Essays in Climate Change Mitigation Strategies

Submitted by:

Yaoyao Ji
Department of Environmental Sciences
Faculty of Science and Engineering
Macquarie University
Sydney, Australia

Supervisor:

Dr. Ram Ranjan
Department of Environmental Sciences
Faculty of Science and Engineering
Macquarie University

Co-supervisor:

Dr. Chi Truong
Department of Applied Finance and Actuarial Studies
Faculty of Business and Economics
Macquarie University

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Declaration

I certify that work in this thesis entitled ‘Essays in Climate Change Mitigation Strategies’ has not previously been submitted for a degree nor has it been submitted as part of requirements for a degree to any other university or institution other than Macquarie University.

I also certify that the thesis is an original piece of research and it has been written by me. Any help and assistance that I have received in my research work and the preparation of the thesis itself have been appropriately acknowledged.

In addition, I certify that all information sources and literature used are indicated in the thesis.

Signed:

Yaoyao Ji (Student ID: 42173868)

Date: 12 June 2014

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List of Abbreviations

CIFOR	Centre for International Forestry Research
CII	Chinese illegal timber imports from Indonesia
CIIN	Corruption perception index for Indonesia
CT	Conservation tillage
DRC	Democratic Republic of Congo
EPIN	Export price in Indonesia
GCOMAP	Generalised Comprehensive Mitigation Assessment Process
GDP	Gross domestic product
GHG	Greenhouse gas
GTM	Global timber model
HC	Huangling County
IAM	Integrated Assessment Models
JII	Japanese illegal timber imports from Indonesia
KMO	Kaiser-Meyer-Olkin
NUDIS	Number of districts in Indonesia
OLS	Ordinary Least Squares
PNG	Papua New Guinea
REDD	Reducing emissions from deforestation and forest degradation
TSLS	Two Stage Least Squares
TT	Traditional tillage
UNEP	United Nations Environment Programme

Abstract

Global emissions from agricultural and forestry sectors account for roughly 22 per cent of the total annual greenhouse gas emissions, which is equal to the emissions from fossil fuel consumption in the global transportation sector. Reducing emissions from these two sectors presents an opportunity to effectively mitigate carbon emissions with relatively low mitigation costs. In Asia, countries such as China and Indonesia present significant potential to mitigate carbon emissions within these two sectors. Using conservation tillage (CT) and reducing emissions from deforestation and forest degradation (REDD) programmes as examples of potential options, the objective of this thesis is to enhance our understanding of the challenges associated with mitigating global greenhouse gas emissions in the agricultural and forestry sectors of Asia. In the following paragraphs, I provide a brief outline of my thesis.

First, I investigate the socio-economic factors that promote or hinder CT adoption in agriculture using a detailed household level survey of the Huangling County in China. A bivariate probit model with sample selection is applied to analyse farmers' decision making associated with adopting CT. Results indicate that variables such as government subsidy programmes and household wealth levels play a key role in the continued adoption of CT. Poorer farmers and those whose neighbours have abandoned CT are more likely to give up on CT. Geographical challenges and fragmented land holdings lead to only partial adoption, even under government subsidies. Next, the effects of social and economic factors on the time to CT adoption are analysed using survival analysis. To explore further the influence of training programmes and subsidy schemes provided by the Government, villages covered by the survey are divided into two groups based on the level of support received from the Government. The analysis reveals that families who have a higher farm income and those who have attended the training programmes tend to adopt CT earlier. In addition, those who have already adopted CT help with speeding up the adoption process of their neighbours.

In terms of reducing greenhouse gas emissions through REDD programmes in the Indonesian forestry sector, illegal logging is considered as a critical challenge and a threat to the success of REDD projects. A simultaneous-equation econometric model is used to estimate factors causing and promoting illegal logging in Indonesia. The effects from Indonesia's main timber trading partners, Japan and China, and policies aimed at curbing illegal logging in these countries are also considered as key explanatory factors. The results reveal that corruption and decentralisation in Indonesia have a significant influence on promoting illegal logging supply. Additionally, excess demand in the Japanese construction and furniture industries is a key driver of illegal logging demand. Whereas, in China, an increase in the gross domestic product (GDP) has not necessarily fuelled a proportional increase in demand for illegal logging due to efficiency in wood usage and an increased domestic wood supply resulting from promotion of afforestation in the last two decades. Law enforcement or policies aimed at curbing illegal harvesting in Indonesia are also effective tools.

Finally, the potential contributions of the REDD programmes to the global carbon mitigation objective are investigated using an integrated assessment model. It is found that the REDD programmes not only contribute positively towards carbon emissions mitigation through reducing deforestation, they also increase optimal abatement efforts through other conventional abatement. The risk of forest loss, however, makes the REDD option less attractive. The insights derived from the optimisation model suggest that, while investing in REDD, countries with lower risk but higher opportunity costs of REDD programmes should be preferred over countries with higher risk but lower opportunity costs.

Chapter 1 Introduction

1.1 Roles of Agriculture and Forestry in Reducing Greenhouse Gas Emissions

In the interests of alleviating global environmental challenges and addressing issues such as food and energy security, it is increasingly important to investigate the economics of carbon mitigation strategies in the agricultural and forestry sectors. In 2010, global fossil fuel consumption accounted for 60 per cent of greenhouse gas (GHG) emissions from the energy, transportation and industrial sectors (UNEP, 2012). However, emissions from agricultural and forestry sectors are also significant, as combined, they accounted for roughly 25 per cent of the total annual GHG emissions in 2010 (Edenhofer et al., 2014). In these sectors, there is large potential for emission reductions with relatively low mitigation costs (UNEP, 2011).

In particular, global GHG emissions from the agriculture sector increased to 4.9 gigatonnes (Gt) of CO_2 in 2010 due to increased demand for food and unsustainable management methods (Edenhofer et al., 2014). Their average increase rate has been 1.6 per cent per year since 1961 (Tubiello et al., 2013). In China, the agricultural emissions reached 1.6 Gt of CO_2 equivalents (CO_2e) in 2009, with an annual average increase of 1.46 per cent since 1980 (Tan, 2011). The emissions from the US agricultural sector have also experienced a similar increase. In 2012, GHG emissions from agriculture had increased by around 19 per cent since 1990 (EPA, 2014). Facing the challenge of increasing GHG emissions in agriculture, several options such as sustainable management in agriculture, including cropland management, grazing land management, organic soils management, livestock management and so on, provide possibilities and opportunities for agricultural GHG mitigation (Smith et al., 2008). Considering the mixed effects of agricultural management practices, the potential for carbon mitigation in agriculture is estimated to be 5500–6000 Mt CO_2e annually (Smith et al., 2008), which would significantly contribute towards global GHG mitigation efforts.

Deforestation and changes in forestland use are other important sources of GHG emissions. Specifically, one hectare of forest contains about 250 tonnes of carbon (Swallow et al., 2007; Olsen and Bishop, 2009), and its clearing is equivalent to burning 320 tonnes of coal in terms of carbon emission generation. Around 5.2 million hectares of forest were cleared every year over the last decade (FAO, 2010), which accounted for 12 per cent of global emissions in 2000–2009 (Edenhofer et al., 2014). Additionally, most deforestation happens in the developing countries since forest produce and land comprise a significant source of income for a majority of the population. To reduce deforestation in developing countries, reforestation and avoided deforestation programmes have been suggested (Niles et al., 2002). These options are estimated to provide a large potential for carbon mitigation: about 2.3 billion tonnes of carbon for developing countries over a decade (Niles et al., 2002).

1.2 Research Questions and the Main Research Objectives

Soil carbon sequestration presents an opportunity to effectively mitigate carbon emissions in the agricultural sector, as well as sequester some of the atmospheric carbon (Antle et al., 2001). One of the available soil carbon sequestration options is through conservation tillage (CT). CT is a package of practices including covering fields with crop residues, minimum soil disturbances and field management (Gao, 2011). The practice of CT offers the benefit of reducing soil loss from water or wind erosion. It also effectively reduces GHG emissions from burning crop residues. In addition, the soil under CT contains more carbon than the soil under the traditional tillage (TT). Another potential benefit of CT is that more efficient use of farm machinery, by reducing reliance on the tilling process, could reduce fossil fuel consumption and associated GHG emissions (Rahm and Huffman, 1984).

Agricultural land including permanent crops and permanent pastures, accounted for approximately 54.8 per cent of total land area in China (TheWordBank, 2014). The GHG emissions from agriculture contributed to around 15 per cent of China's total emissions in 2005 (Wang et al., 2010). Reducing emissions in the agricultural sector and increasing the capability of soil carbon sequestration is increasingly being considered as an important strategy for the national carbon mitigation option (Wang et al., 2010). However, differences in agricultural industry structure can pose problems for implementation of new strategies or techniques. For example, in addition to variations in regional climate, topography and soil, CT adoption in China faces significant challenges due to characteristics that are unique to its local economy and rural society. The traditional family-based small farm size in China is an obstacle to a higher rate of CT adoption, and a barrier to achieving economies of scale using large machinery. Further, it is difficult to change overnight farmers' conventional tillage methods, which have been practised for a thousand years.

In terms of the forestry sector, deforestation in the tropics is one of the most important factors that contributes to GHG emissions and drives the concerning climate change problem (Metz, 2007). Indonesia is the third largest country in terms of tropical forest area (FAO, 2010). It has the second highest deforestation rate in the world, after Brazil. Annual Indonesian forest loss is 498,000 hectares (FAO, 2010), which leads to a release of a large amount of carbon into the atmosphere. Deforestation accounted for about 89 per cent of the total GHG emissions in Indonesia in 2000 (Madeira, 2008).

To reduce deforestation, the programme of reducing emission from deforestation and forest degradation (REDD) provides an economic incentive to forest dependent communities. This generates an attractive option to mitigate GHG emissions through forestry by paying farmers to stop deforestation. However, there are risks that can undermine the effectiveness of REDD. One of the critical risks to REDD projects is illegal logging caused mainly by corruption in REDD countries. Since the late 1990s, illegal logging has been considered a serious problem in countries, such as Indonesia, with significant impacts on the environment, economy, society (Obidzinski et al., 2006) and implementation of REDD programmes.

The broad research aim of my thesis is to increase understanding of the influences and challenges associated with mitigating GHG emissions, through the promotion of conservation practices in the agricultural and forestry sectors of Asia. Using CT and REDD programmes as examples, more specific objectives include: to investigate and understand how to improve the rate of CT uptake in China; and to investigate ways of reducing illegal logging that threatens REDD programmes in developing countries such as Indonesia.

1.3 Thesis Structure

The thesis uses econometric and optimisation models to study two types of carbon mitigation options: CT and REDD programmes. In the analysis of CT, empirical models are used to determine the factors influencing CT adoption and to investigate timing of this adoption. In relation to REDD, the thesis first examines factors affecting illegal deforestation by building simultaneous-equation systems to capture the interrelationship between demand and supply for forest products using Indonesian, Japanese and Chinese data. The last chapter in the thesis uses an integrated assessment model to investigate the potential and challenges faced by REDD programmes as possible options for carbon mitigation.

In Chapter 2, the recent of CT adoption promotion initiative in China is used as a case study. China has a large potential for sequestering carbon through CT. Yet, the uptake of CT programmes in China has been slow. Early in 2013, I conducted an extensive household survey in Huangling County (HC), in north western China, to assess the social-economic factors that promoted or hindered CT in agriculture. The pilot and the main survey were conducted in February and April 2013 respectively. The survey covered 15 villages in HC and led to the generation of 266 valid questionnaires. The survey data indicated that when households decide to adopt CT, they need to make subsequent decisions such as whether to adopt CT on all of their land as well as whether to adopt CT continually. To analyse the farmers' decision-making processes, a bivariate probit model was applied with sample selection approaches to estimate farmers' initial adoption decisions and sequential decisions. The model demonstrated current obstacles to CT adoption, by understanding the influence of social-economic and farm level characteristics in rural Chinese households. The influences of government demonstration and education programmes and subsidies on CT adoption were also investigated.

Having identified the influences and barriers, in Chapter 3, CT adoption in HC was investigated further using a dynamic econometric framework, the survival analysis. This method estimated the effects of social and economic factors on the waiting time for CT adoption. First, a Kaplan-Meier approach was used to depict the durations farmers waited before adopting CT without making any assumptions over the distribution functions relating to the waiting times (Dadi et al., 2004). The Kaplan-Meier approach provides a graphic summary of the diffusion of CT without estimating the effects of covariates. Following that, a survival analysis model analyses the role of social-economic factors and the HC Government's efforts in influencing CT adoption success rate by giving a specific functional form for the waiting times.

To explore further the influences of the training programme held by the Government and of subsidy schemes, villages covered by the survey were divided into two groups based on the level of support received from the Government. Two separate survival analyses were conducted using data in these two categories of villages. Finally, factor analysis was applied to deal with the problem of correlation between some key variables.

After investigating factors and decision-making processes related to CT in China, Chapter 4 switches focus to the threats to the Indonesian REDD forestry programme. Secondary data were analysed to identify factors that cause illegal logging and inhibited promotion of the REDD programme. This chapter develops a simultaneous-equation econometric model to estimate factors causing illegal logging in Indonesia with a dataset extending from 1996 to 2009. The model incorporates both demand and supply characteristics of logging. Japan and China were selected to represent the demand side of Indonesia’s illegal logging, as they are the main trading partners of Indonesia, accounting for half of Indonesia’s annual plywood exports. On the supply side, variables, such as corruption and the increasing number of logging districts in Indonesia are tested. On the demand side, roles of economic factors such as GDP growth, domestic production of log, and number of new housing constructions in Japan and China are accounted for and tested in promoting illegal logging. Further, the main policies aimed at curbing illegal logging in Indonesia and in the importing countries are quantified as dummy variables and tested in the model.

The underlying theme of Chapters 2–4 has been enhancing our understanding of the social-natural influences that may inhibit mitigation of climate change. In Chapter 5, an integrated assessment model, incorporating the REDD option, was developed to estimate the optimal timing and level of carbon mitigation at the global level. Countries with significant carbon mitigation potential through REDD, such as Brazil, Indonesia, the Democratic Republic of

Congo, Cameroon and Papua New Guinea, were selected as potential participants. The model also included a non-linear damage function associated with atmospheric carbon stock accumulation, which incorporates the possibility of catastrophic outcomes. The hypothesis was that when faced with non-linear damages and consequential threshold effects, conventional carbon abatement plans that exclude the cheaper REDD options could possibly lead to high atmospheric carbon concentrations. The assessment model initially only included the conventional abatement options (such as wind power, nuclear technology, carbon capture and storage technology and coal-to gas shift technology etc.) to generate a simulation of the base case scenario. Next, optimal abatement scenarios (including REDD options) were incorporated to compare with the results under the base case scenario. Finally, underlying risks associated with REDD were also considered.

Lastly, Chapter 6 highlights the main findings of the thesis. While the potential offered by the specific CT measure is significant for China, in other Asian countries, REDD programmes are a more important element of abatement strategies. Further, discussion of socio-economic factors and supply-demand interactions is included, together with a brief outline of research limitations and future research directions.

Chapter 2 A Bivariate Probit Analysis of Factors Affecting Partial, Complete and Continued Adoption of Soil Carbon Sequestration Technology in Rural China

Abstract

There remain significant technological as well as socio-economic and behavioural challenges to CT adoption despite its acknowledged carbon mitigation potential. In this chapter, I explore and distinguish between the factors that affect partial, complete and continued adoption of CT in a rural region of north western China. Data used in this study were gathered from an extensive household survey in HC, in north western China in 2013. The survey covered 15 villages in HC and led to the generation of 266 valid questionnaires. Using a bivariate probit analysis, I find that government subsidy programmes and household wealth play a key role in the continued adoption of CT practices. Poorer farmers and those whose neighbours have abandoned CT are more likely to give up on CT. Geographical factors and fragmented land holdings encourage only partial adoption, even with government subsidies. Social networking also plays a key role in promoting complete adoption.

2.1 Introduction

GHG emissions by the agricultural sector amounted to five billion tonnes of CO_2e in 2010, accounting for roughly 10 per cent of global GHG emissions (FAO, 2013). Despite contributing significantly towards annual GHG emissions, the agricultural sector also presents opportunities for sequestering carbon. For instance, soil carbon sequestration can help mitigate some of the carbon released in the process of agricultural farming (Antle et al., 2001; Kimble et al., 1998).

One of the available soil carbon sequestration options is CT. The Food and Agricultural Organization of the United Nations defines CT as ‘any tillage or planting system in which at least 30 per cent of the soil surface is covered by plant residue after planting to reduce erosion by water; or where soil erosion by wind’ (FAO, 1993). The practice of CT offers the added ecological benefits of soil protection compared to TT based farming. The soil erosion prevention benefits associated with CT have been well documented in literature (Rahm and Huffman, 1984; Knowler and Bradshaw, 2007). In addition, the soil is found to contain more carbon under CT than under TT, especially after using CT consistently for prolonged periods (West and Marland, 2002; Holland, 2004). Another potential benefit of CT is that efficient use of farm machinery by reducing reliance on the tilling process could reduce fossil fuel consumption and associated GHG emissions. Further, CT practice can offer direct economic benefits as compared to conventional methods (Derpsch et al., 2010). For instance, it can save labour and machine hours by eliminating steps associated with tilling and burning straws (Rahm and Huffman, 1984). Despite the apparent benefits offered by CT, there remain significant challenges towards promoting its adoption.

The literature exploring CT adoption has been rapidly evolving. Rahm and Huffman (1984) used a probit model to analyse the adoption behaviour of reduced tillage practice. Their finding emphasised the importance of human capital in decision making when the adoption is not economically feasible. Westra and Olson (1997) conducted a survey in two counties in Minnesota with the similar soil type but different levels of CT practices. They concluded that farmers in regions with greater access to CT information are more likely to adopt it than farmers in other regions. Additionally, the size of farms, the level of concern about erosion and management skills for CT are significant determining factors. Traoré et al. (1998) found that farmers' rising concerns about environmental damage and health hazards have a positive effect on their adoption of conservation practice. A study of soil conservation measures adoption in South Africa by Anim (1999) also agrees that the awareness of soil problems is a key factor affecting adoption behaviour. The results of a two-stage probit model in Traoré et al. (1998) revealed that farmers who have higher education levels and participate in farm programmes held by organisations and governments are more likely to adopt conservation practice since they are concerned about the environment. Pautsch et al. (2001) estimated the different carbon sequestration rates possible under CT adoption by varying the level of subsidy that is offered. They conclude that a subsidy is essential for increasing carbon sequestration through CT practices. Kurkalova et al. (2006) also emphasised the importance of providing subsidies for promoting CT, specifically for those farmers who are risk averse. Knowler and Bradshaw (2007), after reviewing 23 conservation agriculture adoption studies, conclude that farmers' knowledge of CT technology is an important variable influencing adoption decision in many studies. Some relevant studies on conservation or organic farming include those by Burton et al. (1999), Pautsch et al. (2001), Burton et al. (2003), D'Emden et al. (2006), D'Emden et al. (2008) and Derpsch et al. (2010).

The arguments in support of subsidy provision are manifold. It helps lower the initial costs associate with CT farming. More importantly, it may help mitigate the risk and uncertainty based inertia experienced by farmers when it comes to adopting new technology. There is a large body of existing literature suggesting that uncertainty can delay investment decisions by firms as well as farmers, whenever sunk costs are involved (Feder et al., 1985; Belknap and Saupe, 1988; Dixit and Pindyck, 1994; Sheikh et al., 2003). In the case of CT adoption, if farmers need to invest in costly machines required for CT practice, then one needs to account for the sunk cost of that investment, as future yield and profit-related uncertainty can lead to an option value of waiting, thereby delaying investment. However, CT adoption can circumvent some of the above-mentioned challenges, as it is a multistage process (Dimara and Skuras, 2003; Amsalu and de Graaff, 2007). Farmers may adopt a new farm technology on a part of their land in the first few years, and then consider expanding their adopted acres or abandoning the technology, depending on the outcome of their initial decision.

China offers significant opportunities for carbon sequestration through CT promotion. The amount of subsidy provided towards promoting CT programmes has varied significantly (between 12 and 108 USD per hectare [ha], per year) in different regions of China (Zhao et al., 2012). The estimated subsidy for CT in Iowa in the US was 10.13 USD per ha for corn land and 14.83 USD per ha for soybeans in 1992 (Kurkalova et al., 2006). In 2004, the estimated average subsidy for CT in the US increased to 43.61 USD per ha (Wade et al., 2012). In comparison, the amount of subsidy offered through government CT promotion programmes appear to be attractive. Yet, the rate of success observed for CT adoption in rural China leaves much to be desired.

The aim of this chapter is to investigate current obstacles to CT adoption in China by understanding the influence of social, economic and farm level characteristics of rural households. In China, the earliest experiments and research associated with CT took place in the 1960s (Gao, 2011). Although significant achievements towards CT experimentation have been made since then, the application of CT technology is still limited and appears to be in a trial phase. China's programme of CT promotion began in 2002. Initially, 38 counties in northern China were selected in the pilot programme (Gao, 2011). In 2008, the area under no-tillage adoption was more than one million ha in China (Derpsch et al., 2010).

Several studies on CT adoption and its potential in China have been conducted in the past. Tan (2011) calculated GHG emissions in Chinese agricultural sector by considering emissions from the planting process, livestock raising and consumption of materials including fertiliser, pesticide and fossil fuel. The calculation revealed that in 2009, the GHG emissions from agriculture were 1.6 Gt of CO_2e in China, which have increased by 52.03 per cent since 1980. Hu et al. (2009) examined the effects of CT on the greenhouse effect by analysing emissions of CO_2, N_2O and CH_4 from different tillage practices and crop residue management methods. They concluded that the conservation practices could effectively reduce emissions of CO_2. Tang and Nan (2013) focused on the potential of soil carbon sequestration on cropland in the Loess Plateau of China. Their study highlighted that soil cropland has a large potential to sequester carbon (1.555-6.054 Tg / year) through CT.

Although a few empirical studies of CT adoption based on household surveys in China exist (Wang and Zhang, 2010; Zhao et al., 2012), none has analysed factors affecting the full decision-making process associated with CT adoption, including adoption and its subsequent continued adoption. Since there is tremendous scope for expanding on CT programmes throughout the country, it is crucial to gain an understanding of factors that particularly lead to sustained CT adoption.

Keeping the above needs in mind, in this chapter, I perform an empirical analysis to estimate the key obstacles to CT promotion in rural China. The influences of government demonstration and education programmes and subsidies on CT adoption are given particular attention. Additionally, famers' sequential decisions over adoption are analysed. In particular, I test for the factors that determine whether farmers who partially adopt CT are likely to progress to full adoption of the technology in the future. It is important to continue with adoption of CT technology for sustained periods in order to benefit from soil quality related productivity improvements. Consequently, I also test conditions that promote continued adoption. A bivariate probit analysis is used to test the influence of variables on farmers' decision over partial CT adoption.

Further, the sequential determinants of continued use of CT are estimated through another binary outcome model. Bivariate probit methods have been applied previously to understand the factors that influence farmers' decisions over continued use of such agricultural technologies (Neill and Lee, 2001; Amsalu and de Graaff, 2007; Tura et al., 2010).

The challenges associated with CT adoption in China are in sharp contrast to those in other countries where CT has been trialled. For instance, in Australia and the US, one main difference is the farm size of the CT adopters. Large farm sizes in Australia and the US not only allow for a higher area of CT adoption, but also provide economies of scale through facilitating use of large machinery. Whereas, in China, small holdings create greater uncertainty with respect to large scale adoption, as household characteristics and neighbourhood characteristics can influence how rapidly and to what extent CT is adopted. This concern is confirmed in this study through the finding that adoption is significantly affected by farm location, neighbourhood and other factors.

A brief outline of the chapter is as follows. Section 2.2 describes the estimation of CT costs and details the survey used to generate primary data in HC in northwest China. Research methods and results are described in Section 2.3. The chapter concludes by highlighting some main findings and makes some policy recommendations in section 2.4.

2.2 Conservation Tillage Adoption in Huangling County

The research area, HC, is located in the Loess Plateau, which is in the north-west part of China. Farmland in this area is prone to wind erosion due to its porous soil, dry climate, scarce rainfall and constant winds. Simultaneously, it also faces the risk of water erosion, as most of the rainfall is concentrated in the summer, leading to flooding. Corn is the major crop grown in HC. It is planted in spring and harvested in autumn. The CT technology is applied mainly on the corn land in this county. There exist several differences between CT and TT farming methods in HC. First, crop residues are pulverised and covered on the field under CT, instead of being burnt after harvesting. Unlike TT, the machine used for CT is a 'subsoiling' machine, which only breaks soil compaction rather than inverting it. During the planting season, a no-till planter machine is used to directly seed on the no-till land under CT. The step involving returning crop residues is considered one of most critical components of CT, compared to TT (Gao, 2011).

2.2.1 Survey Design and Data Collection

A pilot study and the main survey were conducted in February and April 2013 respectively. The study area covered 15 villages in the HC. Participants in the survey were selected randomly, however adequate representation from each village was ensured by including at least 30 per cent of the population from each village. After data cleaning, in total, there remained 266 valid questionnaires comprising 170 CT adopters and 96 non-adopters.

In this study, a household is considered to have adopted CT if it returns crop residues back to the field and is involved in non-till planting. Households are considered 'adopters' once they have adopted the CT technology on any plot of their land, while households who do not return residue back to the farm and non-till planting types are considered 'non-adopters'. Farmers who adopt CT on their entire land holdings are classified as ‘complete adopters’, whereas those who adopt CT only on parts of their land are ‘partial adopters’. Finally, adopters who consistently use CT (on any plot of their land) without ever reverting to traditional farming are classified as ‘continued adopters’. Households that took up CT in the past, but reverted back to TT are considered ‘discontinued adopters’ in the model.

The survey questionnaire contained three main sections: household characteristics, information regarding CT adoption and information relating to government incentive schemes. Information about household characteristics included five capital types: human, natural, physical, financial and social capital. Table 1 provides the summary statistics of the data based on the main survey.

For measuring land size, the unit ‘mu’ is widely used in rural China. One hectare equals 15 mu and one acre equals 6.0703 mu. In this study, I use mu as the measurement unit for land area. For measuring the costs, I use Chinese currency unit (CNY). One CNY equals around US$0.16[1].

[1] The exchange rate on 4 December 2013

Table 1 Description and summary statistics of the variables used in the bivariate probit regression

Variables	Description	Mean	S.D.
Human capital			
eduhh	Education level of the head of household(0-fundamental and middle school,1-high school and higher levels)	0.0977	0.2975
pofffarm	Percentage of family members working off-farm (%)	0.5823	0.3229
nofarming	Number of family members working on farm (N)	0.7105	0.8659
Natural capital			
mloffroad	Size of land fragments away from the road (measured in mu)	5.1425	5.3682
Financial capital			
pincomefarm	Percentage of farm income in the total income (%)	0.3709	0.2950
conhlth	Health related consumption expenses in a year (in 1000CNY)	3.8176	6.6038
Physical capital			
mtfmv	Value of mobiles, televisions, refrigerators and motorbikes (CNY)	4821.135	4441.523
carcompuv	Value of cars and computers (CNY)	3581.203	21933.46
Social capital			
goodrela	Relationship with the village committee (0-other;1-good)	0.1391	
CT promotion			
timefirsthear	Year first heard of CT (in year)	--[1]	
training	Attended CT training (0-no,1-yes)	0.5376	
hearfrom	First heard about CT from government or not (0-no;1-yes)	0.7632	
neibadopt	Neighbour's adoption CT (0-no; 1-yes)	0.7331	
Subsidy			
firstsub	The amount of subsidy received in the first year of adoption (CNY)	9.8684	11.5449
subsidy	Categorical variable relating to receiving subsidies (0-no subsidy; 1-sporadic subsidy and 2-continued subsidy)	0.9173	
Dependent variables			
adopt	Adoption of CT (0-no;1-yes)		
complete adopt	Adoption of CT on entire land area (0-no;1-yes)		
continued adopt	Continued adoption of CT (0-no;1-yes)		

1. Refer to Figure 3 in Chapter 3 for distribution of farmers' year of first hearing CT

2.2.2 Estimating the Costs of Conservation Tillage Adoption

According to information provided by the survey, I estimated costs of CT and TT in HC while including the subsoiling option. In CT, the subsoiling is applied instead of the annual deep tilling due to reduced disturbance of soil (Gao, 2011). Since subsoiling is only required once every three years, machine costs differ each year. To avoid overestimation of cost reduction through CT, I calculate CT costs in HC by averaging costs over three years.

Table 2 Comparison of costs between traditional tillage and conservation tillage technologies (CNY/mu)

		TT			CT		
		1st year	2nd year	3rd year	1st year	2nd year	3rd year
Machine costs	Planting	30	30	30	30	30	30
	Residues returning	-	-	-	30	30	30
	Deep tilling	30	30	30	-	-	-
	Sub soiling	-	-	-	30	-	-
	Rotary tilling	30	30	30	30	30	30
Other costs	Seed	50	50	50	50	50	50
	Fertiliser	180	180	180	180	180	180
	Herbicide & Pesticide	30	30	30	30	30	30
	Labour	-	-	-	-	-	-
Subsidy		-	-	-	-20	-20	-20
Total		350	350	350	360	330	330
Average cost in each year		350	350	350	340	340	340
Costs saving by applying CT					-10	20	20

†TT stands for traditional tillage method and CT stands for conservation tillage method. CNY stands for Chinese currency. A unit 'mu' is used for measuring land size in China. One hectare equals to 15 mu and one acre equals to 6.0703 mu.

Note: Figures in the table are summarised from the information provided by the Huangling Bureau of Agriculture Machinery and data generated from the survey conducted in the study.

Table 2 depicts costs for TT and CT during any three-year period. The primary figures in Table 2 were provided by the Huangling Bureau of Agriculture Machinery (the bureau). However, in reality, the costs vary due to there being different providers of machines and different suppliers of materials. Since subsides are provided by village committees, given their different budget situations, subsidies received by farmers vary from 10 to 35 CNY/mu.

To provide a numerical summary for costs of CT and TT in HC, the primary figures were adjusted referring to the rounded average figures based on the survey.

According to the data generated under the survey, the average price for hiring machines was 30 CNY per mu. Cost of materials was also included in this table. In terms of seed and fertiliser, the quality and quantity of these items differed for different farmers. On average, they spent around 50 and 180 CNY purchasing seeds and fertiliser per mu. Herbicides and pesticides are highly recommended under CT. However, in practice, not every household uses them due to differences in their historical farming traditions. Based on this table, I calculated that every household spends around 30 CNY for herbicides and pesticides on each mu of land. In addition, as recorded in the survey, households rarely spent money on labour hire. During the harvesting season, neighbouring farmers nearby harvested corn together. They took turns to help each other. Therefore, I have assumed that costs for hiring labour are insignificant and have ignored opportunity costs of own labour time for the analysis. The incentive scheme in HC is aimed at reducing the machine costs for adopters. A part of, or the entire fee, associated with hiring machines for returning residues is funded by the bureau or by the village committee. Households only need to pay the remainder amount (on average 10 CNY per mu). In HC, the average subsidy turns out to be 20 CNY per mu.

In total, the estimated costs under TT are 350 CNY per mu per year, while CT costs are 360 CNY per mu in the first year and 330 CNY per mu in the following two years after accounting for the subsidy. The annual average costs under TT and CT are 350 CNY and 340 CNY per mu. Therefore, it is apparent that the two technologies do not differ much in costs, after accounting for the government subsidies. If I exclude the subsidies, the costs under CT become higher than TT. Additionally, according to the survey information gathered, some households have to apply subsoiling more frequently than once every three years when the quality of straw pulverising is not good. Thus, CT adoption in HC does not lead to significant costs savings when compared to TT.

2.3 Analysis of Sequential Decisions after Adoption

Technology adoption often involves a multistage decision-making process (Dimara and Skuras, 2003; Amsalu and de Graaff, 2007). If the households decide to adopt CT, they need to make subsequent decisions on whether to adopt CT on all of their farmland and whether to adopt CT continually (Neill and Lee, 2001). In the survey, 170 farmers adopted CT and 96 farmers had not adopted CT. Among these adopters, 147 adopters chose to adopt CT on the entirety of their land, while 23 adopters chose to adopt CT only on a part of their land. In the same group of adopters, 155 adopters continued to use CT (until the date of the survey) and 15 adopters abandoned it after a few years of adoption (see Table 3). Table 3 provides a numerical summary of the number and characteristics of the adopters, non-adopters, complete adopters and continued adopters. For each group of farmers, the characteristics, such as the mean age of the household head, mean of family size and mean of land size, are similar. To investigate the underlying reasons of farmers' different choices, other covariates need to be estimated.

In the following sections, a bivariate probit model with sample selection is deployed to explore and distinguish reasons that lead to complete adoption from those leading to only partial adoption or abandonment at a later stage.

Table 3 Number and characteristics of adopters, non-adopters, complete adopters and continuing adopters in the sample

	Adopters	Non-adopters	Complete adopters	Continued adopters
Number of households	170	96	147	155
Mean of head of the household age (year)	55.2	54.9	55.2	55.8
Mean of family size (number of people)	3.9	3.8	3.9	3.9
Mean of land size (mu)	8.7	9.3	8.6	8.8

2.3.1 A Bivariate Probit Model with Sample Selection

The single equation analysis of logit and probit models is not appropriate for analysing the multistage decision making process of CT adoption, as unobserved correlations between decisions are not taken into account (Tura et al., 2010). A bivariate probit model with sample selection can help estimate farmers' sequential decisions (complete adoption and continued adoption).

In this study, I have three endogenous variables: households are classified as adopters (y_1=1) and non-adopters (y_1=0). Conditional upon being an adopter, households can be classified on two mutually inclusive criteria: as complete adopters (y_2=1) and partial adopters (y_2=0); as continued adopters (y_3=1) and discontinued adopters (y_3=0) (see Table 4). Thus, conditional upon adoption, a householder may be classified into one of the four subsequent groups (e.g., a partial adopter, who has since discontinued, etc.). A sample selection issue exists because there may be correlation between the unobserved components that determine adoption/non-adoption and the subsequent pattern of adoption.

Table 4 Number of complete adopters and continuing adopters in the sample

	Complete adoption		
Continued adoption	0	1	Total
0	1	14	15
1	22	133	155
Total	23	147	170

†Complete adoption_0 indicates the households who adopted CT on only parts of their land holdings. Complete adoption_1 indicates the households who adopted CT on their entire land holdings. Continued adoption_0 indicates the households who abandoned CT after trying it. Continued adoption_1 indicates the households who continue adopting CT every year.

A bivariate probit model with sample selection is therefore the appropriate modelling framework. The model contains three latent variables that explain observed behaviour:

$$y_1^* = \beta_1 x_i + \varepsilon_1, y_1 = 1, \quad if\ y_1^* > 0; \quad y_1 = 0, \quad otherwise,$$

$$y_2^* = \beta_2 x_i + \varepsilon_2, y_2 = 1, \quad if\ y_2^* > 0; \quad y_2 = 0, \quad otherwise,$$

$$y_3^* = \beta_3 x_i + \varepsilon_3, y_3 = 1, \quad if\ y_3^* > 0; \quad y_3 = 0, \quad otherwise.$$

$$E\left[\varepsilon_1 | x_i\right] = E\left[\varepsilon_2 | x_i\right] = E\left[\varepsilon_3 | x_i\right] = 0,$$

$$Var\left[\varepsilon_1 | x_i\right] = Var\left[\varepsilon_2 | x_i\right] = Var\left[\varepsilon_3 | x_i\right] = 1,$$

$$Cov\left[\varepsilon_1, \varepsilon_2 | x_i\right] = \rho_{12}.$$

$$Cov\left[\varepsilon_1, \varepsilon_3 | x_i\right] = \rho_{13}.$$

$$Cov\left[\varepsilon_2, \varepsilon_3 | x_i\right] = \rho_{23}. \tag{1}$$

Where, y_1*, y_2* and y_3*are latent variables for observed variables y_1, y_2 and y_3. The bivariate probit model with sample selection allows there to be correlation in the error processes: here, ρ_{12}, ρ_{13}, ρ_{23} are covariate coefficients between error terms in the above three equations. The decisions relating to CT adoption, complete adoption and continued adoption need to be estimated jointly using the bivariate probit model with sample selection whenever the null hypothesis that $\rho_{ij}=0$ is rejected, as this points out that the error terms are correlated. In the absence of any evidence of correlation, separate probit models should be used instead (Neill and Lee, 2001).

Normally, a two-step bivariate probit model with three equations has eight possible outcomes: $(y_1=0, y_2=0, y_3=0)$; $(y_1=1, y_2=0, y_3=0)$; $(y_1=0, y_2=0, y_3=1)$; $(y_1=1, y_2=0, y_3=1)$; $(y_1=0, y_2=1, y_3=0)$; $(y_1=1, y_2=1, y_3=0)$; $(y_1=0, y_2=1, y_3=1)$; $(y_1=1, y_2=1, y_3=1)$. However, in the model, if y_1=0 (non-adoption), y_2 and y_3 are not observed. Thus, I only have five possible outcomes:

$$y_1 = 0: \quad P\left(y_1 = 0\right)$$

$$y_1 = 1, y_2 = 1, y_3 = 1: \quad P\left(y_1 = 1, y_2 = 1, y_3 = 1\right)$$

$$y_1 = 1, y_2 = 0, y_3 = 0: \quad P\left(y_1 = 1, y_2 = 0, y_3 = 0\right)$$

$$y_1 = 1, y_2 = 1, y_3 = 0: \quad P\left(y_1 = 1, y_2 = 1, y_3 = 0\right)$$

$$y_1 = 1, y_2 = 0, y_3 = 1: \quad P\left(y_1 = 1, y_2 = 0, y_3 = 1\right)$$

The above model was run in Stata/SE (version 12) using the command *cmp*. The *cmp* is a functional mode that fits multi-equation models (Roodman, 2011). Since there do not exist accurate calculations for higher-dimensional normal distributions in Stata (Cappellari and Jenkins, 2003), a simulation method for maximum likelihood estimation, such as GHK[2], was applied to estimate models involving the cumulative normal distributions above dimension of two, as they are faster in terms of computing speed (Roodman, 2011). There is no hard and fast rule over the size of draws, however, the default number of draws per observation that is

[2] Theory and examples of estimating of M-equation multivariate probit model using GHK simulated maximum likelihood method are provided by CAPPELLARI, L. & JENKINS, S. P. 2003. Multivariate probit regression using simulated maximum likelihood. *The Stata Journal,* 3**,** 278-294..

used in the simulations in *cmp* is twice the square root of the number of observations (Roodman, 2011).

As noted in Table 3, the sample consists of 170 adopters and 96 non-adopters. Table 4 reports the distribution of adopters across the four possible categories, and it provides the basis for the bivariate probit aspect of the model. A bivariate probit model with sample selection is estimated to explore and distinguish reasons that lead to CT adoption as well as complete adoption and continued adoption. Results of the model will be presented in Table 5 and discussed in the following sections.

2.3.2 Analysis of the Adoption Decision

Results obtained through the bivariate probit model with sample selection analysis over adoption, complete adoption and continued decisions are described in Table 5. The associated coefficients of $\rho_{12}, \rho_{13}, \rho_{23}$ indicate the correlation of error terms between the three equations. In Table 5, *atanhrho* is the transformed value of ρ, which is calculated as: $atanhrho = 0.5ln\left[(1+\rho)/(1-\rho)\right]$ (based on Cameron and Trivedi (2010)).

In Model 1, the coefficient of *atanhrh_13* is positive and significant, which means error terms are positively correlated in the adoption equation (y_1) and the 'continued adoption' equation (y_3). However, coefficients of *atanhrh_12* and *atanhrh_23* are positive but not significant. The non-significant coefficients of *atanhrh_12* and *atanhrh_23* are restricted to zero in Model 2, a restriction that is accepted by a LL test (p= 0.3757). Regression results in Model 2 are equivalent to a separate probit regression of *complete adopt* and a bivariate probit with sample selection model of *adopt* and *continued adopt*. In Model 3, all three coefficients of *atanhrh* are restricted to zero; therefore, Model 3 is equivalent to three separate probit models.

However, this further restriction is rejected by a LL test (p= 0.0226). Therefore, I proceed with Model 2 as the preferred representation of adoption behaviour.

The absolute size of estimated coefficients depends on variable definition. Thus, it is meaningless to interpret magnitudes of coefficients in the probit model. To get a realistic interpretation of the outcomes (Baskaran et al., 2013), the 'marginal effects' is a much useful approach. Table 6 reports the average marginal effects on the probability of adoption and continued adoption and the probability of complete adoption (AME) for each variable in Model 2. As explained above, Model 2 is equivalent to a separate probit regression for *complete adopt* and a bivariate probit with sample selection model for *adopt* and *continued adopt* by restricting the non-significant coefficients of *atanhrh_12* and *atanhrh_23* to zero. In Table 6, the AME for the separate probit regression of *complete adopt* presents the effect on the probability of complete adoption ($y_2=1$) of a change in one of the covariates (Cameron and Trivedi, 2010). For the bivariate probit with sample selection model for *adopt* and *continued adopt*, there exist three outcomes ($y_1=0$; $y_1=1, y_3=0$; $y_1=1, y_3=1$). AME for each outcome needs to be estimated separately (Cong, 2001). I only list AME for the outcome relating to both adoption and continued adoption ($y_1=1, y_3=1$) in this table.

In this section, I investigate reasons that lead to households' adoption of CT. Households' characteristics such as income, consumption and labour availability are considered explanatory variables in the model. Besides, intervention efforts over CT promotion made by government officials, such as running training programmes for CT, are also included as potentially important factors influencing adoption decisions. Next, variables found to have significant effects on farmers' adoption decisions are interpreted based on the regression results of Model 2 in Table 5. This is aided by Table 6, which reports marginal effects.

Factors capturing the importance of agriculture to a household could be measured through the number of family members working off-farm (*pofffarm*) and percentage of farm income in the total income of a household (*pincomefarm*). These two variables are not correlated (correlation coefficient is -0.0898). In other words, a lower number of members working on the farm does not necessarily translate into a lower proportion of farm income in the total household income. So, the two variables can be used together in the same model. Results indicate that the coefficient of *pofffarm* is negative and significant, while the coefficient of *pincomefarm* is positive and significant. Families living on agricultural income as their main livelihood source and having more farm labourers are more likely to adopt CT. In short, those who are highly dependent on agriculture are more likely to adopt CT.

Efforts made by the Government to promote CT are tested for their efficaciousness in the model. Farmers who attend the training programmes (*training*) held by the Government are more likely to adopt CT as they receive clear guidelines over CT practice methods and its benefits. Besides, famers have a higher probability of CT adoption if they also receive information about CT through the bureau and the village committee (*hearfrom*). In addition, households who get the information earlier (*timefirstheard*) are expected to be more likely to adopt CT.

An advantageous side effect of CT promotion programmes is the influence from the neighbourhood farmers. A farmer's adoption decisions are heavily influenced by neighbours' behaviours (*neibadopt*). This variable has a high AME, which means the probability of a farmer's adoption increases by roughly 30 per cent if their neighbours have already adopted CT. In other words, more households adopting CT will generate further positive feedback. Lastly, households spending more money on medical care (*conhlth*) are less likely to adopt CT, since an unhealthy labour force within the family will increase anxiety over future incomes.

The second part of Table 5 presents regression results showing determinants for complete adoption. Farmers who lack confidence over future CT benefits or have not fully understood the technology might not go for complete adoption. Variables such as location, fragmentation of land area and number of farm labours are considered factors influencing farmers' adoption decisions. Next, I test for these potential determinants of complete adoption.

Table 5 Obtained coefficient estimates for adoption, complete adoption and continued adoption

		Model 1		Model 2		Model 3	
Decisions	Variables	Coe	SE	Coe	SE	Coe	SE
adopt							
	pofffarm	-1. 0156***	0.3048	-1.0278***	0.3074	-0.9695***	0.3258
	pincomefarm	0.7156**	0.3582	0.7110*	0.3636	0.8021**	0.3752
	conhlth	-0.0351***	0.0119	-0.0348***	0.0131	-0.0269*	0.0138
	hearfrom	0.5943**	0.2639	0.6478**	0.2602	0.9863***	0.2454
	timefirstheard	-0.2634***	0.0644	-0.2708***	0.0635	-0.2091***	0.0672
	training	0.7249***	0.2032	0.6726***	0.1999	0.5596**	0.2117
	neibadopt	1.2982***	0.2208	1.2991***	0.2217	1.2376***	0.2213
	constant	528.265***	129.357	543.1626***	127.4794	419.0457***	134.9931
complete adopt							
	nofarming	0.6183***	0.1931	0.6042***	0.2012	0.6042**	0.2012
	mloffroad	-0.0496*	0.0294	-0.0527*	0.0299	-0.0527*	0.0299
	goodrela	0.8232*	0.4877	0.8784*	0.4998	0.8785*	0.4998
	firstsub	-0.0084	0.0116	-0.0089	0.0123	-0.0089	0.0122
	constant	0.8749**	0.3448	1.1116***	0.3077	1.1116***	0.3077
continued adopt							
	pincomefarm	1.6984***	0.5771	1.6447***	0.5901	1.7820**	0.7198
	mtfmv	0.0001*	0.0001	0.0001*	0.0001	0.0002***	0.0001
	neibadopt	1.3912***	0.3350	1.4191***	0.3431	0.8948**	0.4296
	subsidy						
	_1	0.6415	0.4261	0.6049	0.4365	0.5099	0.5101
	_2	0.9331***	0.3191	0.8948***	0.3261	1.1412***	0.3945
	constant	-2.0909***	0.4975	-2.0450***	0.5126	-1.4515**	0.6331
	/atanhrho_12	0.5538	0.4298	0	-	0	-
	/atanhrho_13	1.3640**	0.5820	1.3110**	0.5264	0	-
	/atanhrho_23	0.5023	0.3230	0	-	0	-
Number of observation		266		266		266	
Censored observations		96		96		-	
Log likelihood		- 197.8527		-198.8316		-201.4316	
LR chi2 (17)/ Waldchi2(17)		187.50		113.27		117.10	
Prob>chi2		0.0000		0.0000		0.0000	

†* P<0.1;**P<0.05; ***P<0.01

Table 6 Average marginal effects on the probability of complete adoption and the probability of adoption and continued adoption in Model 2

	Model 2		
Decisions	Variables	dy/dx	SE
adopt			
	pofffarm	-0. 2307***	0.0656
	pincomefarm	0.1596**	0.0806
	conhlth	-0.0078***	0.0029
	hearfrom	0.1454***	0.0555
	timefirstheard	-0.0608***	0.0131
	training	0.1510***	0.0427
	neibadopt	0.2916***	0.0402
complete adopt			
	nofarming	0.1132***	0.0378
	mloffroad	-0.0099*	0.0054
	goodrela	0.1646*	0.0941
	firstsub	-0.0017	0.0022
continued adopt			
	pincomefarm	0.3501***	0.1131
	mtfmv	0.0000*	0.0000
	neibadopt	0.3021***	0.6166
	subsidy		
	_1	0.1553	0.1066
	_2	0.2173***	0.0773

†* P<0.1;**P<0.05; ***P<0.01

2.3.3 Estimating the Determinants of Complete Adoption

The variable, number of family members working on farm (*nofarming*), is found to be positive and significant in explaining complete adoption. Households with more members working on farms imply a higher level of dependence on agricultural income. Changing the tilling method to improve the fertility of soil is important for them. The variable measuring size of land fragments away from roads (*mloffroad*) has a negative and significant effect on farmers' complete adoption decisions. In HC, it is common for most households to have many fragments of land parcels in different locations. Lands near roads are generally flat and fertile. Lands that are far away from the road are likely to be located on the hilly terrains. Lands in the hills are divided into smaller fragments or have steeper slopes. Further, it is difficult to transport heavy machinery to the hilly terrains. Additionally, it is also not cost-effective to hire a machine to work on just a small piece of land as, in comparison, there are significant economies of scale to be had from machine applications on large and un-fragmented parcels of land. A household with a good relationship with the village committee (*goodrela*) led to a positive and significant impact on their complete adoption decisions. One simple explanation could be that farmers get better information regarding CT benefits from the committee due to the good relationship. Another interpretation of having a good relationship is that the committee provides such households assurance of continued subsidy support. Continued subsidies effectively reduce the uncertainty associated with costs of CT adoption and therefore could be a crucial determinant of adoption.

Finally, farmers, after deciding between partial and complete adoption, also need to make another sequential decision: whether to adopt CT continually after trying it once. Factors affecting continued adoption are explored in the next section.

2.3.4 Estimating the Determinants of Continued Adoption

Factors affecting continued adoption decisions of households are presented in the last part of Table 5. Farmers' decisions over continued adoption are found to be affected by their neighbours' decisions (*neibadopt*). Farmers are more likely to continue with CT adoption if their neighbours do so as well. Farmers share their CT experiences with their neighbours. This improves their knowledge through learning from each other. Additionally, from an economic cost perspective, it is cheaper to hire machines when neighbours share the cost.

Household wealth is an important factor in affecting continued adoption. (*mtfmv*) is a variable indicating value of mobile telephones, televisions, refrigerators and motorbikes possessed by a household. The positive and significant coefficient of this variable suggests that richer families are more likely to continue with CT. Since CT adoption does not reduce costs significantly and its benefits materialise after several years, poorer families are more likely to give it up.

Another significant variable is the percentage of household income derived from farming (*pincomefarm*). It has a positive effect on continued CT adoption. As mentioned above, families living entirely on agricultural income will be attracted by the possible pecuniary benefits of CT. Despite the delayed returns, they are more likely to be patient in expecting rewards. In practice, households with higher percentages of farm income are more likely to use herbicides and pesticides (to preserve their main source of income). Based on the survey, among households with a high percentage of farm income (farm income accounting for more than 50 per cent of total income), 90 per cent of them used herbicides and around 32.87 per cent used pesticides. This contrasts to 78 per cent of herbicide users and 26.31 per cent pesticide users in the total observation. Therefore, crop production under CT has a greater likelihood of seeing increased yields among households that invest in better farm management. Since better farm management is also conducive to enhancing CT benefits, such households are more likely to reap higher CT benefits.

To explore further the effects of CT subsidies on continued adoption, I use a categorical variable, *subsidy*, measuring the continuity of subsidies received by farmers. Unlike a binary variable comprising zeros and ones (yes or no), the categorical variable measures more than two categories (Agresti, 1996; StataCorp, 2013). Based on the survey conducted in this study, adopters could be categorised into three exclusive groups relating to their duration of receiving subsidies. Adopters in the first category received no subsidies during their entire adoption period. In this group, some of them adopted CT on their own. The second category includes adopters receiving subsidies, but not always. In the second category, some may have received a subsidy in the first year, but did not get continued support from the Government. The second category also includes those adopters who did not receive subsidies in the beginning, but qualified for subsidies in the latter years. Lastly, adopters in the third category have received subsidies in each year. Table 7 provides the number of adopters in each subsidy-receiving category. A value of zero means that the adopters did not get any subsidy. One means that the adopters got a subsidy at least once, but not every year during their adoption period; whereas two means the adopters were subsidised in each year.

Table 7 The number of households in the various subsidy categories

	Adoption		
Subsidy	0	1	Total
0	96	38	134
1	0	20	20
2	0	112	112
Total	96	170	266

†Adoption_0 indicates the households who did not adopt CT. Adoption_1indicates the households who adopted CT. Subsidy_0 indicates the households who got no subsidies. Subsidy_1 indicates the households who got subsidies but not every year. Subsidy_2 indicates the households who got subsidies every year.

In Table 5, regression results provide coefficients that correspond to the value of one (*subsidy_1*) and two (*subsidy_2*) of the categorical variable whereas the group of zero was used as the base level (StataCorp, 2013). In Table 5, the coefficient for the value of two (*subsidy_2)* is positive and significant. This means that providing continued subsidies effectively increases the likelihood of continued adoption. The simple explanation for this is that giving monetary support to adopters makes it easier for them to continue waiting until CT benefits start to kick in. Also, the AME for the value of two (*subsidy_2*) is 0.2173 (in Table 6), which means the probability of continued adoption increases by roughly 22 per cent when the households get subsidies every year (in contrast to the base level of no subsidy).

Compared with the continued subsidy (*subsidy_2*), the discontinuous subsidy variable (*subsidy_1*) is not significant. Giving subsidies discontinuously to adopters is not enough to help them overcome the initial years of hesitance. As mentioned before, the benefits from CT adoption, such as increased productivity, only materialise after several years of continued adoption. Providing subsidies sporadically is not conducive to continued adoption for this reason. This is an important finding as it means that the benefits from CT promotion programmes can easily be negated if subsidies are not provided consistently for long periods.

2.4 Discussion and Conclusion

Despite the obvious benefits of soil carbon sequestration through CT practices, several challenges remain in its path to continued adoption for farming communities across the world. In this chapter, I look at the challenges a rural community in China faces in promoting and sustaining adoption of CT. The approach involves a bivariate probit regression analysis using socio-economic and geographical variables to explain the observed differences in adoption across households.

Findings suggest that families that have a higher number of farm labourers or those that are entirely dependent on agricultural income are more likely to adopt conservation farming. They are also more likely to adopt CT on all of their land and to continue adopting it. Another important factor is the role of government intervention efforts in promoting CT adoption. Households that receive CT information earlier and from the local governments are more likely to adopt CT. A household’s socio-economic condition, such as their health or expenditure patterns, could also influence CT adoption. For instance, consumption of medical care has a degree of negative influence on adoption decisions. Medical expenses may add another level of uncertainty to households’ future net income streams.

I also specifically looked at factors that led households to adopt CT on their entire landholdings (instead of adoption only on a part of their land). Adopting CT on entire land holdings is positively influenced by the number of farm labourers within a household. Households that have a good relationship with government officials also tend to opt for complete adoption, perhaps due to better information related to the assurance of continued subsidy support.

Additionally, households owning fragmented land away from roads are less likely to adopt CT on all their landholdings due to the inability of heavy machines to be transported in the hilly terrains. Machine availability has been found to be an important factor in influencing farmers' adoption decision. Some farmers adopt CT only on parts of their lands because machines cannot access lands with steeper slopes. This is also the reason why CT has not been able to cover the southern region of China, which is hillier than the northern part. Besides, it is also not cost-effective to hire a machine for use on a small fragment of land if the nearby fields are not under CT adoption. Further, these geographical limits might also explain why despite receiving the first year subsidy, farmers do not progress to complete adoption in the subsequent years.

Finally, I explored the reasons that led to continued adoption of CT for those who had experimented with it for the first time. Household wealth is influential in determining the continued adoption of CT. Poorer families are more likely to give up easily due to the long wait before crop yield related benefits from CT adoption begin to materialise. While education, training and demonstrations by governments are found to be effective towards encouraging farmers to adopt CT, their effects are not obvious on promoting farmers to continue using CT. On the contrary, government monetary incentive schemes are a powerful mechanism towards encouraging farmers to continue adopting CT. Giving a subsidy to adopters every year is important for building their confidence in the CT option and helping them overcome the initial years of higher costs as well as any behavioural inertia. From a behavioural perspective, a neighbour's adoption behaviour has significant positive effects on the adoption decisions of the farmer and their chances of continued adoption in the future. Therefore, there is a lesson here in terms of policy for CT promotion—the subsidy schemes and other programmes must concentrate on a particular region with the aim to enlist additional adopters within a region and endeavour to find out the reasons behind those who withdraw after initial adoption. Once the neighbourhood effect takes place, there could be a non-linear jump in adoption. From a policy perspective, it would be important to determine the percentage of adopters beyond which a significant neighbourhood effect kicks in.

Based on the findings derived in this chapter, some policy recommendations could be made for further promoting CT adoption. First, small-sized land with steeper slopes will benefit from the introduction of smaller machines for returning straw. Second, the Government should continue investing in educational and demonstration programmes, since the previous programmes have led to noticeable benefits for CT promotion. Third, since subsidy schemes were found to be very effective in encouraging farmers to adopt CT, they must not be discontinued. Although the CT promotion project has been going on for eight years in the HC, it is not advisable to stop or reduce this scheme in the future. An assured long-term subsidy scheme will effectively reduce the uncertainty over CT adoption outcomes for farmers.

Chapter 3 A Survival Analysis of Conservation Tillage Adoption in Rural China

Abstract

Promoting CT has seen varying levels of success in different parts of the world. China is no exception. Despite the introduction of programmes aimed at promoting CT in China since the early 2000s, there remain several obstacles to its significant adoption. Data used in this study are gathered from a household survey in HC, in north western China in 2013. In this chapter, I analyse the social-economic factors that have influenced the rate of CT adoption using survival analysis. Using a discrete time proportional hazards ratio model, the timing of CT adoption in HC is estimated. Results indicate that families who have higher percentages of non-farm workers tended to adopt CT late. Households with a higher farm income and those who had attended the training programmes adopt CT earlier. Those who had already adopted CT assist with hastening the adoption process of their neighbours. Findings also suggest that, even if the subsidies programme could not cover all villages due to the tight budget faced by the Government, the Government should continue investing in the educational and demonstration programmes. In addition, the previous programs have led to noticeable benefits towards CT promotion, especially in the villages without subsidies.

3.1 Introduction

The practice of CT involves adopting a bundle of practice methods, including covering the field with crop residues, minimising soil disturbances and optimising farm management. Apart from preventing soil erosion from wind and water, the CT method offers the added benefits of sequestering carbon.

CT's benefits have been well reported in literature. Soil covered by crop residues preserves soil loss from wind and water and also offers an added advantage of increasing soil moisture (Rahm and Huffman, 1984; Knowler and Bradshaw, 2007; He et al., 2010). CT practice improves the soil structure and stability, and this in turn enhances its capacity for water retention. Therefore, CT can also help with enhancing the drought resilience of farmers (Holland, 2004). The return of residues can also reduce GHG emissions from soil (West and Marland, 2002). Although, only 30 per cent of the carbon in the crop residues is absorbed by soil in the first year, the return of crop residues still reduces GHG emissions in contrast to burning them (Hu et al., 2009). The soil, when using CT, contains more carbon than under TT, especially after using the CT method consistently for prolonged periods (Holland, 2004). Additionally, no-till or reduced-till methods release fewer GHG emissions when compared to TT by decreasing the fossil fuel consumption due to more efficient use of farm machinery (West and Marland, 2002; Hu et al., 2009). Further, additional economic benefits, such as saving labour and machine hours, are provided by cutting steps associated with tilling and burning straws (Rahm and Huffman, 1984).

There exists a large body of existing literature on CT and organic farming technology adoption (Rahm and Huffman, 1984; Anim, 1999; Burton et al., 1999; Burton et al., 2003; D'Emden et al., 2006; D'Emden et al., 2008). Knowler and Bradshaw (2007) have reviewed 31 technology analyses from 23 conservation agriculture adoption studies and summarised the main social-economics factors influencing the adoption of CT. In terms of methods used in these studies, the Ordinary Least Squares (OLS), logit and probit models were applied (Knowler and Bradshaw, 2007).

In recent years, a dynamic econometric framework—survival analysis—which has been widely used in the biomedical research, has also been applied to study agricultural technology adoption and diffusion processes (de Souza Filho et al., 1999). Rather than estimating the probability of adoption (through the use of logit and probit models), survival analysis is aimed at analysing factors affecting the timing of adoption (Burton et al., 2003; Cleves, 2010). This method offers a distinct advantage over logit and probit methods, as it allows better insight into how socio-economic and other factors could change the rate of technology adoption (Abdulai and Huffman, 2005).

Several studies have used survival analysis for studying agricultural technology adoption. Factors affecting the diffusion of agricultural technologies were estimated using the survival analysis model, including farm characteristics, social capital, geography factors and economic factors (Burton et al., 2003; Dadi et al., 2004; Abdulai and Huffman, 2005; Matuschke and Qaim, 2008; Alcon et al., 2011; Genius et al., 2014). To provide an effective dissemination strategy, a study in Western Kenya by Murage et al. (2011) analysed the effects of different and combined dissemination pathways on the speed of technology adoption using survival analysis. Attending the demonstration in the field and the training provided by farmer teachers were established as effective pathways by Murage et al. (2011). Except the time-invariant variables, the time-varying variables, such as changes in the input and output prices, were estimated in the survival analysis model by (de Souza Filho et al., 1999). Their results suggested that the increase in labour wages reduced the speed of sustainable technology adoption due to labour intensive nature of the target technology. The changes of farming input prices were also estimated using the survival analysis in a study of CT adoption in Australia

(D'Emden et al., 2006). D'Emden et al. (2006) found that a decrease in herbicide prices leads to an increase in CT adoption, since weed control is a key process of CT practice.

China's CT promotion programme began in 2002. Initially, in 2002, 38 counties in northern China were selected for promoting CT adoption as a part of the pilot project (Gao, 2011). In the following year, 20 more counties were added to the CT project (Gao, 2011). In 2010, the total area under CT adoption was around five million hectares (Zhao et al., 2012). This still however, only accounted for about four per cent of the total farmland area in China. Although China offers great potential for CT practice, significant challenges lie ahead in terms of mass scale adoption of CT due to variations in regional climate, topography, soil, economic and social issues (Gao, 2011). Besides, it is difficult to change farmers' CT methods, which have been practiced for thousands years, overnight.

The CT adoption challenges and experiences so far in China stand in sharp contrast to those in other countries. In China, the average farm landholding for a farmer is 0.08 ha (Derpsch et al., 2010). In contrast, the mean farm size is 3,263 acres (1,320.489 ha) in Washington State in the US (Wang et al., 2000) and 2.27 thousand ha per farm in Australia (D'Emden et al., 2006). Large farm sizes in Australia and the US not only allow for a higher area of CT adoption, but also provide economies of scale through facilitating use of large machinery. Whereas, in China, small holdings create a higher level of uncertainty with respect to large scale adoption, as household characteristics and neighbourhood characteristics can influence how rapidly and to what extent CT is adopted.

Although survival analysis has been used in the past, few have applied it to the case of China to explore the role of socio-economic conditions in hindering or promoting the growth of CT adoption. The aim of this chapter is to investigate the factors promoting the process of CT adoption in rural China. These factors include household characteristics and intervention efforts made by the local government. In this chapter, prior to conducting the survival analysis model, the Kaplan-Meier approach estimates the ratio of survivors (farmers who have not adopted CT) to the population of the survey sample in each year. Since it provides graphic summaries of the diffusion of CT without estimating the effects from covariates, the Kaplan-Meier method is considered a non-parametric estimate in survival analysis. Following that, a parametric survival analysis model (referred to as survival analysis model in the chapter) is performed to analyse the role of social-economic factors and the Government’s efforts in influencing CT adoptions success rate. To explore further the influences of the training programme administered by the Government and the subsidy schemes provided, villages are divided into two groups based on the level of support received from the Government. Two separate survival analyses are conducted using data in these two categories of villages. Finally, factor analysis is used to manage the problems of some of the key variables being correlated in the analysis.

The next section provides an account of the current CT adoption situation in HC in northwest of China and details of the design of the survey conducted as a part of this study. Following that, the theory of survival analysis model and data organisation for fitting the model is presented in Section 3.3. In Section 3.4, results based on the non-parametric and parametric survival analysis and factor analysis are explained. Finally, some main findings are highlighted and policy implications discussed.

3.2 Survey Design and Conservation Tillage Adoption in Huangling County

The research area is HC, which is located in the north western region of China (35°20’39”~35°49’24”S, 108°34’41”~109°27’17”E). Soils in this area face the risk of wind erosion due to their porous nature, dry climate, scarce rainfall and constant winds. Rainfall is concentrated mostly in the summer, which results in heavy soil losses during this period. Corn is widely grown in this area due to the local climate and topography. It is seeded in spring and harvested in autumn. Winter in HC, which is the fallow period, is dry and cold.

This study is based on a household survey of 266 farmers, comprising 170 CT adopters and 96 non-adopters. The average farm landholding for a household in the survey is 0.547 ha. The survey was conducted in April 2013, covering 15 villages in HC. In this study, adoption is defined as implementing the most critical steps of CT technology, including returning crop residues and non-till planting. Households are considered adopters once they have adopted these technologies on any fragment of their land; otherwise, they belong to the group of non-adopters. The questionnaire was designed to gather information relating to household characteristics, details over CT adoption practices and government incentive schemes. Description and summary statistics of variables based on the survey are presented in Table 8. Information relating to households includes five capitals: human capital, natural capital, physical capital, financial capital and social capital. Explanatory variables used in the models are categorised below:

A. Human capital variables

Human capital includes information about family members' working status. The percentage of family members working off-farm (*pofffarm*) indicates labour availability for farming, which is expected to have negative effect on CT adoption.

B. Natural capital variables

Variables such as the farmland size, planting corn near the road (*mlonroad*), the size of apple orchard (*appleland*) and the land size for wheat and cole (*whcoland*) are included under the category of natural capital. From the perspective of machine availability, farmers owning land near road are more likely to adopt CT. The alternative uses of corn land, such as planting apple trees, wheat and cole, might have negative effects on CT adoption.

C. Financial capital variables

Financial statements relating to income are important variables that need to be tested in the models. Percentage of farming income (*pincomefarm*) is expected to have positive coefficient in models. The variables such as income from the apple tree orchards (*aincome*) and the total income in the households (*totincome*) are also included. In terms of consumption, medical expenses can create an adverse influence on livelihood and farming status. So the coefficient of health consumption (*conhlth*) is expected to be negative.

D. Physical capital variables

Category of physical capital contains variables such as household assets. Having cows and cattle (*nocowcattle*) is predicted to have a negative impact on adoption since crop residues are used as fodder for livestock. In addition, ownership of appliances such as tractors (*tractors*) indicates wealth in a family. I predict that richer families are more likely to adopt the new technology than others are, so this variable might have a positive coefficient.

E. Social capital variables

Social capital variables, such as relationship with the village committee (*goodrela*) and with other farmers (*peopbor*) are also tested in the models. Good social relationship might have positive effects on CT adoption.

F. Variables on CT

In the questionnaire, participants have been asked their self-assessment on the risk related to CT adoption (*risk*) and where they received information about CT (*hearfrom*). Other variables associated with CT adoption are also estimated, such as attending the CT training (*training*) held by the Government and neighbours' adoption (*neibadopt*). They are predicted to have significant effect on farmers' adoption.

For measuring land size, the unit 'mu' is widely used in rural China. One hectare equals to 15 mu and one acre equals to 6.0703 mu. In this study, I use mu as the measurement unit for land area. For measuring the costs, I use the Chinese currency unit (CNY) in this study. One CNY equals around 0.16 US$[3].

[3] The exchange rate on 4 December 2013

Table 8 Description and summary statistics of the variables used in the bivariate probit regression

Variables	Description	Mean	S.D.
pofffarm	Percentage of family members working on off-farm (%)	0.5823	0.3229
whcoland	The farmland size for planting wheat and cole in the households (in mu)	0.1847	1.0164
mlonroad	The farmland size for planting corn near the road in the households(in mu)	2.6244	2.8437
pincomefarm	Percentage of farm income on the total income (%)	0.3709	0.2950
conhlth	Health consumption in a year (in CNY)	3817.669	6603.854
nocowcattle	Number of cow and cattle (N)	0.0714	0.3456
appleland	Size of apple orchard (N)	0.9511	2.6206
tractors	Do the households have tractor (0-no:1-yes)	0.2267	
aincome	Income from the apple and tree orchard (N)	4781.406	15071.74
totincome	The total income in the households (N)	33875.91	31158.45
goodrela	Relationship with the village committee (0-other:1-good)	0.1391	
peopbor	Number of people would like to borrow money in the household (N)	7.5376	6.3132
risk	Risk assessment for CT by farmers(0-low risk:1-high risk)	0.1241	
training	Attending training (0-no:1-yes)	0.5376	
hearfrom	Firstly heard about CT from governments (0-no:1-yes)	0.7632	
neibadopt	Neighbours adopt CT (0-no: 1-yes)	0.7331	
Dependent variables			
adoption	Adoption of CT (0-no:1-yes)		

3.2.1 Conservation Tillage Adoption in Huangling County

The first project relating to CT started in China in 2002. In 2002, 38 counties in the northern region of China were chosen as a part of this project. In the following year, 20 more pilot counties were added to the initial phase of CT project (Gao, 2011). Given the potential for CT adoption in HC, it was selected for the pilot project introduced by the Government of China in 2006. By 2012, CT had already been adopted on around 5,147 ha of land area in HC. In HC, there were 513 machines used for CT, including 338 no-till planters and 175 straws pulverisers (information provided by the bureau).

Although HC joined the national pilot CT project in 2006, in 2005 a few households had adopted CT on their own, based on information obtained through electronic media such as television programmes and from information acquired through farmers in other counties (Figure 1). In 2006 and 2007, CT was officially promoted in HC. In these two years, the number of farmers adopting CT in HC was very low due to the early stages of programme's introduction. From 2008 onwards, however, the number of new adopters and the total land area under CT started to increase significantly (see Figure 1). The cumulative total of adopters and land area under CT has increased significantly since 2008 (refer to Figure 2). In addition, as shown in Figure 1, the numbers of new adopters in 2011 and 2012 are relatively less than those in the period from 2008 to 2010. This is because more than 50 per cent of households sampled in the survey had already adopted CT by 2010. The trend of cumulative adopters and total land area in Figure 2 are in accordance with the s-shaped technology diffusion curve found in the literature (Abdulai and Huffman, 2005). According to the s-shaped pattern of technology adoption, the number of new adopters increases slowly in the first few years, and then there is a significant increase in adoption before the adoption rate finally starts to plateau towards the end.

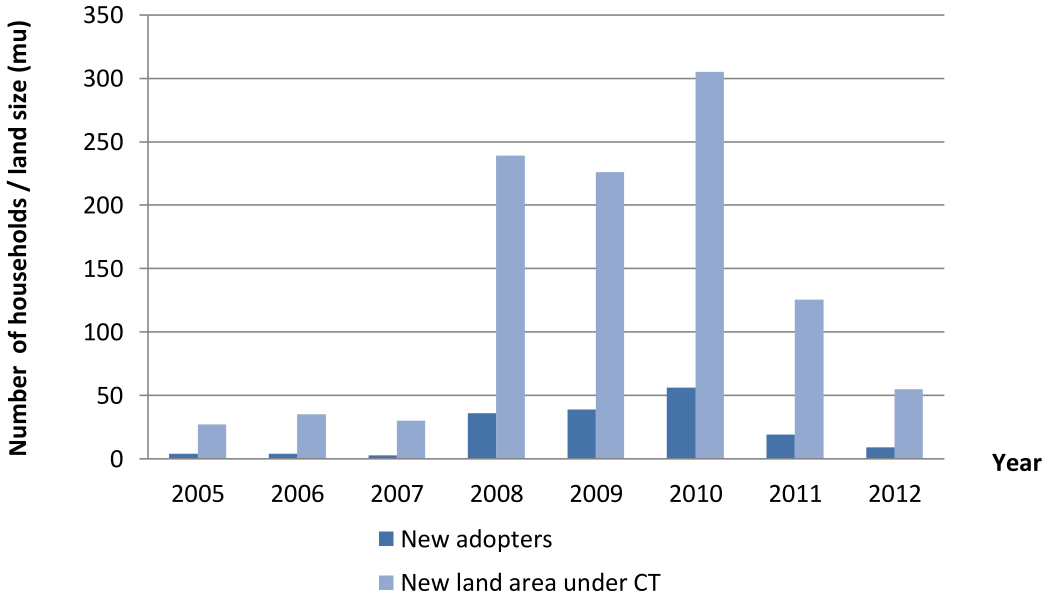


Figure 1 Number of new adopters and land size under conservation tillage in the survey from 2005 to 2012

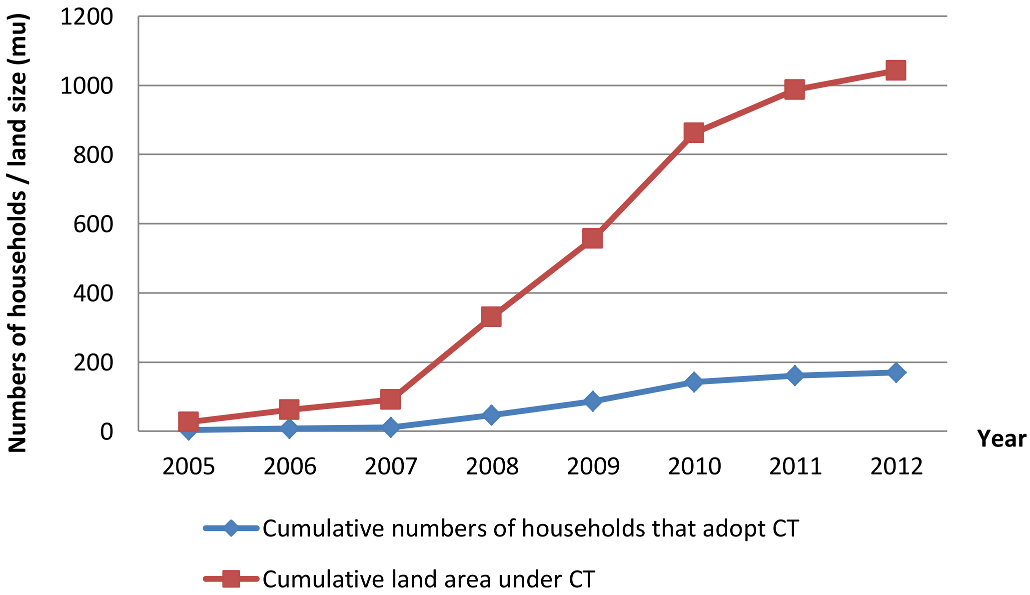


Figure 2 Cumulative numbers of households and land size under conservation tillage in the survey from 2005 to 2012

3.2.2 Estimating the Costs of Conservation Tillage Adoption in Huangling County

CT technology has been promoted on the corn acres in this county. The process of CT application has been designed to fit the local climate and soil conditions. Table 9 describes the process of CT application on corn in HC and contrasts it with the steps associated with TT.

Table 9 Farming processes of conservation tillage and traditional tillage

Steps	CT	TT
1	Harvesting and returning residues	Harvesting and burning residues
2	Subsoiling once in every three years	Deep tilling
3	Rotary tilling or harrowing	Rotary tilling
4	Seeding	Seeding
5	Herb control and field management	Herb control and field management

Source: (Gao, 2011) and information gathered from the survey

During the harvesting process, the manual works associated with TT, such as cutting the corn straws down, assembling them together and burning them, are not required in CT. After farmers pick up the corn, machines pulverise the straw and leave it behind to cover the field. To minimise the disturbance to soil, the process of inverting soil in TT is replaced with breaking soil compactions in CT, which is required to be done once every three years. The step of rotary tilling could be kept under CT in HC, which is used to mix pulverised residues with the top level soil to preserve residues from blowing away in the windy winter. According to information provided by officers in the bureau, the no-till planter is widely used in HC as it can be used both on tilled land and no-till land. Using herbicides and pesticides is highly recommended under CT, since weeds and pests may increase due to covering crop residues on the field during the fallow season and due to the reduced disturbance of the soil. Despite the details, the most critical step of CT is returning the crop residues to cover the field. The minimisation of soil disturbance is also considered very important.

Changing from TT to CT through the steps described above leads to changes in farming costs. Table 10 provides and compares estimates of farming costs in TT and CT based on information gathered through the survey and from the local government. According to the description of farming process associated with CT, subsoiling is only required once every three years, therefore, machine costs for CT vary every year. In this study, I calculate the average farming costs for three years of CT and TT.

In Table 10, costs for each item are calculated based on the survey and information provided by the bureau. The subsidy scheme is also considered in the costs calculation. The primary figures in Table 10 were provided by the bureau. However, in reality, the costs are various due to the different providers of machines and different suppliers of materials. Since subsidies are provided by the bureau or the village committees, given their different budget situations, subsidies received by farmers vary from 10 to 35 CNY/mu. To provide a numerical summary for costs of CT and TT in HC, the primary figures were adjusted referring to the rounded average figures for each cost generated from the survey.

In HC, some of the higher costs of CT can be mitigated through subsidies paid by the Government. Parts of, or the entire fee, for hiring machines for returning residues are covered by the bureau or the village committee. Specifically, the bureau or the village committees helps farmers with contracting the machines for residues returning during the harvesting season. The original price for using the machine is 30–35 CNY/mu. The bureau or the village committees pay 10–35 CNY/mu to the machine providers directly on behalf of the farmers. The farmers only need to pay the remaining fee of 0–25 CNY/mu. Effectively, this implies a subsidy to the farmer. In HC, the average subsidy stands out at 20 CNY per mu. Considering the subsidy, the average cost of CT per year is CNY 340 per mu, while the cost of TT per year is CNY 350 per mu. Thus, CT adoption in HC does not lead to substantial cost savings compared to TT. By lowering the difference between the two methods, it is expected that farmers would go for the more socially preferable option. However, not every household in HC can get the subsidy due to government budgetary restraints. Without subsidies, the annual average costs for CT adoption becomes 360 CNY per mu, which is 10 CNY higher than the TT costs.

Table 10 Comparison of costs between traditional tillage and conservation tillage technologies (CNY/mu)

		TT			CT		
		1st year	2nd year	3rd year	1st year	2nd year	3rd year
Machine costs	Planting	30	30	30	30	30	30
	Residues returning	-	-	-	30	30	30
	Deep tilling	30	30	30	-	-	-
	Subsoiling	-	-	-	30	-	-
	Rotary tilling	30	30	30	30	30	30
Other costs	Seed	50	50	50	50	50	50
	Fertiliser	180	180	180	180	180	180
	Herbicide & pesticide	30	30	30	30	30	30
	Labour	-	-	-	-	-	-
Subsidy		-	-	-	-20	-20	-20
Total		350	350	350	360	330	330
Average cost in each year		350	350	350	340	340	340
Costs saving by applying CT					-10	20	20

Note: Figures in the table are summarised from the information provided by the Huangling Bureau of Agriculture Machinery and data generated from the survey conducted in the study.

3.3 Survival Analysis Model

3.3.1 Continuous Time Survival Analysis Model

The survival analysis has been widely applied in biomedical research. Lately, it has also been applied to study technology adoption and diffusion process. Rather than estimating the probability of adoption (through the use of logit and probit models), the survival analysis model aimed to analyse the factors affecting time of adoption (Burton et al., 2003; Cleves, 2010). The waiting time duration (also called, spell lengths, spell duration or survival time) is defined as the time to the occurrence of event (D'Emden et al., 2006; Cleves, 2010). The waiting time is a continuous random variable, noted as T . The cumulative distribution function (cdf) of T indicates the cumulative probability of the occurrence of event:

$$F(t) = P(T \le t) \tag{2}$$

In biomedical research, the survival analysis has been used for analysing the survival time for patients after undergoing treatment. The occurrence of the event indicates the failure of the treatment. So, the cdf is also called the failure function $(F(t))$. Oppositely, the survival function $(S(t))$ presents the probability of individuals still surviving after time T :

$$S(t) = 1 - F(t) = P(T > t) \tag{3}$$

$f(t)$ is the probability density function (pdf) of T . The probability of an event occurring during a very short interval $(t, t+\Delta t]$ is described as:

$$f(t)\Delta t = P(t < T \le t + \Delta t) \tag{4}$$

In other words, $f(t)$ is the instantaneous probability of failure, calculated by dividing the width of the interval (Cleves, 2010):

$$f(t) = \frac{P(t < T \le t + \Delta t)}{\Delta t} \tag{5}$$

Unlike $f(t)$, the hazard rate ($\lambda(t)$) is a conditional failure probability, which presents the probability of an event occurring in a short interval $(t, t+\Delta t]$, 'conditional on survival up to time t (Jenkins, 2005; Cleves, 2010).

$$\lambda(t)\Delta t = P(t < T \le t + \Delta t | T > t) \tag{6}$$

Based on the rule of conditional probability: $P(A|B)=\frac{P(A\cap B)}{P(B)}$, the hazard function is written as:

$$\lambda(t)=\frac{P(t<T\leq t+\Delta t)}{\Delta t\,P(T>t)}=\frac{f(t)}{S(t)} \tag{7}$$

3.3.2 Discrete Time Survival Analysis Model

In a study analysing the adoption of organic horticultural technology using survival analysis, Burton et al. (2003) suggest that the discrete time survival analysis model is more appropriate for studying agricultural adoption since the times to adoption are normally reported as integer years. In HC, the corn is planted and harvested once a year. The time to adoption was recorded as integers as well. Therefore, the discrete time survival analysis model was used in this study.

The expression of pdf with discrete time data is simpler than under the continuous time data (see equation(4)). It is unnecessary to consider the probability of an event occurring in a time interval. The probability of an event occurring at any time point of t can be calculated:

$$f(t)=P(T=t) \tag{8}$$

Where T is a discrete time variable, t is a set of time point with an equal length ($t\in\{1,2,3,\ldots\}$).

The cdf for T indicates the cumulative probability of the occurrence of event before time t:

$$F(t)=P(T\leq t)=\sum_{0}^{t}f(t) \tag{9}$$

The survival function presents the cumulative probability of an event that has not happened at t:

$$S(t) = 1 - F(t) = P(T \geq t) = \sum_{t}^{\infty} f(t) \tag{10}$$

The hazard function is written as below:

$$\lambda(t) = P(T = t | T \geq t) \tag{11}$$

$$\lambda(t) = \frac{f(t)}{S(t-1)} \tag{12}$$

In the hazard function under the continuous time variable, the condition of the hazard function is $T > t$. Whereas the condition is $T \geq t$ in the discrete hazard function. If the conditional time is greater than t, the event will not occur at time t.

The probability of survival until time t can be written as:

$$S(t) = \prod_{1}^{t} (1 - \lambda(t)) \tag{13}$$

Based on the information generated in the survey conducted in this study, 96 households still had not adopted CT until the date of survey (April 2013) (they may or may not adopt CT in the future). These data are right-censoring. In this study, the likelihood function contains two parts, including censored and non-censored data (Singer and Willett, 1993):

$$L = \prod_{i=1}^{n} \left[\lambda(t_i) \prod_{i=1}^{t-1} (1 - \lambda(t_i)) \right]^{d_i} \left[\prod_{i=1}^{t} (1 - \lambda(t)) \right]^{d_i} \tag{14}$$

Where d_i is indicator for censoring ($d_i = 0$ means the *ith* spell is censored).

3.3.3 Data Organisation for Discrete Time Survival Analysis Model

To fit the discrete time survival analysis model, the 'individual-oriented' data needed to be re-organised to an 'individual-period' pattern (Singer and Willett, 1993; Jenkins, 2005). To do this, there exist three steps. The first step was splitting data. The single row data of individuals (households) was split into multiple rows depending on their survival times (Matuschke and Qaim, 2008; Jenkins, 2005). For example, a household who had waited five years to adopt CT has five rows of the same data after conducting the first step.

The second step was to create a new variable, t_i, which was used to distinguish the same data in rows. The subscript i represents the ith individual (Singer and Willett, 1993). For instance, for a household with five rows of the same data (five years of survival time), the variable of t_i equals one in the first row, and equals two, three, four, five in the following rows. The multiple rows of data for a household can be distinguished by adding the time period variable of t_i.

The last step was creating a new dependent variable, y_{it}.

$$y_{it} = 1, if\ individual\ i\ adopt\ CT\ in\ year\ t,$$

$$y_{it} = 0, if\ individual\ i\ does\ not\ adopt\ CT\ in\ year\ t.$$

For instance, an individual is right-censored if it has the variable of y_{it} equals zero in all its data rows. This indicates that the household had not adopted CT before the date of the survey in this study.

For estimating discrete time data with covariates, there exist few options of models: logit model, probit model and cloglog model. I used the logit model in this study as the difference between these models is trivial (Beck et al., 1998). The logit model is expressed as:

$$\lambda(t,\mathrm{X}) = P(T=t|T \geq t, X) = \frac{1}{1+e^{-(\alpha+\beta' X)}} \tag{15}$$

Where $\lambda(t, X)$ is the hazard rate that presents the probability of an event occurring at time t conditional on survival up to t and other covariates for individuals (X). Here α_j and β' are the constant and parameters for the explanatory variables.

In the continuous time survival analysis model, the shape of the time dependence differed for different baseline hazard rates. For instance, the exponential model has a constant baseline hazard rate, while the weibull model has a monotonic decrease or increase baseline hazard rate. However, the default time dependence in the logit model is constant, $\lambda_0(t) = e^{\alpha}$, which is similar to the exponential survival analysis model. There exist a few options for picking the baseline hazard rate function in the discrete time survival analysis model: $log(t)$ baseline, cubic polynomial, piece-wise constant baseline and fully non-parametric baseline (Jenkins 2005). In this study, I used $\gamma log(t)$ baseline hazard function. The logit model with the time dependence is written as:

$$\lambda(t,X) = \frac{1}{1+e^{-(\alpha+\beta' X+\gamma log(t))}} \tag{16}$$

Where γ is similar to the weibull shape parameter (Jenkins, 2005). If $\gamma > 0$, the shape of the baseline hazard rate is monotonic increase; $\gamma < 0$, the baseline hazard rate decreases (Jenkins, 2005).

3.4 Results and Discussion

The analysis includes a discussion about the starting time of CT adoption in HC. The Kaplan-Meier method provides graphic summaries of the diffusion of CT without estimating the effects from covariates based on two different measurements of the starting time. Following that, the discrete time survival analysis model is applied to analyse the effects of social-economic factors on the speed of CT adoption. To understand further the Government's effects on CT adoption, villages in HC are distinguished into treated and untreated villages, based on the level of support received from the Government. Two separate survival analyses are conducted using data in these two categories of villages. Results of the analysis will be discussed in the following sections.

3.4.1 Discussion over the Same Starting Times and the Individual-Specific Starting Times

Before conducting survival analysis, the length of survival time needs to be clearly defined (Machin et al., 2006). In other words, it is critical to clarify the start point and the endpoint. In this study, for households who adopt CT during the research period (2002–2012), their endpoints of survival time are their years of CT adoption. For those who do not adopt CT by the end of data collection period (right-censoring data), their endpoints of survival time are estimated as the end of research period (2012).

However, for defining the start time, various methods exist in the literature. Some studies set the start period of survival time by using the earliest time when technology adoption took place (de Souza Filho et al., 1999; Fuglie and Kascak, 2001; Matuschke and Qaim, 2008) or the first recorded adoption in that research region (Burton et al., 2003; Abdulai and Huffman, 2005). The starting time can also be set based on the technology promotion programme. Key and Roberts (2006) use the first year that the technology programme began operating as the 'entrance date'. Dadi et al. (2004) and Genius et al. (2014) measure the length of waiting time starting at the first year of technology introduction to the research region. Besides, selecting of starting time can also depend on specific situations. In a study of CT adoption in Australia (D'Emden et al., 2006), the beginning of the time period is 1983 rather than the earliest time of adoption (1964) because very few farmers adopted this technology before 1983.

However, in biomedical studies, the starting time needs to be considered at the individual levels. Take, for example, the case of heart transplants, where survival time is measured from the time a donor heart becomes available for a patient to his or her rejection of the donor heart (Machin et al., 2006). In reality, heart donations are not available for all observed patients at the same time. Therefore, the starting time for patients must be recorded individually. Taking the biomedical example as a reference, agricultural technology adoption researches under survival analysis could also measure the survival time at individual levels. An example is provided in the study of weeds control technology adoption in Kenya. In the study, Murage et al. (2011) provide a figure of distribution of farmers' dates of first hearing of the technology (see Figure 2 in Murage et al. (2011)). The survival time of farmers' technology adoption is calculated from farmers' different starting dates of first hearing of it until the date of adoption.

In this study, two ways of calculating survival times are considered: the same starting time for all observations and an individual-specific starting time for individuals. Although HC started the CT programme in 2006, the earliest adoption of CT in HC happened in 2005, according to the information gathered from the survey. I select 2005 as the initial year of the period for the 'same starting time' option.

A question asking respondents of the year first they had heard of CT was also included in the questionnaire. Although, experiments relating to CT promotion were implemented since the 1960s, China's CT promotion programme officially began in 2002. Counties, such as Fu, Yanchuan, Ansai and others near HC, began to implement CT in 2002.[4] Although the CT

[4] Information provided by the bureau

project of HC began in 2006, a few farmers had already heard of it in television programmes or from farmers in other counties. Figure 3 depicts the distribution of years when farmers first heard of CT; some farmers had heard about it even before 2006. From 2008 onwards, the number of farmers who had heard of CT started to increase. The survival time of CT adoption can be calculated based on the different times of farmers' first becoming aware of this technology.

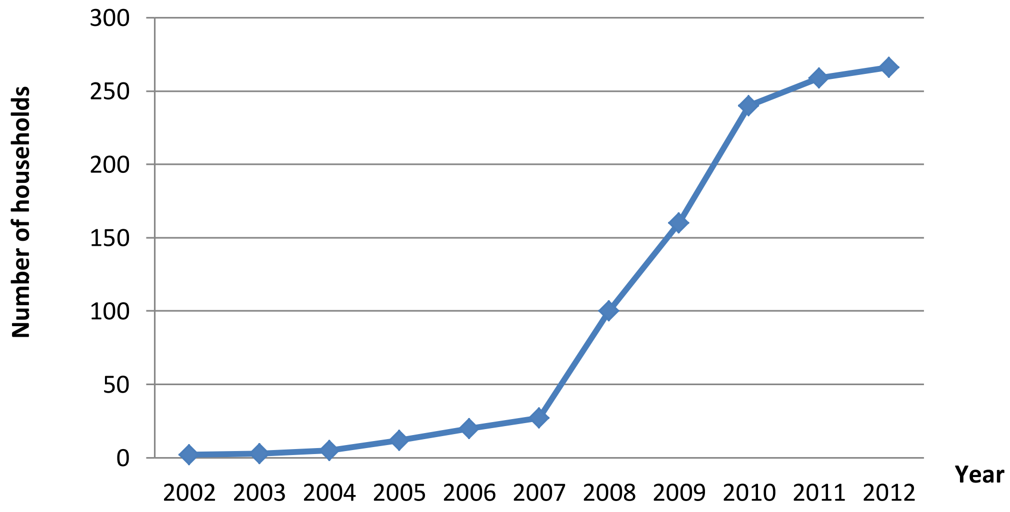


Figure 3 Distribution of farmers' year of first hearing of conservation tillage

Figure 4 and Figure 5 present survival functions with different measurements of survival time. Specifically, Figure 4 depicts survival function calculated using the same starting year, whereas Figure 5 illustrates survival function by considering individual-specific starting times. In Figure 4, survival rate is very high (close to one) in the first three years. This is in accordance with cumulative number of adopters in Figure 2 which shows only few farmers adopting CT in the first three years. With the number of adopters starting to increase from 2008 (Figure 2) the survival rate decreased after period three in Figure 4.

In contrast to Figure 4, which illustrates the CT diffusion process at a regional level, the survival rate is measured by considering individual-specific starting times in Figure 5. The survival rate fell significantly in the first period and decreased slightly in the following analysis periods. This trend of CT diffusion reflects farmers' reactions after they are first exposed to the CT information and the associated promotion programme conducted by the Government. Around 44 per cent of adopters decided to adopt CT in the next year after first hearing of it. This means CT technology can be accepted quickly by nearly half of farmers based on the survey information. However, if households do not adopt CT in the next year of first hearing of the technology, they might hold a pessimistic opinion of CT and doubt its benefits. For those farmers, it may take longer to understand this technology, learn from others and finally accept it.

Figure 4 and Figure 5 indicate CT diffusion trends at the regional level and individual levels respectively. They both provide important information with which to understand CT diffusion history and the current situation in HC. In the following analysis, I use the different starting years to measure the survival time, as more attention will be placed on individuals' adoption decisions in parametric models.

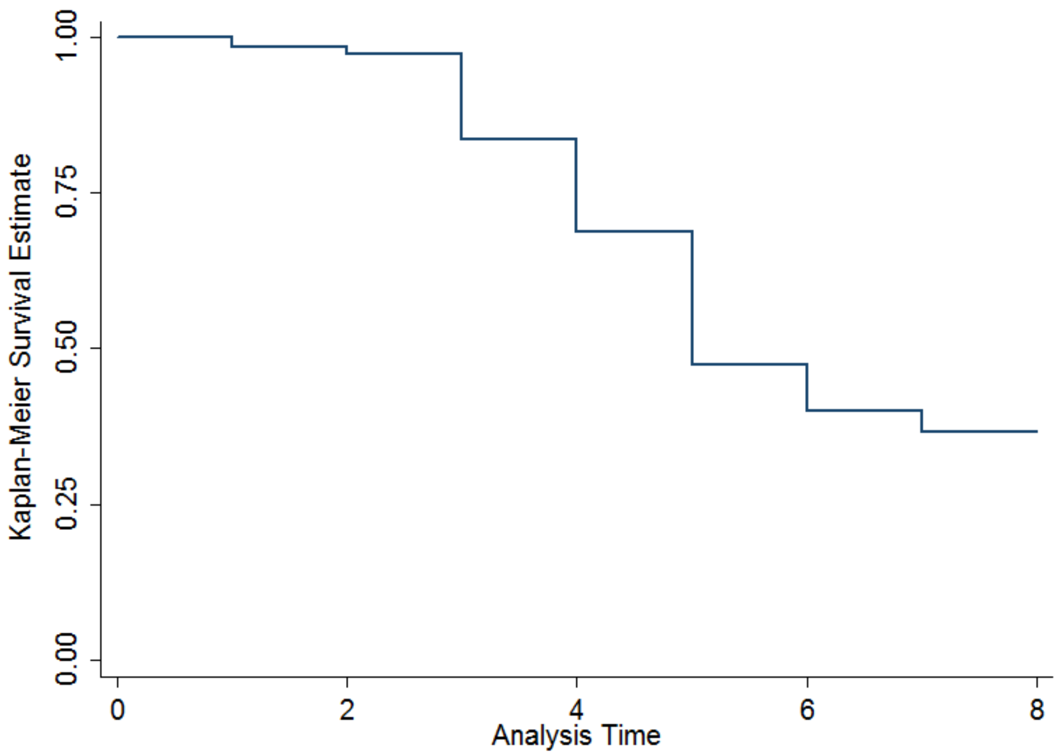


Figure 4 Cumulative survival rate for conservation tillage adoption with the same programme starting time

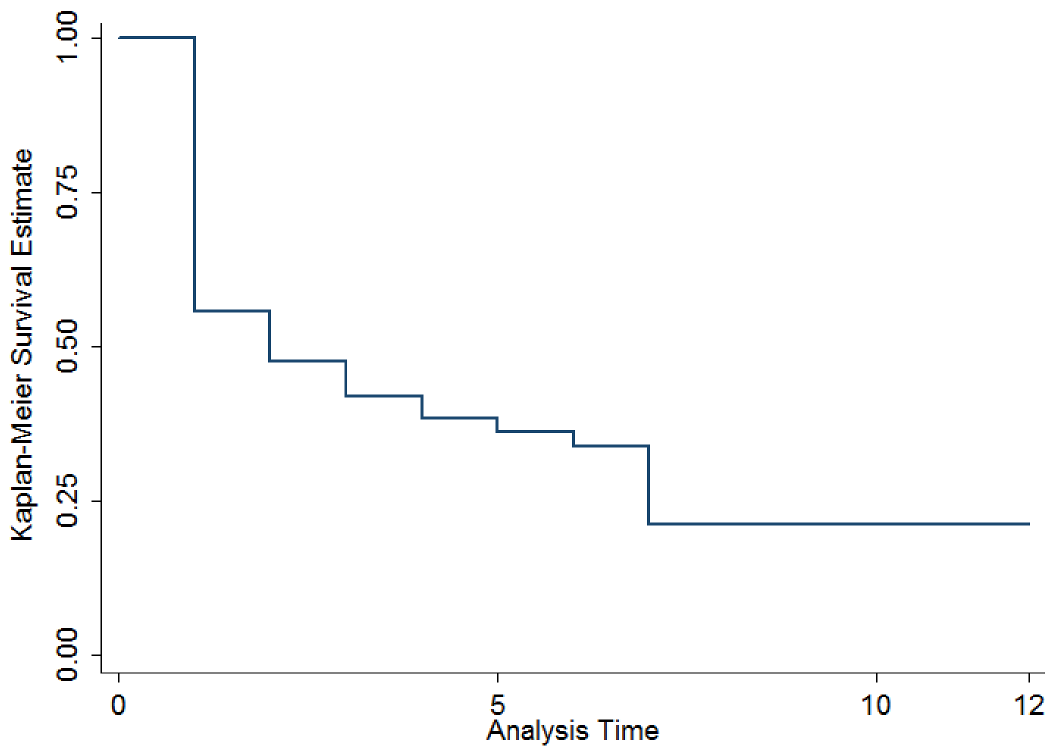


Figure 5 Cumulative survival rate for conservation tillage adoption with individual-specific starting time

3.4.2 Survival Analysis with Discrete Time Model

Regression results of discrete time survival analysis are presented in Table 11. In the discrete time model,

$$logit\left[\lambda\left(t, X\right)\right] = \gamma log\left(t\right) + \beta' X \tag{17}$$

where $\gamma log\left(t\right)$ is the baseline hazard function, which indicates the shape of hazard rate by ignoring the effects from covariates (Jenkins, 2005). In Table 11, the coefficient (γ) of $log\left(t\right)$, is negative, which means that the hazard rate monotonically decreases. The marginal effect value of γ in the fourth and last columns indicates the change in the hazard following a unit change in the attribute, evaluated at the mean of attributes. Other coefficients in Table 11 indicate the effects of covariates on the baseline hazard rate, on a logistic scale. For example, a variable with a positive coefficient has positive effects on the baseline hazard rate (Singer and Willett, 1993). The marginal effects of covariates present the change of baseline hazard rate caused by a unit change of covariates.

Table 11 Regression results of discrete time survival analysis

Variables	Coe	SE	dy/dx
log(t)	-1.2711***	0.1869	-0.1606***
poffplus	-0.9026***	0.3356	-0.1141***
whcoland	0.1028	0.0910	0.0130
mlonroad	0.0233	0.0401	0.0029
pincomefarm	0.8150**	0.3829	0.1030**
conhlth	-0.0000	0.0000	-3.66e-06
nocowcattle	-0.7876*	0.4086	-0.0995*
goodrela	0.2322	0.2987	0.0293
risk	-0.2643	0.3644	-0.0334
training	0.4445*	0.2407	0.0562*
hearfrom	1.0808***	0.3235	0.1366***
neibadopt	1.4548***	0.2975	0.1839***
constant	-2.2991***	0.4313	-
Log likelihood	-287.1628		
Observations	731		
LR chi2(18)	218.59		
Pro>chi2	0.0000		
Pseudo R2	0.2757		
Correct prediction	81.40%		

Note: the asterisk*, **, *** denote significance at the 10%, 5% and 1% level.

The variable representing family members working off-farm has a negative effect on the rate of adoption. Variable of (*poffplus*) is a continuous variable, which presents percentage of family members who work at off-farm jobs. The effect of this variable is negative and significant on the CT adoption process. An explanation could be that households with more family members working off-farm may have a lower degree of dependence on farming. Therefore, they are less interested in applying a new tillage technology. It may also mean that households that rely predominantly on family farm labour are labour constrained when their family members are not available.

The variable measuring farm income also turns out to be an important factor estimated in the model. Notice that correlated coefficient of the percentage of off-farm members (*poffplus*) and the proportion of farm income (*pincomefarm*) are -0.0898. In another words, the proportion of off-farm workers is not positively correlated with proportion of off-farm income, implying that families having a big proportion of members working in the city does not necessarily translate into higher earning potential. Therefore, the two variables are independent of each other and can be tested together in one model. The proportion of farm income (*pincomefarm*) has a positive effect on the CT adoption process. Families with large farm income shares imply a higher reliance on agriculture for livelihood sustenance. Therefore, the possible long-term yield increases caused by prolonged CT adoption become more attractive to them, as agricultural income is important to them. The hazard rate of CT adoption increases by 10 per cent for every unit increase in the farm income proportion.

Next, the effects of livestock ownership are estimated. The CT adoption is postponed if households raise livestock such as cows and sheep. As mentioned earlier, returning crop residues to the field is one of the most critical processes associated with CT practices in China. However, straws are the main fodder for feeding livestock in HC. Thus, there exists a trade-off between livestock ownership and CT adoption. A similar situation was noticed in Australia since raising sheep and planting crops were mostly combined on farms (Derpsch et al., 2010). According to the policy, livestock is forbidden access to the mountainous areas and hills to protect young trees planted there, which has caused large increases in the costs of raising livestock due to lack of pasture. Therefore, the probability of adopting CT earlier increased in the households who abandoned livestock in HC. This also indicates the interaction effects generated by various carbon mitigation policies, such as preserving forestry and encouraging CT.

Intervention efforts by the Government were also considered important factors for testing in the model. Demonstration and education programmes relating to CT held by the bureau (*training*) have positive effects on the speed of CT adoption. That means farmers attending the training programmes tend to adopt CT earlier. The hazard rate of CT adoption will increase five per cent, depending on whether they have attended the training programme.

Another variable indicating the effects of the Chinese Government's promotion efforts is (*hearfrom*), which records when the farmers first heard of CT. It is a binary variable: *hearfrom*=1 means farmers heard of CT from the Government for the first time; *hearfrom*=0 means they heard of CT from other sources, such as through other farmers, television, and so on. Results suggest that famers who heard of CT from the bureau and village committees are more likely to adopt CT earlier, as famers might glean more comprehensive knowledge of CT and CT benefits from government officers. The process of CT adoption is also influenced by the existing mass of adopters. As the results indicate, the rate of CT adoption by farmers is positively affected by neighbours' adoption behaviours. In other words, more households adopting CT generates positive feedback effects.

3.4.3 Considering Separately Conservation Tillage Adoption in the Treated and Untreated Villages

The bureau is mainly responsible for promoting CT in the whole of county. Since HC has 2,295 square kms of land area and a population of 130 thousand, it is impossible for the bureau to promote CT in all nine districts, including 192 villages, at the same time. In the early stages, the programme only covered a few villages, which were selected in each district (referred to as treated villages hereafter). The number of treated villages gradually increased based on the Government's increasing capability to promote CT. In addition, the promotion activities in the treated villages also influenced the nearby villages. Villages that are not treated villages are called untreated villages for the purposes of the analysis. The survey conducted in this study covered nine treated villages and six untreated villages in the nearby regions.

In practice, the bureau gave demonstrations relating to machine operation, held training sessions and distributed materials relating to CT in the treated villages. In terms of economic incentive schemes, the bureau provided subsidies or persuaded village committees to give subsidies to adopters in the treated villages. However, not every adopter is able to secure subsidies, due to government budget constraints.

For farmers in the untreated villages, there is no restriction for them to attend CT demonstrations and trainings in the nearby treated villages. Famers interested in CT adoption can adopt CT and hire machines by themselves. Those who own farmland close to land area of farmers in the treated villages can also ask for machines to be arranged by the bureau or the treated village committees. As explained earlier, a part or all of the cost for hiring machines for returning residues is covered by the bureau or by the village committee. A few adopters in the untreated village using the government machines might be permitted to pay the same machine fee as farmers in the treated villages. In other words, adopters in untreated villages still have the opportunity to become subsidy receivers.

Table 12 presents CT adoption information gathered from the survey in the treated and untreated villages; 172 and 94 filled questionnaires were collected in the treated and untreated villages respectively. More than 80 per cent (142/172) of survey participants had adopted CT in treated villages, while the percentage of adopters in the untreated villages was around 30 per cent. That might be because the proportion of farmers participating in CT training and adopters receiving subsidies in treated villages is higher than in untreated villages. Figure 6 depicts survival functions for the untreated and treated villages. The survival rate for the untreated villages is much higher than the rate for the treated villages. In summary, the main difference between the untreated and treated villages is whether there are direct promotion programmes. In the following sub-sections, CT adoption will be analysed respectively in the untreated and treated villages to explore the effects of different levels of promotion efforts.

Table 12 **Information gathered from the survey about treated villages and untreated villages**

	Treated Villages	Untreated Villages
Village numbers in the survey	9	6
Survey participants	172	94
CT adopters	142	28
Percentage of participants attending CT training	68.02%	27.66%
Percentage of CT adopters receiving subsidy	84.51%	39.28%

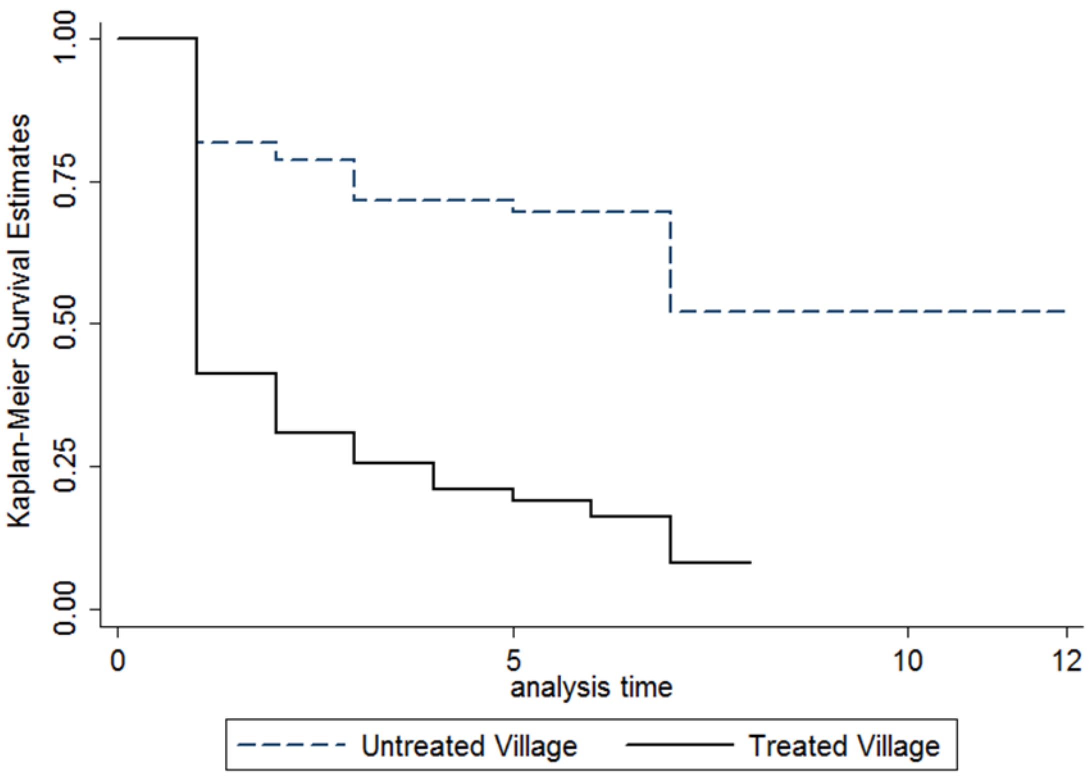


Figure 6 Cumulative survival rates for conservation tillage adoption in the untreated and treated villages

3.4.3.1 Use of Latent Variables Through Factor Analysis

The discrete time model with $\gamma log(t)$ time dependence is used to estimate covariates effects on the hazard rate of CT adoption in the treated and untreated villages. A set of independent variables is selected to fit the survival analysis models. Variables are used one at a time to estimate the dependent variable. A candidate variable is picked if the P value of variable significance test is lower than 0.25 (Bendel and Afifi, 1977; Wang and Guo, 2001). Based on this criterion, several variables were selected. However, latent (unobserved) variables also needed to be created to represent the common relationship between candidate variables that were correlated. Variables for apple land size (*appleland*), annual income from apple (*aincome*) and annual total income (*totincome*) have significant effects on the dependent variable in the treated and untreated villages, but exhibit high correlations among each other (see Table 13 (A) & (B)). The factor analysis method was applied to create two latent variables in the models for the treated and untreated villages.

Table 13 Correlation coefficients between variables in the untreated and treated village model

(A) in the untreated village model

Variables	*appleland*	*aincome*	*totincome*
appleland	-	-	-
aincome	0.8941	-	-
totinome	0.4999	0.5884	-

(B) in the treated village model

Variables	*appleland*	*aincome*	*toincome*
appleland	-	-	-
aincome	0.8481	-	-
totinome	0.7481	0.9290	-

To determine whether the data are suitable for the method, sample size, sample to variable ratio and correlate coefficient of variables are considered. A sample size around 100 in the treated and untreated villages is adequate for using factor analysis (Comrey and Lee, 1973). Ratios of number of observations to number of measured variables are 57.33 observations per variable (172/3) in the untreated villages and 31.33 observations per variable (94/3) in the treated villages. This allows the use of factor analysis as the obtained ratios are higher than the recommended ratios of 10 to 20 observations per variable (Thompson, 2004). Table 13 (A) and (B) present correlation coefficients of the three variables that are correlated in the untreated and treated villages. The coefficients are close to or higher than 0.5, which indicates that factor analysis is appropriate for them (Williams et al., 2010). In addition, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of Sphericity are conducted. The obtained values of KMO are 0.615 and 0.654 in treated and untreated villages and Bartlett's tests of Sphericity are significant by 0.000 (Hair, 1995). Factor analysis was run using Stata/SE 12 software.

According to the 'Eigenvalues greater than one rule' (Bruce et al., 2008) one latent variable can be created in the untreated villages. Table 14 (A) presents estimated factor loadings in the untreated villages. The retained factor is labelled as 'apple income and total income factor in the untreated village (*atincome factor in U*)', which is the latent variable and has high correlation coefficients with variables of (*appleland*), (*aincome*) and (*totincome*). Similarly, another latent variable capturing the same variables of (*appleland*), (*aincome*) and (*totincome*) is created in the treated village (factor loadings in Table 14 (B)), which is named 'apple income and total income factor in the treated village (*atincome factor in T*)'. These new latent variables are then estimated in the survival analysis models.

Table 14 Rotated factor loading for the factor analysis in the untreated and treated village models

(A) in the untreated village model

Variables	Apple Income and Total Income Factor in Untreated Villages	Unnamed Factor
appleland	0.9049	0.1037
aincome	0.9180	0.2092
totinome	0.5473	0.2590

(B) in the treated village model

Variables	Apple Income and Total Income Factor in Treated Villages	Unnamed Factor
appleland	0.5861	0.6313
aincome	0.8355	0.4284
totinome	0.7879	0.5789

3.4.3.2 Discrete time Survival Analysis in Untreated and Treated Villages

The regression results for the discrete time survival analysis in the untreated villages are presented in Table 15. In model 1, households with a higher percentage of income from farming (*pincomefarm*) are early adopters. Those who own tractors (*tractors*) also tend to adopt CT sooner. Not surprisingly, attending training programmes increases the hazard rate of CT adoption of the households. Additionally, apple-based income and total income factor (*atincome factor in U)* has positive effects on farmers' adoption timing. In model 2, the variable relating to neighbours' adoption behaviour (*neibadopt*) is added, while *atincome factor in U* is dropped, as *atincome factor in U* has low correlation coefficients with other independent variables, but a relatively higher coefficient with (*neibadopt*). As expected, farmers' CT adoption decisions are considerably hastened by their neighbours' adoption decisions.

Table 15 Regression results of discrete survival analysis in the untreated village model

Variables	Model 1			Model 2		
	Coe	SE	dy/dx	Coe	SE	dy/dx
log (t)	-1.0962***	0.3869	-0.0679***	-1.0364***	0.3913	-0.0635***
pincomefarm	1.7143**	0.8629	0.1061**	1.2067	0.8666	0.0739
tractors	1.3311***	0.5026	0.0824***	1.2663**	0.5097	0.0776**
peopbor	0.04447	0.0307	0.0028	0.04278	0.0307	0.0026
training	1.3681***	0.4438	0.0847***	1.1127**	0.4447	0.0682**
neibadopt	-	-	-	1.0419**	0.4565	0.0638**
atincome factor in U	0.2722*	0.1407	0.0169*	-	-	-
constant	-3.4967***	0.6164	-	-3.6958***	0.6296	-
Log likelihood	-77.8905			-76.7184		
Observations	315			315		
LR chi2(6)	39.52			41.87		
Pro>chi2	0.0000			0.0000		
Pseudo R2	0.2024			0.2144		
Correct prediction	92.02%			92.02%		

Note: the asterisk*, **, *** denote significance at the 10%, 5% and 1% level.

The regression results for the treated villages are shown in Table 16. Households having a higher proportion of family member s working off-farm (*poffplus*) tend to adopt CT late. This is because of lack of availability of farm labour pool that could be sourced from within the household. As expected, ‘the time when they first heard about CT from the government’ (*hearfrom*) positively influences the adoption rate of households. Proportion of farm income (*pincomefarm*) is estimated in model 2 since it has a high correlation coefficient (-0.54) with *atincome factor in T*. Based on this, households with a high percentage of farm income are more likely to adopt CT earlier.

Table 16 Regression results of discrete survival analysis in the treated village model

Variables	Model 1			Model 2		
	Coe	SE	dy/dx	Coe	SE	dy/dx
log (t)	-1.300***	0.2119	-0.2381***	-1.2827***	0.2113	-0.2377***
poffplus	-1.4566***	0.4039	-0.2099***	-0.9631**	0.3998	-0.1762**
training	0.2408	0.2724	0.0441	0.1672	0.2658	0.0306
hearfrom	0.8957**	0.4137	0.1641**	1.0153**	0.4124	0.1858**
neibadopt	0.8549*	0.4467	0.1566*	0.8879**	0.4467	0.1625**
atincome factor in T	-0.1891**	0.0850	-0.0346**	-	-	-
pincomefarm	-	-	-	0.9826**	0.4177	0.1798**
constant	-0.7568	0.6549	-	-1.3700	0.6367	-
Log likelihood	-210.3825			206.5417		
Observations	380			380		
LR chi2(6)	89.20			89.19		
Pro>chi2	0.0000			0.0000		
Pseudo R2	0.1778			0.1776		
Correct prediction	72.37%			73.68.32%		

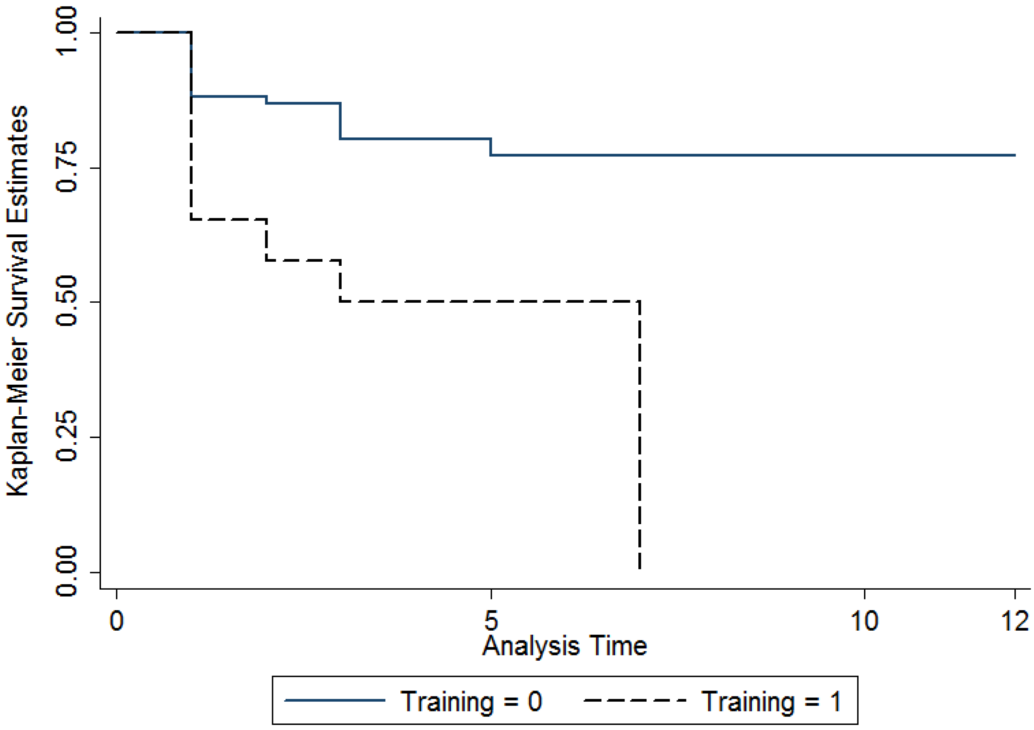
Note: the asterisk*, **, *** denote significance at the 10%, 5% and 1% level.

Notice that variables such as proportion of farm income (*pincomefarm*) and neighbours' adoption (*neibadopt*) have significant positive coefficients in the treated and untreated village models as well as the combined village model. Two differences are observed when comparing results between the untreated and treated villages. First, coefficient of *training* is not significant in the treated villages (Table 16), while it positively and significantly increases the rate of CT adoption in the untreated villages (Table 15). An explanation for this finding could be that although most farmers in the treated villages attended CT promotional trainings, the subsidy is the most critical incentive for them to decide whether to adopt CT. In contrast, fewer people attended the training programmes in the untreated villages since the Government rarely held training in the untreated villages.

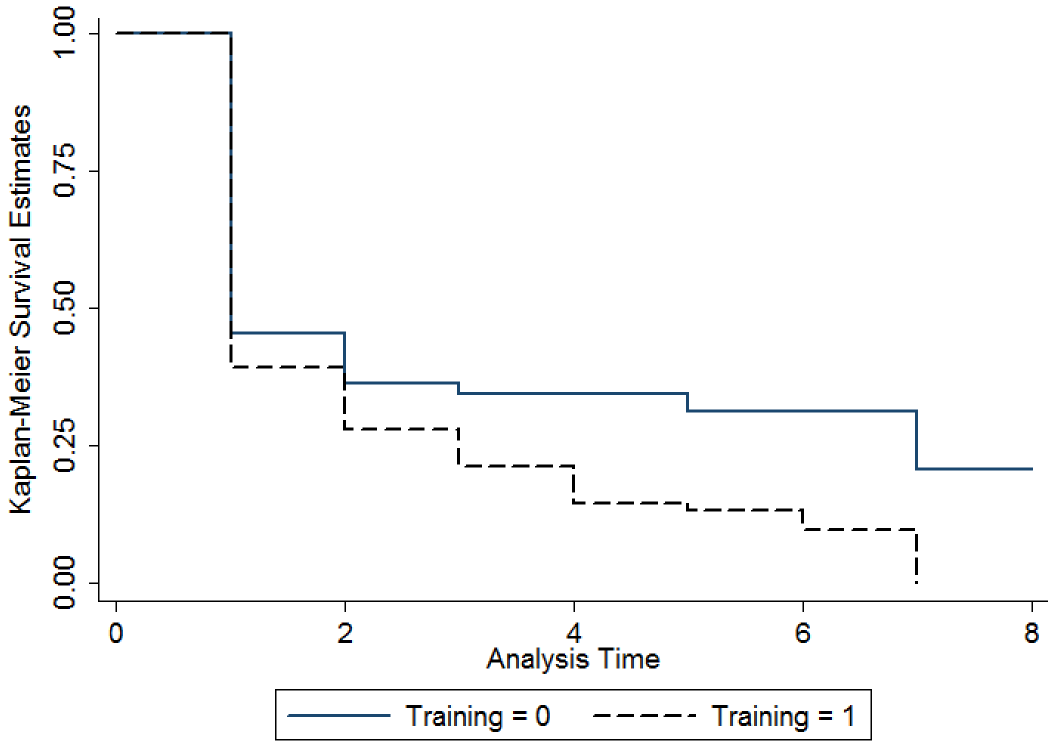
Figure 7 (A) and (B) illustrate survival functions in training and non-training groups in untreated and treated villages. Farmers who attended training have lower survival rates than people who did not in both untreated and treated villages. However, the gap between survival rates for the trained and non-trained groups in the treated village (Figure 7 (B)) is not significant in comparison to the same for the untreated villages.

Second, coefficients of the latent variables capturing effects of (*appleland*), (*aincome*) and (*totincome*) have opposite signs in the models for the untreated and treated villages. Coefficient of *atincome factor in Untreated* is positive, while coefficient of *atincome factor in Treated* is negative. According to information from the survey, planting apples or trees is an alternative way to make money though soil in HC. Income from planting apples in one mu of land area is much higher than planting maize. As described previously, adopters in the untreated villages have less chance to secure subsidies compared to the treated village farmers. They need to pay for the extra subsoiling machine fee on their own. Therefore, households with a higher apple income or total income in the untreated villages display a propensity to adopt CT early.

In the treated villages, most of the adopters can get subsidies to make up for the extra costs of hiring machines. Therefore, income and wealth levels are not significant barriers to CT adoption in the treated village. Additionally, owning and maintaining many apple orchards requires time and effort from farmers. Therefore, high income does not have any positive effects on CT adoption rate in the treated villages.



(A) In the untreated villages



(B) In the treated villages

Figure 7 Cumulative survival rates for conservation tillage adoption in training and non-training groups in the untreated and treated villages

3.5 Conclusion

This chapter investigated the factors promoting the process of CT adoption in HC in China using the survival analysis. These factors include household characteristics and intervention efforts made by the local government. I first estimated the survival functions for CT adoption based on two different methods for calculating the survival time. The first method involves calculating the survival time using the same starting point, which was taken as the first record of CT adoption in HC (the start year is 2005). Another method is to calculate the survival time from farmers' individual-specific starting dates of first hearing of CT to the date of adoption.

Next, parametric survival models were used to explore the effects of covariates on the rate of CT adoption. I used the discrete time model as the time to adoption was recorded in integers (in years). Since the average land holdings for each farmer is 0.08 ha in China (Derpsch et al., 2010), most families cannot live on farming only. Families with higher percentages of non-farm workers tended to adopt CT late. Given the competitive usage of crop residues between feeding livestock and returning to the field, families with a higher number of livestock also adopt CT late. However, households with a higher farm income and those who had attended the training programmes adopt CT earlier. Those who had already adopted CT help with speeding up the adoption process of their neighbours.

To explore further the influences of the training programmes held by the Government and of the subsidy schemes provided, villages are divided between untreated and treated villages based on the level of support received from the Government. Two discrete time survival analysis models were estimated respectively in the untreated and treated villages to explore the differential effects of the different levels of promotion efforts. Several independent variables, such as household's income from apples, trees and the total income, in the models involving the untreated and treated villages, were found to be correlated. Two latent variables were created for representing the common relationship between these variables in the models for the untreated and treated villages using the approach of factor analysis.

Two differences were observed when comparing regression results between the models for untreated and treated villages. First, the variable indicating famers' attending CT trainings is not significant in the model for the treated villages. This is because the subsidy scheme in the treated village is the most critical incentive that leads farmers to adopt CT. In the untreated villages, attending CT training programmes provides significantly positive effects on accelerating farmers' CT adoption. Farmers in the untreated villages need to go to the nearby treated villages to find the training opportunities. They were more likely to become earlier adopters, irrespective of whether a subsidy was provided.

Another difference is evident from the opposite signs of coefficients for the latent variables in the models for the untreated and treated villages. These two latent variables capture effects of income of apples, trees and the total income on the CT adoption in the untreated and treated villages. The positive effects of the latent variable in the model for the untreated villages mean that families with a higher income from apple orchards, tree orchards or a higher total income are more likely to adopt CT earlier. Income and wealth levels are not significant barriers to CT adoption in the treated village due to the subsidies. The high income from planting apples or other sources (family members working in the city) might discourage farmers from farming and adopting the new technology.

Chapter 4 An Empirical Analysis of Factors Affecting Illegal Logging in Indonesia

Abstract

Illegal logging is one of the key drivers of deforestation in developing countries, such as Indonesia. Since Indonesia has a large forested area, it is important to understand the factors that lead to illegal harvesting and evaluate the effectiveness of strategies aimed at curtailing illegal logging. This chapter develops a simultaneous-equation econometric model of illegal logging in Indonesia by using secondary data between 1996 and 2009. Specifically, the influence of illegal demand from Indonesia's main timber trading partners, such as Japan and China, are estimated and analysed. Results indicate that corruption and decentralisation in Indonesia have a significant influence on promoting illegal logging supply. Additionally, excess demand in Japanese construction and furniture industries and China's housing start-ups are key drivers of illegal logging demand. Law enforcement and policies aimed at curbing illegal harvesting in Indonesia are found to be more effective than similar policies aimed at curbing illegal demand from Japan and China.

4.1 Introduction

Forest clearing is one of the most important factors that contributes to carbon emission and worsens the concerning climate change problem. One hectare of forest contains about 250 tonnes of carbon (Swallow et al., 2007; Olsen and Bishop, 2009), and its clearing is equivalent to burning 320 tonnes of coal in terms of carbon emission generation.

Illegal logging is the main cause for deforestation and forest degradation and is a threat to the REDD programme (IGES, 2007). The term ‘illegal logging’ is often used to refer to the cutting of trees in protected forest areas. A more general definition of illegal logging[5] (Brack et al., 2002) expands the notion of illegal logging from harvesting activity to the entire supply and demand process of illegally logged timber.

Indonesia is the third largest country in terms of tropical forest area (FAO, 2010). It has the second highest deforestation rate in the world, after Brazil. Annual Indonesian forest loss is 498 thousand hectares (FAO, 2010), which releases a large amount of carbon into the atmosphere. Illegal logging has been a serious problem in Indonesia since the late 1990s, creating significant effects on the environment, economy and society (Obidzinski et al., 2006). As reported by Creek (2004), 60 per cent of hardwood production, 100 per cent of log exports and 55 per cent of plywood exports from Indonesia are illegal.

Ever since illegal harvesting attracted attention from the global community (Obidzinski et al., 2006), several policies have been implemented to control forestry related crimes in Indonesia. From 1985 to 1997, the first ban on log exports was implemented by the Indonesian Government to promote sustainable harvesting and support the development of the domestic

[5] ‘Illegal logging takes place when timber is harvested, transported, bought or sold in violation of national laws. The harvesting procedure itself may be illegal, including corrupt means to gain access to forests, extraction without permission or from a protected area, cutting of protected species or extraction of timber in excess of agreed limits. Illegalities may also occur during transport including illegal processing and export, mis-declaration to customs, and avoidance of taxes and other charges.’

wood processing industry (Gellert, 2003; Luttrell et al., 2011). The ban was lifted due to the Asian finical crisis and reintroduced in 2001. An anti-money laundering law and an anti-corruption law were also introduced in the same year to curb forest crimes (Luttrell et al., 2011). Two agencies, the Corruption Eradication Commission and the Financial Intelligence Unit, were set up to monitor the law enforcement by relevant agencies (Dermawan et al., 2011). In 2005, the first draft of a specialised law on illegal logging (refer as logging law) was introduced to provide the legal foundation for controlling illegal logging in Indonesia (Luttrell et al., 2011). Further, Indonesia signed bilateral agreements to restrain the trading in illegal timber in 2002. Its main timber-importing partners have also agreed to sign and follow the agreements (Luttrell et al., 2011).

Factors affecting illegal logging have been analysed in several studies. Dieter (2009) uses an adjusted input-output model and trading records of multiple countries to estimate illegal timber trade. He found that international trade contributes to increases in the supply of illegal timber and that lacking effective governance on forestry is an important factor that encourages illegal harvesting activities. Harwell and Blundell (2009) provide a comprehensive report about illegal logging in Indonesia that summarises the results of their fieldworks and information from media, government reports and reports from non-government organisations (NGOs) (e.g., FAO, ITTO). According to Harwell and Blundell (2009), corruption in the forestry sector is a critical factor driving the illegal harvesting. A common corruption activity is to issue fake documents that allow companies to clear more trees than they are entitled to (Harwell and Blundell, 2009). Harwell and Blundell (2009) suggest that improvement in forestry management and the introduction of the anti-money laundering legislation with corresponding bank regulations are very effective tools to curb illegal logging and corruption in Indonesia. Casson and Obidzinski (2002) analyse the problem of illegal logging in Indonesia from the political economy perspective. They argue that most corruption activities relating to illegal logging happen in the regional government, as income from 'illegal' logging contributes to the local budget. Casson and Obidzinski (2002) also suggest that the decentralisation process in Indonesia, which allocates forestry management authorities to the local government, has complex effects on illegal logging in Indonesia. Burgess et al. (2012) also focus on analysing the effect of decentralisation on deforestation (including 'illegal' logging) in Indonesia by using a Cournot competition model. Their results reveal that the increasing number of districts resulting from decentralisation increases deforestation in Indonesia.

Although many studies about illegal logging have been conducted, few of them analysed factors driving illegal logging using econometric models within a multiple market framework. The impacts of domestic and bilateral polices has not been formally estimated either. In this study, I propose a simultaneous-equation model to estimate factors that affect illegal logging. The model incorporates both demand and supply characteristics of logging. I have selected Japan and China to represent the demand side of Indonesia's illegal logging. These are Indonesia's main timber trading partners, accounting for a half of Indonesia's annual plywood export, according to the timber trade reports of the International Tropical Timber Organization (ITTO, 1997-2012). The illegal timber demands of Japan and China were analysed in two separate sets of equations.

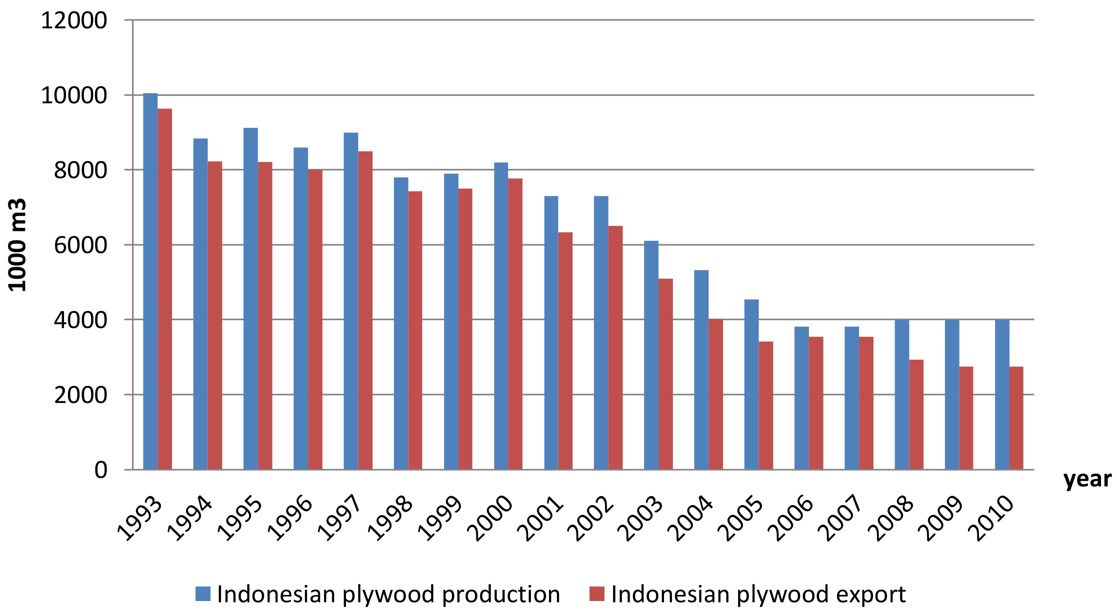
In addition, the impacts of important polices aimed at curbing illegal logging, such as the ban of log exports, draft law of illegal logging law and anti-money laundering and anti-corruption laws in Indonesia are quantified and tested in the model. Key forest related policies in importing countries are also examined and bilateral agreements forbidding illegal logging are tested in both supply and demand equations.

The outline of the chapter is as follows. A summary of economic studies on illegal logging is provided in Section 4.2. In Section 4.3, I describe the model and the dataset. Section 4.4.1 presents the results and analysis of factors causing illegal logging. Section 4.4.2 discusses the impact of political factors in Indonesia. Section 4.4.3 describes the impact of the green purchase laws on curbing illegal timber imports from Japan. The last section discusses and highlights the main findings of this chapter.

4.2 Estimating Illegal Logging in Indonesia

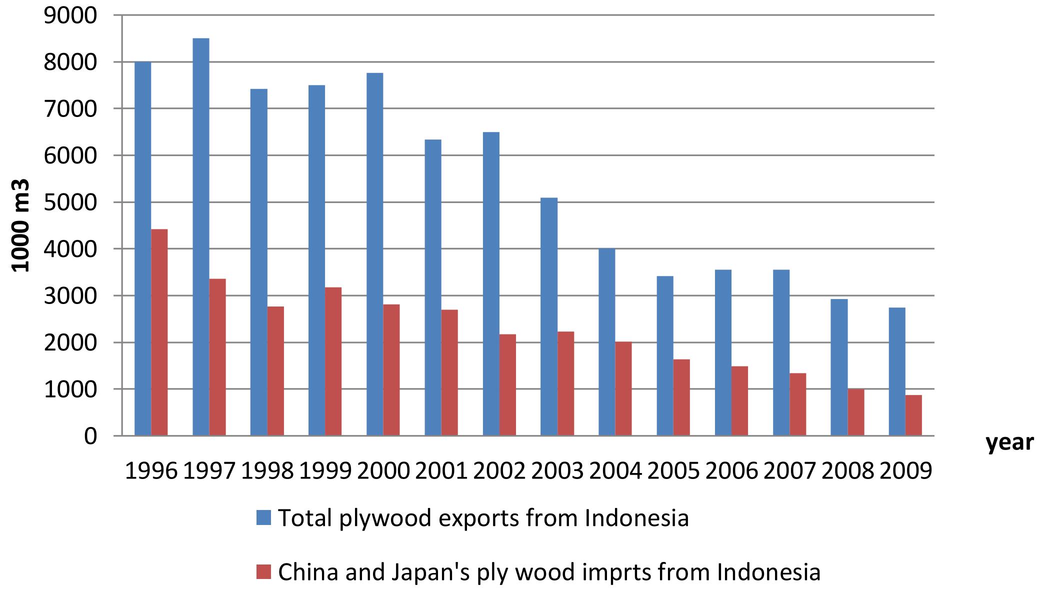
Given the complex and underground networks used by timber smugglers, it is almost impossible to get accurate information to quantify illegal logging and illegal trade in Indonesia. The official statistics are not a reliable estimate for deforestation caused by illegal logging in Indonesia (Burgess et al., 2012), and most quantitative reports of illegal logging are estimated based on 'speculation and anecdotal information' (Creek, 2004). Among frequently cited sources, Palmer (2001) uses a materials balance model to estimate illegal logging by comparing the supply and demand of the round wood in Indonesia. According to Palmer's estimates, illegal logging in Indonesia was 49.176 million m^3 and 64.612 million m^3 of round wood equivalent in 1997 and 1998 respectively. In the report provided by the Indonesian Ministry of Forestry, the level of illegal timber supply is estimated by looking at the differences between the official round wood production and consumption in the processed wood industry from 1980 to 2005 (Manurung et al., 2007). Harwell and Blundell (2009) too estimate the level of illegal timber supply by finding the difference between legal timber supply and the total timber consumption in Indonesia. As per their estimation, the level of illegal timber produced in the country was roughly 30 million m^3 per year from 2003 to 2006 in Indonesia.

After the ban on log exports, which was introduced in the mid-1980s, the log exports from Indonesia have reduced significantly. However, the export of other wood products, such as plywood, has increased rapidly (Makkarennu, 2013). According to the annual review of ITTO (1997-2012) Indonesia has been the largest supplier of plywood since 1997. Figure 8 depicts Indonesian plywood production and exports between 1993 and 2010. It reveals that export accounts for a large proportion (on average 87.60 per cent) of the total plywood production. A large proportion (around 40 per cent) of Indonesia's plywood was exported to Japan and China (Figure 9). These were two major importers of Indonesia's plywood as reported in a study of Indonesia's plywood industry (Makkarennu, 2013). On average, between 1996 and 2009, the amount of plywood imported in Japan and China accounted for 36 per cent and 16 per cent of the total plywood production in Indonesia respectively.



Source: ITTO (1997–2012)

Figure 8 Indonesian plywood production and plywood exports between 1993 and 2010



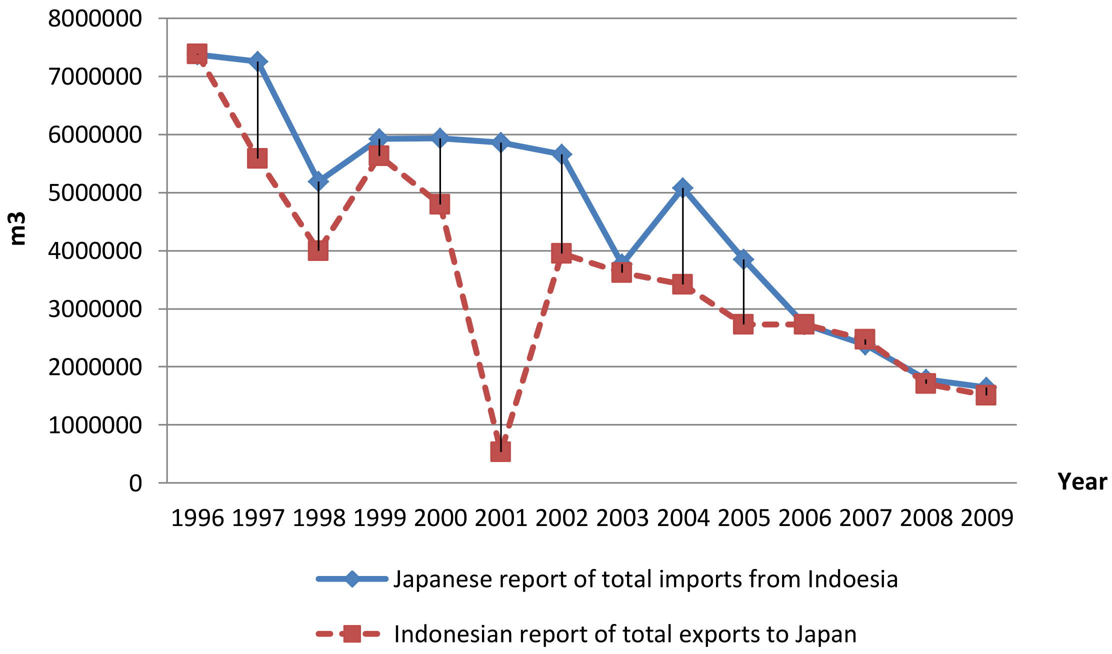
Source: ITTO (1997–2012)

Figure 9 China and Japan plywood imports from Indonesia and Indonesian plywood exports from 1996 to 2009

The ITTO (1997-2012) report provides information on the global annual timber trade based on statistics provided by individual countries. However, there exist significant discrepancies between reported and actual timber trade when one compares numbers provided by individual countries. For instance, in 2002, the plywood exported from Indonesia to Japan was 2,637 thousand m^3 (as reported by Japan), whereas the exports of plywood to Japan was only 1,956 thousands m^3 (as reported by Indonesia). There exists a discrepancy of around 681 thousand m^3. Similar discrepancies were also observed between China and Indonesia’s trading records. In the report by ITTO (1997-2012), these discrepancies have been attributed to different measurement approaches and timber smuggling.

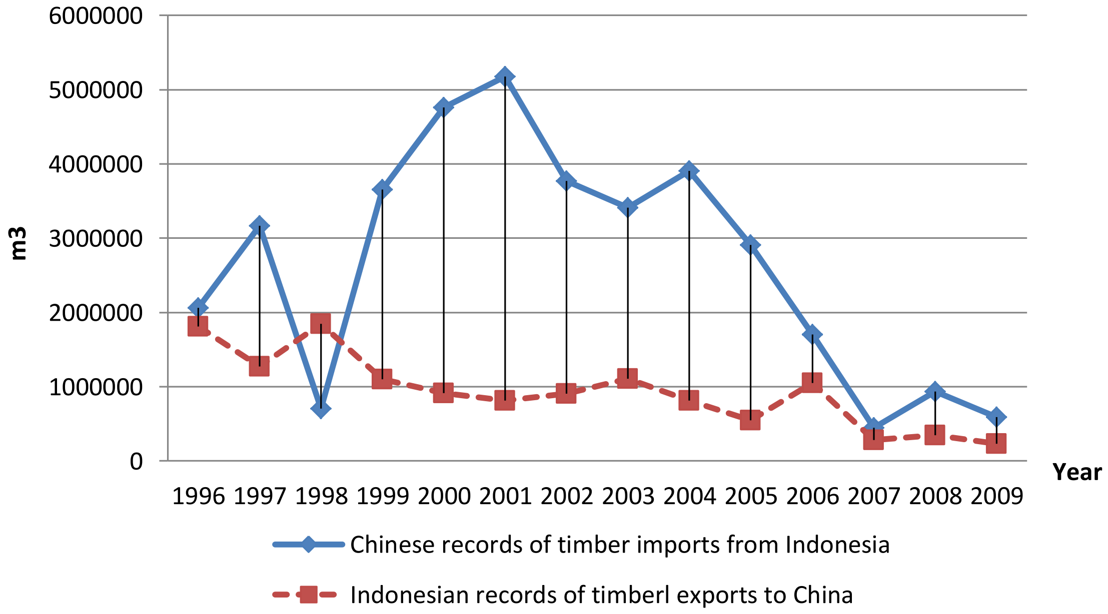
Figure 10 presents the gap between Japan’s timber imports from Indonesia and Indonesia’s timber exports to Japan, whereas Figure 11 illustrates similar discrepancies of timber trade between China and Indonesia.[6] The unexplained gaps have increased after 1998 in Figure 11 and after 1999 (see Figure 10). The biggest differences were observed in 2001; since then, the discrepancies have gradually declined in both Figure 10 and Figure 11. After 2006, these gaps have become smaller. If the reason for the gaps is simply the different measurement approaches in countries, the gaps between trading records should be constant in every year. In terms of the fluctuations in gaps observed in Figure 10 and Figure 11 a possible explanation could be the ongoing trade in illegal timber. It is noticeable in Figure 10 and Figure 11 that the recorded timber trade in the importing countries, Japan and China, is higher than the recorded exports from Indonesia. It seems Indonesia underreports the actual trade records, which have consistently exceeded the annual forest harvesting concessions issued by the Indonesian Government. Therefore, in this study, I estimate the illegal logging amounts using discrepancies in the trading records between Japan and Indonesia, and China and Indonesia separately (see Figure 12).

[6] The timber trading records include trading of log, swan timer, veneer and plywood. These wood products were converted to the log equivalent by index of logs 1:1, swan timber 1:1.43, veneer 1:1.9, plywood 1:2 (HOU, F. & SONG, W. An analysis on the supply and demand of timber in China. E-Business and E-Government (ICEE), 2011 International Conference, 2011. IEEE, 1-4.).



Source: ITTO (1997–2012)

Figure 10 Discrepancy between Japanese records of timber imports from Indonesia and Indonesian records of timber exports to Japan from 1996 to 2009



Source: ITTO (1997–2012)

Figure 11 Discrepancy between Chinese records of timber imports from Indonesia and Indonesian records of timber exports to China from 1996 to 2009

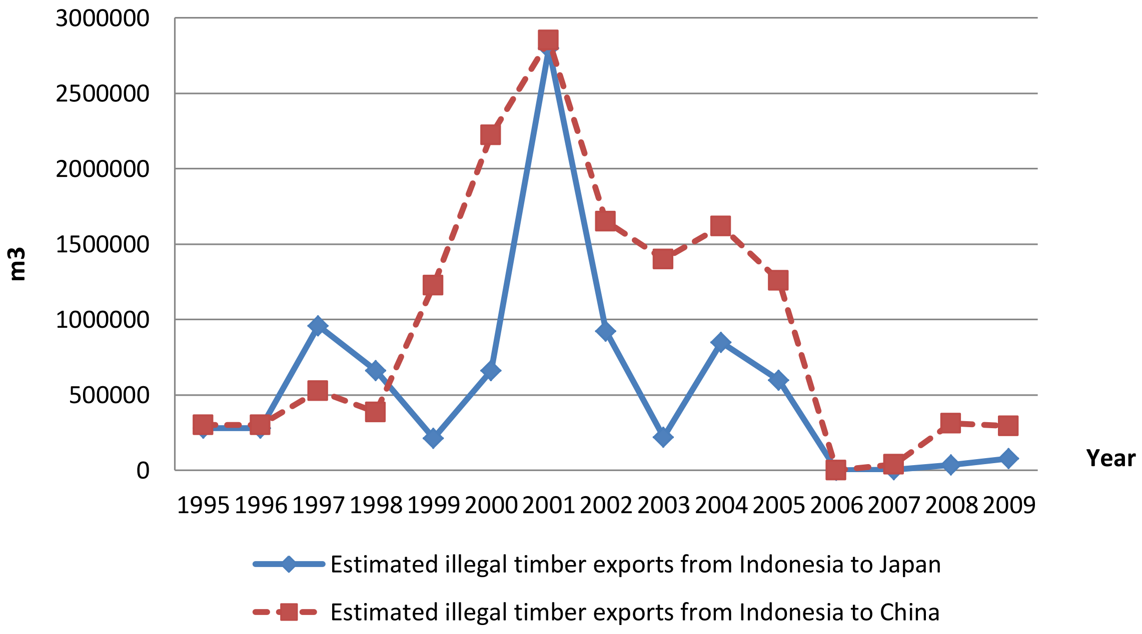


Figure 12 Estimated illegal timber exports from Indonesia to Japan and China from 1996 to 2009

4.3 Data and Model

4.3.1 The Simultaneous-Equation System Model

In this section, I propose a simultaneous-equation model to estimate factors affecting illegal logging from both demand and supply sides of timber trade, using secondary data between 1996 and 2009. The illegal timber demands of Japan and China are analysed in two separate sets of equations. The simultaneous-equations model is described in the following.

Equation for the Illegal Timber Demand in China:

$$CII = \beta_{10} + \beta_{11}EPIN + \beta_{12}GDP2005C + \beta_{13}HSC + \beta_{14}PLOGC + \eta_1 \tag{18}$$

Equation for the Illegal Timber Demand in Japan:

$$JII = \beta_{20} + \beta_{21}EPIN + \beta_{22}FACTORHF + \beta_{23}DSJ + \eta_2 \tag{19}$$

Equation for the Illegal Timber Supply from Indonesia:

$$TOTALII = \beta_{30} + \beta_{31}EPIN + \beta_{32}NUDIS + \beta_{33}GDP2005I + \beta_{34}CIIN + \eta_{3} \tag{20}$$

Equation for Demand and Supply Equilibrium:

$$JII + CII = TOTALII \tag{21}$$

In the illegal timber demand functions, variables associated with the number of new housing starts and the domestic log production in Japan and China were estimated. Variables of Japanese wood floor production and Chinese GDP were also tested in the model. In the supply function, variables relating to the number of districts, corruption index and GDP in Indonesia were considered. Additionally, the main polices aimed at curbing illegal logging were quantified as dummy variables. Variables are log transformed in this model. Descriptions and data sources of these variables are presented below and in Table 17.

Table 17 Descriptions and sources for variables in the model (all variables are log transformed)

Variables	Description	Units	Source
JII	Illegal timber imports in Japan	m^3	ITTO
DSJ	Domestic timber self-sufficiency rate in Japan	%	Araya and Katsuhisa (2008)
HSJ	Number of housing start-ups in Japan	Unit	Ministry of Land, Infrastructure, Transport and Tourism in Japan
FLP	Production of wood floor in Japan	$1000m^3$	Araya and Katsuhisa (2008)
FACTORHF	A latent variable capturing HSJ and FLP	-	-
CII	Illegal timber imports in China	m^3	ITTO
GDP2005C	China’s GDP (basic year is 2005)	US$	World Bank
HSC	Number of housing start-ups in China	Million m^2	Urban housing Markets in China (2009)
PLOGC	Round log production in China	$1000m^3$	National Bureau of Statistics of China
TOTALII	Sum of illegal exports of Japan and China	m3	ITTO
EPIN	Legal timber export price in Indonesia	$\$/m^3$	FAOSTAT
CIIN	Corruption Perception Index of Indonesia	Index	Transparency International
NUDIS	Number of districts in Indonesia	Number	Burgess et al. (2012)
GDP2005I	Indonesia’s GDP (basic year is 2005)	US$	World Bank, CEIC
LAW	The draft illegal logging law introduced in 2005 (1-the policy has been introduced: 0-no policy)	Binary variable	Luttrell et al. (2011) Gellert (2003)
REGU	The ban of log exports first introduced from 1985 to 1997 and reintroduced in 2003(1-the policy has been introduced: 0-no policy)	Binary variable	Luttrell et al. (2011)
ANTIM	The anti-money laundering and anti-corruption law introduced in 2005(1-the policy has been introduced: 0-no policy)	Binary variable	Luttrell et al. (2011)
BIL	The bilateral agreements with timber-importing countries introduced in 2002 (1-the policy has been introduced: 0-no policy)	Binary variable	Luttrell et al. (2011)
GREENJ	The item of ‘legal wood’ was added in the Green Purchasing Law by the Japanese Government in 2006 (1-the policy has been introduced: 0-no policy)	Binary variable	MOE (2007)

In equation(18), the dependent variable is Chinese illegal timber imports from Indonesia (*CII*), which is calculated using the discrepancy between China and Indonesia's trading records (see Figure 11). Since data on illegal timber price are unavailable, I have used the legal price as a proxy into the model (since illegal price is expected to be lower than the legal price, this could be thought of as an upper bound estimate). On the right hand side of equation(18), *EPIN* is a variable associated with the legal timber export price in Indonesia. Many studies argue that illegal timber imports have fuelled the growth in Chinese economy with the rapid increase of GDP in China, the construction and housing sectors have emerged as the biggest consumers of natural wood (Sun et al., 2004). Considering these factors, variables such as the Chinese GDP, the number of new housing starts (*HSC*) and the domestic production of round log (*PLOGC*) are expected to positively influence illegal timber demand from China.

Likewise, in equation(19) the dependent variable is Japanese illegal timber imports from Indonesia (*JII*), which is calculated based on the trading records of discrepancies between Japan and Indonesia (see Figure 10). On the right hand side, the variable indicating timber prices is also *EPIN* (the legal timber export price in Indonesia), which is a critical factor influencing timber imports in Japan (Araya and Katsuhisa, 2008). Additionally, other main factors affecting illegal demand from Japan are the increasing demand of housing and the demand by the furniture industry (Araya and Katsuhisa, 2008). However, it was found that the variable relating to the number of new housing starts (HSJ) and the variable indicating the amount of wood floor production were highly correlated (the correlation coefficient was 0.6615). To address the possible multi-collinearity caused by the correlated variables (Williams et al., 2010), the factor analysis method was applied to create a latent variable capturing the two variables. The latent variable was named *FACTORHF,* which indicates the joint demand of illegal timber in the construction and furniture industries. Table 18 presents the estimated factor loadings for this variable. In addition, the KMO measure of sampling adequacy and Bartlett's test of Sphericity were conducted (Ferguson and Cox, 1993).[7] The obtained value of KMO is 0.5 and Bartlett's test of Sphericity is significant at 0.005. In the model, the latent variable (*FACTORHF*) capturing the number of new houses and the wood floor production is expected to have a positive effect on illegal timber demand.

Table 18 Factor loading for the factor analysis

Variables	FACTORHF
HSJ	0.7413
FLP	0.7413

Further, the domestic production of timber products has decreased in Japan since the early 1990s due to recession and reductions in tariffs resulting from trade liberalisation (Araya and Katsuhisa, 2008). The increasing concerns over the environment have also led to a decline in domestic wood production. According to Araya and Katsuhisa (2008), the self-sufficiency rate (*DSJ*), which measures the volume of domestic supply as a percentage of the total timber supply, dropped from 58 per cent to 22 per cent between 1967 and 2006 in Japan. Therefore, a vast quantity of timber from abroad was required given the big gap between the demand and domestic supply. The cheaper illegal timber from Indonesia, consequently, became very attractive. Therefore, the self- sufficiency rate (*DSJ*) is expected to have a negative impact on the illegal timber demand.

Since Japan and China are two main timber trading partners of Indonesia, the sum of their illegal timber imports has been used as the dependent variable denoting for *TOTALII*, in equation(20) Indonesia embarked on the path of decentralised governance from 1998, leading

[7] The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy tests whether the factor analysis is suitable based on correlation and partial correlation between variables (a minimum value of 0.5 is required); the null hypothesis of Bartlett's test of Sphericity is that variables are unrelated. A significant statistic at 10 per cent level indicates that factor analysis is suitable.

to the addition of several new districts. These district heads have been allowed to issue small-scale forest clear concessions to companies (Casson and Obidzinski, 2002). The increasing of number of districts has been attributed to the acceleration of unsustainable harvesting in Indonesia (Burgess et al., 2012). Given this potential role of new district additions, the role of the variable indicating the number of districts (*NUDIS*) was tested in the model. In addition, corruption has been seen as 'a culture' at the top government levels during the last 32 years of governance by the ex-president Suharto (Palmer, 2001). This 'culture' has gradually spread over to the sub-national governments in Indonesia. The variable 'corruption perception index' (*CIIN*) in Indonesia is tested in the model as illegal logging is believed to have a symbiotic relationship with corruption (Palmer, 2001).

4.3.2 Estimation of the Two Stage Least Square Model

In the simultaneous-equation model, the OLS method cannot be applied directly to each single equation (Gujarati, 2003; Wooldridge, 2012). This is because the explanatory variables in one equation may not meet the assumptions of OLS. For example, under the OLS, the independent variables are assumed to be non-stochastic and uncorrelated with the error terms (Gujarati, 2003). In this model, *EPIN* is an endogenous variable that is not fixed but determined within the model. According to the 'rules for identification' (Gujarati, 2003; Wooldridge, 2012), each equation in this model is over identified. Therefore, the Two Stage Least Square (TSLS) method can be performed. The first stage of TSLS is aimed at finding the Instrumental Variable (IV), which is highly related to *EPIN* but unrelated to the error terms (Gujarati, 2003; Maddala and Lahiri, 1992). In the second stage, the endogenous variable, *EPIN*, is replaced by the estimated IV, which is the predicted *EPIN* from the first stage. Equations with predicted *EPIN* (IV) can be regressed by OLS.

In the first step, *EPIN* was instrumented using all of the exogenous variables in the model in equation(22). The explanatory variables in equation(22) are also called instruments.

$$\begin{aligned} EPIN &= \theta_0 + \theta_1 GDP2005C + \theta_2 HSC + \theta_3 PLOGC + \theta_4 DSJ + \theta_5 FACTORHF \\ &+ \theta_6 NUDIS + \theta_7 GDP2005I + \pi \end{aligned} \tag{22}$$

In the second stage, the endogenous variables (*EPIN*) was replaced by the predicted *EPIN* in equations(18) , (19) and (20). The new equations are written as follows.

Equation for the Illegal Timber Demand in China:

$$CII = \beta_{10} + \beta_{11} predicted\,EPIN + \beta_{12} GDP2005C + \beta_{13} HSC + \beta_{14} PLOGC + \eta_1 \tag{23}$$

Equation for the Illegal Timber Demand in Japan:

$$JII = \beta_{20} + \beta_{21} predicted\,EPIN + \beta_{22} FACTORHF + \beta_{23} DSJ + \eta_2 \tag{24}$$

Equation for the Illegal Timber Supply from Indonesia:

$$TOTALII = \beta_{30} + \beta_{31} predicted\,EPIN + \beta_{32} NUDIS + \beta_{33} GDP2005I + \beta_{34} CIIN + \eta_3 \tag{25}$$

Equation for Demand and Supply Equilibrium:

$$JII + CII = TOTALII \tag{26}$$

As explained above, the regression of TSLS can be done manually and systematically. However, several software programs offer an easier way to perform it automatically. The above model was run in Gretl software.

4.3.3 Tests for Appropriateness of the Instrumental Variable

Three specification tests related to the IV estimation are conducted after the TSLS estimation. The first test is the Hausam test, which indicates whether the simultaneity problem exists in the model (Gujarati, 2003). As mentioned above, in this model, *EPIN* is an endogenous variable that is not fixed but determined within the model. It is also likely to be correlated with the error term. The null hypothesis of the Hausman test is that the simultaneity problem does not exist (the endogenous variable does not exist) (Gujarati, 2003). If there is no simultaneity problem, the estimates of OLS are consistent, and the TSLS is unnecessary. The null hypothesis cannot be accepted when the p value of the test is close to or lower than 0.1.

Some possible problems related to the IV also need to be considered. For instance, if the instruments (the explanatory variables in equation(22)) are only weakly correlated with the endogenous variable (*EPIN*), the estimate of IV will be inconsistent (Bound et al., 1995; Stock and Yogo, 2002). The weak instruments problem could be tested using the F-statistics of the first stage of the TSLS (Bound et al., 1995; Stock and Yogo, 2002). A value larger than ten implies a good fit without the weak instruments problem (Cottrell and Lucchetti, 2012). The F-statistics of the first stage of the TSLS are presented in the third last row of Table 19. They are all higher than 10.

In addition, the Sargan test indicates whether the instruments are exogenous (whether they are independent of the error term) (Gujarati, 2003). If one or some of instruments are endogenous, the estimate of IV will not be consistent. The null hypothesis of Sargan test is that all instruments are valid. If the p values are larger than 0.1, the null hypothesis can be accepted.

Overall, results of these tests (shown in Table 19) demonstrate that the TSLS method performs very well in this model, except for the Hausman test in the equation for China's demand and the Sargan test in the equation for Japan's demand. The p value of the Hausman test indicates that the OLS is consistent in China's demand function. The Sargan test in Japan's function presents that the instruments are invalid. So, the Chinese and Japanese demand functions were regressed separately using OLS. The results are presented in the Table

19. However, the differences between results under TSLS and under OLS for Japan and China's demands turn out to be trivial, as shown in Table 19.

Table 19 Results of the simultaneous-equation model

	Indonesia's supply	Indonesia's supply	Japan's demand	Japan's demand	China's demand	China's demand
	TOTALII	TOTALII	JII	JII	CII	CII
Methods	TSLS	TSLS	TSLS	OLS	TSLS	OLS
constant	216.026*** (46.4999)	99.6510** (43.5398)	48.1906*** (13.3061)	41.1285** (14.3201)	30.4595*** (6.3840)	28.0862*** (5.6552)
EPIN	-	-	-	-0.0083 (1.2401)	-	0.7833 (0.5596)
Predicted EPIN	10.8206*** (3.3386)	-5.4753 (3.3853)	-0.6853 (11751)	-	0.5569 (0.6414)	-
NUDIS	-9.1623*** (1.8614)	-	-	-	-	-
CIIN		11.0817*** (2.9964)	-	-	-	-
GDP2005I	-3.3930*** (0.9585)	-0.9527 (1.0178)	-	-	-	-
DSJ	-	-	-9.1815*** (1.6886)	-9.2179*** (2.0431)	-	-
FACTORHF	-	-	0.4700*** (0.16663)	0.4756* (0.2352)	-	-
PLOGC	-	-	-	-	-2.1459*** (0.2524)	-2.1575*** (0.2468)
HSC	-	-	-	-	0.4137* (0.2308)	0.4368* (0.2411)
GDP2005C	-	-	-	-	13.1167*** (4.7979)	13.4149*** (4.9638)
Hausman test	Chi-square(1)= 5.9591 P value= 0.0146	Chi-square(1)= 4.8737 P value= 0.0273	Chi-square(1)= 3.4012 P value= 0.0651	R-squared =0.7380	Chi-square(1)= 0.4822 P value= 0.4874	R-squared =0.6929
Weak instruments test	F-statistic= 43.319	F-statistic= 18.96	F-statistic= 59.6884		F-statistic= 60.4906	
Sargan test	LM=3.5619 P value= 0.4685	LM=3.6453 P value= 0.4561	LM=8.4078 P value= 0.0777		LM=5.9881 P value= 0.1122	

Note: the asterisk*, **, *** denote significance at the 10%, 5% and 1% level.

4.4 Estimation of Results and Discussion

4.4.1 Analysis of Factors Causing Illegal Logging

The results of the TSLS estimation are presented in Table 19. For the supply function, the variable relating to the number of districts in Indonesia (*NUDIS*) and the variable associated with corruption (*CIIN*) were considered key factors affecting illegal logging supply in Indonesia. The correlation coefficient between them is high (0.8125), which might lead to inaccurate estimates in the model. The P values could be overestimated and the confidence intervals on the coefficients could become wider (Paul, 2006). To avoid the multi-collinearity problem, the two variables were tested separately in two models. As explained in last section, the IV (*predicted EPIN*) was estimated using all exogenous variables in the model. The change of variable affects the estimation of IV, and this, in turn effects estimations of other variables. So, the results from the models dropping the variable *NUDIS* and adding variable of *CIIN* are presented in third column of Table 19.

Since all variables are log transformed in this model, the value of the coefficients indicates the elasticity of the dependent variable with respect to the explanatory variable. For example, the coefficient of *predicted EPIN* (legal timber price in Indonesia) is -10.7362 in Table 19. This means that a one per cent increase in timber price will lead to a 10 per cent reduction in illegal logging. One of the motivations for illegal logging is to earn greater profits by avoiding the cost for certification and tax, which are required for legal timber trade. If selling legal timber could earn the same amount of profits, it would not justify individuals or firms taking big risks to sell timber illegally. Therefore, a higher legal timber price discourages illegal timber trade and leads to a lower illegal timber supply.

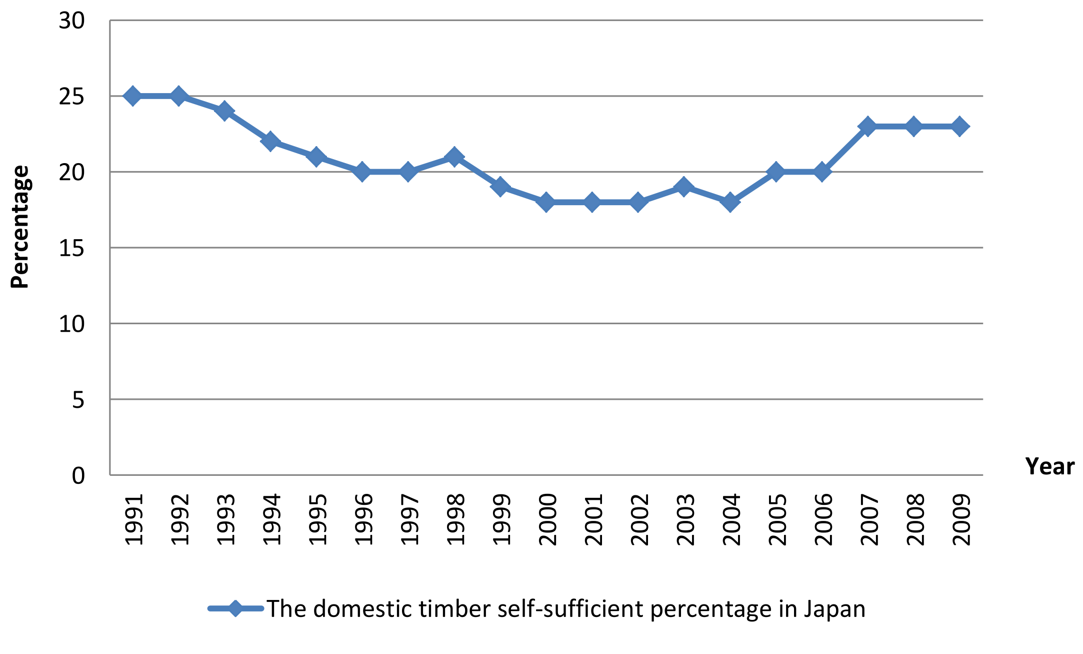
Next, the variable (*NUDIS*) indicating the total number of districts from 1996 to 2009 has a negative and significant effect on the illegal timber supply. An increase in *NUDIS*, leads to a reduction in illegal logging. However, this must be understood in the right context. In 1998, under domestic and international pressure, Indonesia began the process of democratisation. Based on the laws released by the interim Government of President Habibie, some authorities, including the authority for managing natural resources, have been transferred from the central government to the district governments (Casson, 2001; Casson and Obidzinski, 2002). Apart from the forest harvesting concessions issued by the central government, the governments of these districts are allowed to issue small-scale forest extraction permissions (Casson and Obidzinski, 2002; Burgess et al., 2012). Additionally, to enhance the provision of public services, most of the districts in Indonesia have split into two or more since 1998 (Sjahrir et al., 2014). Between 2000 and 2008, the total number of districts increased from 292 to 483, whereas the districts in the main forest island increased from 189 to 312 (Burgess et al., 2012). Burgess et al. (2012) argue that the proliferation of districts has increased deforestation in Indonesia from both legal and illegal logging. This is because the district governments have permitted forest clearing activities without considering the sustainable development of forest. However, the results in Table 19 suggest that the increased number of districts has led to a decline in the illegal logging. This can be explained. An increase in the number of *NUDIS*, by design, leads to more logging rights, so even if they are legal, the amount of forests harvested increases despite a reduction in illegal logging. This is consistent with a previous study (Casson and Obidzinski, 2002), which found that the differentiation between 'legal' and 'illegal' logging has been blurred due to decentralisation. In addition, a factor that contributes to illegal logging is an excess demand for timber in the market; when legal supply increases, the excess demand decreases and illegal logging demand decreases. There are examples in the natural resource management literature of this effect (for instance, see Kremer and Morcom (2000)).

The estimated coefficient of corruption perception index for Indonesia (*CIIN*) is presented in the second column of Table 19. Corruption is higher for lower values of *CIIN*. The coefficient of *CIIN* is negative and highly significant, indicating that higher corruption increases illegal logging. The results confirm the results reported in previous studies (Palmer, 2001; Downs and Tacconi, 2012) that corruption is a key driver for accelerating harvesting and trading in illegal timber. Most illegal and corrupt activities, such as harvesting, delivery and making forged documents, happen in Indonesia rather than in the importing countries. In the model presented here, introducing the variable relating to the corruption index in Indonesia is much more meaningful than including the corruption perception index of importing countries (the corruption perception indexes for Japan and China were tested in the model, but they emerged as insignificant).

GDP in Indonesia (*GDP2005I*) has a negative and significant coefficient. According to Burgess et al. (2012), the rents from illegal logging and rents from other industries, such as oil and gas, contribute to revenue in the districts. If revenue from oil decreases because of the lower price, districts will issue more forest harvesting permits and even allow some illegal logging to make up for the loss in the revenue. Therefore, a low GDP will lead to an increase in illegal logging supply.

The fourth and fifth columns in Table 19 describe the estimates of illegal timber demand in Japan. The factor (*FACTORHF*) capturing the number of new houses (*HSJ*) and the wood floor production (*FLP*) has a positive and significant coefficient at a one per cent level. Wood and wood products used in the construction industry accounted for 40 per cent of total wood demand as the use of wood in buildings has cultural and traditional significance in Japan (MAFF, 2010). In a traditional house, roughly 0.2 m^3 of wood is required for one m^2 of non-structural area (MAFF, 2010). However, 80 per cent of the wood used in construction was imported (MAFF, 2010). Therefore, the increase of the number of new housing starts is considered a key factor affecting the importing of wood and illegal timber.

Additionally, the explanatory variable with the highest impact on Japan's demand is tied to the nation's ability to supply all the timber domestically. This is measured through the variable of the domestic self-sufficiency rate (*DSJ*), which is measured as a ratio of the domestic supply to the total demand. The coefficient of *DSJ* is negative and significant at the one per cent level. As shown in Figure 13, the domestic self-sufficiency rate fell in the beginning of 1990s and rose after 2006. The rate in 2010 was 23 per cent, which is similar to the 1991 rate (25 per cent). During the period from 1992 to 2008, the domestic self-sufficiency rate (*DSJ*) was lower than 25 per cent. This led to a higher demand of illegal timber in Japan due to insufficient domestic supply.

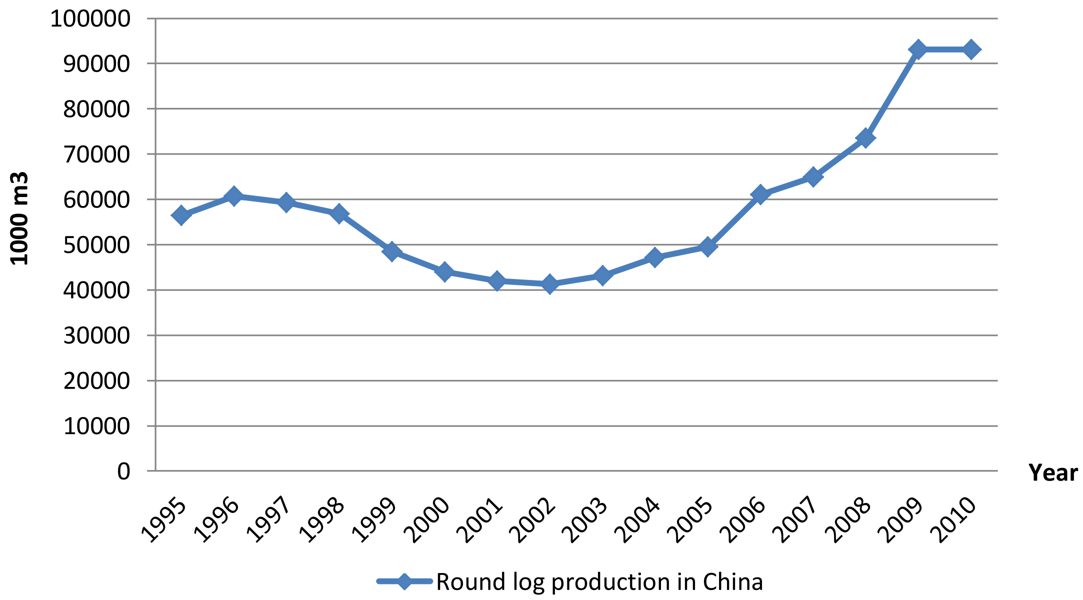


Source: (Araya and Katsuhisa, 2008)

Figure 13 Domestic timber self-sufficiency percentages in Japan from 1991 to 2009

The last two columns in Table 19 describe the estimates of illegal timber demand in China. The variable relating to the number of new houses (*HSC*) has significant and positive effects on illegal timber imports. Although the proportion of wood use has dropped to less than 10 per cent of total material value for houses over the past 30 years in China, the increasing numbers of new housing starts still lead to substantial wood consumption for interior decoration and furniture.

Next, the variable associated with the domestic wood production (*PLOGC*) in China was tested in the model. The coefficient of *PLOGC* is negative and significant. Figure 14 illustrates the round log production in China from 1995 to 2010. As shown in Figure 14, the production has declined since 1998. This is because China’s Natural Forest Protection Programme was implemented in 1998. This programme was aimed at controlling the resource crisis in the national forest area and preventing environment aggravation (Witness, 2009). Timber harvesting for commercial purposes was halted completely in the upper Yangtze River and the middle and upper reaches of the Yellow River. Commercial logging was also sharply reduced in the Northeast and Inner Mongolia. This programme has contributed a great deal towards forest protection. The cover of natural forest has increased by 393.05 million m^3 within the last 10 years, based on the comparisons between the 6th and 7th national forest resources inventory (Cao et al., 2011). In the meanwhile, the numbers of reforestation and afforestation projects have significantly increased in China. In 2000, the reforested area was around 46,000 hectares, including 4,000 hectares of fast-growing forests (Liu et al., 2000). After log production hit a low in 2002, production has increased because of reforestation projects providing additional harvesting options. The fluctuations in domestic wood supply have had significant effects on timber import demands. With a decrease in domestic wood supply, domestic consumption has increasingly relied on imports. This also adds to the demand for illegal timber, especially for tropical wood from Indonesia. However, whenever domestic wood supply has increased in the past, illegal timber demand has declined.



Source: National Bureau of Statistics of China

Figure 14 Production of round log in China from 1995 to 2010

The coefficient for Chinese GDP (*GDP2005C*) is negative and significant at a one per cent level of significance. The sign of this coefficient is opposite from what was anticipated. According to previous studies (EIA&Telapak, 2005; Robbins and Perez-Garcia, 2012), illegal timber imports have fuelled the development of the Chinese economy. However, total Chinese timber imports have dropped sharply since 2008 and imports of tropical timber also decreased slightly after 2003 due to improvements in milling technology and more efficient use of log (Witness, 2009).

4.4.2 Estimating the Effect of Policies to Curb Illegal Logging in Indonesia

In this section, four dummy variables for policies are used and tested in Indonesia's supply equation, one by one (their correlation coefficients among each other are higher than 0.5). These are the draft illegal logging law of 2005 (*LAW*), the banning of log exports (*REGU*), anti-money laundering and anti-corruption laws of 2005 (*ANTIM*) and bilateral agreements with timber-importing countries enacted in 2002 (*BIL*). Since the correlation coefficients between *CIIN* and the regulation related dummy variables, as well as between *NUDIS* and the dummy variables, are higher than 0.5, the variables *CIIN*, *NUDIS* were dropped from these regressions to avoid possible multi-collinearity problems. The results of the estimates are described in Table 20.

Table 20 Results of regulatory influence on illegal trading in Indonesia

	TOTALII			
constant	94.1172** (45.1789)	250.473*** (91.7428)	174.829*** (49.8416)	229.551*** (47.8729)
predicted EPIN	-5.0804 (3.5522)	-19.2447** (7.9533)	-11.4108*** (3.8996)	-15.5242*** (3.8342)
GDP2005I	-1.7120 (1.0827)	-2.1299 (1.5256)	-3.4888*** (1.173)	-4.9109*** (1.0303)
LAW	-3.6010*** (0.8091)	-	-	-
REGU	-	-5.6186** (2.3530)	-	-
ANTIM	-	-	-3.8387*** (0.8750)	-
BIL	-	-	-	-4.6162*** (0.8750)
Hausman test	Chi-square(1)= 6.235 P value= 0.01252	Chi-square(1)= 5.5332 P value= 0.0187	Chi-square(1)= 8.6273 P value= 0.0033	Chi-square(1)= 7.1192 P value= 0.0076
Weak instruments test	F-statistic= 29.6337	F-statistic= 13.7354	F-statistic= 19.6667	F-statistic= 42.4932
Sargan test	LM=2.4788 P value= 0.6484	LM=6.7727 P value= 0.2381	LM=2.7244 P value= 0.6050	LM=2.8579 P value= 0.5819

Note: the asterisk*, **, *** denote significance at the 10%, 5% and 1% level.

The coefficient of *LAW* is negative and highly significant (Table 20) suggesting that law enforcement has effectively reduced the quantity of illegal supplies overseas. The results of regression with *REGU* are presented in the third column of Table 20. The coefficient for *REGU* is significant and negative, which means the total illegal supply has dropped due to the implementation of the log export ban. This effect needs further explanation. In this chapter, the quantity of illegal supply is calculated using the discrepancies between Indonesia and importing countries' trade balances. The volume of illegal trading does not only include the logs, but also other products, veneer, plywood and sawn timber, which were converted to the log equivalent. According to the ITTO (1997-2012) report, the amount of log exported by Indonesia has declined significantly, while at the same time, Indonesia has been the largest exporting country for plywood since 1997. It seems that the log export ban is effective at limiting illegal log exports, but not so much at reducing illegal trading of other timber products. Logs are illegally exported overseas by transforming them to processed products, such as plywood (Burgess et al., 2012). As expected, the coefficient of *ANTIM* (anti-money laundering and anti-corruption laws) is negative and significant (in the fourth column of Table 20. Since corruption is a key driver of illegal harvesting, the laws and related policies are effective in curbing illegal logging by catching the grey money and preventing corruption. The results of regression, including the bilateral agreements (*BIL*), are presented in the last column of Table 20. Notice that the coefficient for *BIL* is also significant. Illegal logging is an activity that involves several parties and countries. Curbing illegal logging requires cooperation between countries. The estimates of their effects on timber-importing countries will be discussed in the following section.

4.4.3 The Green Purchase Law in Japan

Japan is one of the destinations for illegally supplied timbers. Curbing illegal logging imports in Japan contributes to the sustainable management of forests all across the world. The item 'legal wood' was added to the Green Purchasing Law by the Japanese Government after the issue of illegal logging was discussed at G8 Summit in 2005 (MOE, 2007). Based on this law, wood and wood products need to be verified for their legality and sustainability before being imported to Japan (MOE, 2007). Meanwhile, methods, such as tracing timber sources, using satellite data and cooperating with related countries, were developed by the Japanese Government to deal with illegal logging (MOE, 2007). Table 21 presents the regression results using the Green Purchasing Law (*GREENJ*) as a dummy variable. The variable of *GREENJ* has a negative and significant coefficient, which means the law has a positive effect on reducing imports of illegal timber.

Additionally, the tests for bilateral agreements (*BIL*) in Japan and China's demand models are presented in Table 21. This policy is not effective in controlling illegal timber trading from the demanding countries. Such agreements, especially involving several parties, have limited effects.

Table 21 Results of regulatory influence on illegal demand in Japan and China

	JII	JII	JII	JII	CII	CII
Methods	TSLS	OLS	TSLS	OLS	TSLS	OLS
constant	24.6828** (10.8372)	14.7716 (17.2936)	51.5428*** (11.3601)	49.7664*** (15.4560)	31.8234*** (12.0189)	37.2437** (14.4651)
predicted EPIN	-1.0227 (1.0196)	-	-0.8828 (1.0648)	-	-	-
EPIN	-	-0.0869 (1.6325)	-	-0.7041 (1.4089)	0.5302 (1.0008)	0.0058 (1.2014)
FACTORHF	0.2433 (0.3018)	0.2498 (0.3660)	-	-	-	-
DSJ	-	-	-9.4919*** (1.4712)	-9.5339*** (2.2221)	-	-
PLOGC	-	-	-	-	-2.1437*** (0.4121)	-2.1290*** (0.6837)
GREENJ	-1.5961** (0.6312)	-1.6049 (0.6217)	-	-	-	-
BIL			-0.5811** (0.2808)	-0.5644 (0.4226)	-0.3180 (0.2594)	-0.3623 (0.3585)
Hausman test	Chi-square(1)= 2.9385 P value= 0.0865	R-squared= 0.5458	Chi-square(1)= 0.1380 P value= 0.7103	R-squared= 0.6942	Chi-square(1)= 0.8289 P value= 0.3626	R-squared= 0.5374
Weak instruments test	F-statistic= 73.1746		F-statistic= 55.6693		F-statistic= 67.1876	
Sargan test	LM=8.8975 P value= 0.0307		LM=0.0798 P value= 0.9941		LM=5.8073 P value= 0.0548	

Note: the asterisk*, **, *** denote significance at the 10%, 5% and 1% level.

4.5 Concluding Remarks

In this chapter, I constructed a simultaneous-equations model to estimate the key factors responsible for illegal harvesting and illegal trading in Indonesia. The model estimates separate illegal demand functions for Japan and China and the illegal timber supply function for Indonesia. Variables in both demand and supply aspects were estimated in this study.

The increasing number of districts in Indonesia was considered a critical factor relating to unsustainable forestry. Additionally, I also looked at the role of corruption in Indonesia. In the demand models, excessive demand in the Japanese market and the number of new houses in

Japan and China were estimated as key drivers of illegal logging demand from Indonesia. Further, the political factors were also considered in this model since several policies have been implemented to control deforestation related crimes in Indonesia.

The important findings from the analysis above are summarised as follows. First, the problem of domestic corruption is a key driver influencing illegal trade. Second, the increase of forest extraction permissions caused by the increase in the number of districts, merely disguises ‘illegal’ logging as a legal practice. Although the results suggest that ‘illegal’ logging has reduced as a result, the total rate of deforestation has in fact increased.

On the demand side, the growth in Chinese economy has not led to an increase in illegal demand. This could potentially be attributed to improvement in log use efficiency and milling technologies. Therefore, technological progress is a key factor in reducing illegal demand. In China, timber demand has shifted from domestic to imports, including illegal timber, due to the implementation of natural resource protection policies in the recent past. However, the capacity of domestic supply has also increased due to the rapid implementation of afforestation and reforestation projects. Therefore, the demand for imported illegal timber has consequently declined.

Additionally, the number of new houses is significant driver for illegal imports for both Japan and China. The Japanese furniture industry has become the largest consumer of wood products from illegal sources. The analysis also indicates that the level of domestic timber sufficiency is a key factor responsible for illegal trading in Japan.

We also found that law enforcements or policies with legal foundations have made advancements towards curbing illegal harvesting. Since corruption is a key driver of illegal harvesting, the associated laws and related policies are effective in curbing illegal logging by catching the grey money and preventing corruption. However, the results also suggest that fixing the domestic system is more effective than inter-country bilateral agreements aimed at curbing illegal trade.

Chapter 5 Optimal Carbon Mitigation Including the Reducing Emissions from Deforestation and Forest Degradation Option

Abstract

REDD programmes offer an attractive option to cheaply mitigate carbon. However, there are challenges associated with the designing of the optimal level of REDD that society must invest in given the risks and non-uniform costs associated with REDD implementation in various countries. This chapter develops an integrated assessment model for carbon mitigation, incorporating the REDD option. It derives the optimal timing and level of REDD participation for key countries based on their opportunity costs and risks. The data used for calibrating equations in the model are gathered from existing literature and reports. Additionally, the relevance and importance of REDD programmes is explored under the possibility of non-linear damages resulting from the accumulated stock of atmospheric carbon. Results indicate that the REDD programme is an attractive option to consider in the optimal management of the climate change problem. For countries with lower risks, REDD programmes may be more preferable than countries with higher risks if they face the same level of opportunity costs.

5.1 Introduction

REDD programmes are considered an attractive option to mitigate the global warming problem in the short term, as it is cost-effective to pay farmers to stop deforestation compared to other options, such as sequestration through afforestation or conventional abatement methods (Enkvist et al., 2007; Boucher, 2008; Börner and Wunder, 2008; Olsen and Bishop, 2009). However, REDD programmes are not straightforward to implement, due to the diversity in opportunity costs across various regions of the world and the uncertainty associated with implementing, measuring and monitoring carbon preserved under REDD programmes (Alvarado and Wertz-Kanounnikoff, 2007; Pagiola and Bosquet, 2009; Hufty and Haakenstad, 2011). Brazil and Indonesia, which have large REDD potential, offer cheap options of reducing deforestation, as 90 per cent of their opportunity costs are less than US$5 per tonne of CO_2 (Nepstad, 2007; Swallow et al., 2007). However, unresolved challenges exist in the technical aspect for REDD implementation, such as baseline decisions, monitoring and risk of non-permanence (Alvarado and Wertz-Kanounnikoff, 2007).

The previous literature has concentrated on the optimal strategies for climate mitigation through mostly conventional abatement options. Recently Integrated Assessment Models (IAMs) have been developed to examine the possibility of reducing emissions through avoided deforestation. Sohngen and Mendelsohn (2003) integrate the DICE model with the global timber model (GTM) to analyse the potential role of forests in reducing emissions. In their model (see Table 5 in Sohngen and Mendelsohn (2003)), optimal reduction increases from 203.1 billion tonnes to 299.4 billion tonnes when considering carbon sequestration through avoided deforestation. Carbon sequestration from avoided deforestation constitutes about one third of the total mitigation.

There is an emerging body of literature on REDD and REDD-plus programmes basically highlighting the benefits, opportunity costs and implementation challenges (UN-REDD-

Programme, 2009; Karousakis, 2009; Sathaye et al., 2011; Rose and Sohngen, 2011). Besides reducing emissions through deforestation, REDD programmes bring other benefits such as promoting forest and ecosystem conservation and improving the forest carbon stocks (UN-REDD-Programme, 2009; Karousakis, 2009). The implementation of REDD, however, is not without its challenges. It relies heavily on coordination among REDD participants (Bosetti and Rose, forthcoming) and the timing and eligibility of participants needs to be carefully evaluated (Rose and Sohngen, 2011).

Although the forest-based activities may not eliminate deforestation, they can reduce the accelerated deforestation effectively (Rose and Sohngen, 2011). The extensive REDD-plus programme, which 'goes beyond deforestation and forest degradation, and includes the role of conservation, sustainable management of forests and enhancement of forest carbon stocks', is considered effective for developing countries with large forest areas (Sathaye et al., 2011). Additionally, the side effects of REDD programmes is another issue that deserves attention as well. Fuss et al. (forthcoming) argue that the low-cost REDD option, by virtue of being cheaper, may discourage investments in alternative energy and technological innovations. Fuss et al. (forthcoming) use a real option model to derive the optimal timing of REDD participation, while reducing investment in carbon-intensive energy technology.

While a significant amount of work has been done lately, existing REDD-based models have not considered certain features that are crucial towards informing the current debate on climate change mitigation strategies. First, none of the models have explored the optimal strategy of climate change mitigation through REDD when damages from carbon crossing a certain threshold could increase in a non-linear fashion. Second, the risk of large scale carbon release from REDD programmes due to fires or political instability is also not adequately considered. Third, IAMs so far have not looked at the individual opportunity costs (or risks) of countries with large REDD potential to derive their optimal timing and extent of involvement in a global model. An integrated assessment model that includes the REDD option for major countries with high REDD potential, such as Brazil and Indonesia, is still absent. This chapter attempts to fill this gap.

The aims of the study are to investigate the influence of REDD options on overall carbon abatement strategies and the effects of the risks associated with REDD programmes. In this chapter, an IAM is developed to estimate the optimal carbon abatement considering the conventional mitigation methods and the option of preventing carbon deforestation through REDD for developing countries with large forestry areas, such as Brazil, Indonesia, the Democratic Republic of Congo (DRC), Cameroon and Papua New Guinea (PNG). The data used for calibrating equations in the model are gathered from existing literature and reports. To estimate the effects of REDD and REDD risks, scenario analyses are conducted. In the first scenario, I assume there is only the conventional abatement option available in the model. In the second scenario, the REDD option is included in the optimal strategy. In the last two scenarios, the effects of risks on REDD programmes are analysed. Lastly, sensitivity analysis is performed to evaluate the alterations to key findings from key parameter variation.

This chapter explores some key insights through the inclusion of the above features. First, I note that the abatement strategy is sensitive to an increase in average annual emissions. Once average emissions cross a certain threshold, it leads to significantly higher damages and stock of carbon and reduces optimal abatement over time, as high damages do not make it cost-effective to invest significantly in abatement.

Second, adding a REDD option actually increases conventional abatement and leads to a decline in the long-term atmospheric carbon stock. This is because the low cost of REDD reduces the overall costs of abatement. This makes it optimal to invest more abatement effort into avoiding a high stock accumulation. Whereas, without the REDD option, it is suboptimal to invest heavily in abatement. Since damages are non-linear, there is a threshold effect in terms of carbon stock. When high abatement is not optimal, either due to high costs of abatement or due to high emissions, the optimal response is to let carbon stock increase and suffer higher damages in the long term rather than have a higher mitigation at the cost of forgone consumption in the current period. Finally, I find that the risk of release from REDD programmes could reduce the attractiveness of these programmes. At the same time, it also undermines the benefits of conventional abatement strategies. Therefore, more effort should be invested into monitoring factors that increase risks.

5.2 A Brief Background on the Opportunity Costs of REDD

Several studies have pointed towards the significance of the opportunity costs of land use in total REDD costs. Opportunity cost of REDD is the 'largest and most important single component of costs' associated with reducing emissions through REDD programmes (Olsen and Bishop, 2009; Pagiola and Bosquet, 2009). Wertz-Kanounnikoff (2008) has discussed the two main approaches found in the literature to estimate the opportunity costs of REDD—the global models and the regional models (Boucher, 2008; Wertz-Kanounnikoff, 2008). To estimate the supply of REDD services, the global simulation models basically look at the value of a piece of land to be brought under REDD when dedicated to its alternative uses, such as agricultural or other potentially economic uses (Wertz-Kanounnikoff, 2008). Some of these models, described in detail in Kindermann et al. (2008), are the GTM, the Dynamic Integrated Model of Forestry and Alternative Land Use (DIMA) and the Generalised Comprehensive Mitigation Assessment Process Model (GCOMAP).

These models differ in scale, extent of global coverage and methodology. The GTM uses a dynamic optimisation approach, capturing competition between forest land and agriculture land uses, to predict land use and management of various timber types. DIMA derives land use choices between agriculture and forestry by comparing their net present values at a fine scale of 0.5 degree grid cells, whereas GCOMAP predicts the same at a much coarser level using a partial general equilibrium model (Kindermann et al., 2008). Kindermann et al. (2008) use the above three models to estimate the costs of reducing deforestation by 10 per cent and 50 per cent between 2005 and 2030. From the three models, the carbon price is derived to fall between US$1.41 and US$3.50 per tonne of CO_2 for reducing deforestation by 10 per cent, whereas the price of reducing half of deforestation is between US$9.27 and US$20.57 per tonne of CO_2 in 2030 (see Table 3 in Kindermann et al. (2008)).

The global opportunity cost can also be evaluated by using the local-empirical estimates (Boucher, 2008). The local estimates of opportunity costs are based on the regional carbon density, which is the carbon storage of one hectare of forest land and is different in different areas. Using a global average carbon density, one can convert the diverse local opportunity costs into a uniform cost for the world (Boucher, 2008).

The regional opportunity costs of REDD are evaluated using specific surveys and studies and the local carbon density in these areas (Wertz-Kanounnikoff, 2008). Nepstad (2007) evaluate forest land change and opportunity costs on a pixel-level (such as $4km^2$) (see also Wertz-Kanounnikoff (2008)). For reducing deforestation to zero in 30 years, 90 per cent of the opportunity costs are under US$5 per tonne of CO_2 in Brazil's Amazon (Nepstad, 2007). Besides, the general and random sample survey is another basic method to get data for evaluating opportunity costs (Grieg-Gran, 2006; Swallow et al., 2007). Combining local survey and generic estimates, which are from the average results based on surveys, Grieg-Gran (2006) evaluates the opportunity costs of avoiding deforestation. Grieg-Gran (2006) selects eight countries with the most REDD potential—Brazil, Indonesia, PNG, Cameroon, Congo, Ghana, Bolivia and Malaysia. In this chapter, the basic data used for REDD opportunity cost calibration for the five countries selected are taken from Grieg-Gran (2006).

A brief outline of the chapter is as follows. Section 5.3 presents the model details. Section 5.4.1 introduces four key scenarios and Section 5.4.2 discusses the results. Section 5.4.3 performs a sensitivity analysis. Finally, the conclusion highlights and generalises the main findings.

5.3 Model Description

The IAM model used in this chapter interprets the integrated effects of the economic loss caused by the stock of the atmospheric carbon and the costs of carbon abatements on global GDP. The model contains five parts: equations for calculating annual carbon emissions, carbon stock equation, damage equation, carbon abatement costs equations and global GDP equation. The annual carbon emissions contain emissions from deforestation and other sources. The carbon stock is calculated based on the pervious carbon stock and the new emissions in a year. The damage function helps calculate the economic loss caused by the carbon stock. The cost functions for conventional abatement and REDD programme are also considered in the model. In the GDP function, the value of GDP in a year depends on the previous year's GDP, economic damage caused by carbon stock, economic cost of conventional abatement and the cost of REDD programmes.

Annual emissions are assumed to be average emissions for the entire time and are represented in parts per million (ppm).

$$emisson(t) = emi * (1 - abt(t)) \tag{27}$$

where $emisson(t)$ is the annual emission. $abt(t)$ is the percentage of carbon mitigated by conventional abatement. According to World Greenhouse Gas Emissions (GHG) report, in 2005 , the total GHG emissions (including emissions from deforestation) was 44.153 Gt of CO2 equivalent (Herzog, 2009), which is roughly equal to 5.690 ppm (even though ppm is used to represent carbon stocks, I am representing flows in ppm units for simplicity of presentation). In this study, I assume that the global GHG emissions are six ppm per year. I convert the percentage of abatement to $abtppm(t)$, which is the amount of carbon represented in parts per million:

$$abtppm(t) = emi * abt(t) \tag{28}$$

CO_2 emissions from deforestation $femission_i(t)$, are measured separately in the model:

$$femission_i(t) = forestloss_i(t) \tag{29}$$

where i represents the countries (Brazil, Indonesia, Cameroon, the DRC and PNG) and $femission_i(t)$ is the annual carbon emissions from forestry. This equals carbon dioxide released from deforestation in countries, $forestloss_i(t)$, which is estimated as:

$$forestloss_i(t) = forestlossrate_i * SF_i(t) \tag{30}$$

Where $forestloss_i(t)$ represents CO_2 released through deforestation. i represents countries like Brazil, Indonesia, Cameroon, the DRC and PNG. $SF_i(t)$ is the forest stock at time *t* and $forestlossrate_i$ is the annual deforestation rate (see Table 25 in Appendix C), which is modelled as:

$$forestlossrate_i(t) = \frac{\eta fl_i * t^{afl_i}}{t^{afl_i} + bfl_i} + cfl_i \tag{31}$$

where t is the period, and ηfl_i , afl_i , bfl_i and cfl_i are the parameters of the non-linear function described in Table 26 in Appendix C.

The time path of forest stock is given as:

$$SF_i(t+1) = SF_i(t) - forestloss_i(t) - REDD_i(t) \tag{32}$$

The current forest area equals $SF_i(t) - forestloss_i(t)$ (previous forest stock minus forest loss). $REDD_i(t)$ is carbon sequestrated through REDD programmes for country *i*. In the model, the annul forest stock is the existing forest area that excludes forest in REDD programmes. The constraint function to limit the annual potential of REDD programmes to a maximum of annual forest loss is given as:

$$REDD_i(t) < forestloss_i(t) \tag{33}$$

The time path of stock of REDD is given as:

$$SR_i(t+1) = SR_i(t) + REDD_i(t) - riskrate * SR_i(t) \tag{34}$$

where $SR_i(t)$ represents the stock of REDD programmes in year *t*. $SR_i(t)$ equals to the previous stock of REDD-plus current year REDD additions and includes the expected losses, where the risk of loss is given by $riskrate$. The stock of the atmospheric carbon evolves as:

$$\begin{aligned} carbon(t+1) = {} & carbon(t) - \delta * carbon(t) + emission(t) \\ & + femission_i(t) + riskrate * REDD_i(t) \end{aligned} \tag{35}$$

where δ is the rate of decay of atmospheric carbon into deep oceans. In each period, the carbon stock in the atmosphere includes the carbon stock in the previous year ($carbon(t) - \delta * carbon(t)$), emissions from fossil fuels $emission(t)$ and deforestation $femission_i(t)$ and carbon release caused by loss through of REDD programmes $riskrate * REDD_i(t)$.

The atmospheric carbon is converted into economic damages assuming a non-linear relationship:

$$damage(t)=\left(\frac{\eta dam*\left(carbon(t)/\ percarb\right)^{adam}}{\left(carbon(t)/\ percarb\right)^{adam}+bdam}*cdam\right)*gdp(t) \qquad (36)$$

Where $damage(t)$ describes the economic loss caused by carbon stock, which is in terms of percentage of annual $gdp(t)$ loss. Figure 15 shows the non-linear damage function. Notice that a sharp increase in damages is assumed once the carbon stock crosses about 410 ppm. The value of parameters, $percarb$, ηdam, $adam$, $bdam$ and $cdam$, are presented in Table 27 in Appendix C.

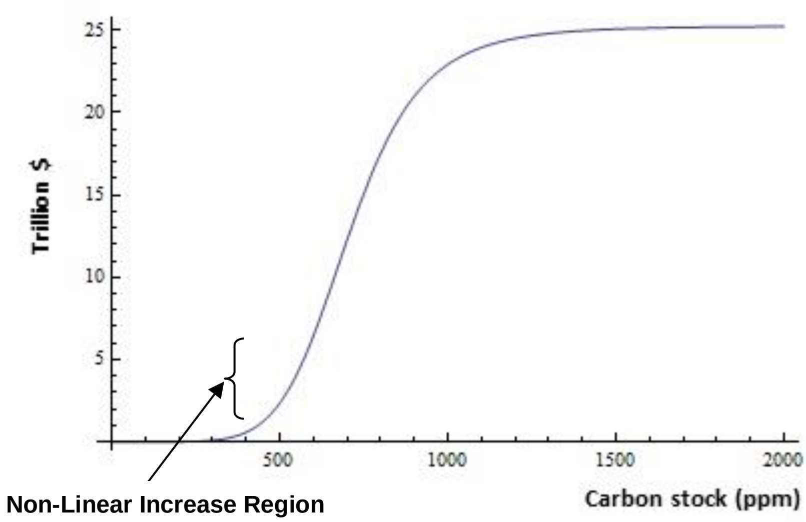


Figure 15 Non-linear damages as a function of atmospheric stock of carbon

The cost of conventional abatement is assumed to take the following form:

$$abcost(t)=\frac{\eta abcst*\left(abtppm(t)\right)^{aabcst}}{\left(abtppm(t)\right)^{aabcst}+babcst} \qquad (37)$$

where $abcost(t)$ represents the cost of conventional abatement, which is dependent on the amount of carbon abatement (in parts per million). $cabcst$, $\eta abcst$, $aabcst$, $babcst$ are the non-linear parameters and their values are depicted in Table 28 in Appendix C. This function is calibrated based on information presented in Table 22. Figure 16 illustrates the functional form associated with the conventional abatement costs (presented in annual terms). The conventional cost increases sharply with an increase of the abatement amount. In the beginning, the cost of abating the first five ppm emissions is about US$ 2 trillion, whereas it would cost more than US$ 6 trillion dollar when 10 ppm emission is abated. I assume that abatement cost eventually stabilises due to technological advances in future.

Table 22 Conventional abatement cost function estimation

	Gt CO_2[3]	Cost per tonne ($)[3]	CO_2 without REDD(Gt)[4]	CO_2 without REDD(ppm)[5]	Total cost without REDD(trillion$)
McKinsey[1]	18	38	16	2.047	0.608
McKinsey	26	61	24	3.07	1.464
McKinsey	33	77	31	3.966	2.541
Dietz and Stern[2]	40	100	38	4.861	3.8

1. Source: Enkvist et al. (2007)
2. Source: Dietz and Stern (2008)
3. The first two columns show the CO_2 abated by conventional methods with different costs. Gt=Giga tonne
4. REDD programmes could abate 2Gt of CO_2 every year.
5. CO2 is divided by a factor of 7.8171 to get CO_2 in terms of ppm. One tonne of carbon= 3.66 tonnes of CO2(Sofo et al., 2005), 1ppm CO2=2.12 Gt of carbon (Burgess et al., 2012).

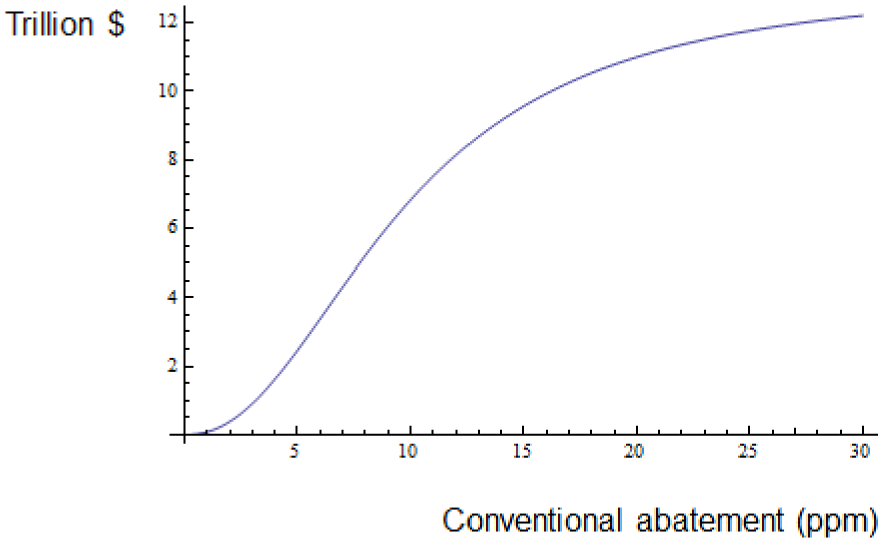


Figure 16 Conventional abatement cost as a function of carbon (ppm) abated

The cost function of REDD programmes is as follows:

$$REDDcost_i(t) = \frac{crdcost * \eta rdcst * \left(REDD_i(t)\right)^{ardcst}}{\left(REDD_i(t)\right)^{ardcst} + brdcst} \tag{38}$$

The cost of REDD depends on the quantity of abatement through REDD programmes ($REDD_i(t)$). The values of parameters, $crdcost$, $\eta rdcst$, $ardcst$ and $brdcst$ are illustrated in Table 29 in Appendix C. The REDD cost functions for each country are estimated based on information presented in Table 23.

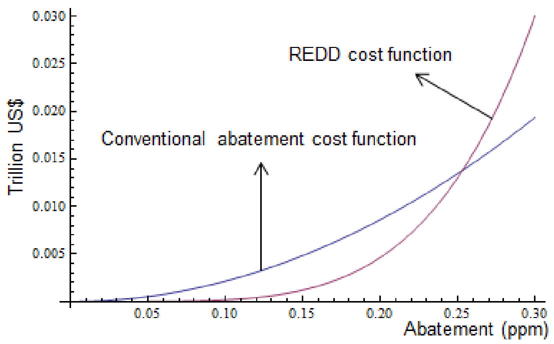
Table 23 REDD cost functions estimation

Country	Land use	US$/ha	No of ha (000)	Carbon storage/ha[1]	Tonne of CO2_e/ha[7]	Amount of CO2_e (ppm)[8]	US$/ppm CO2_e (trillion)
Cameroon				182[2]	667.94		
	Annual food crops short fallow	774	86			0.0073	0.0138
	Annual food crops long fallow	346	44			0.0038	0.004
	Cocoa with marketed fruit	1365	66			0.0056	0.0156
	Cocoa without marketed fruit	740	22			0.0019	0.0087
	Oil palm and rubber	1180	2			0.0002	0.0091
DRC				146[3]	535.82		
	Annual food crops short fallow	774	124			0.0085	0.0113
	Annual food crops long fallow	346	64			0.0044	0.005
	Cocoa with marketed fruit	1365	96			0.0066	0.0199
	Cocoa without marketed fruit	740	32			0.0022	0.0108
	Oil palm and rubber	1180	3			0.0002	0.0172
Brazil				110[4]	403.7		
	Beef cattle medium/large scale	626	1955			0.101	0.0121
	Beef cattle small-scale	2	217			0.0112	0.00004
	Dairy	154	217			0.0112	0.003
	Soybeans	2135	155			0.008	0.0413
	Manioc/rice	2	496			0.0256	0.00004
	Perennials	239	31			0.0016	0.0046
	Tree plantations	2614	31			0.0016	0.0506
Indonesia				151[5]	554.17		
	Large scale oil palm	2705	380			0.0269	0.0382
	Supported growers	2085	109			0.0077	0.0294
	High yield independent	2205	30			0.0021	0.0311
	Low yield independent	1515	79			0.0056	0.0214
	Smallholder rubber	1071	561			0.0398	0.0151
	Rice fallow	26	355			0.0252	0.0004
	Cassava monoculture	18	355			0.0252	0.0003
PNG				151[6]	554.17		
	Oil palm estates	2705	46			0.0033	0.0382
	Smallholder oil palm	1515	23			0.0016	0.0214
	Smallholder subsistence crops	1737	70			0.005	0.0245

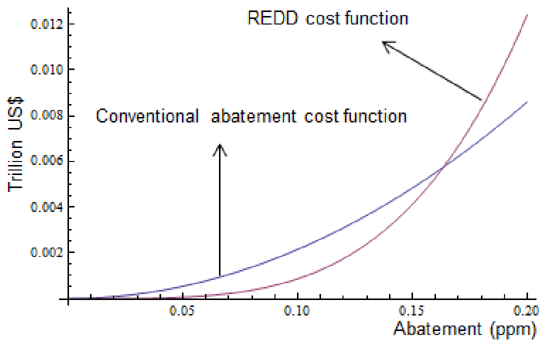
Source: Grieg-Gran (2006), Table 5 Global and National Costs of Foregone Land Uses (medium scenario of one-off timber harvesting)

1. To get REDD cost (US$/tonne of CO_2_e), I need to know the amount of carbon stocked in one hectare in each country's forestry.
2. Source of carbon storage: Swallow et al. (2007).
3. Source of carbon storage: Laporte (2007).
4. Source of carbon storage: Olsen and Bishop (2009).
5. Source of carbon storage: Olsen and Bishop (2009).
6. Source of carbon storage: for PNG I use the same carbon stock per hectare as Indonesia, Olsen and Bishop (2009).
7. Multiply hectares of land by the amount of CO_2_e per hectare to get the amount of CO_2_e for this land use category and convert it to ppm.
8. Calculate the total cost of different categories and divided by the amount of CO_2_e to get the unit cost.

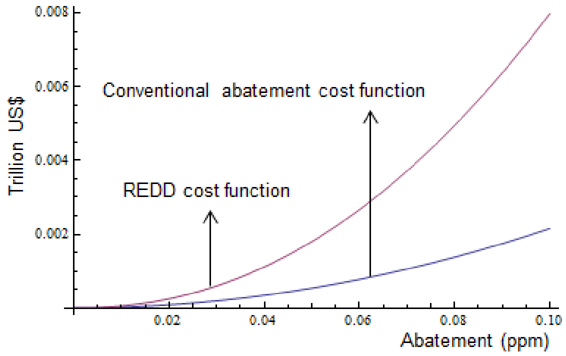
The comparisons between global conventional abatement costs and REDD costs in Brazil, Indonesia, Cameroon, DRC and PNG are provided in Figure 17. In Figure 17 (A), in the beginning, conventional abatement costs are higher than Brazil's REDD costs. The REDD costs increase gradually and surpass the conventional costs after the maximum REDD potential (0.1127 ppm in Brazil) is reached. Figure 17 (B) depicts the comparison between conventional costs and costs of REDD in Indonesia. When abatement exceeds around 1.56 ppm, the REDD cost is higher than the cost of conventional abatement. Comparing their relative REDD costs—Brazil is the cheapest, followed by Indonesia (Figure 17 (B)). In Cameroon (Figure 17 (C)), DRC (Figure 17 (D)) and PNG (Figure 17 (E)), the REDD costs are relatively higher than the costs for Brazil and Indonesia. They are also higher when compared to the conventional abatement costs due to their lower REDD potential.



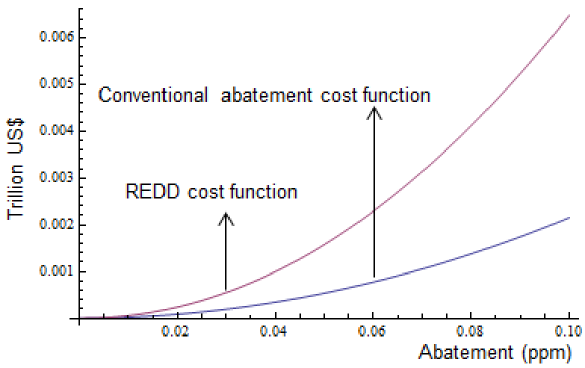
A. Brazil



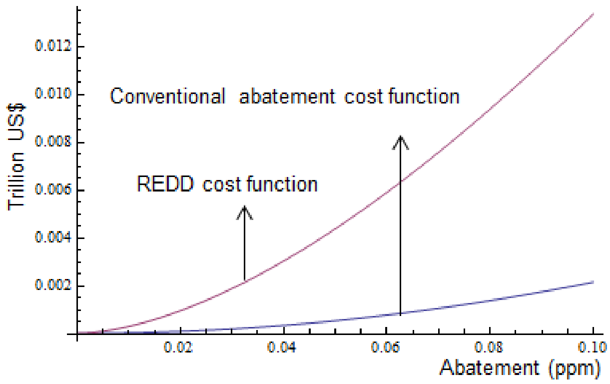
B. Indonesia



C. Cameroon



D. DRC



E. PND

Figure 17 Comparisons between conventional abatement and REDD costs

Next, the GDP growth is modelled:

$$gdp(t+1) = inrate * \left(gdp(t) - damage(t) - abcost(t) - REDDcost_i(t)\right) \tag{39}$$

The value of $gdp(t)$ next year depends on the previous year's GDP, net of any economic damage caused by carbon stock ($damage(t)$), economic cost of conventional abatement ($abcost(t)$) and the cost of REDD programmes ($REDDcost_i(t)$). Annual GDP is assumed to grow by an amount ($inrate$).

Society's objective is to maximise global utility, which is a function of the GDP. Utility is assumed to have a constant elasticity of substitution in GDP:

$$Societal\,Utility = \sum_{t=1}^{\infty} \frac{(gdp(t)+1)^{1-\eta}}{1-\eta} DR(t) \tag{40}$$

where $DR(t)$ is the discount process, $\frac{1}{(1+r)^{t-1}}$. r is the discount rate, which is 0.03. η is the elasticity parameter. The societal utility is the sum of the annual utility. Other parameters in the model and their values are depicted in Table 30 in Appendix C.

5.4 Scenario Description and Empirical Calibration

5.4.1 Scenario Description

Abatement methods, such as nuclear, new coal, wind, biodiesel and so on, are estimated synthetically, as conventional abatement methods. In the first scenario, I assume there is only the conventional abatement option available. In the second scenario, the REDD option is included in the optimal strategy. Five countries, Brazil, Indonesia, the DRC, Cameroon and PNG, are chosen to represent the reality of global forest and REDD programmes, especially REDD costs. There are three reasons for selecting these countries. First, they are located on the main forest areas in the world. More specifically, Brazil sits on the Amazon Basin of South America, which is the largest rainforest area in the world. The Congo Basin is home to roughly one fifth of the world's remaining tropical forests (WWF, 2011). The DRC and Cameroon are the two of the largest countries with forestry in this area. Indonesia and PNG are representative of forestry in South Asia. In addition, the forest area in the five countries accounts for 51 per cent of total forestry in developing countries. According to Global Forest Resource Assessment (FAO, 2010), Brazil, the DRC and Indonesia are included in the top 10 countries with largest forestry areas. The total forest coverage of these five countries is 817 million hectares, which is 20 per cent of global forest area and 51 per cent of forest in developing countries. Finally, the annual deforestation in these countries accounts for 43 per cent of global deforestation. The annual net forest loss in Brazil, Indonesia and the DRC are 2,194, 685 and 425 thousands hectares respectively. Including PNG and Cameroon, annual deforestation in these countries is 3.67 million hectares, which is 43 per cent of annual global deforestation (Butler, 2010). In the third scenario, the risks to REDD programmes are considered in the model. These risks could undermine REDD attractiveness. One of risks to REDD projects is illegal logging caused by corruption in REDD countries. Natural disasters, such as bushfires, floods and pest diseases, could adversely influence the REDD programmes as well. These risks could vary across countries. While the risk to the entire stock may be seen as coming from fires, pest infestations or political instability, the annual risks can come through improper and inadequate implementation, which does not give an accurate idea of actual REDD participation. For sensitivity analysis, I assume that the risk to annual REDD programmes is 10 per cent per year. There could also be a large scale risk present to the entire stock of REDD, possibly stemming from political instability in these countries. This is addressed in the fourth scenario. I assume that the risk to the entire stock is 0.3 per cent. Descriptions of scenarios are also listed in Table 24.

Table 24 Scenario description

Scenarios	Scenarios description
Scenario 1	No-REDD option
Scenario 2	Including REDD option
Scenario 3	REDD option with 10 per cent loss risk to the annual rate of REDD
Scenario 4	REDD option with 0.3 per cent loss risk to the rate of REDD stock

5.4.2 Simulation Results

Figure 18 depicts the changes in abatement time paths caused by inclusion of the REDD programmes. The presence of the REDD option could potentially also increase the optimal conventional abatement efforts. Considering the abatement through REDD (around 1.5 Gt of CO_2 every year), the total abatement under the second scenario including REDD programmes is higher than the first scenario with conventional abatement only. From the above, one key observation can be made: implementation of REDD programmes not only reduces the emissions from forestry, it also promotes higher abatement through conventional methods. As the availability of cheaper REDD option reduces the overall abatement costs and the damages, it becomes optimal to reduce further carbon through conventional abatement as well.

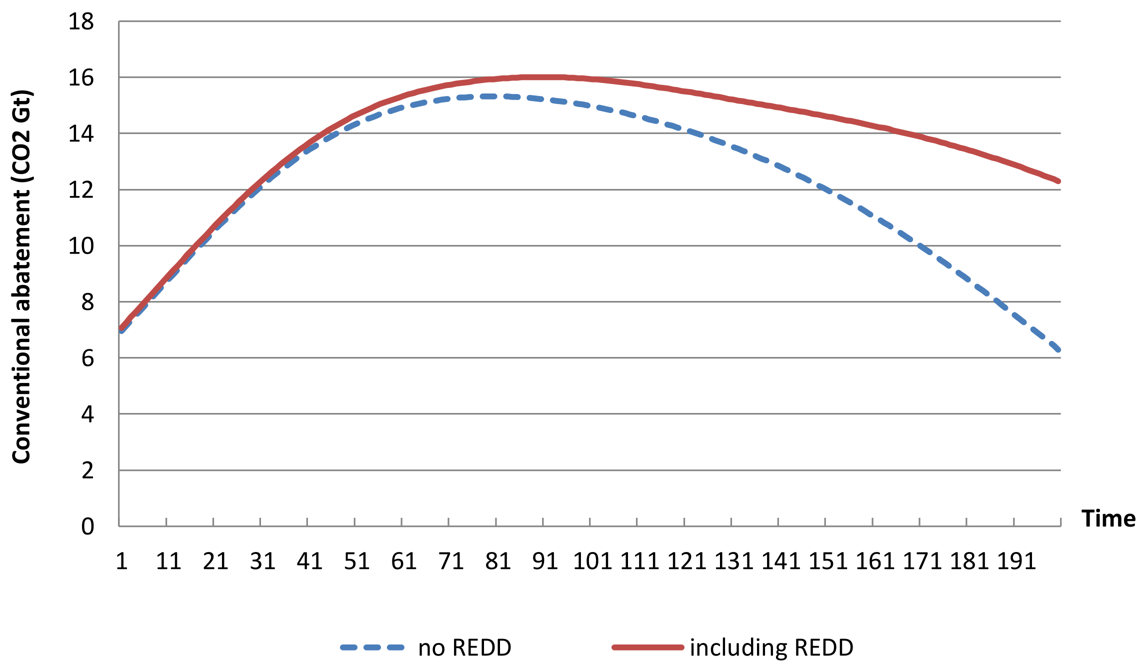


Figure 18 Time path of abatement under no-REDD and REDD scenarios

In the long term, the REDD option has a significant impact on the time path of the carbon stock (Figure 19). For the first 50 years, the carbon stock under both no-REDD and including REDD scenarios are very close (Figure 19). The carbon stock without a REDD option increases gradually after 50 years due to cost-benefit considerations in the latter years. Whereas, the REDD option helps with reducing the growth rate of carbon stock, which keeps the carbon stock stable. This leads to a significant difference, of around 100 ppm of carbon stock, between the no-REDD and including REDD scenarios, in the long term.

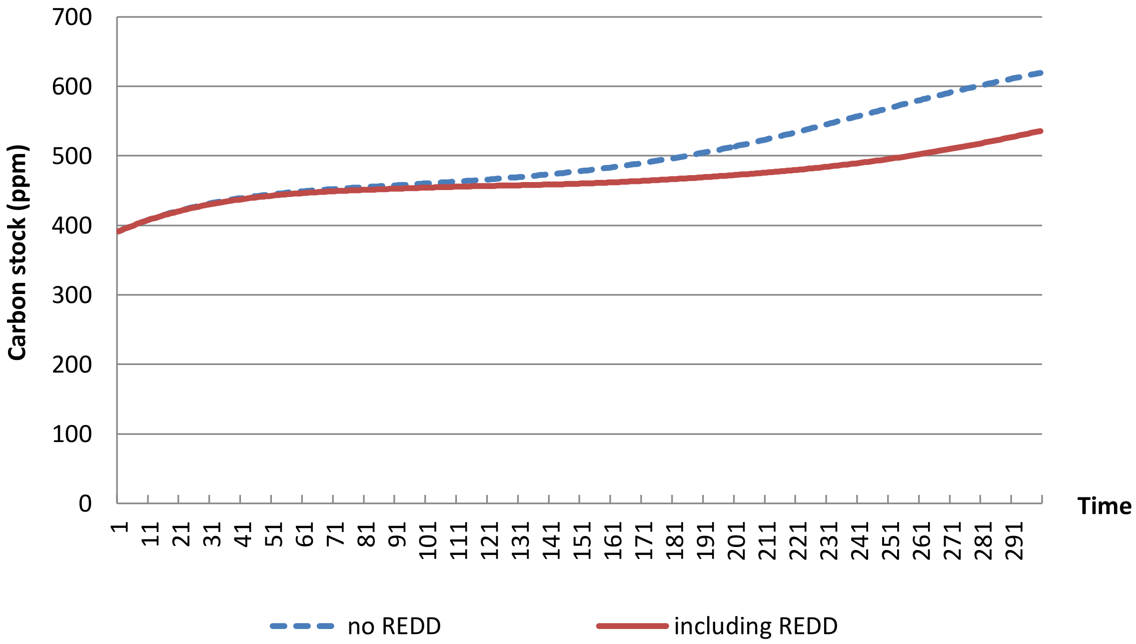


Figure 19 Time path of carbon stock under no-REDD and REDD scenarios

The time paths of the annual damages are illustrated in Figure 20. Due to the REDD option, the damages under the REDD scenarios are lower than the damages under no-REDD scenario for the first 180 years. However, the two scenarios lead to completely different carbon paths in the long term. The damage under the no-REDD scenario sharply decreases. Since the non-linear damage is estimated as a percentage of GDP, its magnitude in the long term decreases as GDP declines significantly too. In contrast, the damage under the REDD scenario is lower and stable as the associated carbon stock is low.

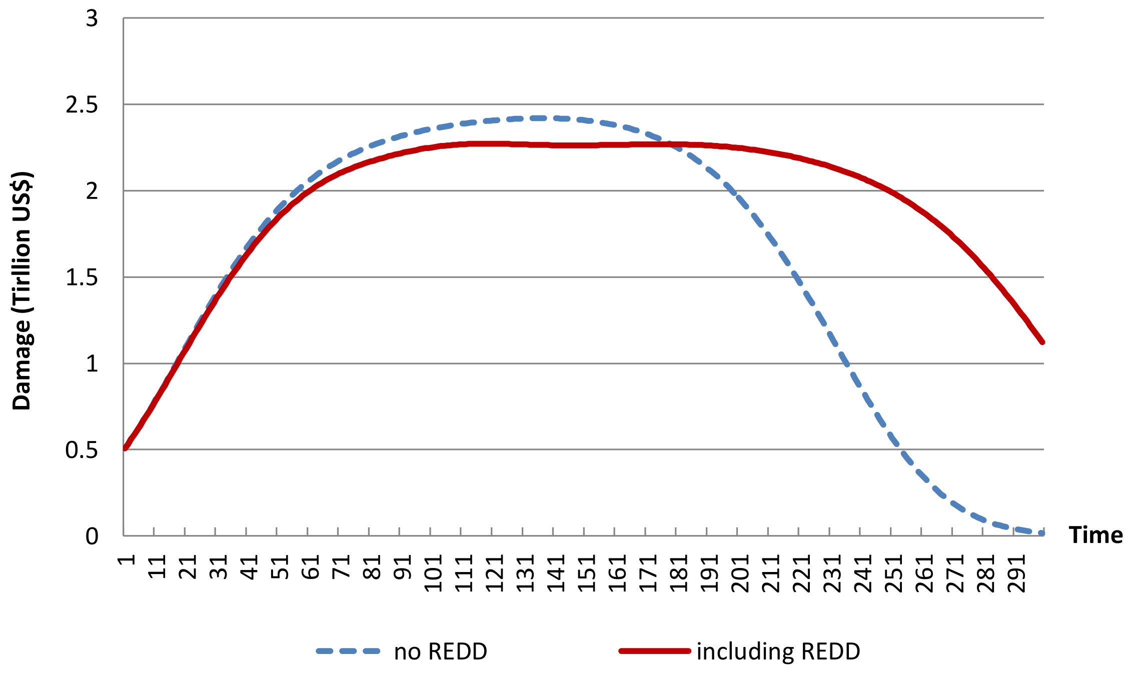


Figure 20 Time path of damages under no-REDD and REDD scenarios

Figure 21 depicts the influence of risk on REDD programmes. The second scenario, REDD option without risks, leads to the highest level of REDD participation. When there is an annual risk present of three per cent loss of REDD forestry through fires and other illegal harvesting, optimal REDD participation is significantly reduced. Additionally, the impact of a small risk to the whole forest area under REDD has similar implications to the impact of a much larger risk, restricted only to the annual REDD implementation (see scenarios of 10 per cent loss risk to the annual rate of REDD and 0.3 per cent loss risk to the rate of REDD stock in Figure 21).

Notice that the annual amount of REDD implementation is restricted from above by the level of the annual forest loss (Figure 22). Under the scenario with no risk of REDD loss, implementation of REDD reaches its maximum potential.

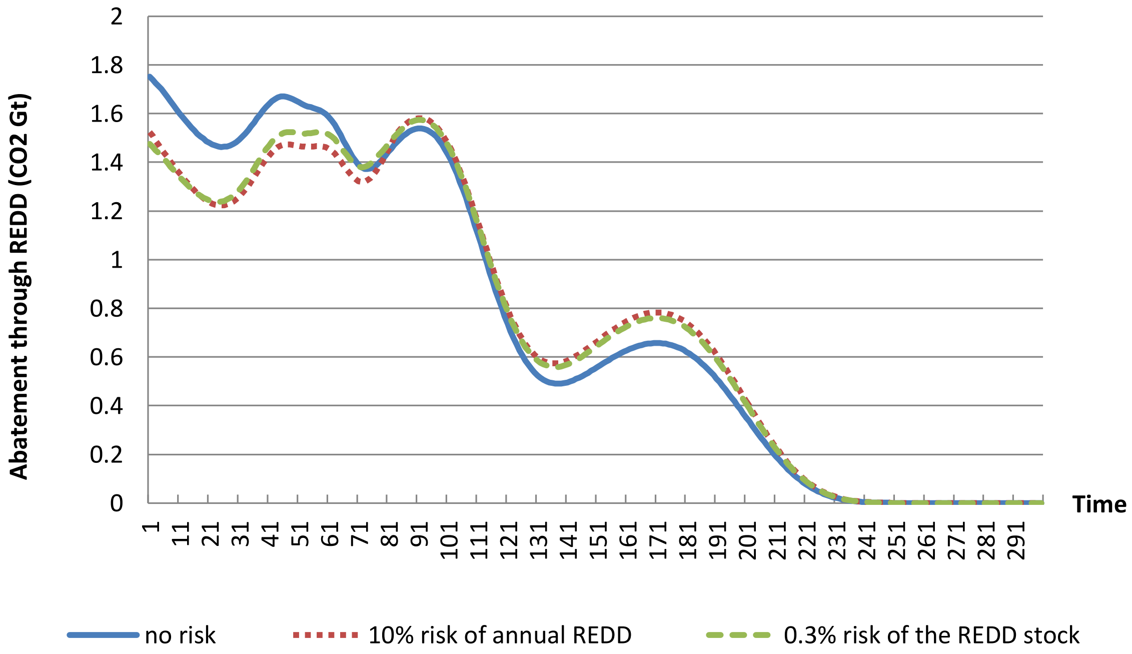


Figure 21 Time path of REDD implementation under various scenarios

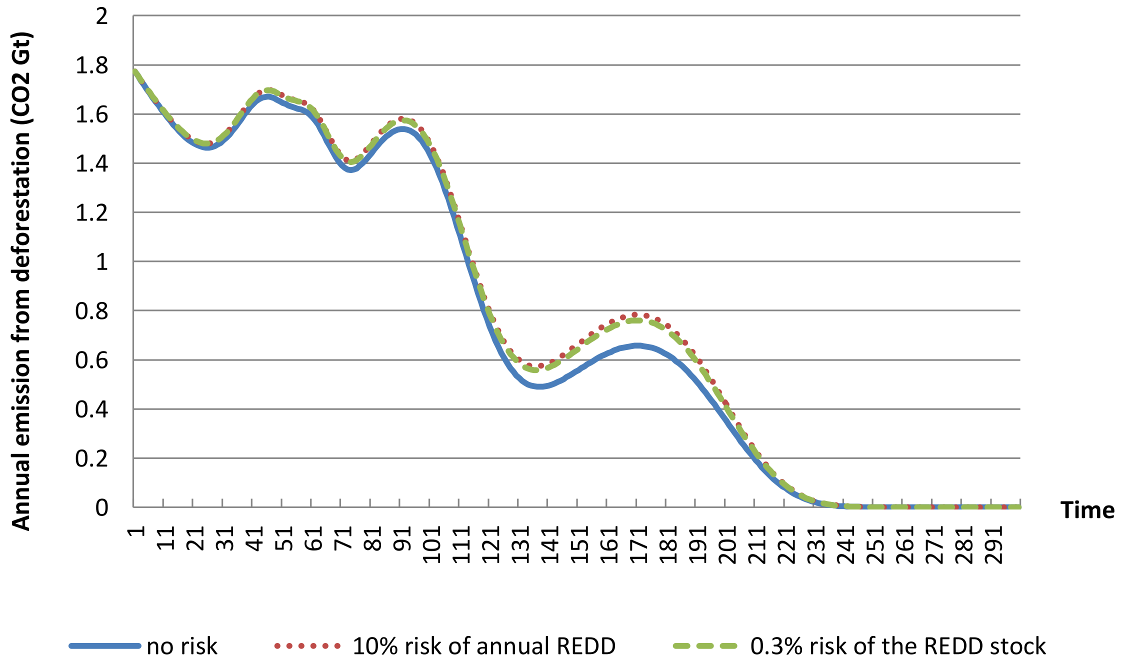


Figure 22 Time path of annual forest loss under various scenarios

So far, I have looked at the estimated parameter values in a deterministic way. It is likely that the parameter values, especially the ones related to cost of abatement, damages and so on, will vary based on the scenarios and specific assumptions. In the next section, I perform sensitivity analysis to evaluate the alterations to key findings from key parameter variation.

5.4.3 Sensitivity Analysis

In the base case, the average emissions are assumed to be six ppm (including those from emissions through fossil fuels and deforestation). I also evaluate the impact of higher emissions (6.5 ppm and seven ppm) on optimal abatement strategies. Next, I estimate the impact of a higher non-linear damage function (maximum damages are now 45 per cent of the GDP compared to a maximum of 40 per cent in the base case) on the optimal strategy (Figure 23). The influence of lower conventional abatement costs is estimated as well. Figure 24 compares the shapes of the conventional abatement cost functions for the base case and for the case with a lower cost[8].

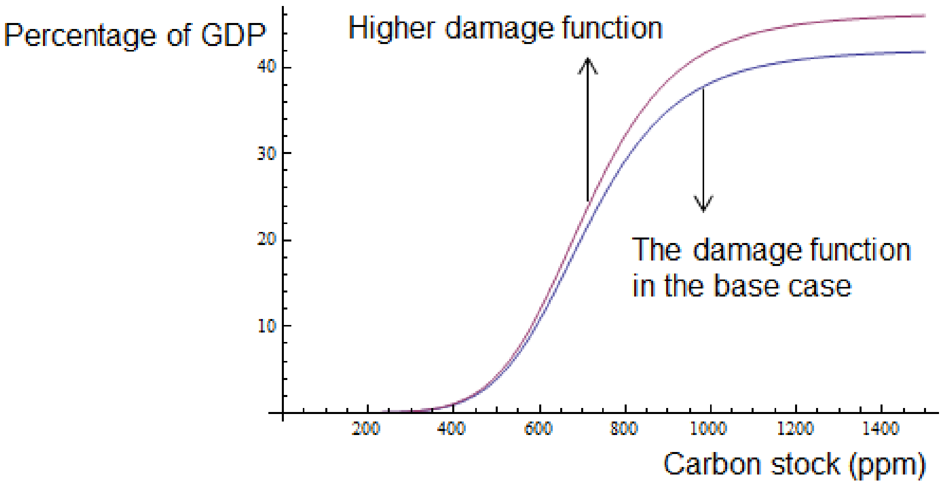


Figure 23 Comparisons between the damage function in the base case and the higher damage function

[8] For the lower conventional abatement cost function, the parameter values are: $\eta abcst$=13.2, *aabcst*=2.22, *babcst*=155

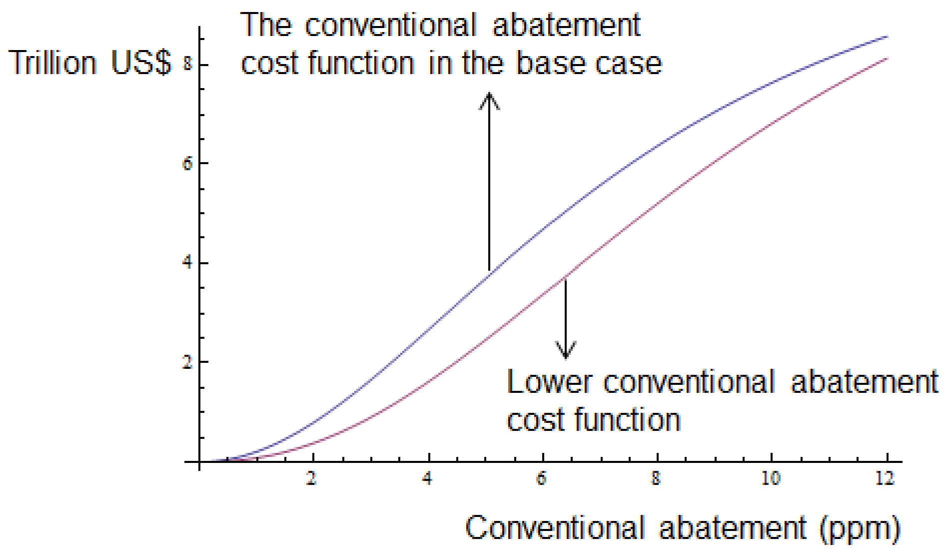


Figure 24 Comparisons between the conventional abatement cost function in the base case and the lower conventional abatement cost function

Figure 25 presents the conventional abatement time paths under the various assumptions described above. Note that the higher average emissions of 6.5 ppm and seven ppm lead to significant reductions in conventional abatement. This is counter-intuitive, as one would expect abatement to increase with an increase in emissions. However, note that these are annual average emissions, so even a marginal increase in the average leads to substantial changes in the time path of projected contributions to the atmosphere. Therefore, it becomes no longer optimal to reduce carbon concentrations, as this would lower GDP significantly. One key observation that can be made from the above is that abatement strategy becomes sensitive to an increase in average emissions beyond a certain threshold. Specifically, if emissions are increased beyond six ppm, optimal strategy is to reduce abatement over time as the associated damages and costs of abatement do not make it cost-effective to invest significantly in carbon abatement. This is primarily due to the non-linear rise in damages once a certain threshold of carbon stock is crossed.

Under the higher damage function assumption, conventional abatement is lower than the abatement under the base case. Again, this is because it is not cost-effective to afford the higher conventional abatement as the GDP. Over time, the low GDP resulting from a higher damage function and higher average emissions makes it costly to continue abating any further, so conventional abatement decreases gradually over time.

One key observation that can be made in this context is that the REDD programme has a significant effect on increasing conventional abatement when facing a higher damage or a higher average emissions scenario (6.5 ppm). As the relatively cheaper REDD option reduces the overall abatement costs and damages, it becomes optimal to increase the conventional abatement as well.

The influence of lower conventional abatement cost on the optimal abatement strategy is also depicted in Figure 25. The base case conventional abatement cost would be US$4.69 trillion for avoiding six ppm of carbon emissions, whereas it would cost US$3.38 trillion when a lower abatement cost is assumed. The lower cost leads to a significant increase in the conventional abatement right from the beginning. However, abatement under the scenario including REDD is lower than the abatement under the no-REDD scenario. This is because the REDD cost is not attractive compared to the lower conventional abatement cost. Please refer to Appendix D for more figures related to sensitivity analysis of carbon stock, damage and GDP.

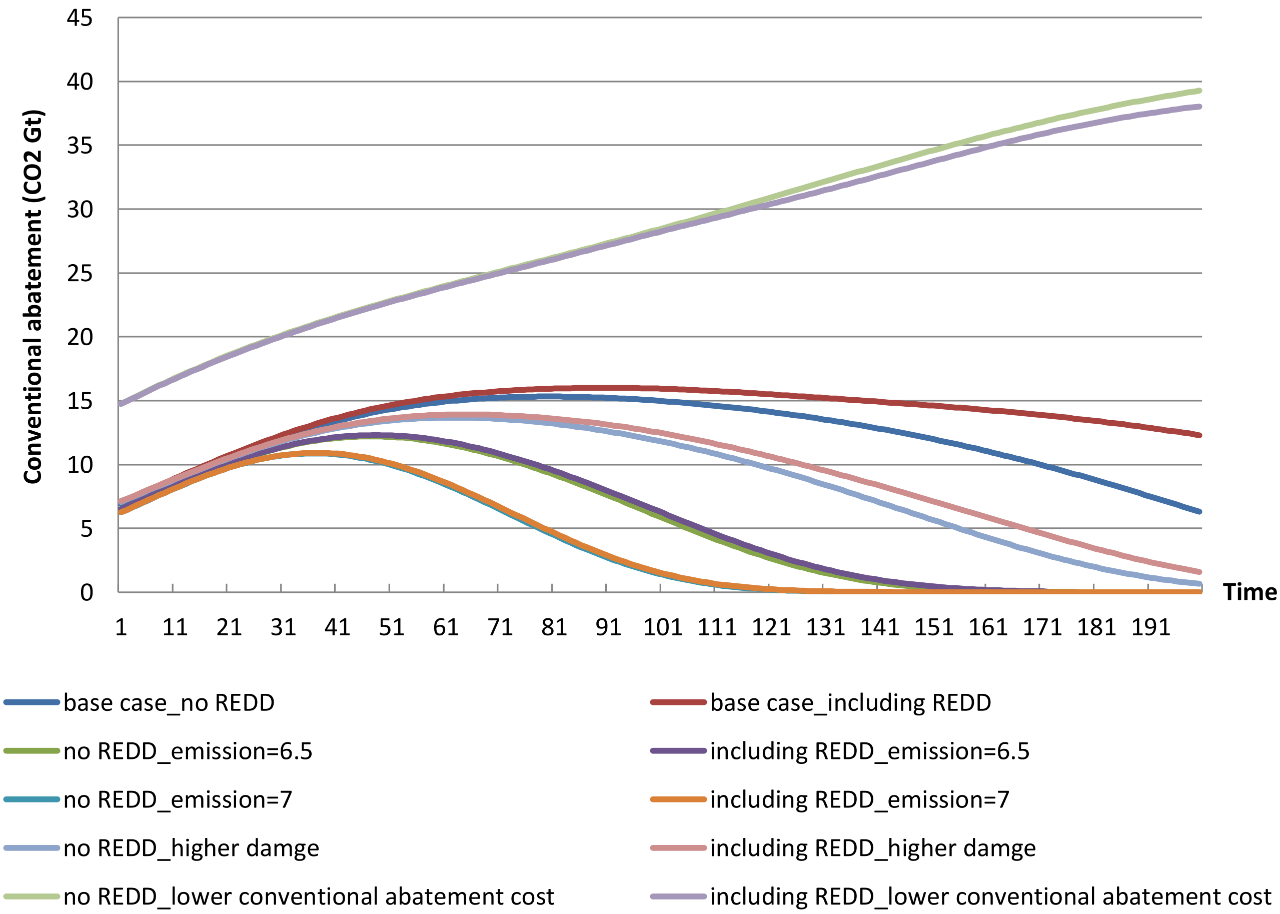


Figure 25 Sensitivity analysis for abatement under various assumptions

5.5 Discussion and Concluding Remarks

In this chapter, I designed an integrated assessment model that has explicitly included the REDD option for five main developing countries with large REDD potential. I considered the possibility of a non-linear damage function associated with the atmospheric carbon stock as well as the forestry loss risks brought under REDD. One of the key findings is that the REDD programme may prevent the carbon stock from crossing a certain threshold in terms of non-linear damages.

The main conclusions from the analysis performed here are that the REDD programme is an attractive option to consider in the optimal management of climate change problem. However, there are certain caveats attached to it. One of the key benefits of including REDD into an integrated assessment model is that it leads to significant reduction in costs. One of the findings from this chapter points to the fact that REDD participation makes conventional abatement attractive as well when damages evolve non-linearly. Therefore, all cheaper options for REDD should be explored and encouraged globally. The risk of forestry loss makes REDD less attractive and decline of about 12 per cent in the REDD is observed compared to the case without risks. There is a distinction to be made between annual REDD loss risks and the risks posed to the entire REDD forestry under REDD as these risks could come from different sources, such as large scale structural shifts and political risks. I find that even a small risk to the total stock of REDD has the same effect on discouraging REDD participation as large risks. Specifically, a 10 per cent risk of annual REDD forestry loss reduces 550 thousand hectares of REDD implementation per year, while a 0.3 per cent risk to the accumulated stock of REDD forestry reduces 650 thousand hectares of REDD forestry per year compared to a case with no risks. The impact of small risk (0.3 per cent) to the stock of REDD programmes is similar to the case of a much larger risk (10 per cent) restricted to the annual REDD implementation.

Therefore, countries with lower risks but higher opportunity costs may be more preferable than countries with higher risks and lower opportunity costs. Although there is a significant diversity of opportunity costs among different countries (Brazil being the cheapest one and PNG with the relatively highest cost of REDD), the optimal strategy allows for REDD enrolment over time, based not only on the cost differentials but also their projected future forest losses and associated risks. Risk assessment and risk management should be considered necessary processes in the implementation of REDD programmes. The costs related to avoiding risks should be included in the total cost of REDD. The policy implication, in terms of investment in REDD, is that if two countries face the same level of risks, REDD should be promoted more in the country with lower opportunity costs. In this study, the same forest risk rate is used in the five countries (Brazil, Indonesia, the DRC, Cameroon and PNG). Future work should be aimed at estimating the specific risk rates for each country, which would help with providing a more realistic idea over REDD investments for each country.

Chapter 6 Conclusions and Implications, Limitations and Future Research

6.1 Key Findings

This chapter highlights the important findings from the thesis and identifies some policy implications. Limitations associated with data and methodologies are also briefly discussed. Finally, some recommendations are made for future research.

Despite the importance and potential of CT in China, a number of socio-economic and behavioural factors are slowing its long-term adoption. Probit analysis shows that government subsidies and household wealth levels play key roles in continued CT adoption—with poorer farmers more likely to discontinue after having adopted initially.

Some social-economic challenges associated with CT promotion are the increasing number of off-farm labourers and the increase in off-farm incomes of rural families. Families living on agricultural income as their main livelihood source and with more farm labourers are more likely to adopt CT. In short, those who are highly dependent on agriculture are more likely to adopt CT. In addition, geographical factors can also act as a barrier to CT adoption. For example, where households own fragmented land away from roads or in hills, it can be difficult to move heavy machines to these sites. It is also not cost-effective to hire a machine for use on a small fragment of land if the nearby fields are not under CT management. Therefore, future CT programs need to cognizant of these limitations and can benefit significantly if they concentrated on reaping the economies of scale that is derived through neighbourhood adoption effects.

Survival analyses to examine rates of CT adoption demonstrated that government intervention plays a key role. Farmers who obtained CT information from the Government, or who attended the CT training and demonstrations, are more likely to adopt CT earlier. In addition, continued governmental subsidies were more effective in encouraging farmers to maintain CT continuously than providing subsidies sporadically. Although the CT project has operated with subsidies for eight years in HC, it is not recommended to stop or reduce this scheme in the future. An assured long-term subsidy scheme will effectively reduce the uncertainty over CT adoption and encourage participation.

The effects of the training programmes held by the Government were further tested in two separate models. Villages covered by the survey were divided into two groups based on the level of support received from the Government. Two discrete time survival analysis models were generated for untreated and treated villages, to explore the differential effects of varying levels of promotional efforts. The findings support the notion that, although the subsidy programme did not cover all adopters due to limited government budgets, it is essential to continue investing in the educational and demonstration programmes in both treated and untreated villages.

The results of the above CT studies, in part, reflect the traditional structure of the agricultural sector in China. The small and scattered land holdings make CT adoption less attractive in terms of benefits from economies of scale through use of large machinery. However, land fragmentation was found to be beneficial in other ways. Neighbours' adoption behaviour has a highly positive effect on a farmer's initial adoption decisions and continued adoption in the future. More households adopting CT will generate further positive feedback effects for CT adoption. Once the neighbourhood effect gains momentum, there could be a non-linear jump in the adoption rate. From a policy perspective, it would be important to determine, through further research, the percentage of adopters beyond which a significant neighbourhood effect kicks in.

As noted elsewhere, another mitigation strategy that is very important in Asian countries is the REDD programme, as illegal logging is one of the main causes of deforestation in developing countries with extensive natural forests. The social and economic challenges faced by Indonesia in promoting carbon mitigation through REDD were analysed in this thesis. The problem of corruption is a key driver influencing illegal logging, which is considered one of the critical risks to REDD projects (Dermawan et al., 2011). In Indonesia, the increase in forest extraction permissions, caused by the increasing number of districts over time, merely disguises ‘illegal’ logging as a legal practice. Although the statistics suggest that ‘illegal’ logging has been reduced, in reality, the total rate of deforestation has increased.

On the demand side, the general growth in the Chinese economy has not led to an increase in illegal demand. This could be potentially attributed to improvements in log use efficiency and milling technologies (Witness, 2009), indicating that technological progress may be a key factor in reducing illegal demand in China. In China, timber demand did shift from domestic to imports, including illegal timber, due to the implementation of natural resource protection policies in the recent past. However, the capacity of domestic supply has also increased due to the rapid implementation of afforestation and reforestation projects. Therefore, the demand for imported illegal timber has declined as a consequence.

Additionally, the number of new houses is a significant driver of illegal imports to both Japan and China. The furniture industry has become the largest consumer of wood products from illegal sources in Japan. The analysis also reveals that the level of domestic timber sufficiency is a key factor responsible for illegal trading in Japan. It was found that policies or law enforcements to curb illegal harvesting have been effective in Indonesia by catching the grey money and reducing corruption. However, policies to reduce illegal demand from Japan or China have not been very successful.

Apart from exploring the challenges faced by REDD projects, the global attractiveness of the programme was estimated in an integrated assessment model. One of the key benefits of including REDD into the integrated assessment model is that it leads to significant reduction in carbon mitigation costs. It was found that the REDD programme not only mitigates carbon emissions through reducing deforestation, but also makes conventional abatement attractive when damages evolve non-linearly. It also leads to a decline in the long-term atmospheric carbon stock as the low cost of REDD reduces the overall costs of abatement. The risk of forest loss makes REDD less attractive, however. Countries with lower risks but higher opportunity costs of REDD programmes may be more preferable over countries with lower opportunity costs but higher risks. For instance, although Indonesia has large potential for carbon mitigation through forestry, the illegal logging problem reduces the attractiveness of the REDD programme.

6.2 Limitations, Recommendations and the Future Study

This study has a number of limitations in terms of data and methodology. First, the survival analysis method provides an approach to estimate an adoption process in a dynamic pattern, normally using a combination of the cross-section and time-series data. However, in Chapter 3, analyses were conducted based only on the cross-section data. Lack of time-series data in the analysis was due to the limited time and frequency of the survey conducted in HC. In future work, additional intensive household surveys and interviews with local governments would help overcome this data limitation.

Some recommendations for future research on this topic are as follows. Since the CT adoption programme in China is still in an early experimental stage, regulations to help with promoting CT have not yet been fully developed. For instance, questions such as whether subsidies should be compulsorily provided to adopters by the local government and what is the optimal level or timing for giving subsidies need to be addressed.

Another limitation relates to the restricted data on illegal logging. The data used in Chapter 4 was gathered from existing literature and reports on illegal logging. As this study related to illegal activities, it was challenging to find detailed data on timber prices or accurate amounts of illegal timber traded. The legal timber price was used in the model as a proxy for the illegal timber price and the amount of illegal timber was estimated using the gap between timber trading quantities reported by exporting and importing countries. In addition, there were challenges in performing quantitative analysis due to the lack of accurate data. Combining qualitative analysis with quantitative analysis, in future, might offset this limitation.

Limitations related to data also exist in the integrated assessment model. In Chapter 5, to estimate the optimal timing and level of carbon mitigation incorporating the REDD option, countries with large forested areas, such as Brazil, Indonesia, the DRC, Cameroon and PNG, were selected for the model due to lack of data for other countries with relatively smaller forest areas. The total forest area in the five countries accounts for 51 per cent of the total forestry in developing countries. In further studies, additional developing countries with carbon reduction potential through REDD programmes could be included in the model.

In summary, considering the above questions, future work should be aimed at investigating optimal subsidy schemes and factors affecting willingness to accept or continue in CT. Carbon abatement through CT adoption could also be introduced into the global integrated assessment model to estimate the influence of agricultural carbon mitigation potential on total abatement outcomes. More accurate estimates of leakages in REDD outcomes from illegal logging will also be crucial to refining the global abatement model. Future work should also pay attention to better policy design for the environmental programmes, such as those using the double dividend principle, which could bring benefits to both the environment and the local economies.

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Appendix A: Declaration of Authorship Contributions

A Bivariate Probit Analysis of Factors Affecting Partial, Complete and Continued Adoption of Soil Carbon Sequestration Technology in Rural China

Contributions to the paper were as follows:

(85 per cent) Yaoyao Ji undertook the data collection by conducting a household survey in the Huangling County of China. She conducted the analytical work, with the supervision of Ram Ranjan and assistance of Michael Burton. Yaoyao was the primary author and correspondent for the manuscript.

(10 per cent) Ram Ranjan acted in his capacity as principal supervisor in helping with preparing the survey and supporting the analytical work. Ram was a major reviewer of the manuscript.

(Five per cent) Michael Burton provided assistance in analytical work. Michael also reviewed the manuscript.

A Survival Analysis of Conservation Tillage Adoption in Rural China

Contributions to the paper were as follows:

(90 per cent) Yaoyao Ji undertook the data collection, modelling and analytical work, with the supervision of Ram Ranjan and assistance of Michael Burton. Yaoyao was the primary author and correspondent for the manuscript.

(10 per cent) Ram Ranjan acted in his capacity as principal supervisor in helping with the analytical work. Ram was a major reviewer of the manuscript.

An Empirical Analysis of Factors Affecting Illegal Logging in Indonesia

Contributions to the paper were as follows:

(85 per cent) Yaoyao Ji undertook the data collection, modelling and analytical work, with the supervision of Ram Ranjan and assistance of Chi Truong. Yaoyao was the primary author and correspondent for the manuscript.

(10 per cent) Ram Ranjan acted in his capacity as principal supervisor in helping with the analytical work. Ram was a major reviewer of the manuscript.

(Five per cent) Chi Truong supported this work as co-supervisor. He provided assistance in the analytical work. Chi also reviewed the manuscript.

Optimal Carbon Mitigation Including the Reducing Emissions from Deforestation and forest Degradation Option

(90 per cent) Yaoyao Ji undertook the data collection, modelling and analytical work, with the supervision and assistance of Ram Ranjan. Yaoyao was the primary author and correspondent for the manuscript.

(10 per cent) Ram Ranjan acted in his capacity as principal supervisor in helping with modelling and the analytical work. Ram was a major reviewer of the manuscript.

Appendix B: Ethics Approval Letter

From: **Faculty of Science Research Office** <sci.ethics@mq.edu.au>
Date: Fri, Dec 7, 2012 at 9:35 AM
Subject: Final Approval - Issues Addressed
To: Dr Ram Ranjan <ram.ranjan@mq.edu.au>, Miss Yaoyao Ji <yaoyao.ji@students.mq.edu.au>
Cc: Prof Richie Howitt <richie.howitt@mq.edu.au>, Ms Katherine Wilson <katherine.wilson@mq.edu.au>, Dr Chi Truong <chi.truong@mq.edu.au>

Dear Dr Ranjan,

RE: Ethics project entitled: "Study of factors promoting soil carbon sequestration in China"
Ref number: 5201200873.

Thank you for your recent correspondence. Your response has addressed the issues raised by the Faculty of Science Human Research Ethics Sub-Committee and you may now commence your research.

This research meets the requirements of the National Statement on Ethical Conduct in Human Research (2007). The National Statement is available at the following web site:

http://www.nhmrc.gov.au/_files_nhmrc/publications/attachments/e72.pdf.

The following personnel are authorised to conduct this research:
Miss Yaoyao Ji
Dr Ram Ranjan
Dr Truong Huu Chi

NB. STUDENTS: IT IS YOUR RESPONSIBILITY TO KEEP A COPY OF THIS APPROVAL
EMAIL TO SUBMIT WITH YOUR THESIS.

Please note the following standard requirements of approval:

1. The approval of this project is conditional upon your continuing compliance with the National Statement on Ethical Conduct in Human Research (2007).

2. Approval will be for a period of five (5) years subject to the provision of annual reports.

Progress Report 1 Due: 7 December 2013
Progress Report 2 Due: 7 December 2014
Progress Report 3 Due: 7 December 2015
Progress Report 4 Due: 7 December 2016
Final Report Due: 7 December 2017

NB. If you complete the work earlier than you had planned you must submit a Final Report as soon as the work is completed. If the project has been discontinued or not commenced for any reason, you are also required to submit a Final Report for the project.

Progress reports and Final Reports are available at the following website:

http://www.research.mq.edu.au/for/researchers/how_to_obtain_ethics_approval/human_research_ethics/forms

3. If the project has run for more than five (5) years you cannot renew approval for the project. You will need to complete and submit a Final Report and submit a new application for the project. (The five-year limit on renewal of approvals allows the Committee to fully re-review research in an environment where legislation, guidelines and requirements are continually changing, for example, new child protection and privacy laws).

4. All amendments to the project must be reviewed and approved by the Committee before implementation. Please complete and submit a Request for Amendment Form available at the following website:

http://www.research.mq.edu.au/for/researchers/how_to_obtain_ethics_approval/human_research_ethics/forms

5. Please notify the Committee immediately in the event of any adverse effects on participants or of any unforeseen events that affect the continued ethical acceptability of the project.

6. At all times you are responsible for the ethical conduct of your research in accordance with the guidelines established by the University. This information is available at the following websites:
http://www.mq.edu.au/policy/

http://www.research.mq.edu.au/for/researchers/how_to_obtain_ethics_approval/human_research_ethics/policy

If you will be applying for or have applied for internal or external funding for the above project it is your responsibility to provide the Macquarie University's Research Grants Management Assistant with a copy of this email as soon as possible. Internal and External funding agencies will not be informed that you have final approval for your project and funds will not be released until the Research Grants Management Assistant has received a copy of this email.

If you need to provide a hard copy letter of Final Approval to an external organisation as evidence that you have Final Approval, please do not hesitate to contact the Ethics Secretariat at the address below.

Please retain a copy of this email as this is your official notification of final ethics approval.

Yours sincerely,
Richie Howitt, Chair
Faculty of Science Human Research Ethics Sub-Committee
Macquarie University
NSW 2109

Appendix C: Algebraic Descriptions of the Model in Chapter 5

Table 25 Forest loss rate estimation

	Brazil	Indonesia	Cameroon	DRC	PNG
2005–2010 annual carbon emissions from forest loss (ppm)[1]	0.112686	0.048561	0.018798	0.0363	0.0100
Forest loss rate in 2010 (%)[2]	0.4236	0.7361	1.1294	0.2774	0.4994
Forest loss rate in 2020 (%)[3]	0.4585	0.8486	1.4176	0.292	0.5548
Forest loss rate in 2030 (%)	0.5084	1.022	1.9786	0.3101	0.6163
Forest loss rate in 2040 (%)	0.5615	1.2846	3.2743	0.3306	0.703
Forest loss rate in 2050 (%)	0.6325	1.7287	9.4868	0.354	0.818

1. Source: MONGABAY.COM, http://rainforests.mongabay.com/ 2. Source: MONGABAY.COM, http://rainforests.mongabay.com/ 3. After 2010, forest loss rates assumed to stay constant.

Table 26 Parameters of forest loss rate function for each country

Country	Parameter	Value (scalar)
Brazil	*ηfl_brazil*	1.16
	afl_brazil	4.48
	bfl_brazil	46×10^{9}
	cfl_brazil	0.0042
Indonesia	*ηfl_indonesia*	1.52
	afl_ indonesia	5.7
	bfl_ indonesia	39×10^{10}
	cfl_ indonesia	0.0073
Cameroon	*ηfl_cameroon*	8.62
	afl_ cameroon	4.96
	bfl_ cameroon	1×10^{10}
	cfl_ cameroon	0.011
DRC	*ηfl_DRC*	6.8
	afl_DRC	6.02
	bfl_DRC	708×10^{13}
	cfl_DRC	0.00277
PNG	*ηfl_PNG*	2.32
	afl_PNG	5.76
	bfl_PNG	1×10^{13}
	cfl_PNG	0.00499

Table 27 Parameters of the carbon stock related damage function

Parameter	Value
percarb	280
ηdam	42.1
adam	6.58
bdam	440
cdam	0.01

Table 28 Parameters of conventional abatement cost function

Parameter	Value
ηabcst	11.85
aabcst	2
babst	55

Table 29 Parameters of REDD cost function for each country

Country	Parameter	Value
Brazil	crdcst_brazil	0.66
	ηrdcst_brazil	3.4
	ardcst_brazil	4.64
	brdcst_brazil	0.276
Indonesia	crdcst_ indonesia	0.525
	ηrdcst_indonesia	1.82
	ardcst_indonesia	3.86
	brdcst_ indonesia	0.152
Cameroon	crdcst_ cameroon	0.41
	ηrdcst_cameroon	1.82
	ardcst_cameroon	2.16
	brdcst_cameroon	0.64
DRC	crdcst_DRC	0.7
	ηrdcst_DRC	0.45
	ardcst_DRC	2.06
	brdcst_DRC	0.415
PNG	crdcst_PNG	0.25
	ηrdcst_PNG	0.76
	ardcst_PNG	1.68
	brdcst_PNG	0.276

Table 30 Other parameters of the model

Parameter	Definition	Value	Equation
emi	Global annual carbon emission	6	(27)(28)
δ	Rate of decay of atmospheric carbon	0.0083	(35)
inrate	Growth rate of global economy	1.03	(39)
η	Elasticity Parameter in the CES utility function	0.1	(40)

Appendix D: Sensitivity Analysis for Carbon Stock, Damage and GDP in Chapter 5

The time paths of carbon stocks for corresponding scenarios are presented in Figure 26. Note that some of these sensitivity scenarios depict completely different carbon paths in the long term. The carbon stocks under the base case, under average emissions of 6.5 ppm and seven ppm and under the higher damage scenarios gradually increase over time. Whereas, the lower conventional abatement cost sensitivity scenario leads to significantly reduced carbon stocks in the long term due to the high conventional abatement undertaken (see Figure 25).

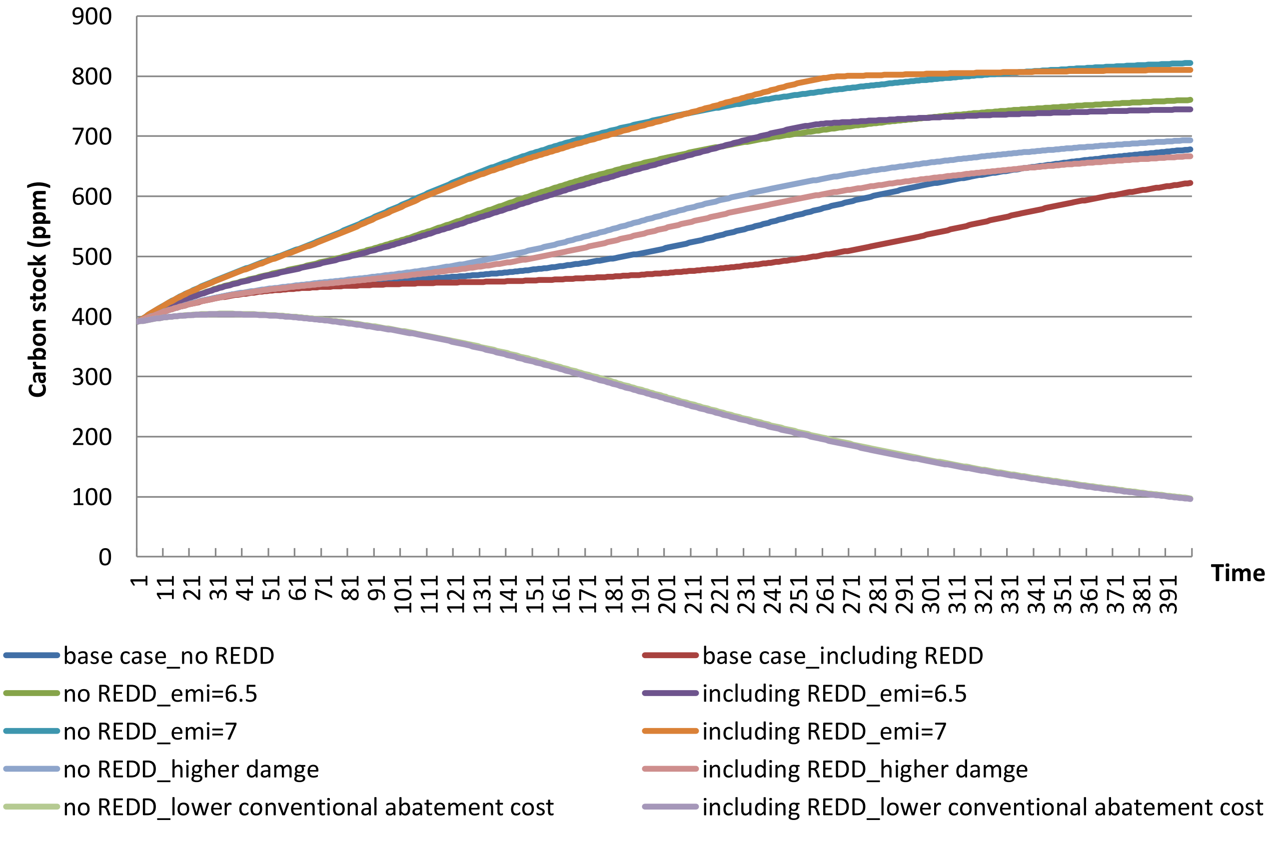

Figure 26 Sensitivity analysis for carbon stock under various assumptions

Additionally, the associated annual damages under various assumptions are presented in Figure 27. Figure 28 shows the GDP corresponding to these scenarios. Note that damages drop to zero in the long term. Since the damages are calculated as a percentage of the GDP, their magnitude in the long term decreases as GDP level declines to zero due to the high abatement costs and damages (see Figure 28). However, higher damages still lead to lower overall societal utility as the damages fall to zero (see Table 31).

Under the low conventional abatement cost scenario, the GDP in fact increases substantially in the long term (see Figure 28) as higher abatement leads to lower carbon and hence helps avoid higher damages.

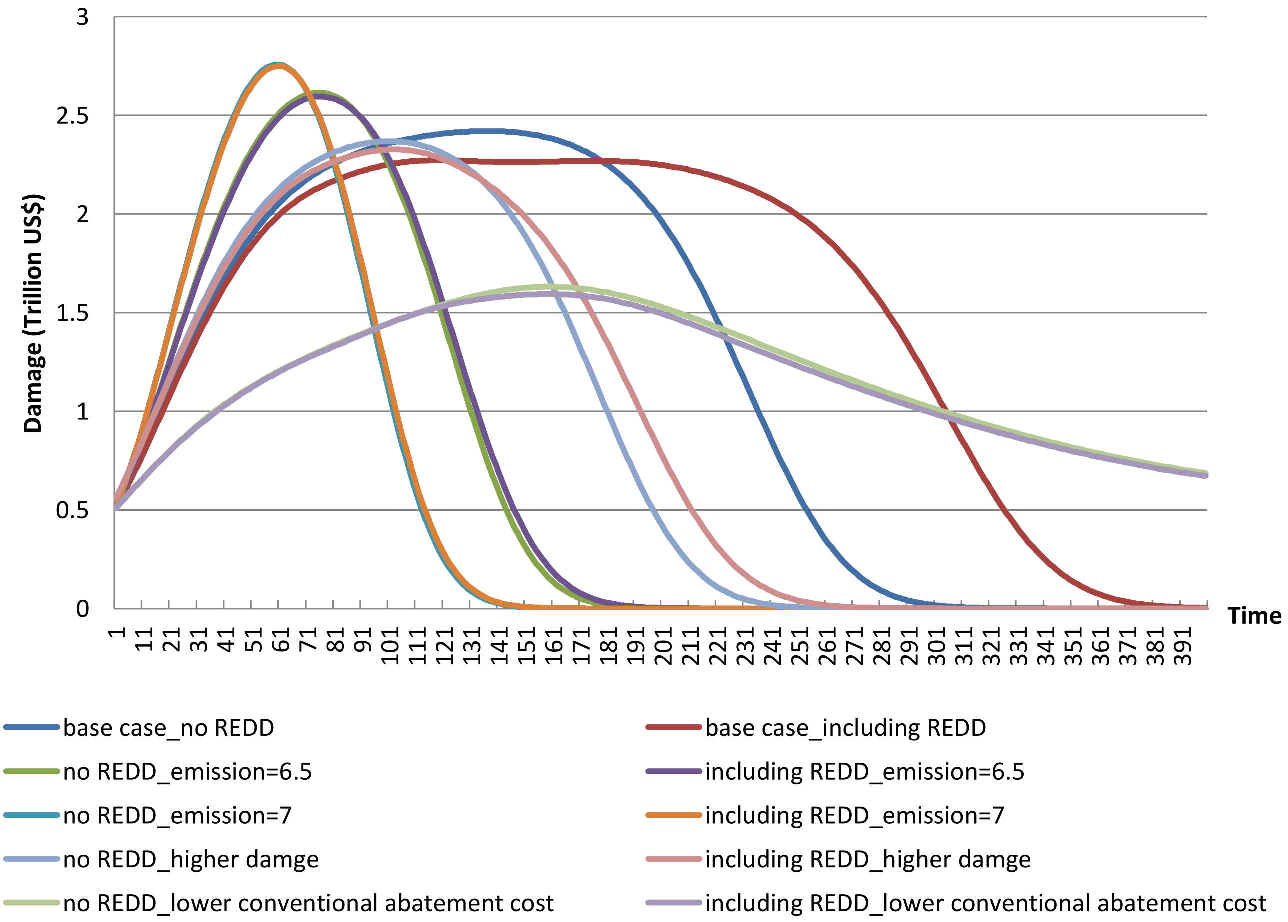

Figure 27 Sensitivity analysis for damage under various assumptions

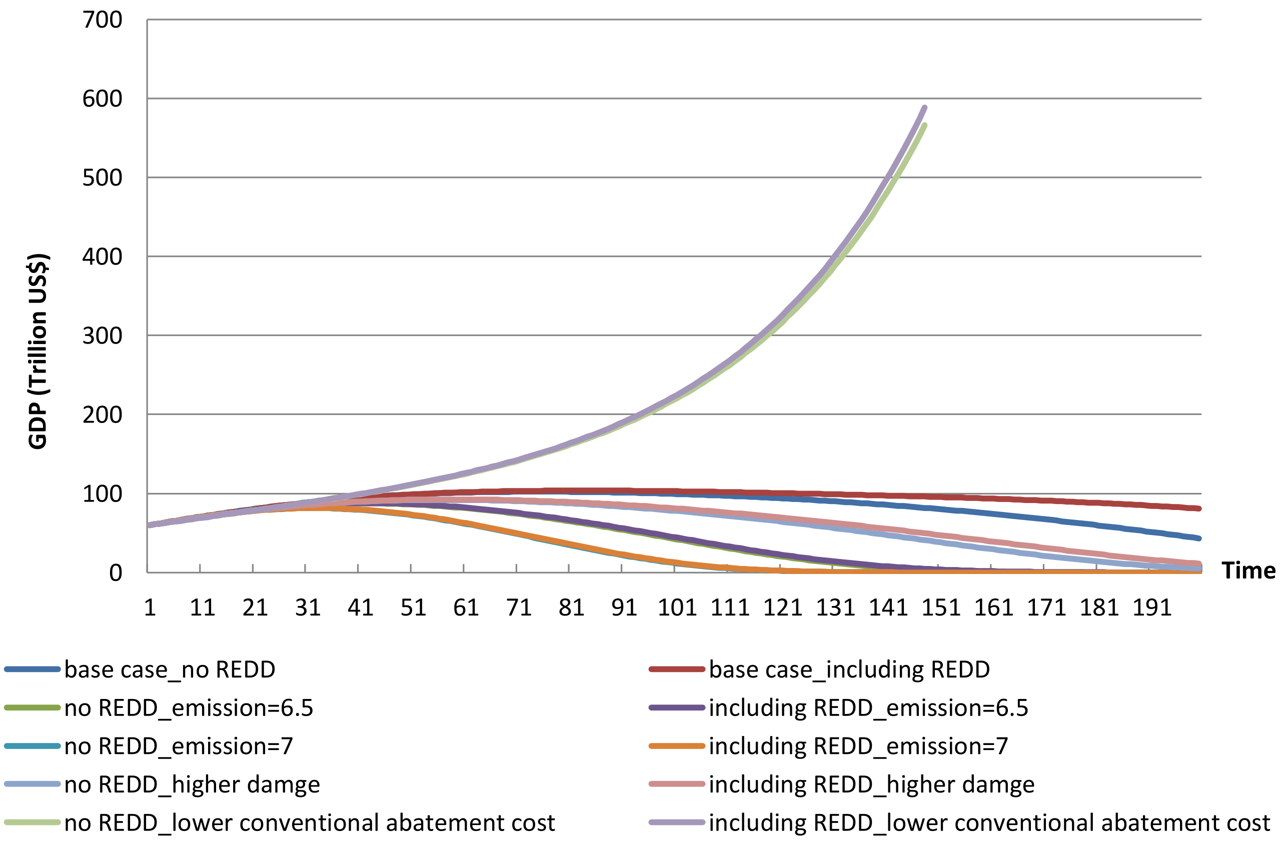

Figure 28 Sensitivity analysis for gross domestic product under various assumptions

Table 31 Societal utility under various sensitivity scenarios

Sensitivity scenarios	Societal utility (unit)
Base case_no-REDD	2038
Base case_including REDD	2054
No-REDD_emission=6.5	1814
Including REDD_emission=6.5	1822
No-REDD_emission=7	1657
Including REDD_emission=7	1663
No-REDD_higher damage	1921
Including REDD_higher damage	1933
No-REDD_lower conventional abatement cost	3130
Including REDD _lower conventional abatement cost	3184