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ESSAYS ON PUBLIC GOOD DECISIONS
THE ROLE OF CONTEXT AT THE MICRO AND MACRO LEVELS

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ESSAYS ON PUBLIC GOOD DECISIONS

The Role of Context at the Micro and Macro levels

Jonathan Gheysens

Abstract

This thesis is a collection of submitted or published papers that I wrote during my four years of doctoral studies in development economics at the NADEL Institute of the ETH Zurich. The general idea for this thesis is to address how social decisions (decisions involving socially relevant goods or services) are influenced by their environmental context. The definition of the environmental context was deliberately broad to accommodate different settings, from micro-decision at the individual level to aggregated macro-analysis of economic activity. The four papers that comprise this thesis all have a strong common thread which is the influence of external environmental contexts on the optimal decisions of agents. These contexts can be the existence of risk (first paper), the influence of group decisions (second paper), the existence of environmental services (third paper) or the recognition of climate change impacts at the global level (fourth paper). In each case, the nature of the exogenous context greatly influences the optimal decisions and in turn gives information about the choices of the best policy frameworks.

These papers cover the two research fields that were at the center of my research during the PhD: empirical decision theory for individuals in developing countries and the analysis of forestry and adaptation strategies in developing countries in the context of climate finance. These topics are examples of the different layers of analysis that permeate the economic analysis of social and collective decisions, from individual preferences to macroeconomic strategies. The papers comprising this thesis also share the same policy objective, albeit at different levels: how are our decisions impacting the welfare of developing countries and poor people?

ESSAIS SUR DES DECISIONS DE BIENS COMMUNS

Le rôle du contexte aux niveaux micro et macro

Jonathan Gheysens

Resumé

Cette thèse est une collection de documents présentés ou publiés que j'ai écrit pendant mes quatre années d'études doctorales en économie du développement à l'Institut NADEL de l'EPF de Zurich. L'idée générale de cette thèse est d'examiner comment les décisions sociales (décisions impliquant des services ou produits à caractère publics) sont influencées par leur contexte environnemental. La définition du contexte environnemental était délibérément large pour s'adapter à différents contextes, depuis les micro-décisions prises au niveau individuel jusqu'au macro-analyse de l'activité économique agrégées à l'échelle de l'économie mondiale. Les quatre articles qui composent cette thèse ont tous un fort dénominateur commun qui est l'influence des contextes environnementaux externes sur les décisions optimales d'agents. Ces contextes peuvent être l'existence du risque (premier article), l'influence des décisions de groupe (deuxième papier), l'existence de services environnementaux (troisième papier) ou la reconnaissance des impacts du changement climatique au niveau mondial (quatrième papier). Dans chaque cas, la nature du contexte exogène influe grandement sur les décisions optimales et à son tour, donne des informations sur le choix des meilleurs cadres politiques.

Ces documents couvrent les deux domaines qui ont été au centre de mes recherches au cours de cette thèse : théorie de la décision pour les individus dans les pays en développement et analyse de l'économie des services environnementaux et des stratégies d'adaptation dans les pays en développement dans le cadre du financement climatique. Ces sujets sont des exemples des différents niveaux d'analyse qui imprègnent l'analyse économique des décisions sociales et collectives, des préférences individuelles à des stratégies macroéconomiques. Les papiers qui forment cette thèse partagent également ce même objectif, mais à différents niveaux : celui d'évaluer l'impact de nos décisions sur le bien-être des pays en développement et des populations pauvres ?



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WORK EXPERIENCE

Principal Investigator, ETH

Zurich — January-October 2013

Was responsible for the design and structure of a 6-year proposal on mobile services for water and sanitation access (budget: 4 million CHF). Conducted baseline analysis of current operational ICT projects and defined operational and research axes.

Coordinated feasibility analysis and project responsibilities for 3 targeted African countries (Tanzania, Kenya, Uganda), with the involvement of 4 academic departments, 5 partner universities, 14 private-sector partners (e.g. WaterAid, SNV, UN-Habitat, iHub Kenya), telecom operators (Airtel, Orange, Safaricom) and national ministries.

Research Assistant - Development Economics NADEL ETH

Zurich — 2009-2013

Conducted household surveys related to a large scale estimation of access to basic services in Benin (more than 2000 households).

Designed and conducted behavioral field experiments with more than 500 households in rural Benin to evaluate risk aversion, time preference and trust. The goal was to assess the obstacles constraining take-up rates for micro-insurance schemes. The results have been published by the United Nation University (UNU-Wider) and largely disseminated within the development community.

Published academic research on the topics of risk assessment, micro-insurance, micro-finance and climate finance.

Research Assistant - Climate Finance, University of Zurich

Zurich — September 2009:August 2013

Principal research assistant of Prof. Marc Chesney on environmental Finance. Lectured the Environmental Finance course at Uni Zurich (4 years). Liaised with professionals within the environmental finance network in Switzerland.

Advisor on deforestation contracts, German Development Bank

Frankfurt — 2011

Presented deforestation models designed to select optimal “payments for forest protection” schemes under the new UNFCCC REDD framework.

Senior Consultant Risk Management, Deloitte

Paris —2007-2008

Designed strategic risk assessment tools for industrial groups, using econometric techniques (Strategic Value at Risk, SVaR). Recommended activity portfolio based on SVaR.

Senior Analyst, National Bank of Canada

Montréal —2006-2007

Worked for an ad hoc team, liaising with the Risk Management Department and the Finance Department, to assess optimal capital allocations according to strategic targets and regulatory landscape (Basel II).

Junior Consultant, Cap Gemini (ex Bossard Consulting) & Roland Berger

Paris — 2001-2003

Various responsibilities: cash-flow models (using VBA), brainstorming seminars, project management, powerpoint presentations (pitch and in-mission), interviews, SWOTs, price matrix.

EDUCATION

ETH Zurich — PhD in Development Economics (November 2013)

Swiss Finance Institute (Uni Zurich) — PhD First Year Program in Finance (2009-2010)

HEC Montreal (Uni Montreal) — M.Sc. in Applied Economics, 2006 (Highest GPA)

IEP Paris (Sciences PO) — M.A. in Political Sciences, Finance Major (with bilingual distinction), 2003

SKILLS

Extensive programming skills: VBA, Python, Matlab, R, Stata, Maple, GAMS

Extensive knowledge of web technologies: Javascript, PHP, Python, SQL, NoSQL (MongoDB), Ruby, CURL, API, frameworks (backbone, flask, django)

ACTIVITIES

Former competitive tennis player, avid skier (freetouring with the Carouge Alpine Club, freeriding) and scuba diver (Advanced PADI, want to become dive master), runner. Love history and politics.

CODE DEVELOPMENT

Python algorithm for natural language detection of places (geoparser):

Geoparser designed to understand geographical context in sms exchanges between african villagers and water service providers. Can be used with a large variety of sources.

STATA module for automatic selection of explanatory variables in regression:

The algorithm selects from a set of potential candidates the number and combination of independent variables yielding the highest explanatory power. The module works with a large set of econometric models.

VBA program to simulate credit consumption patterns:

Used to forecast a credit portfolio structure based on a set of parameters (rates, historical purchase patterns, user attrition/acquisition, alternatives).

PUBLICATIONS

- *Environmental Finance and Investment*, M.Chesney, J.Gheyssens and L.Taschini, Springer Texts in Business and Economics (2013)

- *Handbook of Multi-Commodity Markets and Products, Economics and Markets for Emission* (chapter), M.Chesney, J.Gheyssens and L.Taschini, forthcoming in Wiley (2013)

- *The effect of proactive adaptation on green investment*, O. Bahn, M. Chesney and J. Gheyssens, 2012, Environmental Science and Policy

- *Risk aversion in losses, risk taking in faith, an experiment in poor rural communities*, J. Gheyssens and I. Gunther, UN University (WIDER) Working Paper (2012)

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Contents

Acknowledgements	i
List of Figures	iv
List of Tables	vi
Introduction	1
1 Risk Averse in Losses, Risk Taking in Faith. An Experiment in Poor Rural Communities	6
1.1 Introduction	6
1.2 Methodology and experimental design	9
1.3 Data and Field Description	14
1.4 Econometric analysis	17
1.4.1 Risk Aversion in Gains and Losses	17
1.4.2 Drivers of Risk Preferences	22
1.5 Conclusion	26
2 Does Cooperation Depend on the Circumstances? The Case of Rural Villagers in Benin	28
2.1 Introduction	28
2.2 Experimental design and data description	30
2.2.1 Experimental design	30
2.2.2 Data description	35
2.3 Experimental results	37
2.3.1 Are conditional contribution profiles different in a poor and rural setting?	37
2.3.2 Are conditionals contribution profiles stable in presence of risk and losses?	40
2.3.3 Are conditional contribution profiles relevant for predicting actual contributions?	47
2.4 Conclusion	52
3 Baseline Choice and Performance Implications for REDD	54
3.1 Introduction	54
3.2 Methodology	58
3.2.1 Model setting	58
3.2.2 Baseline alternatives	61
3.2.3 A numerical application	66
3.3 Results and discussion	68
3.3.1 Performance indicators	68
3.3.2 A first comparison	69
3.3.3 The influence of deforestation context and scheme attributes	72
3.3.4 Optimal Design and Welfare Transfers	74

3.4	Conclusions and Further Discussions	77
4	The Effect of Proactive Adaptation on Green Investment	80
4.1	Introduction	80
4.2	BaHaMa with explicit adaptation	84
4.2.1	Model description	84
4.2.1.1	Production dynamics	84
4.2.1.2	Climate change dynamics	85
4.2.1.3	Damage and adaptation frameworks	86
4.2.1.4	Welfare maximization	87
4.2.2	Model calibration	88
4.3	Results	90
4.3.1	Capital accumulation paths	91
4.3.2	GHG concentration, temperature and net damages	93
4.3.3	Economic output paths	95
4.4	Sensitivity analysis	95
4.4.1	Sensitivity analysis on adaptation effectiveness	96
4.4.2	Sensitivity analysis on climate sensitivity	98
4.5	Comparison to previous studies	100
4.6	Conclusion	102
	Conclusion	104
A	Appendix for Chapter 1	107
A.1	Annex 1: Initial variables for the selection algorithm	107
A.1.1	Annex 1: Gain and loss lotteries	107
A.2	Annex 2: Initial variables for the selection algorithm	109
A.3	Annex 3: Computation of the asset index	110
B	Appendix for Chapter 2	111
B.1	Details of the experiment narratives	111
B.2	Variables retained in the OLS regressions	112
B.3	Comparison of profile identification from Fischbacher et al. (2001) using the three-point method	114
B.4	Conditional contributions statistics for the different profiles and the different games	116
C	Appendix for Chapter 3	117
	Bibliography	127

List of Figures

1.1	Distribution of risk classes for gain-only games (small and large stakes).	18
1.2	Distribution of risk classes for loss-only games (small and large stakes).	18
1.3	Distribution of risk classes for different framing.	20
1.4	Distribution of risk classes with "own" endowments.	21
1.5	Distribution of risk classes with "own" endowments.	21
2.1	Distributions of conditional contributions for the three different group contributions in the "benchmark" game (Kernel density estimation)	40
2.2	Distribution of conditional contribution profiles for the four different games	42
2.3	Kernel estimation for the conditional contribution when group participation = 0 FCFA & 500 FCFA for the four games	43
3.1	Deforestation Paths	70
3.2	REDD improvements over BaU	70
3.3	Performance Indicators of Different Baseline Scenarios	72
3.4	Dominant Baseline Scenarios across Different Historical Deforestation Rates	76
4.1	Schematic overview of Ada-BaMaMa.	84
4.2	Damage levels (in percentage of production) for different temperature increases in Ada-BaHaMa and AD-DICE (in °C).	89
4.3	Economic production paths in Ada-BaHaMa and DICE2007.	90
4.4	Temperature deviation paths in Ada-BaHaMa and DICE2007 (in °C).	91
4.5	"Dirty" capital K_1 accumulation paths.	91
4.6	"Clean" capital K_2 accumulation paths.	92
4.7	Adaptation capital K_3 accumulation paths and maximal amount of adaptation capital (K_{3max}).	92
4.8	GHG concentration paths.	93
4.9	Temperature deviation paths from preindustrial levels (in °C).	94
4.10	Evolution of net damages.	94
4.11	Economic output difference (in %) relative to the combined scenario.	95
4.12	"Clean" capital K_2 accumulation paths for different levels of adaptation effective- ness.	96
4.13	Adaptation capital K_3 accumulation paths and maximal amount of adaptation capital (K_{3max}) for different levels of adaptation effectiveness.	97
4.14	Temperature deviation from preindustrial levels in °C for different levels of adap- tation effectiveness.	97
4.15	"Dirty" capital K_1 accumulation paths for different climate sensitivity.	98
4.16	"Clean" capital K_2 accumulation paths for different climate sensitivity.	99
4.17	Adaptation capital K_3 accumulation paths and maximal amount of adaptation capital (K_{3max}) for different climate sensitivity.	100
4.18	Temperature deviation from preindustrial levels in °C for different climate sensi- tivity.	100
A.1	Risky gain game: representation in the field	107

A.2	Risky loss game: representation in the field	108
C.1	Discounted Profits	120
C.2	Discounted Profits: View from top	120
C.3	Dominant Baseline Scenarios across Different Historical Deforestation Rates	122
C.4	Baseline Performance across Different Historical Deforestation Rates	123
C.5	Performance of the Fixed Corridor 2	123
C.6	Performance of the Variable Corridor 2 at Different Corridor Widths	124
C.7	Performance Indicators for The Narrow Variable Corridor 2	124
C.8	Performance Indicators and Dominant Baselines	125
C.9	Overall Scores of Baseline Dominance	126

List of Tables

I	Calibration for the gain-only games with small amounts.	12
II	Calibration for the loss-only games with small amounts.	12
III	Descriptive statistics for key variables (N = 122)	16
IV	Ordered Probit regression on the full set, gain-only and loss-only subsets	24
V	Ordered Probit regression on the full set, small-only and large-only subsets	24
I	List of profiles based on the form of their relative variations	35
II	Descriptive statistics for selected individual variables (N = 122)	36
III	Descriptive statistics for selected social variables (N = 122)	36
IV	Conditional cooperation profiles in developed and developing countries using the “strategy method” of Fischbacher et al. [63]	38
V	Regression on the “partial warm-glow” contribution levels for selected explanatory variables	45
VI	Unconditional contributions statistics for the different profiles and the different games	48
VII	Regression of the “unconditional” contribution levels on selected explanatory variables	50
I	Calibration parameters for the numerical models	67
II	Performance Criteria of Baseline Schemes	68
III	Baseline Dominance over Different Historical Deforestation Averages	75
I	Overview of the four different experiments based on the linear public good game	111
I	Weighting Alternatives for the Overall Performance Indicator	125

Introduction

This thesis is a collection of submitted or published papers that I wrote during my four years of doctoral studies in development economics at the NADEL Institute of the ETH Zurich. The general idea for this thesis is to address how social decisions (decisions involving socially relevant goods or services) are influenced by their environmental context. The definition of the environmental context was deliberately broad to accommodate different settings, from micro-decision at the individual level to aggregated macro-analysis of economic activity. The four papers that comprise this thesis all have a strong common thread which is the influence of external environmental contexts on the optimal decisions of agents. These contexts can be the existence of risk (first paper), the influence of group decisions (second paper), the existence of environmental services (third paper) or the recognition of climate change impacts at the global level (fourth paper). In each case, the nature of the exogenous context greatly influences the optimal decisions and in turn gives information about the choices of the best policy frameworks.

These papers cover the two research fields that were at the center of my research during the PhD: empirical decision theory for individuals in developing countries and the analysis of forestry and adaptation strategies in developing countries in the context of climate finance. These topics are examples of the different layers of analysis that permeate the economic analysis of social and collective decisions, from individual preferences to macroeconomic strategies. The papers comprising this thesis also share the same policy objective, albeit at different levels: how are our decisions impacting the welfare of developing countries and poor people?

The first paper (the first chapter) of this thesis analyzes how the preference for risk of poor and rural people can be influenced by external and internal motivators. While this paper remains experimental, it gives insights on the possible dynamics at play when it comes to socially risky behaviors and the crucial influence played by religious beliefs. This paper was written with my thesis supervisor Isabel Günther at NADEL.

The second paper extends on this idea and experimentally assesses the preferences of individuals subjected to collective decisions, under partial knowledge of the actions of their fellow villagers and under different and controlled contexts. I demonstrate that collective decisions are often shaped by external factors but are also driven by intrinsic preferences. It makes optimal collective decisions the subject of careful implementation (“choosing the right context”) as well as intelligent matching (“choosing the right partners”).

The third paper was written in the context of evolving climate change policies and increased influence of climate finance in the decision of forest-rich developing countries. Using a single-player model representing decisions for a typical local land owner, this paper deals with the effect of choosing a specific REDD contract design (i.e. baseline) in order to limit deforestation while maintaining welfare for the local stakeholders. This paper was written with my co-author Anca Pana at the University of Zurich.

Finally, the last paper extends the environmental context to its most general setting, with a macroeconomic integrated assessment model designed to test the role and influence of adaptation strategies to limit climate change. It is now well accepted that adaptation measures will be the only viable strategy for developing countries willing to limit the damages of climate change. This paper offers insights on the possible deployment of significant adaptation financing and their timing. This paper was written with my co-authors Olivier Bahn at University of Montreal (HEC Montreal) and Marc Chesney at University of Zurich. It was published in 2012 in *Environmental Science and Policy*.

The structure of the thesis is chosen to represent an upward analytical process, from local, individual and community-based decisions to environmental and nationally-enforced contracts to global and international decisions attached to the climate public good. Each of the papers bears a specific form of a social dilemma, from risk perception to natural resource depletion to public good free-riding.

Each paper is also deeply embedded in natural and resources economic issues, either directly (as with the third paper on REDD and the fourth paper on climate mitigation and adaptation) or indirectly, through a clearer understanding of risky and collective decisions (most environmental public and club goods belong to this decision group).

The rest of this introduction extends and details each paper and outlines my contributions for the co-authored papers. It gives an immediate idea of the questions, methodology and results offered by each paper.

The first paper is entitled “Risk Averse in Losses, Risk Taking in Faith. An Experiment in Poor Rural Communities”. Its aim is to expand knowledge on risk aversion among the poor by conducting experiments in 12 rural villages of Benin that do not only test risk aversion for small and large stakes but also for risky gains and risky losses. To my knowledge, this is the first

attempt to conduct experiments in poor communities strictly focused on the loss domain. The experiments were conducted with 120 poor rural households in Benin. In contrast to results in industrialized countries, I find that playing lotteries constrained to the loss domain dramatically increases risk aversion. I also find a strong negative relationship between the level of risk aversion (both in gains and losses) and the level of religious faith. My interpretation of this result is that villagers with strong beliefs tend to rely more on God's goodwill at the expense of a proper risk assessment, resulting in larger risk-taking. For this paper, I conducted the different experiments in all the villages and designed and implemented a step-wise algorithm that selects sequentially covariates among a large set of potential candidates and optimally implements the "least-expensive" model, for the econometric analysis of the results. I designed the methodology and wrote the paper in collaboration with Isabel Günther.

The second paper is entitled "Does Cooperation Depend on the Circumstances? The Case of Rural Villagers in Benin". In this paper, I use a modified version of the strategy vector method in rural villages of Benin to test if the introduction of risk and loss framing affects the nature and distribution of conditional cooperation profiles. I first find that the change of context, influenced by strong poverty and informal social collaboration between households, has a significant influence on the types of conditional profiles found and their respective shares. While free-riding is totally absent in the sample, it is replaced by a large share of 'U-shaped' profiles who play the role of contributors of last resort when no one in the group contributes. As intended, I also observe a strong effect for loss framing. Presenting the voluntary contribution as a way to alleviate a public loss increases the general level of contribution while reinforcing altruistic profiles for a significant share of the sample. This positive role of loss framing on public game contribution also applies to unconditional linear public-good games. On the contrary, the presence of risk deters group participation and limit conditional contributions. However, when both risk and loss framings are played jointly, the positive effect of a loss narrative dominates clearly. It suggests that the way collective projects are presented is an important instrument that could play an effective and inexpensive role to nudge proper levels of participation in public or club goods, especially in presence of risk.

The third paper is entitled "Baseline Choice and Performance Implications for REDD". The paper first acknowledges that the significant contribution of deforestation to global CO₂ emissions has recently favored the emergence of new schemes (REDD), which offer carbon payments in

exchange for reductions in emissions from deforestation. These price instruments target deforestation levels below business-as-usual scenarios, therefore requiring a good understanding of the differences between alternative baseline approaches. While multiple baseline schemes have been proposed in the past, this paper is, to the best of my knowledge, the first attempt to specifically assess their impacts on deforestation levels and REDD efficiency in a dynamic setting. Using a general timber extraction model, I compare the performance of four different baseline models that cover a large spectrum of the proposed schemes for future REDD projects. I find that different indicators promote different baselines. This paper is also exploring further ways to improve baseline performance, and highlights the importance of design features, namely corridor bandwidth and symmetry. I find a symmetric and narrow variable corridor 2 as the overall best performer, offering top results in terms of effectiveness in reducing emissions from deforestation and guaranteeing at the same time a positive though modest increase in welfare. For this paper, I designed the dynamic methodology, the equations of motion and the different numerical modules for their resolutions. Interpretations of the results were done collaboratively.

Finally, the fourth and final paper is entitled “The Effect of Proactive Adaptation on Green Investment”. To assess the relationship and effects of both mitigation and adaptation on the global economy, I use an integrated assessment model (IAM) that includes both proactive adaptation strategies and access to “green” investments (clean technologies) for mitigation. I find that the relationship between adaptation and mitigation is complex and largely dependent on their respective attributes, with weakly effective adaptation acting as a late complement to mitigation efforts. As its effectiveness increases, adaptation becomes more and more a substitute for mitigation. Sensitivity analysis on the potential magnitude of damages also indicates that scientific efforts to better describe GHG impacts will have immediate and important consequences on the sequence of mitigation and adaptation strategies. The core IAM module was modeled in collaboration with Olivier Bahn. I implemented the adaptation extensions, calibrated the model and analyzed the results. The writing of the paper was done in collaboration.

Each of the four papers demonstrates that decisions, whether they incur at the micro/individual or the global/macro level, are highly dependent on small differences in their context. This is especially true when policies are designed to incentivize a proper set of decisions. At the micro level and in the developing setting of rural Benin, I demonstrated that framing devices can have a central role for the perception of risk and collective collaboration. Policies targeting public goods in situations of risk should pay attention to their narrative and to the way they

present the situation. A risky project will not gather a large support if it is not presented as a loss-preventing project or if it does not account for the influence of social factors (such as religion). This importance of details also apply to larger situations, such as forestry contract and forest preservation schemes. I highlighted that small variations of only one element of the contract design (here the baseline) was enough to generate significant variations of performance and fairness for the entire scheme. At the macro level, the principle remains true. To curb the damages caused by climate change, optimal decisions will be largely influenced by the relative efficiency of some of the available strategies or the proper measurement of climate damages.

The next four chapters cover the four papers. They are followed by the general conclusion of the thesis, the appendixes and the general bibliography.

Chapter 1

Risk Averse in Losses, Risk Taking in Faith.

An Experiment in Poor Rural Communities

Published as Jonathan Gheysens, Isabel Günther in UNU-WIDER Working Papers Series, 2012

1.1 Introduction

Risks play a crucial role in decision making and well-being both in developing as well as in industrialized countries. Yet, the exposure to negative shocks is more exacerbated in developing countries because of the lack of access to dedicated markets that allow for risk hedging. Moreover, without those markets it is extremely difficult to determine risk aversion or the price people are willing to pay to remove negative risks from their daily life. An extensive literature has therefore emerged which aims to empirically elicit risk-preference parameters in developing countries (Antle 15, Bar-Shira et al. 19, Bardsley and Harris 20). The problem is that econometric techniques have difficulties in disentangling risk aversion from budget constraints, time preferences and limited insurance possibilities, resulting in an overestimation of risk aversion

of poor people (Binswanger 26). To circumvent this problem, Dillon and Scandizzo [52] and Binswanger [25] initiated field experiments applying budget- and time-neutral lotteries to elicit risk preferences among the populations of several developing countries. Our study follows their approach but extends the experiments along two important dimensions which have so far been neglected in the literature: (1) capturing risk preference not only in lotteries of positive outcomes but also in situations of pure losses, and (2) improving the quality of the estimated risk-aversion parameters by reducing the possible cognitive bias (lack of understanding) associated with the usually applied lottery selection procedure.

To our knowledge, this is the first attempt to conduct lotteries in poor communities strictly focused on the loss domain (each lottery alternative resulting in a loss). Apart from Yesuf and Bluffstone [147] who introduced lotteries of gains-and-losses and compared them to the traditional gain-only lotteries, the change in risk preferences when the context shifts from pure gains to pure losses remains unknown for rural and poor settings. Such an analysis is, however, crucial from both a theoretical and a policy perspective to better understand individuals' behaviors in situations of risky losses.

From a policy point of view, the reasons behind the risky behavior, which is often observed among the poor when it comes to risky losses, remain unknown. For example, it has been shown that households across developing countries invest very little in mosquito nets (Cohen and Dupas 45) despite their proven protective effects against malaria (Erlanger et al. 55), and despite considerable household expenditure on treating malaria (e.g. Russell [122]). Is this risk taking in losses the consequence of a preference for risks in losses, a consequence of large time discount rates, a consequence of budget constraints, or a lack of understanding of and/or trust in mitigation strategies. Understanding the drivers behind suboptimal hedging is important to design improved mitigation strategies against such risks. The worst-case scenario for governments and development agencies would be to target policies towards riddance of budget constraints and improved access to risk-mitigating measures, only to discover that poor households are risk-seekers when it comes to risks involving losses. Estimating preferences for negative risks and the key socio-economic variables that influence them is therefore necessary to prioritize development interventions.

From a theoretical perspective, understanding risk preferences in losses is an attempt to bridge the gap between the extensive prospect theory literature that has emerged in industrialized

countries and research on risk preferences in developing countries. Since the pioneering work of Kahneman and Tversky [89], it has been shown that individuals do not always behave along the lines of expected utility theory. Instead of making decisions based on final wealth, individuals tend to be influenced by reference points and to distinguish between gains and losses. Most people value a loss higher than its symmetrical gain, and tend to show risk-seeking behavior in losses despite being risk-averse in gains (Fennema and Assen 58, Harbaugh et al. 72).¹ Empirically, several attempts have been made to compute risk-aversion coefficients within a prospect theory framework (Harrison et al. 73, Galarza 67) but their complexity prevents them from being used outside of well-educated populations. Conscious of this limitation, our approach is to test for risk preferences in loss-only lotteries but using a calibration that relies on expected utility theory (and that has been applied in various developing countries before). Statistically significant deviations between loss-only and their gain-only lottery counterparts will support the idea that poor populations also show different risk preferences in losses in comparison to gains.

Moreover, we try to improve on the experiments that have been used in the past to estimate risk-aversion parameters. Across the literature, most risk-aversion elicitation procedures are based on the selection of one lottery out of a set of (mostly 6) comparable lotteries with varying expected means and variances. While this approach is perfectly valid on a theoretical ground, it has in our opinion two limitations. It is a purely hypothetical exercise with no comparable real-life application. It rarely occurs that individuals are presented with a win-win situation, with only different risk levels involved. Second, the cognitive effort required to compare different lotteries on their mathematical terms seems too demanding for populations with limited educational backgrounds. This limitation has already been acknowledged in numerous papers (Harrison et al. 74, Schechter 127), which relied on an elicitation procedure through pair-wise selections.² Our approach is to replace the process of comparing several lotteries with a one-time decision to invest (mirroring real-life situations). The respondent has to decide on the level of investment, which is multiplied by a multiplier greater than one in a good state and which has a zero pay-off in a bad state (see Section 2 for more details).

In contrast to experiments from industrialized countries, where individuals have shown to take higher risks in losses than in gains (e.g. Fennema and Assen 59, Harbaugh et al. 72), we find

¹Another argument is the certainty effect proposed by Allais [3]: while on the gain domain, people tend to prefer a sure gain to a risky prospect, the effect reverses in the loss domain and enhances risk-seeking behaviors.

²For a thorough review of the different methodologies, we refer the reader to Cox and Harrison [47].

for our sample of poor populations that playing lotteries constrained on the loss domain dramatically reduces risk-taking behavior in comparison to gains. This finding is robust to several modifications of the experiment. We also find a strong negative relationship between the general level of risk aversion (both in gains and losses) and the level of religious faith. A possible explanation is that individuals with strong beliefs tend to rely more on God's good-will at the expense of a proper risk assessment, resulting in larger risk-taking. Moreover, whereas villagers display - in line with the literature - increasing partial risk aversion (IPRA), we find that higher wealth among generally poor individuals is negatively correlated with risk taking, indicating increasing absolute risk aversion (IARA). This contradicts most of the literature which generally assumes decreasing absolute risk aversion (DARA). We also observe that risky decisions are path-dependent: while a previous win in a sequence of games leads to increased risk appetite, the experience of an income shock has the expected inverse effect of increased risk aversion.

The paper is structured as follow: section 1 presents the methodology and experimental design, followed by section 2 with the data and field description. Section 3 presents our econometric analysis, including various robustness checks, and section 4 concludes.

1.2 Methodology and experimental design

Despite various applications of the methodology originally designed by Binswanger [24], eliciting risk aversion profiles in poor and low-educated communities remains a challenge. First, the often applied experimental design - asking players to choose one lottery out of many based on varying expected means and variances - assumes a degree of mathematical proficiency which is rarely achieved by low educated populations.³ Concepts of mean and variance are sometimes difficult to convey, especially for individuals who have no experience with written numbers (while being good at mental calculation). Second, we think that lotteries should be meaningful to individuals, i.e. related to real-life choices, since individuals - at least in our sample - always grounded choices in daily situations, whether implicitly or explicitly.

To facilitate decision making and avoid noise generation coming from cognitive impediment, our experimental design is based on a set of simple investment choices. First, individuals have to decide on the level of investment into a risky project with uncertain profits (gains), followed by a decision on the level of investment into an insurance coverage against uncertain costs (losses).

³Despite the recent arguments made by Delavande et al. 50.

Both choices are presented in the form of a binary lottery with either zero pay-offs or a pay-off that is determined by the level of investment times a multiplier larger than one (positive or negative depending on testing for risk preferences in gains or losses). Contrary to the usual approach of asking players to choose from a list of win-win situations, our method is therefore very close to actual cognitive processes that are part of the daily life of poor individuals. While households rarely (or never) have to choose between different returns with varying risks, individuals often have to decide on investments for which rewards (or prevented losses) are uncertain. Moreover, we are able to present only one lottery (for gains and losses) with a constant multiplier, which simplifies the decision process for the participants.

Formally, and in line with previous literature (e.g. Binswanger 24, Yesuf and Bluffstone 147), we base our experiments on a utility-maximizing approach using a constant partial risk aversion (CPRA) utility function:

$$U(x) = (1 - \gamma)x^{(1-\gamma)} \quad (1.1)$$

where γ is the coefficient of risk aversion. For the risky-gain experiment, the participant has to maximize her utility by deciding on the level of investment i into a risky project out of an initial endowment I :

$$\max_i \alpha(1 - \gamma)(I - i)^{(1-\gamma)} + (1 - \alpha)(1 - \gamma)((I - i) + \beta i)^{(1-\gamma)} \quad (1.2)$$

where I is the initial endowment, i is the investment in the risky bet, β is the (positive) multiplier (larger than one) for the risky investment, and γ is the coefficient of risk aversion. α is the probability of zero pay-offs and $1 - \alpha$ is the probability of a gain (which is equal to the investment times the multiplier). We set $\alpha = 0.5$. The outcome is decided upon the toss of a coin by the participant. Using a coin with probabilities of 50/50 is both easy to explain and easy to implement. It also gives the player full responsibility over the outcome, ensuring that the participants trust the game and the outcome of the toss. With an increasing level of risk aversion (i.e. with increasing γ), the respondent will choose to make a lower investment i to maximize his/her utility. This allows us to elicit the risk-aversion coefficient γ for each participant based on his/her investment decision into the risky project.

We use the same calibration approach for the loss domain with a slight adjustment that accounts for a negative multiplier for the risky investment leading to the following maximization

problem:

$$\max_i \alpha(1 - \gamma)(I - i)^{(1-\gamma)} + (1 - \alpha)(1 - \gamma)((I - i) - \beta(j - i))^{(1-\gamma)} \quad (1.3)$$

where j represents the amount at risk that can be reduced through an investment i . In contrast to equation 1.2, where a higher initial investment i leads to a higher risky gain, a higher initial investment i leads to a lower risky loss.

To compare our results with previous literature, the participants are not allowed to choose their level of investment freely but are provided with an initial set of 6 investment options that mirror the risk-aversion brackets of Binswanger [24] and Yesuf and Bluffstone [147]. Table I presents our calibration for the games in the gain domain (“gain-only”) and table II the calibration in the loss domain (“loss-only”). For the gain domain (equation 1.2), the investment alternatives range from no investment in the risky investment option (highest risk aversion) to full investment into the risky investment option (risk neutral to loving). For the loss domain (equation 1.3), the alternatives range from high investment to lower the amount at risk (highest risk aversion) to no investment to lower the amount at risk (risk-neutral to loving). For both the gain and loss lottery expected mean and expected variance increases across options. Since this initial calibration does not provide the distinction between risk-neutral preference and risk-preferring/seeking behavior, whenever a participant selected the largest investment in the risky bet, we asked her to play an additional hypothetical game where he/she had to choose between a risk-neutral lottery and a risk-seeking one. The procedure is similar to the rest of the experiments.

TABLE I: Calibration for the gain-only games with small amounts.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Choice	Invest. i	If Coin Tail (Win)	If Coin Head (Lose)	Expected Risky Gain	Expected Mean	Expected StD.	Risk coeffi- cient (γ)	Risk aver- sion
1	0	0	0	0	500	0	∞ to 7	Extreme
2	25	75	0	37.5	512.5	53	7 to 3	Severe
3	50	150	0	75	525	106	3 to 1.2	Intermediate
4	150	450	0	225	575	318	1.2 to 0.5	Moderate
5	350	1050	0	525	675	742	0.5 to 0.2	Slight
6	500	1500	0	750	750	1061	0.2 to $-\infty$	Neutral to preferring
Endowment I : 500 FCFA				Multiplier β : 3				

Notes: Column(3)=[Column(2)*3]; Column(6)=[500-Column(2)+ Column(5)]

TABLE II: Calibration for the loss-only games with small amounts.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	
Choice	Invest. i	If Tail (Win)	If Head (Lose)	Expected Risky Loss	Expected Mean	Expected StD.	Risk coeffi- cient (γ)	Risk aver- sion	
1	1000	0	0	0	500	0	∞ to 7	Extreme	
2	950	0	-75	-37.5	512.5	53	7 to 3	Severe	
3	900	0	-150	-75	525	106	3 to 1.2	Intermediate	
4	700	0	-450	-225.5	575	318	1.2 to 0.5	Moderate	
5	300	0	-1050	-525	675	742	0.5 to 0.2	Slight	
6	0	0	-1500	-750	750	1061	0.2 to $-\infty$	Neutral to preferring	
Endowment I : 1500 FCFA				Multiplier β : -1.5			Risky Loss j : 1000		

Notes: Column(4)=[(1000-Column(2))*-1.5]; Column(6)=[1000-Column(2)+ Column(5)]

The initial endowments (500 FCFA for the gain-lottery and 1500 FCFA for the loss-lottery) are chosen high enough in order to motivate individuals to participate and to take the games seriously. 500 FCFA represent an average daily wage for unskilled rural labor in the sampled villages.⁴ The multipliers (3 for the gain lottery and -1.5 for the loss-lottery) are chosen in conjunction with the initial endowment to ensure that the games are self-sustaining, i.e they are not influenced by existing budget constraints and shielding the players from potential personal losses. Moreover, initial endowments and multipliers were chosen to assure the same risk-aversion brackets (columns 8 and 9) and the same expected mean (column 6) and standard deviation (column 7) in final wealth for the gain and loss lotteries. The difference between the calibration in Table I and Table II is the reference-point which leads to a risky gain in Table I and a risky loss in Table II (column 5). In addition to the two lotteries presented above, each participant played one additional gain and one additional loss lottery, where we doubled the initial endowments I and possible investments i to test for increasing partial risk aversion (IPRA) in gains and losses.

In practice, before each game (hence four times), each participant receives an initial endowment I .⁵ In a next step, each participant is asked to put the received endowment in front of him/her in a special box representing her budget.⁶ Facing this budget box, a sheet with 6 separated investment areas and the potential pay-offs - representing the choices in table I and II - is presented to the participant (see Annex 1).

For the risky gain game, each investment area shows a small square with the possible investments (representing column 2 of Table I) and a second part with the printed change representing the added value in case of a gain (representing column 3 of Table I). The participant is then asked to take the chosen investment amount from her budget box and to put it on the respective investment square of the investment areas (see Annex 1). This investment represents the share she is willing to invest in a risky project (with a multiplier of 3). We match the selected option by adding twice the invested money. The randomness of the outcome of the risky project is materialized by a coin that the player has to flip. If it lands tails up, the participant recovers her investment and earns twice the amount invested. If lands heads up, the participant loses her investment. Before flipping the coin, the participant is asked to describe the potential pay-offs

⁴To conduct the full experiment, we asked participants to stay with us for a full day at a time when the first days of rain required field work of the farmers. The game payments were therefore a fair compensation for the productivity loss with the monetary gains of participating in the experiments for one day being on average the same as a usual weekly income.

⁵More precisely, 500 FCFA for the small-scale gain-lottery (see Table I), 1000 FCFA for the large-scale gain-lottery, 1500 FCFA for the small-scale loss-lottery (see Table II), and 3000 FCFA for the large-scale loss-lottery.

⁶ We ensure that the compensation is paid with enough small change to allow for all possible investment options.

for the chosen alternative to make sure that she fully understands her investment choice. Upon the result of the flip, the final pay-off is settled immediately. We pay out real money (in FCFA) for each single game instead of tokens with payments only at the end of a series of games. For individuals who often do not know the meaning of written numbers but are used to coins and bills (and their respective values) it limits errors and forces the participants to consider their decisions carefully. For the risky loss game, the interpretation is slightly different. An investment (column 2 of Table II) represents a sure loss but reduces the amount at risk (column 4 of Table II). To facilitate understanding, the participant has to divide his/her endowment between a sure loss (=insurance) i in the lower part of the sheet presented in Annex 1 and a risky loss $(j - i) * \beta$ in the upper part of the sheet presented in Annex 1. If the flipped coin lands heads up, the participant loses the amount at risk and her insurance. Tails up: the participant only loses her insurance.

1.3 Data and Field Description

The experiments were administered at the end of a large-scale panel household survey covering 2000 randomly selected individuals from 200 villages in two regions of Benin.⁷ From the 200 villages surveyed between January 2009 and July 2010, a sub-sample of 12 villages in the region of Collines was systematically selected to conduct the experiments in August 2010.⁸ The villages were selected to both represent the socio-economic diversity of the region but at the same time to represent the highest possible level of literacy using an aggregated index comprising years of schooling, highest degree achieved and fluency in French (the official language in Benin). The aim was to reduce the inevitable noise coming from an insufficient understanding of the games. We are, however, confident that this deliberate trade-off in favor of a higher level of education does not create a large selection effect: the average completed years of schooling in the selected villages was still only 3 years and we observed large variation of education levels within the villages, covering the full distribution from no schooling to high school levels. In each village, we played with all individuals (10 per village) who were previously randomly selected (from complete household listings) for the panel household survey.

⁷The study was financed by the Federal Ministry of Economic Cooperation and Development (BMZ) Germany, the German KfW Development Bank, and the Policy and Operations Evaluation Department (IOB)- Ministry of Foreign Affairs of the Netherlands. The financing and use of the 4th wave of this survey for complementing our experimental results is gratefully acknowledged.

⁸The villages were Adourekouman, Assromihoue, Bethel and Tankossi in the commune of Glazou; Agbomadin, Koutago, Lema, Lowozoungo, Mondji, Segbeya and Zongo in the commune of Savalou; Atchakpa and Gobé in the commune of Savé.

Despite recent economic and structural reforms that sustained a moderate growth rate in per capita income up to US\$1500 (PPP) per capita in 2009 (WDR, 2011), Benin remains a poor country, ranking 134th in the Human Development Index (out of 169 countries). The region of Collines relies mainly on agriculture, with both subsistence (maize, yam) and cash (cotton, cashew, sugar cane) crops, as well as on transit services to the neighboring countries. Almost all individuals in our sample are subsistence farmers, living on crop consumption and marginally on local market revenues from the sale of excess production. Benin has two seasons which dictate most of the population's activities and income. During the wet season, field activities are at their peak and generate revenue inflows that are then depleted during the dry season. Without easy access to credit or insurance markets, villagers are highly vulnerable to both shortened wet seasons and unexpected patterns between dry and wet months. Our experiments were conducted in August, the traditional first rainy month used to seed crops. To smooth income variations, an informal process of gifts and reciprocations is also present in all of the sampled villages.

Table II presents some descriptive statistics of key socio-economic variables which were used as regressors in the econometric analysis in section 1.4. Details are provided in Annex 2. The average years of schooling is 2.94 years, with 20% of the respondents having more than 7 years or more of schooling. As expected, a majority of the participants are farmers, followed by a group of artisan/merchants, often representing housewives either selling excess productions on markets or working as dressmakers. A minimal number of participants are employed while the "other" category covers students, trainees, unemployed and retired people. The average household size is just below 6 household members with a predominance of young children and with 10% of the respondents coming from households with more than 10 individuals. It was beyond the scope of the household survey to elicit consumption or income estimates, which are not only very time-consuming to collect but often imprecise when it comes to poor rural communities. As proposed in the literature (see e.g. Filmer and Scott 60, Howe et al. 83, Sahn and Stifel 124, 125) we therefore constructed an asset index from 30 assets to proxy for the relative household wealth of the participating individuals. Annex 3 describes the used assets and the applied methodology.

To test for the potential effect of background risk on risk preferences we also include perceived volatility of earnings (*earning stability*), access to a saving scheme (in cash or kind), and self-reported experience of water shortages in our final econometric analysis. Earning volatility is in general high, as incomes largely depend on (fluctuating) weather conditions and agricultural

TABLE III: Descriptive statistics for key variables (N = 122)

Variable	Mean	Std.Dev.	Min	Max
Age	44.8	16.86	22	99
Gender (1=Male, 0=Female)	0.64	0.48	0	1
Years of schooling	2.94	4.09	1	15
Position in household				
- <i>Head</i>	73%			
- <i>Wife/Husband</i>	21%			
- <i>Relative</i>	6%			
Main activity				
- <i>Farmer</i>	66.84%			
- <i>Artisan/Merchant</i>	11.76%			
- <i>Salaried Employee</i>	5.88%			
- <i>Housewife</i>	4.20%			
- <i>Other</i>	11.32%			
Household size	5.85	2.96	1	15
Asset index (1=Highest, 0=Lowest)	0.19	0.14	0	1
Earning stability (1=Yes)	0.72	0.45	0	1
Access to savings/insurance (1=Yes)	0.74	0.44	0	1
Water shortage (1=Yes)	0.85	0.35	0	1
Religion				
- <i>Catholic</i>	44.70%			
- <i>Voodoo</i>	29.55%			
- <i>Christian</i>	13.64%			
- <i>Muslim</i>	6.82%			
- <i>Agnostic</i>	3.03%			
- <i>Jehova's witness</i>	1.52%			
- <i>Apostolic</i>	0.76%			
Faith				
- <i>Strong</i>	79%			
- <i>Moderate</i>	16%			
- <i>Low</i>	4%			
- <i>None</i>	1%			

production. To hedge some of the unexpected or larger shocks, most households are aware of the role of savings and a large proportion of them (74%) participate (in the past or currently) in personal or collective thrift schemes. Being vital to individuals while inexpensive and without substitute, the inability to pay for drinking water and hence to experience water shortages, is most likely to be the result of severe income shocks and not the result of preferred budget allocations.

Two final, but very important, variables for our econometric analysis are the religion and faith/fate of individuals. Religion plays a significant role in Benin, with complex interactions between official churches and a strong “voodoo” heritage - Benin is the historical cradle of voodoo. Within our sample, Catholicism is predominant with a share of 44%, followed by Voodoo (29.55%), other Christian churches (13.64%), and Islam (6.82%). The influence of Voodoo is in reality larger than its relative share, since most of the households maintain a cohabitation between their official religion and certain voodoo practices, either publicly or in private. Apart from religion, we

also try to understand the faith of individuals. We therefore asked to what extent God/Allah (or any representation of a higher spiritual being) is responsible for the outcomes in their daily lives. Since the question is both conceptually difficult and potentially sensitive, the interviewers spent an appropriate amount of time with each participant to ensure that the question was perfectly understood. The question was adjusted in accordance with the religion of each villager to account for religious differences. As shown in Table II, 78.7% of individuals consider that they have almost no influence on their daily life as they fully rely on God's decisions, 16.4% report a shared influence with God and 4.1% a strong personal influence without much help from God. Less than 1% considers that God has no influence at all on their lives. As an example, when asked what strategies the villagers deployed to limit the impacts of a dry August, a widespread response was *"to seed as usual and pray for God to bring the rain."*

1.4 Econometric analysis

1.4.1 Risk Aversion in Gains and Losses

Figure 1.1 displays the general distribution of the CPRA parameter γ for the "gain-only" games. The distribution of γ displays a shape similar to a Bell curve, centered around the intermediate and moderate levels of risk aversion and with a unique mode. It is apparent that playing games with larger stakes shifts the distribution slightly towards more conservative risk taking. The shape of the distribution is similar to Wik et al. [146] and is somewhat less skewed than Yesuf and Bluffstone [147] towards highly risk-averse categories.

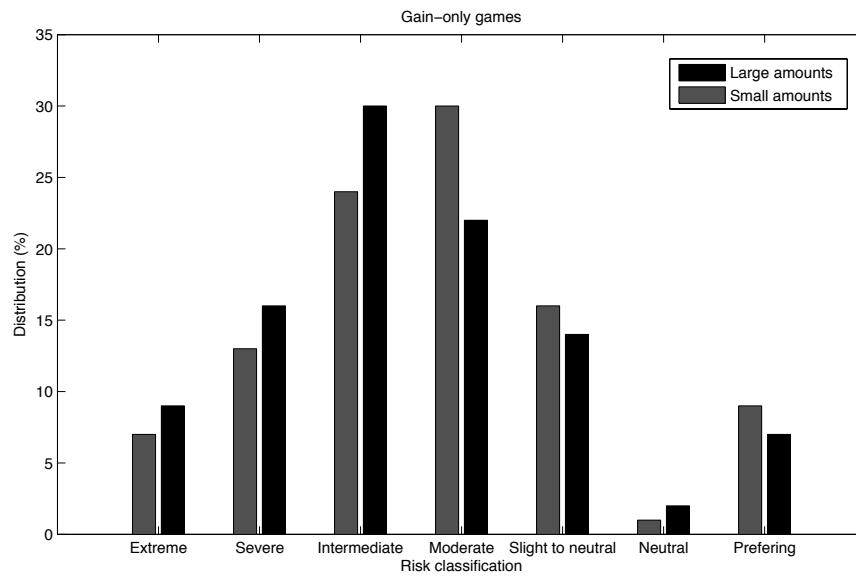


FIGURE 1.1: Distribution of risk classes for gain-only games (small and large stakes).

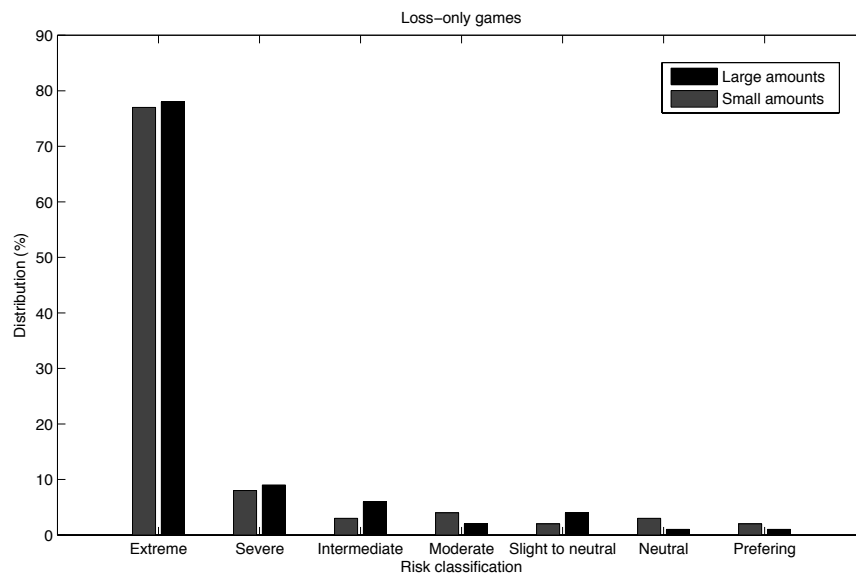


FIGURE 1.2: Distribution of risk classes for loss-only games (small and large stakes).

Figure 1.2 gives the γ (CPRA coefficient) distribution for the “loss-only” (small and large stakes) games. It is apparent that in losses and in comparison to gains, the distribution of the risk classes shifts heavily to higher risk aversion. This means that individuals prefer a sure loss to a lower

but risky expected loss. This result tends to confirm the existence of reference points when evaluating risks. On the other hand, this result clearly contradicts the assumed view of increased risk taking in losses that emerged from experiments conducted in industrialized countries (Fennema and Assen 59, Harbaugh et al. 72). Moreover, the results of the large-scale socio-economic survey that interviewed the same individuals indicate that participants take high risks with regard to their personal health. We can either hypothesize that most of the poor are indeed budget constrained and are forced to give up on basic insurance techniques, that participants have high discounting rates for the future which prevents them from investing in preventive health measures, or that they have internalized certain risks as facts of life, no longer considering some of the shocks as risks possible to hedge.⁹ All of these topics are starting points for future research.

To validate our results, we conducted several robustness checks during the experiments in August 2010 and in a follow-up round in August 2011. Already during the first round, we noticed that participants were reluctant to select between alternatives with only loss related pay-offs. To test for a possible distinction between real life framing and simple lotteries (which might lead to biased results) we slightly framed the games for a subgroup of individuals as a choice between different levels of insurance/protection. We used two framing scenarios: one on health coverage for children¹⁰ and one on reparation costs for a specific asset.¹¹ The additional scenarios were used randomly across villages, which allows us to test for framing distortion when playing games in the loss domain. Our results show that there is no significant framing effect on the elicited risk aversion parameter distribution (see Figure 1.3). Presenting the loss experiment within a real life framework only slightly increases extreme risk aversion.

⁹Malaria is a good example of this form of “determinism”. Despite being educated and trained on the subject, many of the interviewed villagers consider that episodes of high fevers are an irrepressible part of their lives that they have to live with.

¹⁰The participant is placed in a situation where one of the children has to be treated for malaria. Each proposed category for the sure loss represents a certain amount the participant will spend on medications, with the highest investment leading to the child being fully treated. But with lower medical expenditures, the risk of a relapse would trigger higher additional costs.

¹¹The participant has an important piece of equipment (which is selected in accordance with the player’s assets) that is on the verge of failure. She can either pay for a partial reparation, hoping that it will suffice or she can decide to replace entirely the equipment, ensuring that in any circumstance, it will not fail in the future. To frame the story along the lines of our game, the participant can decide to have no reparation, or an increasingly costly reparation scheme that will decrease the amount of a second reparation in case of failure (but has no effect on the probability of failure).

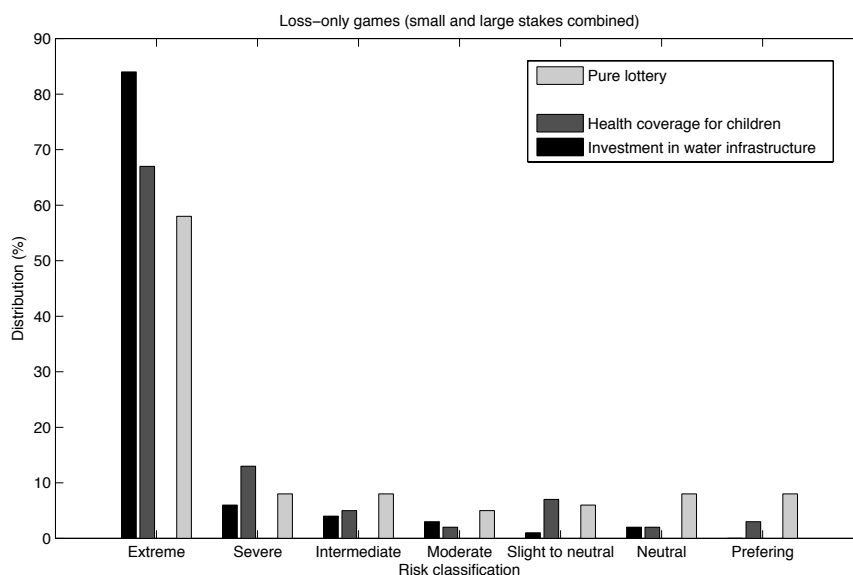


FIGURE 1.3: Distribution of risk classes for different framing.

Another limitation of our study might be that we assume for the purpose of our analysis that the players internalize the endowments provided by us within their available budget *before* we start playing (see Section 2). This is of course a strong assumption, albeit one commonly assumed (Harbaugh et al. 72, Harrison and Rutström 75). A valid criticism could be that the participants, receiving some external income and being asked to play a monetary game right away consider this new wealth as “game money” (or “drink money”) and not as part of their current budget. In general, we would argue that this effect should decrease risk aversion (and not increase it) and that this effect should mainly have an influence on risk aversion globally (i.e. a willingness to gamble) and less on the observed difference between gain and loss games. We, nevertheless, conducted another round of experiments in August 2011 to account for this possible phenomenon of mental accounting between the player’s own budget and the received endowments for playing the games. The best solution would have been to ask people to play with their own money but this would have resulted in some people being poorer after the games, a situation we wanted to avoid at all costs considering their already difficult conditions. As an alternative we played several rounds of gain games and then asked individuals to play a loss game with their “own” money (without giving them another initial endowment). Results for the distribution of risk classes in the loss domain do not change (see Figure 1.4). Last, our results in the loss domain might be biased because we allow for a totally risk-free scenario, which might be attractive enough for individuals to discard their true risk preferences in favor of this (maybe unrealistic)

scenario. As a last robustness check, we therefore played the loss game again in August 2011, but without the option of full insurance. Results are presented in Figure 1.5: individuals simply shift to the next category, but the distribution remains the same.

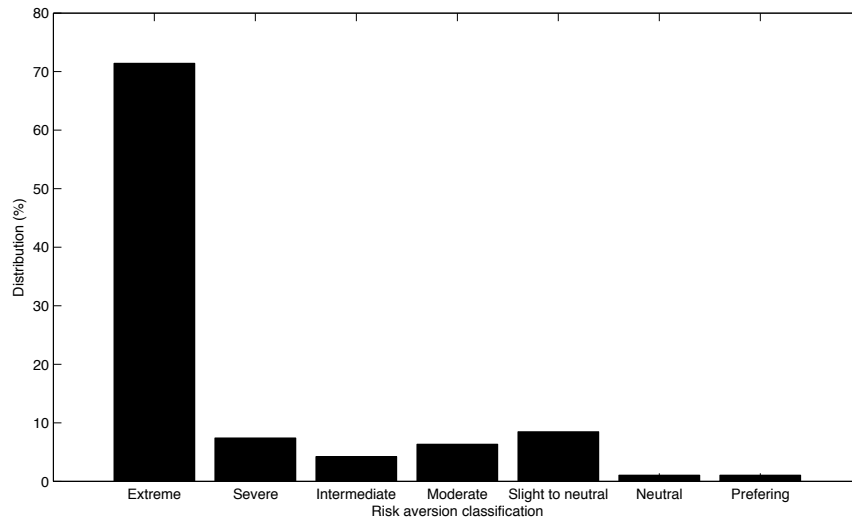


FIGURE 1.4: Distribution of risk classes with "own" endowments.

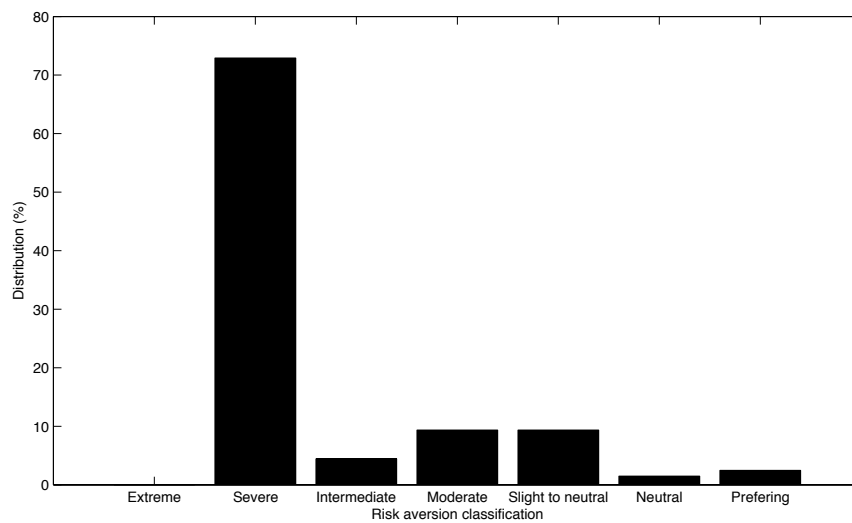


FIGURE 1.5: Distribution of risk classes with "own" endowments.

1.4.2 Drivers of Risk Preferences

When analyzing the drivers of risk preferences, we have to account for (i) the ordered nature of our risk classification (7 discrete categories from extreme risk aversion (1) to risk seeking (7)) and (ii) for the panel structure of our observations (the players are represented four times in our data structure, as they play four different games each). We use an ordered probit model in which risk aversion is a latent variable of the following linear form:

$$y_{ij}^* = x_i\beta + u_{ij}$$

where y_{ij}^* is the latent risk aversion expressed by player i in game j , x_i is the vector of explanatory variables for the player i and u_{ij} is the residual error term. To account for the individual clustering in our observations, we model the error term as the sum of an individual effect c_i and an idiosyncratic error ϵ_{ij} , such that:

$$u_{ij} = c_i + \epsilon_{ij}$$

Since y_{ij}^* is never observed, the observed variable y_{ij} is assumed as follow:

$$y_{ij} = 1 \quad \text{if} \quad \alpha_0 = -\infty \leq y_{ij}^* \leq \alpha_1$$

$$y_{ij} = 2 \quad \text{if} \quad \alpha_1 \leq y_{ij}^* \leq \alpha_2$$

$$y_{ij} = 3 \quad \text{if} \quad \alpha_2 \leq y_{ij}^* \leq \alpha_3$$

$$y_{ij} = 4 \quad \text{if} \quad \alpha_3 \leq y_{ij}^* \leq \alpha_4$$

$$y_{ij} = 5 \quad \text{if} \quad \alpha_4 \leq y_{ij}^* \leq \alpha_5$$

$$y_{ij} = 6 \quad \text{if} \quad \alpha_5 \leq y_{ij}^* \leq \alpha_6$$

$$y_{ij} = 7 \quad \text{if} \quad \alpha_6 \leq y_{ij}^* \leq \alpha_7 = +\infty$$

where α_i represents the upper and lower boundaries of the risk coefficient brackets (see Table I and Table II). To limit selection bias when it comes to selecting the explanatory variables for the final econometric specification, we use a step-wise algorithm that selects sequentially variables among a large set of potential candidates (see Annex 2 for all variables included). At each step, the algorithm adds to the existing vector of explanatory variables x ¹² the variable from the remaining set providing the lowest p-value among the used variables. The number of variables included in the estimation is bounded using a Likelihood-ratio (LR) test that compares the latest

¹²Before the first run, the vector is empty as no variable is assumed to be relevant *a priori*.

iteration (nesting model) to the model obtained one step before (nested model), such that:

$$LR = -2\{\ln L(\hat{\theta}_r) - \ln L(\tilde{\theta}_u)\} \overset{q}{\sim} \chi^2(h) \quad \text{under } H_0$$

with $\hat{\theta}_r$ being the parameters of the restricted (nested) regression, $\tilde{\theta}_u$ the parameters of the unrestricted (nesting) regression, h the number of restrictions imposed (equals to 1 in each loop), and H_0 representing the hypothesis to test that the two models are identical. When the test cannot reject at a specific level that the two latest iterations provide identical results, the algorithm is stopped. The selected variables are then used to first regress the full data set, then the subsets of gain-only and loss-only observations and finally the subsets of small stakes and large stakes. From the full set of variables (see Table II and Annex 2) the following variables were *not* selected as relevant by the algorithm: position within the household, household size, years of schooling, main activity, experience of water shortage, access to savings, religion and village dummies and are hence not included in the final specification (see Tables V and IV).

This approach, akin to a forward selection process, is motivated by its computational speed, several orders of magnitude faster than the (optimal) unconstrained algorithm that would have tested for all possible combinations of explanatory variables. Compared to related literature, this approach is an improvement since it does not rely on personal judgements and allows for an alternative list of variables that can then be compared with a qualitative selection based on economic theory and empirical literature. In addition to the variables selected by the algorithm, we provide a second specification where we add a set of control variables that were not preselected during the step-wise algorithm, but that are usually controlled for in similar work on risk aversion.

Table IV shows the estimation results for the full data set (column A) and the gain/loss (column C/E) subsets. Table V presents the results for the full data (column A) set and the small/large (column C/E) subsets. For each subset (column A/C/E) we further provide a second specification with additional control variables (column B/D/F), namely household size, village dummies and education levels. None of these control variables turned out to be significant. Note that a negative coefficient indicates lower risk taking, e.g. higher risk aversion, whereas a positive coefficient indicates higher risk taking or lower risk aversion.

One of the two main results of this study - and already discussed in detail in the previous section

TABLE IV: Ordered Probit regression on the full set, gain-only and loss-only subsets

DV: Risk appetite	A(full)	B(full+contr.)	C(gain)	D(gain+contr.)	E(loss)	F(loss+contr.)
	(1)	(2)	(3)	(4)	(5)	(6)
Strong faith influence	0.621 (0.159)***	0.458 (0.180)**	0.775 (0.221)***	0.656 (0.256)**	0.538 (0.300)*	0.426 (0.289)
Loss games	-1.769 (0.164)***	-1.836 (0.189)***				
Previous luck	0.335 (0.107)***	0.387 (0.108)***	0.639 (0.178)***	0.667 (0.195)***	0.619 (0.273)**	0.712 (0.284)**
Earning stability	0.291 (0.134)**	0.153 (0.182)	0.359 (0.195)*	0.158 (0.248)	0.231 (0.235)	0.311 (0.321)
Large payout game	-0.161 (0.085)*	-0.162 (0.088)*	-0.496 (0.135)***	-0.537 (0.154)***	0.299 (0.244)	0.349 (0.264)
Asset index	-0.831 (0.361)**	-1.312 (0.438)***	-0.856 (0.469)*	-1.740 (0.669)***	-0.987 (0.607)	-2.138 (0.694)***
Age	-0.008 (0.004)**	-0.008 (0.004)*	-0.003 (0.005)	-0.004 (0.006)	-0.019 (0.006)***	-0.019 (0.008)**
Gender: F	-0.419 (0.136)***	-0.352 (0.136)***	-0.187 (0.182)	-0.201 (0.204)	-0.884 (0.219)***	-0.887 (0.228)***
Selfishness	-0.431 (0.230)*	-0.586 (0.315)*	-0.688 (0.259)***	-1.012 (0.386)***	-0.095 (0.340)	-0.206 (0.486)
Obs.	476	460	238	230	238	230
e(r ² -p)	0.177	0.199	0.058	0.143	0.075	0.139
χ^2 statistic	164.789	196.806	33.916	126.223	28.205	3048.264

Source: Authors' results

TABLE V: Ordered Probit regression on the full set, small-only and large-only subsets

DV: Risk appetite	A(full)	B(full+contr.)	C(small)	D(small+contr.)	E(large)	F(large+contr.)
	(1)	(2)	(3)	(4)	(5)	(6)
Strong faith influence	0.621 (0.159)***	0.458 (0.180)**	0.607 (0.195)***	0.540 (0.213)**	0.628 (0.185)***	0.393 (0.213)*
Loss games	-1.769 (0.164)***	-1.836 (0.189)***	-2.024 (0.283)***	-2.241 (0.322)***	-1.552 (0.222)***	-1.621 (0.255)***
Previous luck	0.335 (0.107)***	0.387 (0.108)***	0.549 (0.303)*	0.716 (0.323)**	0.542 (0.158)***	0.629 (0.169)***
Earning stability	0.291 (0.134)**	0.153 (0.182)	0.247 (0.153)	0.141 (0.205)	0.312 (0.163)*	0.166 (0.214)
Large payout game	-0.161 (0.085)*	-0.162 (0.088)*				
Asset index	-0.831 (0.361)**	-1.312 (0.438)***	-0.574 (0.496)	-0.852 (0.588)	-1.076 (0.406)***	-1.841 (0.542)***
Age	-0.008 (0.004)**	-0.008 (0.004)*	-0.008 (0.004)*	-0.007 (0.005)	-0.008 (0.004)*	-0.008 (0.005)*
Gender: F	-0.419 (0.136)***	-0.352 (0.136)***	-0.499 (0.138)***	-0.359 (0.161)**	-0.351 (0.176)**	-0.368 (0.174)**
Selfishness	-0.431 (0.230)*	-0.586 (0.315)*	-0.341 (0.365)	-0.657 (0.487)	-0.500 (0.264)*	-0.528 (0.299)*
Obs.	476	460	238	230	238	230
e(r ² -p)	0.177	0.199	0.17	0.203	0.193	0.229
χ^2 statistic	164.789	196.806	98.463	168.266	118.408	161.685

Source: Authors' results

- is that games constrained to the loss domain are highly negatively correlated with risk taking behavior, a phenomenon intensified in games with large stakes (see Table V). Our second main result is the very strong influence of the participants' perception of God's influence on his/her life on risk aversion. *Faith* is a dummy that takes the value 1 if an individual announces that God had a strong influence of her life, and the value 0 otherwise (for the three other cases of moderate, low and no influence). *Faith* has a highly significant as well as large positive impact on risk taking in any of the games played: for both the gain-only and loss-only games (Table IV)

as well as for the small and large stake games (Table V). The results indicate that faith has an important effect on decision making in the presence of uncertainty, a phenomenon also observed in Sjoerberg and Wahlberg [129]. The coefficient is positive which indicates that villagers who believe in God are more susceptible to take on larger risks (maybe due to a change in perceived probabilities). It is also noteworthy that, apart from the loss domain game dummy, this is the coefficient with the largest magnitude, before wealth, background risk or gender. Interestingly, the type of religion (Catholic, Muslim, Christian, other) does not seem to matter for decisions involving risks. Coefficient on religious dummies never turned out to be significant (irrespective of the specification chosen). What remains unclear and beyond the scope of this paper is the ultimate causal relationship between external fate and risk taking: It could either be that faith in God's fortune leads to lower risk aversion or that risk-taking behaviour in the absence of insurance mechanisms reinforces the coping mechanism of faith. We think the first relationship is more plausible, but this finding clearly calls for further research. Moreover, it is also not clear if this negative relationship between faith and risk aversion is true in general or a special artifact of the Benin sample with a very religious population in general.

We partially test for path dependency by analyzing whether previous luck in tossing the coin has a significant effect on the villager's risk preferences. To do so, a dummy is constructed that takes the value 1 when the previous game ends with a win.¹³ In all sample subsets, a previous win has a significant and positive impact on risk exposure. This change of risk preferences could either be caused by the increase in wealth obtained in the previous game (validation of a DARA hypothesis) or by a change in the perceived probabilities. However, when the impact of previous luck is jointly analyzed with the coefficient associated with the wealth levels of households, it seems that the DARA hypothesis cannot be validated: larger wealth among villagers is actually negatively correlated with risk taking for all subsets, indicating increasing absolute risk aversion (IARA). Compared to similar experiments in developing countries, this result is puzzling since the DARA hypothesis is generally assumed and frequently observed in experiments (Binswanger 24, Wik et al. 146, Yesuf and Bluffstone 147). Since wealthier participants are also the most educated ones (and maybe also the ones who better understand the implications of risk), we added the education level (number of years of schooling) to our list of explanatory variables to test for a potential education bias. However, the education level does not influence the significance or the magnitude of wealth's influence on risk aversion.

¹³We do not consider anterior games when designing the dummy. This is to assume that an immediate win/loss has a stronger effect than previous wins/losses.

We can think of two explanations for this somewhat surprising results. First, all of the participants in our experiments are poor by international and even national standards. The less (but still) poor might hence care more about their investments than the very poor, who consider risky endeavors as the only way to get out of their current situation; in a manner similar to what is observed among casino players, who at the brink of losing everything, go for the most risky bet. This phenomenon would approximate the disposition effect (see Weber and Camerer 145). A second potential explanation could be that the observed positive correlation between wealth and risk aversion is not the result of increasing absolute risk aversion (IARA) but the result of a reverse causality or a selection bias, where highly risk averse people tend to perform better in accumulating wealth. Further investigations of the causality between wealth and risk aversion will be carried out in future research.

In line with the literature (e.g. Binswanger 24, Sillers 128), the regressions confirm that villagers display increasing partial risk aversion (IPRA), with a negative and significant coefficient for the dummy on large stake games (taking the value 1 when playing games with larger amounts). The exception are the loss games for which the relationship is insignificant. Turning to other collected information on participants apart from religion and faith, we found that background risk (measured as household's self-reported earnings stability) has a positive and significant impact on risk taking. This indicates that individuals with fluctuating incomes tend to be more risk averse. Moreover, older participants are slightly more risk-averse, but the effect is almost negligible. Women are also significantly more risk-averse, a behavior particularly noticeable in the games played in the negative domain.

1.5 Conclusion

Despite the widely known results of Kahneman and Tversky [89] on risk perceptions in gains and losses and their implications on decision making under uncertainty, it remains unknown how poor populations perceive uncertain losses. Such an understanding is, however, crucial to evaluate whether additional hedging schemes are the right mechanisms to improve the welfare of the poor in highly uncertain environments. Empirical evidence suggests that poor rural populations take unconsidered high amounts of negative risks in their daily lives. To test if these limited hedging behaviors are the results of risk preferences in losses, we conducted several lottery-based games to elicit risk preferences in both positive (gains) and negative (losses) domains in a context devoid of time and budget arbitrages.

Our econometric results indicate a very strong shift towards risk aversion when limiting the games to the negative domain. This result tends to confirm the existence of reference points - also for the poor - when evaluating the impact of risks on decision making. However, this result also clearly contradicts the assumed view of increased risk taking in losses that emerged from experiments conducted in industrialized countries (Fennema and Assen 58, Harbaugh et al. 72). It is a sign that the poor are indeed predominantly risk-averse when faced with potential losses and no budget constraint and/or time considerations and indicates a high demand for hedging schemes. It remains, however, to be seen if the payment of a minimal premium (a basic condition for ensuring a sustainable risk mitigating scheme) can compete with other expenses and does not reach budget limits. It is also unclear if villagers display the same risk preferences in real situations with a time dimension, and/or if they fully realize the nature of the risks involved in their daily lives as clearly as the risks presented during the games. Last, it could be that revealed risk aversion in the theoretical, out-of-context games is not a perfect predictor of real-life behavior.

We also found, in line with the literature, that the hypothesis of IPRA was valid among our sample, while we rejected the DARA hypothesis, which also calls for further research. Moreover, our results indicate some form of path dependency, where past experiences lead to perception errors. Last, we observed a strong influence of faith (but not religion) on risk aversion, with stronger faith increasing risk taking for both positive and negative stakes. While the results was expected on the basis of earlier research (Hilary and Hui 79, Kumar et al. 96), its magnitude indicates that any attempt to increase hedging mechanisms among poor rural populations has to target religious backgrounds as a key factor of success.

Chapter 2

Does Cooperation Depend on the Circumstances?

The Case of Rural Villagers in Benin

Jonathan Gheysens

2.1 Introduction

It is now well documented, both in developed and developing countries, that experiments that should elicit free-riding behaviors as the rational best strategy often end up with a substantial share of contributors. Using a simple voluntary contribution mechanism (taking the form of a linear public good game presented in section 2.2.1), numerous papers have reported positive average contribution levels. In the US, Andreoni [6] and List [100] find percentages of contribution varying between 30% and 45%. In developing countries, Carpenter et al. [39] observe contribution levels of 76% in Vietnam and 61% in Thailand, Gächter et al. [66] find between 44% and 55% in Russia and Henrich and Smith [77] find a share of 23% in Peru.

In African countries, Barr [21] and Barr and Kinsey [22] report contribution levels of 50% in Zimbabwe, while Ensminger [54] find large cooperation levels averaging 58% in Kenya.

A common explanation for this deviation from rationality is the presence of conditional cooperators (e.g. Brandts and Schram [31], Keser and Winden [90]) who align their contributions with the contributions of others. While the empirical existence of those conditional cooperators have been demonstrated (Cason et al. [40], Frey and Meier [64], Kachelmeier and Shehata [88]), the inability to distinguish between pure free-riders and conditional cooperators with low to zero expectation has justified the elicitation of conditional profiles using the *strategy method* developed by Fischbacher et al. [63]. Applying this method, participants are asked for their contribution level *knowing ex ante* the contributions of the others in the collective investment. These experiments allow for the identification of profiles that represent the individual best responses since the question is repeated to cover the group's contribution spectrum, from no group investment to high collective participation.

Considering the potential of this method to explain “illogical” behaviors, it remains surprising that its study has not been more broadly extended to different contexts and settings. To the best of my knowledge, only recent contributions by Kocher et al. [94] in the US, Austria and Japan, Herrmann and Thöni [78] in Russia and Rustagi et al. [123] in Ethiopia have geographically expanded these experiments.

My aim with this paper is to contribute to this recent field by investigating the nature and distribution of the conditional contribution profiles for various settings and framings. A first contribution comes from the field of analysis, rural Benin, which constitutes the first research on conditional profiles in Western Africa. A first question that I address in this paper is whether or not conditional contribution profiles in a poor and rural setting present differences from the traditional developed experimental settings? My results indicate that in the context studied, I observe both a difference in the distribution of traditional profiles (absence of free-riders) and the emergence of a new profile (the inverse hump-shaped referred to as the “U-shaped” profile in the paper) that has not yet been observed in the literature.

I also benefit from additional research that we conducted on risk aversion in presence of losses (Gheysens and Günther [68]) to address the question of the impact of risk and loss framing on conditional profiles. I find that loss framing has a strong and significant positive impact on intrinsic or “warm-glow” generosity (when individuals do not expect others to participate) while risk has a negative but more limited general impact on contribution levels in our sample. It indicates that conditional profiles are not only sensitive to geographical context but also to the project narrative.

Finally, I combine conditional and unconditional responses to similar linear public good games

to assess if there is any predictive relation between conditional contribution profiles and actual contributions. I notice a significant link between a profile and its average contribution.

The paper is structured as follows: Section 2.2 presents the experimental design and gives a brief summary of the data used, Section 2.3 provides the results to our three research questions and Section 2.4 concludes.

2.2 Experimental design and data description

2.2.1 Experimental design

For the assessment of the conditional contribution profiles, we use the standard linear public good approach (Ledyard [98]) used by Fischbacher et al. [63] but we differ from their methodology in three important aspects.

Firstly, our experiments are not constructed as a replication of their “*strategy vector method*” but relies on a contingent valuation method by which participants are directly asked about their participation in a specified project, conditional on some predetermined levels of contribution by the other group participants. To limit the risks associated with our stated preference formulation, each game is framed in a context relevant to the villagers and in direct relation with either daily activities (i.e. farming decisions) or with a future water infrastructure project (i.e. installation/reparation of water installations and latrines) to which our interviews we related (as an assessment phase).

Secondly, we specify four different projects instead of a single one, each a slightly different version of the linear public good game. The first game, considered as our benchmark, is a replication of the original public good game while games 2, 3 and 4 are modified to introduce risk and negative payoffs (loss framing) in the payoff structure.

Finally, conditional contribution levels are asked on a three-point subset of all the possible strategies, with stated contributions asked for no group participation ($\sum_{j \neq i} x_j = 0$), intermediate group participation ($\sum_{j \neq i} x_j = \frac{X}{2} * (n-1)$) and full group participation ($\sum_{j \neq i} x_j = X * (n-1)$), with X the maximum amount that can be individually invested in the group project¹ and n the number of participants in each group². The players are informed that their stated conditional contributions can take any value between 0 and X .

Instead of collecting conditional responses from participants for 20 points of others’ average

¹Which is equal to 500 FCFA for each game.

² n was fixed across the games, groups and villages.

contribution levels as in most of the existing literature, we limited conditional responses to three points across the group’s possible contribution distribution, including both no and full contribution of others. This approach allows us to map almost all known cooperation profiles (see Appendix B.3) while limiting the cognitive fatigue induced by repeating long sequences of almost similar questions. We are confident that this “simplified” approach does not miss or inaccurately depict conditional profiles: past experiments have shown that individuals are not erratic in their conditional contribution decisions and tend to contribute along a limited number of simple structures of cooperation (free-riding, altruism, (weak) conditional cooperation, and hump-shape) that rule out purely random decisions - except for a very limited number of participants. Against this background, a three-point observation method (with zero, median and full contributions of others) can effectively depict the same tendencies. We simply loose the notion of weak/strong cooperation from the Spearman rank correlation.

Participants are matched by groups of four from a list of preselected households³ that was obtained in each village from a large-scale randomized impact evaluation on water infrastructure (see Section 2.2.2). The initial matching procedure is done randomly⁴. To avoid group contamination and direct cooperation, participants are not allowed to talk to each other and each answer is recorded privately by the interviewer.

The first game (the so-called “benchmark”) is designed as follows. A realistic project is presented to each participant within each created group, such that the project payoffs take the form of the linear public good game:

$$I - c_i + \alpha \left(\sum_j c_j \right) \quad (2.1)$$

where I represents an initial hypothetical payment of 500 FCFA offered to all the participants, c_i is the contribution of subject i in the public good and α represents the individual rate of return on the public good. α is chosen to ensure that the strategy to maximize expected income is to free-ride ($\alpha < 1$). We use $\alpha = \frac{1.5}{4} = 0.375$, which is close to the value of 0.4 used by Fischbacher et al. [63].

In practice, the project was presented as a collective investment in crop plantations. Since most of the villagers are farmers or at least benefit from subsistence farming, activities related to

³The households were selected randomly in each village from complete household listing and we made no attempt to modify this list.

⁴Groups are then eventually adjusted on a *ad hoc* basis to have enough variation between mixed-sex and same-sex groups (Barr and Kinsey [22], Carpenter et al. [39], Greig and Bohnet [69]).

crops are well known and relevant to them. The type of crop linked to the collective investment was carefully selected to match the prevalent type of culture of each village. The project was announced with a profit rate of 50% and it was made clear that the collective profits, if any, were to be shared equally between the four group members.⁵

Participants are then asked privately and sequentially what would be their private contribution to the project knowing that the other group members decided to invest 0, then 250 and then 500 FCFA. Answers are collected by the interviewers but are not shared at any point in time with the group, meaning that other group participants cannot be aware of the conditional contribution profile of the others.

The second experiment is similar to the first one but introduces the notion of exogenous risk through a lottery payoff. Instead of providing a deterministic α , the individual rate of return on the public good is now stochastic ($\tilde{\alpha}$), with two states (each with probability $\frac{1}{2}$). In the positive state $\alpha(1)$, the group contribution is tripled, while in the negative state $\alpha(2)$, the group investment is lost.

The linear public good is hence modified as follow:

$$I - c_i + E \left[\tilde{\alpha} \left(\sum_j c_j \right) \right] \Leftrightarrow 500 - c_i + 0.5 * \left(\frac{3}{4} \left(\sum_j c_j \right) \right) \quad (2.2)$$

The first and second experiments are designed to be identical for a risk neutral individual since $E[\tilde{\alpha}] = \alpha = \frac{1.5}{4} = 0.375$. However, the second game introduces variance in the payoff structure, a characteristic that should influence decisions on conditional participation for risk averse villagers.

In practice, the second project was presented as an investment in cotton production, a cash crop known in Benin to be highly profitable but also very risky. It was not difficult for the participants to imagine that such an investment could have an equal probability of tripling the investment or giving no result at all.

To account for possible changes in preference when participation is framed as a group expense instead of a group investment, we design the third experiment as a negative public good (a shared cost), with negative payoffs instead of positive ones. The payoff function is modified to

⁵The field assistants were also briefed to discuss rate of return of the different crops produced in the village, in order to make sure that the idea of 50% yield could be perceived as reasonable by the participants

reflect this change:

$$2 * I - c_i - \frac{1}{4} \left((S * 4) - 1.5 \sum_j c_j \right) \Leftrightarrow 500 - c_i + 0.5 * \left(\frac{3}{4} \left(\sum_j c_j \right) \right) \quad (2.3)$$

with S a negative shock (or cost) equal to the initial payment I ($I = S = 500$ FCFA).

The collective contribution $1.5 \sum_j c_j$ can offset the shared cost ($(I * 4)$). It is designed to mitigate for each villager the sum of individual contribution c_i and the shared cost, in case of a full collective contribution.

The participants have to support an equal share of the cost, irrespective of their revenues, assets or position within the village (or within the experiment group). They have to decide on the amount they are willing to contribute to a collective effort to pay for the expense. This collective effort takes the form of a scheme that ensures that collective contributions are topped by an additional 50%. Group players have then to pay their remaining share of the cost, eventually reduced by the participations of the group in the scheme.

To ensure that the participants' answers are not distorted by variations in the payoff structure, we increase the hypothetical endowment and choose an collective cost of 2000 FCFA ($500 * 4$). With this calibration, the final payoffs for the project are perfectly equivalent to those of the first game but presented in a cost-sharing setting.

In practice, we were fortunate that the main projects justifying our presence in the field (the installation of water pumps and laterines in villages as part of a large randomized trial) were also perfectly justifying a setting involving group expenses. We explained this new situation as maintenance costs for the newly installed water pumps. Each member of the group was hence offered the possibility to invest in a maintenance scheme that was partially subsidized by the NGO responsible for the project (through an increase of 50% of the collective payment). NGOs often contribute to maintenance efforts in Benin and the idea of an external benefactor was considered realistic by the participants.

Finally, the fourth experiment is a combination of the shared cost setting of the third experiment and the stochastic payoff structure used in the second experiment, such that:

$$0.5 \left(1000 - c_i - \frac{1}{4} \left((500 * 4) - 3 \sum_j c_j \right) \right) + 0.5 \left(1000 - c_i - \frac{1}{4} (500 * 4) \right) \quad (2.4)$$

In this setting, participants face a collective expense and shall support the cost equally. As in the previous experiment, they have the possibility to put money in a reimbursement scheme.

But collective participation in the scheme is now dependent on a specific random event. With probability $\frac{1}{2}$, the expense never materializes and the amounts versed in the reimbursed scheme are lost (similar to an insurance scheme). With probability $\frac{1}{2}$, the expenses materializes and the scheme ($3 * \sum_j c_j$) is used to repay the cost. Outstanding amounts are split evenly between the players.

Similar to the second game, the increase in risk is done so that the expected payoff structure of the third and fourth games are identical for a risk neutral individual. As before, we expect risk averse participants to exhibit variations in the levels of their conditional contributions between the two games.

In practice, our story was slightly more complicated for this final experiment: using the example of the water pump's maintenance costs, we presented the role of the NGO differently. Our goal was to approximate the structure of an insurance contract without relying on the concept explicitly (in our sampled villages, insurance was a concept often completely new to the villagers, who are more used to in-kind savings to smooth out shocks). In the occurrence of a positive outcome, the NGO doubled the collected amount, the outstanding amount having to be paid equally within the group. However, in the occurrence of a negative outcome, the maintenance was unnecessary and the collective outcome remained the property of the NGO. Such a concept was coherent with known investment schemes for which collective investments are locked and can only be used for some specific purposes.

Details of the project narratives are given in Annex [B.1](#).

To identify and define the conditional profiles on the three-point response domain, we use the relative variation between each point (increasing, flat or decreasing) and combine variations in the 0-250 range with variations in the 250-500 range. Table [I](#) gives the details of our identification approach:

TABLE I: List of profiles based on the form of their relative variations

#	Relative variation from 0 to 250	Relative variation from 250 to 500	Initial profile	Included in
1.	Flat	Flat	Flat	Warm-glow
2.	Increasing	Increasing	Conditional increasing	Conditional cooperation
3.	Increasing	Flat	Conditional kink	Conditional cooperation
4.	Flat	Increasing	Conditional stick	Conditional cooperation
5.	Decreasing	Decreasing	Conditional decreasing	Other
6.	Decreasing	Flat	Conditional kink decreasing	Other
7.	Flat	Decreasing	Conditional stick decreasing	Other
8.	Increasing	Decreasing	Hump-shaped	Hump-shaped
9.	Decreasing	Increasing	U-shaped	U-shaped

2.2.2 Data description

The experiments were administered in coordination with a large-scale panel household survey covering 2000 randomly selected individuals from 200 villages in two regions of Benin.

From the 200 villages surveyed between January 2009 and July 2010, a sub-sample of 12 villages in the department of Collines was selected in August 2010 to conduct the experiments.⁶ The villages were selected to both represent the socio-economic diversity of the region but at the same time to represent the highest possible level of literacy using an aggregated index comprising years of schooling, highest degree achieved and fluency in French (the official language in Benin). The aim was to reduce the inevitable noise coming from an insufficient understanding of the games⁷. Almost all villagers in our sample are subsistence farmers, living on crop consumption and marginally on local market revenues from the sale of excess production.

Tables II and III present some descriptive statistics of key socio-economic variables which are used as regressors in the econometric analysis of sections 2.3.2 and 2.3.3⁸).

⁶The villages were Adourekouman, Assromihoue, Bethel and Tankossi in the commune of Glazou, Agbomadin, Koutago, Lema, Lowozoungo, Mondji, Segbeya and Zongo in the commune of Savalou and Atchakpa and Gobé in the commune of Savé.

⁷We are confident that this deliberate trade-off for more education does not create a large selection effect: the average completed years of schooling in the selected villages was still only 3 years and we observed large variation of education levels within the villages, covering the full distribution from no schooling to high school levels.

⁸Detail of their use is given in Annex 1. We also refer to Gheysens and Günther [68] for more detailed description of the selected individual variables.

TABLE II: Descriptive statistics for selected individual variables (N = 122)

Variable	Mean	Std.Dev.	Min	Max
Age	44.8	16.86	22	99
Gender (1=Male, 0=Female)	0.64	0.48	0	1
Household size	5.85	2.96	1	15
Years of schooling	2.94	4.09	1	15
Wealth Asset index (1=Highest, 0=Lowest)	0.19	0.14	0	1
Earning stability (1=Yes)	0.72	0.45	0	1
Absence of coping mechanism (1=No coping mechanism)	0.26	0.44	0	1
Water shortage (1=Yes)	0.85	0.35	0	1
Bad Health (1=Yes)	0.20	0.40	0	1
Strong faith influence	0.78	0.41	0	1
Value of openness	0.67	0.47	0	1
Risk aversion parameter	2.60	1.76	1	7

We were also able to utilize information on water use from the panel survey to infer numerous information on the social exposures and group behaviors of the villagers in the various contexts of water projects and infrastructures. It allowed us to confront our experiments in the linear public games with traditional covariates such as past participation in collective projects, collective payments and management.

TABLE III: Descriptive statistics for selected social variables (N = 122)

Variable	Mean	Std.Dev.	Min	Max
Participation in the construction of the water hole	0.15	0.36	0	1
Responsibility for the collection of village water fees (1=collective)	0.16	0.37	0	1
Waiting time at the collective water source (in min)	26.2	37.83	0	270

The variable “Responsibility for the collection of village water fees” is a proxy of the current experience of the group dealing with collective goods. We want to assess if cooperation and conditional contribution can be dependent on a familiarity with collective management (i.e. cognitive dependency).

The second variable “Waiting time at the collective water source” is a proxy of the perceived experience about public goods. If this experience is poor, we can expect lower contributions in collective public projects (whether they are investments or costs).

2.3 Experimental results

Our results are divided in three sections. Section 2.3.1 addresses the structure of conditional cooperation profiles in a rural and poor context. Section 2.3.2 expands the analysis to assess the possible effects of risk and loss on the conditional profiles. Finally, Section 2.3.3 concludes by testing if profiles can be good predictors of actual contributions in unconditional games.

2.3.1 Are conditional contribution profiles different in a poor and rural setting?

Considering that our experiments are conducted in rural villages of Benin, our first aim is to assess if conditional cooperation profiles observed in a rural and poor environment yield similar results to what was observed by Fischbacher et al. [63], Fischbacher and Gächter [61] and Kocher et al. [94] in developed countries. We also benefit from the results of a similar experiment in Ethiopia (Rustagi et al. [123]) to test for difference in conditional cooperation profiles between two African developing countries.

To be able to compare our results with other experiments, we restrict our analysis to our first “benchmark” game, which involves gains without the presence of risk.

Our results are shown in comparison with the existing literature in Table IV:

TABLE IV: Conditional cooperation profiles in developed and developing countries using the “strategy method” of Fischbacher et al. [63]

C.C profiles	Our results	Fischbacher et al. [63] & (2006)	Herrmann and Thöni [78]	Kocher et al. [94]	Rustagi et al. [123]
Country	Benin	Switzerland	Russia	US/Austria/Jap.	Ethiopia
Free-rider	0%	30% (2001), 22.9% (2006)	6.3%	8.3% (US), 22.2% (A), 36.1% (J)	11.5%
Condit. coop. (strong & weak)	61%	50% (2001), 55% (2006)	55.6%	80.6% (US), 44.4% (A), 41.7% (J)	45.6%
Hump-shaped	6%	14% (2001), 12.1% (2006)	7.5%	0% (US), 11.1% (A), 11.1% (J)	3%
Warm-glow/Altruist	5%	-	-	-	2.2%
Inverse hump-shaped	22%	-	-	-	-
Other types	6%	7% (2001), 10% (2006)	30.6%	11.1% (US), 22.2% (A), 11.1% (J)	37.7%

Compared with the results obtained in developed countries (Switzerland, US, Austria and Japan), we observe two salient differences.

A first difference in our result is the total absence of free-riders, who represent between 8% (US) and 36.1% (Japan) of the total elicited profiles in rich countries. An intuitive interpretation would be to link the absence of this profile to a traditional “African generosity” that prevent villagers from free-riding. However, results in Ethiopia (10% of free-riders) seem to indicate that this behavioral trait cannot be generalized to the entire continent. Nonetheless and with the notable exception of the US (8%), a strong difference in “profit maximizing” cooperation levels seems to exist between developed and developing countries.

The second important difference is the very limited presence of hump-shaped profiles. The result is similar to what was found in Ethiopia (3%), in Russia (7.5%) and in the US (0%), ruling out any explanation based on a simple developed/developing difference. Unique to our results, we find that this absence of hump-shaped profile is replaced by a large share (22%) of so-called U-shaped behaviors. Villagers with such a profile start their cooperation schedule high

(regardless of the group’s non-participation), reduce their cooperation at the intermediate group contribution level (250 FCFA) and increase again when the group’s participation is maximal. As such, a U-shaped profile can be compared to a conditional profile for which the “unconditional” participation (when the group contributes 0 FCFA) is unreasonably high (or generous)⁹. We envision two possible interpretations for this profile.

A first possibility would be that some villagers in our sample display a form of warm-glow that is exacerbated by the unconditionality. As predicted by Harsanyi [76], Collard [46] and Andreoni [5], “warm-glowed” individual gets pleasure from contributing, irrespective of the contributions of other. Their intrinsic motivation is either a direct utility from the act of giving (pure warm-glow) or the manifestation of the just thing to do (‘Kantian’ behavior). However, the warm-glow theory asserts that utility of giving shall remain the same irrespective of the other’s actions, resulting in a flat and positive conditional profile. On the contrary, U-shaped individuals shift from unconditional actions to conditional ones, which rules out a unique or pure warm-glow justification.

To account for this shift in behaviors, a second possibility would be that villagers derive a social positioning utility from signaling their generosity (while setting them apart from the group): contributing when no one contributes implies a flattering act of kindness for any individual willing to make an impression on their community. This behavior was clearly visible during the organization of our experiments¹⁰ but considering the private nature of the reporting in our experiments, generous unconditional contributions remain unknown to the group, which nullifies any positive social benefits. The influence of positive signaling could then be interpreted as a behavior’s persistence (i.e. influential villagers would transfer their habits into the games, without paying attention to the lack of effectiveness)¹¹.

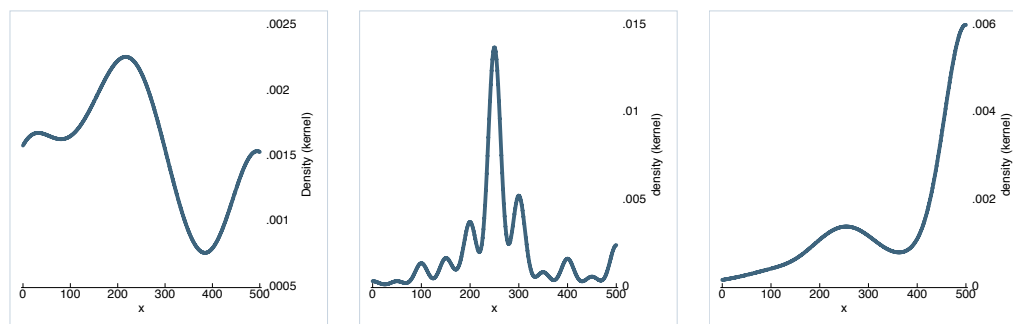
What appears clearly in our results is that most of the heterogeneity in the villagers’ behaviors comes for dispersion in the distribution of the “intrinsically generous” contribution. As shown in Figure 2.1, we observe the largest variation in the distribution of conditional contributions in the 0 contribution segment, with a mean of 233.5 FCFA and a variance of 176.11.

⁹At least higher than the strategic response for a group participation of 250 FCFA.

¹⁰When we conducted our experiments, it was clear that influential individuals within the villages were willing to play a major organizational roles, helping us finding a local to conduct the experiments, looking for the participants and offering drinks and snacks.

¹¹A related explanation would be that this reputation mechanism was reinforced by the presence of the research team who in effect acted as a monitoring tool. Following [?], the presence of a “cue for monitoring [...] enhanced the participant’s altruistic behavior.”

FIGURE 2.1: Distributions of conditional contributions for the three different group contributions in the “benchmark” game (Kernel density estimation)



Group's contribution = 0 Group's contribution = 250 Group's contribution = 500
 $(\mu = 233.5, \sigma = 176.11, \frac{\sigma}{\mu} = 0.75)$ $(\mu = 268.8, \sigma = 97, \frac{\sigma}{\mu} = 0.36)$ $(\mu = 417.8, \sigma = 130.4, \frac{\sigma}{\mu} = 0.31)$

By contrast, distributions of conditional contributions for group contributions of 250 and 500 FCFA are located around the obvious focal points represented by the group contribution while being less dispersed. This result suggests that for intermediate and maximum group contribution, villagers behave more like conditional cooperators. Our findings seem to indicate that villagers in our sample have multiple motivations when collectively contributing. Their profiles cannot be entirely explained by either a warm-glow effect or a conditional cooperation as they often appear to derive from a mixture of both.

2.3.2 Are conditionals contribution profiles stable in presence of risk and losses?

Acknowledging that conditional profiles are context-specific, we expand the games settings to accommodate two significant characteristics that are often present in group investment decisions: risk and losses (i.e. expenses). Having multiple games with similar payoff structures but different framing allows us to test for the robustness of the conditional contribution profiles when these two characteristics are introduced independently or in conjunction. By doing so, we acknowledge the importance of framing in cooperative games (Andreoni [7], Cronk [48], Raub and Snijders [118], Sonnemans et al. [131]) and partially follow up this field of research.

The introduction of risk in the strategy method is important for two reasons. While decision under risk in poor and rural settings have become recently the subject of numerous empirical

and experimental research (Binswanger [24], Wik et al. [146], Yesuf and Bluffstone [147]), the impact of exogenous risk on conditional contribution profiles remain largely unknown in both developed and developing countries. Since most behaviors under conditional cooperations depart from the rational free-riding equilibrium, the explicit elicitation of risk influence on conditional cooperation cannot be theoretically derived and requires an empirical assessment. Our paper is a first step in that direction for a poor and rural sample. Moreover, our analysis of the impact of risk on conditional profiles benefits from the fact that group participation is known *a priori*, removing the potential influence of trust/trustworthiness in our results.

Moreover, the introduction of risk is important to link experimental results on conditional cooperations with actual group decisions in villages. When villagers are solicited to contribute to a group investment, the project often bears some aspects of risk in relation to the expected outcomes (as with agricultural cooperatives). Understanding variations in cooperation when risk exists could then help design better group investment schemes.

The influence of loss framing is also essential to understand real life cooperative decisions. Since the pioneering work of Kahneman and Tversky [89], it has been shown that people tend to have reference points that influence what they consider as a gain and what they consider as a loss. This distinction is important since most people tend to value a loss higher than its symmetrical gain, and to show risk seeking behavior in losses despite being risk averse in gains.

In a recent research on risk aversion that we conducted in the same villages (Gheysens and Günther [68]), we observe that the introduction of losses has a very significant effect on the investment profile of the villagers, dramatically shifting their initial risk preference towards strong risk aversion.

In the context of collective games, the positioning role of losses is less clear due to the complexity of the group game interactions. It is therefore important to assess if loss framing has an impact on conditional cooperation levels similar to what we observed in simpler lottery games. As with the introduction of risk, a better understanding of the influence of losses in the investment narrative could help explain participation decisions, since numerous group investment involve negative outcomes (for instance, most water sanitation projects reduce negative health shocks but have no direct upward impact on revenues).

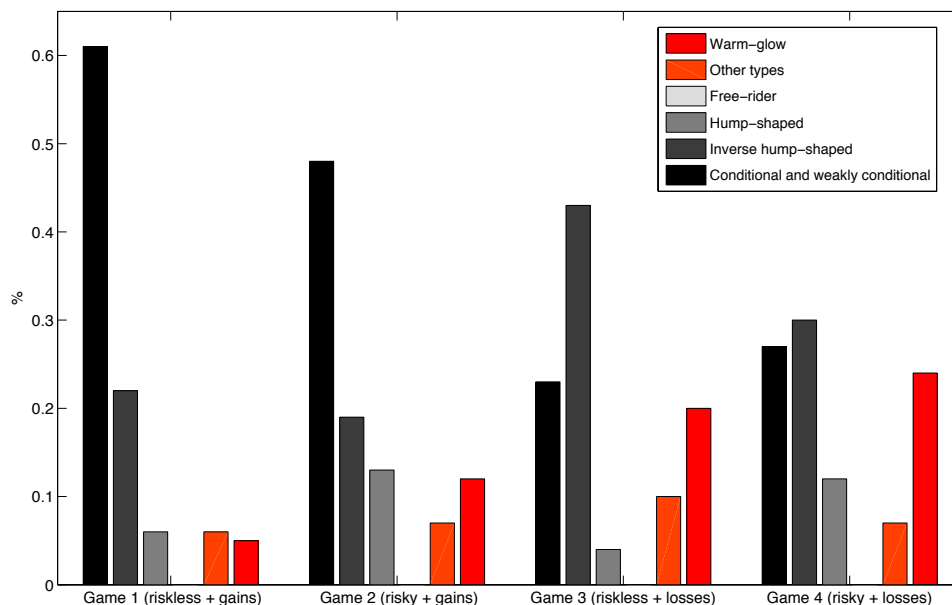
Our main hypothesis regarding the direction of the effect is that loss is a more powerful motivator than gain, as stated in Walder [143]¹² and that villagers should therefore be contributing more

¹²According to Walder, historical evidence suggests the following assertion: "that loss is a more powerful motivator than gain, or that groups threatened with loss will be more likely to protest than groups that seek proactively to achieve a gain"

in loss-games than in gain-games.

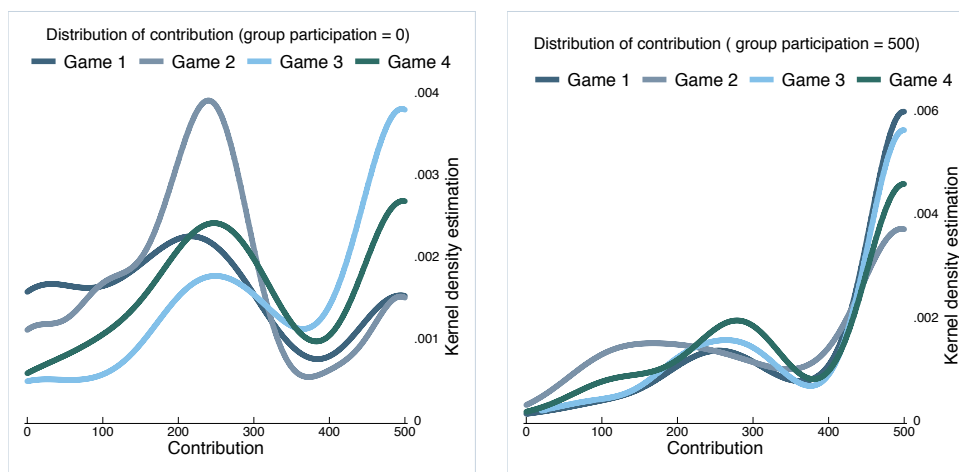
To test for the individual and combined roles of risk and losses, we compare the profile distribution obtained under the “benchmark” game to the distributions obtained under our three game variations (as presented in section 2.2.1). The results are summarized in Figure 2.2 below.

FIGURE 2.2: Distribution of conditional contribution profiles for the four different games



The first immediate result is a shift between conditional and U-shaped profiles when loss framing is introduced. When we play games in the gain domain and even in presence of risk, conditional and weak conditional profiles dominate the distribution in our sample, with the U-shaped as a distant second. However, when the third and fourth games are played in presence of loss framing, the U-shaped becomes the most important profile. This indicates that in presence of losses, more villagers tend to increase their “warm-glow” contributions, a result confirmed by an analysis of the distribution of conditional contribution when the group’s contribution is zero (see first panel of Fig.2.3). This tends to contradict the results of Keser and Winden [90] who find that university students in Canada contribute less when the public game is presented as a public loss.

FIGURE 2.3: Kernel estimation for the conditional contribution when group participation = 0 FCFA & 500 FCFA for the four games



The risk influence is more homogeneous and affects similarly the absolute levels of contribution of the three different segments. Our sampled villagers being largely risk averse, a reduction in their level of contribution was expected. It manifests itself through decreased contributions at the tails of group participation, for both 0 FCFA and 500 FCFA (see second panel of Fig.2.3 for the impact when group participation is equal to 500). As a result, conditional and U-shaped profiles are partially replaced by hump-shaped behaviors (which happens when the contribution level is decreased for group participation of 500 FCFA) and warm-glow profiles (when contributions at the 0-level and 500-level are decreased to create a flat profile).

When both risk and losses are introduced, risk also limit contribution levels in the tails, which results in an increased share of conditional cooperators (low contributions when group participation is equal to 0) and hump-shaped profiles (see Appendix 2 for an overview of the variations in the mean and standard deviation of the conditional contribution distributions).

Interestingly, we observe an increasing share of pure “warm-glow” (flat) profiles through the four games. This may be the result of simultaneous but opposite effects played by loss and risk framings. While a loss framing increases overall conditional contribution levels, risk tend to decrease maximum exposures to the group investment (whether it is when the group invests nothing or everything). These results would be in line with what we observed during games of risk preference played with the same villagers. We found in our experiments on risk aversion that villagers were willing to eliminate as effectively as possible any risk involving losses¹³. Similarly,

¹³For almost all villagers, the introduction of losses shifted their risk aversion profile toward strong and extreme risk aversion. As they explain to us, villagers really disliked having to face a potential loss and usually preferred paying large amount to cover it.

the presence of losses increased the willingness to cover the collective loss in the third and fourth games.

Considering the importance of the “partial warm-glow” contribution (when group contribution is 0) to explain profile variations between villagers and between games, we complete our analysis on the variability of conditional contribution profiles by regressing the villagers’ conditional contribution levels when there is no group contribution on a set of explanatory variables. Our objective is to test for the importance of risk and loss framing to explain shifts in profiles when other important variables are taken into account. As shown in the literature (Barr and Kinsey [22], Greig and Bohnet [69]), it is also known that other factors, such as personal (gender, education) and social characteristics (position in household, income, access to market, chatting) could have an impact on conditional cooperation levels.

We model our regression using a simple OLS approach, such that:

$$c_{ig} \left(\sum_{j \neq i} c_{jg} = 0 \right) = x_i \beta + x_v \gamma + x_g \delta + \epsilon_{ig} \quad (2.5)$$

where $c_{ig} \left(\sum_{j \neq i} c_{jg} = 0 \right)$ represents the conditional contribution of individual i for game g when the group contributes nothing, x_i is a vector of covariates for individual i , x_v is a vector of covariates for the individual’s village v , x_g is a vector of game characteristics and ϵ_{ig} is the error term. To treat for potential heteroskedasticity in the error terms, we use a weighted least squares approach that relies on standard robust errors.

The results are given in Table V¹⁴.

¹⁴Table VII displays all the variables that were selected as significant plus important control variables that were expected to have a significant role.

TABLE V: Regression on the “partial warm-glow” contribution levels for selected explanatory variables

	A	B(+controls)
DV: conditional contribution (group participation = 0)	(1)	(2)
Loss framing	104.271 (13.605)***	112.068 (15.246)***
Risk framing	-20.521 (13.605)	-17.200 (13.120)
Participation in the construction of the water hole	-87.432 (18.280)***	-7.587 (38.119)
Earning stability (1=stable)	-53.340 (15.961)***	-27.881 (18.001)
Gender: F	46.181 (14.250)***	52.220 (17.183)***
Value of openness (1=open)	37.440 (14.740)**	26.986 (16.739)
Responsibility for the collection of village water fees (1=collective)	-50.420 (20.713)**	-59.600 (23.775)**
Bad health	36.021 (17.389)**	39.631 (19.007)**
Absence of coping mechanism	-42.605 (16.494)***	-44.951 (19.705)**
Household size		-4.426 (2.448)*
Years of schooling		2.442 (2.032)
Wealth (asset index)		-20.139 (67.553)
Risk aversion parameter		1.817 (4.902)
Age		-.650 (.532)
Obs.	480	460
R^2	.245	.36
F statistic	17.262	17.371

A strong result of our regression is the effect of loss framing on the conditional profile of the villagers. When the linear public good game is presented in terms of losses, villagers tend to contribute more, even if the group does not contribute at all. The willingness to cover for potential losses that we observed in the descriptive analysis of the distribution is hence robust to other explanatory variables. It suggests that losses have a very specific impact on the decision process

of our sampled villagers, an impact larger than traditional “usual suspects” such as wealth or risk aversion profiles. It would also imply that any collective payment scheme that bases its strategy on observed participation levels in positive projects probably limit the willingness to participate of the villagers, at least in contexts similar to our own.

The second covariate with a strong effect is the gender of the villager. In line with other studies (Greig and Bohnet [69]), we find that women tend to be more committed (or initially warm-glowed) to the group’s good than men. This gender effect has a significant impact (almost 10% of the total available amount) and is robust to the introduction of control variables.

A third result comes from the relative importance of what we call “openness” to explain warm-glow behaviors. During the experiments, we played an introductory game that was initially designed to assess if the participant understood the concept of average. This game was a simple coin flipping where each outcome resulted in a loss for the villager. After presenting the possible (negative) outcomes, we asked each participant if he or she was willing to participate to the game. In practice, the villagers attributed a completely different meaning to this game: playing head-or-tail was interpreted as a welcoming gesture in the village, a way to create a social link with the interviewer. Based on these results, we use this question as a proxy for the villager’s openness towards strangers and guests, a value that can be linked to research on market integration and social openness (Henrich and Smith [77]). As expected, the more welcoming villagers are also the ones who are the more altruistic.

A surprising result is the negative relation between the unconditional contribution level and the experience of collective payment collection (for water fees). It would imply that villagers that are used to a collective scheme of group expenses (i.e. water infrastructure maintenance) are less inclined to act out of pure generosity when the group at large refuses to cooperate. A possible explanation is that villagers used to group collaboration are also more familiar with the principle of conditional cooperation. They cooperate when the group cooperates. This intuition is confirmed by an analysis of the average conditional contribution when group investment is equal to 500 FCFA. In this case, participants to a collective payment collection contribute in average 10% more than the villagers who have individual collection schemes. Similarly, the dummy indicating the participation in the construction of a water hole has also a negative sign, which can signal the expectation of collaboration. However, the variable loses its significance in presence of controls, which can be the result of collinearity with the wealth dummy (villagers had to decide either to give money or to participate directly to the construction of the water hole and richer people preferred to send money).

Another finding is the potential influence of background risk on the level of partial warm-glow

contribution. The experience of severe health shocks (represented by the bad health dummy) has a positive impact on the level of contribution. It could be justified as an increased awareness on the necessity for group's altruism: a villager would display a more salient other-regarding behavior since he is in situation of need and value higher the role of the group as a coping mechanism. While the earning stability variable is insignificant in presence of controls, its sign and magnitude would suggest the same interpretation.

The vulnerability of being without any coping mechanism¹⁵ has a negative and significant effect, robust to the level of wealth and education in the household. This effect somehow contradicts our previous finding on background risk and remains to be analyzed.

Finally, our results indicate that risk aversion profiles, education, wealth and age have no significant impact on the partial "warm-glow" contribution. Age and wealth seem to have a negative effect on contribution while education and risk appetite¹⁶ increase the contribution.

To limit selection bias when it comes to selecting the explanatory variables for the econometric specification, we use a step-wise algorithm that selects sequentially variables among a large set of potential candidates (see Annex B.2 for all variables tested and those included). At each step, the algorithm adds to the existing vector of explanatory variables¹⁷ x the variable from the remaining set providing the lowest sum of p-values among the used variables¹⁸. The selected variables are then compared to a naive choice of relevant variables and a combination of the two are selected and regressed. We add to our first regression a set of control variables that were not previously selected to control for possible endogeneity. Those variables are the age of the respondent, the education level in terms of schooling years, the wealth and the size of the household and the risk aversion coefficient of the participant from our risk aversion experiments.

2.3.3 Are conditional contribution profiles relevant for predicting actual contributions?

Our experiments were not limited to conditional contribution elicitation. In each game, the villagers received an actual amount of money that was equivalent to the hypothetical reward defined for the game and that was justified as a fair compensation for the productivity loss of playing with us. With this money, they were asked to play each game unconditionally:

¹⁵The coping mechanism variable is an account of all possible strategies that a villager had at his disposal to smooth negative shocks out: money or in-kind savings, participation in collective saving schemes or family reciprocities.

¹⁶The risk aversion level is defined such that greater values of the variable indicate increased risk appetite.

¹⁷Before the first run, the vector is empty as no variable is assumed to be relevant *a priori*.

¹⁸For additional details on this method, see Gheysens and Günther [68]

contribution had to remain secret from the other members of the group¹⁹ and they had to decide simultaneously, without any chance of knowing the others' contribution levels. Since the conditional contributions were asked privately, the participants were unaware of the response profiles of the other participants within their groups²⁰. Table VI presents the details of the mean and variance of the unconditional contributions for each conditional cooperation profiles.

TABLE VI: Unconditional contributions statistics for the different profiles and the different games

C.C profiles	Game 1	Game 2	Game 3	Game 4	Average
Condit. coop (strong & weak)	$\mu = 245.9, \sigma = 136.9$	$\mu = 223.3, \sigma = 107.7$	$\mu = 233.9, \sigma = 128.4$	$\mu = 322.7, \sigma = 138.7$	$\mu = 250.5, \sigma = 131.4$
Inverse hump-shaped	$\mu = 303.7, \sigma = 169.8$	$\mu = 219.6, \sigma = 91.4$	$\mu = 348, \sigma = 142.1$	$\mu = 344.4, \sigma = 153.9$	$\mu = 317, \sigma = 150.2$
Hump-shaped	$\mu = 214.3, \sigma = 114.4$	$\mu = 146.9, \sigma = 78.5$	$\mu = 320, \sigma = 168$	$\mu = 360, \sigma = 113.7$	$\mu = 252.3, \sigma = 142.3$
Warm-glow	$\mu = 275, \sigma = 186.4$	$\mu = 283.3, \sigma = 131.9$	$\mu = 458.3, \sigma = 89.2$	$\mu = 429.3, \sigma = 119.2$	$\mu = 396.6, \sigma = 138.6$
Other types	$\mu = 257.1, \sigma = 109.6$	$\mu = 155.5, \sigma = 88.2$	$\mu = 233.3, \sigma = 68.5$	$\mu = 231.2, \sigma = 146.2$	$\mu = 218, \sigma = 105$
Average	$\mu = 259.1, \sigma = 145$	$\mu = 214.9, \sigma = 109$	$\mu = 331, \sigma = 147.3$	$\mu = 353.3, \sigma = 144.1$	$\mu = 289.6, \sigma = 147.7$

Having collected information about the unconditional contributions for the four games and their associated conditional profiles, we are able to test for correlation between them. Our assumption is that conditional profiles can be good predictors of the actual participation levels of villagers in group projects. For response functions that are monotonic such as conditional cooperators, it would also imply that villagers not only share a similar conditional profile but also expectations about the group participation (since there exists only a one-to-one correspondence between the response and the expectation of the group contribution).

To test for robustness in our results, we regress the unconditional contributions on two different variations of the conditional profiles. Our first variation is a series of dummies for each of the profiles that we identified. The “other” profile plays the role of the baseline²¹.

To allow for a more detailed identification of the conditional response functions (accounting for

¹⁹To ensure the proper level of secrecy, we used a system of envelopes and tags that were shuffled between each game.

²⁰Since we played four different games, we chose not to shuffle groups between each game. Based on our results (see Table VI), we are confident that the unconditional contributions were not affected by the repetitions.

²¹The other category includes individuals who were strongly or weakly conditionally decreasing: as the group investment becomes larger, their individual contribution becomes smaller.

inflection points and absolute levels), we choose a quadratic response function that is able to uniquely define all the villagers' profiles for each game, such that:

$$CP_{ig}(X_j) = f_{ig}(X_j) = a_{ig}X_j^2 + b_{ig}X_j + c_{ig} \quad (2.6)$$

where $CP_{ig}(X_j)$ represents the conditional participation of individual i during game g for a group contribution of X_j ²² and a_{ig} , b_{ig} and c_{ig} are the parameters of the quadratic response function which is regressed for each individual. The idea of this approach is to assess the different elements of the conditional response function: a represents both the long term conditional reaction and the curvature of this reaction (based on the first and second derivatives of the conditional response function²³). b is a measure of the absolute conditional reaction and c summarizes the "intrinsic" conditional response (when $X_j = 0$).

Using the definitions of the conditional profiles CP_{ig} alternatively, we regress the unconditional participation (UP) such that:

$$UP_{ig} = x_i\beta + CP_{ig}\eta + \sum_j (UC_{jg}(G-1))\theta + x_v\gamma + x_g\delta + \epsilon_{ig} \quad (2.7)$$

where UP_{ig} and CP_{ig} are respectively the unconditional participation and the conditional profile of individual i for game g ²⁴, $\sum_j (UC_{jg}(G-1))$ is the observed average unconditional participation of the group from the previous game²⁵, x_i is a vector of covariates for individual i , x_v is a vector of covariates for the individual's village v , x_g is a vector of game characteristics and ϵ_{ig} is the error term. As before, we use a weighted least squares approach to treat for potential heteroskedasticity. We also include a set of regressions for which we add controls that were not selected initially. Results are presented in Table VII.

From the results of our regressions, our key finding is that we cannot reject a strong relationship between conditional profiles and unconditional contributions in linear public good games. It suggests that villagers with a similar profile tend to have stable beliefs about the total group's contribution. As such, our results (albeit using a different approach) are in line with those of Frey and Meier [64] and Fischbacher and Gächter [62] who show that people have heterogeneous preferences (or profiles) that motivate their decisions to contribute.

²² X_j takes respectively the values 0, 250 and 500 FCFA.

²³ $\frac{dCP}{dX} = 2aX + b$

²⁴In our settings, CP_{ig} is either the triplet of function parameters a_{ig}, b_{ig}, c_{ig} defined before or a dummy representing the individual's profile based on our initial classification.

²⁵As such, we assume an participation of 0 for the first game, which is consistent with the rational equilibrium.

TABLE VII: Regression of the “unconditional” contribution levels on selected explanatory variables

DV: Unconditional contribution	A (Estimates)	A(+controls)	C (Dummies)	C(+controls)
	(1)	(2)	(3)	(4)
a_{ig}	33692.930 (10802.700)***	31983.340 (11897.050)***		
b_{ig}	98.506 (22.571)***	94.562 (25.986)***		
c_{ig}	.446 (.056)***	.440 (.067)***		
Conditional cooperation profiles (strong & weak)			25.536 (21.780)	23.554 (24.172)
U-shaped			61.299 (22.722)***	57.278 (24.539)**
Hump-shaped			45.858 (27.432)*	54.252 (28.765)*
Warm-glow			113.622 (24.767)***	95.211 (29.368)***
Loss framing	35.463 (16.190)**	46.989 (17.271)***	36.554 (17.653)**	53.468 (18.309)***
Risky game	-55.037 (16.183)***	-38.336 (17.253)**	-69.709 (16.496)***	-47.432 (17.594)***
Risk aversion parameter	-5.890 (3.703)	-5.278 (4.046)	-5.248 (4.110)	-5.145 (4.397)
Waiting time at the collective water source (in min)	-.475 (.128)***	-.378 (.151)**	-.563 (.133)***	-.515 (.145)***
Average group participation from previous game	.244 (.065)***	.155 (.070)**	.288 (.068)***	.174 (.072)**
Strong faith influence	-21.969 (13.805)	-34.262 (16.848)**	-21.375 (14.497)	-31.688 (17.005)*
Value of openness (1=open)	24.125 (12.659)*	27.587 (14.861)*	31.820 (12.826)**	34.226 (15.035)***
Years of schooling		.456 (1.400)		.665 (1.473)
Household size		-.145 (2.301)		-2.210 (2.327)
Wealth (asset index)		46.993 (42.589)		53.355 (44.145)
Age		.249 (.377)		-.011 (.389)
Const.	171.484 (31.001)***	203.818 (49.344)***	255.989 (30.802)***	305.955 (46.749)***
Obs.	480	460	480	460
R^2	.368	.404	.316	.363
F statistic	40.164	19.882	30.342	15.555

When we use dummies to characterize the profiles, all types are significant with the notable exception of the conditional cooperation profiles. This could be caused by the broad definition of this profile, which accounts for strong conditional response functions but also for weaker ones whose shapes are conditional for certain segments (i.e. from 0 to 250 or 250 to 500) but not for the entire contribution schedule (i.e. from 0 to 500). By using the response function estimates that give a much more detailed distinction of the conditional response effects, the function parameters a_{ig} , b_{ig} and c_{ig} are jointly significant²⁶ and are also individually significant at the 1% level. It confirms that there exists a relation between the key dynamics of the response functions and the unconditional contributions. For instance, villagers who are “warm-glowers” ($a, b, c > 0$) are also the most generous ones unconditionally. If the villagers are U-shaped, ($a > 0, b < 0, c > 0$), unconditional contributions are reduced which is line with what we observed with the dummies.

²⁶With a a F(3, 432) value of 15.57 (p-value = 0.000).

As expected, “warm-glow” participants are contributing the most in average, followed by U-shaped (a combination of warm-glow and conditionality), hump-shaped and finally conditional individuals. However and without information on the villagers’ expectations about group contributions, it remains to be seen if the generous investment levels of inverse hump-shaped and hump-shaped villagers were the results of a low or high expectation about group participation.

Apart from the predictive role of conditional profiles, an important result, already observed with the “partial warm-glow” conditional contributions, is the importance of loss framing in the decision to unconditionally invest. Presenting the outcomes in negative terms increases substantially the participation level of the villagers²⁷.

On the contrary, the presence of risk has a significant and negative effect on the unconditional participation. This effect is independent on the risk aversion of each villager, which turns out to be insignificant²⁸. This overall risk influence could explain why collective projects in rural contexts similar to our own, which are often risky in nature, are underfunded. As already mentioned, a possible mitigation strategy would be to present these projects as losses, benefiting from the behaviors that comes with loss framing.

We observe a significant influence of actual collective experiences on participatory behaviors. Villagers who face longer waits when collecting water at collective water points were less inclined to contribute to the public good. It could result from a negative background appreciation of a collective good (the water point), which in turn would negatively impact willingness to contribute in the collective projects that were described in our games.

Villagers played the four games with the same group and contrary to the conditional games, unconditional amounts were known at the end of each game (but could not be traced back to the participants). We therefore want to control for a possible signaling effect by which the total contribution level observed in the previous game would have an impact on the contribution expectation of the current game for the villagers (and *in fine* on their unconditional participations). Our results show a positive relationship between past levels of group contribution and individual contribution. It could indicate that in general, villagers in our context prefer to move “up the contribution ladder” and increase their contribution when they experience improved group investment in the previous game instead of reducing their investments as it is often observed in repeated games (Croson et al. [49], Gächter [65])²⁹.

²⁷These results can be partially compared to those of Raub and Snijders [118] (negative framing in prisoner’s dilemma games) who find a positive but insignificant distinction between gains and losses based on their entire sample.

²⁸This result is in line with Kocher et al. [95] who find that “even though contributing unconditionally to a public good resembles a situation of making decisions under risk, elicited risk preferences do not seem to explain cooperation in a systematic way”.

²⁹We are confident that this result is not caused by a group selection bias since villagers were matched randomly.

We also observe a negative relation between the participants' perception of God's influence on his/her life on risk aversion and unconditional contributions. *Faith* is a dummy that takes the value 1 if an individual announces that God had a strong influence of his life, and the value 0 otherwise (for the three other cases of moderate, low and no influence). It would imply that the most religious participants are less inclined to participate in public goods, a result slightly at odd with the most recent literature on contribution and religion (Anderson and Mellor [4])³⁰. A potential explanation is that villagers with a strong faith consider that they receive individual protection from their God, which in turns would act as a substitute for group cooperation³¹ and limit the need for other-regarding behaviors. Further research will be conducted to improve on our understanding of this relationship.

The impact of openness is positive, significant and similar to what we observed with the "partial warm-glow" conditional participations. The justification is also probably similar: the villagers with the most acute perception of their collectivity have also a higher probability of contributing more to a public/group good with collective benefits.

Other key control variables turned out to be insignificant with the notable exception of the village dummies, which are jointly significant.

2.4 Conclusion

In this paper, we use a modified version of the linear public good game in rural villages of Benin to test different assumptions related to conditional cooperation profiles. Our goal is threefold. Firstly, we perform a comparative exercise to assess if the different conditional profiles and their respective shares are similar to what was observed in comparable experiments mostly played in developed countries. We find two notable facts: a total absence of free-riders and a very small share of hump-shaped profiles which are replaced by "U-shaped" profiles indicating an important but partial warm-glow effect among the villagers.

Secondly, we expand the initial setting of the linear public game to introduce risk and loss framings to determine their impacts on the conditional profile distribution. More precisely, we assess if the warm-glow effect, which is the main differentiator in our results, remain stable in presence of risk and losses. We find that loss framing has a strong and significant positive impact on generosity when individual do not expect other to participate while risk has a negative but insignificant impact in our sample.

³⁰While Anderson and Mellor [4] do not find a significant relationship between religious affiliation and participation, they observe that decline in repeated games is lower among religious subjects.

³¹Strong faith acts also as a substitute for risk hedging strategies, see Gheysens and Günther [68].

Finally, using results on the conditional profiles in conjunction with results on unconditional contributions (i.e. actual participation in one-period games) for the same games and settings, we investigate if elicited conditional profiles are good predictors of unconditional contributions. We notice a significant link between a profile and its average contribution, at least in our sample. It may suggest that villagers with a similar profile tend to have stable unconditional expectations based on their profile.

Our results provide new evidence on the dynamics of conditional cooperation. It appears that conditional cooperation is highly sensitive to the economic and cultural context but also to the framing (or meaning) of the group project. In the context of Benin, generosity is a fundamental concept that echoes strongly with the renowned “African altruism”. It is however impeded by the presence of risk, a phenomenon that could explain limited participation levels in collective projects.

Our experiments show in our limited sample that a possible and effective way to solve this problem would be to modify projects’ narratives and to transform expected gains in outstanding losses in an effort to nudge villagers’ decisions. Contributions would then be expected to improve substantially. The effectiveness of a loss framing instrument will be the subject of further research to expand our sample base and to test if it retains its impact for different cultural and socio-economic backgrounds.

Chapter 3

Baseline Choice and Performance Implications for REDD

Jonathan Gheysens, Anca Pana

3.1 Introduction

The importance of forest protection is now recognized for its role to curb global warming. According to United Nations [139], deforestation has been estimated to contribute 17% of total greenhouse gas emissions (GHG) and while it has globally slowed down recently¹, it remains a global issue with numerous damages to habitat and biodiversity, increased desertification, and soil erosion. Combined with agricultural land uses, forestry contributes to a quarter of all GHG emissions, a proportion which is expected to grow in absence of effective new policies [120].

To address this problem, the thirteenth UNFCCC conference of the parties (COP 13, 2007) established a clear mandate to create solutions for emission reductions from deforestation and forest degradation (REDD and REDD+, Chatterjee [41])² in the climate change mitigation framework [136].

REDD programs, like other Payment for Environmental Services (PES) schemes, support the

¹According to the FAO, around 13 million hectares of forests were converted to other uses or lost through natural causes each year between 2000 and 2010 as compared to around 16 million hectares per year during the 1990s.

²The + in REDD+ refers to conservation, sustainable management of forest and enhancement of carbon stocks through soil management or agricultural activities that would maintain carbon stock levels in existing ecosystems. [137]. REDD schemes concentrate on forest preservation.

idea that external funds could be offered in exchange for forest preservation. They give the possibility to forest owners from developing countries to be financially rewarded for reducing GHG emissions coming from deforestation and forest degradation, that would have otherwise occurred for timbering value or land transformation (e.g. agricultural activities such as palm oil production).

Under REDD schemes, reducing deforestation below a certain reference level generates carbon credits, eligible for sale on various carbon markets [117]. International emitters³ that are above their compliance level and short of CO₂ permits may find reducing emissions internally to be too expensive [51] and would therefore benefit from the comparative affordability of REDD permits⁴. Despite this economic advantage, REDD schemes remain complex to implement and prone to failure. As pointed out by Angelsen et al. [13], they require “*transformational change in the form of altered economic, regulatory and governance frameworks, removal of perverse incentives and reforms of forest industry and agribusiness policies.*”. They require either strong land rights if land owners are primarily responsible for deforestation (and can be identified) or a set of policy measure to align the various interests of the stakeholders in case of uncertain and mingled responsibilities. In not applied broadly (at the regional or national levels), they can promote leakages whereby land owners transfer their deforestation activities to areas outside of the REDD schemes, creating some “hot air permits”⁵.

The success of REDD schemes depends on a strong coordination between multiple actors at different levels, from international institutions to local communities, to ensure that the international demand for permits remains aligned with the interests and welfare of forest stakeholders, from land owners, local communities to governments. A good coordination is critically sensitive to the incentive structure promoted by the schemes⁶.

A central aspect of the incentive structure is the establishment of reference levels, the so-called *baselines*, against which reductions in deforestation are measured. Reference levels give a measure of the efforts required to reduce deforestation rate and ensure additionality⁷. The performance of REDD depends on the linkage between accessible activities, their GHG reduction effectiveness

³These emitters could be found among the European polluting companies who, due to the EU’s commitment to fight climate change, need to comply with emission reduction targets.

⁴According to the Stern report [133], permits from REDD+ could be as inexpensive as US \$1-2 per tCO₂ on average and while these low estimates have been subject of criticisms [91], experts tend to share the idea that deforestation permits will be comparatively cheap.

⁵“Hot airpermits are permits that do not represent actual efforts towards emissions reduction [?]Anger2008).

⁶This critical role of incentives has been formalized in the UNFCCC definition of REDD: “*policy approaches and positive incentives on issues relating to reducing emissions from deforestation and forest degradation*” [137]

⁷Additionality represents the the additional and tangible efforts towards CO₂ emissions reduction. A project that is not additional does not reduce emissions below its Business as Usual scenario.

and the effort required⁸:

$$\text{Emission reduction} = (\text{activities} \cdot \text{emissions factors}) - \text{reference emissions} \quad (3.1)$$

The present paper belongs to the stream of literature dedicated to optimal contract design applied to REDD schemes [37, 38, 121, 126]. It compares the impact of different baselines on optimal land transformation from forest to arable lands (and the related emissions) in a dynamic setting. In a second step, the paper ranks baselines according to different performance indicators, namely an indicator of forest preservation, an indicator of the marginal cost of this preservation per hectare and a final measure of monetary transfer to the land owner. Finally, the paper explores different possibilities to improve the baseline indicators and highlight the importance of design features.

While several baseline models have been proposed in the past and new ones are introduced on a regular basis, none of them have garnered a broad political and scientific consensus. Huettner et al. [84] compare qualitatively three different historical baselines with a model-based benchmark and find that each has strengths and weaknesses, depending on the indicators considered. Historical baselines benefit from a relative ease of implementation but cannot match the economic performance and environmental effectiveness of the model-implied baseline (a result similar to ours).

Busch et al. [38] improve on these first result by testing different baseline under a one-period partial equilibrium model at the national level. They conclude that baselines that are able to balance the incentives required for high and low national historical deforestation rates are the ones offering the best performance, depending on the severity of leakages. A cap and trade baseline model where countries are liable to exceeding deforestation above their historical BaU is the one with the best climate-effectiveness and cost-efficiency (with small differences between the different schemes). Busch et al. [37] extend this approach by introducing different levels of annual finance available to the REDD scheme, either through fund or access to a dedicated market. Under this approach, they confirm their previous result.

To keep the analysis comparable with these single-period studies on reference levels [37, 38, 84], we focus on two of the most popular baseline categories, a retrospective baseline based on the fixed historical average and a model-implied prospective baseline. We also introduce a new and potentially more complexed method, the conditional-based corridor approach, which was first outlined in a joint submission to SBSTA in 2006 by Joanneum Research, Union of Concerned

⁸ Angelsen et al. [13]

Scientists, Woods Hole Research Center, and the Instituto de Pesquisa Ambiental da Amazonia. Additionally, we take the chance to propose a new type of baseline, the variable corridor approach, which tries to bring together the strong points of the model-implied and the corridor baselines. Each baseline is detailed in Section 3.2.2 of the paper. An overview of the main baseline methodologies can be found in either Huettner et al. [84] or Griscom et al. [70].

Previous research on REDD design overlooked the inter-temporality dimension in forest decisions. We attempt to fill this gap by analyzing our selected baselines in a dynamic context of agricultural land use change. The highly dynamic nature of land use change has been studied in numerous papers (see Verburg et al. [140] for an review of current research developments) and benefits from a large variety of models. However, only a few papers deal explicitly with dynamic land use change in presence of REDD. Vitel et al. [142] for instance defines a reference REDD scenario for the Amazonia's Surui indigenous reserve but does not introduce explicitly REDD payments in the revenue mix of local communities. Lu and Liu [103] propose a land use model accounting for the the profitability gap between maintaining palm oil plantations and complying with REDD+ and conclude that with the current price dynamics for palm oil and REDD PES favoring agricultural development, carbon prancing policies may remain limited. However, their approach does not test for different baseline methodologies.

In the special case of forestry dynamics in presence of carbon payments, Chladná [44] determines the optimal rotation period by considering uncertain revenue streams from timbering and carbon trading. Rose and Sohngen [121] and Sohngen and Sedjo [130] use a dynamic partial equilibrium model to account for temporal variations in REDD prices and access.

We model the decisions of a single land owner who has to optimize its agricultural expansion in presence of a voluntary REDD scheme. We use a single agent model for several reasons. First, it simplifies our setting and allow our methodology to remain aligned with optimal control theory. This setting is also coherent with a new literature stating that REDD will face the same issues as traditional integrated conservation and development projects (ICDPs), since it will have to account for incentives at the community and individual levels [27] and with the literature on optimal forest extraction [10, 119]. It differs however from most of the existing literature on REDD baselines, which uses either scenario analysis [70] or static models of partial equilibrium [37, 38] at the national level. Aggregate national estimates are important to underline specific baseline differences and interactions between country “types”, but obscure the motivational “drivers” faced by each land owner invested in agricultural activities and land use change.

To facilitate the comparison between the different baselines, we choose an approach similar to Busch et al. [38], by which the land owner's opportunity cost of deforesting is modeled as a stylized and unique composite commodity (or agricultural rental price), representing both the harvesting value of timber and a perpetual discounted flow of agricultural activities on the land. This simplification allows us to concentrate our analysis on the dynamic decisions between maintaining the forest cover and harvesting, and limit the complexity of the harvesting function, which is not central to compare the reference levels.

Our paper provides insights into various issues regarding the design of conservation projects. Firstly, we show that baseline choice impacts land-use behavior, with REDD having a great potential in reducing deforestation and the inherent GHG emissions. Secondly, with REDD contracts designed as voluntary projects, land owner's welfare is expected to rise above business-as-usual levels, signaling high opt-in rates. Thirdly, in our attempt to rank baselines, we demonstrate that forward-looking baselines outperform retrospective ones (which is in line with results of Busch et al. [37, 38]). Finally, our results show that the final ranking of baselines depends on the preferred performance indicator and the deforestation history in the area. The optimal baseline choice unfolds as a balancing act between effectiveness and efficiency criteria.

The rest of the paper is organized as follows: Section 3.2 introduces our methodology and the main assumptions of the dynamic model. We also take the chance to describe the chosen baseline approaches. In Section 3.3 a numerical application is performed and key findings are highlighted. The robustness of our results is tested by varying the deforestation context and specific scheme attributes. The paper concludes with the policy implications of our results and the link with broader issues of REDD+ implementation.

3.2 Methodology

3.2.1 Model setting

The model developed here describes the behavior of a land owner that initially gets revenues from timber and agricultural output at market value (in our model, prices are exogenous). As the owner of a large patch of forested land, he can decide if, when and to what extent he will exploit part of his forest for agricultural activities. To limit his opportunity to deforest, he has been offered the possibility to take part in a REDD program, that rewards him with carbon credits each time his deforestation rate is below a pre-specified threshold (or a combination of thresholds as

with the corridor approaches). We model the voluntary access to the REDD along the approach of Busch et al. [37, 38], where the owner can “opt in” if the REDD discounted expected rental value is higher than the agricultural rental price and “opt out” otherwise. However, the land owner cannot reforest areas dedicated to agricultural activities, which assumes that costs to switch back are prohibitive (as well as forgone discounted cash-flows from agriculture).

The land owner’s revenues are determined by the trade-off between a composite commodity income net of costs and REDD rewards. The more the owner deforests his parcel, the higher his incomes from selling timber and subsequently using land for agricultural activities and the lower his endowment of CO_2 permits. Alternatively, lower deforestation (below the defined baseline level) results in smaller incomes from agriculture and timbering, but higher REDD revenues.

A rational owner would maximize the sum of total discounted profits, taking into account the parameters that define his investment environment: the state of the forest, the dynamics of composite commodity and carbon permit prices, the land switching costs, and the specified deforestation baseline.

For the prices of the composite commodity and CO_2 permit, we make the relatively strong assumption that both prices follow deterministic processes. Another assumption is that the growth rate of CO_2 permit price is slightly higher than the commodity price.

$$dP_t^F = \delta P_0^F dt \quad (3.2)$$

$$dP_t^R = \gamma P_0^R dt \quad (3.3)$$

Above, P_t^F and P_t^R stand for the instantaneous prices of composite commodity and REDD permits, and δ and γ for their corresponding growth rates.

Using deterministic processes simplifies the resolution of our model but leaves outside of the scope of our analysis the role and influence of risk on the optimal land allocation of the owner. Under the hypothesis of a risk neutral land owner, the presence of risk would have no specific effects. However, in presence of a risk averse agent, the decision between preservation and deforestation will be significantly impacted by the relative volatility of the two prices and would favor the strategy giving the smallest cash flow variability.

Being a composite price, P_t^F is a simplification of the actual commodity flow generated from harvesting one hectare of forest and using the area for perpetual agricultural activities, which could be modeled as follow:

$$P_t^F = P_h(t) + \int_t^\infty A(t)e^{-\psi t} dt \quad (3.4)$$

where $P_h(t)$ represents the one-time timber harvest selling price and $A(t)$ are the annual monetary flows of agricultural activities permitted by the land transformation. We assume a higher gross rate for CO₂ on the basis of two assumptions. First, increased pressure on countries to reduce their emissions due to severe effects of climate change will likely drive demand up and will create a tension on permit prices, especially on REDD markets that are expected to start low and could become highly attractive for new “regulated ” countries (e.g United States, China). Second, in the case of some price interventions at the national level (if REDD revenues go through governments before reaching forestry funds), we expect REDD rewards to progressively include additional compensations to indirect services, community and individual supports (similar to ICDP payments).

Contrary to the traditional dynamic setting, we enforce a very loose constraint on the total owned patch of forest at t_0 , $(\bar{F}(0))$. However, we impose a time window $[0, T]$ during which the optimization occurs. While $\bar{F}(0)$ is not infinite, we consider its value so large that forest depletion is not likely. In this sense, we allow for a positive terminal stock at period T . We consider this setting to be in line with the reality of many land owner’s decision processes in tropical countries. In Latin America, few large owners tend to concentrate a disproportionate share of land ownership rights [28, 32]. On the second hand, future REDD schemes may have an explicit time frame [114]⁹, which compels us to consider the time constraint as the most binding for the land owner.

Land transformation involves various operational costs. We follow the approach of Cherian et al. [42] and allow for quadratic harvesting and transformation costs. This stylized representation is coherent with the classical approach of Thünen [134] where land is abundant and homogeneous and the limits on expansion are related to increased accessibility costs measured by the distance from the center [9]. This assumption allows for the existence of an interior solution for the optimal deforestation rate, and guarantees increasing marginal costs, a feature confirmed empirically (Cherian et al. [42]). No costs are incurred for zero deforestation rates.

$$C_t = a_1 d(t) + a_2 d(t)^2 \tag{3.5}$$

where a_1 and a_2 represent the parameters of the quadratic cost function and $d(t)$ is the amount of forest transformed.

The offsetting scheme proposed by REDD has a voluntary feature: the manager is rewarded if

⁹This time frame is expected to be aligned with phases of either the EU ETS or the successor of the Kyoto protocol

his deforestation rate is below a certain reference level, but does not have to pay penalties in case he exceeds this limit¹⁰. We assume that the land owner has a monopoly on his land, enforced by his land ownership rights, which prevents other agents to enter a similar activity and increase competition¹¹.

The owner's revenues from participating in the REDD project can be described with a simple step function:

$$RR_t = P_t^R(dB - d(t))^+ \quad (3.6)$$

where RR_t represents REDD cash flows for period t , P_t^R is the REDD permit price for the same period, dB is the baseline level and $d(t)$ the actual deforestation rate occurring during the period. In this setting and contrary to the cap-and-trade baseline of Busch et al. [38], the “opt-out” clause means that the owner is not responsible for excessive emissions above the baseline and does not have to pay penalties.

A number of factors influence the revenue generated by the REDD project: the price of the CO_2 permit, and the relationship between the specified deforestation baseline (dB) and the deforestation rate ($d(t)$).

We consider five different scenarios: business-as-usual (no REDD project in place), historical, model-implied, and two types of corridor 2. After presenting the conditions of each setting, we provide the analytical solution for the optimal deforestation path in each case. We begin our analysis with the simple case when the forest brings only timbering benefits, in the absence of REDD initiatives.

3.2.2 Baseline alternatives

The Business-as-usual Scenario (Without REDD)

The *business-as-usual* scenario serves as an illustration of the deforestation trend under standard conditions, in the absence of a REDD program targeting the reduction of emissions from deforestation. The results derived here will serve as the crediting reference for computing the REDD rewards under the model-implied and the variable corridor 2 scenarios.

When the forest is dedicated to timbering purposes only, the net cash flows at time t takes a reduced form:

$$\pi(d(t)) = P_t^F d(t) - (a_1 d(t) + a_2 d(t)^2) \quad (3.7)$$

¹⁰This approach is similar to Busch et al. [37] and in line with the nature of PES by which “forest users will opt for conservation only if the net benefits are higher than those arising from forest exploitation” [13].

¹¹For the purpose of our analysis, we assume that while prices are exogenous and market-given, total forested land is divided between a fixed number of land owners whose respective shares are held constant

where $\pi(d(t))$ represents the owner's cash flows from his land plot, P_t^F is the composite commodity price, $d(t)$ is the deforestation rate and a_1 and a_2 are the parameters of the quadratic cost function.

The optimal control problem can be described as a maximization over the deforestation rate of the total discounted net revenues resulting from land transformation:

$$\max_{d(t)|t \in [0, T]} \left\{ \int_0^T e^{-rt} \pi(d(t)) dt \right\} \quad (3.8)$$

where r is the discount rate and T is the last period under consideration. Moreover, the variation in the stock of forested land is as such:

$$s.t. \quad \dot{F} = -d(t) \quad (3.9)$$

where F is the stock of forest and \dot{F} represents its variation between two periods.

We follow the solution approach of [43] for determining the optimal deforestation path¹². The rate of deforestation at each moment of time is recursively linked to the initial deforestation level:

$$d(t) = d_0 e^{rt} + \frac{P_0^F (e^{\delta t} - e^{rt}) - a_1 (1 - e^{rt})}{2a_2} \quad (3.10)$$

According to equation 3.2.2, and with $\delta > r$, the long-term trend for $d(t)$ is higher than the initial deforestation rate d_0 and continuously $d_0 e^{rt}$ increasing (as shown in Fig.).

The Historical Baseline

Most of the papers analyzing baseline performance propose the inclusion of the historical average deforestation rate in the computation of the crediting baseline¹³, recognizing that average past deforestation, although an imperfect measure, is the best predictor at hand for short-to-medium term deforestation [14] and does not require intensive data collection and model computation. We thus start the analysis of the deforestation behavior under REDD with a simple historical baseline, in which no specific adjustments are made to a fixed level calculated from past mean emissions. This baseline type is a simplification of what has been proposed by Brazil [114].

The merit of a fixed baseline consists in its fair simplicity of computation and in its appeal to

¹²For the complete derivation steps we refer to Annex 1.

¹³Out of the 6 baseline rules studied by Griscom et al. [70], 5 rely partially or totally on historical reference levels.

forest managers who need to get used to new operation rules. The baseline has received support due to its ability to reflect local deforestation trends and avoid the one-measure-for-all caveats. The historical reference level has, however, a number of limitations. Firstly, many countries do not dispose of accurate data records [71]. Secondly, an imperfect predictor of future deforestation has high chances of undermining the additionality principle and distorting country participation, especially if one considers the specific stage of each country with respect to the forest transition theory [10]¹⁴. Forest-rich states with low deforestation might decide to opt out of the REDD schemes if offered programs based on historical baselines. On the other hand, low-forest high-deforestation nations would gladly join but be rewarded on fake premises [11].

In presence of the REDD scheme, the instantaneous income is generated by two counter-balancing activities, i.e. timbering and trading of REDD permits:

$$\pi(d(t)) = P_t^F d(t) - (a_1 d(t) + a_2 d(t)^2) + P_t^R (dB - d(t))^+ \quad (3.11)$$

The timbering activity involves proportional operational costs, while REDD revenues are eligible only for deforestation rates below a fixed threshold.

The Model-implied Baseline

An alternative to the retrospective historical baseline is the prospective method [84]¹⁵ of projected future deforestation trends. The *model-implied* baseline relies on a time-varying level reflecting predicted deforestation paths under the *business-as-usual* scenario. Here, the forester is rewarded for deforesting less than in the absence of the REDD program. Its design could be accommodated to include information regarding the next forest transition stage of the applying country. If the forecasting is accurate, it enforces additionality, since only actual efforts would be rewarded. However, model-implied baselines are not exempt from criticisms, stemming primarily from its vulnerability to forecasting errors and for its reliance on model assumptions.

The ability of prospective models to combine spatial and non-spatial influences with forest extraction dynamics make them particularly relevant for our dynamic approach.

Under our REDD approach, the optimal control problem has the same specification as before, with the notable difference of the reference level $dB(t)$, which can fluctuate across time according

¹⁴According to Angelsen [10], “the *FT* theory describes a sequence over time where a forested region goes through a period of deforestation before the forest cover eventually stabilizes and starts to increase. This sequence can be seen as a systematic pattern of change in the agricultural and forest land rents over time.”

¹⁵According to Huettner et al. [84], prospective methods model land-use change and deforestation “using analytical, regression and simulation models. Simulation models assess the interactions between drivers and are often spatially explicit.”

to the projections of the model used:

$$\pi(d(t)) = P_t^F d(t) - (a_1 d(t) + a_2 d(t)^2) + P_t^R (dB(t) - d(t))^+ \quad (3.12)$$

Compared to the formulation of the historical baseline, the key difference of this approach is the transformation of the baseline level, from a static threshold dB to a dynamic parameter $dB(t)$. In our model, $dB(t)$ is chosen to match the counterfactual deforestation pattern of the no-REDD scenario, such that:

$$dB(t) = d(t)^c \quad \forall t \quad (3.13)$$

where $d(t)^c$ represents the deforestation path under the BaU scenario.

The Corridor 2 Baseline

The Fixed Corridor 2

The corridor approach has been jointly proposed in 2006 by the Joanneum Research Institute, the Union of Concerned Scientists, the Woods Hole Research Center, and the Instituto de Pesquisa Ambiental da Amazonia [70]. The program introduces a lower and an upper reference level (hence its corridor name) for comparing current emissions and establishing the volume of carbon credits generated by the REDD scheme.

In this paper we analyze the so-called *corridor 2* methodology, whereby deforestation rates below the lower boundary are entirely eligible for CO₂ permits, as they would under a fixed-baseline scheme. Deforestation levels above the upper boundary do not receive any REDD payment. However, deforestation levels within the corridor are weighted proportionally to distance from the upper boundary. It leads to rewards that increase when deforestation decreases toward the lower bound, up to a full payments (if this lower bound is reached). Conversely, rewards are reduced if deforestation increases towards the upper bound, down to no payment (if the upper bound is reached).

Similar to the other models, deforestation rates above the upper boundary, while not be eligible for carbon credits, do not result in owed emissions [70]. The upper and lower limits of the fixed corridor are constant and historically determined, over an agreed time period of five to fifteen years.

Imposing a *corridor* baseline is motivated by the need to address an important feature of deforestation, namely the inter-annual fluctuations in the levels of deforestation, caused by shifts in key market parameters, such as commodity prices, interest rates, or climate impacts ([87]).

It is believed that the corridor could act as a *buffer* against these factors, while still allowing countries to receive rewards for deforestation rates below the *business-as-usual* scenario. Under our simplest historical baseline, the threshold is fixed as a long-term average of past deforestation rates, resulting in years above the cut and years below. The aim of the corridor is to create buffers around the fixed threshold to account for this annual variability: during years of intensive deforestation, the upper bound ensures that incentives are maintained, while in low years, it rewards strong efforts and ensure additionality.

The corridor is also useful when measurement errors cripple the estimation of the historical baseline. The corridor creates an “error” band around the threshold and maintain incentives in absence of perfect knowledge about past deforestation rates.

Under the REDD scheme, the shape of the profit function will be strongly influenced by the new design of the reward program:

$$\pi(d(t)) = P_t^F d(t) - (a_1 d(t) + a_2 d(t)^2) + P_t^R \left(1 - \frac{(d(t) - dB^L)^+}{dB^U - dB^L} \right) (dB^U - d(t))^+ \quad (3.14)$$

where dB^U is the upper bound and dB^L the lower bound.

In equation (3.14) the third term represents the incomes generated by the REDD project, which is determined by two indicator functions. The first indicator function behaves such that:

$$1 - \frac{(d(t) - dB^L)^+}{dB^U - dB^L} = \begin{cases} 1 - \frac{d(t) - dB^L}{dB^U - dB^L} & , \text{ if } d(t) > dB^L \\ 1 & , \text{ if } d(t) \leq dB^L \end{cases}$$

This formulation is necessary for the corridor weighting mechanism: in case the deforestation rate lies within the corridor, rewards will be proportional to the distance between the deforestation rate and the lower boundary. Deforestation rates smaller than the lower boundary are rewarded full credits.

The second term of the REDD income, $(dB^U - d(t))^+$, makes sure that rewards are received only in case deforestation remains below the upper boundary of the corridor.

The Variable Corridor 2

Similar to the difference between the static fixed historical baseline and its dynamic model-implied counterpart, we suggest to improve the proposed corridor baseline by implementing it dynamically. The variable corridor 2 replaces the constant lower and upper corridor bounds with time-varying levels, established below and above the deforestation rate of the dynamic business-as-usual scenario (in absence of REDD).

With this new baseline rule, we bring together the strong points of both the model-implied and the fixed corridor baseline schemes. Firstly, linking corridor boundaries to the baseline-as-usual deforestation trend is expected to offer not only a dynamic but also a forward-looking perspective on deforestation paths, more likely to insure additionality. Secondly, the corridor reward system should dampen the negative effects coming from estimation errors and protect against inter-annual fluctuations in deforestation levels.

In terms of profits, the scheme is similar to the one of the fixed corridor 2 baseline, the only difference being the dynamic boundary levels:

$$\pi(d(t)) = P_t^F d(t) - (a_1 d(t) + a_2 d(t)^2) + P_t^R \left(1 - \frac{(d(t) - dB^L(t))^+}{dB^U(t) - dB^L(t)} \right) (dB^U(t) - d(t))^+ \quad (3.15)$$

To summarize, the different REDD rewards ($RR(t)$) offered to the land user under the different baseline methodologies are the following:

$$RR(t) = \begin{cases} P_t^R (dB - d(t))^+ & , \text{ if Historical} \\ P_t^R (dB(t) - d(t))^+ & , \text{ if Model-implied} \\ P_t^R \left(1 - \frac{(d(t) - dB^L(t))^+}{dB^U(t) - dB^L(t)} \right) (dB^U - d(t))^+ & , \text{ if fixed Corridor 2} \\ P_t^R \left(1 - \frac{(d(t) - dB^L(t))^+}{dB^U(t) - dB^L(t)} \right) (dB^U(t) - d(t))^+ & , \text{ if variable Corridor 2} \end{cases} \quad (3.16)$$

3.2.3 A numerical application

Considering the relative complexity and non-linearity of the profit functions (especially for the Corridor 2 schemes), we resort to a numerical approach to compare the land owner's decisions under the different baseline rules. The details of our solution method as well as the calibration details are provided in Annex 2 and 3.

For the numerical solution, we calibrate the model to match observed data. Considering the representativeness of the region for future REDD projects, we take the view of a forest owner in Peru invested in agricultural transformation. The country is highly representative of the REDD candidate regions both in terms of specificities and market volume¹⁶. Peru is rich in forest

¹⁶According to Diaz et al. [51], the Peruvian and Brazilian Amazon dominate the forest carbon market, with Latin America accountable for not less than 60% of the 2010 total primary market volume.

resources with a generally low deforestation rate ([14], [70]). With 70 million hectares of tropical forest covering nearly 60% of its territory, it has the fourth largest area of tropical forest in the world¹⁷. Of this, more than 80 percent classifies as primary forest. The annual deforestation rate for 1990 - 2005 ranged between 0.35-0.5%, remaining at low levels relative to its neighboring countries [56]. However, more recent estimates show that during 2000 - 2010 deforestation rates experienced an increasing trend, which is predicted to persist in the near future mainly due to cropland expansion in the Andes [144].

The list of parameters used in our simulations and their sources are presented in the Table below:

TABLE I: Calibration parameters for the numerical models

Parameter	Explanation	Value	Source
P_0^F	Composite commodity price	500 Eur/m^3	ITTO (2010)
δ	Composite commodity growth rate	2.3% p.a.	ITTO (2010)
C	Eur/m^3 to Eur/ha	158 m^3/ha	IPCC (2003)
P_0^R	REDD permit price	5 Eur/tCO_2	Forest Trend (2011)
γ	Carbon growth rate	2.5% p.a.	Forest Trend (2011)
Ω	ha to tC emitted	179 tC/ha	OSIRIS (v3.4)
ψ	tC to tCO_2	3.67 tCO_2/tC	[16]
r	Discount rate	2% p.a.	Engel et al. [53]
a_1	Cost parameter	3.3198 Eur/ha	Angelsen [8], [141]
a_2	Cost parameter	798.0811 Eur/ha^2	Angelsen [8], [141]
dB	Historical baseline	[1, 500] ha	-
dB^U	Upper boundary	$dB(1+x)$ ha	-
dB^L	Lower boundary	$dB(1-x)$ ha	-
x	Corridor width	[0.1, 1]	-
T	Time horizon	100 years	-

For consistency of computational base, we convert the price of the composite commodity (timber and agriculture) from $\$/m^3$ into $\$/ha$, relying on the IPCC Good Practice Guide LULUCF [116]. The price of the commodity and its long term mean (δ) are computed for the Peruvian market from the Annual Review and Assessment of the World Timber Situation [86]. We use the State

¹⁷After Brazil, the Democratic Republic of Congo and Indonesia.

of the Forest Carbon Markets 2011 [51] for the identification of the REDD permit price and its growth rate. The conversion of the deforested area into tons of carbon emitted is achieved with the help of another converter (Ω), whose value for Peru can be found in the OSIRIS model for the above and below ground biomass carbon and for soil carbon [38]. Another converter, ψ , transforms the quantity of tons of carbon emitted into tons of CO_2 emitted [16]. The discount rate used for comparing profits over time is of 2%, a standard value also employed by Engel et al. [53]. For the calibration of the production cost, we adapt the cost function of Angelsen [8], calibrating it to data from Verissimo et al. [141] for the Amazonian forest. We allow the historical baseline level to vary in a large interval (between 1 ha and 500 ha per annum), in order to cover a broad spectrum of scenarios¹⁸.

3.3 Results and discussion

3.3.1 Performance indicators

A successful REDD program should target the reduction of CO_2 emissions at low costs and contribute to the sustainable development of the host country [11]. We evaluate the performance of the REDD program under different baseline schemes with the help of three indicators constructed in the spirit of the *3E Criteria* proposed by [133]. The performance measures we consider are: effectiveness, efficiency, and forester's welfare, with and without the presence of REDD programs in the region. Their computation is detailed in Table II.

TABLE II: Performance Criteria of Baseline Schemes

Indicator	Definition	Formula
1. Effectiveness (E_1)	Avoided deforestation (%)	$E_1 = \frac{S_T^{BaU} - S_T^i}{S_T^{BaU}}$ $S_T = \int_0^T d(t)dt$
2. Forester's welfare (E_2)	Change in profits (%)	$E_2 = \frac{\Pi_T^i - \Pi_T^{BaU}}{\Pi_T^{BaU}}$ $\Pi_T = \int_0^T e^{-rt} \pi(d(t))dt$
3. Efficiency (E_3)	Average cost per ha (Eur/ha)	$E_3 = \frac{\int_0^T RR(t)^i dt}{\int_0^T d_{BaU}(t)dt - \int_0^T d(t)dt}$

Notations: BaU = business-as-usual, $d(t)$ = deforested area; $\pi(t)$ = total land use profit at time t ; $RR(t)$ = REDD revenue.

¹⁸The mean of the deforestation rate obtain in the business-as-usual scenario (absence of REDD) was close to 200 *ha/period*.

The effectiveness indicator (E_1) is an overall measure of avoided deforestation, and the inherent abstained emissions. It quantifies differences in deforested area between the business-as-usual (no REDD) and the different baseline scenarios for REDD, being therefore a measure of additionality. As [11] points out, it assumes the verifiability of realized emissions through reliable monitoring and the accurate estimation of deforestation paths in the absence of REDD programs.

REDD initiatives target additional benefits besides the carbon reduction goals, such as positive externalities on local communities. For measuring the financial co-benefits of REDD we introduce a simple indicator (E_2) quantifying the changes in forester's income with and without REDD. Finally, the efficiency indicator (E_3) is relevant for the financial performance of REDD, providing an estimate of the average cost of forest preservation (assuming an exogenous price) per hectare of avoided deforestation.

While consensus has been reached on the desirability of achieving high effectiveness levels and low costs of avoided deforestation, the discussion on the advantages of high monetary transfers in REDD is still on-going. With large financial transfers, the country opt-in rates are expected to be very high, which may produce an overflow of inexpensive permits in the market, with the risk of jeopardizing climate negotiations. This is the argument [107] make when promoting programs that minimize transfers across national borders, underlying that climate treaties are vehicles that focus primarily on mitigation and not poverty alleviation. As [12] points out, since poverty is indeed an important issue in the candidate REDD countries, positive expected net benefits are needed in order to insure country participation in climate programs. Reward levels should however be case-specific, being biased towards the more needy, while avoiding large transfers to middle-income countries that are progressively responsible for greenhouse gas accumulations in the atmosphere.

3.3.2 A first comparison

We start the analysis of the different baseline schemes by first assuming a historical deforestation rate of 200 hectares per year. This rate corresponds to the average level of the yearly deforested area in the business-as-usual case for the period under consideration, and can be thought of as a scenario in which deforestation trends remain similar over our time window. We compare the performance of the historical (H), model-implied (MI), and corridor 2 baselines. For simplicity, the *fixed* and *variable* corridors are labeled $C2(f)$ and $C2(v)$ hereafter.

The $C2(f)$ type assumes that the upper and lower bounds of the corridor are fixed at 10% below and above the historical baseline respectively. While maintaining the corridor bandwidth

assumption, the $C2(v)$ sets the bounds in relation to the business-as-usual deforestation path and is therefore time-varying¹⁹. Even if the difference in design seems small, the change in performance will prove to be considerable. The assumptions regarding the corridor width and its symmetry around the reference level are relaxed later on (Section 3.3.3).

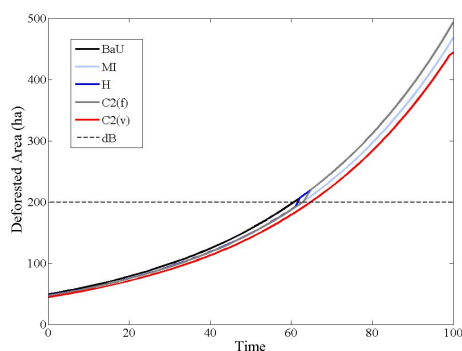


FIGURE 3.1: Deforestation Paths

Indicator	Effectiveness	Welfare	Efficiency
	E_1 (%)	E_2 (%)	E_3 (Eur/ha)
MI	4.77	12.84	4,680.18
H	1.54	2.26	73,096.66
$C2(f)$	1.76	2.76	78,043.75
$C2(v)$	9.08	0.92	9,318.13

Notations: $i \in MI, H, C2$; MI = model-implied; H = historical; C2 = corridor 2; BaU = business-as-usual.

FIGURE 3.2: REDD improvements over BaU

Figure 3.1 illustrates the optimal deforestation path chosen under each crediting baseline scheme. The pattern of deforestation follows the increased value of the forest resulting from the upward-trending price dynamics.

By comparison, the area of deforested land in the different baseline scenarios remains each year lower or equal to the business-as-usual case. This is an important result, showing that REDD programs provide significant incentives to decrease deforestation in all baseline cases. Moreover, this feature entails positive permanence indications: reductions in deforestation at a certain moment of time will not be counterbalanced by raising deforestation trends at later periods above the business-as-usual scenario. REDD incentives appear sustainable - as opposed to temporary - conservation efforts.

The baseline scenarios differ in their performance (Figure 3.2). Interestingly, each indicator reveals a new ranking of the baselines. The variable corridor 2 ($C2(v)$), with its dynamic reward system, achieves the best results in terms of avoided deforestation (E_1). It is followed at quite some distance by the model-implied baseline (MI). The fixed corridor 2 ($C2(f)$) and the historical baseline (H) lag far behind in terms of effectiveness. A likely explanation is that the variable corridor 2 incentivizes strong deforestation reductions by linking the full benefit to the lower boundary (which works because the attractiveness of REDD is initially high).

¹⁹The lower and upper bounds for the fixed corridor are set as $dB^U = (1+x)dB$ and $dB^L = (1-x)dB$, while for the variable corridor they are computed as $dB^U = (1+x)dBaU(t)$ and $dB^L = (1-x)dBaU(t)$.

The outcome on any REDD scheme on the owner's welfare ($E2$) is essential on both a moral ground (it could be hard to argue in favor of programs that impoverish local communities) and for cooperation reasons, since REDD projects that provide positive net benefits are expected to have high country opt-in rates. Due to their voluntary participation and limited liabilities design, all baseline schemes guarantee an increase in profits from the business-as-usual scenario. The MI baseline is the most attractive for the forester, providing an increase in total revenues by around 13% over the entire optimization horizon. This is due to the combination of strong incentive to preserve (already observable with the effectiveness metric) and the full payment of permits below the baseline threshold. Both types of corridor 2 together with the historical baseline allow for only modest changes in welfare. It is however not clear whether substantial REDD transfers can be considered an unquestionably desirable feature of the program. One should therefore be careful when declaring the superiority of the model-implied baseline based on welfare considerations.

Finally, a successful REDD scheme should provide a cost-efficient solution to the emissions reduction problem, otherwise buying countries might be discouraged from financially supporting the programs. The model-implied baseline is the top performer based on the cost-efficiency criterion ($E3$), followed by the $C2(v)$ and the distant historical baseline and $C2(f)$, with almost twenty times higher costs than the model-implied baseline rule. The dominance of model-implied baselines was expected as the rewards required to preserve were aligned with the dynamic context of the land owner.

Overall, the poor results of the historical baseline across the different criteria can be explained by its static threshold, kept constant during the time span of the project while deforestation slopes upward. The scheme is weak in matching the dynamic nature of the deforestation path and fails to provide the forester with continuous incentives to preserve.

The findings presented here offer contrasting support for either the variable corridor or the model-implied baseline. A robust ranking of the different schemes requires however the careful consideration of both the deforestation context (the historical reference level dB) and the attributes of each family of baselines. This is the task we tackle in the next section, first by testing the sensitivity of the baseline models to different reference levels and then by addressing two key aspects of the corridor methodology, the corridor bandwidth and its symmetry.

3.3.3 The influence of deforestation context and scheme attributes

Deforestation history

We focus first on testing the sensitivity of baseline performance to different past deforestation contexts. This translates into adjusting the constant boundary against which rewards are accrued for the historical and fixed corridor 2 schemes below and above the assumed level of 200 ha per year²⁰. Results are displayed in Figure 3.3.

The performance and ranking of the baseline schemes is not constant across the different performance measures. Changing the assumptions regarding the fixed threshold leads to different choices regarding the most appropriate baseline scheme. The fixed corridor 2 and the historical baselines gain ground as the crediting level is increased above the average past deforestation, both in terms of effectiveness and welfare. The result is not surprising, since higher crediting baselines are more generous in terms of REDD revenues. However, these advantages come at a high cost: from an efficiency point of view performance deteriorates considerably.

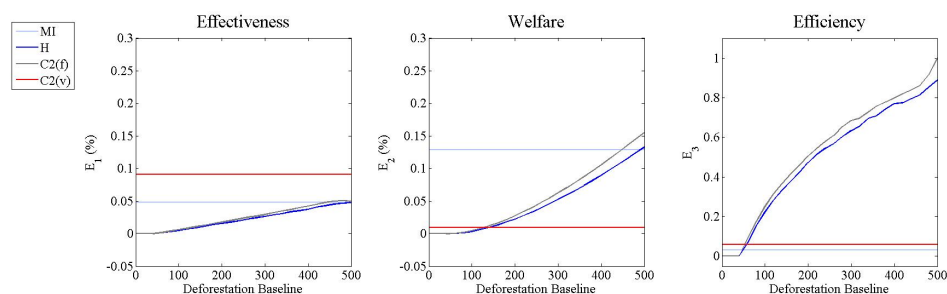


FIGURE 3.3: Performance Indicators of Different Baseline Scenarios

Note: The figure illustrates performance results of the model-implied, historical, and fixed and variable corridor 2 baselines based on three indicators (Table II). The efficiency indicator is normalized such that the highest cost takes value 1. The past deforestation average is allowed to range between 1 and 500 ha/year. Corridor width is maintained at 10%.

Let us now identify the cause for the improvements in performance of the historical and fixed corridor 2. We have seen in Figure 3.1 that optimal deforestation paths curb upwards in time. Anchoring REDD rewards to a higher crediting threshold determines a later switch to a no REDD regime, and a longer substitution between forestry and REDD revenues. The constant reward

²⁰The level of 200 ha/year was based on the projected average of the business-as-usual deforestation path and the assumption that averages over consecutive time periods remain constant. Considering different fixed crediting levels corresponds to either allowing for different past deforestation averages or keeping the assumption regarding the historical average and adjusting the fixed crediting threshold below and above this level. The first case allows us to assess the performance of each baseline scheme for countries that are at different stages in their forest transition curve.

level reflects in this case the higher end of future deforestation trends. To sum up, if steep slopes are expected, regulators should adjust the fixed threshold well above the deforestation average. This kind of adjustment requires however to have reliable forecasts at hand.

Corridor Bandwidth and Symmetry

The complexity of selecting the most appropriate reference level for REDD consists not only in identifying the best-performing baseline type, but also in defining the optimal attributes for the selected scheme. The corridor bandwidth is one of the factors policy makers need to analyze and choose optimally.

We relax the previous assumption regarding the fixed corridor width and allow it to vary widely ($x \in [0.1, 1]$), corresponding to different reward magnitudes granted for reducing deforestation in the case of the fixed and variable corridor 2 baselines.

Let us first discuss the changes in performance for the fixed corridor ²¹. Varying the corridor width brings new insights into the ranking of crediting baselines. Firstly, for past deforestation levels above 150 ha/year, wide corridors where the upper and lower bounds are set far away from the historical average ($x \geq 0.8$) lead to large increases in effectiveness for the fixed corridor 2, above those attained by the model-implied scheme. Secondly, such wide corridors also ensure the highest increases in forester's welfare, for crediting levels above 300 ha/year. Moreover, the positive impact on welfare is marginally increasing. Thirdly, broadening the corridor width lowers the efficiency performance, and here the model-implied baseline remains the sole dominant choice.

Another baseline attribute that should undergo careful scrutiny is the corridor symmetry around the historical deforestation average. We hereby allow for both an upward- and downward-biased corridor²².

Our previous findings regarding the effects of widening the corridor bandwidth hold across the different assumptions of corridor symmetry.

After loosening the symmetry assumption, a threefold conclusion emerges. Firstly, the upward-biased corridor dominates in terms of effectiveness, regardless of the corridor width. Also, welfare increases are best supported by upward-biased broad corridor baselines. Efficiency reasons argue strongly for a downward-biased corridor. Secondly, as corridor width increases, differences in performance across distinct symmetry scenarios widen considerably. Lastly, results depend on

²¹For a detailed overview of the results, we refer the reader to Annex 4.

²²Corridor bounds in the upward-biased case are computed as $db^L = db(1 - x)$ and $db^U = db(1 + 2x)$, while in the downward-biased case they are equal to $db^L = db(1 - x)$ and $db^U = db(1 + x/2)$, where $x \in [0.1, 1]$

past deforestation levels, such that lower corridor bandwidths perform better in terms of effectiveness and efficiency for smaller past averages, but worse for higher cases.

The performance responses of the fixed corridor 2 to widening corridor size and loosening the restrictions on symmetry were positive. We are now motivated to check whether the variable corridor 2 would benefit as well from such changes. The results are detailed in Annex 5.

Contrary to the findings obtained in the case of the fixed corridor, wider bandwidths are less effective in reducing deforestation for the symmetric and the downward-biased cases. Symmetric wide corridors lead instead to ample welfare transfers and poor efficiency levels. Effectiveness and welfare performance is even weaker under the downward-biased corridor assumption; however, large improvements in efficiency are realized ($x \leq 0.9$). Effectiveness improvements are noticed for the upward-biased corridor type. This case also achieves higher welfare transfers, but sluggish efficiency results.

Let us now conclude our investigation regarding the design of the variable corridor 2 by going back to the discussion started earlier regarding the support for or against large improvements in financial welfare due to REDD programs. Parties in favor of large financial transfers to REDD countries should rely on a symmetric corridor 2 of narrow to medium intensity ($x \in [0.1, 0.5]$). Those that put more weight on efficiency and effectiveness criteria than on welfare, should advocate for a downward-biased corridor, with a lower bound of 20% below and an upper bound of 10% above the business-as-usual scenario ($x = 0.1$). This would entail considerable deforestation reduction (at least as high as the model-implied baseline), at high efficiency levels and modest but positive changes in welfare.

3.3.4 Optimal Design and Welfare Transfers

This section aims at offering a brief overview of baseline dominance, after taking into account the possible improvements in design discussed above.

Our analysis has individualized four baseline alternatives with strong performance results: the model-implied (*MI*), the upward-biased broad corridor 2 ($C2(f, x1, ubias)$), the symmetric narrow variable corridor 2 ($C2(v, x01, sym)$), and finally the downward-biased narrow variable corridor 2 ($C2(v, x01, dbias)$). We also consider the historical (*H*) baseline for comparison purposes.

TABLE III: Baseline Dominance over Different Historical Deforestation Averages

Historical Deforestation (ha/year)	Effectiveness	Welfare	Efficiency
1	C2(v,x01,sym)	MI	H
100	C2(v,x01,sym)	MI	MI
200	C2(v,x01,sym)	MI	MI
300	C2(v,x01,sym)	C2(f,x1,ubias)	MI
400	C2(f,x1,ubias)	C2(f,x1,ubias)	MI
500	C2(f,x1,ubias)	C2(f,x1,ubias)	MI

The table captures the dominant baseline type in terms of different indicators (effectiveness, welfare, efficiency) for different assumptions regarding the historical deforestation average ($dB \in [1, 500]$ ha/year).

Notations: MI = model-implied, H = historical, C2(v,x01,sym) = symmetric variable corridor 2 with corridor width equal to 10% below and above the reference, C2(v,x01,dbias) = downward-biased variable corridor 2 with corridor width equal to 10%, C2(f,x1,ubias) = fixed upward-biased corridor 2 with corridor width equal to 100%.

Each performance indicator points to a different superior baseline type (Table III and Figure C.3). In terms of effectiveness, the symmetric variable corridor 2 is the best choice for low to medium historical deforestation rates; for high deforestation levels ($db > 300$ ha), the upward-biased fixed corridor 2 proves to be the most successful in avoiding emissions from deforestation. Promoters of large financial transfers towards REDD participators should advocate for either a model-implied baseline or for an upward-biased fixed corridor 2 with boundaries computed for large deforestation averages. The efficiency indicator points in favor of the model-implied baseline, with the downward-biased corridor 2 as second runner²³.

²³For the full description of the results please refer to Annex 6.

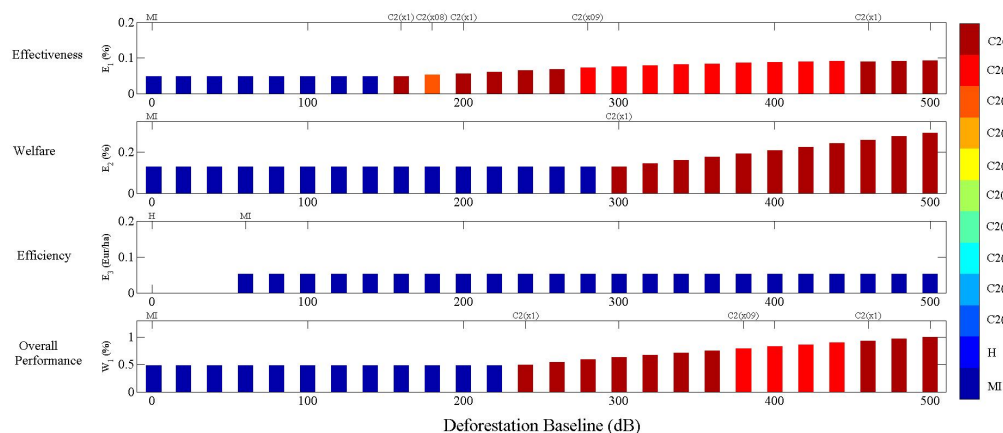


FIGURE 3.4: Dominant Baseline Scenarios across Different Historical Deforestation Rates

Figure C.3 offers a clear image of the dominant baseline schemes when considering each indicator separately. However, decision makers are frequently interested in rankings based on the overall performance of the alternative REDD reward schemes. With this aim, we build several scores that weight the performance of each baseline in a different manner. We distinguish between indicators that favor large financial transfers to the REDD countries (High Transfer), and those that promote more conservative welfare changes (Low Transfer). Also, we are interested in observing changes in rankings when allowing each indicator to have a stronger weight in the overall performance evaluation. To bring the different indicators at the same magnitude, we replace their values by their actual rank, given each historical deforestation level. The different weighting schemes for constructing the overall indicator as well as the results are presented in Annex 7.

Two important conclusions emerge: first, baseline dominance is not influenced by the region's deforestation history when large financial transfers are promoted, as baseline choice is constant across all deforestation averages. However, threshold levels play an important role when preference is placed on low transfers. Second, taking a pro-transfer position regarding increases in financial welfare individuates the model-implied baseline as the best performer, unless the effectiveness criterion is primarily weighted and crediting levels are set above 300 ha/year; supporting moderate transfers brings the symmetric variable corridor 2 to the forefront across most weighting alternatives, with the downward-biased variable corridor 2 as a good alternative for the case when the welfare is biased negatively. The historical and the fixed corridor 2 baselines dominate in very few positions.

3.4 Conclusions and Further Discussions

REDD programs are designed to avoid business-as-usual emission levels from cutting down existing forests that are exposed to the risk of land-use change. A key issue of REDD is the establishment of reference levels, the so-called *baselines*, against which reductions in deforestation are measured.

The aim of the present paper is to assess the performance of different crediting baselines for the REDD projects. In the process, we are also able to determine optimal land use changes when REDD activities are available. We analyze differences in behavior in the case of the most frequently proposed baselines: historical, model-implied, and fixed corridor 2. We also take the chance to propose a new type of baseline, namely the variable corridor 2, whose bounds form a corridor around the business-as-usual deforestation path.

Past studies have focused primarily on differences in distribution of benefits and total costs arising under different baseline types. While we give considerate attention to these issues, one of the main findings we were able to identify is that baseline choice has a significant impact on land-use behavior. Land users choose different deforestation paths when incentivized by distinctive crediting reference levels. We believe this point is key for REDD programs that aim at counteracting climate change.

For evaluating the success of the different baselines in achieving REDD goals, we build three performance indicators that describe the effectiveness, welfare increases, and efficiency levels for the analyzed baseline types. We find that each indicator individuates a different baseline as the best performer, similar to the results of [84]. In our analysis, the model-implied and the corridor 2 baselines emerge as the strongest candidates.

Our study is also exploring further ways of improving baseline performance, by adjusting two key design features, namely corridor width and symmetry. We find that the fixed corridor 2 benefits from being more generous on the upside, i.e. when the upper bound is set far away from the fixed historical deforestation level. On the other hand, the variable corridor 2 is performing best when its bounds are set very close and symmetric to the business-as usual scenario.

A preference for a strong effectiveness indicator leads to choosing the variable corridor 2, with narrow and symmetric bounds. The model-implied and the upward-biased corridor 2 provide the highest increase in forester's welfare above the business-as-usual scenario. Efficiency reasons advocate for the model-implied baseline, with the downward-biased variable corridor as runner-up.

The baseline types with highest performance, namely the model-implied and the variable corridor 2, allow for dynamic REDD rewards when reducing emissions below the business-as-usual scenario. We thus confirm the findings of [70] that the best-performing crediting schemes need to anchor payments to forward-looking baselines. One should note that our results are based not only on credited versus actual emissions as in the study mentioned above, but on considerations of effectiveness, efficiency and welfare.

Similar to actual REDD proposals, our model assumes no liability for deforestation rates above the crediting baseline. As proved by our results, this feature actually ensures that if forest managers opt-in, their total profits will be superior to the baseline-as-usual level, for all baseline approaches. We can conclude that all baseline types analyzed promote country participation.

We have also seen that high crediting baselines lead to increases in effectiveness, which might initially appear counterintuitive. This was the case of the historical baseline for large deforestation averages, as well as for the upward biased fixed and variable corridor 2 types. In order to understand this result, we need to go back to the forest manager and his optimization function, which is defined as a trade-off between composite forestry and agricultural rent and REDD revenues. As baseline levels are increased his total REDD rewards are larger, i.e. standing forests become more valuable and the owner has stronger incentives to keep the forest intact and cash in REDD revenues, with negative effects on efficiency. Establishing levels for the crediting baselines turns out to be a balancing act between efficiency and effectiveness considerations.

Due to the delicate trade-off that appears between the different performance measures, it is difficult to individuate an overall winner scenario. To this adds the discussion on welfare transfers between participating countries. Trying however to disentangle the complexity in order to draw a final conclusion, we advocate for the symmetric and narrow variable corridor 2, which has the capacity to offer top results in terms of effectiveness in reducing emissions from deforestation, guaranteeing at the same time a positive though modest increase in welfare, achieved at medium efficiency levels. This approach has the advantage of being forward-looking, and in this sense of rewarding as much as possible only *de facto* emission reductions. Also, due to the corridor design, it reduces estimation errors that occur inevitably when trying to predict the business-as-usual scenario against which rewards are accrued. We consider this to be a strong point ahead of the model-implied baseline.

This paper assumes a market-based mechanism for the funding of REDD rewards. In comparison to voluntary funds, international carbon markets can mobilize much larger amounts of money and favor cost-efficient emission reductions [12]. However, the weak carbon markets we face

nowadays, characterized by low liquidity and permit overallocation, will most probably have difficulties in handling additional amounts of permits coming from the forestry sector. Therefore, when trying to decide on the most appropriate baseline type, one might postpone the implementation of the most effective one in order to avoid collapses in CO_2 prices until the stabilization of the carbon market. In this sense, REDD programs could be designed to allow for a less effective baseline, as the model-implied, in its initial phases and then switch to the variable corridor 2. We believe the variable corridor 2 should be the long-term goal in the climate negotiations.

Our one-player study is limited through its assumption that all accrued credits will be cashed in, such that the supply of permits will always be satisfied by a counterparty demand. We have therefore neglected liquidity issues on the carbon markets or potential drops in permit prices occurring in case a huge amount of forest credits are released at the same time. While we acknowledge that accounting for this feature might have a significant impact on baseline performance, it will however not influence baseline ranking and we would remain true to our conclusions.

A more robust understanding of the optimal decision process would require an improved description of the different players having a say in REDD implementation. As [70] point out, the selection of reference levels will be based not only on technical considerations (like effectiveness), but also on political negotiations among participating countries. REDD projects implemented at the national level will motivate countries to take a strategic position at the negotiation table and try to influence the decision regarding the crediting levels in their favor. Seen in this way, the adjusted deforestation decision will result in emission reductions of other magnitudes than the ones presented in this study, and might as well reveal a different ranking of baseline approaches. Future research built on a dynamic decision model placed in a setting of multiple players with contrasting interests could be relevant for this issue.

Chapter 4

The Effect of Proactive Adaptation on Green Investment

Published as Olivier Bahn, Marc Chesney, Jonathan Gheysens in *Environmental Science and Policy*, 2012

4.1 Introduction

Climate change is one of the greatest challenges facing our planet in the foreseeable future. It is expected, according to the Intergovernmental Panel on Climate Change [85], to impact ecosystems and the environmental services they provide (in terms of food and water in particular) but also human societies (affecting human health and regional economies, for instance). Besides, the IPCC argues that human activities, through the greenhouse gases (GHG) they release in the atmosphere, are responsible for most of the observed increase in global average temperatures up to now. Furthermore, the IPCC estimates that, in the absence of ambitious climate policies to reduce anthropogenic GHG emissions, global warming will continue at an accelerated pace.

Despite the urgency of the situation, global GHG emissions are still increasing, in particular because there is not yet an overall agreement to curb world emissions. In this context, and since future climate changes appear now unavoidable to some extent, adaptation measures have recently gained a new political momentum as an important component of climate policies. Contrary to mitigation options, adaptation measures do not reduce emission levels, but provide strategies

to deal effectively with climate change effects by reducing their impacts [1, 93, 135]. Adaptation strategies cover a large array of sectors and options, from new agricultural crops, modified urban planning (dikes, sewerage systems), medical preventions against pandemic to controlled migrations of population and activity changes. Depending on the degree of anticipation (and requirement for it), adaptation measures can be preventive or reactive: vaccination campaigns can be made mandatory without any materialized threat (as precautionary principle) or could be implemented only in reaction to pandemic urgency, for instance.

Compared to mitigation strategies, adaptation measures have several strengths. On the one hand, in the case of “reactive” adaptation, benefits should be rapidly achieved. This short lag between costs and benefits should reduce adaptation exposure to uncertainty and discounting preferences. This should also be beneficial for populations already vulnerable to certain impacts of climate change [115]. On the other hand, “preventive” adaptation should provide long-lasting effects that may incur delays before being effective, a feature similar to mitigation. Moreover, adaptation measures in effect privatize policies against climate changes by largely limiting the benefits of adaptation to those having invested in it. Adaptation avoids the free-riding problem traditionally associated with mitigation¹ and does not require concerted and simultaneous actions, fostering the advancement of regional or local projects. As pointed by Olson [1965], “*only a separate and ‘selective’ incentive will stimulate a rational individual in a latent group to act in a group-oriented way*” and to that goal, adaptation is effective. However, adaptation measures are not exempt from drawbacks. Since they have at best very limited impact on the causes of climate change, they may encourage unsustainable emission trajectories. They are therefore highly vulnerable to catastrophic climate thresholds. Moreover, as pointed out by de Bruin and Dellink [36], uncertainty about the exact impacts of climate change may prevent optimal levels of adaptation. Finally, it seems highly questionable that adaptation measures by themselves will be sufficient to fully protect populations from all the damages of climate change, and thus some levels of mitigation should also be implemented.

Both international institutions and governments have recognized these strengths and have now started to conceive and finance portfolios of adaptation projects. For instance, the World Bank has initiated a US\$500 million Pilot Program for Climate Resilience and prepared in 2009 a new study to assess adaptation costs, areas and applicability in developing countries [106]. Under the United Nations Framework Convention on Climate Change (UNFCCC), a new adaptation fund has also been launched, financed with 2% of the shares of proceeds coming from the issuances

¹A country may hesitate to pay for emission reductions that will also impact favorably those who did not participate in any mitigating efforts, thus unbalancing its competitiveness [23, 113].

of certified emission reduction units (CERs) under the clean development mechanism (CDM). During the recent Copenhagen conference (COP15), it was also decided to create the Copenhagen Green Climate Fund (CGCF), with a first budget of US\$30 billion in the 2010-2012 period to invest in mitigation and adaptation projects. This fund should eventually reach US\$100 billion by 2020 [138]. In addition to those dedicated projects, adaptation strategies are now more and more blended into more traditional development projects and official development assistances (ODA) [92]. They are also pushed forward in developed countries albeit without the kind of targeted recognition used for developing countries.

Considering the simultaneous promotion of adaptation strategies and the relative weaknesses of mitigation policies so far, the question of their respective role should be assessed, both for policy and investment purposes. It could be that adaptation strategies become inexpensive alternatives to mitigation approaches, at least as long as no clear international agreement forces the world's economies to transition into a more efficient economy (in terms of GHG emissions). If this is the case, what would be the impact on the transition timing towards such an economy? More importantly, what could be the long run effects, both in terms of GHG concentrations, overall costs and damages and growth trajectories?

To answer these questions, one may use an integrated assessment, an interdisciplinary approach that uses information from different fields of knowledge, in particular socio-economy and climatology. Integrated assessment models (IAMs) are tools for conducting an integrated assessment, as they typically combine key elements of the economic and biophysical systems, elements that underlie the anthropogenic global climate change phenomenon. Examples of IAMs are DICE [110, 111], MERGE [104, 105], RICE [112] and TIAM [101, 102].

Research incorporating adaptation measures into integrated assessment models has been rare until recently, despite the importance of these models for current policy decisions. Hope et al. [82] [updated in 81] were the first to integrate adaptation as a policy variable in an IAM, the PAGE model. Bosello [29] uses a FEEM-RICE model with both adaptation and mitigation options. de Bruin et al. [35] have proposed to include adaptation as an explicit strategy in the DICE model (AD-DICE). In follow-up studies, de Bruin et al. [34] expand this methodology to the RICE model (AD-RICE), Felgenhauer and de Bruin [57] introduce uncertainty in the climate outcome, Hof et al. [80] test for the effectiveness of the 2% levy proposed to finance the UNFCCC adaptation fund in a combined AD-RICE/FAIR model, de Bruin and Dellink [36] explore the effects of restrictions (barriers) to adaptation with AD-DICE (AD-DICE08), and de Bruin [33] advances further the modeling of adaptation in AD-DICE (AD-DICE09). Finally,

Bosello et al. [30] have proposed to consider adaptation within the WITCH model (AD-WITCH). Note also that Agrawala et al. [2] present a comprehensive “*inter-model comparison of results*” from AD-DICE, AD-RICE and AD-WITCH.

We use in this paper the deterministic version of a simple integrated assessment model [17, 18, thereafter referred to as BaHaMa] enriched to consider explicitly adaptation options.² BaHaMa is in the spirit of the DICE model but distinguishes between two types of economy: the “carbon economy” (our present economy) where a high level of fossil fuels is necessary to obtain output and a so-called “carbon-free” or “clean economy” (an hydrogen economy, for instance) that relies much less on fossil fuels to produce the economic good. In terms of energy sector representation, our model stands therefore somehow between DICE and WITCH, as the latter model includes a detailed bottom-up representation of the energy sector distinguishing in particular among 7 different energy technologies. Likewise, in terms of adaptation modeling, our model stands somehow between the AD-DICE08 model [36] and the models AD-DICE09 [33] and AD-WITCH [30]. In the former model, adaptation efforts are considered as costs (“*flow*”) only. In our approach, we consider adaptation efforts as investments (“*stock*”). As such, we emphasize the proactive component of adaptation in lieu of its reactive element [see 97]. This choice is motivated by Agrawala et al. [2], p. 11 that claim that “... *adaptation will consist predominantly of investments in adaptation stock...*”.³ Note however that AD-DICE09 and AD-WITCH consider both reactive and proactive adaptation. Despite these simplifications in the modeling of the energy sector (compared to WITCH) and in the modeling of adaptation (compared to AD-DICE09 and AD-WITCH), our objective is to contribute with a new IAM to an adaptation literature that so far relies only on a very limited number of (peer reviewed) models. Besides, compared to the different versions of AD-DICE, our approach provides a better representation of the energy sector. We can therefore assess the timing of adoption of clean technologies in the presence of adaptation strategies and evaluate the sensitivity of their interactions to specific parameters. This element could be of importance in the current debate about the required incentives to foster adequate “green” R&D investments. Moreover, our model, while being close in certain aspects to the DICE model for comparison purposes, remains largely autonomous in its calibration procedure, allowing us to test a variety of parameter’s specifications.

²Given the rather sophisticated treatment of uncertainty (through a stochastic control approach) in the original BaHaMa model and the complexity of the numerical approach involved to solve this model, we have chosen as a first step and for simplicity to implement adaptation only in a deterministic version of BaHaMa. A more interesting and meaningful approach would be to include adaptation in the original BaHaMa model. We leave this for a future research.

³Agrawala et al. [2], p. 11 add also that “*This does not necessarily imply that fewer reactive or “flow” adaptation actions will be undertaken. Rather, investments in adaptation infrastructure ... might tend to be more expensive, and would therefore tend to dominate the adaptation budget.*” In that respect, our approach should be viewed as a first modeling exercise only. We leave a more sophisticated modeling of adaptation for future research.

The paper is structured as follows. Section 4.2 details our IAM with explicit adaptation options, thereafter referred to as Ada-BaHaMa. The section covers also some of the economic rationales behind the modeling choices. Sections 4.3 and 4.4 give the model's results and sensitivity analyses on adaptation effectiveness and climate sensitivity. Section 4.5 provide a comparison of our results with the ones of the existing literature. Finally we conclude in Section 4.6 and propose some further improvements that provide additional directions for research.

4.2 BaHaMa with explicit adaptation

4.2.1 Model description

An overview of Ada-BaHaMa is given in Fig.4.1.

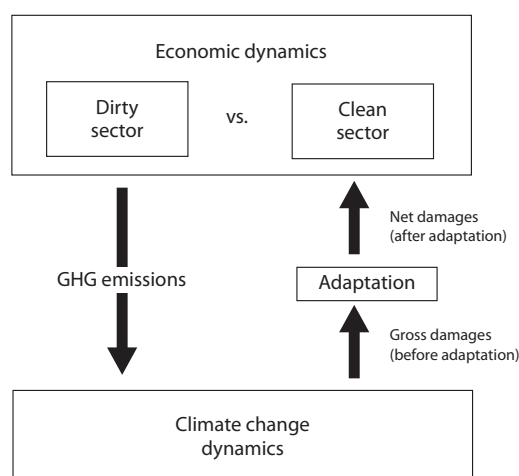


FIGURE 4.1: Schematic overview of Ada-BaHaMa.

We next describe the different component of the original BaHaMa model and its new adaptation feature.

4.2.1.1 Production dynamics

Production (Y) occurs in the two types of economy (the carbon economy, referred to by an index 1, and the clean economy, referred to by an index 2) according to an extended Cobb-Douglas

production function in three inputs, capital (K), labor (L) and energy (measured through GHG emission level E):

$$Y(t) = A_1(t)K_1(t)^{\alpha_1}(\phi_1(t)E_1(t))^{\theta_1(t)}L_1(t)^{1-\alpha_1-\theta_1(t)} \\ + A_2(t)K_2(t)^{\alpha_2}(\phi_2(t)E_2(t))^{\theta_2(t)}L_2(t)^{1-\alpha_2-\theta_2(t)}, \quad (4.1)$$

where for each economy i ($i = 1, 2$): A_i is the total factor productivity, α_i the elasticity of output with respect to capital K_i , ϕ_i the energy efficiency and θ_i the elasticity of output with respect to emissions. Notice that capital stock in each economy evolves according to the choice of investment (I_i) and a depreciation rate δ_{K_i} through a standard relationship:

$$K_i(t+1) = I_i(t) + (1 - \delta_{K_i})K_i(t) \quad i = 1, 2. \quad (4.2)$$

Besides, total labor (L) is divided between labor allocated to the carbon economy (L_1) and labor allocated to the carbon-free economy (L_2):

$$L(t) = L_1(t) + L_2(t). \quad (4.3)$$

4.2.1.2 Climate change dynamics

Stocks of GHGs are computed using the following dynamic equations from the DICE model [111], that distinguish between three reservoirs, an atmospheric reservoir (M_{AT}), a quickly mixing reservoir in the upper oceans and the biosphere (M_{UP}), and a slowly mixing deep-ocean reservoir (M_{LO}) which acts as a long-term sink:

$$M_{AT}(t+1) = (E_1(t) + E_2(t)) + \psi_{11}M_{AT}(t) + \psi_{21}M_{UP}(t) \quad (4.4)$$

$$M_{UP}(t+1) = \psi_{12}M_{AT}(t) + \psi_{22}M_{UP}(t) + \psi_{32}M_{LO}(t) \quad (4.5)$$

$$M_{LO}(t+1) = \psi_{23}M_{UP}(t) + \psi_{33}M_{LO}(t) \quad (4.6)$$

where $\psi_{i,j}$ are calibration parameters. Relationship between accumulation of GHGs and temperature deviation is also from DICE and is given by the following equations:

$$F(t) = \eta \log_2 \left(\frac{M_{AT}(t)}{M_{AT}(1750)} \right) + F_{EX}(t) \quad (4.7)$$

$$T_{AT}(t+1) = T_{AT}(t) + \xi_1 [F(t+1) - \xi_2 T_{AT}(t) - \xi_3 (T_{AT}(t) - T_{LO}(t))] \quad (4.8)$$

$$T_{LO}(t+1) = T_{LO}(t) + \xi_4 (T_{AT}(t) - T_{LO}(t)) \quad (4.9)$$

where F is the total atmospheric radiative forcing, F_{EX} an exogenous radiative forcing term, T_{AT} the earth's mean surface temperature, T_{LO} the average temperature of the deep oceans, and ξ_i and η calibration parameters for an assumed climate sensitivity of 3 °C that corresponds to the best estimate⁴ given by the IPCC [108]. Accumulation of GHGs increases the earth radiative forcing, warming the atmosphere and then gradually the oceans. This allows for the existence of inertia between GHG concentration and climate change.

4.2.1.3 Damage and adaptation frameworks

To model climate change damages and their economic impacts, we follow an approach used in the MERGE model [105]. We compute in particular an economic loss factor (ELF) due to climate changes at time t , which is adapted to take into account the effects of adaptation $AD(t)$ as follows:

$$ELF(t) = 1 - AD(t) \left(\frac{T_{AT}(t) - T_d}{cat_T - T_d} \right)^2, \quad (4.10)$$

where T_d is the temperature deviation (from pre-industrial level) at which damages start to occur and cat_T is the climate sensitivity dependent “catastrophic” temperature level at which the entire production would be wiped out. For the illustrative purposes of this paper and to have a comparable basis with the current literature on IAM with adaptation, T_d and cat_T are calibrated in order to replicate the damage intensity of DICE; see Section 4.2.2. Notice further that this loss factor applies on production levels, see Section 4.2.1.4, such that damages are computed as: $AD(t)Y(t) \left(\frac{T_{AT}(t) - T_d}{cat_T - T_d} \right)^2$.

In our model, adaptation reduces the damaging effects of GHG concentration and, to simplify, has neither impact on the total factor productivity (no innovation breakthrough is coming from adaptation investment) nor direct correlation with GHG emissions (as in the often cited air conditioned example). Contrary to the recent efforts by de Bruin and Dellink [36] that model adaptation as a cost (flow), but in a fashion similar to Bosello [29], we consider adaptation as an investment (stock). To use the words of Lecocq and Shalizi [97], we thus favour the proactive type of adaptation over the reactive one. This modeling choice is motivated by the expectation that, for a large part, adaptation projects will be directed towards infrastructure and medium-to-long-term economic transformations. This view is supported by Agrawala et al. [2] that conclude their comparison of results from AD-DICE, AD-RICE and AD-WITCH stating that, p. 11, “...

⁴In Section 4.4, we test our model for different values of climate sensitivity, using the ‘likely’ range of 2–4.5 °C given by the IPCC.

*adaptation will consist predominantly of investments in adaptation stock...".*⁵ Moreover, using proactive instead of reactive adaptation gives us greater flexibility over the nature of adaptation policies. By controlling for capital depreciation rate in the model, we can test for proactive effectiveness: if adaptation investments are in line with realized impacts, depreciations should be slow. On the contrary, inadequate strategies or incapacity to predict future damages will force to reinvest frequently, imposing a high depreciation rate on the adaptation capital. At the margin, with an annual depreciation of 100%, the adaption investment corresponds to a cost.

The adaptation dynamics is as follows:

$$AD(t) = 1 - \alpha_{AD} \frac{K_3(t)}{K_{3\max}(t)} \quad (4.11)$$

with α_{AD} representing the maximal adaptation effectiveness, $K_3(t)$ the amount of adaptation capital in period t and $K_{3\max}(t)$ the maximal amount of adaptation capital⁶ to be invested in each period to ensure the optimal effectiveness of adaptation strategies.

In our framework, adaptation costs should increase whenever temperature (and therefore damages) broadens. To take this into account, we model $K_{3\max}(t)$ as an increasing function of temperature level:

$$K_{3\max}(t) = \beta_{AD} \left(\frac{T_{AT}(t)}{T_d} \right)^{\gamma_{AD}}, \quad (4.12)$$

where β_{AD} and γ_{AD} are calibration parameters. The behavior of this function is determined by the calibration process. Nonetheless, we force the calibration to be bounded such that $\beta_{AD} \geq 0$ and $\gamma_{AD} \geq 1$. Hence, getting the full offsetting potential of adaptation will require more and more investment if mitigation is not also considered jointly.

4.2.1.4 Welfare maximization

A social planner is assumed to maximize social welfare given by the integral over the model horizon (T) of a discounted utility from per capita consumption $c(t) = C(t)/L(t)$. Pure time preference discount rate is noted ρ and the welfare criterion is then given by:

$$W = \int_0^T e^{-\rho t} L(t) \log[c(t)] dt. \quad (4.13)$$

⁵Note that AD-DICE09 [33] and AD-WITCH [30] consider both reactive and proactive adaptation. Indeed, if one should rely mostly on proactive adaptation when the effects of climate change are still relatively limited, reactive adaptation may become important when damages increase; see for instance Agrawala et al. [2]. Reactive adaptation shall be introduced in Ada-BaHaMa as a component of our future research.

⁶In other words, we impose at all time periods t that $K_3(t) \leq K_{3\max}(t)$.

Consumption comes from an optimized share of production, the remaining being used to invest in the production capital (dirty and/or clean), in the adaptation capital and to pay for energy costs. The presence of damages (defined by the ELF factor) reduces the available production such that:

$$\text{ELF}(t)Y(t) = C(t) + I_1(t) + I_2(t) + I_3(t) + p_{E_1}(t)\phi_1(t)E_1(t) + p_{E_2}(t)\phi_2(t)E_2(t), \quad (4.14)$$

where I_3 is the investment in the adaptation capital and p_{E_i} are energy prices. Note also that adaptation stock evolves according to a relation similar to Eq. (4.2):

$$K_3(t+1) = I_3(t) + (1 - \delta_{K_3})K_3(t), \quad (4.15)$$

where δ_{K_3} is a depreciation rate.

4.2.2 Model calibration

The different modules of Ada-BaHaMa (adaptation, economy and climate) are basically calibrated on DICE (version 2007⁷, thereafter referred to as DICE2007) and on the original AD-DICE model [35].

We start our calibration procedure by the adaptation component which is new the feature in the Ada-BaHaMa model. First, we calibrate ex-ante parameters defining the maximal amount of efficient adaptation capital ($K_{3\max}$). We use for this a recent report that the World Bank [106] issued on the cost of adaptation in developing countries for the period 2005-2055: to fully offset⁸ climate change impacts in developing countries, US\$ 100 billion should be spent each year until 2055. Despite representing only a small share of the global economy, these adaptation costs, when adjusted for our model, still correspond to high values compared to the AD-DICE estimates. They are also conservatively close to the estimates obtained in Bosello et al. [30]. Second, the maximal adaptation effectiveness (parameter α_{AD}) is set to 0.33 (at most 33% of damages are avoided)⁹ following results reported with AD-DICE. Third, to reproduce the magnitude of climate change damages estimated by DICE and AD-DICE, we use values of GHG concentration, temperature, gross damage and production from these models in order to calibrate parameters of

⁷See: <http://www.econ.yale.edu/nordhaus/DICE2007.htm>.

⁸This view that climate change damages can be fully offset is obviously optimistic and certainly questionable. Note however that such an “optimistic” view is somehow shared by Mendelsohn [109] that estimates that some climate damages could be reduced by up to 80%, and thus almost fully offset. Besides, in our calibration approach, [106] is only used as a benchmark.

⁹However and considering its importance in the determination of the optimal mix of strategies, we conduct in Section 4.4 sensitivity analyses for different—lower and higher—values of α_{AD} .

our damage function (ELF). Consequently, our damage estimates follow rather closely those of AD-DICE as displayed in Fig. 4.2. The other modules of Ada-BaHaMa (economy and climate)

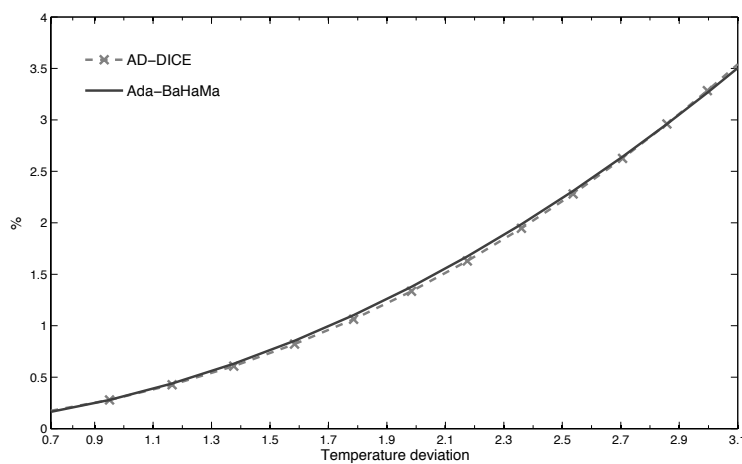


FIGURE 4.2: Damage levels (in percentage of production) for different temperature increases in Ada-BaHaMa and AD-DICE (in °C).

are again basically calibrated on DICE2007. In particular, parameters in Eqs. (4.1), (4.2) and (4.4) to (4.9) are mostly from DICE2007. Moreover, we calibrate our (counterfactual) baseline, in which only the current dirty economy is producing, to match as closely as possible production, concentration and temperature trajectories of the DICE2007 baseline (see Figs. 4.3 and 4.4, where our baseline is labelled “Ada-BaHaMa Dirty economy only” and DICE2007 baseline “DICE2007 No Controls”). However, compared to the dirty economy, production in the clean economy has better energy efficiency but higher energy costs in the short term. To calibrate our clean economy, we rely on a progressive deployment path of “advanced” clean energy technologies, following results obtained with the MERGE model [105] when imposing as constraints the temperature levels reached in Ada-BaHaMa. The clean technologies we focus on correspond on the one hand to advanced “high-cost” electricity generation systems (relying on biomass, nuclear, solar and/or wind) whose capacity is not limited, and on the other hand to an unlimited carbon-free supply of non-electric energy (such as technologies producing hydrogen using carbon-free processes). Since Ada-BaHaMa does not distinguish among different clean technologies, we summarize in our model the two most distinctive elements of the clean economy development path according to MERGE: when clean technologies are first significantly deployed (around 2045, following MERGE results) and when they become the main energy production mean (around 2075, following MERGE results).¹⁰ Calibrating our clean economy on MERGE, we are thus able

¹⁰See the trajectory labelled “Mitigation only” in Fig. 4.6, page 92. We have indeed calibrated the clean economy for a scenario where only mitigation strategies are possible; see also Section 4.3 below.

to benefit from the MERGE detailed portfolio of energy technologies (MERGE distinguishes between 13 electricity generation technologies and 7 sources of non-electric energy supply) and of its estimate of their respective contribution to energy supply. Interestingly, at the end of our calibration procedure, the resulting overall production in Ada-BaHaMa happens to reproduce the economic output of DICE2007, at least until the first quarter of the 22nd century; cf. Fig. 4.3 (comparing the trajectory labelled “Ada-BaHaMa” with the one labelled “DICE2007”). Note

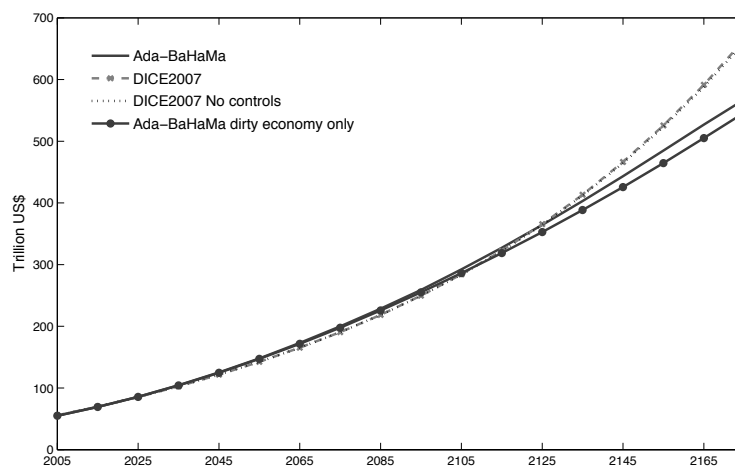


FIGURE 4.3: Economic production paths in Ada-BaHaMa and DICE2007.

however that, compared to DICE2007, the modeling of two types of economies implies an optimal trajectory, conditioned by a transition to the clean economy after 2055 to reduce climate change damages, that involves much less GHG emissions and thus lower temperature increase over the long run; cf. Fig. 4.4 (comparing the trajectory labelled “Ada-BaHaMa” with the one labelled “DICE2007”).

4.3 Results

In this section, we report on four different scenarios: a counterfactual baseline without any adaptation or mitigation (investments in the clean technology) efforts, an adaptation-only scenario where the clean technology is not available, a mitigation-only scenario where adaptation is not possible and finally a combined scenario with both mitigation and adaptation efforts. More precisely, we first detail impacts of these scenarios on dirty and clean production capital stocks as well as on adaptation capital stocks. We then look at effects on climate change and the corresponding damages. Finally, we detail the overall effects on economic output.

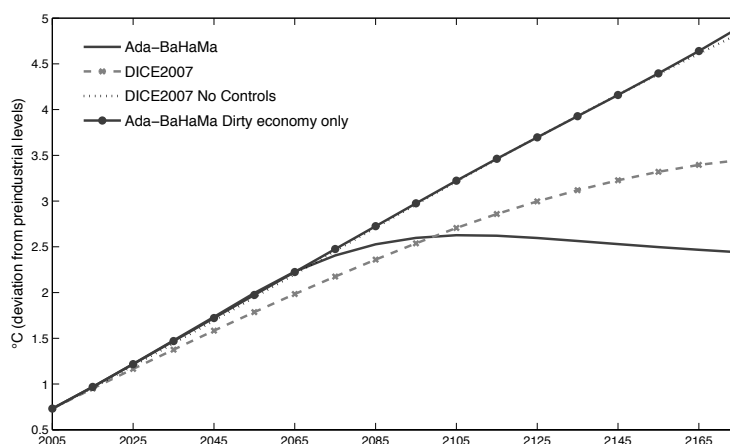


FIGURE 4.4: Temperature deviation paths in Ada-BaHaMa and DICE2007 (in °C).

4.3.1 Capital accumulation paths

When comparing our scenarios, two important components stand out in the strategies deployed to address climate change: first, the existence and timing of a transition between the dirty and the clean economy (mitigation strategy), see Fig. 4.5 and 4.6, and second, the importance awarded to adaptation, especially when the clean technology is not available, see Fig. 4.7. When

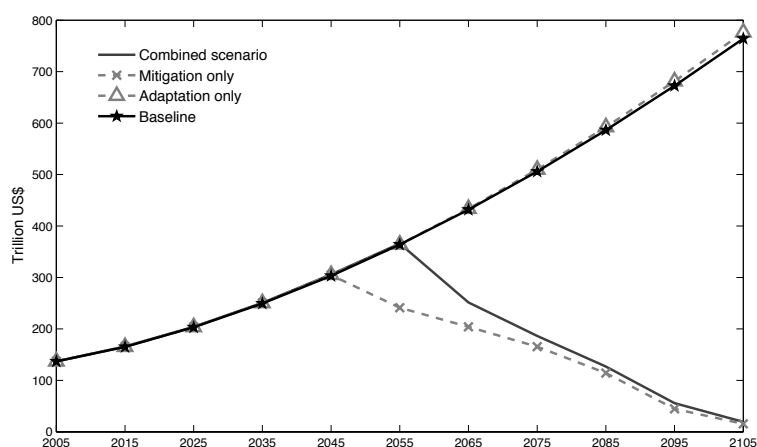
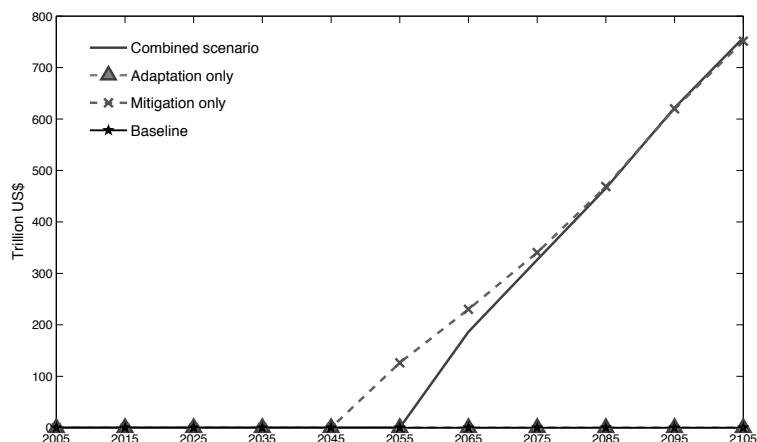
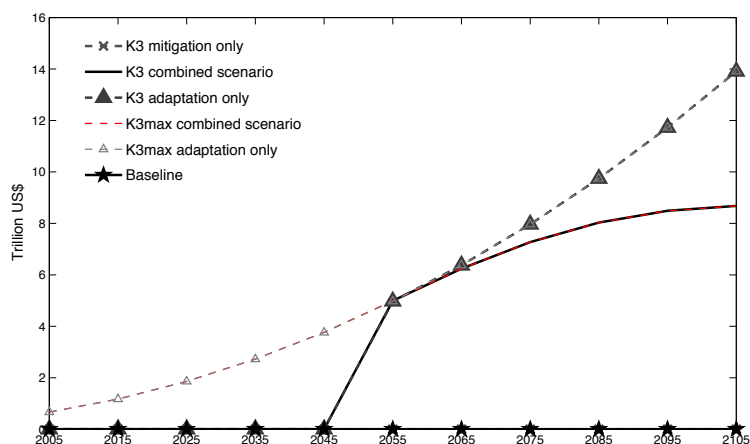


FIGURE 4.5: "Dirty" capital K_1 accumulation paths.

the clean technology is not available (adaptation-only scenario), clean capital does not of course accumulate. In addition, accumulation of dirty capital is slightly higher compared to the baseline scenario, as (net) damages and thus the necessity to limit dirty production are reduced through adaptation. Conversely, when the clean technology is available (mitigation-only and combined

FIGURE 4.6: “Clean” capital K_2 accumulation paths.

scenarios), there is a clear transition between the two economies: dirty capital is rapidly phased out after 2045 or 2055 and almost completely replaced by clean capital by the end of the century. Discrepancies coming from not allowing adaptation (mitigation-only scenario) are noticeable, as a transition from dirty to clean capital is started ten years earlier to prevent harmful damage levels. As far as adaptation capital is concerned, it does not of course accumulate in the mitigation-

FIGURE 4.7: Adaptation capital K_3 accumulation paths and maximal amount of adaptation capital ($K_{3\max}$).

only scenario (where the adaptation option is not available). Both in the adaptation-only and combined scenarios, adaptation is used after 2045, where the accumulation of adaptation capital (K_3) reaches immediately its maximal level ($K_{3\max}$) and stays at this level afterwards. In this two scenarios, the delay in implementing adaptation measures results from the low-effectiveness

of adaptation and signs a trade-off between costs of adaptation and its positive effect on welfare. In Section 4.4.1, we will test for different values of adaptation effectiveness. Notice also that the maximal level of adaptation capital ($K_{3\max}$) depends on temperature level; cf. Eq. (4.12). As the latter reaches lower levels in the combined scenario (see Fig. 4.9, page 94) due to the transition to the clean economy, the required amount of capital for a maximal effectiveness of adaptation is significantly reduced in this scenario (compared to the adaptation-only scenario).

4.3.2 GHG concentration, temperature and net damages

Greenhouse gas concentration in the atmosphere, given in Fig. 4.8, follows the mitigation efforts detailed in the previous Section 4.3.1. Thanks to the rapid adoption of clean technologies (after 2045) in the mitigation-only scenario and the corresponding transition toward a cleaner economy, concentrations in the mitigation-only scenario peaks in 2075 and temperature increase (given in Fig. 4.9, page 94) stabilizes by the end of the century around 2.5 °C. For the combined scenario, the offsetting effect of adaptation, postponing the transition to “green investment” by about 10 years, has for consequence a higher concentration peak (reached in 2075) and temperature increase stabilizes by the end of the century slightly above 2.6 °C. Conversely in the adaptation-only scenario, the lowest mitigation effort (with dirty production being slightly higher than the “business-as-usual” baseline), concentration keeps always increasing as well as temperature that reaches around 3.3 °C by the end of the century.

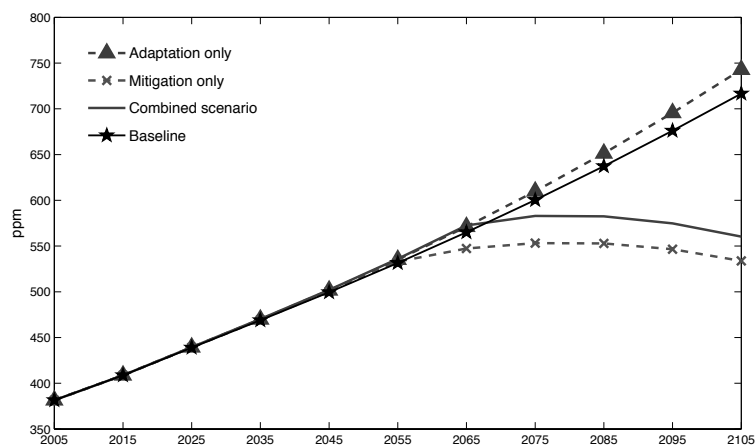


FIGURE 4.8: GHG concentration paths.

into gross damages; cf. Eq. (4.10). Hence as reported in Fig. 4.10, page 94, net damages in the mitigation-only scenario (that correspond to gross damages in the absence of adaptation)

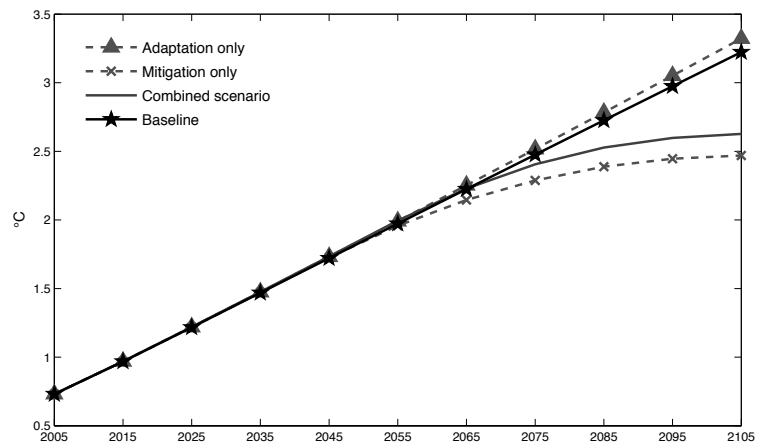


FIGURE 4.9: Temperature deviation paths from preindustrial levels (in °C).

peak at the end of the century (2105) before gradually decreasing. Gross damages may however be “reduced” through adaptation. In the adaptation-only scenario, net damages are initially reduced (by 2055, compared to the mitigation-only scenario) when adaptation measures start to be implemented. But as they immediately reach their full potential (33% of gross damages avoided) they cannot afterwards compensate for the continuous increase in temperature and thus in damages. When both adaptation measures and adoption of clean technologies are enacted in the combined scenario, it is interesting to note that exposure to damages is the lowest of all scenarios.

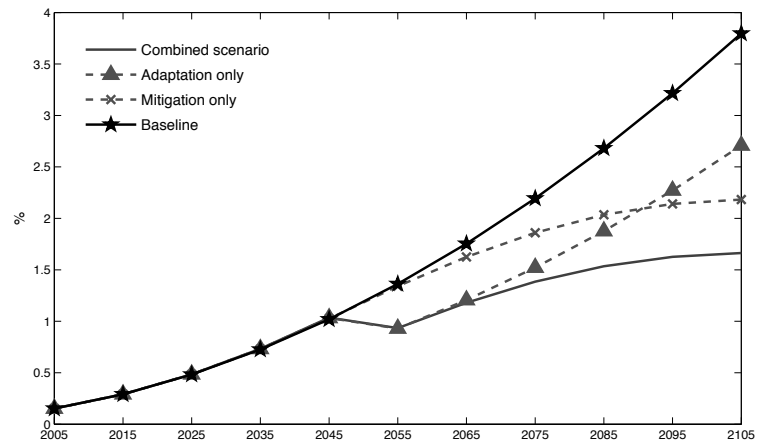


FIGURE 4.10: Evolution of net damages.

4.3.3 Economic output paths

Fig. 4.11, page 95, reports on GDP losses due to climate change damages, with the combined scenario being used as a comparative level. As expected, reducing the choice of policy options to address climate changes yields an overall decrease in economic output compared to the combined scenario. This is in particular the case in the adaptation-only scenario over the long term, where the inability to prevent significant temperature increase (thus significant net damages) yields increasing GDP losses. The decrease in economic output is also significant in the mitigation-only strategy. Note that the absence of massive adaptation investments (to the detriment of investments in production capital) in period 2055 allows for a short-lived surplus over the adaptation-only strategy (but below the combined strategy). Besides, GDP losses are again lower at the end of the century (compared to the adaptation-only strategy) as one reaps the benefits of limiting temperature increase. Here, preventing the use of adaptation measures is indeed not very disadvantageous for the economy due to our low setting for adaptation effectiveness (at most only 33% of damages can be avoided).

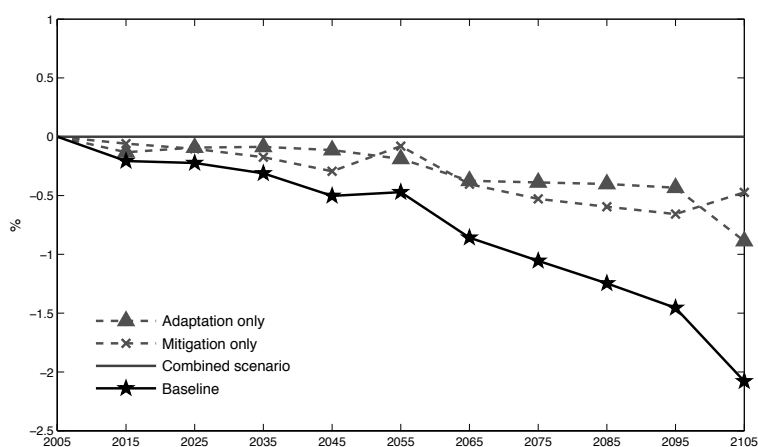


FIGURE 4.11: Economic output difference (in %) relative to the combined scenario.

4.4 Sensitivity analysis

The influence played by adaptation measures on the timing of adoption of clean technologies is largely dependent upon certain key parameters, like the degree of adaptation effectiveness or the climate sensitivity assumed in the model. In sections 4.4.1 and 4.4.2, we test for different levels for these two key parameters.

4.4.1 Sensitivity analysis on adaptation effectiveness

According to past and current research on adaptation policies, it seems indisputable that the effectiveness of adaptation measures will be highly influenced by geographical, political and societal idiosyncrasies, as well as by the quality and reliability of preventive efforts which in turns largely depend upon the accuracy of damage predictions. Considering the high level of uncertainty surrounding damage assessments, our basic parameter setting uses a relatively low level of effectiveness for adaptation. As such, it penalizes regions for which adaptation could be both inexpensive and efficient. For instance, Agrawala et al. [2] reports that costal adaptation could offset up to 95% of costal damages in the case of India. At the end of the spectrum, the World Bank¹¹ [106] reports that adaptation in developing countries could be completely effective and fully offset climate change damages in all sectors. Although likely over-optimistic, an effectiveness level of 100% ($\alpha_{AD} = 1$) can thus be also envisioned [if only to test the view of 106].

When increasing the adaptation effectiveness, we observe a strong substitution effect between increasingly efficient adaptation measures and adoption of clean technologies. As reported in Fig. 4.12 and 4.13, the adoption of clean technologies is delayed by a few decades (or even postponed after 2105 for $\alpha \geq 0.8$) and its preventive role against climate change damages is replaced by adaptation measures. Note that a stronger reliance on adaptation has the drawback

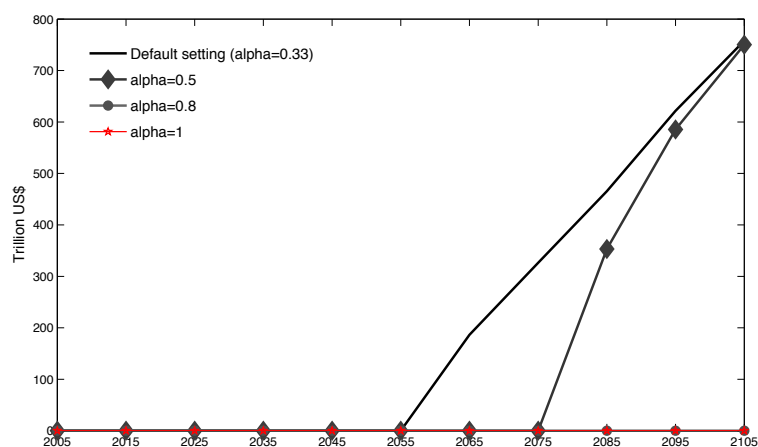


FIGURE 4.12: “Clean” capital K_2 accumulation paths for different levels of adaptation effectiveness.

of pushing temperature to much higher levels; see Fig. 4.14, page 97. For instance, with a value

¹¹which provides our cost estimates for the calibration of the maximal amount of efficient adaptation capital K_{3max} .

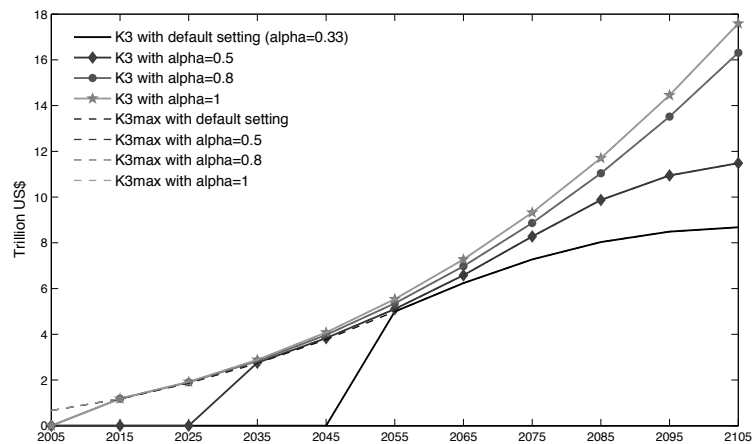


FIGURE 4.13: Adaptation capital K_3 accumulation paths and maximal amount of adaptation capital ($K_{3\max}$) for different levels of adaptation effectiveness.

of 100% for the adaptation effectiveness, temperature increase reaches 3.7°C by 2105 (compared to around 2.6°C under our standard setting). By shielding the world's economy from (most of) climate change damages, improvement in adaptation effectiveness favours more polluting practices and delays thus a transition toward a cleaner economy.

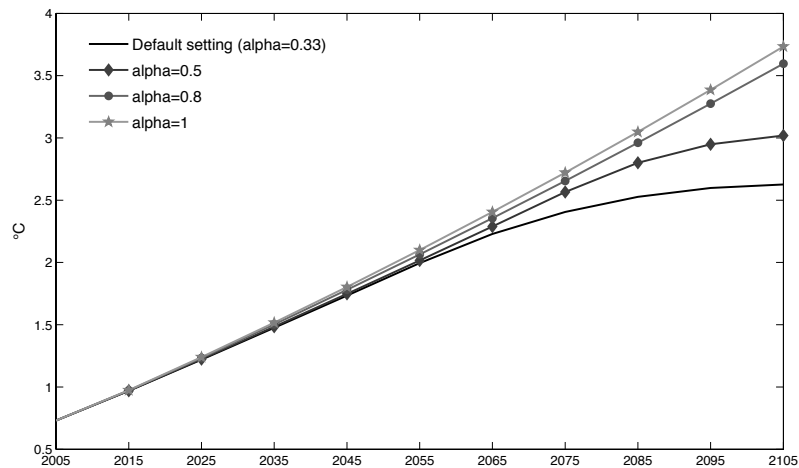


FIGURE 4.14: Temperature deviation from preindustrial levels in $^\circ\text{C}$ for different levels of adaptation effectiveness.

This could however turn out to be a risky policy, especially in presence of uncertainty about

climate change effects, which may include “abrupt” changes¹² [see for instance 99], which in turn could hinder the capacity to successfully—and continuously—provide efficient adaptive solutions in the future.

4.4.2 Sensitivity analysis on climate sensitivity

According to the IPCC [2007], the equilibrium impact of doubling atmospheric CO₂ concentration may in average lead to an increase in temperature from pre-industrial levels of about 3 °C, recognizing “*an upper bound of likely range of climate sensitivity of 4.5 °C and lower bound of likely range of climate sensitivity of 2 °C*”. To account for this level of uncertainty, which has a direct and immediate impact on damages, we conduct a sensitivity analysis on our combined strategy (mitigation and adaptation) for a low (2 °C), medium (3 °C) and “high”¹³ (4.5 °C) levels of climate sensitivity. As expected, a low climate sensitivity, yielding lower damages, postpones dramatically “green” investments and the transition towards clean energy. In our simulation, a climate sensitivity of 2 °C delays transition by 40 years. When climate sensitivity is high, we obtain an opposite effect, the transition being speeded up by 20 years; see Fig. 4.15, page 98, and Fig. 4.16, page 99.

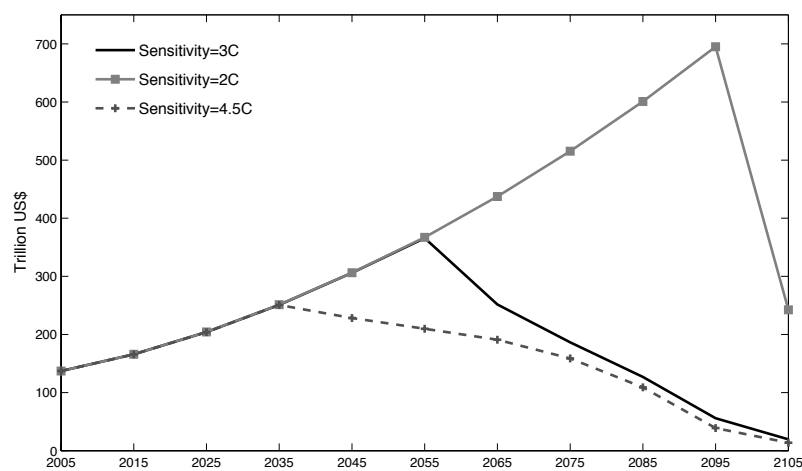


FIGURE 4.15: “Dirty” capital K_1 accumulation paths for different climate sensitivity.

Adaptation plays here a complementary role, with an identical timing for the three scenar-

¹²Examples of such extreme events include a melting of the West Antarctic ice sheet and a collapse of the Atlantic thermohaline circulation.

¹³It must be emphasized that the range of possible values of climate sensitivity may be much wider than those used here; see for instance Stainforth et al. [132].

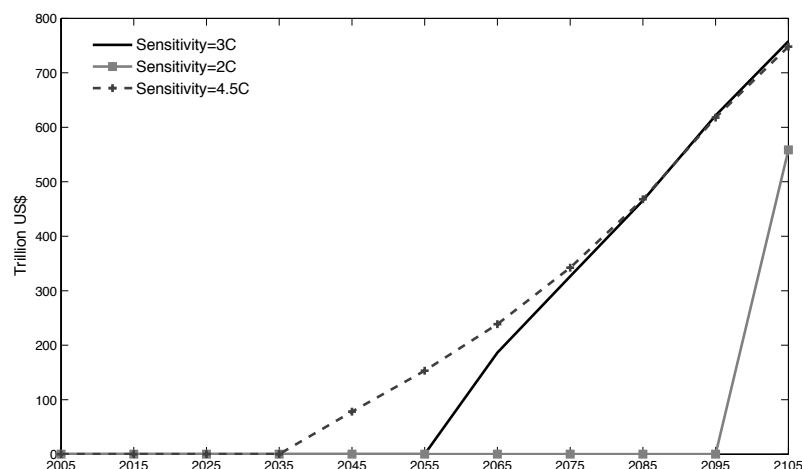


FIGURE 4.16: “Clean” capital K_2 accumulation paths for different climate sensitivity.

ios (starting after 2045) but with different investment levels; see Fig. 4.17, page 100. Again, higher climate sensitivity yielding larger damages forces a larger investment in adaptation. The convergence towards the end of the century observed in our results for low and medium climate sensitivities can be explained by a similar pattern in temperature increase; see Fig. 4.18, page 100. A medium climate sensitivity, provoking an earlier transition towards clean production, has the effect of limiting temperature increase and thus damages by the end of the century. Conversely, for a low climate sensitivity, continuous emissions from “dirty” production until 2095 yield temperature (and thus damages) increase to the point where the two temperature curves converge by the end of the century. In our sensitivity analysis, it appears clearly that a change of scientific consensus on climate sensitivity will have major effects on the best policy mix to deploy and on its timing. However, because of the relatively high level of uncertainty surrounding this parameter, assuming a “low” climate sensitivity induces the risk that, if this assumption turns wrong, no adaptation policy might be able to offset the potentially irreversible effects due to a large increase in GHG concentration. Mitigation strategy, in the words of Bosello et al. [30], p. 86, could be “*the starting point. Its characteristics should be determined on the basis of the precautionary principle and independently of adaptation because adaptation cannot avoid irreversibility*”.

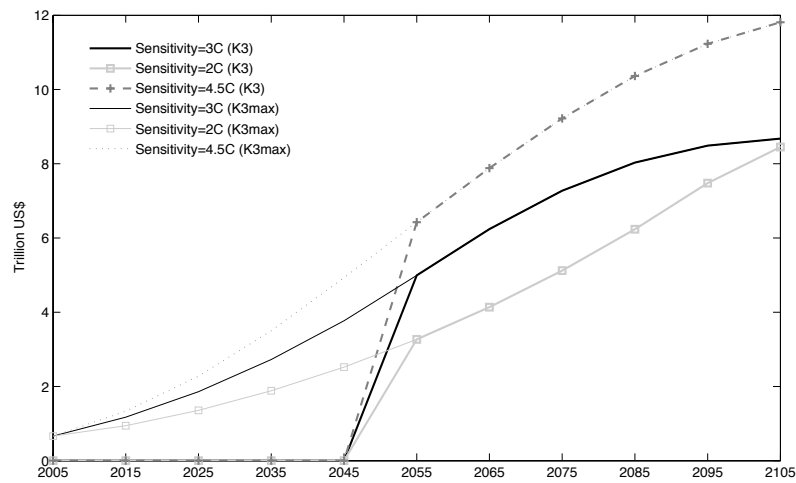


FIGURE 4.17: Adaptation capital K_3 accumulation paths and maximal amount of adaptation capital ($K_{3\max}$) for different climate sensitivity.

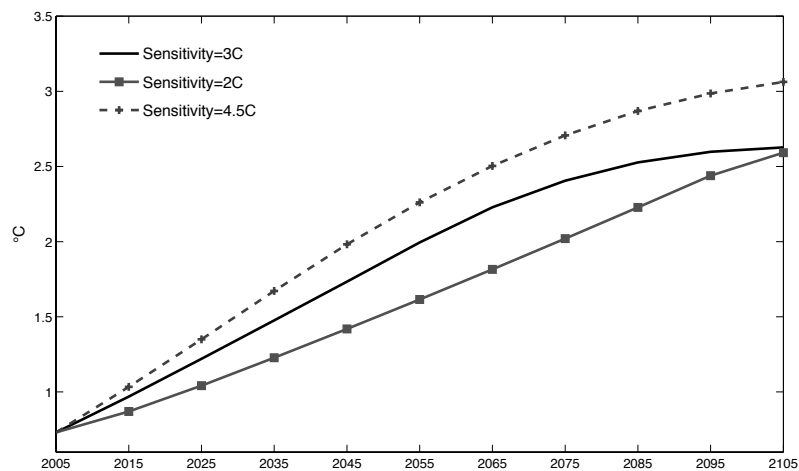


FIGURE 4.18: Temperature deviation from preindustrial levels in $^{\circ}\text{C}$ for different climate sensitivity.

4.5 Comparison to previous studies

Ada-BaHaMa belongs to a limited number of integrated assessment models, such as AD-DICE [33, 35, 36], AD-WITCH [30] and FEEM-RICE [29], that take explicitly into account strategies to adapt to the negative impacts of climate change. The particularity of Ada-BaHaMa is to model both a reactive adaptation strategy through an adaptive capital and a mitigation strategy taking the form of a clean technology. As already stated in Section 4.1, our model stands

somehow between DICE and WITCH in terms of energy sector modeling, and between (the different versions of) AD-DICE and AD-WITCH in terms of adaptation modeling. Having acknowledged these differences in the modeling approaches, we can however compare some insights Ada-BaHaMa provides with the ones obtained with FEEM-RICE, AD-DICE and AD-WITCH.

Bosello [29] considers in FEEM-RICE proactive adaptation using a dedicated investment variable, therefore modeling the adaptation strategy in a fashion similar to our own. Besides, the efficiency of adaptation depends on the current temperature deviation level, as in our model. It does not however include a maximum investment in adaptation K_{3max} , therefore expanding the potential of adaptation to offset damages. In our initial setting adaptation efficiency is capped at 33%, while in Bosello [29], p. 11 adaptation “*starts to be appreciable after 2040 – when damage is reduced the 14% – and booms afterward – when damage is reduced up to the 50%*”. As a result, and contrary to Bosello’s conclusions, our model finds that adaptation with weak efficiency is triggered *before* mitigation, (except under a high climate sensitivity assumption, where the potential magnitude for damages combined with a weak adaptation efficiency forces to quickly abate GHG emissions).

Similarly to de Bruin et al. [35], which incorporates adaptation as a cost option (reactive adaptation) within a DICE structure, we find that in our initial setting mitigation and adaptation act as strategic complement. However, whereas they use a separable model for mitigation and adaptation, we use an interdependent model, in which adaptation costs increase with higher temperature deviation. As a result, whereas they report (p. 74) that “*mitigation decreases the benefits of adaptation*”, our results tend to indicate that mitigation could increase adaptation efficiency by reducing the investments required for its deployment.

Compared to Bosello et al. [30] which uses the AD-WITCH model, we also find that mitigation and adaptation are strategic complement (at least when adaptation effectiveness is limited). Adaptation “*becomes detectable in 2035*”, a result comparable to our optimal run (in which adaptation starts a decade later, in 2045). However, their model is not constrained by a maximum adaptation investment level and the high discount rate they impose on their initial run decreases the appeal of mitigation. As a result, they find only marginal differences between their adaptation-only and mitigation-and-adaptation scenarios, while we observe noticeable differences between the two. As with Bosello [29], they find that it is optimal to start mitigating before adapting, which is the opposite of our results (again except when assuming a high climate sensitivity).

Finally, in line with de Bruin [33] and her AD-DICE09 model, we find that both mitigation and adaptation measures are important in responding to climate change. We also find that

total costs of climate change are the lowest when both mitigation and adaptation are used together. Note that these two insights are also highlighted in Agrawala et al. [2]. However, de Bruin [33] finds that there should be a greater emphasis on (proactive) adaptation in earlier decades while adaptation in our model starts comparatively later. This is due to difference in the capital formulation between our two models: adaptation stock in AD-DICE09 is immediately fully effective, whereas in our model adaptation should first reach a required level $K_{3\max}$ to be fully effective. Our approach is more consistent with a situation where adaptation requires full completion to be effective (e.g. dikes building).

4.6 Conclusion

In this paper, we introduce both adaptation and mitigation strategies as decision variables in an integrated assessment model and assess their respective economic and environmental impacts as well as their influence on each other.

Our model presents several distinctive characteristics in view of the IAM literature on adaptation and mitigation. In terms of adaptation strategy modeling, Ada-BaHAMa stands somehow between the AD-DICE08 model and the models AD-DICE09 and AD-WITCH, focusing on proactive adaptation only (as this form of adaptation is expected to be the dominant one). In terms of mitigation strategy modeling, our model stands somehow between DICE and WITCH, as mitigation is done through a transition towards clean production systems. This sheds light on trade-offs between existing (fossil) technologies and new cleaner (renewable or fossil with carbon capture and sequestration) production systems. Note also that Ada-BaHaMa allows for interaction between adaptation and mitigation. Indeed, we model the required adaptation investment as being dependent on temperature level and thus on the mitigation strategy deployed.

We find that interaction between adaptation and mitigation is complex and largely dependent on their respective attributes. Our results show that adaptation, when weakly effective, is used as a complement to mitigation strategies. Investment in adaptation is done in conjunction with investment in clean production systems and do not hinder the transition from dirty to clean technologies (in our combined scenario). However, resorting to an adaptation-only strategy causes significant temperature increase and thus significant net damages that yield increasing GDP losses. Sensitivity analysis reveals however that this situation changes with increasing adaptation effectiveness. In particular, highly effective adaptation acts as a medium- to long-term

substitute to mitigation efforts, that could even prevent long-term investments in clean production systems (in the extreme case of perfectly efficient and certainly unrealistic adaptation measures). Analysis on the climate sensitivity indicates also that the choice of a climate sensitivity parameter is certainly not innocuous on the policy recommendations and represents a crucial element for our mitigation/adaptation model. In our framework, higher climate sensitivity has in particular the effect of accelerating mitigation efforts while increasing adaptation investments. On the opposite end of the sensitivity spectrum, a low sensitivity value hinders significantly the mitigation efforts and reduces adaptation investments.

We view this paper has an essential (first) step for implementing adaptation in the BaHaMa model. But we do envision several other steps to enrich the modeling framework of Ada-BaHaMa, to be carried out in future research. A first improvement will be to consider simultaneously reactive and proactive adaptation strategies to better capture the different adaptation options. Besides, we also acknowledge that the choice of adaptation and mitigation policies has to take into account heterogeneity in regional costs, exposures and achievable benefits. Therefore, a second improvement of our model will be the development of a multi-regional version of Ada-BaHaMa, building on the two-region version of BaHaMa reported in Bahn et al. [18]. A third important improvement will be to introduce uncertainty, for instance on the magnitude of climate change damages, on the adaptation effectiveness or on a technological breakthrough that would provide access to the clean economy. As in Bahn et al. [17], the resolution of uncertainty could be modeled as a stochastic control problem.

Conclusion

To conclude the thesis, this section summarizes the main findings of the four papers.

The first paper (“Risk Averse in Losses, Risk Taking in Faith. An Experiment in Poor Rural Communities”) tests if the observation of limited risk-hedging behaviors in rural communities are the results of pure risk preferences in losses, the consequence of some budget constraint, a high discount rate, a form of fatalism or a lack of insurance supply. To answer this question, I conducted several lottery-based games to elicit risk preferences in both gains and losses amongst rural villagers in Benin, in a context devoid of time and budget arbitrages.

The econometric results indicates a strong shift towards risk aversion when limiting the games to risky losses: a sign that villagers are predominantly risk averse when faced with potential losses and without budget constraint and/or time considerations. This result would indicate a demand for hedging schemes.

I also find, in line with the literature, that the hypothesis of increasing partial risk aversion (IPRA) was valid among our sample, while I reject the decreasing absolute risk aversion hypothesis (DARA). Moreover, my results indicate some form of path dependency, where past experiences can lead to risk perception errors.

Last, I observe a strong influence of faith on risk aversion, with stronger faith increasing risk taking for both positive and negative stakes. While the results was expected on the basis of earlier research (Hilary and Hui 79, Kumar et al. 96), its magnitude indicates that attempts to increase hedging mechanisms among poor rural populations may strongly benefit from targeting religious backgrounds as a key factor of success.

For the second paper (“Does Cooperation Depend on the Circumstances? The Case of Rural Villagers in Benin”), I find two notable facts in my sample: a total absence of free-riders and a very small share of hump-shaped profiles that are replaced by “U-shaped” profiles indicating an important but partial warm-glow effect amongst the villagers.

Secondly, by expanding the initial setting of the linear public game in order to introduce risk and loss framings as a way to assess their impacts on the conditional cooperation distribution profile, I find that loss framing has a strong and significant positive impact on unconditional generosity (when individual do not expect other to participate), while risk has a negative but insignificant impact in the sample.

Finally, using results on the conditional profiles in conjunction with results on unconditional

contributions (i.e. actual participation in one-period games) for the same games and settings, I notice in the sample a significant link between a profile and its average contribution. It may suggest that villagers with a similar profile tend to have similar expectations about group contribution.

These results provide new evidence on the dynamics of conditional cooperation. It appears that conditional cooperation is highly sensitive to the economic and cultural context but also to the framing (or meaning) of the group project. In the context of Benin, generosity is a fundamental concept that echoes strongly with the renowned “African altruism”. It is however impeded by the presence of risk, a phenomenon that could help explain limited participation levels in collective projects.

My experiments show, at least in the sample, that a possible and effective way to solve this problem would be to modify projects’ narratives and to transform expected gains in outstanding losses in an effort to nudge villagers’ decisions. Contributions are then expected to improve substantially. The effectiveness of a loss framing instrument would benefit from further research to expand the sample size and to test if it retains its impact for different cultural and socio-economic backgrounds.

The third paper on REDD baseline selection (“Baseline Choice and Performance Implications for REDD”) finds that each different indicator (efficiency, effectiveness and land owner’s welfare) promotes its own “champion” baseline, which is similar to the results of [84].

In my analysis, the two most flexible baselines, the model-implied and the corridor 2, emerge as the strongest candidates. The paper also highlights two important aspects of REDD transfers. First, baseline dominance is not influenced by the region’s deforestation history when large financial transfers are promoted, as the optimal baseline set is constant across all deforestation averages. On the contrary, threshold levels play an important role when preference is placed on low transfers.

Second, a pro-transfer position towards increases in financial welfare singles out the model-implied baseline as the best performer.

Finally, the fourth paper (“The Effect of Proactive Adaptation on Green Investment”) concludes with the following insights: interaction between adaptation and mitigation is complex and largely dependent on their respective attributes. My results show that adaptation, when weakly effective, is used as a complement to mitigation strategies. Investment in adaptation is

done in conjunction with investment in clean production systems and do not hinder the transition from dirty to clean technologies (in our combined scenario)

In the meanwhile, resorting to an adaptation-only strategy causes significant temperature increase and thus significant net damages that yield increasing GDP losses. In particular, highly effective adaptation acts as a medium- to long-term substitute to mitigation efforts, that could even prevent long-term investments in clean production systems.

These different results, gathered through a variety of settings and conceptual models, tend to show that the context in which problems of collective action are taken play a central role in their optimal resolutions. More often than not, these contexts are implicit, which makes their identification difficult and often result in sub-optimal decisions. In the case Africa for instance, I discovered that framing and beliefs play a central role in risky and collective decisions. Failing to acknowledge them may result in sub-optimal cooperation and investments.

The different papers also demonstrate that the issue and importance of implicit contextual framework is not limited to experimental studies at the micro level. The REDD research shows that in the case of a simulation, contract details (such as bandwidth size and symmetry) can have significant influence on the effectiveness and efficiency of forest preservation policies.

At the macroeconomic level, on an issue as big as climate change, the subtle co-influences of two different strategies, mitigation and adaptation, can produce vastly different results and performances.

While the goal of each paper in this thesis was not to demonstrate the role of overlooked details in economic decisions, taken together they start to form a compelling story in favor of a thorough analysis of the implicit and subtle elements of context in economic analysis. Academic research may favor clarity and simplicity (and stylized facts) to convey impactful results. We should as well pay attention to the small details if we want these results to have any practical significance.

Appendix A

Appendix for Chapter 1

A.1 Annex 1: Initial variables for the selection algorithm

A.1.1 Annex 1: Gain and loss lotteries

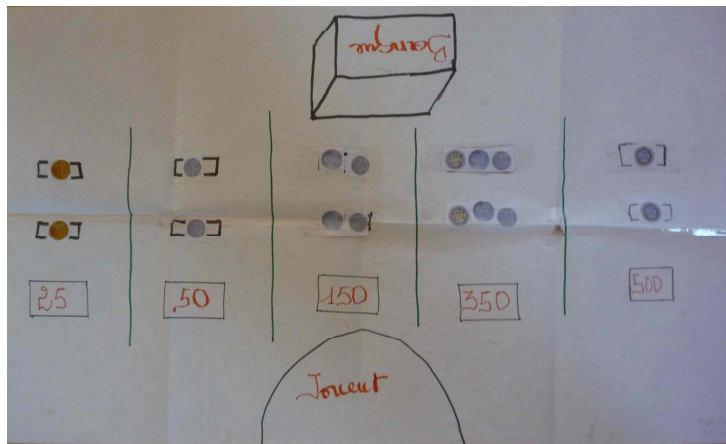


FIGURE A.1: Risky gain game: representation in the field

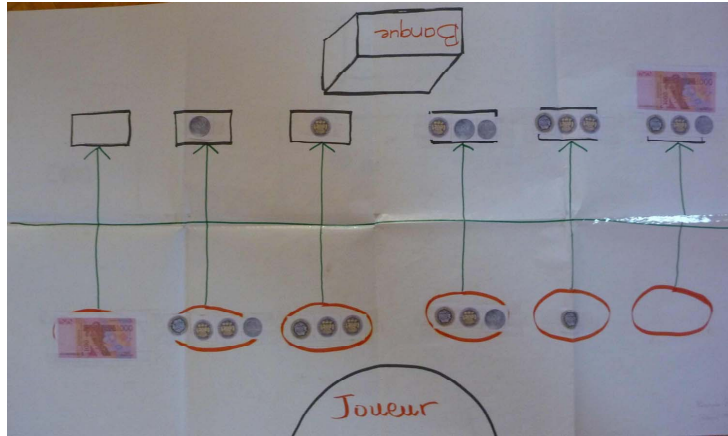


FIGURE A.2: Risky loss game: representation in the field

A.2 Annex 2: Initial variables for the selection algorithm

Variable	Definition	Selected by the algorithm
Village	Dummy indicator for the village (12 villages in total)	NO
Age	Age of the participant	YES
Gender	Gender of the participant	YES
Position in household	Head, wife, children	NO
Household size	Number of household members	NO
Years of schooling	Number of years spent in school	NO
Asset index	Assets owned - index normalized to 1 (highest category)	YES
Religion	Dummies for Catholic, Christian, Muslim, Voodoo, Other	NO
Faith	Influence of a higher spiritual being on daily activities	YES
Earning stability	Perceived stability of annual earnings	YES
Access to savings	Current or past participation in an individual or group saving scheme	NO
Water shortage	Occurrences of a water shortage in the past year	NO
Loss game	Indicates if the experiment is a “loss-only” or a “gain-only” game	YES
Large amounts	Indicates if the experiment is a large amount or a small amount game	YES
Previous luck	Indicates if the player has won in the preceding game	YES

A.3 Annex 3: Computation of the asset index

The asset index A_i for the household i was computed as a ordered index of an equi-weighted portfolio of possibly owned assets j_i , such that:

$$A_i = \left(\frac{1}{\max_i(\sum_{j_i=1}^J n_{j_i}) - \min_i(\sum_{j_i=1}^J n_{j_i})} \right) \left(\sum_{j_i=1}^J n_{j_i} - \min_i \left(\sum_{j_i=1}^J n_{j_i} \right) \right)$$

with n_{j_i} the number of items for the owned asset j_i . Each household is ranked within the sample on a $[0, 1]$ scale.

The list of assets is displayed in the table below:

Assets		
Communication/Transport	Farming	Household
Car	Horse/Donkey	Mattress
Motocycle	Pig	Bed
Bicycle	Cattle	Table
Canoe	Poultry	Armchair
Moto	Sheep	Fridge
Landline	Plow	Stove
Mobile phone	Farming tools	Fan
Television	Construction Tools	Jewels
Radio	Size of Land owned	Sewing machine
Audio System	Mill	Electric iron

Appendix B

Appendix for Chapter 2

B.1 Details of the experiment narratives

Experiment	Test for risk aversion effect	Test for invest. / expense framing	Project description
Game 1	No	No	Group investment in crop activities (the type of crop is dependent of the village). Crops generates a sure profit of 50% that is shared equally with the all village.
Game 2	Yes	No	Group investment in cotton production. Participants are reminded that every odd year, they obtain excellent yields (profits of 200%), while every even year, harvests are plagued by drought and non-existent.
Game 3	No	Yes	Group payment for the maintenance of the newly installed water pumps. The collective effort is partially subsidized by the NGO involved in the project, adding 50% to their group contribution.
Game 4	Yes	Yes	Group payment for the maintenance of the newly installed water pumps. The collective effort goes to a fund before knowing if the pump will need to be repaired (i.e commitment saving). The NGO responsible for the project will double the amount collected in case of maintenance but will keep this amount for future need if the maintenance is not required. Therefore, investment in the collective effort is final.

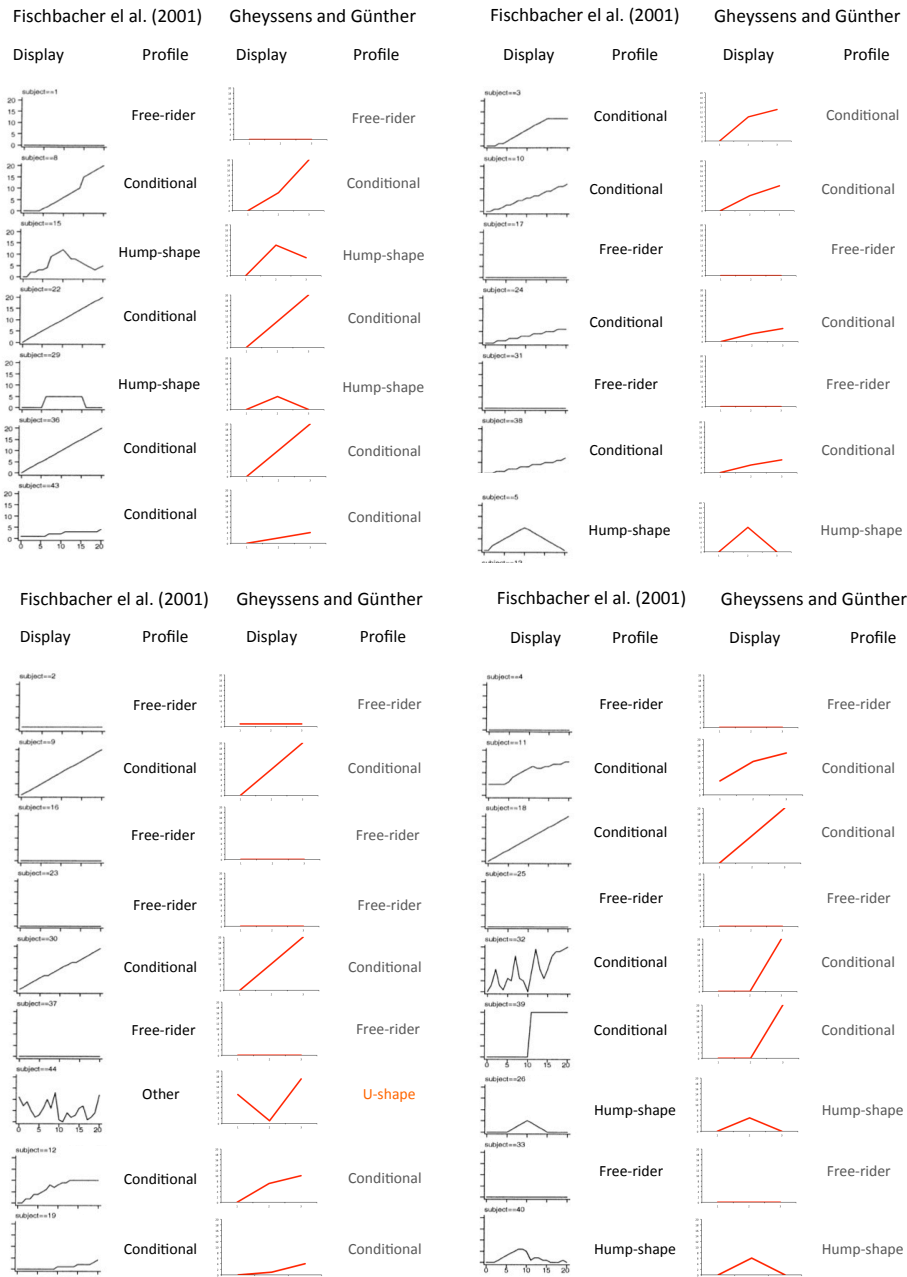
TABLE I: Overview of the four different experiments based on the linear public good game

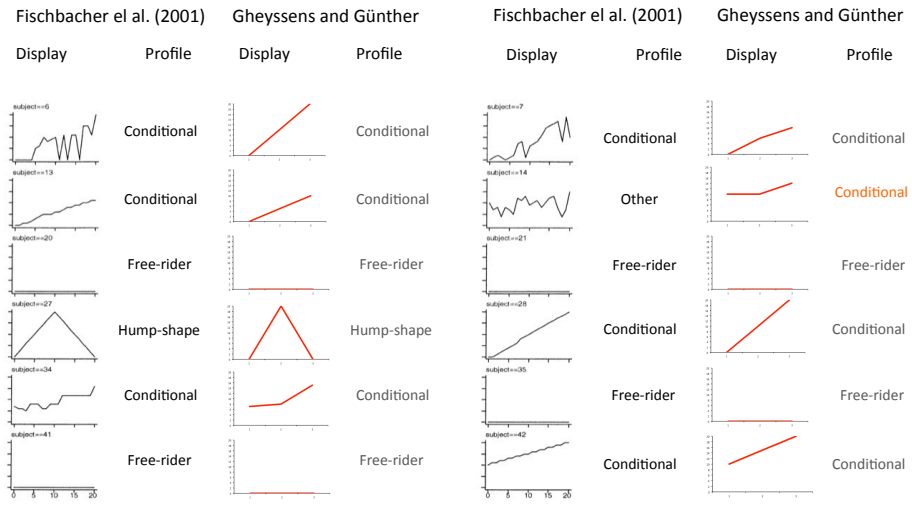
B.2 Variables retained in the OLS regressions

Variable	Definition	Variable used for regression
Village	Dummy indicator for the village (12 villages in total)	YES (control)
Age	Age of the participant	YES (control)
Gender	Gender of the participant	YES
Household size	Number of household members	YES (control)
Years of schooling	Number of years spent in school	YES (control)
Wealth (Asset index)	Size of the assets owned; index normalized to 1 (highest category)	YES (control)
Bad Health	Dummy indicating if the household experienced in average many occurrences of illnesses in the last month	YES
Degree of openness	Openness of villagers towards interviewers (see 2.3.1).	YES
Religion	Dummies for Catholic, Christian, Muslim, Voodoo, Other	NO
Faith	Influence of a higher spiritual being on daily activities	YES
Earning volatility	Perceived volatility of annual earnings	YES
Access to coping mechanism	Current or past ownership of an insurance scheme or a similar safety net scheme (individual or group savings)	YES
Water shortage	Occurrences of a water shortage in the past year	NO
Use of mosquito nets	# of members of household using a mosquito net	NO
Risk aversion parameter	Parameter from 1 (risk averse) to 7 (risk appetent)	YES
Loss framing	Indicates if the experiment is a “loss-only” or a “gain-only” game	YES
Risky game	Indicates if the game is a risky or riskless game	YES
Average group participation from previous game	Indicates the collective group contribution in the unconditional games	YES

Variable	Definition	Variable used for regression
Waiting time at the collective water source	Indicates in minutes the reported wait to get access to water	YES
Discussing time at the collective water source	Indicates in minutes the time spent for chats when collecting water	NO
Social conflict at the collective water source	Indicates in conflicts arise from the use of the water source	NO
Payable water during dry season	Experience of collective payment scheme for water during the dry season	NO
Payable water during wet season	Experience of collective payment scheme for water during the wet season	NO
Responsibility for the collection of water fees	Indicates if the collection is collective or individual	YES
Selection process for the collection scheme	Indicates if the process was collective or not	NO
Principal water source used during dry season	Indicates if the source is collective or private	NO
Principal water source used during wet season	Indicates if the source is collective or private	NO
Participation in the construction of the water point	Indicates if the villagers contributed or not	YES
Responsibility for the maintenance of the collective water point	indicates if the responsibility is collective or not	NO
Appreciation of the fund set up for the maintenance of the water point	Indicates if appreciation is positive or negative	NO
Appreciation of the maintenance work for the water point	Indicates if appreciation is positive or negative	NO
Type of toilets used	Collective or private	NO
Affluence using collective toilets	Indicates is the influence is important or not	NO
Willingness to contribute to public toilets	Give WTP for collective toilets	NO

B.3 Comparison of profile identification from Fischbacher et al. (2001) using the three-point method





B.4 Conditional contributions statistics for the different profiles and the different games

We present here the mean and standard deviation of the conditional contributions segmented by profile and game:

C.C profiles	Game 1	Game 2	Game 3	Game 4	Average
Condit. coop (strong & weak)	$\mu = 282.4, \sigma = 81.8$	$\mu = 282, \sigma = 88.6$	$\mu = 281.8, \sigma = 92.5$	$\mu = 294.4, \sigma = 86.7$	$\mu = 284.3, \sigma = 85.8$
Inverse hump-shaped	$\mu = 383.4, \sigma = 81.9$	$\mu = 308.3, \sigma = 88.4$	$\mu = 356.5, \sigma = 70.4$	$\mu = 338.4, \sigma = 108.12$	$\mu = 352.2, \sigma = 89.3$
Hump-shaped	$\mu = 209.5, \sigma = 55.1$	$\mu = 183.3, \sigma = 67.5$	$\mu = 246.7, \sigma = 96.7$	$\mu = 251.1, \sigma = 100$	$\mu = 218.6, \sigma = 85.1$
Warm-glow	$\mu = 433.3, \sigma = 163.29$	$\mu = 426.66, \sigma = 128$	$\mu = 481.2, \sigma = 64$	$\mu = 458.6, \sigma = 92.6$	$\mu = 457.4, \sigma = 99.9$
Other types	$\mu = 259.5, \sigma = 101.3$	$\mu = 237.4, \sigma = 132.3$	$\mu = 289.4, \sigma = 40.6$	$\mu = 268.7, \sigma = 114.9$	$\mu = 266, \sigma = 96.6$
Average	$\mu = 306.7, \sigma = 102.2$	$\mu = 288.6, \sigma = 113.9$	$\mu = 356.7, \sigma = 103.3$	$\mu = 339.8, \sigma = 121.1$	$\mu = 322.9, \sigma = 113.3$

Appendix C

Appendix for Chapter 3

Annex 1: Determination of optimal deforestation rate under the business-as-usual scenario

When no REDD program is in place, the net revenue of the forest manager at time t takes a simplified form:

$$\pi(d(t)) = P_t^F d(t) - (a_1 d(t) + a_2 d(t)^2) \quad (\text{C.1})$$

The optimal control problem can be described as follows:

$$\max_{d(t)} \int_0^T e^{-rt} \pi(d(t)) dt \quad (\text{C.2})$$

$$s.t. \dot{F} = -d(t) \quad (\text{C.3})$$

$$F(0) = F_0 \quad (\text{C.4})$$

We build the current-value Hamiltonian as:

$$H^c = \pi(d(t)) - \mu d(t) \quad (\text{C.5})$$

The equations of motion follow immediately:

$$\frac{\partial H^c}{\partial d(t)} : \pi'(d(t)) - \mu = 0 \quad (\text{C.6})$$

$$-\frac{\partial H^c}{\partial F} + r\mu = \dot{\mu} \quad (\text{C.7})$$

$$\dot{F} = -d(t) \quad (\text{C.8})$$

Given that the partial derivative of the Hamiltonian with respect to the forest stock is zero, we obtain that:

$$\dot{\mu} = r\mu \Rightarrow d\mu = \mu r dt \quad (\text{C.9})$$

Solving this simple partial differential equation leads us to the following identity:

$$\mu(t) = \mu(0)e^{(rt)} \quad (\text{C.10})$$

Letting $\mu(0) = k$, for an arbitrary k , it follows that we can find a solution for each $\mu(t)$:

$$\mu(t) = ke^{(rt)} \quad (\text{C.11})$$

By replacing the last result into Equation 16, we can solve for $d(t)$:

$$d(t) = \frac{P_0^F - a_1 - ke^{(rt)}}{2a_2} \quad (\text{C.12})$$

Replacing for $d(t)$ into the third equation of motion and integrating both sides of the equality leads us to the following identity, where c is the constant of integration:

$$F(t) = c - \frac{1}{2a_2} \left[P_0^F \frac{e^{\delta t} - 1}{\delta} - a_1 t - \frac{k}{2a_2} \frac{e^{rt} - 1}{r} \right] \quad (\text{C.13})$$

What we have obtained is an equation in two unknowns, k and c . The system can be easily solved by imposing the boundary conditions. Replacing for the first boundary condition, gives us the solution to c :

$$c = F(0) \quad (\text{C.14})$$

Further on,

$$k = \left[P_0^F \frac{e^{\delta T} - 1}{\delta} - a_1 T - a_2 F_0 \right] \frac{r}{e^{rT} - 1} \quad (\text{C.15})$$

From here, the solution to the optimal deforestation rate is easily determined:

$$d(t) = \frac{P_0^F e^{\delta t} - a_1}{2a_2} - \frac{e^{rt} r}{e^{rT} - 1} \left[P_0^F \frac{e^{\delta t} - 1}{\delta} - a_1 T - a_2 F_0 \right] \frac{1}{2a_2} \quad (\text{C.16})$$

Annex 2: Solution Method for the deforestation path under REDD

The simultaneous presence of REDD rewards for lower-than-baseline and absence of penalties for higher-than-baseline deforestation levels brings discontinuities to the profit function. The resulting non-smoothness in the objective function impedes the application of standard optimization methods. To overcome this difficulty, we develop a solution approach based on regime switches. This method allows for a break in the continuity of the deforestation path, which would otherwise be forced under the standard Hamiltonian procedure. A smooth deforestation path would not be able to guarantee optimality in the context of a non-smooth objective function. Here, we allow the manager to decide at each moment of time whether to deforest below or above the reference level, i.e. he makes his choice between a *REDD regime* (later referred to as Regime 1) and a *No REDD regime* akin to business-as-usual (Regime 2).

One observation is key for solving the optimization problem: in the absence of stochasticities, the decision regarding deforestation levels at each moment of time can be taken from the beginning for all future periods. Otherwise said, the entire optimal deforestation path can be computed based on the initial relationship between parameters and will not be altered during the lifetime of the project. While it could be possible in theory that the forester switches between regimes multiple times, in practice, the dynamic requirement at equilibrium ensures smooth evolution for the deforestation path within each regime and limited shifts between regimes over the entire horizon. We begin by explaining the solution approach for the historical and the model-implied cases. Since it requires an additional modification, we present the solution to the corridor 2 scenario at the end of this section. In the case of the historical and the model-implied baselines, the forester chooses moderately sized deforestation rates and stays in *Regime 1* as long as the benefits received from emission reductions (REDD credits) remain higher than the benefits of harvesting and selling larger quantities of timber. Once profits from lavish harvesting out-pace REDD benefits, a switch to *Regime 2* takes place. Depending on the values of the parameters, the regime switch can occur either from the beginning, somewhere during the lifetime of the maximization period, or never at all.

Formally, the optimization procedure can be described as follow:

$$\max_{d(t)|_{t \in [0, T]}} \left\{ \int_0^{t^{Switch}} e^{-rt} \pi^{R1}(d(t)) dt + \int_{t^{Switch}}^T e^{-rt} \pi^{R2}(d(t)) dt \right\} \quad (C.17)$$

with

$$t^{Switch} = \inf\{t \geq 0 | d(t) \geq dB\} \quad (C.18)$$

We adapt the solution method of [43], by allowing for the regime switches. We build the current-value Hamiltonian as:

$$H^c = \begin{cases} H^{R1} = \pi^{R1}(d(t)) - \mu_1(t)d(t) & , \text{ if } t \in [0, t^{Switch}) \\ H^{R2} = \pi^{R2}(d(t)) - \mu_2(t)d(t) & , \text{ if } t \in [t^{Switch}, T] \end{cases} \quad (C.19)$$

It is important to underline that if Regime 1 occurs in our parametrization, it will precede Regime 2, due to the different profit dynamics of the two activities. On the one hand, the manager can gain by increasing his production of timber, as long as his revenues do not exceed operating costs. In time, his marginal profits raise due to the increasing price of timber. On the other hand, even if revenues from REDD increase due to raising permit prices, these profits are limited, since the deforestation rate is bounded from above by the reference level and from below by zero (we do not allow for reforestation). Therefore, even if initially absolute marginal benefits from REDD could be higher than marginal benefits from timbering, this advantage decreases in time. As a

consequence, for low permit prices, remaining in Regime 1 might become suboptimal at a certain moment of time (t^{Switch}) and the manager will decide to move on to Regime 2. Figure C.1 captures the evolution of discounted

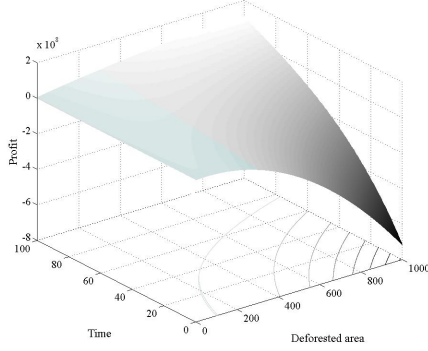
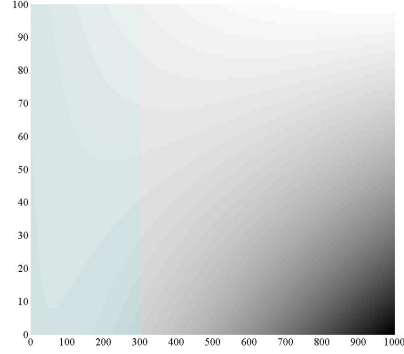


FIGURE C.1: Discounted Profits

FIGURE C.2: Discounted Profits:
View from top

profits in time and for different deforestation rates. The gray area represents profits occurring when the forest takes part in the REDD project, while the blue area symbolizes profits realized under the No-REDD scenario. Within each color palette, lighter colors stand for higher profit values. The two surfaces of REDD and No-REDD scenarios are dominant in terms of higher profits in different parts of the graph. As long as the deforestation rate is below the fixed baseline, the optimal regime to choose is the REDD one, as can be observed in Figure C.2. This holds for initial time periods. As time passes, the overall optimum is to be found in the No-REDD regime. The two figures support the hypothesis that if a regime switch does occur at some moment of time, this switch is expected to take place one time only, as the color alternation takes place only once. Moreover, Figure C.1 shows that the REDD regime should precede the No-REDD one, since for later periods of time profits are increasing in deforestation rates and the manager will be better off opting for the No-REDD regime. The solution for the optimal deforestation path is given by:

$$d(t) = \begin{cases} d_{0,1}e^{rt} + \frac{P_0^F(e^{\delta t} - e^{rt}) - a_1(1 - e^{rt}) - P_0^R(e^{\gamma t} - e^{rt})}{2a_2} & , \text{ if } t \in [0, t^{Switch}) \\ d_{0,2}e^{rt} + \frac{P_0^F(e^{\delta t} - e^{rt}) - a_1(1 - e^{rt})}{2a_2} & , \text{ if } t \in [t^{Switch}, T] \end{cases} \quad (\text{C.20})$$

Considering the lack of continuity at t^{Switch} , we solve the forester's maximization using a numerical search algorithm that combines all possible combinations of Regime 1 and Regime 2 paths at different switching points¹. We select the combined path that yields the highest profits.

In the case of the corridor 2 scenario, we deal with a profit function which is non-smooth at two points, i.e. at the boundaries of the corridor (dB^U and dB^L), and therefore the manager can switch between three different regimes. Depending on the relationship between initial parameter values, he will choose an optimal deforested

¹We allow for all possible switching points in the range $[0, T]$

area that satisfies:

$$d(t) = \begin{cases} d_{0,1}e^{rt} + \frac{P_0^F(e^{\delta t} - e^{rt}) - a_1(1 - e^{rt}) - P_0^R(e^{\gamma t} - e^{rt})}{2a_2} & , \text{ if } t \in [0, t^{S_1}) \\ d_{0,2}e^{rt} \frac{a_2 - \frac{P_0^R}{dB^U - dB^L}}{a_2 - \frac{P_0^R e^{\gamma t}}{dB^U - dB^L}} + \frac{P_0^F(e^{\delta t} - e^{rt}) - a_1(1 - e^{rt}) - P_0^R(e^{\gamma t} - e^{rt}) \left(1 + \frac{dB^U + dB^L}{dB^U - dB^L}\right)}{2 \left(a_2 - \frac{P_0^R e^{\gamma t}}{dB^U - dB^L}\right)} & , \text{ if } t \in [t^{S_1}, t^{S_2}) \\ d_{0,3}e^{rt} + \frac{P_0^F(e^{\delta t} - e^{rt}) - a_1(1 - e^{rt})}{2a_2} & , \text{ if } t \in [t^{S_2}, T] \end{cases} \quad (\text{C.21})$$

In our setting, the order of the switching times, i.e. $0 \leq t^{S_1} \leq t^{S_2} \leq T$, is due to the combination of two characteristics of our model. Firstly, the benefits of taking part in the REDD program decrease over time: for later periods of time, net timber revenues outpace REDD revenues due to higher timber prices and higher deforestation rates. Secondly, REDD gains get marginally smaller as the deforestation level gets closer to the upper corridor boundary until it eventually fades away for rates above the corridor. Therefore, the motivation to stay in REDD decreases over time, but at different paces within each interval.

Formulating the forester's optimization requires in this case to account for three regimes:

$$\max_{d(t)|t \in [0, T]} \left\{ \int_0^{t^{S_1}} e^{-rt} \pi^{R1}(d(t)) dt + \int_{t^{S_1}}^{t^{S_2}} e^{-rt} \pi^{R2}(d(t)) dt + \int_{t^{S_2}}^T e^{-rt} \pi^{R3}(d(t)) dt \right\} \quad (\text{C.22})$$

To determine the optimal moments for switching regimes and the overall profit maximization for the forester, we first define optimal paths within each regime for all possible combinations of switching times. We then use a numerical search algorithm that selects the combination of the three paths yielding the highest profits. From this, we infer the optimal switching times t^{S_1} and t^{S_2} .

Annex 3: The fixed corridor 2: corridor bandwidth and symmetry

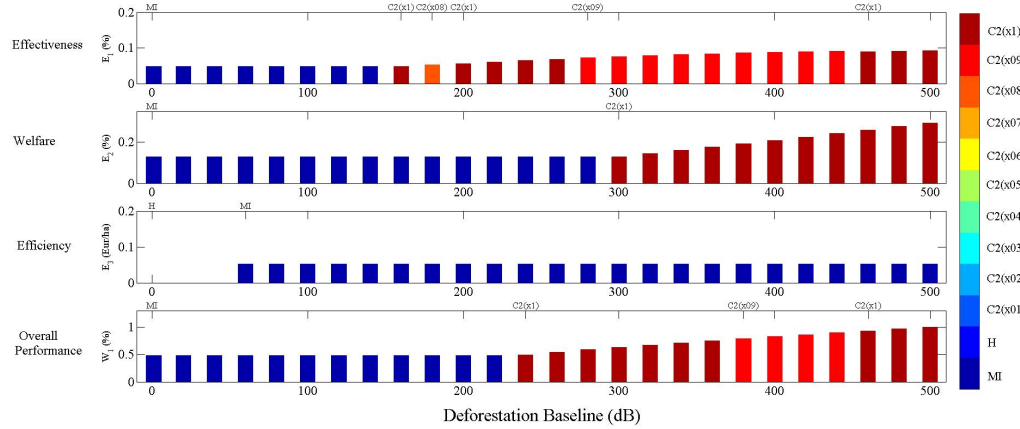


FIGURE C.3: Dominant Baseline Scenarios across Different Historical Deforestation Rates

Note: We compare performance results of the model-implied, historical and fixed corridor 2 baselines. The figure emphasizes the results of the dominant baseline at each deforestation average. The first three panels refer to individual indicators, while the last one captures overall performance, based on equally weighting the individual indicators. Various widths are considered for the fixed corridor 2: the bounds are set between 10% and 100% above and below the historical baseline ($x \in [0.1, 1]$). The moment a baseline starts dominating is marked on the upper x-axis.

Figure C.3 captures the performance dominance when opting among the model-implied, historical, and fixed corridor 2 baselines at different corridor widths. The variable corridor 2 is not considered momentarily. We evaluate the performance based on the three individual indicators (Table II) and an overall score computed by weighting the indicators equally. Figure C.4 below displays effectiveness, welfare, and efficiency results for different widths of the fixed corridor 2 baseline.

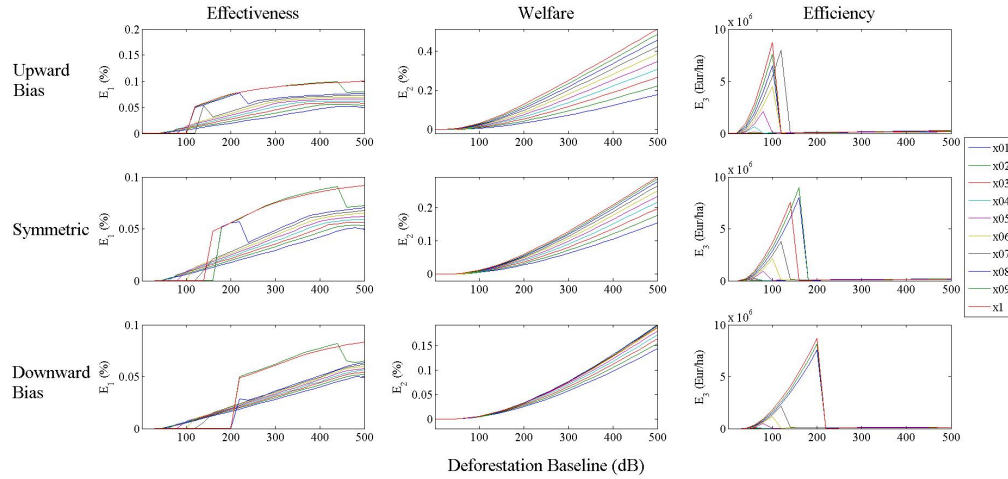


FIGURE C.4: Baseline Performance across Different Historical Deforestation Rates

Note: The figure captures performance results of the fixed corridor 2 when both the corridor width and its symmetry assumptions are relaxed. We allow the corridor to be either symmetric, upward or downward-biased. The corridor bounds are set between 10% and 100% above and below the historical baseline ($x \in [0.1, 1]$).

Let us also specifically investigate differences in performance when playing around with the symmetry assumption regarding the corridor width. We present in Figure C.5 only the extreme cases, when the corridor width is either very low ($x = 0.1$) or very large ($x = 1$).

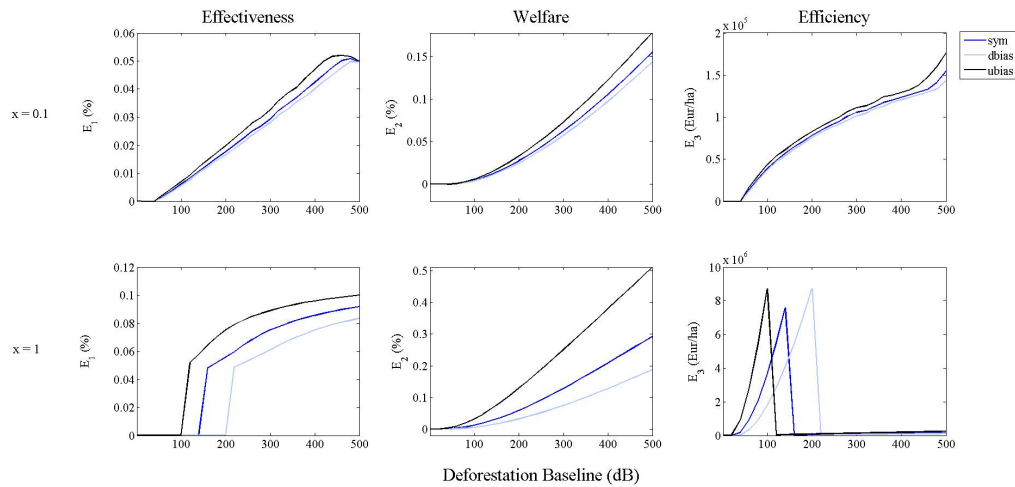


FIGURE C.5: Performance of the Fixed Corridor 2

Note: The figure captures performance results of the fixed corridor 2 when both the corridor width and its symmetry assumptions are relaxed. We allow the corridor to be either symmetric, upward or downward-biased. Here we study two extreme cases of corridor width of either 10% or 100% above and below the historical baseline ($x \in [0.1, 1]$).

Annex 5: The variable corridor 2: corridor bandwidth and symmetry

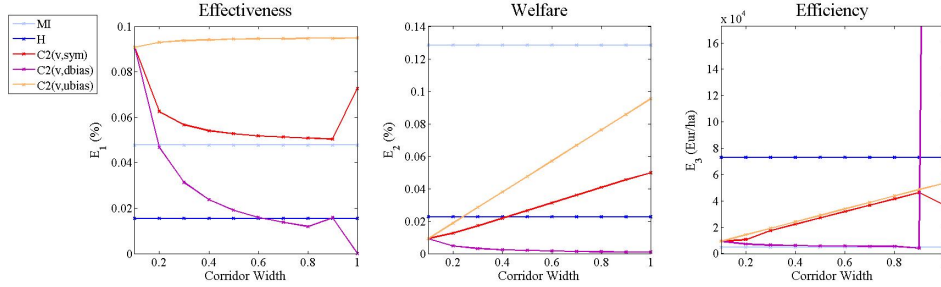


FIGURE C.6: Performance of the Variable Corridor 2 at Different Corridor Widths

Note: The figure captures performance results of the variable corridor 2 compared to the model-implied and the historical baselines. We allow the corridor to be either symmetric, upward or downward-biased. The corridor bounds are set between 10% and 100% above and below the business-and-usual deforestation scenario. For the downward-biased case, the corridor bounds are computed as $dbU = 1.1d_{BaU}(t)$, $dbL = (1 - x)d_{BaU}(t)$, while for the upward-biased case $dbU = (1 + x)d_{BaU}(t)$, $dbL = 0.9d_{BaU}(t)$, with $x \in [0.1, 1]$.

Figure C.6 displays changes in the performance of the variable corridor 2 baseline as we allow for different corridor widths ($x \in [0.1, 1]$) and both symmetric, and upward and downward-biased corridor bounds around the business-and-usual deforestation scenario. We compare these results with those of the model-implied and the historical baseline². Since effectiveness was highest for the narrow corridors, we detail the analysis here and allow the corridor width to vary in the range $[0.01, 0.2]$. Figure C.7 presents the results for the three performance criteria and checks sensitivities to small variations in corridor width for the symmetric case.

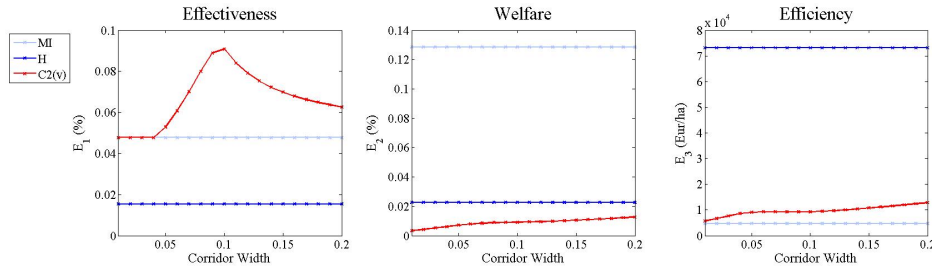


FIGURE C.7: Performance Indicators for The Narrow Variable Corridor 2

Note: The figure captures performance results of the symmetric variable corridor 2 compared to the model-implied and the historical baselines. The corridor bounds are set between 1% and 20% above and below the business-and-usual deforestation scenario.

The results form a clear image. Effectiveness performance is non-linear and peaks at a corridor width of 10% ($x = 0.1$), while welfare is an increasing function in corridor size. Broader corridors diminish the efficiency of the REDD programs.

²Considering an average deforestation rate of 200 ha per year.

Annex 6: Overall performance indicators

Figure C.8 displays the values obtained for the three performance indicators. Below each indicator, we place an emphasis on baseline dominance across the broad range of historical deforestation rates.

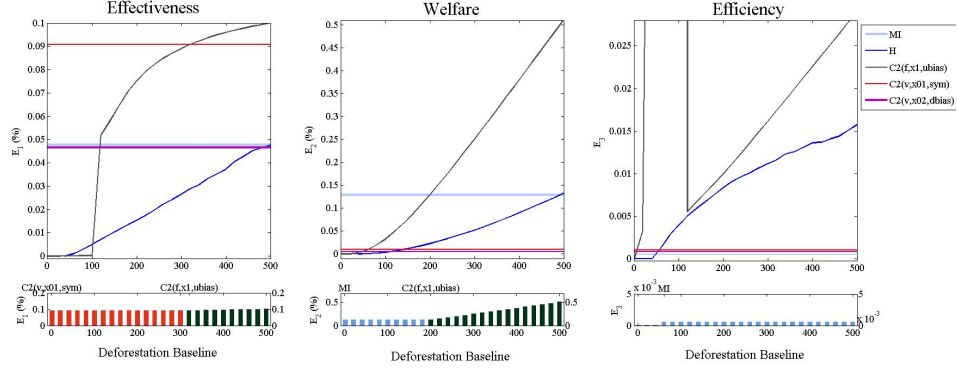


FIGURE C.8: Performance Indicators and Dominant Baselines

Note: The figure displays performance results for five baseline types (historical, model-implied, upward-biased fixed corridor 2, symmetric variable corridor 2, and downward-biased corridor 2). While the upper panel illustrates results for all baselines, the lower one focuses only on the dominant baseline at each past deforestation average (the moment a baseline starts dominating is marked on the upper x-axis).

TABLE I: Weighting Alternatives for the Overall Performance Indicator

	High Transfer	Low Transfer
1. Equal Weights	$W_1 = \frac{R_{E_1} + R_{E_2} - R_{E_3}}{3}$	$W_5 = \frac{R_{E_1} - R_{E_2} - R_{E_3}}{3}$
2. Effectiveness Bias	$W_2 = \frac{2R_{E_1} + R_{E_2} - R_{E_3}}{4}$	$W_6 = \frac{2R_{E_1} - R_{E_2} - R_{E_3}}{4}$
3. Welfare Bias	$W_3 = \frac{R_{E_1} + 2R_{E_2} - R_{E_3}}{4}$	$W_7 = \frac{R_{E_1} - 2R_{E_2} - R_{E_3}}{4}$
4. Efficiency Bias	$W_4 = \frac{R_{E_1} + R_{E_2} - 2R_{E_3}}{4}$	$W_8 = \frac{R_{E_1} - R_{E_2} - 2R_{E_3}}{4}$

Note: Here $\{R_{E_j}\}_{1 \leq j \leq 3}$ refers to the ranking obtained when ordering baselines according to each performance criterion and not the value of the indicator itself. The rank takes values from 1 to 5, where 5 corresponds to the highest indicator value. The efficiency indicator refers to average cost of avoiding one hectare of deforestation and is taken into account with the minus sign, to reflect preference for lower costs. Preference for high transfers (E_2) is captured by the plus sign, while preference for low transfers by the minus sign.

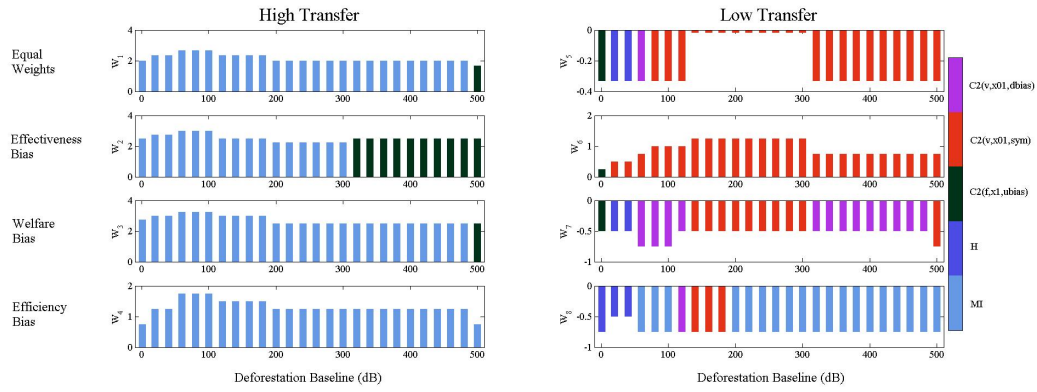


FIGURE C.9: Overall Scores of Baseline Dominance

Note: The overall scores of baseline dominance $\{W_j\}_{1 \leq j \leq 8}$ are computed as detailed in Table I, reflecting the average ranking obtained by each baseline type. Only scores of the dominating baseline are displayed for each average past deforestation level.

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