework for specific practices.

Once on the ‘positive list’, practices will be reviewed periodically by the Department of Climate Change and Energy Efficiency (DCCEE) in consultation with ABARES and the Domestic Offsets Integrity Committee (DOIC) or when new information becomes available. Following review, practices may remain on the list or be removed. Assessing whether and when practices should be removed from the ‘positive list’ is an issue that will require consideration by the Minister of Climate Change and Energy Efficiency in the future and is largely beyond the scope of this report.
The Carbon Farming Initiative: A proposed common practice framework for assessing additionality

Figure S1 A proposed common practice assessment framework for the Carbon Farming Initiative

Notes: <= less than; >= greater than; ≤ = less than or equal to; ≥ = greater than or equal to.
1 Introduction

On 23 August 2011, the Australian Parliament passed legislation to establish the Carbon Farming Initiative (CFI). The initiative, which commenced on 8 December 2011, operates as a voluntary offset scheme to facilitate the sale of carbon credits generated from eligible activities within the land sector to international and domestic carbon markets.

Like all offset schemes, the CFI is expected to meet internationally recognised integrity standards. These include the requirement for additionality, which ensures all CFI credits are ‘additional’ to business-as-usual and would not have happened without the CFI. To meet this integrity principle, the Explanatory Memoranda to the CFI Bill outlines the use of a common practice test for additionality. This test is designed to ensure on-farm emissions reduction and carbon sequestration activities undertaken as part of the CFI are not common practice within a sector or region.

This report does not critically review the concept of additionality, as this standard is already a legislated feature of the CFI. Instead, additionality standards are described as background to common practice assessments.

There is growing recognition of the merits of common practice additionality tests in various international schemes and academic forums. The common practice test is a standardised approach and represents a move away from project-specific assessments adopted in other offset schemes in the past (for example, the Clean Development Mechanism of the Kyoto Protocol). Standardised approaches, such as common practice tests, with clearly defined thresholds are considered to be more streamlined, transparent and objective than project-specific assessments (Climate Action Reserve 2010; Hayashi et al. 2010; Kartha et al. 2005). According to the Explanatory Memorandum to the CFI Bill (2011), project-level additionality tests were removed to reduce complexity and address concerns that these would limit scheme opportunities.

Given the diversity of Australian farming businesses, their practices and the environments they operate in, careful consideration is required to design a common practice test for additionality.

In this report, a proposed framework for the CFI common practice assessment is outlined. A standardised quantitative approach, primarily using survey data, is recommended to increase the objectivity, consistency and transparency of the test. The proposed framework, described in Chapter 6, aims to streamline additionality assessment while maintaining the integrity of the offset credits generated.

The proposed framework will inform policy development and, if adopted, will support CFI integrity through a standardised approach. While there are a range of practices that result in a reduction of emissions from agriculture, this framework is designed to cover only those that can be assessed for inclusion in the CFI ‘positive list’.

The report is organised as follows. Chapter 2 provides an overview of the Australian Government’s CFI policy framework, focusing on the additionality integrity principle. Chapter 3 discusses the additionality criteria for carbon offset credits. Examples from other offset schemes and the theoretical literature are examined for potential approaches to the common practice test and presented in Chapters 4 and 5. Chapter 6 of the report proposes a common practice test framework for threshold analysis for the CFI. Chapter 7 concludes and provides further research directions. The mathematical analyses are presented in Appendixes A, B and E. Information on regional and industry classifications are provided in Appendixes C and D.
2 The Carbon Farming Initiative

Key points

- Carbon Farming Initiative (CFI) offset credits can be generated by practices that either reduce or avoid direct emissions or remove carbon from the atmosphere through carbon sequestration, and that meet the international integrity standards, including for additionality.

- Internationally recognised integrity standards are important for ensuring the environmental integrity of the CFI.

- An ‘additional’ offset project results in abatement that is beyond business-as-usual.

- ‘Additional’ practices cannot be required by law or be common practice and widely adopted.

- A ‘positive list’ is being used to support the process of additionality assessment. The ‘positive list’ identifies activities that are deemed to go beyond common practice in the relevant ‘comparison group’ or ‘population’ (industry and/or region).

- The ‘positive list’ is one, but an important, part of the policy process that makes a project eligible for the CFI.

Introduction

The Carbon Farming Initiative (CFI) is a voluntary offset scheme designed to credit greenhouse gas abatement in the land sector and from legacy waste emissions. Greenhouse gas abatement will be achieved under the CFI by either:

- reducing or avoiding emissions, for example by the capture and conversion of methane emissions from livestock manure

- removing carbon from the atmosphere and storing it in soil or trees, for example by farming in a way that increases soil carbon.

For abatement projects under the CFI, Australian Carbon Credit Units will be issued for each tonne of carbon (or carbon dioxide equivalent) sequestered or not emitted as a result of these activities. These units (henceforth, carbon offsets) can then be sold to individuals, businesses and governments to either trade or offset their emissions. More information about the CFI can be found on the Department of Climate Change and Energy Efficiency website.

Agricultural, fisheries and forestry sectors are exempted from the direct liability for their greenhouse gas emissions under the Australian carbon pricing mechanism (Australian Government 2011). However, the CFI provides a long-term policy mechanism for the land sector to take up technologies or practices that reduce emissions and generate carbon offsets. The carbon stored in soils and trees and the emissions reduced by ‘CFI accredited landholders’ will have market value allowing carbon offsets to be bought and sold as a commodity through domestic and international markets.
Additionality under the CFI

The CFI is underpinned by legislation that ensures offset credits are issued only for abatement projects that meet the internationally recognised integrity standards. Adherence to integrity standards is essential to give buyers of the CFI credits confidence that the abatement they are buying is genuine. The initiative also provides protection under the law to sellers of the CFI credits.

Additionality is an important CFI integrity standard and a key requirement of all offset schemes. An offsets project is deemed to be ‘additional’ if it results in abatement that would not have occurred in the absence of the scheme. That is, the abatement under the project can be considered beyond ‘business-as-usual’.

Section 41 of the Carbon Credits (Carbon Farming Initiative) Act 2011 stipulates that Australian Carbon Credit Units will only be issued for ‘additional’ abatement. This excludes projects that are ‘required by law (regulatory additionality) or activities that are common practice and already widely adopted’.

Practices and technologies that have already been adopted widely are viewed to have overcome any significant impediments to adoption and/or have had substantial benefits such as productivity gains, making these practices or technologies cost-competitive and commercially viable. Therefore, such practices and technologies are most likely to be adopted under a business-as-usual scenario regardless of the CFI.

The CFI is expected to encourage farmers and landholders to adopt technologies or practices that would otherwise not be perceived as cost-competitive. As such, the initiative is likely to affect the adoption of different practices or technologies in a number of ways. For example, it may speed up the adoption of a new or existing (but not widely adopted) practice or technology. Also, it could help a practice or technology to remain commercially viable for longer than it otherwise would. Furthermore, the CFI may make new and specific types of technologies, such as those with no productivity or other co-benefits, commercially viable. It is also possible that the initiative will adversely affect the adoption of practices or technologies without any greenhouse mitigation potential as farmers and landholders may prefer practices and technologies with CFI potential over those without. Adoption of new technologies or practices is also supported by improved access to information delivered through the research, demonstration and extension programs of the Land Sector Package (a complementary activity to the CFI within the Clean Energy Future Plan). While the description of possible adoption effects provided above is not exhaustive, and some effects may overlap, many of these will result in environmental benefits through the reduction of greenhouse gas concentrations in the atmosphere.

To support the process of additionality assessment, a CFI ‘positive list’ is being used to identify activities that are deemed to go beyond common practice in the relevant industry or environment. Anyone can propose activities for the ‘positive list’, with submissions undergoing an administrative process for approval as outlined in Figure 1.
Figure 1 Summary of the administrative process for the ‘positive list’

Source: Department of Climate Change and Energy Efficiency (2011)

The Minister for Climate Change and Energy Efficiency recommends activities for inclusion on the ‘positive list’ based on advice from the Domestic Offsets Integrity Committee (DOIC), who draw on expertise from ABARES and other sources. A number of offset practices have already been identified and placed on the CFI ‘positive list’, including: the establishment of permanent plantings, human induced regeneration, capture and combustion of methane from livestock manure, early season savanna burning, and the application of nitrification inhibitors to fertiliser.

The ‘positive list’ will be regularly reviewed by the Department of Climate Change and Energy Efficiency (DCCEE), and follow-up common practice assessments will occur in consultation with ABARES and the DOIC.

The DCCEE published ‘positive list’ guidelines explaining the process for proposals and their assessment in October 2011 (Department of Climate Change and Energy Efficiency 2011).

The ‘positive list’ is only one part of the policy process that makes a project eligible for CFI crediting. The CFI Handbook outlines the CFI Eligibility flowchart, including five stages that a landholder or project proponent must check to determine if the activity is eligible for the CFI (Department of Climate Change and Energy Efficiency 2012). Included in these stages is the adherence of the project to one of the approved CFI ‘methodologies’ that establishes a project’s baseline of ‘usual’ emissions against which abatement is measured.
Assessing additionality: issues and challenges

Key points

- Additionality is difficult to measure, but clearly defined, consistent and objective approaches to additionality can help reduce policy uncertainty.

- Project-specific additionality assessments have been heavily criticised for being costly, subjective, lacking transparency, and being able to be manipulated, resulting in the crediting of non-‘additional’ abatement.

- The Australian Government has ruled out project-level additionality tests for the CFI to reduce complexity and address concerns that these would limit scheme opportunities.

- Standardised approaches such as emissions benchmarks or common practice tests with clearly defined thresholds are suggested as more streamlined and objective assessments of additionality. However, they may be less flexible than project-specific approaches and, in certain circumstances, pose a risk of allowing non-‘additional’ abatement to be credited.

Introduction

Additionality is a key requirement of all offset schemes. An offsets project is deemed to be ‘additional’ if it results in abatement that would not have occurred in the absence of the scheme. Crediting non-‘additional’ abatement refers to credits that are provided to practices or technologies that would have occurred without the scheme in the normal course of business.

The concept of additionality for carbon offset schemes appears in literature after the signing of the Kyoto Protocol in 1997, where it is applied to emissions abatement under the Clean Development Mechanism (CDM). Assessing additionality presents an operational challenge in all offset schemes, and is one of the most controversial and debated concepts in the environmental policy literature (Michaelowa & Purohit 2007; Muller 2009; Schneider 2009). This debate occurs because additionality is, by nature, a counter-factual concept and determining what might have happened in the absence of an offset scheme is difficult. No additionality test is infallible (Kartha et al. 2005); however, clearly defined, consistent and objective approaches to additionality can help reduce policy uncertainty.

This chapter discusses various methods to assess additionality and provides an overview of lessons that can be learned from existing schemes.

Methods to assess additionality

Additionality assessment methods can be divided into two main categories (Kollmuss et al. 2010): project-specific and standardised approaches. Tests that fall under these categories can sometimes be combined in multi-step additionality assessments.

Project-specific approaches involve examining the unique circumstances of a proposed offset project on an individual or case-by-case basis. Evaluations may be based on one or more additionality tests, such as investment or barrier analysis (see Table 1). Although these tests allow for the specific circumstances of each project to be assessed in detail, there are concerns
about their subjectiveness, transparency, and the financial and administration costs involved in their application.

According to the Explanatory Memorandum to the CFI Bill (2011), project-level additionality tests were removed to reduce complexity and address concerns that these would limit scheme opportunities.

Standardised approaches base offset emissions/practice assessments on uniformly applicable criteria such as adoption-level data, emission rates, market penetration rates and technology benchmarks (see Table 1). According to the Climate Action Reserve (2010, p.1), standardised approaches have several distinct advantages.

- They reduce the administrative costs and delays associated with subjective, case-by-case evaluations of a project’s circumstances.
- They are administratively easier to apply and improve consistency in how additionality determinations are made.
- They alleviate uncertainties for project developers and investors about which projects are eligible.

However, they can be less flexible than project-specific approaches and are less able to consider project-specific conditions. Therefore, applying a standardised approach to agricultural practices should consider variability within and between regions and industries (for example, differences in agricultural activities that are the result of agro-climatic variability between regions).

Standardised approaches may present a risk of non-‘additional’ abatement because of their limited capacity to consider whether an individual landholder would have been likely to undertake the activity in the normal course of business. Project-specific baselines, an integral part of offset ‘methodologies’, can address some of these concerns (see Appendix E). However, it is not possible to know exactly how the CFI will influence adoption levels—for example, through increasing knowledge or providing carbon credits. This presents the risk of crediting practices not attributable to the scheme, which is often termed non-‘additional’ abatement. See Appendix E for more discussion on this issue.

As mentioned previously, the CFI will influence the adoption of practices and innovations. Questions may arise about identifying this influence and the possibility of factoring it out when doing additionality assessments for practices already on the ‘positive list’. Identifying and factoring out the effect of an offset scheme applies to both project-specific and standardised approaches to additionality assessment. Policymakers may have to consider the impact of removal of activities from the ‘positive list’ once activities are considered to have exceeded common practice. Removal of activities from the ‘positive list’ may lead to disadoption because of removal of the CFI incentive. Disadoption can be defined as a decrease in the proportion of those who have adopted a practice under the CFI, leading to the proportion of adopters falling below the common practice threshold. Any adoption of practices or technologies under the CFI will be subjected to a specific crediting period and other conditions as required under the approved ‘methodologies’. Also, disadoption may not be a cost-free exercise. Consequently, determining what practices or technologies to remove and when to remove them may become an involved policy deliberation exercise. See Appendix E for more discussion on this issue.
Table 1 A selection of common tests used to determine additionality

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<th>General description (of activity)</th>
<th>Project-specific or standardised</th>
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<tr>
<td>Legal or regulatory threshold</td>
<td>Better than any legally required actions</td>
<td>Project</td>
</tr>
<tr>
<td>date</td>
<td>Must be initiated before set date. Test often used in combination with another</td>
<td>Project or standardised</td>
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<tr>
<td>Barriers</td>
<td>Implementation barrier that is not faced by the alternative action</td>
<td>Project</td>
</tr>
<tr>
<td>Financial</td>
<td>Project could not occur without additional financing generated by climate policy</td>
<td>Project</td>
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<tr>
<td>Common practice</td>
<td>Better than common practice, better than business-as-usual</td>
<td>Standardised</td>
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<td>Technology</td>
<td>New technology, not business-as-usual</td>
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<tr>
<td>Performance benchmark</td>
<td>Better than predetermined benchmark of emissions or sequestration</td>
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</tbody>
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Source: Adapted from Olander (2009)

Additionality assessments vary greatly between offset schemes. Historically, project-specific approaches were the norm, but recently standardised approaches have attracted increased support. Examples of project-specific and standardised assessments can be found in compliance and voluntary offset schemes, as described below.

Compliance scheme: lessons from the CDM

Much of the debate around additionality focuses on how it has been applied under the Clean Development Mechanism (CDM). The CDM experience provides valuable insight into concerns with additionality assessment, and the recommendations discussed have provided background to the common practice framework presented in Chapter 5 of this report. Chapter 4 includes additional examples from other schemes on applying the common practice test.

The CDM is the largest emissions offset scheme in the world. It allows developed countries (Annex I countries) to invest in emission reduction and sequestration projects in developing countries (non-Annex I countries). It operates under a currency of ‘Certified Emissions Reductions’, with each unit equivalent to one tonne of carbon dioxide equivalent avoided emissions. Certified Emissions Reductions can be traded, and Annex I countries can use these to meet part of their emission reduction obligations under the Kyoto Protocol. Under the CDM, as of 19 April 2012 there were 4013 registered projects and 100 projects requesting registration. There were 151 registered agricultural projects, with most of these relating to methane flaring and electricity cogeneration in intensive livestock production systems.

Additionality is assessed under the CDM by the Executive Board using two alternative tools. These are the ‘Tool for the demonstration and assessment of additionality’ (CDM Executive Board 2011b) and the ‘Combined tool to identify the baseline scenario and demonstrate additionality’ (CDM Executive Board 2011c). Project developers may also propose alternative methods to demonstrate additionality. Both CDM tools use an approach that involves four steps:
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Step 1: Identify alternatives to the project that are consistent with local mandatory laws and regulations

Step 2: Investment analysis

Step 3: Barrier analysis

Step 4: Common practice analysis.

Projects must pass steps 1 and 4, and either steps 2 or 3 to be deemed ‘additional’. Evaluations of the CDM scheme carried out by Schneider (2007 & 2009) and Michaelowa and Purohit (2007) found that a significant proportion of registered projects were likely to be non-‘additional’. Explanations for how non-‘additional’ projects were credited generally surrounded the use of the project-specific investment analysis and barrier analysis, with the main criticisms being that these approaches are too subjective, costly and are susceptible to gaming and manipulation (Schneider 2009; Kartha et al. 2005). To address these concerns, the additionality assessment under the CDM has recently been improved following critical analysis (see for example: Haya 2007; Schneider 2009; Michaelowa & Purohit 2007; Wara & Victor 2008; Pottinger 2008). A greater focus on standardised approaches is being applied in this and other schemes, including the use of a common practice test (see Chapter 4 for more details).

**Voluntary schemes: the Verified Carbon Standard**

The recent progress toward using standardised approaches to additionality is being reflected in their use in voluntary schemes. Examples include the Climate Action Reserve (CAR) and Verified Carbon Standard (VCS). The US-based VCS program develops ‘methodologies’ and validation and verification standards for voluntary offset projects. It is used by implementers of voluntary offset projects around the world and is developing new requirements and guidelines for standardised approaches.

In September 2011, the VCS released a report for public consultation defining two types of standardised methods (Verified Carbon Standard 2011):

- **performance methods**: project needs to meet a predetermined benchmark for emissions
- **activity methods**: ‘positive list’ stipulates given classes of a project that are deemed ‘additional’.

The VCS notes that, when using standardised methods, clear specification of the project is required to limit the number of non-‘additional’ projects (Verified Carbon Standard 2011).

In line with a push for the use of standardised approaches, examples of common practice assessments under the CDM, the Alberta-based Offset Credit System, the former Chicago Climate Exchange offset scheme and the Climate Action Reserve are addressed in more detail in Chapter 4 of this report.
4 The common practice test and other schemes

Key points

- The Australian Government has legislated a common practice assessment to meet the additionality standard for the CFI.
- Common practice tests in the land-sector generally represent a shift toward standardised approaches to assessing additionality.
- While there are a number of examples of common practice tests from other schemes, these have been applied in a variety of ways.
- The common practice tests use either scheme-wide or activity-specific threshold levels.
- Thresholds applied by the CDM and the Alberta-based Offset Credit System appear to be based on limited empirical evidence.
- This report attempts to offer some theoretical underpinnings as well as an empirical basis for estimating adoption thresholds and a streamlined common practice assessment framework for the CFI.

Introduction

To meet the additionality standard for the CFI, the Australian Government has legislated an assessment of common practice (Section 41 of the Carbon Credits (Carbon Farming Initiative) Act 2011). Common practice tests for additionality measure the extent to which an abatement activity has already occurred in the relevant sector and/or region (Schneider 2009). It involves comparing technologies or practices that are in operation in similar biophysical and economic environments or that have similar access to information, skills and technologies. Typically, a certain level of activity adoption will be chosen as a threshold, and projects that have an adoption level above this threshold are deemed common practice and non-‘additional’. This is based on the premise that activities that are common practice are already well-established for other reasons without the additional incentive provided by the offset scheme. Developing and applying a common practice assessment framework is challenging for a number of reasons, including because uptake of a particular technology and the adoption threshold may vary by practice, technology and region due to different bio-physical and socio-economic conditions.

This chapter reviews how common practice tests have been applied in the following offset schemes for agriculture and forestry:

- the Clean Development Mechanism
- the former Chicago Climate Exchange
- the Alberta-based Offset Credit System
- the Climate Action Reserve.
These schemes have been chosen as they all include provisions for land-sector offset credits. Each of these schemes has applied the common practice test in different ways but generally represent a shift toward standardised approaches. More details are provided below.

The Clean Development Mechanism

The Clean Development Mechanism (CDM) has been described in Chapter 3. Under the CDM, common practice analysis is described as a credibility check to complement either the investment or barrier analyses. Project developers must review activities that are ‘similar to the proposed project activity’ (CDM Executive Board 2011b). According to the CDM Executive Board (2011b):

Projects are considered similar if they are in the same country/region and/or rely on a broadly similar technology, are of a similar scale, and take place in a comparable environment with respect to regulatory framework, investment climate, access to technology, access to financing, etc.

While the CDM has recently developed a more detailed approach to common practice assessment for some project types (CDM Executive Board 2011a), previous assessments were criticised for their subjective nature (see for example Haya 2007; Schneider 2009; Hayashi et al. 2010; Muller 2009). In particular, providing quantitative data to establish meaningful baselines and thresholds was optional, as this is considered one of the biggest challenges for project proponents.

The recently developed stepwise approach for common practice assessment of CDM projects, describes a 20 per cent threshold level and takes into account the number of similar projects in the applicable geographic area (CDM Executive Board 2011a). The 20 per cent threshold determined by the CDM Executive Board does not appear to have been underpinned by any rigorous empirical analysis, but is consistent with the fixed proportion threshold proposed later in this report.

The Chicago Climate Exchange

The Chicago Climate Exchange (CCX) operated between 2003 and 2010 as a cap and trade scheme with an offset component. The CCX now operates the Chicago Climate Exchange Offsets Registry Program to register verified emission reductions. Approved ‘methodologies’ for agricultural mitigation options in the land sector include:

- capture and combustion of agricultural methane
- conservation tillage and grassland management
- forestry carbon sequestration
  - maintaining or increasing forest area: reducing deforestation and degradation
  - maintaining or increasing forest area: afforestation/reforestation
  - forest management to increase stand and landscape level carbon density
  - increasing offsite carbon stocks in wood products and enhancing product and fuel substitution.
The CCX uses the following definition for common practice:

Common practice refers to the predominant technologies or practices in a given market, as determined by the degree to which those technologies or practices have penetrated the market (defined by a specified geographic area) (World Resources Institute & World Business Council for Sustainable Development 2005).

Each of the 10 protocols used by the CCX includes common practice criteria with requirements unique to each. These protocols can be likened to the ‘methodologies’ used under the CFI. Two examples are given below.

**Agricultural methane**

During protocol development, the CCX reviewed information from the United States Environmental Protection Authority on uptake of agricultural methane digesters on farms (Chicago Climate Exchange Inc. 2009a). This review found that only 0.06 per cent of dairy and swine farms in the United States have anaerobic digesters in operation; consequently, the practice was deemed uncommon by the CCX. The CCX states that periodic review of data will enable future modifications to the ‘performance benchmark’ if necessary. There is no threshold stipulated for common practice and instead assessments of commonness are undertaken on a case-by-case basis and are determined from the current adoption levels for practices. This exemplifies the most straightforward application of a common practice test where:

- existing data meet the information required to determine the adoption level
- the practice is a new technology with little variation in how it is applied.

**Conservation tillage and grassland management**

Soil scientists have estimated that only between 5 and 10 per cent of US farmland is currently managed under continuous conservation tillage (Chicago Climate Exchange Inc., 2009b). Occasional conservation tillage is more widespread. Only continuous conservation tillage could earn offset credits under the CCX rules. The CCX periodically reviews this data to assess whether the level of adoption has changed.

Conservation tillage includes planting methods commonly referred to as:

- no-till
- strip-till
- direct seed
- zero till
- slot till
- zone till.

Conversion of cropland to grassland is considered an uncommon practice in the United States. Land converted from crop to grassland for conservation purposes under the Conservation Reserve Program and the National Grazing Lands Initiative is commonly returned to cropland at the end of the enrolment period. For the CCX, this information justified all conversion from crop to pasture as ‘additional’.
In summary, there was no scheme-wide threshold level determined for protocols developed under the CCX. Even at the protocol scale there is no benchmark for commonness against which assessments of common practice are made; instead a combination of expert opinion and survey data form the basis for each protocol-specific common practice assessment.

The Alberta-based Offset Credit System

The Alberta province’s greenhouse gas reduction program has been in place since 1 July 2007. The associated voluntary offset scheme has developed and approved a large number of protocols for a range of land sector offsets. Approved quantification protocols for agriculture include:

- cattle feed supplements
- reducing days on feed for beef cattle
- nitrous oxide emissions reductions in agriculture
- emissions reduction from dairy cattle
- swine feeding and swine manure management
- tillage system management.

The scheme provides limited information on how the common practice test is applied. It appears that project proponents are responsible for assessing whether or not an activity is common practice. The ‘Offset Protocol Development Guidance’ document outlines integrity standards for additionality, including one titled ‘Sector Level Adoption’. This is outlined as the final test for assessing additionality, which states that:

If a significant number of other people have engaged in the same activity, then the arguments for financial, technological and/or social barriers do not hold true and it is assumed that remaining members of the sector can also adopt the activity and/or practice change (Government of Alberta 2011).

A 40 per cent level of adoption has been set as the point at which an activity is considered business-as-usual. However, protocol developers can propose alternative levels if necessary. The 40 per cent threshold does not appear to be supported by any rigorous empirical analysis.

Climate Action Reserve

The Climate Action Reserve (CAR) develops protocols and verification processes for the North American carbon market. In the CAR agriculture-related protocols there is no scheme-wide threshold for common practice assessment; instead thresholds are stipulated for each practice. Thus far, protocols have been developed or are in development for the following activities:

- cropland management
- nitrogen management
- rice cultivation
- manure biogas control for livestock production.
The CAR outlines the range of data sources specifically needed to conduct common practice tests for agriculture and supports the use of additional data sources and research ‘to identify distinguishing features that would allow a protocol to differentiate between common practice (“business as usual”) projects and those that would be truly ‘additional’. (Climate Action Reserve 2010, p. 4). Further, the CAR outlines several ways through which to specify performance standards (Climate Action Reserve 2010):

- emission or sequestration rate thresholds (for example, GHG emissions per unit of production)
- practice or technology-based thresholds (for example, a specific practice is rarely or never implemented)
- other qualifying conditions or criteria (for example, characteristics related to the project site).

**A summary of common practice tests in various offset schemes**

Table 2 presents key features of the common practice approach from the offsets schemes outlined above. Each scheme has approached common practice determinations differently using standardised approaches with either scheme-wide or activity specific adoption or threshold levels. Thresholds stipulated for common practice tests under the CDM and the Alberta-based Offset Credit System do not seem to be based on any rigorous empirical analysis.

The remainder of this report attempts to fill this gap by offering some theoretical underpinnings and empirical basis for identifying adoption thresholds for common practice tests and developing a streamlined common practice assessment framework for the CFI.

**Table 2 Summary of approaches to common practice used in other schemes**

<table>
<thead>
<tr>
<th>Scheme</th>
<th>How is common practice applied?</th>
<th>Common practice threshold</th>
</tr>
</thead>
<tbody>
<tr>
<td>CDM</td>
<td>Projects apply a stepwise common practice test on a case-by-case basis</td>
<td>Threshold is 20 per cent</td>
</tr>
<tr>
<td>CCX</td>
<td>Standardised common practice assessment made at the time of protocol development</td>
<td>Uses survey data and expert opinion to determine activity adoption level</td>
</tr>
<tr>
<td>Alberta-based Offset Credit System</td>
<td>Standard threshold level set across all projects. Process for common practice test decided by project proponent</td>
<td>Scheme-wide threshold is 40 per cent</td>
</tr>
<tr>
<td>CAR</td>
<td>Standardised threshold set for each practice</td>
<td>Uses survey data and research to set activity threshold</td>
</tr>
</tbody>
</table>

**Note:** CDM = Clean Development Mechanism, CCX = Chicago Climate Exchange, CAR = Climate Action Reserve.
5 Theoretical underpinnings for common practice tests

Key points

- The literature reviewed supports the use of a standardised common practice test as a measure of additionality.

- The diffusion of innovations theory describes the spread of an innovation through a system, and is based on the idea that individuals do not all adopt a practice at the same time. When mapped as a cumulative function, the diffusion of a technology or practice is typically represented by an S-shaped curve.

- Analysing the diffusion curves of abatement practices could form the basis of common practice threshold levels.

- Two approaches emerge from the literature: the first is the maximum acceleration of adoption derived from the nature of the adoption curve called the take-off point; and the second is a common practice threshold based on a fixed proportion threshold.

- The academic literature suggests that the take-off point occurs somewhere between 5 and 23 per cent, and that the take-off point could be considered as a common practice threshold.

- This report builds on existing approaches and reduces knowledge gaps related to applying common practice thresholds by providing a comprehensive analysis using diffusion models (Appendixes A and B). The analyses find that the major barrier to using the take-off point as the common practice threshold is that it is difficult to determine with limited data. For this reason, a fixed proportion threshold is recommended in most cases. Fixed proportion thresholds can provide a valid approximation of the take-off point for a broad range of model parameters and modelling approaches.

- There are a number of challenges presented by using a common practice test based on adoption information. For example, different practices may have different shaped S-curves or even different shaped curves with multiple plateaus (that is, with multiple inflection or take-off points) because of the biophysical, economic and social context of the practice or technology.

- While these challenges are largely circumvented by using a fixed proportion threshold, the issue of factoring out the effect of the CFI on adoption requires further analysis.

Introduction

This chapter reviews theories for standardised approaches to common practice assessments. It focuses on the theories of:

- market penetration

- adoption based on risk perception and diffusion theory.

Both approaches support the notion that technologies or practices that are not adopted at all or not widely implemented are more likely to be ‘additional’, and are often applied using a threshold approach. A number of quantitative approaches can be used to inform the
The establishment of a threshold using an analysis of different adoption groups and the rate and nature of the diffusion process, although for each there are associated problems. These approaches are particularly relevant to this report as they provide further guidance to developing the common practice framework described in Chapter 6.

**Market penetration rate thresholds**

The use of technology penetration rate thresholds to assess additionality is first described by Kartha et al. (2005). They proposed that, as emerging technologies are more likely to be ‘additional’, defining a specific threshold based on technology penetration can provide a streamlined, simple and quantitative tool to assess additionality. For example, an offsets project employing low-carbon technology may be deemed non-‘additional’ if that technology commands more than a certain percentage of a given product market. This idea is similar to measurements of adoption levels for common practice.

The authors defined penetration rates as being the extent to which a given technology (or practice) has entered a given market jurisdiction, and suggest market share or uptake saturation as useful indicators. Their review focused on the practical aspects of applying the test and gave particular consideration to:

- data requirements and how they can be measured and tracked
- the sectors and projects for which the test is most applicable
- the advantages and disadvantages of possible approaches to setting thresholds.

The authors found that survey data are likely to be sufficient to estimate penetration rates in several sectors, including agriculture. They estimated a reasonable generic threshold as between 2 and 10 per cent, but stated that this will depend on the design of the test, the nature of the sector, the ‘population’ size, and technologies being considered.

**Adoption based on risk perception**

Mathur et al. (2007) approached additionality from another perspective. They proposed that the level of adoption of a technology within a community can be used to predict the degree of risk perceived by potential adopters, which in turn provides an effective assessment of additionality. For example, a technology in the early stages of adoption is seen as being much more risky than one that is already well-established. This level of risk may prevent the project from being implemented without the additional incentive under an offsets scheme or incentive program, and therefore it should be considered ‘additional’.

Basing the assessment on the level of perceived risk lends itself to a comprehensive analysis of additionality because it encompasses many of the factors that influence decision-making, including ‘investment uncertainty, technological uncertainty, policy and regulatory uncertainty’ (Mathur et al. 2007).

The approach proposed by Mathur et al. (2007) bases the assessment of what represents an emerging, risky and therefore ‘additional’ practice on the diffusion of innovations theory. This theory involves mapping the spread of an innovation as a function of time, and is characterised by an S-shaped curve (Figure 3) described below in some detail. Mathur et al. (2007) suggested that an estimation of the take-off point on the curve (which they believe generally occurs at 10–20 per cent of total adoption) be used to define the additionality criterion.
**Diffusion of innovations theory**

The diffusion of innovations theory is based on the idea that individuals in a social system do not all adopt an innovation at the same time, but can be divided into categories depending on how readily and quickly they adopt. In this context, an innovation is defined as ‘an idea, practice or object that is perceived as new by an individual or other unit of adoption’ (Rogers 2003). It is not related to the amount of time the activity has been available for adoption; it is related to a change in an individual’s knowledge, persuasion or decision to adopt it.

Research into the diffusion of innovations started in a series of independent intellectual enclaves during the 1940s and 1950s and the dominant model is that described by Rogers (2003) in *Diffusion of Innovations*, first published in 1962. This model has since been applied to about 5000 studies across a wide variety of academic disciplines (Rogers 2004).

The distribution of the various adopter categories is given below in Figure 2. Rogers (2003) divides the ‘population’ into groups associated with the adoption sequence (Figure 2), with innovators considered approximately 2.5 per cent of the ‘population’, followed by early adopters comprising 13.5 per cent, and the early majority 34 per cent. These are based on standard deviations from the mean. Similarly Bass (Mahajan et al. 1995) reported innovators to range from 0.2 per cent to 2.8 per cent of the ‘population’, early adopters from 9.5 per cent to 20 per cent, and the early majority from 29.1 per cent to 32.1 per cent. These divisions, for a normally distributed (or bell) curve, are derived from one or two standard deviations from the mean time of adoption.

*Figure 2 Adopter categorisation on the basis of innovativeness*

![Diagram showing the distribution of adopter categories with 2.5% innovators, 13.5% early adopters, 34% early majority, 34% late majority, and 16% laggards over time.](source: Rogers (2003))

When mapped as the cumulative rate of diffusion of a technology/innovation over time, the adoption trajectory is characterised by an S-curve (Figure 3). The uptake of an innovation is slow in the early stages. Innovators make up only a small percentage of the ‘population’ and have negligible market share (for example, less than 2 per cent; see Kartha et al. 2005). As the diffusion proceeds, the rate of adoption increases, with a transition point corresponding to the maximum increase in the rate of diffusion or what is termed as a ‘take-off’, as early adopters start building on the experiences of the innovators (Mathur et al. 2007). According to Rogers (2003), the point of take-off is expected to occur following the transition from innovators to early adopters (approximately 5 per cent adoption level) and following the transition between...
early adopters and early majority (at 20 per cent adoption level). A technology that is able to achieve wider acceptance begins the process of pervasive diffusion. Beyond the take-off point, the diffusion may become self-sustaining and ‘eventually the rate of uptake reaches saturation’ (Mathur et al. 2007; Kartha et al. 2005). Mathur et al. (2007) proposed that the take-off point be used to define the additionality threshold or the transition to common practice.

Figure 3 Cumulative S-curve of technology or practice adoption and adopter categories

Further to Rogers’ (2003) estimation of an approximate take-off of between 5 and 20 per cent, Mathur et al. (2007) claimed that the take-off point generally occurs between 10 and 20 per cent of total adoption depending on the shape of the S-curve (Figure 3), and Mahajan et al. (1995) suggested that this point will occur somewhere between 10 and 23 per cent. As the position of the take-off point depends on the biophysical, economic and social context of the system (Mathur et al. 2007; Rogers 2003), Mathur et al. (2007) suggested that rather than making assumptions about take-off threshold values it is best to empirically determine the take-off points by examining the trajectory of diffusion using the past as a prologue. However, Mathur et al. (2007) did not identify appropriate diffusion models for determining take-off points or provide analytical approaches to determine take-off points with few historical data points—a prerequisite when dealing with a technology or practice innovation early in its diffusion process.

Geoffrey Moore, in his 1991 book *Crossing the Chasm*, discussed the difficulty in marketing high-tech products to mainstream customers, and identified a chasm in adoption between the early adopters (visionaries) and the early majority (pragmatists) (Moore 1991). This suggests there is a critical period that is likely to determine whether an innovation will take-off in future (as early adopters start to build on the experience of innovators). Marketing or the introduction of a market solution such as offset credits, during this period could affect the outcome. The length of this critical period is likely to be situation-specific, and to depend on socio-economic and biophysical differences. These situation-specific differences that enable or prevent practices progressing through this critical period will be considered in common practice assessments. See Chapter 6 and Appendixes C and D for more information on how these aspects are considered in the proposed common practice assessment process.
Defining common practice

From the above discussion, two approaches emerge: the first is the rate of adoption derived from the nature of the adoption curve (Mathur et al. 2007); and the second is the common practice threshold based on a fixed penetration rate. The former approach requires an assumed mathematical adoption model with parameters estimated from data as they become available, with the threshold thus determined by the particular diffusion process. Alternatively, the latter requires a decision on the fixed threshold rate, a known ‘population’ size, and data about adoptions in real time. Once all these are known, it is simple to assess whether a practice is common.

Mathematical analysis of diffusion models and consideration of a range of potential common practice thresholds is provided in Appendixes A and B. The analyses find that the major barrier to using the take-off point (referred to as $Y_1$ in Appendixes A and B) as the common practice threshold is that it is difficult to determine with limited data. For this reason, a fixed proportion threshold (referred to as $Y_3$), which is simply a fixed proportion of the target ‘population’ is recommended in most cases. The analysis identifies a fixed proportion threshold of 20 per cent (a value for $Y_3$) as this represents approximately the upper bound for the estimates for the take-off point ($Y_1$), and in many cases is close to the true value. The 20 per cent threshold can be adjusted proportionately depending on the maximum level of adoption of the practice.

The diffusion of a particular technology or practice may not necessarily follow a smooth path, although this is convenient for theoretical exposition, as depicted in Figures 2 and 3. More specifically, it is possible that a technology or practice diffusion curve may not follow a smooth S-curve, but may be characterised by several ‘maximum’ acceleration points and several plateaus (Golder & Tellis 2004; Peres et al. 2010; Van den Bulte & Joshi 2007). In calculating the take-off point from limited early data, it is not possible to know which phase the adoption process might be in, and the resulting threshold determination may not be correct. However, using a fixed proportion threshold, based on the upper bound for the take-off point, largely circumvents these problems and the threshold may remain robust.

For technologies or practices with diffusion paths that are not currently known, it may be argued that some of these technologies or practices are likely to become cost-competitive and profitable over time without any policy incentives. It is also possible that there are certain technologies or practices that will never be cost-competitive without certain policy incentives. As discussed earlier, the CFI is expected to influence the adoption of technologies or practices by farmers and landholders in a variety of ways. Adoption of new technologies or practices is also supported by improved access to information delivered through the research, demonstration and extension programs of the Land Sector Package (a complementary activity to the CFI within the Clean Energy Future Plan). Many of these adoption effects of the CFI are expected to result in some environmental benefits through the reduction of greenhouse gas concentrations in the atmosphere.

Further, in some cases an innovation may undergo step-changes throughout the adoption process, characterised by newer generations of a technology. This presents more of a challenge when calculating the take-off point than when using a fixed proportion threshold as S-curve characteristics, for future adoption would have to be based on previous generations of the innovation. Assuming that each common practice assessment is conducted separately, using a well-defined practice and a fixed proportion threshold, this issue can be largely addressed (see Appendix A for more details on this issue).
Another challenge in assessing common practice relates to the issue of factoring out the effect of the scheme on adoption for those practices previously included in the CFI ‘positive list’ and subject to periodic review. In accordance with the CFI legislation, the Minister for Climate Change and Energy Efficiency will ‘factor out the impact of the scheme when assessing whether an activity is common practice’ to ensure activities that become common practice because of the scheme do not fail the additionality test. The effect of the CFI on practice adoption is hard to predict as adoption is influenced by a broad range of factors (see Appendix E for more details).
A proposed common practice assessment framework for the CFI

Key points

- A framework for the common practice test is proposed in this chapter and outlined in Figure 4.
- The proposed common practice assessment framework can operate with at least one year of fit-for-purpose survey data or additional information.
- Abatement practices with an adoption rate of less than 5 per cent of the target ‘comparison group’ or ‘population’ may be considered ‘additional’ and practices with an estimated adoption rate of greater than 20 per cent may be deemed non-‘additional’.
- Projects that have an adoption level between 5 and 20 per cent of the target ‘population’ may be subject to further threshold assessment.
- Thresholds may be adjusted using expert opinion on the maximum practice adoption uptake.
- Based on mathematical analyses (Appendixes A and B), the use of a fixed proportion adoption threshold is recommended. The main reasons are: limited early data are not adequate to predict the take-off threshold accurately; the fixed proportion threshold proposed provides a valid approximation to the take-off threshold for a broad range of parameter values and modelling approaches; and the fixed proportion threshold provides a simpler approach that circumvents a number of implementation problems discussed in the report.
- In the short term, it is likely that a combination of information sources and methods will be required to assess practice level additionality.
- Practices on the ‘positive list’ will be reviewed periodically or when new information becomes available, to assess whether individual practices are still ‘additional’.

Introduction

This chapter focuses on the recommendation of, and an application of, a common practice test for the CFI. It describes a proposed common practice assessment framework, which was developed in consultation with the Department of Agriculture, Fisheries and Forestry’s Climate Change Policy Branch and the Department of Climate Change and Energy Efficiency. The chapter also draws on lessons from other schemes, the diffusion of innovations literature, and outcomes from the quantitative analysis outlined in Appendixes A, B and E. The framework, together with the recommended mathematical approach to defining a threshold, provides a consistent, robust and quantitative determination for additionality.

Proposed framework

The common practice test framework provides a streamlined assessment of practices that are likely to be ‘additional’ or non-‘additional’. The framework could operate with at least one year of fit-for-purpose survey data or additional information, and directs assessments into one of three streams dependent on the adoption proportion (Figure 4). The lower boundary of 5 per
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cent adoption is taken from the lowest suggested value for the take-off point proposed by Rogers (2003). The upper boundary of 20 per cent is supported by ABARES analyses in Appendix A, Mathur et al. (2007) and is being used in the CDM’s common practice test.

- **Stream 1:** If the level of adoption is below 5 per cent of the target ‘population’, it is likely that practices are in the early stages of diffusion (see Chapter 4) and that transition to widespread adoption is yet to occur. Therefore, these practices are likely to be considered ‘additional’.

- **Stream 2:** If the level of adoption is between 5 and 20 per cent, then further analysis may be required to determine the common practice activity specific threshold (options are described briefly below and expanded in Appendix A). Once the threshold has been estimated then the practice may be considered either ‘additional’ or non-‘additional’.

- **Stream 3:** If the level of adoption is above a threshold of 20 per cent, practices could be considered non-‘additional’. This will depend on the level of adoption and an assessment of the factors that affect adoption of that practice. Because the framework is based solely on the level of estimated adoption of a practice, there may be other factors determined by the DCCEE that could be considered for inclusion in the scheme of practices with an estimated adoption rate above the 20 per cent threshold.

The proposed framework is general enough to be applied to the appropriate spatial scale and take into account underlying variations in biophysical and socio-economic characteristics.

Over time, practices will likely progress along the practice adoption curve (Figure 3), and will need to be reassessed periodically. Following periodic review, some practices originally considered as ‘additional’ may be found to be non-‘additional’.
The previously released ABARES Outlook conference paper proposed a lower bound of 2.5 per cent for Stream 2 (Woodhams et al. 2012). This was based on the transition between innovators and early adopters as is described in Figure 2 (Chapter 5) of this report. This estimate is derived purely from standard deviations from the mean. Subsequently, ABARES has adjusted the lower bound for Stream 2 and the upper bound for Stream 1 to 5 per cent as reported here, as Rogers (2003) proposed that ‘...peer influence usually makes the diffusion curve take-off somewhere between 5 and 20 per cent of cumulative adoption’, making a direct connection between adoption level and take-off. The actual boundaries differ between innovations, but Rogers (2003) provided empirical support for the new framework intervals.

### The common practice threshold assessment

The adoption level for a practice will be determined using data from customised surveys, other surveys and additional information. Depending on available data, the threshold test could involve rigorous processes of mathematical modelling and empirical estimates of the model parameters, described in Appendixes A and B. Based on this theoretical and numerical analysis, and ensuing recommendations, this report has explored two different ways to conduct the common practice test using fit-for-purpose survey data:

1) Determine the take-off point ($Y_1$) with survey data. The take-off point is the point on the adoption S-curve where the rate of uptake reaches maximum acceleration. It represents the...
point when a practice changes from one that is in its early innovation stages, and adopted by only a few, to one that is more widespread and gaining significant popularity. It can be used as a criterion to define common practice thresholds. When limited data are available, estimates of the take-off point are likely to be highly uncertain. However, as the frequency of data collections increases over time, certainty around calculations of the take-off point could improve. Expert opinion or survey data may be used to determine changes in the saturation level (or the maximum level of adoption that could be achieved for an abatement practice) with the threshold (take-off point) adjusted proportionately.

2) Use the fixed proportion threshold ($Y_3$). The assessment of a number of diffusion models has indicated that the take-off point has an upper limit close to 20 per cent of the target ‘population’. This provides a default threshold in cases where data are insufficient and for instances when the take-off point does not exist (that is, when the curve does not follow a typical S-shape). Expert opinion or survey data may be used to determine changes in the saturation level (or the maximum level of adoption that could be achieved for an abatement practice), with the 20 per cent threshold adjusted proportionately to the saturation level. ABARES is considering the use of the CSIRO ADOPT model (Kuehne et al. 2011) to investigate the total number of potential adopters for each practice.

Based on mathematical analyses (Appendixes A and B), the second approach above is recommended in most cases. The main reasons for this are:

- limited early data are not adequate to predict the threshold $Y_1$ accurately
- the fixed proportion threshold $Y_3$ provides a valid approximation to the threshold $Y_1$ for a broad range of parameter values and modelling approaches
- the fixed proportion $Y_3$ is not compromised by limited data
- the fixed proportion $Y_3$ provides a simpler approach that circumvents a number of implementation problems for $Y_1$ discussed in this report.

**Proposed common practice assessment process**

To apply the framework, the abatement practice and ‘comparison group’ or ‘population’ must first be identified. The process for assessments may differ between practices. Practice uptake is likely to vary according to biophysical and socio-economic characteristics and, therefore, common practice assessments will consider the ‘comparison group’ carefully and how these factors influence adoption. The ‘comparison group’ will be determined in consultation with the DCCEE and other relevant stakeholders in line with the practice stipulated in the ‘positive list’ assessment. The regional scale at which each common practice threshold test will occur will initially depend on the industry and the practice defined. To determine the circumstances/region where the practice is taking place, the ‘comparison group’ may need to be refined further in consultation with the DCCEE. These scales may range from a single Australian Agricultural Environment (described in Appendix C) to the national level, but could also consider other non-regional factors like property size, scale of operation, and distance from facilities.
The common practice assessment could follow the following process:

1) Using data and information from appropriate sources assess the current practice adoption level. This stage will direct the assessment process into one of the three streams presented in Figure 4.

2) For practice adoption that falls below 5 per cent, no further assessment is required (Stream 1). For practice adoption that falls between 5 per cent and 20 per cent of adoption (Stream 2), determine whether data are sufficient to calculate the take-off point \( Y_1 \). If not, then use the fixed proportion \( Y_3 \) as the common practice threshold. Adjustments to the threshold may be made through further threshold analysis including using expert opinion surrounding the maximum uptake potential. Practices with adoption levels that fall below this threshold are likely to be deemed ‘additional’. Practices with adoption levels above 20 per cent (Stream 3) could be considered non-‘additional’. However, as mentioned previously, because the framework is based solely on the level of estimated adoption of a practice, there may be other factors determined by the DCCEE that could be considered for inclusion in the scheme of practices with adoption rates above the 20 per cent threshold.

3) Provide assessment results to the DCCEE to assist in determining whether the practice meets the ‘positive list’ requirements or is considered non-‘additional’.

The ‘positive list’

Once on the ‘positive list’, practices will be reviewed periodically by the DCCEE (in consultation with ABARES and the DOIC) or when new information becomes available. Following review, practices may remain on the list or be removed. Assessing whether practices should be removed from the ‘positive list’ is beyond the scope of this report.

Data requirements

At least one year (and/or one collection) of recent survey data is required to conduct the common practice assessment for each abatement practice. One year of survey data provides an indication of the level of adoption for that practice. While there are many surveys conducted with agricultural businesses in Australia, few pose questions that are adequately related to mitigation practices. To meet this need, the Australian Bureau of Statistics (ABS) has been contracted to run a purpose-built biennial Land Management Practices (LaMP) survey to obtain information on practices that have abatement potential across Australian agricultural industries. To conduct the common practice threshold assessment, the data from this survey may be supplemented with data from the ABS census and surveys (namely, AgCensus and the Australian Resource Management Survey), ABARES surveys and industry data collections, published literature and expert opinion. This information will be used to assign abatement practices to one of the three assessment streams outlined in Figure 4.

Uptake of a particular practice and the potential common practice threshold may vary by land management practices, region and farm size associated with different biophysical and socio-economic conditions. As a result, the LaMP survey has been designed to provide the most representative picture of a sector and region by stratifying by appropriate industry categories and Australian Agricultural Environments.

To inform the development of the LaMP survey, various regional and industry classifications have been assessed and a classification scheme has been chosen by ABARES in consultation with the ABS. These processes were conducted in late 2011 to ensure an appropriate and representative sample of agricultural businesses are surveyed across a range of Australian
environments. More information on the regional and industry classifications can be found in Appendixes C and D.

As the number of data collections increases, common practice threshold determination will become more reliable. In the short term it is likely that a combination of methods, including the fixed proportion threshold will be required for those practices falling in Stream 2 of Figure 4.
7 Conclusions and future research

This report has outlined a potential common practice framework for additionality assessment for the CFI. The framework has drawn on lessons learned from other schemes, academic literature and the results of mathematical analyses, and has been developed in consultation with a number of key stakeholders. The framework has been designed to inform policy development and, if adopted, will support CFI integrity by using a streamlined approach to common practice assessments.

There is growing recognition of the merits of common practice additionality tests in various international schemes and academic forums. However, each international scheme reviewed in this report seems to have approached common practice determination differently. Importantly, the specific thresholds stipulated for common practice tests under the Clean Development Mechanism under the Kyoto Protocol and the Alberta-based Offset Credit System—two well-known international carbon offset schemes—do not appear to be based on any rigorous empirical analysis. This report has attempted to fill this gap by offering some theoretical underpinnings and empirical basis for identifying adoption thresholds for common practice tests and by developing a streamlined common practice assessment framework for the CFI.

This report has also briefly described the legislated CFI and its additionality standard to set the context for common practice assessments. Given that the additionality standard is a legislated feature of the CFI, no critical review of the standard has been attempted in this report. As such, the report emphasises that, while a range of practices and technologies can result in a reduction of emissions from agriculture or sequestering carbon from the atmosphere, the ABARES common practice framework has been designed to cover only those practices and technologies that can be assessed for inclusion in the CFI ‘positive list’.

Furthermore, the process of developing the common practice framework has identified a number of areas that require further research or consideration. Some of the key challenges or issues are described below, outlining a possible course for future research.

**Analysing the effect of the scheme for ‘positive list’ reviews**

Reassessment of practices that are placed on the ‘positive list’ will occur periodically. Practices that reach or exceed the adoption threshold may be removed from the ‘positive list’ following review. When conducting this review, policymakers may have to consider how to factor out the effect of the scheme. The reason for this is that removal of such activities from the ‘positive list’ may lead to disadoption due to removal of the CFI incentive. The process of disadoption could result in a decrease in the proportion of those who have adopted a practice under the CFI, leading to the proportion of adopters falling below the common practice threshold.

Any adoption of practices or technologies under the CFI will be subjected to a specific crediting period and other conditions as required under the approved ‘methodologies’. Also, disadoption may not be a cost-free exercise.

In view of the above, determining what practices and technologies to remove and when to remove them may become an involved policy deliberation exercise. This issue is discussed more comprehensively in Appendix E, and additional work is proposed on exploring the use of a Farm-Size Model to assess when practices are not commercially viable without CFI credits.
Minimising non-‘additional’ abatement

Crediting non-‘additional’ abatement refers to credits that are provided to practices or technologies that would have happened without the CFI. Like other additionality tests, a standardised approach, such as the common practice test, cannot eliminate the risk of non-‘additional’ abatement completely. This issue is outlined more comprehensively in Appendix E, and further work is suggested on exploring the use of emissions baselines and an ‘integrity buffer’ to reduce the risk of non-‘additional’ abatement.

Data and the ‘comparison group’

Adoption of a particular practice may vary by land management practices, region and farm size associated with different biophysical and socio-economic conditions. Common practice assessments need to consider to what degree each of these factors affects the definition of the ‘comparison group’. In some cases, data limitations may reduce the ability to conduct a common practice assessment on a particular practice or technology with an associated ‘comparison group’. The LaMP survey, described in Chapter 6 and Appendixes C and D, will reduce information gaps and assist in ‘comparison group’ refinement. However, in certain circumstances, other specialised surveys may be required.

Adjusting the threshold by the number of potential adopters

As detailed in Appendix A, the common practice threshold can be adjusted proportionally to the expected number of total adopters (m). However, it is difficult to determine the maximum level of adoption early on in the adoption process. Further research could be conducted investigating the possible use of CSIRO’s ADOPT model (Kuehne et al. 2011) to determine the saturation level using expert opinion and survey data.
Appendix A: Diffusion models and calculating the common practice thresholds

Key points

- The Bass model has been shown to describe the diffusion process well for a wide range of practice types, scenario testing and adoption mechanisms. For this reason, it has been used as the basis for our analyses.

- There are many possible threshold approaches to determining common practice: two options have been considered in detail in this report. The first is the maximum rate of acceleration in adoption ($Y_1$) as proposed by Mathur et al. (2007), and the second is a fixed proportion threshold ($Y_3$).

- The third approach presented, ($Y_2$), where the innovators equals imitators, is not considered suitable because it varies most to small changes in model parameters ($p$ and $q$).

- A fixed proportion threshold ($Y_3$) circumvents many of the problems associated with calculating $Y_1$. It does not require diffusion analysis or model fitting procedures. Estimates of $Y_3$ offer a practical solution when only one data point is available and multiple peaks and saddles in adoption data will not influence estimates of the threshold. Setting $Y_3$ to approximately 20 per cent represents an approximate upper bound for a range of parameter estimates and is valid for a range of diffusion models. This is consistent with the upper level for the threshold proposed by Mathur et al. (2007) and is the threshold used by the CDM.

- If $Y_3$ is set as the upper limit of $Y_1$, it can be easily adjusted when the adoption potential $m$ is believed to be below its maximum. The disadvantage of $Y_3$ (set as the upper limit for $Y_1$) as a threshold for additionality is that it will almost always exceed $Y_1$, potentially resulting in more false non-‘additional’ projects credited by the CFI than if $Y_1$ were the threshold point.

- It is proposed that $Y_3$ be used as the common practice test to account for cases when $Y_1$ cannot be estimated or there is uncertainty. The value of $Y_3$ can be adjusted for changes in ‘population’ size if there is evidence that saturation is likely to be different from the original assumption.

Introduction

This appendix provides a mathematical approach to establishing three distinct common practice thresholds, leading to a validated and practical recommendation for adoption that is based on the results of the mathematical analysis undertaken.

Diffusion models are commonly used to predict the rate of practice or technology adoption within a ‘population’. There are a plethora of models, particularly in the market research literature, that explain the diffusion process (see Chapter 4 of this report for explanation of the diffusion process), and many of these have been applied to agricultural practices. For example, the Bass (Bass 1969), logistic (Mahajan et al. 1990), Gompertz (Dixon 1980), Nelder (Nelder 1962) and von Bertalanffy (1957) models have all been used to describe agricultural practice diffusion, while the Stanford model (Teotia & Raju 1986) has been proposed for energy efficient
practices. All of these models vary in their assumptions of how the diffusion process occurs and have a different number of parameters that can influence the shape of the S-curve.

The Bass model was chosen for further threshold analysis in this report because it:

- is the foundation model for all diffusion research
- has been applied successfully to a wide range of agricultural practices (Mahajan et al. 1990; Nelder 1962; Marsh et al. 2000)
- is relatively simple, having only a few parameters that describe important influences in the diffusion process.

The Bass model assumes that the traditional S-shape of adoption curves comes from a mixture of internal and external influences. External influences include factors such as individual research, mass media, government agencies and promotional efforts. Individuals who adopt a practice because of external influences are labelled ‘innovators’. Internal influences are those that arise from interactions within the social system, such as word of mouth and the observation of peers. Individuals who adopt because of internal influences are termed ‘imitators’ because their decision to adopt is influenced by the behaviour of others. There are many other factors that could influence the parameters, including financial factors, which may influence either parameter. Although this approach has been applied extensively to market research, these mechanisms for adoption are not specific to any product type. In the absence of considerable data, this approach allows the effect of aggregated information to be analysed in a general way, and, when data are available, provides a means to assess the likely impact.

This appendix starts by discussing how these factors influence the shape of the diffusion curve and hence the take-off point, before proposing three possible common practice thresholds:

- the take-off point referred to here as $Y_1$
- the point where innovators equal imitators $Y_2$
- a fixed proportion of the ‘population’ $Y_3$.

The advantages and disadvantages of these thresholds are then discussed in the context of a common practice test.

The following section describes the above threshold concepts. While the components of each equation are introduced in each section, Table A1 describes the key elements of these concepts in terms of variables and coefficients.

Table A1 Key variables and coefficients for diffusion models

<table>
<thead>
<tr>
<th>Equation component</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$y(t)$</td>
<td>cumulative number of adopters by time $t$</td>
</tr>
<tr>
<td>$Y(t)$</td>
<td>cumulative proportion of the ‘population’ who have adopted by time $t$</td>
</tr>
<tr>
<td>$Y_1$</td>
<td>the point of maximum increase in diffusion rate (generally $\frac{d^2Y_1}{dt^2} = 0$)—the take-off point</td>
</tr>
<tr>
<td>$Y_2$</td>
<td>the point at which the number of imitators equals the number of innovators</td>
</tr>
<tr>
<td>$Y_3$</td>
<td>the point at which a fixed proportion of the target ‘population’ has adopted the practice</td>
</tr>
</tbody>
</table>
The Carbon Farming Initiative: A proposed common practice framework for assessing additionality

\[ \frac{dy(t)}{dt} = p(m - y(t)) + \frac{q}{m} y(t)(m - y(t)) \]

where \( y(t) \) is the number of individuals who have adopted the practice at time \( t \), \( m \) is the total target ‘population’, \( p \) is the ‘innovation coefficient’ describing the rate of adoption as a consequence of external influences, and \( q \) is the ‘imitation coefficient’ describing adoption as a result of internal influences. This equation can be solved so that the number of adopters can be explicitly calculated over time:

\[ y(t) = m \left( 1 - \frac{e^{-t(p+q)}}{1 + \frac{q}{p} e^{-t(p+q)}} \right) \]

or

\[ Y(t) = \frac{1 - e^{-t(p+q)}}{1 + \frac{q}{p} e^{-t(p+q)}} \]

where \( y(t) \) is the cumulative number, and \( Y(t) = y(t)/m \) is the cumulative proportion of the ‘population’ who have adopted a practice, and it is assumed that \( y(0) = Y(0) = 0 \) (that is, initially no one has adopted the practice).
The cumulative adoption curve describing the proportion of adopters over time is illustrated in Figure A1a. The different curves show how the shape of the Bass model can change depending on the values of $p$ and $q$ ($m$ is set at 1 in this case). For example, the blue curves illustrate the Bass model when $p$ ranges from 0.01 to 0.1 (for a given value of $q=0.38$), while the black curves show the cumulative adoption curve when $q$ ranges from 0.1 to 1 (for a given value of $p=0.03$). Variation in $p$ has considerable effect on the early stages of the curve, while the effect of $q$ is greatest as time progresses (although ultimately all curves approach the upper limit). The red curve in Figure A1a illustrates the Bass model when $p$ equals 0.03 and $q$ equals 0.38—these particular values for $p$ and $q$ were taken from Sultan et al. (1990). These authors reviewed the adoption curve for 213 innovations from the 1950s to the 1980s and reported $p$ and $q$ values. In this report, the average of these values have been used as a benchmark, and variation above and below have been considered to provide a more general understanding, since agricultural innovations may have different average values when considered separately.

Figure A1b demonstrates how adoption is influenced by innovators and imitators over time, assuming particular values for $p$ and $q$ and with $m = 1$. Here, the adoption curves for innovators and imitators are plotted separately, with the total cumulative proportion of adopters also represented. The innovators exceed the imitators initially, but over time the proportion of imitators takes over and dominates the adoption rate—this follows because imitators are influenced by the number of people who have already adopted. However, this is not the case for all combinations of $p$ and $q$ values. Figure A1b shows the point at which imitators take over from innovators for the average parameter values. This occurs at approximately 10 per cent of the total proportion of adopters and can be roughly associated with those in the innovators and early adopters categories in Figure 2 (Chapter 5). However, these two groups can only be roughly associated because Figure A1b is given for a particular parameter combination, while Figure 2 is an average result where ranges for adopter categories can vary.
Assumptions in the Bass model

The Bass model makes the following important assumptions about the diffusion process.

- External factors influence innovators to adopt, who in turn influence individuals imitating their behaviour to adopt. Thus, the social network into which a practice diffuses is assumed to be fully connected and homogeneous.

- The Bass model only considers the case of initial adoption; that is, it assumes repeat adoption is excluded and individuals can only adopt a practice once. Individuals in a social system are assumed to have either adopted an innovation or not adopted (partial adoption is not considered).

- When conducting an analysis using the Bass model, the market potential/adoption potential \( (m) \) of a new product or technology is determined at the time of introduction and remains unchanged over its life. Therefore, variables that might change the market adoption potential of an innovation over time, such as price, are not explicitly incorporated in the model.

- Adoption is assumed to be independent from all other innovations.

- The nature of the innovation remains constant, meaning that successive generations of an innovation are not considered.

- There are no supply limits on the innovation.

Various extensions of the Bass model have been developed to incorporate flexibility in these assumptions (Bass et al. 1994). For example, subsequent modifications to the Bass model account for a dynamic ceiling in the number of potential adopters over time, the effect of competition between markets and the influence of a number of marketing variables on the adoption process. While these modifications have not been used in the analyses for this report, their incorporation into subsequent modelling may help to address some of the considerations raised elsewhere in this report.

Potential common practice thresholds

A common practice test requires a threshold point to be provided, beyond which the particular practice is deemed to be common. Using the Bass model, three potential thresholds can be examined:

1) \( Y_1 \): the point of maximum increase in diffusion rate; which is given by the value of \( y(t) \) (when it is defined for positive values of \( y \)) such that

\[
\frac{d^3 y}{dt^3} = 0
\]

This is the 'take-off point' (\( Y_1 \)) proposed by Mathur et al. (2007).

2) \( Y_2 \): the point at which the number of imitators equals the number of innovators

3) \( Y_3 \): the point at which a fixed proportion of the target 'population' has adopted the practice (\( Y_3 \)).

Maximum increase in diffusion (calculating the take-off point) \( Y_1 \) First consider the case of maximum increase in diffusion rate as the threshold. This is given by the maximum of 0 or \( y \), where
\[
\frac{d^3y}{dt^3} = 0.
\]
Figure A2a illustrates the curves for the first, second and third derivatives of the solution to Equation 2 (for the case of the average values of \(p\) and \(q\) taken from Sultan et al. (1990) and illustrates their location on the cumulative function curve (Figure A2b). The proportion of the target ‘population’ that has adopted the practice at the take-off point is:

**Equation 3**

\[
Y_1 = \frac{2 - \sqrt{3} - p/q}{3 - \sqrt{3}} \quad \text{when} \quad \frac{p}{q} < 2 - \sqrt{3}
\]

\[Y_1 = 0 \quad \text{otherwise.}\]

As indicated in Equation 3, depending on the values of \(p\) and \(q\), positive values for this threshold point may not exist. For example, a positive \(Y_1\) cannot be calculated using Equation 3 when the diffusion curve does not follow an S-shaped curve. Further, calculating \(Y_1\) requires estimates for \(p\) and \(q\).

In summary, to calculate the proportion of adopters at the take-off point, \(Y_1\), information about \(p\) and \(q\) is required as well as an S-shaped diffusion curve. These requirements affect the ability to calculate a positive value for \(Y_1\) under all possible scenarios, which is required for a robust common practice test. This is explored further in Appendix B. Since \(p\) and \(q\) are positive, \(Y_1\) is bounded above by 0.21 (approximately).

**Figure A2 Maximum increase in the diffusion rate**

**Note:** For \(p=0.03\), \(q=0.38\) and \(m=1\), the first, second and third derivatives are illustrated. The first threshold point \((Y_1)\) is where the third derivative is zero (the take-off point). In Figure A2b, the cumulative diffusion curve with vertical lines indicates the inflection point maximum rate of adoption \(\frac{d^2y}{dt^2} = 0\) (dashed line) and the points at which the maximum rate of adoption increase (take-off)/decrease occurs \(\frac{d^3y}{dt^3} = 0\) (dotted lines).

**Imitators equal innovators \((Y_2)\)**

A second threshold measure can be derived from the point at which imitators equal innovators (the point where the blue and black lines intersect in Figure A1b). At this point the driving mechanism for adoption switches from the innovators to the imitators. This point could be considered to be the point of transition to common practice. The equation is given by:
Equation 4
\[ Y_2 = \left[-\ln \left( \frac{p + q e^{-(p+q)T}}{p + q} \right) \right] \frac{p}{q} \]

where \( T \) is the time for which the proportion of innovators equals that for imitators:

Equation 5
\[ \frac{1 - e^{-(p+q)T}}{1 + \frac{q}{p} e^{-(p+q)T}} + 2 \ln \left( \frac{p + q e^{-(p+q)T}}{p + q} \right) = 0 \]

and can be found numerically. This threshold is not defined for all values of \( p \) and \( q \). As above for \( Y_3 \), the values of \( p \) and \( q \), as well as 'population' size \( m \), are required to calculate this threshold.

**Fixed proportion (\( Y_3 \))**

This is the approach used for common practice assessments in the Alberta-based Offset Credit System. Commonness is defined by a proportion of the target 'population' (for example, 40 per cent) and an assessment involves calculating the proportion of the 'population' who have adopted the practice.

In existing offsets schemes, the rationale for the fixed proportion threshold \( Y_3 \) is not evident; however, the literature and model analysis suggests a range of possible levels for \( Y_3 \), most at approximately 20 per cent (Rogers 2003; Mathur et al. 2007; Mahajan et al. 1995). Alternatively, \( Y_3 \) threshold could be defined as 15 per cent, which is the estimate of \( Y_1 \) when \( p \) and \( q \) are assumed to equal the averaged values reported across a range of practices by Sultan et al. (1990); that is, \( p = 0.03 \) and \( q = 0.38 \).

Unlike for \( Y_1 \) and \( Y_2 \) above, this threshold is not model-based (directly) and does not require estimates for \( p \) and \( q \), although it does require an estimate of 'population' size (\( m \)) for definition.

**Comparison of three potential thresholds**

Figure A3 compares the three thresholds for a range of values for the parameters \( p \) and \( q \) (with \( m \) set at 1) that have been previously reported in the literature. Lawrence and Lawton (in Mahajan et al. 1990) report \( q \) values ranging from 0.5 to 0.66, while Sultan et al. (1990) report a range from 0.2 to over 1; and Sultan et al. (1990) also establish a range of \( p \) values across innovations from 0.0001 to 0.033. By testing the three thresholds with a range of parameter values, it is possible to determine the appropriateness of each threshold for the common practice test.
Figure A3 Comparison of three thresholds for a variety of parameter values

Note: The threshold proportions $Y_1$ (maximum rate of adoption increase; solid curves), $Y_2$ (imitators equals innovators; dashed curves) and $Y_3$ (fixed proportion thresholds; grey horizontal lines) are plotted for a variety of $p$ (colours) and $q$ (x-axis) values. The red curves are for the average values from Sultan et al. (1990) with $p=0.03$ and $q=0.38$. In Figure A3a, $p$ values either side of $p=0.03$ are considered, while in Figure A3b, $p$ decreases by two orders of magnitude. The maximum possible penetration ($m$) is set at 1.

The take-off point ($Y_1$) for parameter values of $p<0.04$ and $q>0.3$ approximately, lies between 10 and 20 per cent (Figure A3a), which agrees with those in Mathur et al. (2007). As $q$ increases ($q\leq1$), or $p$ decreases ($p\geq0$), the threshold increases and approaches 21 per cent. It can be shown theoretically that this is an upper bound. While this threshold is particular to each innovation in that it is uniquely determined by the values of $p$ and $q$ for that practice, defining a non-zero $Y_1$ is not always possible.

The second threshold, $Y_2$ (dashed lines), decreases with $p$ and $q$. For $p>0.02$ and $q>0.3$, this threshold fluctuates considerably and exceeds, is equal to, or is below the other two thresholds. When $q>0.3$ and $p<0.03$ (approximately) this threshold is below 20 per cent. Compared with the thresholds $Y_1$ and $Y_3$, $Y_2$ varies most with changes in parameters (particularly for small values of $q$), suggesting this proportion is a less reliable measure for common practice assessments when there is parameter uncertainty. For this reason, $Y_2$ is not supported as a threshold measurement in the proposed common practice framework in Chapter 6. In addition, as for $Y_1$, defining $Y_2$ is not always possible for all values of $p$ and $q$. $Y_2$ decreases with increasing $q$, which is the opposite response of $Y_1$.

The third threshold ($Y_3$) is a fixed proportion value. The advantages are that this approach does not require a model and the associated estimates for $p$ and $q$. For the Bass model, an upper bound of 21 per cent was established above (see also Figure A3a and b), which supports a value for $Y_3$ of approximately 20 per cent. This value is used by the CDM and also coincides, approximately, with the division between early adopters and the early majority (of Rogers and Bass in Mahajan et al., 1995), which contributes validation.

A threshold of $Y_3$ at 20 per cent will almost always exceed $Y_1$, potentially resulting in more non-‘additional’ projects credited in an offsets scheme than if $Y_1$ were the threshold point. Further, as $q$ decreases and/or $p$ increases, the difference between $Y_1$ and $Y_3$ will increase, which will exacerbate this issue. However, in the case of limited data with which to estimate $p$ and $q$ (explored closely in Appendix B), and based on typical values for these parameters, $Y_3$ provides a
valid and mathematically informed and practical alternative. Below it is shown that this upper bound of 20 percent is supported by a number of alternative models used in agriculture, providing further credence to adopting this threshold.

**New technology supersedes an innovation**

In practice, a particular technology is often substituted with newer generations of the technology with even more advanced attributes. New product growth across technology generations has gained considerable interest among diffusion researchers. A major issue raised in the literature is whether diffusion accelerates between technology generations (Peres et al. 2010). This question is of practical importance for forecasting because projection about the growth of advanced generations of a product must be made during the early stages of product penetration and thus based on S-curve characteristics from previous generations. This is more of an issue for calculating $Y_1$ and using a fixed proportion threshold largely circumvents this issue. By assuming that each technology is a new technology, it is possible for each practice to have its own common practice assessment, precluding the requirement for using S-curve characteristics from previous generations.

**A review of other diffusion models**

As mentioned in the introduction, a number of diffusion models have been mooted as appropriate for agricultural innovations. For example, the logistic and Gompertz curves have been used to model the uptake of agricultural innovations (Dixon 1980; Mahajan et al. 1995; Marsh et al. 2000; Mahajan et al. 1990), while others such as the Stanford model have been suggested as appropriate for energy efficient innovations (Teotia & Raju 1986). Unlike the Bass model, these models do not incorporate the ‘innovation’ mechanism for adoption and, in some cases, have fewer parameters.

Some of the alternative models are special cases or approximations of others. For example, as $p$ approaches 0, the Bass model approaches the logistic model, and a first order approximation of the Gompertz function is also the logistic model. Recognising these relationships between the models, the above defined thresholds for the Bass, logistic, Gompertz and Stanford models are compared to understand how a different model might affect a defined common practice threshold (Figure A4). $Y_2$ has not been calculated for these alternative models because they do not incorporate an innovation parameter explicitly. In this example, only $Y_1$ is compared between the models.

Figure A4a illustrates the shape of the alternative models. Although they have not all been tuned to describe a particular innovation, the general qualitative nature of the curves can be compared. As $q$ increases and $p$ decreases, the Bass model results for $Y_1$ approach those for the logistic model, as expected (Figure A4b). Results for the threshold for alternative models in Figure A4b illustrate the same upper bound. The parameter values used for each are not provided in the figure; they are arbitrary, but serve to illustrate this bound. As discussed above, the logistic curve provides a first order approximation to the Gompertz model, and the second order approximation illustrates the transition between the models as higher order terms are included (Figure A4). The higher order terms in this model reduce the value of $Y_1$ considerably (Figure A4b). These results follow directly from the different mathematical formulations which determine the manner of early innovation uptake (as is evident in Figure A4).

An important result is that, for these models, the threshold for the proportion of ‘population’ adoption when the rate of diffusion increase is maximised ($Y_1$) remains bounded above by
approximately 20 per cent. This adds weight to the argument for a fixed 20 per cent threshold value for $Y_s$. A further consequence is that the Bass model can be related to a number of other diffusion models, and thus provides general applicability to a wide range of innovation types, scenario testing and adoption mechanisms when compared with the alternatives.

Figure A4 Diffusion curves for the three models and threshold proportions for $Y_1$ as $q$ varies

![Diffusion curves](image)

Notes: (a) Diffusion curves for the three models with $q=0.038$, $m=1$, and $p=0.03$ and 0.003. (b) Threshold proportions for $Y_1$ (the maximum rate of increase in innovation uptake) as $q$ varies for given values for $p$. 

Many alternative diffusion models have been developed that consider the same underlying structure of innovators and imitators (Mahajan et al. 1990) but include more parameters to account for other influences on $p$, $q$ and $m$. For example, agent-based diffusion models vary the mathematical relationship between the variables and the probabilities of adoption at time $t$, given no previous adoption. It is questionable how much better these models perform in general (Mahajan et al. 1990) and particularly in terms of the purposes of a common practice test.

Mahajan et al. (1990) discussed a number of flexibilities to the Bass model, such as time-dependent changes in the parameters. This will affect certain threshold points; however, including such characteristics in the model requires prior knowledge as to how parameters vary, requiring considerable data.

**Impact of the saturation level on common practice thresholds**

A further parameter that affects the threshold adoption proportions is the final adoption level (also termed saturation). It is difficult to know during the early stages of adoption what the final uptake of a practice will be, and therefore understanding how changes in $m$ affect the thresholds is important. If the target ‘population’ is overestimated, or there is uncertainty in the ‘population’ size that can adopt the practice, any common practice threshold may be over or underestimated and may inevitably determine the number of non-‘additional’ projects credited in an offsets scheme.
Figure A5 illustrates the effect of final uptakes of between 50 and 100 per cent on $Y_1$. It is simple to establish algebraically (from Equation 2) that the percentage reduction in the thresholds ($Y_1$, $Y_2$, and $Y_3$) is equivalent to that in the final uptake. For example, a reduction in final uptake by 30 per cent will also result in a reduction of 30 per cent in all three thresholds. This relationship between $m$ and $Y_1$ is illustrated in Figure A5. In the event that the total ‘population’ reduces dramatically during the course of the CFI, the threshold level may undergo adjustments of this nature.

Figure A5  The threshold proportions ($Y_1$ and $Y_2$) for the Bass model as the final proportion of ‘population’ adoption varies

Note: The threshold proportions ($Y_1$ and $Y_2$) for the Bass model, as the final proportion of ‘population’ adoption ($m=1, 0.75$ and $0.5$) changes, are plotted against $q$ ($p=0.04$). The reduction in the black solid line compared with the red solid line is the same (0.5) as the reduction in $m$.

Consideration will need to be given to what adoption means in relation to each particular practice. Partial adoption could be possible, and will need to be considered as adopted or not adopted for the currently recommended threshold test.
Appendix B Predicting the common practice threshold $Y_1$ with limited data

Key points

- Many model fitting procedures are available to estimate the parameters $p$, $q$ and $m$ for estimates of the common practice threshold $Y_1$. Non-linear least squares (NLS) is the preferred method reported in the literature.

- The Bass model provided a very good fit to the case study adoption data. Estimates of $p$ and $q$ using NLS were within the ranges reported in the literature; however, $p$ was found to be particularly small in this study.

- Our analysis demonstrates that estimates of model parameters using NLS are likely to be highly uncertain when only limited data points are available. In most cases, robust estimates of $Y_1$ will only be obtained well after adoption has exceeded the threshold. Bayesian methods were examined for their ability to reduce uncertainty in estimates of $Y_1$ through the use of expert opinion. The case study results suggested that Bayesian methods are only useful when there is high expert confidence in parameter values. It is unlikely that confidence in parameter estimation will be sufficient to improve estimates of $Y_1$ through Bayesian methods.

Introduction

If $Y_1$ is used as the common practice threshold, estimates of the model parameters $p$, $q$ and $m$ will be required. These provide information on the shape of the S-curve and enable $Y_1$ to be calculated. Although $Y_1$ is determined by the ratio $p/q$, and the ‘population’ size $m$, the focus here is on the individual parameter estimates and the threshold itself. An estimate of the latter is the purpose of this analysis. There are a variety of parameter estimation procedures in the literature that could be used in a common practice test for estimating these parameters. The purpose of this section is to demonstrate the use of a parameter estimation technique on three existing practice adoption datasets.

A common practice threshold needs to be established in real time, from data deriving from the early stages of the adoption process. This section demonstrates how difficult it can be to obtain reliable parameter estimates with limited adoption data and raises the question of whether reasonable predictions of $Y_1$, with very inaccurate parameter estimates, could underpin robust policy. Methods that may produce more reliable estimates of $Y_1$ using few data points are proposed and the practicality of adopting such approaches in the context of a common practice test is discussed. Different practices may have very different time scales to adoption. One practice may become saturated within one or two years, while another may span 20 years.

Parameter estimation and model fitting

As illustrated in Equation 3, calculating $Y_1$ requires estimates of model parameters $p$, $q$ and $m$. A number of procedures have been proposed to estimate these parameters including: ordinary least squares (OLS); non-linear least squares (NLS); and maximum likelihood estimation (MLE). The choice of parameter estimation procedure is important because each have advantages and disadvantages, such as predictive performance, biases, and software requirements. A detailed
comparison of OLS, MLE and NLS is beyond the scope of this report. However, some further discussions and considerations are included below.

Bass (1969) developed an OLS procedure to estimate parameters of the Bass model. The method is relatively simple to implement compared with MLE and NLS but has a number of disadvantages in the context of a common practice test. For example, OLS must be conducted on the non-cumulative adoption curve (Putsis 1998), may result in the wrong value for one or more of the parameters, and does not provide standard errors of parameter estimates (Mahajan et al. 1986; Schmittlein & Mahajan 1982; Van den Bulte & Lilien 1997).

The shortcomings of OLS have meant that MLE and NLS are the preferred model estimation procedures in diffusion modelling. The main advantage of these methods is that they provide standard errors and can be conducted on the cumulative adoption curve. Both procedures can be run in standard statistical software and can be used to estimate the parameters of any diffusion model. However, these methods have a number of limitations. MLE and NLS can result in biased estimates of $p$, $q$ and $m$ for the Bass model. For example, Van den Bulte and Lilien (1997) demonstrate that the Bass model parameters estimated by NLS are biased, with $m$ and $p$ underestimated and $q$ overestimated. These biases may also influence estimates of $Y_1$.

Another consideration when using MLE and NLS for parameter estimation is that starting values of the parameters need to be specified. MLE and NLS fit the model to the adoption data by first using the starting values and then varying them accordingly until they converge to a best model fit. In some cases, when starting values are very different to the true best fit of the model, MLE and NLS may not converge, resulting in an inability to provide parameter estimates. This means that, to properly implement MLE and NLS, users must have some idea about what the parameters $p$, $q$ and $m$ are likely to be. While it is possible to guess initial values from previous studies (for example Sultan et al. 1990), this may not be possible for innovations that do not share any similarities with previous technologies. Methods are available to reduce this difficulty, but have not been explored here.

In this analysis, model parameters are estimated using NLS. NLS is reported in the literature as the preferred parameter estimation procedure for the Bass model (Srinivasan & Mason 1986). It works by finding parameter values that minimise the sum of the squared residuals. In other words, NLS searches for values of $p$, $q$ and $m$ so that the fitted curve lies as close as possible to the observed data points and so that the average distance between the curve and points is minimised. The effect on adoption of associated policies or incentives has not been explored with these datasets.

**Fitting diffusion models to adoption data: a few examples**

Using NLS to estimate the parameters, diffusion curves were fitted to three long-term adoption datasets and the threshold point ($Y_1$) was found along these curves (Figure B1). The data consisted of annual cumulative adoption data for the following farming practices:

- no-till cultivation practices in Western Australia (Llewellyn & D’Emden 2010), which are based on the stated time of adoption by the grower population
- hybrid seed corn (Rogers 2003)
- lupin farming in Western Australia (Marsh et al. 2004).
These datasets were chosen because they cover a range of agricultural practices and ‘population’ sizes. Each dataset also has a sufficient number of data points to allow the interrogation of diffusion models. Using NLS, the Bass model was fitted to the cumulative adoption data to estimate model parameters $p$, $q$ and $m$, which in turn were used to calculate $Y_1$ for the diffusion curves (Figure B1). These values are also tabulated in Table B1.

**Figure B1 The Bass model fitted to cumulative adoption data**

![Graphs showing adoption over time for different practices](image)

**Source:** Llewellyn & D’Emden (2010); Rogers (2003); Marsh et al. (2004)

**Note:** The Bass model fitted to cumulative adoption data of a) no-till cultivation practices in WA; b) the adoption of hybrid seed corn; c) the adoption of lupins, and in each case time is shown in years. Dashed lines represent the threshold point for common practice as defined as the maximum rate of acceleration of adoption ($Y_1$).
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ABARES

Table B1 Parameter estimates (with standard errors), model fit and threshold cut-off points for the Bass model fitted to the three case study datasets

<table>
<thead>
<tr>
<th>Data</th>
<th>Bass model parameters</th>
<th>Model fit</th>
<th>Threshold (proportion of 'population')</th>
<th>Threshold (scaled to final uptake)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>$p$</td>
<td>$q$</td>
<td>$m$</td>
</tr>
<tr>
<td>No-till</td>
<td>0.0002 (0.00006)</td>
<td>0.306 (0.014)</td>
<td>0.937 (0.017)</td>
<td>0.996</td>
</tr>
<tr>
<td>Hybrid</td>
<td>0.0004 (0.00018)</td>
<td>0.693 (0.053)</td>
<td>0.989 (0.032)</td>
<td>0.995</td>
</tr>
<tr>
<td>Lupins</td>
<td>0.001 (0.001)</td>
<td>0.789 (0.093)</td>
<td>0.669 (0.016)</td>
<td>0.988</td>
</tr>
</tbody>
</table>

The Bass model provided a good fit to the three datasets. $R^2$ values provide an estimate of ‘goodness of fit’ and ranged from 0.988 for the lupins dataset to 0.996 for the no-till adoption data. The estimated value of the innovation parameter $p$ for the three case studies ranges from 0.0002 (no-till cultivation) to 0.001 (lupins). These values are an order of magnitude smaller than the average value of $p$ (0.03) across numerous innovations (Sultan et al. 1990) but within the plausible range reported by these authors. This suggests that innovators had little effect on the adoption of these three practices and means that, for example, at time 0 the likelihood of an innovator adopting no-till cultivation practices is approximately 0.0002.

Estimates of $q$ reflect the effect of prior cumulative adopters on adoption and ranged from 0.3 for no-till cultivation practices to 0.69 for the adoption of hybrid seed corn. The threshold point ($\frac{d^2Y}{dx^2} = 0$) for no-till cultivation practices occurred when 19.7 per cent of the ‘population’ of potential adopters had adopted the practice. For lupins cropping, $Y_1$ was calculated at 14 per cent of the ‘population’ of potential adopters. The threshold for hybrid seed corn was the highest at almost 21 per cent; thus, for the three practices, a threshold of $Y_3 = 20$ per cent provides a very reasonable estimate. The rightmost column in Table B1 scales $Y_1$ to $m$.

Fitting diffusion models to limited data

The previous section demonstrated how the NLS procedure can be used to estimate model parameters required for estimates of $Y_1$. The difference between what was done in the analysis above and a common practice test is that a common practice threshold must be estimated from limited data points early in the adoption series. In theory, model fitting procedures can be conducted on a minimum of 3–4 data points (Bass 1969; Schmittlein & Mahajan 1982). However, many studies have demonstrated that parameter estimates obtained from limited data can be unreliable and can only be obtained if the data under consideration include the peak of the non-cumulative adoption curve (Srinivasan & Mason 1986).

To test the stability of parameter estimates to limited data, the parameter estimation procedure above was repeated, but the first four data points from each of the three datasets were started with. Starting with these data points, $p$, $q$ and $Y_1$ were estimated, and the estimation process was repeated iteratively by adding a single data point to the data until the complete time series was analysed. For this analysis, $m$ was not estimated and instead assumed to equal one so that only the two parameters $p$ and $q$ were estimated. Figure B2 shows how estimates of $p$, $q$, and $Y_1$ fluctuate as data are added to the model fitting process, where the x-axis is the proportion that have adopted as data points are included.
Figure B2 Estimates of $p$, $q$ (column 1 y-axis) and $Y_1$ (column 2 y-axis) for the no-till, hybrid seed corn and lupins case studies against the proportion of the ‘population’ that has adopted the innovation as the number of data points increases.

Source: Llewellyn & D’Emden (2010); Rogers (2003); Marsh et al. (2004)

Notes: Using the Bass model and NLS fitting, parameters $p$ and $q$ are estimated from the first four points of the data, then five points and so on. Parameter $m$ is fixed at 1. As the number of points used increases, so does the proportion adopted, but at a different rate for each practice. This proportion is plotted against the parameter estimate, as is the threshold $Y_1$, which is calculated from parameter estimates. a) and b) illustrate the results for the no-till dataset, c) and d) for the hybrid seed corn dataset and e) and f) for the lupins dataset.

Figure B2 demonstrates that estimates of $Y_1$ can stabilise before or after the threshold has been reached. At what point estimates of $Y_1$ stabilise will depend on the characteristics of the adoption data, such as the number of data points, the spread of the adoption data and the rate of adoption compared with the sample period.
For the no-till dataset, estimates of \( p \) and \( q \) are erratic until approximately 10 per cent of the ‘population’ adopt, or approximately 15 data points are used to calculate \( Y_1 \) (figure B2a). For the remainder of the adoption period, estimates of \( p \), \( q \) and \( Y_1 \) remain relatively stable. In this case, when \( Y_1 \) will be reached can be predicted with reasonable confidence before it occurs (figure B2b).

Estimates of \( p \), \( q \) and \( Y_1 \) for the hybrid seed corn dataset are erratic with limited data points, with \( p \) gradually decreasing, and \( q \) gradually increasing, as data are added to the analysis (figure B2c). Estimates of \( Y_1 \) fluctuate, before stabilising after approximately 20 per cent of the ‘population’ have adopted (figure B2d). In this case, stabilisation occurs approximately on or after the threshold point has been exceeded. As data are collected it would be difficult to say with confidence that \( Y_1 \) had been reached.

In contrast, estimates of \( p \), \( q \), and \( Y_1 \) for the lupins dataset are influenced by data late in the adoption process. Figure B2 illustrates that, when limited data points are available, estimates of \( p \), \( q \) (figure B2e) and \( Y_1 \) (figure B2f) remain relatively stable. However, at the end of this adoption period, estimates of \( Y_1 \) decrease considerably because of low adoption levels after 60–70 per cent of the ‘population’ had adopted (figure B2f). This ‘flattening out’ of the adoption curve dramatically affects estimates of \( p \) and \( q \) and \( Y_1 \). The data reflect disadoption (see figure B1), and thus the proportion adopted declines. This analysis illustrates that reasonable predictions of \( p \), \( q \) and \( Y_1 \) with early data are not always possible before the threshold is reached. Thus, using \( Y_1 \) as the threshold for an innovation adoption in real time and the method of NLS is likely to be unreliable. Further, while in these examples \( Y_1 \) stabilises at or close to adoption of 20 per cent, this is not the case for \( p \) and \( q \). These parameters stabilise at much higher adoption proportions (see figure B2c and e).

**Bayesian methods**

There has been growing interest in incorporating expert opinion into threshold analysis tests. Statistically, this can be done using Bayesian methods in model parameter estimation. Bayesian methods are less common than other statistical approaches (such as NLS) in diffusion studies and are used to combine historical information or expert knowledge with data to estimate parameters or make predictions. A distribution of model parameters, developed with expert opinion or from previous studies, is combined with a likelihood function (that is, the likelihood of observing the data given a particular parameter value). A Bayesian approach, using historical information, may be used to enhance limited data points by stabilising parameter estimates.

When historical information about model parameters is difficult to obtain, one option is to specify non-informative distributions, which assign the same probability to each possible value of the parameter. As shown below, such non-informative distributions have little effect on the results and there is little value in using them.

**Examples using Bayesian methods**

Bayesian methods have been used in sales forecasting by a handful of authors and in this context are considered a suitable way for making predictions with limited or no adoption data. Lilien et al. (1981) predicted the uptake of an ethical drug using prior knowledge of historical sales for similar products. The authors developed one historical distribution describing the variation among model parameters of similar products. Using this information they were able to predict the adoption of the drug before data were available. These forecasts were then updated once adoption data for the product became available.
A similar approach was applied by Lenk and Rao (1990) to obtain early forecasts for the sales of new durable products. Rather than using an historical distribution describing the variation among model parameters, the authors developed a second historical distribution of unknown parameters of the first distribution. This approach is known as Hierarchical Bayes. Before adoption data for these products were available, Lenk and Rao (1990) predicted the adoption curve based on the expectations of the first historical distributions. As data were available, these forecasts were updated to the unique features of the practice.

**Case study: Using Bayesian methods to inform parameter estimation**

This no-till case study explores the effect of Bayesian methods on parameter estimation using the Bass model. In this analysis, parameter $m$ has been set to 1. The approach incorporates prior knowledge and/or belief concerning parameter values, thereby increasing information used in the estimation process when limited data points are available. Parameters $p$ and $q$ were estimated for the no-till dataset, starting with three data points and repeating the estimation procedure by iteratively adding a data point to the analysis.

Three prior beliefs for $p$ and $q$ were selected to explore the effect of prior information on parameter estimates.

1) **Limited confidence/non-informative beliefs**

The first prior distributions (figure B3a and b) were set as non-informative, which means that it was believed a priori that all values of $p$ and $q$ were equally likely to lie between 0 and 1. In this case, no prior knowledge of $p$ and $q$ values was assumed.

2) **Average confidence/parameter values taken from Sultan et al. (1990)**

The analysis was then repeated by incorporating prior beliefs for $p$ and $q$ normally distributed about the mean values reported by Sultan et al. (1990). These authors reported $p$ to average 0.03 with a standard deviation of 0.03 (Figure B3c) and $q$ to average 0.38 with a standard deviation of 0.35 (Figure B3d). The relatively large standard errors suggest that the authors were not very confident in these beliefs.

3) **High confidence/parameter values taken from Sultan et al. (1990) with reduced standard deviations**

The analysis was then repeated by assuming greater confidence in these prior beliefs. $p$ (Figure B3e) was assumed to be normally distributed with a mean of 0.03 (sd = 0.009) and $q$ was also assumed to have a normal distribution, but with a mean of 0.38 (sd = 0.07 Figure B3f). In this scenario, the standard deviation in prior distributions was reduced to reflect a more confident prior belief in $p$ and $q$.

There are other approaches to including priors, such as setting a prior on the threshold proportion $Y_1$. However, these have not been explored here.
Figure B3 Prior distributions used in the Bayesian analysis

Source: Sultan et al. (1990)

Note: The assumed distributions for graphs a, c and e represent prior beliefs of the parameter $p$ while the distributions for graphs b, d and f represent prior beliefs of parameter $q$. There was more confidence in the prior belief towards $p$ and $q$ from top to bottom.

Results for the analysis of the three prior beliefs found:

1) Limited confidence/non-informative beliefs

Figure B4 illustrates the influence of the three prior distributions on estimates of $p$ and $q$ using different numbers of data points given as increasing proportion of adoption. The solid line represents the median value of the parameter estimates and the dashed lines represent 95 per cent credible intervals. Parameter estimates using non-informative priors are presented for $p$ in Figure B4a and for $q$ in Figure b. Given that the priors are non-informative, the data alone determine estimates of $p$ and $q$. These estimates of parameters fluctuate greatly when only limited data points are available, before stabilising after approximately 20 per cent of the
'population' have adopted the practice. Parameter estimates using Bayesian methods and non-informative priors result in similar estimates of $p$ and $q$ when compared with using NLS methods (Figures B4a and b). The small differences in $p$ and $q$ are due to Bayesian methods using maximum likelihood estimation instead of NLS, as well as the assumption of $m=1$ in the Bayesian approach.

2) Average confidence/parameter values taken from Sultan et al. (1990)

The influence of incorporating prior knowledge into the analysis can be seen in Figure B4c and d. Although the credible intervals are slightly smaller than when the non-informative priors were used, estimates of $p$ and $q$ still fluctuate greatly when limited data points are available. Estimates of $p$ and $q$ are similar to when non-informative priors were specified, suggesting these priors had little influence on the analysis compared with estimates using the data alone. In this case, the data are dominating the estimation procedure as a result of considerable uncertainty in the priors.

3) High confidence/parameter values taken from Sultan et al. (1990) with reduced standard deviations

The effect of strengthening prior beliefs of $p$ and $q$ is illustrated for $p$ in Figure B4e and for $q$ in Figure B4f. Estimates of $p$ and $q$ are much more stable when few data points are available because there was much more confidence a priori in $p$ and $q$. In this case, estimates of $p$ and $q$ are dominated by the prior distribution when limited data points are available. At approximately 10 per cent adoption, the influence on $p$ and $q$ switches from the prior distribution to the data (see Figure B4c, d, e and f).
Figure B4 Estimates of $p$ and $q$ for the bass model fitted to the no-till dataset using a Bayesian approach

Source: Llewellyn & D’Emden (2010)

Note: Three prior beliefs are incorporated into the analysis; 1) a non-informative prior (top row – graphs a and b); 2) a prior with mean and standard deviation set to values reported by Sultan et al. (1990) (second row – graphs c and d); and 3) a prior with a relatively small standard deviation (third row – graphs e and f). Solid lines represent median parameter estimates and dashed lines represent 95 per cent credible intervals. The spike in parameter estimates after approximately 15 per cent of the ‘population’ has adopted is due to an outlier in the dataset. The potential ‘population’ ($m$) has been set to 1 in this analysis.

This analysis demonstrates that, while a Bayesian approach can be used to stabilise parameter estimates when limited data points are available, very confident beliefs in $p$ and $q$ are needed for this to occur. Using these estimates for $Y_1$, only the prior with the small standard deviation provides a reasonable estimate of the ‘true’ threshold. In reality, prior information of $p$ and $q$ is unlikely to be obtained with any more confidence or detail than the average values reported by
Sultan et al. (1990). This is because experts would have to have a sound knowledge of the abatement practice and the 'population', and would also have to be confident in estimating parameters for the Bass model and how these influence the shape of the S-curve, adding another element of complexity. Thus, it is unlikely that reliable priors as precise as those explored in scenario 3 will ever be able to be obtained. Another added impediment to adopting a Bayesian approach is the expense associated with the time and effort required to repeatedly elicit subjective historical distributions.
Appendix C Regional classification

The draft Australian Agricultural Environments (AAEs) (Figure C1) are based on agroecological regions produced by Williams et al. (2002), which aligned climate and environmental features to the 1986 ASGC Local Government Area boundaries. These regions will be used as one of the regional scales for common practice tests and inform the data collection for the LaMP survey. While ABARES recognises there will be in-region differences in practice adoption, a certain level of aggregation is required in standardised approaches. To standardise data collection for the Land Management Practice Survey and make it comparable with other ABS census and surveys, ABARES has realigned these boundaries to the nearest ABS Statistical Area 2 (SA2) boundaries. The SA2 boundaries are designed to be standard boundaries with little change. This alignment also takes into consideration:

- Hutchinson agroclimatic regions (Hutchinson et al. 2005): a global climate classification relating to plant growth. Climate data for Australia was interpolated from field sites from 1931 to 1990

- National land use map (2000–2001) (BRS 2006), particularly between grazing and cropping, and some major industries such as sugar cane. The land use map is modelled from ABS agricultural census data and time series satellite imagery using a probability surface. The 2000–2001 version of the National land use map was chosen because this presents the total area of sown pastures more comprehensively than the 2005–2006 version

- the likely population numbers of agricultural businesses based on advice supplied by the ABS.

Figure C1 Australian Agricultural Environments
These boundaries are approximate but take into account the underlying agroecological and agroclimatic regions, and land use, and suit the region size needed for adequate sampling.

From many classifications of regions that could be used for monitoring agricultural practices, the agroecological regions of Williams et al. (2002) were chosen because they:

- gave a more reasonable approximation of similar agricultural industries than natural resource management regions or statistical divisions
- gave a better coverage of the number of farms than the agroclimatic classes of Hutchinson et al. (2005)
- produced a manageable number of regions compared with the many IBRA regions
- had already been used for reporting on sustainable agriculture, for example by the Standing Committee on Agricultural Resource Management (1998)
- were developed with input from a wide range of regional agencies.

Although this classification provided the best available fit, some regions did need to be modified. The original 46 agroecological regions of Williams et al. (2002) were deemed too many for surveying region by industry responses and the original 11 agroecological regions of Williams et al. (2002) were too coarse in some cases for important practices such as conservation tillage. There were also too few farms in some areas and too many in others. Therefore, ABARES developed a modified version of 18 agroecological regions, largely patterned on the 11 region classification of Williams et al. (2002) but:

- based on the new ABS Statistical Area 2 (SA2) regions. These will remain constant in future years and will allow for easy sampling and reporting
- using the National land use map (2000–2001) (BRS 2006) to allocate SA2 regions to most appropriate agroecological region
- combining the wet/dry tropical north-eastern tropics (4) with the wet/dry north-west tropics (9) and the northernmost parts of the semi-arid tropical and subtropical plains (8) to produce an area labelled as ‘1. Tropics’. It approximates the Hutchinson (2005) agroclimatic classes of H, I1, I2 and I3. Even so, this region contains the second fewest farms
- breaking up:
  - the wet temperate coast (1) into three regions because of its geographical spread and relatively high number of farms into ‘5. Temperate coast south’, ‘10. Temperate coast east’ and ‘17. Temperate coast west’
- modifying the boundary of semi-arid tropical and subtropical plains to accommodate the tropics region and align roughly with the distribution of Mitchell grass (Thackway et al. 2007)
• some further reclassification is possible in south-east Queensland, eastern NSW and Victoria/Tasmania. This reclassification should be done in consultation with the state agricultural industries.

The boundaries are uneven because they follow those of the constituent Statistical Area 2 regions. ABARES considers this is only a minor complication because most agroecological regions diffuse into each other and the boundaries between them cannot be precisely defined.

The AAEs so developed are listed below with their percentage of total agricultural businesses (farms), taken from the 2005–06 agricultural census.
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Table C1 Australian Agricultural Environments with percentage of total agricultural businesses (farms)

<table>
<thead>
<tr>
<th>AAE</th>
<th>Description</th>
<th>%total</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Tropics</td>
<td>2.1</td>
</tr>
<tr>
<td>2</td>
<td>Tropical coast</td>
<td>3.6</td>
</tr>
<tr>
<td>3</td>
<td>Semi arid</td>
<td>2.6</td>
</tr>
<tr>
<td>4</td>
<td>Subtropical plains</td>
<td>2.4</td>
</tr>
<tr>
<td>5</td>
<td>Temperate coast (south)</td>
<td>1.7</td>
</tr>
<tr>
<td>6</td>
<td>Subtropical coast</td>
<td>10.3</td>
</tr>
<tr>
<td>7</td>
<td>Wheatbelt (downs)</td>
<td>3.4</td>
</tr>
<tr>
<td>8</td>
<td>Wheatbelt (north)</td>
<td>5.2</td>
</tr>
<tr>
<td>9</td>
<td>Subtropical highlands</td>
<td>8.8</td>
</tr>
<tr>
<td>10</td>
<td>Temperate coast (east)</td>
<td>9.3</td>
</tr>
<tr>
<td>11</td>
<td>Wheatbelt (central)</td>
<td>8.8</td>
</tr>
<tr>
<td>12</td>
<td>Wheatbelt (central east)</td>
<td>5.9</td>
</tr>
<tr>
<td>13</td>
<td>Temperate highlands</td>
<td>8.3</td>
</tr>
<tr>
<td>14</td>
<td>Wheatbelt (east)</td>
<td>15.5</td>
</tr>
<tr>
<td>15</td>
<td>Wheatbelt (west)</td>
<td>2.8</td>
</tr>
<tr>
<td>16</td>
<td>Mediterranean (west)</td>
<td>2.7</td>
</tr>
<tr>
<td>17</td>
<td>Temperate coast (west)</td>
<td>2.4</td>
</tr>
<tr>
<td>18</td>
<td>Arid</td>
<td>4.3</td>
</tr>
</tbody>
</table>

Note: Taken from the 2005–06 agricultural census.

A description of each of these regions is provided below.

1) Tropics

The Tropics stretches across northern Australia, covering plains, undulating hills and high plateaux. The climate transitions from hot, seasonally wet and dry in the north to hot and very dry in its south. Extensive sheep and cattle grazing predominate, with some intensive cropping and horticulture under irrigation.

2) Tropical coast

This area along the north-west coast of Australia consists of mountains and plains and produces beef cattle, sugar cane, rice and horticulture. The climate is relatively uniformly hot and wet.

3) Semi arid

Semi arid is an interior region that captures most of the Mitchell grass country (Thackway et al. 2007). It is relatively flat tussock grasslands and has a climate that is hot to very hot with strongly summer dominant rainfall. The region is predominantly used for extensive sheep and cattle grazing.

4) Subtropical plains

This area has a climate with hot summers and warm winters, and moderate summer-dominant rainfall. It is composed of plains divided by ranges, with extensive cracking clay soils. Mixed cattle grazing and cropping, summer cropping and cotton predominate.
5) **Temperate coast (south)**

This southern coastal region is predominantly wet and cool, with strongly winter-dominant rainfall. It is coastal or coastal hinterland ranging from plains to mountains. Primary agriculture is dairying, intensive cropping, grazing and horticulture.

6) **Subtropical coast**

This region, along the east coast of Australia, with a warm and wet climate and mostly uniform distribution, consists of coastal lowlands, plains and bordering ranges. Principal activities include dairying, sugar cane, beef grazing, and horticulture.

7) **Wheatbelt downs**

This region has hot summers and mild winters with slightly summer-dominant, moderate rainfall. It is an upland characterised by plains of cracking clays and is noted for mixed wheat/summer cropping with specialist irrigation of cotton and some horticulture.

8) **Wheatbelt (north)**

This region of slopes and plains has extensive cracking clay soils. Its climate is hot summers and mild winters, with moderately low summer-dominant rainfall. There are large areas of irrigated cotton and grain cropping, with more grazing westward.

9) **Subtropical highlands**

This region characteristically has rolling, undulating and hilly uplands. The climate is warm, although winters are mostly cool, and rainfall is uniformly distributed throughout the year. Irrigated horticulture is important in some river valleys, between intensive grazing of sheep and cattle livestock.

10) **Temperate coast (east)**

This coastal region in south-east Australia is predominantly wet and cool to warm, with strongly winter-dominant rainfall. The primary agriculture is dairying, intensive cropping, beef grazing and horticulture.

11) **Wheatbelt (central)**

This forms the middle section of the Australian wheatbelt, with a climate characterised by hot summers, cool winters and a winter-dominant rainfall. The soils range from sands to duplex supporting extensive sheep and beef grazing and grain cropping, with horticulture in areas supplied with irrigation water.

12) **Wheatbelt (central east)**

This is also part of the Australian wheatbelt, with its climate of hot summers, cool winters and a winter-dominant rainfall. These soils tend to have a high clay content, with mixed grazing and cropping, and often support dairying and horticulture where irrigation water is available.

13) **Temperate highlands**

This area is higher rainfall tableland and mountainous areas in the south-east of Australia, with some coastal slopes and plains. The climate is predominantly cool and wet with summers becoming drier and hotter towards the inland. There is considerable diversity in this region because of large variation in altitude and proximity to coastal influences. Agricultural activities
concentrate on grazing of sheep and cattle on improved temperate pastures for wool, lamb, beef and dairy products.

14) Wheatbelt (east)

In this wheat/sheep/cattle belt the climate consists of hot summers and cool winters, with winter-dominant rainfall. The native vegetation has been extensively cleared for grain cropping and temperate pastures. There are also important areas of irrigation farming and horticulture along the major rivers.

15) Wheatbelt (west)

In this wheat/sheep/cattle belt the climate consists of hot summers and cool winters, with strongly winter-dominant rainfall. There are extensive areas of saline ephemeral lakes in its flat to undulating topography. The native vegetation has been extensively cleared for grain cropping and temperate pastures.

16) Mediterranean (west)

In this region the climate consists of hot summers and cool winters, with strongly winter-dominant rainfall. There are extensive areas of saline ephemeral lakes in its flat to undulating topography. Horticulture is prominent and the native vegetation has been extensively cleared for grain cropping and temperate pastures.

17) Temperate coast (west)

The climate in this region is predominantly wet and cool with strongly winter-dominant rainfall. It is primarily a coastal region supporting dairying and horticulture.

18) Arid

This is a very large area with warm to hot, semi-arid to arid climate and encompasses diverse soils and vegetation. While generally low relief, there are significant ranges, flood plains, dune fields and stony hills. This area is mostly used for extensive grazing of native vegetation by sheep and cattle.
Appendix D Industry classification

Industries sampled in the Land Management Practices Survey are listed in Table D1. These are presented in Australian and New Zealand Standard Industrial Classification (ANZSIC) code and were chosen based on size of industry, likely abatement opportunities, and known or likely ‘methodology’ submissions under the Carbon Farming Initiative.

Following data collection, some industries will not be cross-classified by region because their management practices are similar regardless of the regional location of the industry. For example, piggeries have similar management practices across Australia. In these instances these industries will be reported at a national scale.

<table>
<thead>
<tr>
<th>ANZSIC code</th>
<th>Industry</th>
</tr>
</thead>
<tbody>
<tr>
<td>110</td>
<td>Nursery and floriculture</td>
</tr>
<tr>
<td>111</td>
<td>Nursery production (under cover)</td>
</tr>
<tr>
<td>112</td>
<td>Nursery production (outdoors)</td>
</tr>
<tr>
<td>113</td>
<td>Turf growing</td>
</tr>
<tr>
<td>114</td>
<td>Floriculture production (under cover)</td>
</tr>
<tr>
<td>115</td>
<td>Floriculture production (outdoors)</td>
</tr>
<tr>
<td>120</td>
<td>Mushroom and vegetable growing</td>
</tr>
<tr>
<td>121</td>
<td>Mushroom growing</td>
</tr>
<tr>
<td>122</td>
<td>Vegetable growing (under cover)</td>
</tr>
<tr>
<td>123</td>
<td>Vegetable growing (outdoors)</td>
</tr>
<tr>
<td>130</td>
<td>Fruit and tree nut growing (excluding grapes)</td>
</tr>
<tr>
<td>131</td>
<td>Grape growing</td>
</tr>
<tr>
<td>141</td>
<td>Sheep farming (specialised)</td>
</tr>
<tr>
<td>142</td>
<td>Beef cattle farming (specialised)</td>
</tr>
<tr>
<td>143</td>
<td>Beef cattle feedlots (specialised)</td>
</tr>
<tr>
<td>144</td>
<td>Sheep–beef cattle farming</td>
</tr>
<tr>
<td>145</td>
<td>Grain–sheep or grain–beef cattle farming</td>
</tr>
<tr>
<td>146</td>
<td>Rice growing</td>
</tr>
<tr>
<td>149</td>
<td>Other grain growing</td>
</tr>
<tr>
<td>151</td>
<td>Sugar cane growing</td>
</tr>
<tr>
<td>152</td>
<td>Cotton growing</td>
</tr>
<tr>
<td>159</td>
<td>Other crop growing n.e.c.</td>
</tr>
<tr>
<td>160</td>
<td>Dairy cattle farming</td>
</tr>
<tr>
<td>170</td>
<td>Poultry (includes meat and egg poultry)</td>
</tr>
<tr>
<td>190</td>
<td>Other livestock (excluding pig farming)</td>
</tr>
<tr>
<td>192</td>
<td>Pig farming</td>
</tr>
</tbody>
</table>

For each of the regions described in Appendix D, industries were prioritised to inform survey sampling. This was informed by 2006 ABS Agricultural Census data and based on the percentage of national production of a particular commodity occurring in that region.
Database

A database of survey data is being compiled by ABARES and will be used to inform the common practice assessments.
Appendix E Non-‘additional’ abatement and factoring out the effect of the scheme

**Non-‘additional’ abatement**

One of the limitations of a standardised approach is that it has limited capacity to consider whether or not an individual landholder would have been likely to undertake the activity in the normal course of business. Project-specific emissions baselines stipulated in ‘methodologies’ can address this to some extent by preventing early adopters from being awarded certain credits. It is not possible to know exactly how the CFI will influence adoption levels (for example, through an increase in knowledge or the provision of carbon credits). This may present a risk of crediting practices not attributable to the scheme, which is often termed ‘non-‘additional’ abatement’.

Consider a hypothetical carbon permits market and an activity which had been adopted by a small proportion of potential adopters before the CFI but, following the introduction of the CFI, its adoption level has increased to 10 per cent of the potential adopters over a period of time. Also suppose that one-quarter of projects based on this activity would have happened under a business-as-usual scenario. If all projects based on this particular activity receive CFI credits, then the proportion of activities that would have occurred without the CFI financing (in other words, effectively non-‘additional’) is 25 per cent. Such a possibility is depicted in Figure E1. This issue, if pervasive, could certainly affect the environmental credibility of the CFI and therefore requires further consideration.

*Figure E1 ‘Additional’ and non-‘additional’ abatement for a hypothetical carbon permits market*
Notes: The diffusion under the CFI curve and the diffusion under the BAU curve show the diffusion of the activity throughout the ‘population’ under the Carbon Farming Initiative (CFI) and under the business-as-usual (BAU) case, respectively. $T = 0$ is the time of the scheme inception, and $T=1$ is some point in the future. The difference between the two curves at any point in time is the effect of the CFI. Project-specific baselines may prevent prior adopters from being awarded certain offset credits, but if credits are awarded to all landholders that undertake the activity after the introduction of the CFI then there may be a risk of non-‘additional’ abatement. The area marked as ‘A’ shows ‘additional’ abatement that is credited under the CFI, over the period $T=0$ to $T=1$. In contrast, the area marked as ‘B’ shows the potential amount of non-‘additional’ abatement credited under the CFI, over the same period, when early adopters are not eligible for credits.

Common practice thresholds that are too relaxed or too high will increase the risk of crediting non-‘additional’ abatement, while those that are too restrictive or too low will preclude projects that may be ‘additional’ and may discourage innovation. Trexler et al. (2006) identified that it is impossible to eliminate these errors completely no matter what threshold is chosen. The potential for crediting non-‘additional’ abatement will vary substantially across different activities and regions. For example, the amount of non-‘additional’ abatement credited for activities such as the capture and flaring of methane from animal waste is likely to be negligible. This is because there are little to no economic benefits from undertaking this activity and, as such, is unlikely to be undertaken in the normal course of business. In contrast, the amount of non-‘additional’ abatement credited for activities such as no-till is likely to be higher as the activity is practiced in many regions for environmental and production benefits.

Trying to reduce the risk of crediting non-‘additional’ abatement will always involve some trade-offs. When designing a common practice test and choosing an appropriate threshold level, it is necessary to consider such trade-offs and ensure they support the integrity of the scheme. To address this issue, additional work could be undertaken in the following areas.

Exploring the ability of emissions baselines to reduce the risk of non-‘additional’ abatement

Appropriate emissions baseline setting under the CFI ‘methodology’ development process could reduce the likelihood of crediting non-‘additional’ abatement. While early adopters may not be omitted through the common practice test, their ability to apply for credits through the scheme depends on the emissions baseline approach stipulated in the project ‘methodology’. The common practice test identifies projects that would not otherwise occur, while the baseline is used to identify the amount of abatement that would otherwise not occur. There are various approaches to estimating baselines including:

- historical baselines: it will sometimes be reasonable to assume that, in the absence of a project, emissions and removals will be the same in the future as they have been in the past. In these cases it would be reasonable to derive baselines from historical emissions data, but often these data are not available

- projected baselines: baselines can be set using projected or modelled estimates of future emissions under various scenarios

- comparison baselines: baselines can be derived by monitoring and comparing emissions from the abatement project to that of a comparison or control project

- standardised baselines: in some cases it may be possible to identify a standardised baseline that represents the emissions or sequestration that occur in an industry under particular conditions. Standardised baselines are useful when it is not possible or practical to use a historic, projected or comparison baseline and when there is little variability in the practices
across an industry. Standardised baselines also reduce the costs associated with determining individual project baselines

- hybrid approaches: in some cases, different methods for developing baselines will be justifiable depending on the particular circumstances of a project. Some draft ‘methodologies’ may need to present several approaches to identifying the project baseline and provide clear guidance on how project proponents should select the one that best suits their particular circumstances.

It is likely that the historical baselines would not credit early adopters because emissions and removals would be the same between the start of the project and the past. In contrast, for standardised baselines there is a risk of crediting abatement from early adopters. To reduce the risk of over-crediting, a comprehensive analysis examining this risk is desirable.

An accurate measure of the impact of the CFI on practice adoption, and the associated ability to measure and account for non-‘additional’ abatement, is very difficult to establish. For some practices (for example, methane flaring from piggeries) there is evidence that without the CFI there would be no, or marginal, adoption. In that case, the problem is relatively straightforward, but this is unlikely for many practices.

**Exploring the use of an ‘integrity buffer’ for CFI offset projects to account for the non-‘additional’ abatement**

One proposed method to account for non-‘additional’ abatement is to introduce an ‘integrity buffer’ for each practice. An ‘integrity buffer’ would work in the same way that the risk of reversal buffer works for sequestration projects. For example, if the ‘integrity buffer’ is set at 10 per cent then projects will be eligible to earn credits for 90 per cent of the estimated abatement at the project level. This is similar to the way a risk of reversal buffer is applied to sequestration projects addressing carbon losses from natural events across participants. The advantage of this approach is that it recognises that there will be non-‘additional’ abatement from the commencement of the scheme as a result of early adoption of practices before the CFI commenced and addresses this to some extent. The level of the buffer should, in theory, account for the likely proportion of non-‘additional’ abatement over the long term.

The ‘integrity buffer’ should be set at a level that offsets the non-‘additional’ abatement expected to be credited over the lifetime of the scheme. Since the proportion of non-‘additional’ abatement credited under the CFI depends on the uptake of activity under the BAU relative to the uptake under the CFI case, both diffusion schedules need to be estimated when considering the level of the ‘integrity buffer’. The uptake of the activity under the CFI can be estimated using data from the LaMP survey, which, because it will be implemented following the inception of the CFI, will measure practice adoption under the CFI.

Non-‘additional’ abatement could be quantified by estimating the uptake under the BAU case relative to the case with the CFI, over equivalent time periods, using an economic modelling approach.

- A Farm-Size Model can be developed to estimate adoption schedules for various agricultural technologies based on cost, price and farm distribution data to construct a business-as-usual uptake curve. The Farm-Size Model includes a lag adjustment equation at the farm group level (the farm group level is the smallest ‘unit’ in the model). This lag adjustment equation assumes that adoption occurs gradually once the technology becomes economically viable. The lag adjustment equation is assumed to take an S-curve shape and is based on a process of innovation and imitation. The parameters of the lag adjustment equation are based on an
average of parameter estimates from past studies and could be informed by the mathematical approach outlined in Appendix A. The lag adjustment factor can also be modified using the results of the LaMP survey.

Figure E2 shows how a 10 per cent ‘integrity buffer’ would operate under the assumption that participation in the CFI is not affected by its implementation. The solid lines show diffusion under the CFI and diffusion under two alternative BAU cases, respectively. The dashed line is simply 10 per cent of the ‘diffusion under the CFI’ curve and shows the proportion of participation in the scheme that would not earn credits. This is spread across all participants in the scheme who now receive credit for 90 per cent of the abatement they would have been credited for in the absence of an ‘integrity buffer’. For example, if a total of 1 000 000 tonnes of abatement is generated under the scheme, then only 900 000 tonnes would be credited. In this sense, the ‘integrity buffer’ effectively dilutes the carbon price received by participants in the CFI. This may or may not have a material effect on participation but the higher the ‘integrity buffer’ the more likely it is that participation will be affected.

In the case shown in Figure E2, the ‘integrity buffer’ closely matches the ‘low’ BAU adoption schedule. This means that the ‘integrity buffer’ would be relatively effective in addressing the non-‘additional’ abatement under this scenario. There would be no need to remove the activity from the ‘positive list’ because non-‘additional’ abatement is roughly accounted for over the life of the scheme through the ‘integrity buffer’. However, under the ‘high’ BAU adoption schedule, a 10 per cent ‘integrity buffer’ would not account for all non-‘additional’ abatement, especially in the later years. The ‘integrity buffer’ could be increased but, as mentioned previously, doing so might adversely affect participation in the scheme. However, a high BAU uptake rate in itself provides a strong indication that the activity should be removed from the ‘positive list’ anyway.

A major advantage of the ‘integrity buffer’ approach is that it is a simple way of accounting for the abatement credited to early movers/adopters, which is non-‘additional’. On the downside the ‘integrity buffer’ may over or underestimate the true amount of non-‘additional’ abatement. Furthermore, if the buffer is set at a high level, this may adversely affect participation in the scheme.

While the initial level at which the ‘integrity buffer’ is set may over- or under-account for the actual level of non-‘additional’ abatement, the ‘integrity buffer’ is a flexible instrument which might be changed at any point in the future (although it is acknowledged that a change in the ‘integrity buffer’ could cause uncertainty and could affect participation under the scheme). The ‘integrity buffer’ could be reviewed in line with crediting reviews and be adjusted to ensure that non-‘additional’ abatement is offset within a reasonable timeframe. This will require that the amount of ‘additional’ and non-‘additional’ abatement that has already occurred for that particular activity be estimated along with the amount expected to occur in the future.
Factoring out the effect of the scheme

Associated with issues of predicting a business-as-usual scenario and how the scheme influences adoption, policymakers may have to consider how to factor out the effect of the scheme. This presents specific challenges when the proportion of adopters rapidly exceeds the threshold within the reassessment period. The reason for this is that removal of such activities from the ‘positive list’ may lead to disadoption (which may not be cost-free) because of removal of the CFI incentive. Disadoption can be defined as a decrease in the proportion of those who have adopted a practice under the CFI, leading to the proportion of adopters falling below the threshold. The process of potential disadoption is not currently accounted for in the Bass model (for a description of the Bass model, see Appendix A). However, further research using the aggregated Farm-Size Model may be able to address this.

A Farm-Size Model would assess the economic viability of a CFI practice relative to the business-as-usual case for a given farm or project size. It could be used to determine whether the financial incentive associated with the scheme would be sufficient to lead to a risk of disadoption if the practice was removed from the ‘positive list’. This method relies heavily on the assumption that adoption is driven primarily by financial incentives, but can also incorporate the effects of information diffusion.

It may not be necessary to estimate business-as-usual under some circumstances. If the profitability of an activity does not change significantly over time, and information was not a barrier to its adoption before the CFI, then it can be assumed that there would be very little or no uptake in the absence of the scheme. There are a number of activities for which we might expect these conditions to hold. For example, the profitability of an approved activity cannot change over time if that activity has no discernible productivity benefits to begin with. The capture and flaring of methane from manure storage ponds falls under this category. This practice was not profitable before the CFI and would remain unprofitable in the absence of any
revenue from the CFI (unless the size of the project is big enough to be commercially viable for generating electricity).
## Glossary

<table>
<thead>
<tr>
<th>Term</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Abatement activity</td>
<td>Any activity that leads to a reduction in or sequestration of greenhouse gases</td>
</tr>
<tr>
<td>Activity adoption</td>
<td>The number or percentage of landholders in the relevant ‘population’ that are conducting the abatement activity</td>
</tr>
<tr>
<td>‘Additional’ abatement</td>
<td>Abatement that occurs as a result of the offset scheme and can be considered as beyond business-as-usual</td>
</tr>
<tr>
<td>Barrier analysis</td>
<td>An assessment of the barriers which may prevent the implementation of an offsets project without an incentive scheme</td>
</tr>
<tr>
<td>Common practice assessment</td>
<td>An analysis of the extent to which an offset project has already occurred in the relevant sector and region</td>
</tr>
<tr>
<td>Diffusion of innovations theory</td>
<td>A theory that seeks to explain how and why and at what rate a new technology or practice is adopted by a ‘population’ over time</td>
</tr>
<tr>
<td>Investment analysis</td>
<td>An assessment of whether a project is financially attractive without the additional revenue from an offsets scheme</td>
</tr>
<tr>
<td>Offsets project</td>
<td>A carbon sequestration activity, or an emissions avoidance activity</td>
</tr>
<tr>
<td>Penetration rate</td>
<td>Can represent either the market share (the fraction of total sales in a particular market, the ‘flow’ of a technology into a market) or the market saturation (the proportion of total equipment in use, is the stock of the technology in a market) as defined by Kartha et al (2005)</td>
</tr>
<tr>
<td>Performance benchmark</td>
<td>This is not the same as the level of adoption. Performance benchmark refers to the amount of emissions generated from a given practice</td>
</tr>
<tr>
<td>S-curve</td>
<td>The cumulative function of the diffusion of an innovation through a system is characterised by an S-curve</td>
</tr>
<tr>
<td>Take-off point</td>
<td>The take-off point is the point where the rate of activity adoption reaches maximum acceleration (where the second derivative of the S-curve reaches its maximum value)</td>
</tr>
<tr>
<td>Threshold</td>
<td>The upper level of activity adoption permissible by an offsets scheme. Past this point any further adoption is deemed to be common and therefore non-‘additional’</td>
</tr>
</tbody>
</table>
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