JUSTUS LIEBIG UNIVERSITY GIESSEN

DOCTORAL THESIS

Essays on the Econometric Analysis of Energy Markets and Climate Change

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Statement of Originality

This thesis is being submitted to Macquarie University and Justus Liebig University Giessen in accordance with the Cotutelle agreement dated March 12, 2018.

To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made in the thesis itself.

Christoph FUNK

Giessen, March 17, 2021

JUSTUS LIEBIG UNIVERSITY GIESSEN

Abstract

Department of Statistics and Econometrics
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Doctoral Thesis

Essays on the Econometric Analysis of Energy Markets and Climate Change

by Christoph FUNK

This PhD thesis uses econometric techniques to provide new insights into energy markets and climate change. The developed econometric models are applied in six research articles that focus on energy markets, financial economics, climate vulnerability and adaptation strategies, and the impacts of climate change on coastal regions. The first part of the thesis is dedicated to the econometric analysis of the oil market. Crude oil and its derivatives are the world's most commonly traded commodities. Although the energy landscape is in a state of transition, crude oil has been and will likely remain important in the context of global energy consumption. By focusing on econometric and time series regression models, Chapter 2 examines whether it is possible to generate reliable long-term monthly forecasts of the real price of crude oil and how these can be improved using forecast combinations. Chapter 3 investigates the North American oil industry using firm-level data. The relationship between oil prices, oil market volatility, and the cost of debt for oil firms is analyzed empirically using a distributed lag model and a panel data "within-between" approach. The second part of the thesis focuses on climate change vulnerability and adaptation strategies in the context of smallholder farmers in the Indian watersheds. The global climate has changed relative to the pre-industrial period. Moreover, this change already affects ecosystems and livelihoods worldwide. This has severe implications for food production and security, especially for the rain-fed agricultural systems that dominate much of tropical agriculture and are extremely vulnerable to projected climate change. Consequently, Chapters 4 and 5 focus on two research questions related to watershed development programs and factors that affect the adaptation strategies of smallholder farmers in India. Chapter 4 provides a theoretical framework for developing a climate vulnerability index. Chapter 5 is aimed at investigating how smallholder farmers perceive climate change and how they adapt their behavior in response to perceived changes in the climate. Using a binary logistic model, this thesis quantifies the impact of various explanatory variables that affect households' choices of adaptation strategies. The final part of this thesis investigates the impacts of climate change on coastal regions. Anthropogenic climate change has caused global mean sea levels to rise substantially over the last century. As a result, local and regional sea level variations and the occurrence of sea level extremes increase climate change related risks for coastal regions. This amplifies the need to understand how waves and extremes change over the long term to assess the impacts of climate change. Thus, Chapter 6 provides a literature review and guide for policy makers on how to evaluate coastal adaptation projects. Moreover, Chapter 7 empirically investigates long-term trends in and extreme values of wave power and height on a local scale along Australia's east and southeast coasts. A comparison of the distribution of wave power employing the Jensen-Shannon divergence and Laplacian embedding is used as a potential tool for investigating temporal and spatial variations of the wave climate between and within different locations. This provides new insights on Australia's wave climate on a local and regional scale in the context of climate change.

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This PhD thesis also includes joint papers written with the following co-authors: Lutz Breuer, Peter Winker, Stefan Trück, Thomas Aenis, Archana Raghavan Sathyan, Chi Truong, Supriya Mathew, Johannes Lips, and Karol Kempa. I would like to thank them all for their constructive and rewarding cooperation.

I would like to thank all my colleagues at Giessen and Macquarie University for their support. Special thanks go to my friends Johhannes Lips, Jana Brandt, and Daniel Grabowski for their valuable input and especially for creating a fun, engaging work environment. I am thankful to Archana Raghavan Sathyan for her cooperation, friendship, and support over the course of this PhD. Moreover, I would like to thank Carmen Hersener for always having an open ear for my problems during our morning coffee breaks and for her countless administrative support.

Last but surely not the least, I would like to thank all my friends, my family, and my fiancée for their love, patience, and support throughout this journey. Without you, this thesis would not have been possible. Thank you!

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List of Abbreviations

2D	Two-dimensional
A	Agriculture
AR	Autoregressive
ARMA	Autoregressive Moving Average
AUC	Area Under the Curve
Brent	Brent North Sea Crude Oil
Btu	British Thermal Unit
CBA	Cost Benefit Analysis
CEA	Cost Effective Analysis
CEAS	Coastal Erosion Adaptation Strategies
CPI	Consumer Price Index
CRB	Commodity Research Bureau
CUA	Cost Utility Analysis
CUSIP	Committee On Uniform Security Identification Procedures
CV	Climate Variability
CVI^{RFT}	Climate Vulnerability Index for Rainfed Tropics
EIA	U.S. Energy Information Administration
F	Food
FE	Fixed Effects
FINRA	Financial Industry Regulatory Authority
FRASER	Federal Reserve Archival System for Economic Research
FRED	Federal Reserve Economic Data
GMSL	Global Mean Sea Level
H	Health
Hs	Significant Wave Height
JONSWAP	Joint North Sea Wave Observation Project
JSD	Jensen–Shannon Divergence
LG	Local-Self Government
LIBOR	London Interbank Offering Rate
LS	Livelihood Strategies
MCA	Multi-criteria Analysis
MSPE	Mean Squared Prediction Error

NAICS	North American Industry Classification System
ND	Natural Disaster Impact
NGO	Non-Governmental Organisation
NPV	Net Present Value
NSW	New South Wales
NYSE	New York Stock Exchange
OECD	Organisation for Economic Co-operation and Development
OPEC	Organization of the Petroleum Exporting Countries
OTC	Over-the-counter
QE	Quantitative Easing
RAC	U.S. Refiners' Acquisition Cost
RE	Random Effects
ROA	Real Options Analysis
ROC	Receiver Operating Characteristic
SD	Socio-Demographic Profile
SDGs	Sustainable Development Goals
SE	Socio-Economic Assets
SG	State Government
SIC	Standard Industrial Classification
SN	Social Network
Tp	Peak Energy Wave Period
TRACE	Trade Reporting and Compliance Engine
UN	United Nations
US	United States
VAR	Vector Autoregressive
W	Water
WDPs	Watershed Development Programs
WP	Wave Power
WRDS	Wharton Research Data Services
WTI	West Texas Intermediate

To all who believed in me

A special thanks goes to my father, Peter, who has supported me through my entire life, who taught me to work hard for the things that I aspire to achieve and who prepared me for the challenges of life. My brother, Markus, who has always been a great resource of help and advice, my grandparents who helped me through tough times after the death of my mother as well as Sylvia for her aid throughout the years. Last but not least, I would like to thank my fiancée, Flordelyn, for her continuous love and support, especially during the final months of writing this thesis. I am truly thankful to have you in my life.

Part I

Introduction

Chapter 1

Introduction

This PhD thesis uses econometric techniques to provide new insights into energy markets and climate change. In particular, econometric models are applied to the forecasting of oil prices, analyzing the relationship between oil prices and the costs of debt for firms in the US oil industry, climate vulnerability and adaptation strategies in the context of smallholder farmers in the Indian watersheds, and long-term trends in the Australian wave climate. Figure 1.1 provides an overview of the structure of this thesis and its six research articles.

The following three sections, Section 1.1, 1.2 and 1.3, will give a brief introduction by outlining the motivations and objectives for this work, summarizing the research questions, and illustrating the contributions made by each of the six research papers. The main work of this thesis is then divided into three parts. Part II will take a closer look at the oil market and focuses on the broad categories of empirical energy economics and finance. Chapter 2 focuses on forecasting the real price of oil using forecast combinations, while Chapter 3 is dedicated to the North American oil industry and analyzes how the cost of the debt of oil firms is affected by oil price fluctuations. Part III addresses climate change vulnerability and adaptation strategies in the context of smallholder farmers in the Indian watersheds. Chapter 4 lays the theoretical framework by developing a climate vulnerability index and 5 focuses on perceived climate change and the factors that are influencing the choice of adaptation strategies. Part IV is dedicated to the impact of climate change on coastal regions. Thereby, Chapter 6 provides a literature review for the project valuation for coastal adaptation projects and Chapter 7 investigates recent trends in the wave climate along the eastern and southeastern coasts of Australia. A short conclusion of the main results of this work and an outlook of possible further research opportunities are provided in part V.

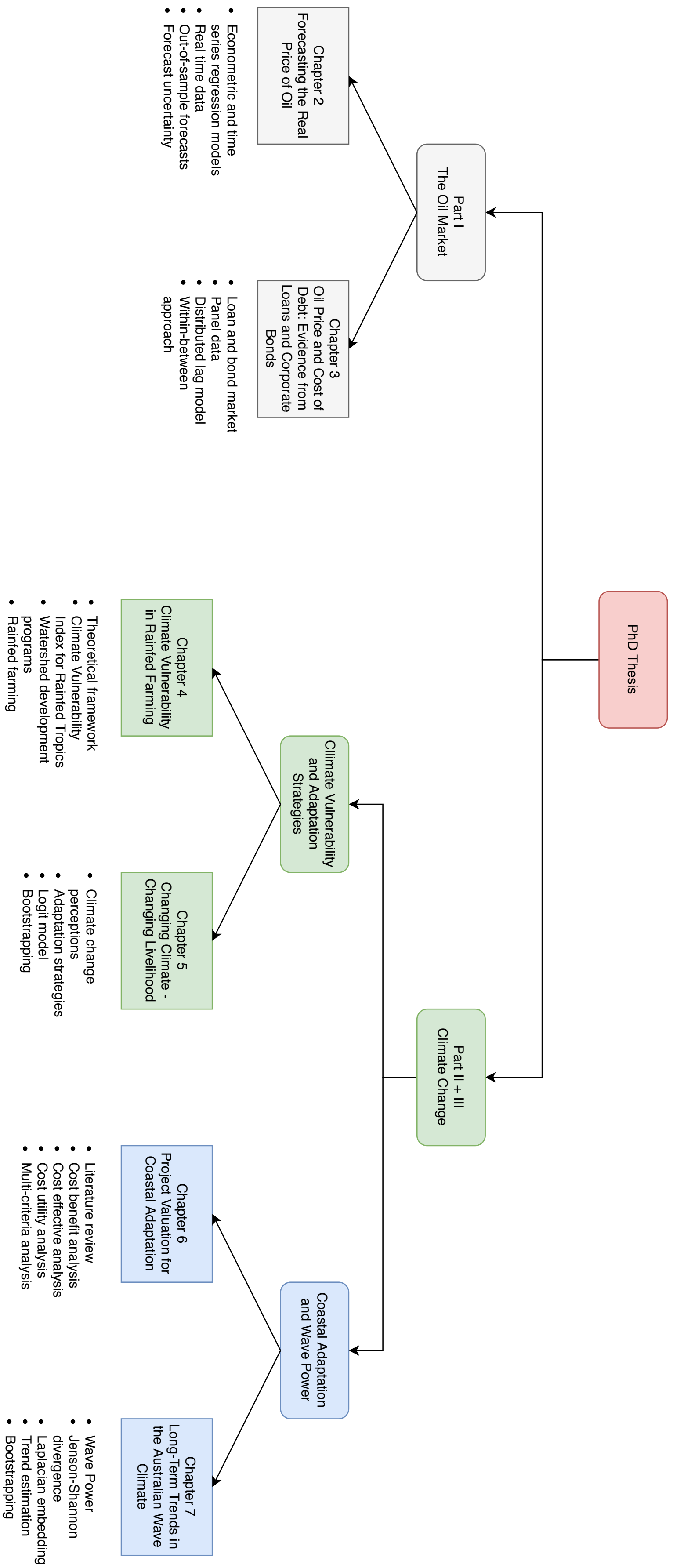


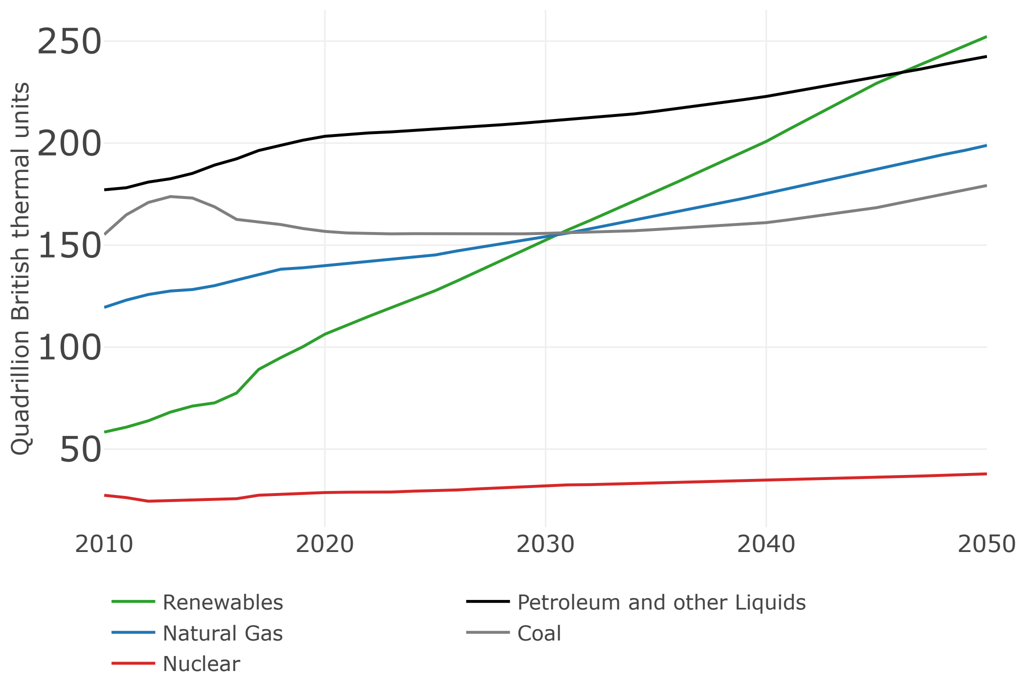
FIGURE 1.1: Structure of the thesis

1.1 Developments in the US Oil Market

The energy landscape is currently in a state of transition and radical changes for energy consumption, the electricity and transport sector, and the role of fossil fuels are likely to occur over the next decades. However, the oil market has been and will likely continue to be important in the context of global energy consumption. Figure 1.2 depicts the world energy consumption since 2010 in British thermal unit (Btu) and its projections between 2019 and 2050 as estimated by the U.S. Energy Information Administration (EIA) in the International Energy Outlook 2019 (EIA 2019). Three important trends can be inferred from this figure. First, the total world energy consumption is projected to increase by nearly 50% by 2050. As of 2018, petroleum products and its derivatives make up 32% of the global primary energy consumption (Fig 1.3). Second, renewable energy sources, e.g., solar, wind and hydroelectric power, will increase its share from 15% to 28%. This corresponds to a projected increase by 3.1% per year. Third, while the share of natural gas remains at 22%, coal and petroleum products are projected to have decreased by 5 and 6 percentage points, respectively. However, the share of petroleum and other liquids is projected to be at 27% of the total energy consumption by 2050. Given the world's dependence on crude oil as an energy source, the main objective of part II of this thesis is to investigate the oil market and its determinants in more detail.

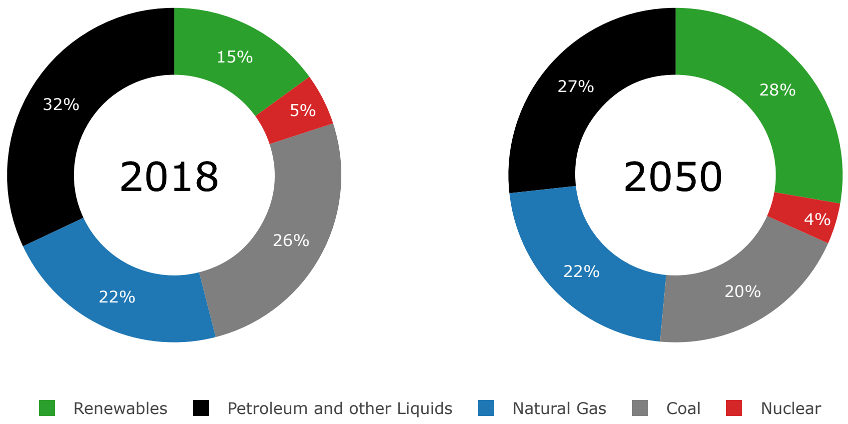
Since the mid-2000s, there has been a major increase in United States (US) crude oil production mainly driven by the so-called "shale oil revolution". The term "shale oil" refers to the production of crude oil that is based on rock formations with a low permeability. New extraction methods such as horizontal drilling and hydraulic fracturing (the so-called "fracking") make it possible to exploit and process crude oil that would have been impossible to release through conventional drilling methods (Kilian 2016). Since the 2008 financial crisis, oil production has increased sharply after a long-lasting decline that started in the 1980s (EIA 2017a). As of 2016, the EIA estimates that 48% of the total US oil production can be attributed

FIGURE 1.2: Primary energy consumption by energy source



Note: Own representation based on (EIA 2019).

FIGURE 1.3: Share of primary energy consumption by energy source



Note: Own representation based on (EIA 2019).

to shale oil production. Connected to this, Domanski et al. (2015) describe an interesting phenomenon in which there has been a contemporaneous increase in debt-driven investments in the oil sector since the shale oil revolution started. This growth in debt was driven by a macroeconomic environment with low interest rates and investors searching for profitable investments after the financial crisis. This has led to a vicious cycle, where increasing oil prices have led to a higher evaluation of commodity assets and thus increased return expectations. This is particularly important in situations such as that of June 2014, where the market price for crude oil started to decline sharply. This has two main implications for the oil industry: it reduces the cash flow generated by an oil field, which leads to a devaluation of the assets backing a company's debt. In order to finance their investments, a company could either reduce its assets position or increase its oil production. Both Lehn and Zhu's (2016) and Lips's (2019) empirical evidence supports the latter because highly leveraged oil producers cut their investment and increase production to generate cash to pay off their debts. This could lead to an even higher downward pressure on oil prices, which in turn suggests that oil price dynamics are affected by an oil company's capital structure. Consequently, the increasing leverage will lead to a higher risk exposure in the non-financial corporate sector, which may ultimately even put the global financial system at risk (Domanski et al. 2015). Given the latest development in the crude oil market, Chapter 2 and 3 will try to answer two related research questions.

Chapter 2 – *Forecasting the Real Price of Oil - Time-Variation and Forecast Combination*
This chapter examines the question whether it is possible to generate an accurate forecast of the real price of oil. This is particularly important because central banks, international organizations such as the International Monetary Fund or national institutions like the EIA use real-time forecasts to evaluate possible economic fluctuations as well as to improve macroeconomic policy responses (Baumeister and Kilian 2012, 2015).

This work discusses whether it is possible to generate reliable long-term monthly forecasts of the real price of Brent North Sea Crude Oil (Brent), and how these forecasts could be improved by using forecast combinations. The focus of the study also lies on using real time data for constructing out-of-sample forecasts. Thus, the collection of the used data and the challenges in constructing a real-time data set are discussed in detail.

Focusing on econometric and time series regression models, this work contributes to the literature of oil price forecasting by providing an overview of existing models and their performance. In addition, some of these existing models will be extended by either introducing more suitable real-time measures for the Brent crude oil price or by using various measures for economic activity. These extensions show improvements in the mean squared prediction error

(MSPE) ratio in the medium and long run, compared to the original version of these models. Additionally, the performance of the individual models through time is investigated by using recursively constructed MSPE ratios. This demonstrates potential weaknesses of the used models as none of them consistently outperforms the no-change forecasts over time as well as across the different horizons. As such, forecasters have to pay great attention to the sample period they are using. This links directly to the idea of using combination approaches to potentially improve the forecasts. Despite having higher MSPE ratios in the long run, a combination of four models outperforms the best individual models over the medium run, while the overall time performance is less volatile.

The second main contribution of this work relates to the forecast uncertainty associated with the point forecasts of the investigated models. By recursively estimating the 5th, 25th, 50th, 75th and 95th quantile of the out-of-sample forecast errors, the study also provides information about the uncertainty of future forecasts. In addition, this rather simplistic approach is compared to a more sophisticated method using quantile regression analysis. Even though it is possible to construct a forecast that is superior to the no-change benchmark, the uncertainty analysis reveals the limitations of these models.

The Appendix discusses the robustness of the newly introduced models and the four-model combination by using the West Texas Intermediate (WTI) as an alternative benchmark. The WTI is a widely accepted benchmark in comparable forecasting studies. Therefore, the results obtained for the Brent crude oil price are robust and can even be improved when using the WTI.

Chapter 3 – *Oil Price and Cost of Debt: Evidence from Loans and Corporate Bonds*
This chapter examines the effects of oil price fluctuations on the cost of debt for US oil firms. Particularly between January 2011 and June 2014, the crude oil price saw a comparatively stable sideways shift, closely followed by a major decline until January 2015. This could have been the result of a supply shock from the fracking boom in the US as well as OPEC's refusal to reduce supply quantities. On the other hand, there was evidence that the price depreciation was driven by a demand shock based on a slowdown of the world economy (Baumeister and Kilian 2016). In addition, the appreciation of the US dollar could have lowered the demand even further, as dollar-denominated crude oil imports became more expensive (Baffes et al. 2015). It is particularly interesting that the supply increased even further despite the oil price decline in 2014. This seems to be counterintuitive, as one would expect a cut in production similar to the one after the 2008 financial crisis. By investigating firms' borrowing decisions and creditworthiness, my colleagues Johannes Lips, Karol Kempa and I will address how the US oil industry was affected by oil price fluctuations.

Thus, in this work, we empirically analyze the relationship between oil price and its volatility and the cost of debt in the US oil industry. Although the impacts of oil price shocks on the world economy and macroeconomic aggregates such as real GDP and real consumption expenditure have been extensively studied, little is known about the potential impacts on the oil industry itself. However, this is particularity relevant for the capital-intensive oil industry as oil price fluctuations are likely to have a high impact on the default risk of firms and ultimately their refinancing costs. Thus, we contribute to the literature by investigating whether oil prices, in addition to directly affecting oil firms' revenues, have an impact at the individual firm level, especially with respect to their cost of debt. We discuss the characteristics of corporate bonds and syndicated loans as two potential sources of debt and the implications the oil price has on their evaluation. We collect data on individual syndicated loans, bond issued by US oil firms, and bonds traded on the secondary market and combine it with data from corporate financial statements. This allows us to analyze how firms' characteristics such as firm size, profitability, or leverage affect the credit spread of loans and bonds.

To answer the research question, we use a comprehensive database that includes 1,504 publicly held firms active in the North American (US and Canada) oil market between Q2 2000 to

Q1 2018. This includes firm-specific financial variables and detailed information about bond and bank loan data. We categorize these companies according to their position in the value chain in upstream, midstream, downstream and support services firms and discuss the different potential impacts of oil price and oil price volatility might have on them.

Using two different strategies, we estimate the potential impacts of oil price changes on the cost of debt. The first approach focuses on the costs of debt of individual loans or bonds at issuance, and the second approach takes into account secondary market transactions after the issuance. We use a distributed lag model for estimating the credit spread on the loan and bond level at issuance. Additionally, we use a panel data "within-between"approach to estimate the continuous spreads on the secondary market. This approach is advantageous as it deconstructs the combined effect in the random effect models into between- and within-firm effects. Thus, we can differentiate the effects that oil prices have on a firm depending on its position in the oil industry's supply chain.

Overall, we find that, even after controlling for loan/bond and firm characteristics as well as the macroeconomic environment, the oil price and its volatility have an effect on a firm's cost of debt. However, the size and direction of the effects is dependent on the firms' source of refinancing. For syndicated loans and bonds at issuance we find that higher oil prices increase the cost of debt. These findings are intuitively plausible in the case of midstream and downstream firms as crude oil is an input for these firms. Thus, higher oil prices mean higher costs for these firms, which results in higher premiums on the price of debt. Moreover, credit spreads of loans decrease with the volatility of the oil price when considering the full samples of firms, while we find no significant effect for bonds at issuance. This is a surprising result as one would expect banks to charge higher prices for debt in such periods.

When accounting for time-invariant firm heterogeneity, within-between effects estimates for bonds traded on the secondary market indicate that a higher oil price leads to lower financing costs for firms. In addition, between effects reveal significant differences between the costs of debt for firms in the different industry categories. Overall, the bond market seems to consider high price volatility a risk that increases uncertainty and thus reduces the creditworthiness of oil firms. As a result, for credit spreads of bonds traded on the secondary market, we find that firms have to pay higher credit spreads if the volatility increases.

1.2 Climate Change: Vulnerability and Adaptation Strategies

Climate change is a global phenomenon and the greatest challenge that humankind faces in the current era. According to the IPCC (2018), the global climate has changed relative to the pre-industrial period and, moreover, is already affecting ecosystems and livelihoods worldwide. This includes, among other things, an increase in the land surface temperature (twice the global average) and an increase in the frequency and intensity of some climate and weather extremes, such as extreme temperatures, heavy precipitation, droughts, and heat waves. This poses a threat to world food security and terrestrial ecosystems and contributes to desertification and land degradation in many regions (IPCC 2018, 2019). With the Paris Agreement signed by 197 countries in 2015, the international community has committed itself to taking ambitious effort to combat climate change, adapt to its effects, and enhance the support to developing countries to strengthen their ability to deal with the impacts of climate change (United Nations 2015). To that end, the United Nations (UN) adopted 17 Sustainable Development Goals (SDGs) and 169 targets as part of the 2030 Agenda for Sustainable Development, which provides a 15-year plan to achieve the Goals (UN General Assembly 2015). However, the UN recognized that during the implementation of these goals, too little attention has been given to what should be measured and too little investment has been made to strengthening statistical quality and standards (United Nations Department of Economic and Social Affairs 2019). Part III of my thesis will contribute to the literature by giving attention to climate change vulnerability and adaptation strategies in the context of smallholder farmers in the Indian watersheds.

Expectedly, developing countries in the tropics and subtropics will be hit hardest by climate change (Burney et al. 2014; Hertel and Rosch 2010). This has severe implications for food production and security in these regions as a majority of these countries are characterized by smallholder farming (Harvey et al. 2014). These farmers have a low asset base and operate on less than 2 ha of cropland (World Bank 2003). Of the 3 billion people who live in rural areas, over 80% depend on farming as their main source of income (FAO 2013). Because of their limited available resources, this makes them particularity vulnerable to climate-induced shocks (Frank and Penrose-Buckley 2012; Harvey et al. 2014).

Smallholder farming is prevalent in the Asian continent, with India ranking second in this regard as half of its agricultural production occurs under rainfed farming (FAO 2018). These rainfed areas are characterized by rainfall variability, temperature fluctuations and frequent droughts. Thus, the Indian government decided to initiate watershed development programs (WDPs) to promote this area by providing location-specific support, thus reducing vulnerability, enhancing resilience and building adaptive capacities of rainfed farming communities to climate-induced shocks. Part III of this thesis will focus on two research questions related to WDPs and factors affecting adaptation strategies of smallholder farmers in India.

Chapter 4 – *Climate Vulnerability in Rainfed Farming: Analysis from Indian Watersheds*
This chapter investigates how climate vulnerability of rainfed farming can be measured and compared. With the global indicator framework adopted by the UN General Assembly in 2017, indicators are recognized as the backbone of monitoring progress toward SDGs at the regional, national and global level (Schmidt-Traub et al. 2015). Thus, my colleagues Archana Raghavan Sathyan, Thomas Aenis, Lutz Breuer and I will contribute to the literature by developing a new kind of Climate Vulnerability Index for Rainfed Tropics (CVI^{RFT}) that is specifically designed to analyze and compare the climate vulnerability of watershed areas. This index can be used to investigate the vulnerability of spatial entities to climate changes in a human dimension. The bottom-up approach described in this work is replicable to similar physio-geographic areas of rainfed farming and can be used to evaluate the potential effectiveness of WDPs used to adapt to climate change. We discuss the concepts used in assessing climate vulnerability and

follow the widely accepted definition of vulnerability: being a function of *exposure*, *sensitivity* and *adaptive capacity*. Based on an extensive literature review, we modify well-established approaches for estimating climate vulnerability and modify them according to the local situation at the watershed level. The index is comprised of the aforementioned three dimensions and is subdivided into 10 major components. In total, the CVI^{RFT} is based on 59 indicators that capture the determinants of vulnerability.

This study is based on three watersheds established by the Indian government in Kerala, with the goal of promoting development in these areas and addressing the problems associated with climate change for future planning and implementation. We apply the newly developed CVI^{RFT} and test it for comparing the vulnerability of the WDPs that are implemented by three different agencies. We use primary data collected from household surveys (n = 215) to construct the CVI^{RFT}. When comparing the three different implementing agencies, we find a strong variation in the *exposure* dimension, moderate in sensitivity and a negligible difference in adaptive capacity across the watersheds. After analyzing the major components under the dimensions, we suggest focusing on policy orientation toward redesigning the WDPs. Specifically, we suggest an emphasis on economic diversification, livelihood strategies, social networking coupled with stakeholder participation, natural resource management and risk spread through credit and insurance flexibility.

Chapter 5 – *Changing Climate - Changing Livelihood: Smallholder's Perceptions and Adaptation Strategies*
This chapter examines how households perceive climate change and what factors mainly influence their selection of adaptation strategies. This work is an extension of the previous works (Raghavan Sathyan et al. 2016, 2018a,b) that focused on establishing a sensitivity analysis of the CVI^{RFT}. The index is used to compare three watersheds in Kerala where WDPs have been implemented. Although the index provides an overall picture of the various levels of vulnerability, it lacks a detailed analysis of the factors that promote adaptation strategies. My colleagues Archana Raghavan Sathyan, Peter Winker, Lutz Breuer and I will fill this gap and investigate how households perceive climate change, how they adopt their behavior in response to perceived changes in climate and what influences their choices of adaption measures. This will help to increase the credibility in examining the impacts of climate change on different scales to find key areas for better policy planning.

For our study site, we find that households perceive an increase in both temperature and the unpredictability of the monsoon season, which is in accordance with actual observed weather trends. Thus, we provide a brief overview of the underlying concepts of perceived climate change and how these perceptions affect farmers' selection and use of adaptation strategies to cope with climate vulnerability. Households generally use various adaption strategies simultaneously to cope with such perceptions of climate change. In addition, the three watersheds show considerably different variations in using the actual adaptation strategies implemented.

Based on an extensive literature review, we discuss a broad spectrum of factors that could potentially influence the selection of adaptation strategies used by farmers. These factors are then used as explanatory variables in a binary logistic regression model. Our analysis shows there are various factors that significantly correlate with adaptation strategies used by households to cope with climate change.

1.3 Climate Change: Coastal Adaptation and Wave Power

Part IV of this thesis is dedicated to the impacts of climate change on coastal regions. Anthropogenic climate change has caused global mean sea levels to rise substantially over the last century. As a result, local and regional sea level variations and the occurrence of sea level extremes increase climate change related risks for coastal regions. This is especially problematic for low-elevation coastal regions, as they are are not only the most attractive in which to live (Kron 2013), but are also characterized by significantly higher populations (Balk et al. 2009) and high asset and infrastructure values. Therefore, coastal flood damages are expected to increase significantly during the 21st century (Hinkel et al. 2014) and are projected to exceed $1 trillion a year by 2050 in major coastal cities if current adaptation measures are not upgraded Hallegatte et al. (2013). Thus, Chapters 6 and 7 will focus on two research questions related climate change's effects on coastal regions.

Chapter 6 – *Project Valuation for Coastal Adaptation – A Literature Review*
This chapter presents a literature review of various valuation methods that can be used to evaluate coastal adaptation projects. Given the apparent increase in climate change related risks for coastal regions, the use of suitable adaptation strategies has grown in importance over the last decade. My colleagues Chi Truong, Stefan Trück, Supriya Mathew, and I presents a review of various valuation methods and provide a guide for policy makers on how to evaluate and choose between potential strategies for the management of coastal regions. We discuss cost benefit analysis (CBA), cost effective analysis (CEA), cost utility analysis (CUA) and multi-criteria analysis (MCA) as possible valuation methods and provides examples for their practical application. In addition, an overview of studies that have evaluated coastal adaptation projects using cost benefit and optimal timing approaches is provided to highlight methodological issues in this area of research.

Chapter 7 – *Long-Term Trends in the Australian Wave Climate*
This chapter examines how the wave climate and extreme values for wave power along Australia's coast have changed since the 1970s. My colleague, Stefan Trück, and I contribute to the literature by using a comprehensive data set to investigate the wave climate and extreme values along Australia's east and southeast coasts at the regional level. We focus on long-term trends in wave power (and wave height) by using 18 wave rider buoys, ranging between 17 and 42 years of effective record years. We investigate and compare the distributions of wave power by using the Jensen-Shannon divergence and Laplacian embedding simultaneously, which allows us to draw conclusions about the temporal and spatial variations of the wave climate between and within different locations. Through this, we find that stations within a close proximity seem to share similar behavior in terms of their wave power distributions. In addition, we find potential decadal changes in the distribution, which we further address using bootstrapping to test for significant differences. We also illustrate an increase in the yearly mean wave power for a number of locations, including Brisbane, Tweed Head, Coffs Harbour, and Port Kembla. More importantly, we also find an alarming increase in the 99th percentile, or the maximum, over the evaluation period for seven out of the 18 locations. This is of particular interest from a risk management perspective and underlines the importance of location-specific adaptation measures.

Part II

The Oil Market

Chapter 2

Forecasting the Real Price of Oil – Time-Variation and Forecast Combination

The following chapter is based on the paper:

Title:	Forecasting the Real Price of Oil - Time-Variation and Forecast Combination
Authors:	Christoph FUNK (contribution: 100%)
Status:	Published: *Energy Economics*, 2018, vol. 76, pp. 288-302
Available from:	https://doi.org/10.1016/j.eneco.2018.04.016

Earlier versions of this work were presented at the following scientific conferences with review process:

- 5th International Symposium on Environment and Energy Finance Issues (ISEFI), Paris, France, May 2017.
- 9th CFE-CMStatistics 2016, Seville, Spain, December 2016.
- 22th Young Researchers Workshops of the German Statistical Society, Augsburg, Germany, September 2016.

Forecasting the Real Price of Oil – Time-Variation and Forecast Combination[1]

Christoph FUNK[2]

Abstract

This paper sheds light on the questions whether it is possible to generate an accurate forecast of the real price of oil and how it can be improved using forecast combinations. For this reason, the following paper will investigate the out-of-sample performance of seven individual forecasting models. The results show that it is possible to construct better forecasts compared to a no-change benchmark for horizons up to 24 months with gains in the MSPE ratio as high as 25%. In addition, some of the existing models will be extended, e.g. the US inventories model by introducing more suitable real-time measures for the Brent crude oil price and the VAR model of the global oil market by using different measures for the economic activity. Furthermore, the time performance investigated by constructing recursively estimated MSPE ratios discovers potential weaknesses of the used models. Hence, several different combination approaches are tested with the goal of demonstrating that a combination of individual models is beneficial for the forecasting performance. A combination consisting of four models has proven to have a lower MSPE ratio than the best individual models over the medium run and, in addition, to be remarkably stable over time.

Keywords: Oil price, Forecasting, Combinations, Real-time data, Brent

JEL classification: C53, Q43

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2.1 Introduction

Crude oil and its derivatives are the most commonly traded commodities in the world. It is widely accepted that the price of oil is a driving factor of the world economy, which is why a reliable forecast of crude oil is important to evaluate possible economic fluctuations[3] as well as to improve macroeconomic policy responses (Baumeister and Kilian 2012, 2015).

This paper sheds light on the question whether it is possible to generate an accurate forecast of the real[4] price of oil and how it can be improved using forecast combinations. Although most studies have focused on the U.S. Refiners' Acquisition Cost (RAC) and the WTI as a price benchmark so far, recent research suggests that Brent is the new benchmark that central bankers monitor and predict. This is mainly due to the fact that the WTI has increasingly suffered from structural instability and thus reflects US rather than global oil market dynamics since 2010/2011 (Baumeister and Kilian 2015; Manescu and van Robays 2016). For this reason, this paper will concentrate on forecasting the Brent oil price using real-time data to generate the forecasts.

This work will investigate the out-of-sample performance of seven individual forecasting models. Some of the existing models will be extended by either introducing more suitable real-time measures for the Brent crude oil price or by using various measures for the economic activity. These extensions show improvements in the MSPE ratio in the medium and long run as compared to the classic versions. However, only the average forecast performance over the complete evaluation period has been addressed with this static indicator. Therefore, the time performance of the investigated models by constructing recursively estimated MSPE ratios discovers potential weaknesses of the used models. None of the analyzed models consistently outperform the no-change forecast over time as well as across the different horizons. Given the difference in the model performance over time, there should at least theoretically exist a model combination that might increase the accuracy of the forecast (Timmermann 2006). Hence, several different combination approaches will be tested with the goal of demonstrating that a combination of individual models is beneficial for the forecasting performance. The results show that it is possible to construct better forecasts as compared to a no-change benchmark for horizons up to 24 months with gains in the MSPE ratio as high as 25%.

Moreover, the used models will be evaluated by means of measuring their forecast uncertainty. This is of particular interest, as it allows the forecasters to compare their models based on the uncertainty associated with the obtained point forecasts. Here, the forecast intervals will be computed using a quantile regression approach and quantiles which both are based on previous out-of-sample forecast errors.

The remainder of this paper is organized as follows. Section 2.2 gives a review of recent research and the selected forecasting models considered. Section 2.3 provides a comprehensive description of the used data and the data preparation. Section 2.4 evaluates the forecasting performance of the selected models. Section 2.5 explains the use of forecast combinations and the different approaches that are used to construct them. Section 2.6 extends the analysis of the models by means of an uncertainty analysis. The concluding remarks are in section 2.7.

[3] There exists broad evidence in the literature that changes in the price of oil can be used to predict US real GDP growth (see, e.g. Alquist and Kilian (2010), Bachmeier et al. (2008), Hamilton (2011), Kilian and Vigfusson (2011), and Ravazzolo and Rothman (2013) and references therein).

[4] Although most of the changes in the nominal price of oil are incorporated in variations of the real price, it is the inflation component that matters when the forecast horizon increases. Besides, when it comes to economic modeling, it is the real price that is the most relevant in that context (Alquist et al. 2013).

2.2 Selected Forecasting Models

The purpose of this chapter is to present an overview of different models used in this work to predict crude oil prices. While there have been numerous studies[5] that deal with forecasting the price of oil in general, this study will focus on econometric methods and their predictive power based on time series regression and alternative methods based on oil futures prices, crude oil inventories, non-oil industrial raw materials and oil sensitive stocks.

2.2.1 No-change Benchmark

The random walk without drift is the conventional benchmark in the literature on forecasting asset prices (Alquist et al. 2013). This refers to the idea, that the best forecast for tomorrow is the price of today. Therefore, an h step ahead forecast is set equal to the oil price today:

$$Y^f_{t+h|t} = Y_t, \tag{1}$$

where $Y^f_{t+h|t}$ denotes the h-period forecast of the oil price and Y_t refers to the actual real price of oil. The performance of other models is typically measured relative to this benchmark since a better forecasting performance indicates that the oil price can be predicted at least to some extent. This model will be referred to as the 'RW'.

2.2.2 AR and ARMA

Autoregressive (AR) and autoregressive moving average (ARMA) processes are two other widely used methods for generating forecasts from time series. Baumeister and Kilian (2012) and Alquist et al. (2013) provide evidence that real oil price forecasts constructed from these models can be more accurate than a no-change benchmark for horizons up to one year evaluated based on the MSPE and their directional accuracy. Moreover, their results are robust whether the WTI or the RAC is used as the real price of oil in question. As the performance of these two models are very similar, only the results for an ARMA(1,1) model based on the log oil price will be examined in more detail. Additional information about the forecasting performance of the AR model can be found in the supplementary material section.

2.2.3 Futures

Another widely used method is to generate forecasts based on futures prices. This follows the idea that futures contracts might include market expectations about the shift in oil prices. This approach has the advantage that it is relatively simple to generate and easy to communicate to the public (Manescu and van Robays 2016). One can easily generate an h-step forecast for the nominal price of oil by using a futures contract with maturity h. There are several different variations and modifications discussed in the literature.[6] Following the suggestion by Baumeister and Kilian (2012, 2014), the forecast for the real price of oil will be generated by subtracting the expected inflation:

$$Y^f_{t+h|t} = Y_t(1 + f^h_t - s_t - E(\pi^h_t)), \tag{2}$$

where Y_t is the current level of the real price of oil, f^h_t is the log of current oil futures price with maturity h, s_t is the corresponding log of the spot price and $E(\pi^h_t)$ the expected inflation rate over the next h periods. This was done by using the monthly average growth rate of the US Consumer Price Index (CPI) up to time t multiplied by h. This approach could be refined

[5] The interested reader may find a comprehensive overview of various forecasting techniques in Frey et al. (2009), Bashiri Behmiri and Pires Manso (2013) and Gabralla and Abraham (2013).

[6] See for example Alquist et al. (2013) who describe several variations of this basic model.

further, but as argued by Baumeister and Kilian (2012, 2014), the deviations are negligible given that the variations of the nominal oil price typically dominate the magnitude of the inflation rate over the horizon of interest.

Although there exists evidence that futures prices are not particularly accurate when it comes to forecasting the oil price (e.g. Alquist and Kilian (2010), Baumeister and Kilian (2012), and Reeve and Vigfusson (2011)), it is still a widely used baseline forecast of central banks (Baumeister and Kilian 2012). Furthermore, when using the Brent oil price as a benchmark, the results of Manescu and van Robays (2016) show slight improvements between 3 and 8 quarters ahead forecasts for the time period between 1995Q1 and 2015Q2. However, the results of Baumeister and Kilian (2014) indicate no improvement for up to 4 quarter ahead forecasts for the evaluation period between 1992.01 and 2012.09. This model will be referred to as the 'Futures' model.

2.2.4 Forecasts based on Crude Oil Inventories

The fourth class of models considered in this study is based on the theory developed in Alquist and Kilian (2010). A shift in expectations about the real price of oil, ceteris paribus, is reflected in changes in expectations of crude oil inventories. This model has been discussed in Baumeister et al. (2015, 2014) and can be represented as:

$$Y^f_{t+h|t} = Y_t(1 + \widehat{\beta}\Delta inv^h_t), \tag{3}$$

where Δinv^h_t reflects the percentage change in US crude oil inventories over the preceding h months and $\widehat{\beta}$ is a regression parameter that is obtained by regressing the cumulative percentage changes in the real price of oil on the lagged cumulative percentage change in US inventories without intercept. Especially, using forecasting horizons of more than 14 months, this approach has been useful in a forecasting combination as it lowers the MSPE as shown in Baumeister and Kilian (2014). Additionally, Baumeister et al. (2015) find MSPE reduction up to 30% as compared to a no-change benchmark between 1992.01 and 2012.09 for monthly data using a MIDAS approach. Results for this classic approach can be found in the supplementary material section. However, this work proposes a new variation of this model by using Organisation for Economic Co-operation and Development (OECD) crude oil inventories as there is reason to believe that the US inventories might not be representative for the Brent crude oil price. While there do not exist monthly crude oil inventories data for this model directly, it has been modeled by multiplying US crude oil inventories with the ratio of OECD petroleum stocks over US petroleum stocks. This new approach outperforms the classic model that uses the US inventories. This model will be referred to as the 'Inventories OECD' model.

2.2.5 VAR Model of the Global Oil Market

The fifth class of models considered is the Vector Autoregressive (VAR) model of the global oil markets which has been extensively studied over the past several years. According to Baumeister and Kilian (2014), this can be illustrated as a reduced form representation:

$$B(L)Y_t = c + \epsilon_t, \tag{4}$$

where Y_t is a vector of four variables which include the percentage change in global crude oil production, a measure of global real activity, the log of RAC for crude oil imports deflated by the log of the US CPI, and the change in global crude oil inventories. Furthermore, $B(L)$ denotes the autoregressive lag order polynomial, c a vector of constants, and ϵ_t represents a vector of white noise error terms. Only a few works have examined the forecasting ability of this VAR approach for Brent. Baumeister and Kilian (2014) have done this indirectly by modeling the spread between Brent and RAC as a random walk and Manescu and van Robays (2016) have modeled the forecasts of Brent directly. However, both methods offer only relatively small or no gains in terms of forecast accuracy as compared to a no-change forecast using quarterly projections.

There exist two different measures for the global real activity that are discussed in the literature so far. Commonly, the "Shipping Index"developed by Kilian (2009), which is constructed from data on global dry cargo ocean shipping freight rates, is used for this purpose. Alternatively, one could use the monthly index of industrial production for the OECD and six major non-OECD countries to measure the economic activity. Results for both models can be found in the supplementary material section.

However, two variations of the VAR model will be introduced in the forecasting literature of oil prices by using alternative ways of measuring the global economic activity. Ravazzolo and Vespignani (2015) have shown that the world steel production has a higher predictive accuracy of the world GDP as compared to the OECD industrial production and the Kilian shipping index. Therefore, it seems plausible to use this indicator in order to forecast the real price of Brent crude oil as well. In this case, the log difference of the crude oil price and of the steel production are used in this specification as this outperforms the model using the log-levels. This model will be referred to as the 'VAR Steel' model. Additionally, the composite leading indicator of the OECD and six major non-OECD countries will be used to measure the economic activity. This indicator is available on a monthly basis and is designed to detect turning points in business cycles with a lead time of 6 to 9 months. Although it is not a common proxy for the world GDP itself, it might give an advantage for forecasting due to its leading co-movement to the reference series.[7] Here, using the log-levels of the oil price and the composite-leading indicator outperforms the specification using log-differences. This model will be referred to as the 'VAR CLI' model.

2.2.6 Non-Oil Industrial Raw Materials

An additional way of constructing a real-time forecast would be to use the non-oil industrial raw materials index as discussed in Baumeister and Kilian (2012):

$$Y^{f}_{t+h|t} = Y_t(1 + \pi^{h,irm}_t - E(\pi^n_t)), \tag{5}$$

where $\pi^{h,irm}_t$ is the percentage change of the Commodity Research Bureau (CRB) index of the spot price of industrial raw materials other than oil over the preceding h months and $E(\pi^n_t)$ is the expected inflation over the same time horizon. Baumeister and Kilian (2012) find MSPE reductions of up to 25% in the short run for this model. Similarly, improvements have been confirmed by Alquist et al. (2013) for the nominal WTI and by Manescu and van Robays (2016) for the real price of Brent. This model will be referred to as the 'CRB Index' model.

2.2.7 Price Movements with Oil Sensitive Stocks

S.-S. Chen (2014) has introduced another model that is easy to implement for forecasting the real price of oil. Using monthly data from 1984.10 to 2012.08 S.-S. Chen (2014) shows that using oil sensitive stock price indices can improve the forecasts of nominal and real crude oil prices at short horizons. In particular, the New York Stock Exchange (NYSE) Arca AMEX oil index, which is a price-weighted index of the leading international oil and natural gas companies, can be used to improve the MSPE ratio up to 21% for forecasting the real WTI and real Brent crude oil price. The suggestions made in this paper will be adopted and the model will be referred to as the 'Oil Stock' model.

[7] In April 2012, the OECD replaced the index of industrial production covering all industry sectors excluding construction with the GDP as its new reference series.

2.2.8 Other Forecasting Methods

There exists a broad variety of other models in the literature of forecasting oil prices. For the sake of clarity, only two promising possibilities will be discussed in this section. Hence, one can model the forecast for oil prices by using the spread between the spot prices of gasoline and crude oil or by using a time-varying parameter model of gasoline and heating oil spreads which are both proposed by Baumeister et al. (2017). Both models have been shown to be more accurate than a no-change forecast especially at forecasting horizons beyond 1 year for the WTI price. Nevertheless, as pointed out by Baumeister and Kilian (2015), there is no long enough time series available of the relevant Rotterdam market for the gasoline spot price in order to forecast the Brent crude oil price.

In addition, the forecasting ability of several other models have been extensively studied which are not discussed in further detail in this paper. However, the interested reader will find a large number of other related forecasting techniques in the literature, including the use of forward prices (Chernenko et al. 2004), different variations of future price models (Alquist and Kilian 2010; Reeve and Vigfusson 2011), risk adjusted futures prices (Pagano and Pisani 2009), the price of crack spread futures (Murat and Tokat 2009), exchange rates (Y.-C. Chen et al. 2010), convenience yield predictions (Knetsch 2007), relative inventory and low- and high-inventory variables (Ye et al. 2005, 2006), model selection with parameter restricted models (Y. Wang et al. 2015), professional survey forecasts (Sanders et al. 2009), high frequency financial variables (Baumeister et al. 2015), hybrid methods (Han et al. 2017; J.-L. Zhang et al. 2015), technical indicators (Yin and Yang 2016) and time-varying parameter models (Y. Wang et al. 2017).

2.3 Data Sources and Preparation

The main focus of this work is to generate real-time forecasts of the real price of oil and to evaluate their out-of-sample performance. All the data used in this work are based on the premise of being subject to real-time data constraints. Table 2.1 summarizes the complete description of the data including the variable names, the sources and the used sample period. Some of the data used are available in real-time and are not revised over time, such as the Brent and WTI crude oil spot prices, monthly Brent and WTI futures prices with various maturities, the CRB index of the spot price of industrial raw materials other than oil and the NYSE Arca Amex oil index.

However, there are time series that are not available in real-time and are subject to revisions, which include global crude oil inventories, global crude oil production, US crude oil inventories, US petroleum stocks, OECD petroleum stocks, OECD composite leading indicator, world steel production and the US consumer price index for all urban consumers.

In order to estimate the out-of-sample forecasts, a real-time dataset has to be constructed first. Therefore, this work will follow the suggestions made by Baumeister and Kilian (2012) in constructing a real-time dataset for the variables required and extend it for the additional variables. To be precise, the time series for global crude oil inventories, global crude oil production, US petroleum inventories, US petroleum stocks and OECD petroleum stocks have been recovered by hand from the 'Monthly Energy Review' published by the EIA and consist of monthly vintages of data from 1991.01 to 2017.08 each dating back to 1973.01.[8] In addition, the used data are becoming only available with a notable delay and are subject to revisions.[9] The gaps in the real-time dataset will be extrapolated using the average rate of change in the earlier data up to that point in time of the time series in question as described in Baumeister and Kilian (2012).

[8] OECD petroleum stocks are not available prior to 1988.01 and have been extrapolated backwards by the growth rate of US petroleum stocks.

[9] Also the revisions are being potentially large, the real-time forecasts cannot be improved by taking into account a revision bias as the in-report revisions have shown to be near zero on average (Baumeister and Kilian 2012).

TABLE 2.1: Description of data

Name	Source	Code	Sample Period
Brent	FRED	DCOILBRENTEU	1987.06 - 2017.11
WTI	FRED	WTISPLC	1974.01 - 2017.11
RAC	FRED	-	1974.01 - 1987.06
CRB BLS Spot Index Raw Industrials	Datastream	CRBSPRI	1974.01 - 2017.11
NYSE Arca Oil Index	Yahoo Finance	ˆXOI	1983.09 - 2017.11
Global Crude Oil Inventories	EIA	-	1974.01 - 2017.08
US Crude Oil Inventories	EIA	-	1974.01 - 2017.10
Global Crude Oil Production	EIA	-	1974.01 - 2017.08
US Petroleum Stocks	EIA	-	1974.01 - 2017.08
OECD Petroleum Stocks	EIA	-	1974.01 - 2017.08
US Consumer Price Index	FRASER	CPIAUCSL	1988.01 - 1998.10
US Consumer Price Index	Federal Reserve Bank of Philadelphia	-	1974.01 - 2017.11
Continuous Futures WTI	Quandl	CME_CLXX	1983.01 - 2017.11
Continuous Futures Brent	Quandl	ICE_BXX	1983.01 - 2017.11
OECD CLI	OECD.Stat	-	1974.01 - 2017.10
World Steel Production	Datastream	WDSTEELPP	1990.01 - 2017.10
US Industrial Production of Construction Steel	FRED	IPN3311A2BN	1974.01 - 1990.01

The real-time US CPI data have been constructed by combining the Federal Reserve Archival System for Economic Research (FRASER) database of the Federal Reserve Bank of St. Louis with the real-time data set of the Federal Reserve Bank of Philadelphia. The latter consists of monthly vintages from 1998.11 to 2017.11 of which each dates back to 1947.01. The missing vintages between 1988.01 and 1998.10 have been added by using the FRASER data. Due to a lack of the complete history for these vintages, only the 18 recent months of each vintage can be found in this dataset. Therefore, the missing data have been filled in with values of the earlier vintages in this dataset. As before, missing data due to release delays have been extrapolated using the average rate of change of the time series.

Monthly averages of the Brent crude oil prices have been obtained from the Federal Reserve Economic Data (FRED) of the Federal Reserve Bank of St. Louis and are only available back to 1987.06. Hence, this time series has been backcasted by using the rate of change in the RAC for crude oil imports to 1974.01 as described in Baumeister and Kilian (2014). Since the oil price is typically traded in dollars, it is common to use the US CPI to deflate the nominal price of oil. Therefore, the monthly averages of Brent and WTI will be deflated using the real-time US CPI data described above. Monthly Brent and WTI futures prices used for this work are the end-of-the-month values of non-adjusted prices based on spot-month continuous contract calculations. The missing data of the Brent Futures contracts of different maturities are backcasted by the growth rate of the WTI contracts. Hence, the constructed Futures are available between 1988.12 and 2017.11. In addition, the OECD composite leading indicator is available only partially in real-time, is subject to revisions and has a publication lag of two months. The OECD provides an original release data and revisions database which includes the leading indicator in real-time with vintages from 2006.06 to 2017.10 for the amplitude adjusted indicator, which is constructed for the lead time optimization. Therefore, the missing data have been filled in with values of the latest vintage. Again, missing data due to release delays have been extrapolated using the average rate of change of the time series.

The world steel production is published with a delay of one month and is subject to revisions. Due to the revisions, the suggestions of Baumeister and Kilian (2014) will be followed while a three month publication lag is assumed and the missing data are extrapolated based on the average growth rate of the steel production. Values prior to 1990.01 are backcasted using the US production of construction steel. As such, the OECD composite leading indicator and the world steel production are only available in pseudo-real-time.

2.4 Individual Model Performance

Accounting for the different sample periods of the available data, recursively estimated monthly pseudo out-of-sample forecasts are constructed for the period between 1991.01 and 2017.11. The main objective is to forecast the latest release of the real Brent crude oil price.[10] All the models described in section 2 will be evaluated by means of a quadratic loss function. Thus, the MSPE ratios of the individual model will be compared to the no-change benchmark.

It is not possible to provide accurate p-values for equal predictive accuracy as no such tests are available at the moment. This is due to the fact that the forecasts are generated in real-time and are subject to revisions which violates the assumption of the data being stationary which in turn is required for standard tests. Furthermore, these tests are based on the population MSPE and not on the out-of-sample MSPE used in this work. However, as it is hard to draw conclusions about the forecasting performance without statistical tests, p-values for the test of equal predictive accuracy of Clark and West (2007) are reported. Nevertheless, these p-values should only be interpreted with caution as they are biased towards rejecting the null hypothesis of equal MSPE. A more detailed reasoning of why the available tests do not apply in this context can be found in Baumeister et al. (2015), Baumeister and Kilian (2012), Inoue and Kilian (2005), and Y. Wang et al. (2017) and references therein.

Moreover, the success ratio of the different models will be tested using the directional accuracy test by Pesaran and Timmermann (1995). Subsequently, the bias of the forecast errors will be examined to address a possible systematic distortion of the forecasts.

2.4.1 Forecasting Results

Table 2.2 summarizes the average forecasting performance of the individual models for forecasting horizons up to 24 months. A value lower than one indicates an improvement of the individual forecast as compared to the no-change benchmark on average over the complete sample period. Throughout all models under consideration, the 'Futures' model consistently outperforms the no-change forecast over all horizons and reduces the MSPE between 2% and 25%. The 'ARMA', 'VAR Steel' and the 'CRB Index' model offer gains in the MSPE ratio for short-term projections. However, for medium- and long-term projections the 'Inventories OECD', the 'Oil Stock' and the 'VAR CLI' model provide considerable reductions in the MSPE ratio. Additionally, the average forecasting performance across all 24 horizons confirms a good forecasting performance for the 'Futures', 'Inventories OECD', 'VAR CLI' and 'Oil Stock' model on average. The results for the directional accuracy test can be found in Table 2.3. At each horizon, there is at least one model that predicts the direction of change significantly better than the no-change benchmark. Again, the 'Futures' model seems to have the best performance and is significantly better at almost all horizons. While the 'Oil Stock' model shows a poor performance in this context, the 'CRB Index' shows the highest success ratio of all the models considered with up to 64% and the second highest performance on average with 58% across all horizons. In addition, the results for the 'Inventories OECD' and 'VAR CLI' model seem to be in alignment with the results obtained for the MSPE ratios.

[10] The results are robust with regard to the WTI price as well as to the chosen specification of the benchmark. The latter has been tested using an AR process and using the average growth rate of the real price of oil. A robustness check can be found in Appendix B.

TABLE 2.2: Recursive MSPE ratios relative to the no-change benchmark

Horizon	ARMA	Futures	Inventories OECD	VAR CLI	VAR Steel	CRB Index	Oil Stock
1	**0.9153** (0.1114)	**0.7549** (0.0004)	1.0751 (0.9956)	**0.8867** (0.1449)	**0.9535** (0.3046)	**0.9819** (0.4116)	1.0782 (0.9783)
2	**0.9453** (0.2309)	**0.9312** (0.0680)	1.0599 (0.9293)	**0.8612** (0.1537)	**0.9721** (0.2299)	**0.9302** (0.1980)	1.0005 (0.7316)
3	**0.9639** (0.3265)	**0.9641** (0.2095)	1.0239 (0.6973)	**0.8600** (0.1826)	**0.9675** (0.1728)	**0.9648** (0.3177)	**0.9988** (0.4433)
4	**0.9799** (0.4089)	**0.9763** (0.2908)	1.0219 (0.6911)	**0.8949** (0.2748)	**0.9982** (0.4723)	1.0334 (0.6824)	**0.9936** (0.3699)
5	**0.9880** (0.4493)	**0.9806** (0.3275)	1.0453 (0.8714)	**0.9539** (0.4149)	1.0188 (0.7898)	1.1246 (0.9429)	1.0051 (0.5280)
6	**0.9944** (0.4781)	**0.9746** (0.2888)	1.0619 (0.9254)	**0.9128** (0.3294)	1.0295 (0.9148)	1.1728 (0.9636)	**0.9876** (0.3749)
7	**0.9981** (0.4931)	**0.9616** (0.2044)	1.0455 (0.8855)	**0.8936** (0.2806)	1.0242 (0.8714)	1.1912 (0.9574)	**0.9843** (0.3699)
8	1.0007 (0.5023)	**0.9448** (0.1356)	1.0077 (0.6081)	**0.8853** (0.2497)	1.0211 (0.8359)	1.1814 (0.9395)	**0.9745** (0.3156)
9	1.0067 (0.5202)	**0.9287** (0.0998)	**0.9643** (0.1599)	**0.8993** (0.2573)	1.0230 (0.8584)	1.1653 (0.9075)	**0.9684** (0.2944)
10	1.0097 (0.5268)	**0.9285** (0.1245)	**0.9283** (0.0680)	**0.9181** (0.2869)	1.0150 (0.8131)	1.1230 (0.8240)	**0.9588** (0.2626)
11	1.0092 (0.5238)	**0.9003** (0.0753)	**0.9104** (0.0506)	**0.9399** (0.3357)	1.0084 (0.7847)	1.0942 (0.7448)	**0.9458** (0.2402)
12	1.0062 (0.5153)	**0.8486** (0.0143)	**0.9067** (0.0443)	**0.9550** (0.3762)	1.0058 (0.7745)	1.0807 (0.7019)	**0.9421** (0.2400)
13	1.0039 (0.5093)	**0.8314** (0.0130)	**0.9075** (0.0397)	**0.9677** (0.4109)	1.0097 (0.9288)	1.0802 (0.6962)	**0.9387** (0.2412)
14	1.0042 (0.5098)	**0.8154** (0.0143)	**0.9103** (0.0358)	**0.9759** (0.4343)	1.0071 (0.8714)	1.0856 (0.6962)	**0.9351** (0.2483)
15	1.0051 (0.5112)	**0.8071** (0.0218)	**0.9115** (0.0269)	**0.9873** (0.4658)	1.0058 (0.8723)	1.1114 (0.7393)	**0.9351** (0.2609)
16	1.0065 (0.5136)	**0.7977** (0.0288)	**0.9146** (0.0212)	**0.9992** (0.4979)	1.0058 (0.9221)	1.1537 (0.7952)	**0.9309** (0.2571)
17	1.0093 (0.5187)	**0.8001** (0.0428)	**0.9252** (0.0269)	1.0127 (0.5329)	1.0075 (0.9430)	1.1899 (0.8282)	**0.9341** (0.2706)
18	1.0138 (0.5374)	**0.7970** (0.0534)	**0.9427** (0.0981)	1.0246 (0.5630)	1.0080 (0.9221)	1.2369 (0.8654)	**0.9326** (0.2756)
19	1.0183 (0.5335)	**0.7978** (0.0701)	**0.9537** (0.0803)	1.0354 (0.5888)	1.0090 (0.9388)	1.2893 (0.8895)	**0.9285** (0.2732)
20	1.0214 (0.5374)	**0.8003** (0.0896)	**0.9585** (0.1409)	1.0451 (0.6099)	1.0093 (0.9462)	1.3316 (0.8932)	**0.9251** (0.2695)
21	1.0235 (0.5393)	**0.8040** (0.1099)	**0.9591** (0.1535)	1.0525 (0.6227)	1.0078 (0.9428)	1.3747 (0.8912)	**0.9307** (0.2814)
22	1.0222 (0.5358)	**0.7905** (0.1064)	**0.9595** (0.1600)	1.0614 (0.6367)	1.0065 (0.9065)	1.3983 (0.8816)	**0.9316** (0.2890)
23	1.018 (0.5284)	**0.7823** (0.1122)	**0.9660** (0.2039)	1.0669 (0.6443)	1.0065 (0.9060)	1.4237 (0.8751)	**0.9208** (0.2707)
24	1.0127 (0.5198)	**0.7542** (0.0816)	**0.9763** (0.2812)	1.0734 (0.6543)	1.0041 (0.8314)	1.4572 (0.8758)	**0.9181** (0.2701)
Average	**0.9990** (0.4737)	**0.8613** (0.1076)	**0.9723** (0.3403)	**0.9651** (0.4145)	1.0052 (0.7814)	1.1740 (0.7715)	**0.9583** (0.3482)

Note: Bold values denote an improvement relative to the no-change benchmark. P-values in parenthesis are based on the test of Clark and West (2007). The average across all 24 horizons is presented to assist the reader in summarizing the overall performance of the models and the average p-values should not be interpreted as anything other than a summary measure.

Subsequently, a systematic bias of the forecasts will be examined based on the 1-, 12-, 18- and 24-month forecast horizons. For this purpose, the following test equation was used:

$$Y_t = \beta_0 + \beta_1 Y^f_{t+h} + u_{t+h}, \tag{6}$$

where Y_t is the real price of oil and Y^f_{t+h} are the respective forecasts of the individual models. A good forecast under the given loss function should have no bias on average ($H_0 : \beta_0 = 0$) and should have a similar volatility ($H_0 : \beta_1 = 1$). However, a rejection of the null hypothesis for β_0 would lead to the conclusion of too high ($\beta_0 > 0$) or too low ($\beta_0 < 0$) forecasts on average whereas values less than one for β_1 would indicate a higher volatility of the forecasts on average. Table 2.4 summarize the forecast efficiency and asymptotic p-values for the t- and Wald-tests based on HAC standard errors which are used to account for the possible autocorrelation of u_{t+h} for horizons greater than one month.

TABLE 2.3: Recursive success ratios relative to the no-change benchmark

Horizon	ARMA	Futures	Inventories OECD	VAR CLI	VAR Steel	CRB Index	Oil Stock
1	0.52	**0.64**	0.53	0.53	0.51	0.55**	**0.56**
2	0.54*	**0.58**	0.47	0.53	0.49	0.52	0.36
3	0.50	0.53	0.52	**0.57**	0.52	**0.57**	0.50
4	0.51	**0.58**	0.47	**0.58**	0.50	**0.59**	0.47
5	0.50	0.53	0.46	0.55**	0.47	**0.56**	0.46
6	0.51	0.54**	0.49	0.54**	0.49	**0.57**	0.48
7	0.50	**0.57**	0.53	**0.57**	0.48	**0.58**	0.47
8	0.49	0.54**	0.56**	**0.56**	0.53	**0.58**	0.49
9	0.50	**0.59**	**0.58**	0.55**	0.54*	**0.57**	0.50
10	0.50	**0.59**	**0.58**	0.55**	0.52	**0.63**	0.50
11	0.53	**0.62**	**0.57**	**0.56**	0.52	**0.63**	0.53
12	0.52	**0.63**	**0.62**	0.56**	0.50	**0.63**	0.51
13	0.52	**0.61**	**0.59**	0.54**	0.49	**0.59**	0.49
14	0.53	**0.61**	**0.59**	0.54**	0.50	**0.62**	0.50
15	0.53	**0.60**	**0.61**	0.55**	0.52	**0.64**	0.49
16	0.55**	**0.62**	**0.57**	**0.57**	0.51	**0.63**	0.51
17	0.56**	**0.61**	**0.59**	0.55**	0.47	**0.61**	0.51
18	0.55*	**0.62**	**0.59**	0.54*	0.49	**0.60**	0.48
19	0.55**	**0.61**	0.56**	0.55*	0.48	**0.58**	0.50
20	0.54*	**0.61**	0.56**	0.52	0.46	**0.58**	0.47
21	0.55**	**0.61**	0.56**	0.54*	0.47	0.55**	0.46
22	0.55**	**0.60**	**0.57**	0.51	0.46	0.54*	0.47
23	0.54*	**0.63**	**0.58**	0.52	0.50	0.52	0.46
24	0.54*	**0.56**	0.52	0.52	0.50	0.52	0.49
Average	0.52	0.59**	0.55	0.55*	0.50	0.58**	0.49

Note: Bold values denote a significance level of $P<0.01$, ** and * 0.05 and 0.1, respectively based on the directional accuracy test by Pesaran and Timmermann (1995). The average across all 24 horizons is presented to assist the reader in summarizing the overall performance of the models and the average p-values should not be interpreted as anything other than a summary measure.

All models have no systematic distortion for 1-month ahead forecasts. This is different for greater forecast horizons. For 12-, 18- and 24-month horizons, all the examined models produce significantly too high forecasts on average except for the 'ARMA' model at 24 months. The results for the volatility are mixed for longer horizons between 18 and 24 months. While the 'Inventories OECD', 'Var Steel', 'CRB Index' and 'Oil Stock' model seem to underestimate the volatility on average, all other models are either closer to the desired level or overstate it on average. However, one has to reject the joint null hypothesis for all the models for horizons greater than one month. This leads to the conclusion, that it is possible to find a model that is better than a no-change benchmark for each particular horizon but that all the considered models have the disadvantage of being systematically biased at least at horizons greater than one month.

2.4.2 Individual Model Performance Over Time

This section addresses the idea of time-variation in the forecast accuracy for the considered models. Therefore, the MSPE ratios of the described models will be estimated using a 60-months window and plotted over time. This allows for a better illustration of the time-variation in the forecast performance than using a recursive approach where the MSPE ratio would still depend on forecasts of the beginning of the evaluation period (Manescu and van Robays 2016). Hence, a value lower than one states that the particular model outperforms the benchmark on average over the last 60 months and vice versa for values greater than one. The results are

TABLE 2.4: Forecast efficiency

1 Month Horizon	RW	ARMA	Futures	Inventories OECD	VAR CLI	VAR Steel	CRB Index	Oil Stock
β_0	0.2962	0.0934	−0.0140	0.3120	0.2439	0.4332	0.3710	0.3314
$H_0 : \beta_0 = 0$	0.0796	0.3194	0.4701	0.0788	0.1073	0.0154	0.0384	0.0698
β_1	0.9879	1.0013	0.9910	0.9868	0.9942	0.9811	0.9853	0.9885
$H_0 : \beta_1 = 1$	0.1404	0.4502	0.1824	0.1353	0.2804	0.0331	0.0961	0.1734
$H_0 : \beta_0 = 0, \beta_1 = 1$	0.3339	0.4392	0.0628	0.3330	0.2573	0.0960	0.1622	0.2000
12 Month Horizon								
β_0	4.8127	2.1842	3.8807	4.2386	3.5315	4.8609	6.3823	3.7167
$H_0 : \beta_0 = 0$	0.0000	0.0112	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
β_1	0.7966	0.9767	0.8634	0.8182	0.9012	0.7928	0.7300	0.8756
$H_0 : \beta_1 = 1$	0.0000	0.3344	0.0014	0.0000	0.0083	0.0000	0.0000	0.0035
$H_0 : \beta_0 = 0, \beta_1 = 1$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
18 Month Horizon								
β_0	6.6320	3.1715	5.4134	6.3033	5.2930	6.7253	8.9748	5.0379
$H_0 : \beta_0 = 0$	0.0000	0.0017	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
β_1	0.7289	0.9700	0.8446	0.7397	0.8619	0.7242	0.6218	0.8314
$H_0 : \beta_1 = 1$	0.0000	0.3113	0.0003	0.0000	0.0027	0.0000	0.0000	0.0002
$H_0 : \beta_0 = 0, \beta_1 = 1$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
24 Month Horizon								
β_0	6.7910	1.4691	4.8310	6.7817	4.8703	6.8523	11.2475	4.6521
$H_0 : \beta_0 = 0$	0.0000	0.1343	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
β_1	0.7600	1.1206	0.9335	0.7536	0.9428	0.7569	0.5451	0.8818
$H_0 : \beta_1 = 1$	0.0000	0.0550	0.0919	0.0000	0.1891	0.0000	0.0000	0.0112
$H_0 : \beta_0 = 0, \beta_1 = 1$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

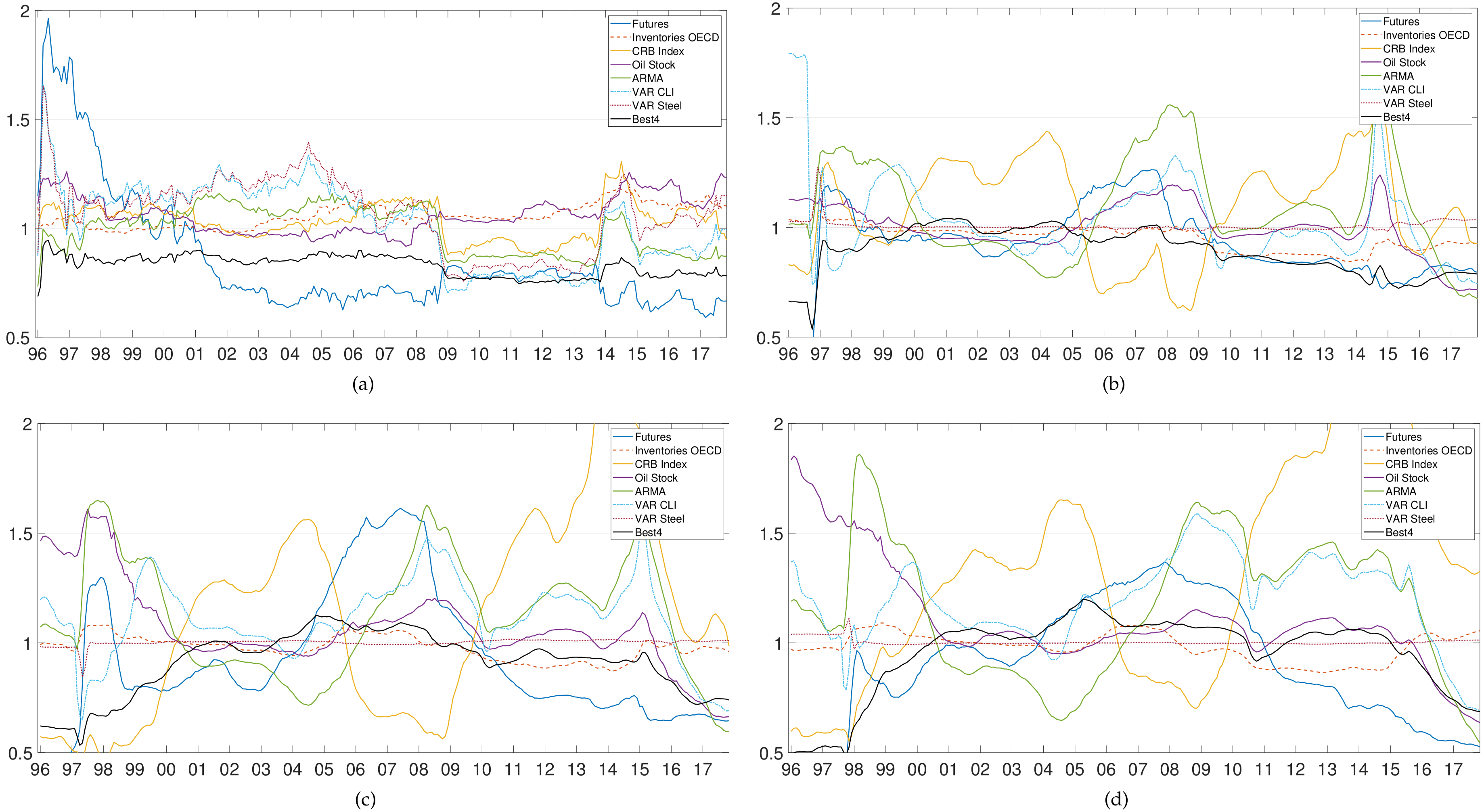
Note: Asymptotic p-values based on HAC standard errors.

summarized in Figure 2.1 for the individual models again for the 1-, 12-, 18- and 24-month forecasting horizon. First, when comparing the forecasting performance of the different models relative to the no-change benchmark, one can conclude that none of the models consistently outperforms the no-change forecast over time as well as across the different horizons.[11] Particularly apparent is that the two estimated VAR models, the 'ARMA' and the 'CRB Index' model have great problems over longer horizons when the market for oil is not in a calm situation. Nevertheless, at each point in time, there is at least one different model that works well.

There is an interesting pattern that emerges when comparing the 'Futures' model for horizons greater than one month. Even though, the 'Futures' model was better on average over the complete sample horizon, there exists a time period between 2004 and 2009 where the 'Inventories OECD' and the 'CRB Index' models outperform the 'Futures' model on average. However, we have to keep in mind that this graph shows the average performance over the preceding 60 months. Hence, this is mainly the 'relatively calm market' period described by Fan and Xu (2011) between 2000 and 2004. This reverses during the period of rapidly increasing prices between 2004 and 2008 and beyond as the 'Futures' model outperforms all the other models. These structural breaks can be best seen in Figure 2.1 (a) and explain the clearly visible breaks in this graph as the oil price is shifting from the 'relatively calm market' to the rapid increase in prices over to the post financial crisis with a delay of 60 months each. In addition, the 'VAR' model seems to capture different dynamics when compared to the three alternative VAR models. While the latter three face increasing MSPE ratios, the classic model points in the other

[11] The large MSPE ratios in the beginning of the sample can be explained due to the Gulf War shortly before the begin of the evaluation period.

FIGURE 2.1: Time-Variation of recursive MSPE ratio with a 1-, 12-, 18- and 24- month forecasting horizon



Note: This graph shows the recursive MSPE ratios estimated over a rolling window with a length of 60 months for all individual models and the best 4 model combination. Panel (a) shows the 1-, (b) the 12-, (c) the 18- and (d) the 24-month forecasting horizon.

direction. This effect reverses during the financial crisis. Nevertheless, none of the four variations seem to capture the price decline during the middle of 2014 well. All things considered, one can conclude that there might exist a combination of models that could be beneficial for the forecasting performance.

2.5 Forecast Combination Approaches

As of today, little is known about forecast combinations in the literature of oil price forecasting.[12] Nevertheless, combining different types of forecasting models has several advantages[13] that are motivated by the argument of portfolio diversification against risk (Timmermann 2006).

First of all, not all models work equally well at all times. For example, the 'CRB Index' model seems to work well during times of rising oil prices and low variation in economic fundamentals while others like the 'Futures' model show a better performance during times with high uncertainty. Second, there exist numerous models, such as the 'Inventories OECD' and the 'Oil Stock' model that are more accurate at longer horizons while others have shown to be more accurate at short term horizons on average. Furthermore, a combination of several models might gain efficiency when used to protect against structural breaks. While some models adjust rather quickly others might have parameters that adjust slowly to new post-break data. As a consequence, one would expect that quickly adjusting models perform relatively better as compared to slowly adapting models if only a limited amount of observations is available after the break and vice versa (Timmermann 2006). Hence, a combination of these two types of models might outperform the individual models as structural breaks are hard to detect in real-time (Pesaran and Timmermann 2007). As it is the standard approach in the literature, a combination that consists of all models and a combination selection based on the four most promising models, e.g. 'Futures', 'Inventories OECD', 'VAR CLI' and 'CRB Index' will be examined in more detail.[14] Furthermore, three different combination methods, which are summarized in Table 2.5 and 2.6, will be evaluated further. First, an equal weighted combination of all the used models will be investigated. In addition, there will be a combination where the weights of the models are based on the past forecasting performance of the preceding 36 months measured by the standard deviation of the forecast errors and by means of the MSPE ratio. Hence, the combination approaches will be examined during the time period 1994.01 to 2017.11. There are two main implications that can be drawn from the combination approaches: First, it is possible to generate a forecast that beats the no-change benchmark over all the examined horizons. This result holds for the all-model combination as well as for the one with the best four models. The latter combination has substantially larger reductions as high as 6% as compared to the all-model combination. In addition, the four-model combination reduces the MSPE ratio by up to 7% as compared to the 'Futures' model for horizons between 3 and 12 months but is outperformed over longer horizons. In addition, these results can be confirmed for the average forecasting performance over all horizons as well.

Second, a sensitivity analysis based on the three other different weighting schemes described above shows that an equal weighted combination is in general better suited than the other combination approaches examined. This is in line with the findings of Manescu and van

[12] See for example Baumeister and Kilian (2014, 2015) and Manescu and van Robays (2016) for an application of different types of combination approaches in the context of real-time forecasts of crude oil.

[13] A more detailed discussion about advantages and disadvantages of forecast combinations can be found in Timmermann (2006). Additionally, the reader will find more detailed information about how to construct such combinations and the obstacles associated with different loss functions.

[14] Although the 'CRB Index' model is outperformed by the benchmark for horizons greater than three months, it is the most promising one when it comes to the 'relatively calm market' period. Based on the graphic inspection in the previous section, it will offset the disadvantages of the 'Futures' forecast during this period.

TABLE 2.5: Recursive MSPE ratios relative to the no-change benchmark for an all model and a 4 model combination

Horizon	Equal	1/std	1/MSPE	Equal	1/std	1/MSPE
1	**0.8361** (0.0011)	**0.8457** (0.0016)	**0.8527** (0.0119)	**0.7880** (0.0000)	**0.8048** (0.002)	**0.8145** (0.0002)
2	**0.8994** (0.0180)	**0.9018** (0.0186)	**0.9030** (0.0187)	**0.8579** (0.0078)	**0.8704** (0.0136)	**0.8716** (0.0132)
3	**0.9097** (0.0458)	**0.9115** (0.0465)	**0.9122** (0.0474)	**0.8732** (0.0235)	**0.8815** (0.0333)	**0.8810** (0.0314)
4	**0.9267** (0.0889)	**0.9294** (0.0905)	**0.9303** (0.0937)	**0.9040** (0.0694)	**0.9052** (0.0726)	**0.9057** (0.0699)
5	**0.9402** (0.1390)	**0.9439** (0.1417)	**0.9465** (0.1560)	**0.9346** (0.1205)	**0.9333** (0.1068)	**0.9366** (0.1113)
6	**0.9513** (0.1381)	**0.9552** (0.1409)	**0.9592** (0.1650)	**0.9434** (0.1127)	**0.9474** (0.1160)	**0.9533** (0.1340)
7	**0.9480** (0.1197)	**0.9508** (0.1156)	**0.9564** (0.1062)	**0.9360** (0.0718)	**0.9429** (0.0822)	**0.9504** (0.1039)
8	**0.9348** (0.0855)	**0.9358** (0.0774)	**0.9424** (0.0943)	**0.9131** (0.0337)	**0.9205** (0.0412)	**0.9284** (0.0552)
9	**0.9227** (0.0698)	**0.9232** (0.0639)	**0.9318** (0.0756)	**0.8926** (0.0215)	**0.9001** (0.0284)	**0.9099** (0.0421)
10	**0.9063** (0.0473)	**0.9057** (0.0474)	**0.9160** (0.0654)	**0.8696** (0.0131)	**0.8766** (0.0179)	**0.8869** (0.0281)
11	**0.8918** (0.0359)	**0.8909** (0.0392)	**0.9028** (0.0515)	**0.8520** (0.0093)	**0.8587** (0.0131)	**0.8687** (0.0205)
12	**0.8816** (0.0349)	**0.8808** (0.0316)	**0.8920** (0.0300)	**0.8368** (0.0061)	**0.8442** (0.0088)	**0.8516** (0.0125)
13	**0.8786** (0.0387)	**0.8775** (0.0299)	**0.8892** (0.0491)	**0.8332** (0.0051)	**0.8419** (0.0077)	**0.8502** (0.0115)
14	**0.8765** (0.0501)	**0.8764** (0.0345)	**0.8892** (0.0555)	**0.8330** (0.0052)	**0.8449** (0.0090)	**0.8550** (0.0139)
15	**0.8783** (0.0652)	**0.8793** (0.0469)	**0.8944** (0.0737)	**0.8385** (0.0078)	**0.8543** (0.0147)	**0.8678** (0.0238)
16	**0.8808** (0.0848)	**0.8843** (0.0665)	**0.9009** (0.0993)	**0.8468** (0.0142)	**0.8686** (0.0304)	**0.8854** (0.0493)
17	**0.8869** (0.0316)	**0.8933** (0.0931)	**0.9111** (0.1347)	**0.8590** (0.0264)	**0.8855** (0.0591)	**0.9039** (0.0935)
18	**0.8940** (0.1073)	**0.9028** (0.1219)	**0.9235** (0.1779)	**0.8719** (0.0412)	**0.9053** (0.1002)	**0.9268** (0.1596)
19	**0.8997** (0.1313)	**0.9122** (0.1586)	**0.9357** (0.2299)	**0.8827** (0.0631)	**0.9249** (0.1667)	**0.9493** (0.2551)
20	**0.9017** (0.1498)	**0.9165** (0.1869)	**0.9431** (0.2713)	**0.8879** (0.0869)	**0.9368** (0.2302)	**0.9645** (0.3396)
21	**0.9037** (0.1693)	**0.9195** (0.2136)	**0.9491** (0.3095)	**0.8910** (0.1141)	**0.9447** (0.2856)	**0.9772** (0.4095)
22	**0.8996** (0.1752)	**0.9153** (0.2196)	**0.9464** (0.3157)	**0.8863** (0.1254)	**0.9419** (0.2975)	**0.9764** (0.4171)
23	**0.8957** (0.1808)	**0.9125** (0.2269)	**0.9462** (0.3269)	**0.8847** (0.1399)	**0.9432** (0.3175)	**0.9807** (0.4386)
24	**0.8967** (0.1923)	**0.9153** (0.2439)	**0.9437** (0.3267)	**0.8880** (0.1578)	**0.9500** (0.3477)	**0.9800** (0.4401)
Average	**0.9017** (0.0924)	**0.9075** (0.1024)	**0.9216** (0.1414)	**0.8752** (0.0532)	**0.8970** (0.1000)	**0.9115** (0.1364)

Note: The left panel shows the all model combination and the right panel shows the 4 model combination consisting of the 'Futures', 'Inventories OECD', 'VAR CLI' and 'CRB Index' model. Bold values denote an improvement relative to the no-change benchmark. P-values in parenthesis are based on the test of Clark and West (2007). The average across all 24 horizons is presented to assist the reader in summarizing the overall performance of the models and the average p-values should not be interpreted as anything other than a summary measure.

Robays (2016) and Baumeister et al. (2015, 2014). Furthermore, a leave one out sensitivity analysis of the four-model combination in Table 2.7 reveals that the results are remarkably robust over all horizons. In addition, when looking at the time-variation in Figure 2.1, one can see that a combination is stable in the short and medium run. This result does only hold partially for the calm market period when looking at 18- and 24-month forecasting horizons. Nevertheless, the conclusion holds that the four-model combination is exceptionally stable in the short and medium-run and should be preferred over a single model.

TABLE 2.6: Recursive success ratios relative to the no-change benchmark for an all model and a 4 model combination

Horizon	Equal	1/std	1/MSPE	Equal	1/std	1/MSPE
1	**0.58**	0.56**	0.57**	**0.63**	**0.62**	**0.63**
2	0.55**	0.56**	0.55**	**0.58**	**0.57**	**0.58**
3	**0.58**	**0.57**	0.56**	0.55**	**0.57**	0.56**
4	**0.59**	**0.59**	**0.62**	0.56**	**0.57**	**0.58**
5	0.55**	0.55**	0.55**	0.55**	0.55**	0.55**
6	0.52	0.52	0.51	0.53*	0.55**	0.53*
7	0.53*	0.53*	0.51	**0.60**	**0.61**	**0.59**
8	0.51	0.52*	0.51	**0.60**	**0.61**	0.56**
9	0.55**	0.55**	0.53**	**0.62**	**0.62**	**0.59**
10	**0.56**	**0.56**	**0.56**	**0.63**	**0.61**	**0.58**
11	**0.59**	**0.60**	**0.56**	**0.66**	**0.62**	**0.60**
12	**0.59**	**0.59**	**0.56**	**0.65**	**0.62**	**0.60**
13	**0.58**	**0.56**	0.55**	**0.61**	**0.58**	**0.56**
14	**0.59**	**0.60**	0.55**	**0.64**	**0.61**	**0.59**
15	**0.58**	**0.57**	**0.55**	**0.66**	**0.63**	**0.59**
16	**0.57**	**0.56**	0.54**	**0.64**	**0.61**	**0.58**
17	**0.56**	0.54**	0.51*	**0.61**	**0.58**	**0.53**
18	**0.57**	**0.55**	**0.55**	**0.63**	**0.59**	**0.54**
19	**0.57**	0.54**	**0.54**	**0.59**	**0.55**	0.49
20	**0.56**	**0.55**	0.53**	**0.56**	0.53**	0.47
21	**0.57**	**0.55**	0.52*	0.53**	0.51*	0.46
22	0.54**	0.52*	0.50	0.55**	0.48	0.48
23	**0.56**	0.52	0.48	0.55**	0.49	0.50
24	0.53**	0.51	0.46	0.52	0.44	0.49
Average	0.56**	0.55**	0.54	0.59**	0.57*	0.55*

Note: Bold values denote a significance level of P<0.01, ** and * 0.05 and 0.1, respectively based on the directional accuracy test by Pesaran and Timmermann (1995). The average across all 24 horizons is presented to assist the reader in summarizing the overall performance of the models and the average p-values should not be interpreted as anything other than a summary measure.

2.6 Uncertainty Analysis

In recent years, there has been paid increased attention to the uncertainty associated with the obtained point forecasts. A prominent example amongst others, in this context is the UK inflation forecast of the Bank of England which is communicated by using fan charts. This is particularly important as it gives a researcher information about the risk involved in using forecasting models. Hence, the forecast interval of the real price of oil provides an estimate of the probability of future values and gives a description of the associated uncertainty. For this reason, this section gives a brief overview of the uncertainty of the used forecasting models. Here, the probability of future values is based on the distribution of previous out-of-sample forecast errors. First, recursively estimated 5%, 25%, 50%, 75% and 95% quantiles of the out-of-sample forecast errors will be used to approximate the uncertainty of the obtained forecasts. For this, a starting window of 60 months, which leads to an evaluation period between 1996.01 and 2017.11, is chosen. Furthermore, this rather simple approach will be compared to a more sophisticated method as it is widely accepted that the coverage of these prediction intervals is in general too narrow (Chatfield 1996).

Again, recursively estimated forecast errors will be used for this purpose. However, the quantiles of interest will be determined by means of a quantile regression approach. The results for the density forecasts based on the quantiles of a 12-month forecasting horizon can be found in Figure 2.2. There are several things that are noteworthy. As to be expected, there is a general

TABLE 2.7: Leave one out sensitivity analysis of the 4 model combination

Horizon	Equal	Futures	Inventories	VAR	CRB
1	0.7880	−0.1078	0.0512	−0.0308	0.0143
2	0.8579	−0.0274	0.0286	−0.0524	−0.0214
3	0.8732	−0.0030	0.0192	−0.0592	−0.0121
4	0.9040	0.0088	0.0212	−0.0584	0.0093
5	0.9346	0.0103	0.0269	−0.0686	0.0322
6	0.9434	0.0010	0.0241	−0.0778	0.0345
7	0.9360	−0.0054	0.0172	−0.0783	0.0332
8	0.9131	−0.0081	0.0098	−0.0737	0.0259
9	0.8926	−0.0096	0.0024	−0.0642	0.0185
10	0.8696	−0.0057	−0.0022	−0.0564	0.0043
11	0.8520	−0.0080	−0.0013	−0.0484	−0.0049
12	0.8368	−0.0172	0.0022	−0.0428	−0.0088
13	0.8332	−0.0244	0.0019	−0.0388	−0.0114
14	0.8330	−0.0317	0.0015	−0.0359	−0.0106
15	0.8385	−0.0382	−0.0010	−0.0343	−0.0060
16	0.8468	−0.0461	−0.0037	−0.0336	0.0011
17	0.8590	−0.0499	−0.0020	−0.0309	0.0073
18	0.8719	−0.0582	−0.0026	−0.0331	0.0127
19	0.8827	−0.0646	−0.0042	−0.0356	0.0183
20	0.8879	−0.0680	−0.0054	−0.0374	0.0203
21	0.8910	−0.0704	−0.0070	−0.0405	0.0217
22	0.8863	−0.0744	−0.0059	−0.0405	0.0197
23	0.8847	−0.0784	−0.0036	−0.0414	0.0180
24	0.8880	−0.0854	−0.0007	−0.0426	0.0208
Average	0.8752	−0.0359	0.0069	−0.0482	0.0099

Note: Positive values indicate a decrease in the forecast performance relative to the equal weighted combination of all 4 models in column 1 if the model is left out of the combination. Including a model with a negative value would have increased the forecast performance if included in the forecast combination. The average across all 24 horizons is presented to assist the reader in summarizing the overall performance of the models.

tendency of having too narrow prediction bands which is clearly not desirable when it comes to forecast uncertainty. Nevertheless, there is a substantial difference between the individual models in terms of the width of the prediction band (especially after the financial crisis). For instance, the four VAR models have a considerable wider band as compared to the best four-model combination or the three inventories models. Additionally, none of the models was able to capture the financial crisis in a sufficient manner. However, the major decline in the Brent crude oil price between June 2014 and January 2015 was accounted for by most of the models in an adequate way. Especially, the four VAR models almost completely captured this decline within their 5% to 95% quantile band. Table 2.8 summarizes all the models by means of their failure rate. The failure rate is computed as the ratio between number of times that the Brent price lies outside the 90% prediction band and an expected failure rate of 26 observations. A value of '1' is the desirable outcome as it would indicate that the fit of the probability band is as good as expected. As stated in the beginning, the predictive bands are too narrow. This is confirmed by the failure rates, which are considerably high with values even greater than 5. All the models show this tendency over each forecasting horizon and display similar failure rates on average around 3.52 to 4.07.

However, this problem can be solved at least to some extent by using the quantile regression approach. First, Figure 2.3 shows a noticeable improvement of the coverage. Now, most of the models are able to capture the financial crisis and the decline in the oil price thereafter. This can also clearly be seen in Table 2.9. The failures are systematically closer to the desired outcome of '1' although the prediction bands are now overstating the uncertainty especially between 6-

TABLE 2.8: Failure rate based on quantiles of previous out-of-sample forecast errors

Horizon	RW	ARMA	Futures	Inventories OECD	VAR CLI	VAR Steel	CRB Index	Oil Stock	Best 4
1	2.81	2.85	2.50	2.77	2.62	2.92	2.62	2.46	2.65
2	2.73	2.73	2.58	2.65	2.50	2.69	2.58	2.73	2.73
3	2.50	2.92	2.54	2.31	2.42	2.42	2.62	2.50	2.50
4	2.73	3.04	3.00	2.54	2.50	2.38	2.54	2.73	2.54
5	2.77	3.23	3.38	2.46	2.46	2.58	2.65	3.15	2.42
6	2.85	3.23	3.58	2.77	2.54	2.77	2.50	2.92	2.58
7	3.00	3.58	3.62	3.00	3.08	3.00	2.88	3.19	2.69
8	2.96	3.62	4.00	2.96	3.38	2.96	2.96	3.12	3.08
9	3.15	3.96	4.04	3.08	3.50	3.27	3.23	3.23	3.38
10	3.35	4.15	4.08	3.27	4.04	3.73	3.77	3.58	3.73
11	3.77	4.23	4.35	3.62	3.85	3.65	3.46	3.85	4.04
12	3.73	4.27	4.23	3.69	3.65	3.65	3.77	3.69	3.92
13	3.85	4.12	4.00	3.77	3.81	3.50	3.50	4.04	4.08
14	3.69	4.12	4.08	3.58	3.69	3.58	3.81	3.65	4.19
15	3.58	4.15	4.00	3.92	3.81	3.58	3.85	3.65	4.42
16	3.88	3.96	4.31	3.96	4.12	3.88	4.19	4.00	4.31
17	4.08	4.23	4.42	4.12	4.12	4.08	4.19	4.00	4.19
18	4.31	4.35	4.50	4.19	4.00	4.19	4.12	4.08	4.23
19	4.54	4.69	4.54	4.04	4.46	4.69	4.73	4.08	4.77
20	4.50	4.62	4.73	4.42	4.50	4.58	5.23	4.04	4.77
21	4.50	4.69	5.31	4.46	4.38	4.35	5.19	4.04	4.54
22	4.62	4.85	5.38	4.50	4.46	4.54	5.35	4.08	4.42
23	4.35	4.50	5.50	4.23	4.65	4.27	5.50	4.12	4.38
24	4.42	4.58	5.08	4.23	4.62	4.42	5.46	4.04	4.54
Average	3.61	3.94	4.07	3.52	3.63	3.57	3.79	3.54	3.71

Note: The failure rate is computed as the ratio between number of times that the Brent price lies outside the 90% prediction band and an expected failure rate of 26 observations. The average across all 24 horizons is presented to assist the reader in summarizing the overall performance of the models.

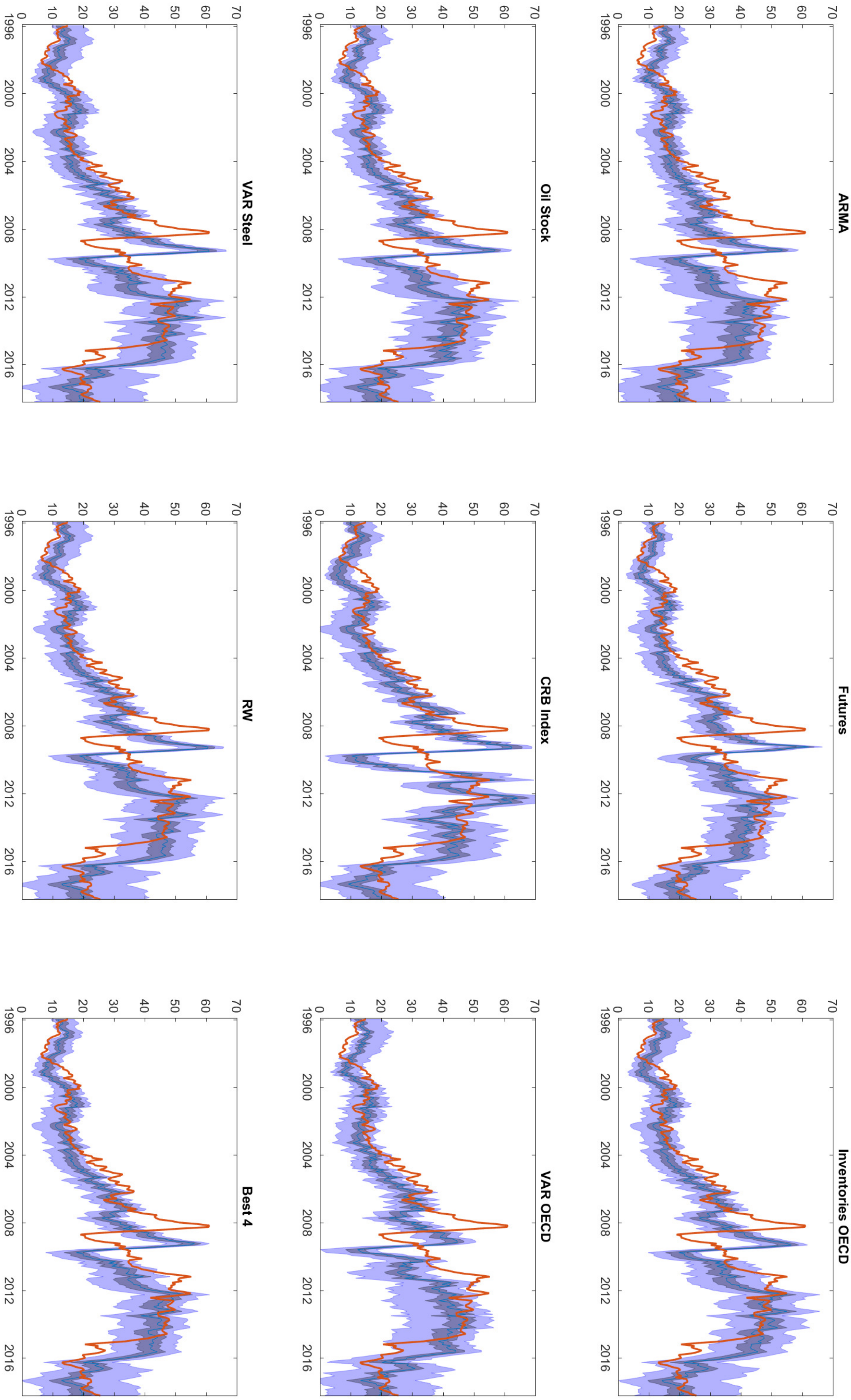
and 18-month forecasting horizons. However, the average failure rate confirms this impression as it ranges between 0.64 and 1.88. Yet, the 'ARMA', 'Futures' and 'VAR CLI' model have a too low coverage on average while all the others have the opposite problem.

TABLE 2.9: Failure rate based on a quantile regression approach using previous out-of-sample forecast errors

Horizon	RW	ARMA	Futures	Inventories OECD	VAR CLI	VAR Steel	CRB Index	Oil Stock	Best 4
1	1.58	1.21	2.46	1.83	1.25	1.54	1.46	1.54	1.29
2	1.92	1.92	1.96	1.71	1.42	1.88	1.38	1.83	1.75
3	1.50	1.92	1.79	1.38	1.42	1.54	1.25	1.54	1.54
4	1.13	1.38	1.29	1.33	1.88	1.00	0.75	1.17	1.38
5	0.83	1.67	1.17	0.96	1.67	0.88	0.88	1.50	1.21
6	0.71	0.75	1.00	0.71	1.29	0.79	0.96	0.75	0.75
7	0.54	0.54	1.08	0.63	0.42	0.54	0.54	0.50	0.50
8	0.54	0.71	1.13	0.79	0.42	0.58	0.63	0.46	0.50
9	0.54	0.92	1.21	0.71	0.54	0.54	0.58	0.46	0.46
10	0.63	0.79	1.04	0.71	0.83	0.54	0.50	0.46	0.50
11	0.79	0.63	0.79	0.71	0.96	0.79	0.88	0.38	0.71
12	0.67	0.79	0.88	0.63	0.96	0.79	0.88	0.29	0.58
13	0.79	0.96	0.33	0.63	1.33	0.79	0.92	0.46	0.75
14	0.54	1.00	0.42	0.50	1.29	0.46	1.00	0.38	0.54
15	0.63	1.08	0.38	0.54	1.42	0.25	1.17	0.21	0.33
16	0.71	1.29	0.33	0.75	1.92	0.71	0.88	0.21	0.21
17	0.58	1.50	0.42	0.54	2.42	0.67	0.46	0.38	0.17
18	0.29	1.54	0.46	0.38	2.54	0.33	0.54	0.33	0.33
19	0.50	1.88	0.25	0.67	2.96	0.54	0.50	0.33	0.29
20	0.33	2.21	1.58	0.46	2.92	0.42	0.33	0.13	0.29
21	0.50	2.71	2.33	0.96	3.38	0.50	0.29	0.50	0.29
22	0.50	3.17	2.46	1.13	3.75	0.50	0.21	0.67	0.67
23	0.79	3.38	2.83	1.63	3.79	0.79	0.38	0.50	1.46
24	1.08	3.21	2.71	1.88	4.25	1.04	0.63	0.42	2.04
Average	0.78	1.55	1.26	0.92	1.88	0.77	0.75	0.64	0.77

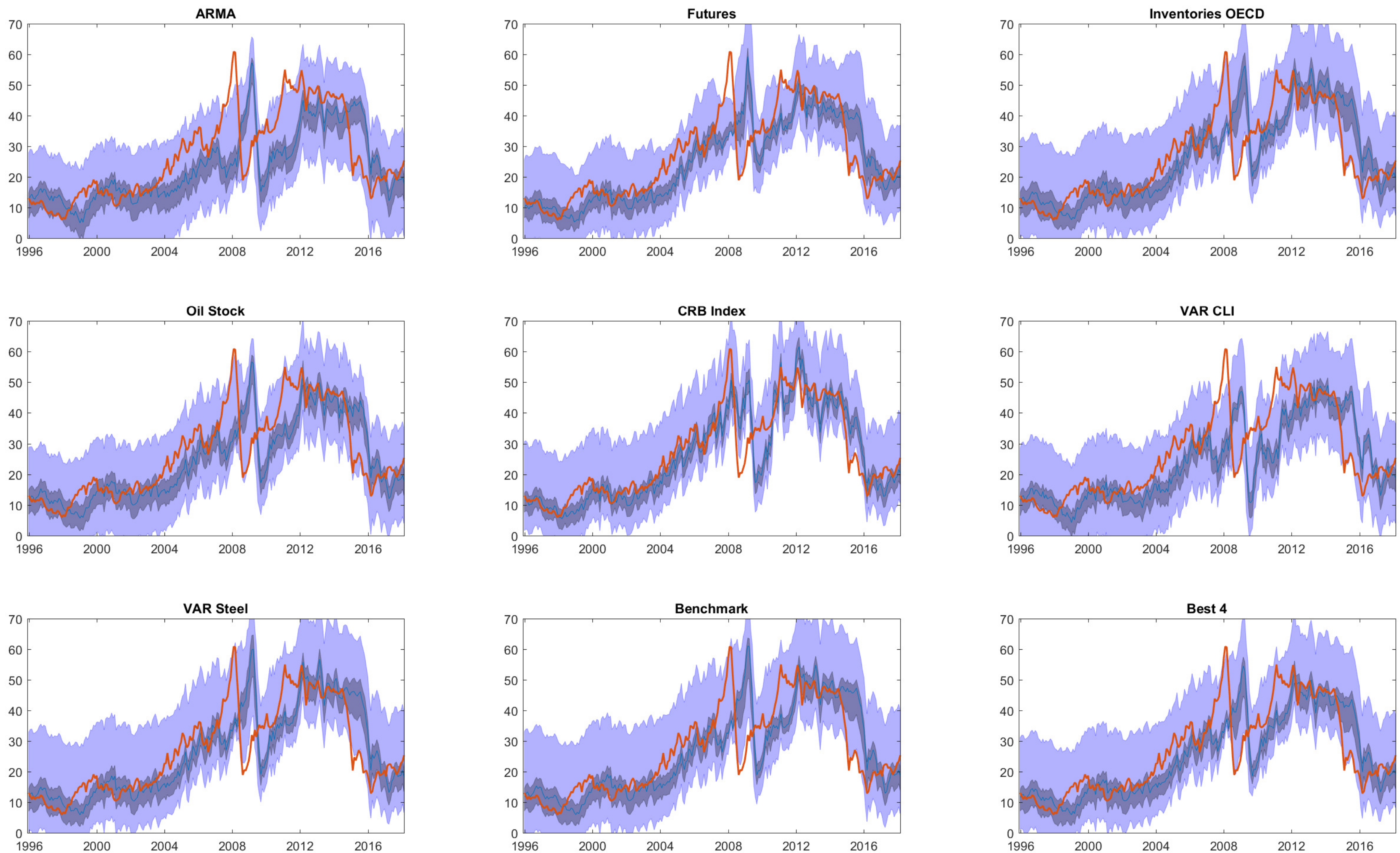
Note: The failure rate is computed as the ratio between number of times that the Brent price lies outside the 90% prediction band and an expected failure rate of 26 observations. The average across all 24 horizons is presented to assist the reader in summarizing the overall performance of the models.

FIGURE 2.2: Interval forecasts based on quantiles with a 12 month forecasting horizon



Note: The dark blue shaded area corresponds to the 25% and 75% quantiles. The light blue shaded area represents the 5% and 95% quantile. The blue line is the median forecast and the red line corresponds to the real price of crude oil.

FIGURE 2.3: Interval forecasts based on a quantile regression with a 12 month forecasting horizon



Note: The dark blue shaded area corresponds to the 25% and 75% quantiles. The light blue shaded area represents the 5% and 95% quantile. The blue line is the median forecast and the red line corresponds to the real price of crude oil.

2.7 Conclusion

The price of oil is a driving factor of the world economy, which is why a reliable forecast is important to evaluate possible economic fluctuations as well as to improve macroeconomic policy responses. The main focus of this work is to answer the question of whether it is possible to generate reliable long-term forecasts of the real price of Brent crude oil on a monthly basis. In addition, this work investigates the question if it is possible to obtain a forecast combination of different models which has a lower MSPE ratio as compared to individual models. For this purpose, some of the literature's standard models have been examined and extended by new model variations. Given the performance of the individual models it is possible to find a model that is better than a no-change benchmark for each particular horizon. The 'Futures' model provides substantial gains in terms of lowering the MSPE ratio by up to 25%. In addition, the newly introduced model variations of the classic inventories model provides better forecast over the medium and long run. Nevertheless, only the average forecast performance over the complete evaluation period has been addressed with this performance indicator. By evaluating the time performance of these models there are several interesting conclusions that can be drawn by using recursively MSPE ratios. First, when comparing the forecasting performance of the different models relative to the no-change benchmark over time, one can conclude that none of the models consistently outperforms the no-change forecasts over time as well as across the different horizons. This links directly to the idea of using a forecast combination approach. A combination consisting of four models, e.g. 'Futures', 'Inventories OECD', 'VAR CLI' and 'CRB Index' has shown to have a lower MSPE ratio than the best individual models over the medium run and, in addition, is remarkably stable over time. Although, the MSPE ratios are higher in the long run, the overall performance is clearly less volatile and thus seems to provide insurance against structural breaks. Furthermore, time variation plays an important role when predicting the future. Thus, the model used to construct reliable forecasts is not only highly dependent of the current economic situation but also on the loss function applied by the respective forecaster. Even though it is possible to construct a forecast that is superior to the no-change benchmark, the uncertainty analysis reveals the limitations of these models. The forecast interval of the real price of oil has been estimated by means of the quantiles of distribution of previous out-of-sample forecast errors and a quantile regression approach. The latter shows a great improvement of the failure rate and thus is able to capture the uncertainty of oil price substantially better. However, future research should concentrate more on the forecast uncertainty associated with the individual models as there is room for improvement.

B Appendix to Chapter 2

B.1 Other Forecasting Models

TABLE 2.10: Recursive MSPE ratios relative to the random walk benchmark

Horizon	AR	Inventories US	VAR	VAR IP
1	**0.9477** (0.2558)	1.0356 (0.9806)	**0.9956** (0.4839)	**0.9360** (0.2626)
2	**0.9677** (0.3506)	1.0338 (0.9172)	**0.9632** (0.3843)	**0.9131** (0.2323)
3	**0.9967** (0.4854)	1.0255 (0.8164)	**0.9642** (0.3925)	**0.9403** (0.3191)
4	1.0339 (0.6467)	1.0264 (0.8254)	1.0049 (0.5149)	**0.9987** (0.4959)
5	1.0551 (0.7241)	1.0333 (0.9060)	1.0389 (0.6213)	1.0550 (0.6767)
6	1.0616 (0.7384)	1.0342 (0.9145)	1.0565 (0.6879)	1.0803 (0.7843)
7	1.0694 (0.7542)	1.0177 (0.7875)	1.0770 (0.7673)	1.1118 (0.9053)
8	1.0780 (0.7707)	**0.9940** (0.3835)	1.0889 (0.7962)	1.1422 (0.9641)
9	1.0917 (0.7947)	**0.9709** (0.1289)	1.1060 (0.8200)	1.1747 (0.9833)
10	1.0980 (0.7930)	**0.9521** (0.0652)	1.1231 (0.8378)	1.1981 (0.9860)
11	1.0976 (0.7703)	**0.9430** (0.0502)	1.1366 (0.8411)	1.2105 (0.9841)
12	1.0909 (0.7351)	**0.9406** (0.0422)	1.1462 (0.8406)	1.2088 (0.9768)
13	1.0818 (0.7010)	**0.9400** (0.0355)	1.1447 (0.8263)	1.2000 (0.9639)
14	1.0763 (0.6771)	**0.9415** (0.0326)	1.1342 (0.7925)	1.1909 (0.9444)
15	1.0731 (0.6594)	**0.9417** (0.0244)	1.1282 (0.7639)	1.1832 (0.9204)
16	1.0719 (0.6484)	**0.9422** (0.0195)	1.1241 (0.7380)	1.1820 (0.9026)
17	1.0736 (0.6433)	**0.9469** (0.0230)	1.1235 (0.7196)	1.1863 (0.8933)
18	1.0781 (0.6437)	**0.9552** (0.0361)	1.1309 (0.7162)	1.1946 (0.8917)
19	1.0840 (0.6459)	**0.9604** (0.0609)	1.1384 (0.7148)	1.2064 (0.8949)
20	1.0888 (0.6465)	**0.9632** (0.0862)	1.1408 (0.7098)	1.2163 (0.8965)
21	1.0913 (0.6437)	**0.9639** (0.0954)	1.1408 (0.7016)	1.2219 (0.8925)
22	1.0918 (0.6389)	**0.9654** (0.1094)	1.1398 (0.6932)	1.2288 (0.8897)
23	1.0880 (0.6303)	**0.9710** (0.1500)	1.1352 (0.6826)	1.2342 (0.8884)
24	1.0821 (0.6201)	**0.9781** (0.2155)	1.1357 (0.6790)	1.2397 (0.8866)
Average	**0.9990** (0.4737)	**0.8613** (0.1076)	**0.9723** (0.1076)	1,1439 (0.8098)

Note: Bold values denote an improvement relative to the no-change benchmark. P-values in parenthesis are based on the test of Clark and West (2007). The average across all 24 horizons is presented to assist the reader in summarizing the overall performance of the models and the average p-values should not be interpreted as anything other than a summary measure.

TABLE 2.11: Recursive success ratios relative to the random walk benchmark

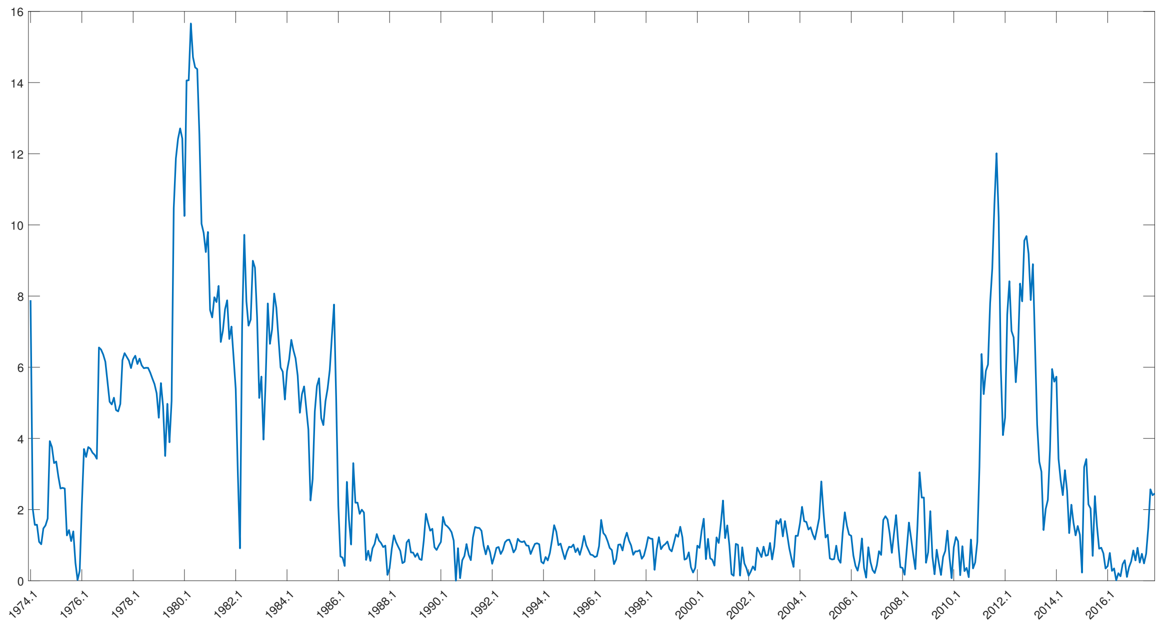
Horizon	AR	Inventories US	VAR	VAR IP
1	0.49	0.49	0.50	0.53
2	0.50	0.50	0.53	0.49
3	0.50	0.51	0.54	0.51
4	0.52	0.47	0.54	0.51
5	0.50	0.46	0.52	0.50
6	0.50	0.52	0.53	0.46
7	0.48	0.55**	0.50	0.45
8	0.47	**0.58**	0.51	0.44
9	0.46	0.56*	0.54	0.44
10	0.47	**0.58**	0.50	0.41
11	0.49	0.57*	0.51	0.43
12	0.47	0.55**	0.49	0.44
13	0.48	0.53	0.48	0.47
14	0.50	0.56*	0.48	0.48
15	0.49	0.56*	0.48	0.46
16	0.53	0.54**	0.50	0.49
17	0.53	**0.58**	0.52	0.47
18	0.53	0.56*	0.52	0.49
19	0.54*	0.54*	0.54**	0.49
20	0.52	0.54	0.52	0.48
21	0.54*	0.50	0.53	0.49
22	0.54	0.54	0.53	0.50
23	0.53	0.54**	0.53	0.49
24	0.53	0.49	0.56*	0.49

Note: Bold values denote a significance level of P<0.01, ** and * 0.05 and 0.1, respectively based on the directional accuracy test by Pesaran and Timmermann (1995). The average across all 24 horizons is presented to assist the reader in summarizing the overall performance of the models and the average p-values should not be interpreted as anything other than a summary measure.

B.2 Robustness Check

Of particular importance is the question to what extent the newly introduced models and the four-model combination are robust with regard to the chosen oil price benchmark. The WTI is a suitable benchmark as it is available in real time and as it is a widely accepted benchmark in comparable forecasting studies. Thus, the only thing that has been changed for this purpose is to replace the Brent futures prices by their respective WTI contracts. The results of this robustness check are presented in Table 2.12, 2.13 and 2.14. The statements made in the paper can in principle be confirmed for the WTI as well. Again, it is possible to find a forecast that is better than the no-change benchmark over each horizon. In addition, the 'Futures' model substantially outperforms the benchmark over all horizons with gains in the MSPE of more than 33% for the 1-month horizon. Besides, the 'Inventories OECD' performs worse than the classic model over all forecasting horizons and has even lower ratios as compared to the previous exercise with the Brent oil price by up to 12%. This is not surprising, as the US inventories should be better suited for the US rather than for the world market, and confirms the initial results in that sense. Moreover, the 'VAR CLI' exceeds the performance of the 'VAR Steel' model over all horizons with gains in the MSPE ratio of up to 11% as compared to the benchmark. It is worth noting, that the remaining models also show distinct improvements in many cases. One reason for this might be, that most of the considered models in this work were initially developed for the US market which differs from the market for Brent crude oil in a sense that the US government restricted the export of crude oil over the past 40 years. This is supported by the fact that the spread between WTI and Brent is not stable over time as can be seen in Figure 2.4. As argued in the beginning, the WTI reflects rather US than global oil market dynamics in particular, when the prices are more volatile during unstable economic times. This is notably evident during the recent financial crisis when the spread between Brent and WTI increased heavily. A forecast combination approach for the four-model combination shows a similar performance as well. This combination outperforms the WTI benchmark over all horizons and beats the 'Futures' model over the medium and long run with gains up to 5% in the MSPE ratio. Thus, we can conclude that the results are robust and can even be improved when compared to the WTI benchmark.

FIGURE 2.4: Spread between Brent and WTI



Note: Own calculation of the spread between the real price of Brent and WTI.

TABLE 2.12: Robustness check - Recursive MSPE ratios relative to the no-change benchmark for WTI

Horizon	ARMA	Futures	Inventories US	Inventories OECD	VAR CLI	VAR Steel	CRB Index	Oil Stock
1	**0.9028** (0.0791)	**0.6682** (0.0003)	1.4367 (1.0000)	1.4938 (1.0000)	**0.9029** (0.1913)	**0.9497** (0.2982)	**0.9553** (0.3249)	1.1230 (0.9938)
2	**0.9170** (0.1285)	**0.8596** (0.0296)	1.3317 (0.9972)	1.3592 (0.9982)	**0.8888** (0.2190)	**0.9623** (0.2150)	**0.8969** (0.1373)	1.0003 (0.6358)
3	**0.9379** (0.2077)	**0.8780** (0.0357)	1.2137 (0.9591)	1.2122 (0.9491)	**0.9041** (0.2660)	**0.9464** (0.1210)	**0.9427** (0.2298)	**0.9980** (0.3906)
4	**0.9487** (0.2660)	**0.8974** (0.0513)	1.1611 (0.9095)	1.1550 (0.8784)	**0.8813** (0.2411)	**0.9660** (0.1803)	1.0290 (0.6565)	**0.9949** (0.3735)
5	**0.9534** (0.2951)	**0.9066** (0.0694)	1.1922 (0.9394)	1.1951 (0.9239)	**0.8624** (0.2235)	**0.9791** (0.2473)	1.1337 (0.9536)	**0.9930** (0.4532)
6	**0.9581** (0.3241)	**0.9120** (0.0934)	1.2354 (0.9596)	1.2610 (0.9600)	**0.8566** (0.2085)	1.0032 (0.5633)	1.1955 (0.9742)	**0.9912** (0.3888)
7	**0.9587** (0.3370)	**0.9107** (0.1090)	1.1940 (0.9500)	1.2361 (0.9627)	**0.8667** (0.2037)	1.0056 (0.6232)	1.2196 (0.9694)	**0.9855** (0.3530)
8	**0.9568** (0.3411)	**0.9015** (0.1082)	1.0813 (0.8252)	1.1226 (0.9206)	**0.8723** (0.1909)	1.0055 (0.6280)	1.2165 (0.9601)	**0.9765** (0.2948)
9	**0.9555** (0.3475)	**0.8847** (0.0964)	**0.9586** (0.3504)	**0.9853** (0.4373)	**0.8825** (0.1847)	1.0065 (0.6587)	1.2092 (0.9424)	**0.9693** (0.2600)
10	**0.9523** (0.3477)	**0.8758** (0.0972)	**0.8573** (0.1601)	**0.8691** (0.1633)	**0.8931** (0.1922)	1.0017 (0.5592)	1.1799 (0.9029)	**0.9607** (0.2271)
11	**0.9478** (0.3431)	**0.8538** (0.0808)	**0.8017** (0.1079)	**0.8017** (0.1006)	**0.9009** (0.2036)	**0.9990** (0.4568)	1.1690 (0.8753)	**0.9522** (0.2146)
12	**0.9423** (0.3345)	**0.8320** (0.0708)	**0.7769** (0.0811)	**0.7756** (0.0764)	**0.9038** (0.2117)	**0.9998** (0.4894)	1.1677 (0.8615)	**0.9481** (0.2091)
13	**0.9392** (0.3308)	**0.8100** (0.0631)	**0.7684** (0.0669)	**0.7725** (0.0670)	**0.9050** (0.2110)	1.0029 (0.6682)	1.1862 (0.8716)	**0.9462** (0.2124)
14	**0.9371** (0.3309)	**0.7950** (0.0648)	**0.7715** (0.0594)	**0.7765** (0.0602)	**0.9058** (0.2092)	**0.9997** (0.4791)	1.1995 (0.8679)	**0.9422** (0.2174)
15	**0.9366** (0.3358)	**0.7827** (0.0713)	**0.7834** (0.0545)	**0.7888** (0.0562)	**0.9092** (0.2168)	**0.9985** (0.3696)	1.2253 (0.8735)	**0.9424** (0.2332)
16	**0.9376** (0.3451)	**0.7763** (0.0822)	**0.7995** (0.0568)	**0.8103** (0.0633)	**0.9187** (0.2421)	1.0008 (0.5937)	1.2596 (0.8825)	**0.9440** (0.2516)
17	**0.9393** (0.3554)	**0.7826** (0.1045)	**0.8330** (0.0821)	**0.8496** (0.0986)	**0.9281** (0.2697)	1.0041 (0.8707)	1.2848 (0.8874)	**0.9495** (0.2715)
18	**0.9427** (0.3689)	**0.7865** (0.1223)	**0.8833** (0.1417)	**0.9129** (0.2017)	**0.9396** (0.3026)	1.0064 (0.9162)	1.3223 (0.9037)	**0.9494** (0.2809)
19	**0.9467** (0.3835)	**0.7935** (0.1453)	**0.9137** (0.2149)	**0.9533** (0.3270)	**0.9482** (0.3308)	1.0071 (0.9106)	1.3815 (0.9180)	**0.9455** (0.2760)
20	**0.9509** (0.3976)	**0.8036** (0.1716)	**0.9166** (0.2350)	**0.9625** (0.3682)	**0.9543** (0.3539)	1.0070 (0.8955)	1.4332 (0.9192)	**0.9447** (0.2766)
21	**0.9546** (0.4099)	**0.8150** (0.1971)	**0.9011** (0.2073)	**0.9496** (0.3337)	**0.9606** (0.3792)	1.0051 (0.8759)	1.4738 (0.9128)	**0.9506** (0.2882)
22	**0.9561** (0.4163)	**0.8213** (0.2166)	**0.8852** (0.1826)	**0.9309** (0.2843)	**0.9675** (0.4053)	1.0034 (0.8099)	1.4913 (0.9014)	**0.9574** (0.3140)
23	**0.9561** (0.4187)	**0.8271** (0.2327)	**0.8930** (0.2026)	**0.9325** (0.2918)	**0.9714** (0.4198)	1.0034 (0.8198)	1.5038 (0.8916)	**0.9491** (0.2940)
24	**0.9568** (0.4219)	**0.8347** (0.2502)	**0.9252** (0.2796)	**0.9606** (0.3749)	**0.9811** (0.4484)	1.0026 (0.7708)	1.5172 (0.8867)	**0.9497** (0.3016)
Average	**0.9452** (0.3278)	**0.8337** (0.1068)	**0.9798** (0.4176)	1.0028 (0.4541)	**0.9127** (0.2636)	**0.9944** (0.5842)	1.2331 (0.8127)	**0.9693** (0.3338)

Note: Bold values denote an improvement relative to the no-change benchmark. P-values in parenthesis are based on the test of Clark and West (2007). The average across all 24 horizons is presented to assist the reader in summarizing the overall performance of the models and the average p-values should not be interpreted as anything other than a summary measure.

TABLE 2.13: Recursive success ratios relative to the no-change benchmark

Horizon	ARMA	Futures	Inventories US	Inventories OECD	VAR CLI	VAR Steel	CRB Index	Oil Stock
1	0.54*	**0.67**	0.42	0.47	0.56**	0.56**	0.53*	0.55**
2	0.55**	**0.59**	0.47	0.47	0.55**	0.51	0.55**	0.39
3	0.51	**0.57**	0.53	0.52	**0.59**	0.54	**0.59**	0.49
4	0.49	**0.58**	0.53	0.50	**0.61**	0.54*	**0.60**	0.49
5	0.48	0.54**	0.50	0.50	**0.59**	0.49	0.56**	0.50
6	0.48	0.56**	0.47	0.48	**0.59**	0.48	0.56**	0.46
7	0.49	**0.58**	0.47	0.47	**0.60**	0.49	0.55**	0.47
8	0.50	**0.58**	0.49	0.49	**0.60**	0.51	0.54**	0.47
9	0.48	**0.59**	0.53	0.51	**0.57**	0.51	0.55**	0.50
10	0.47	**0.62**	0.55**	0.54*	**0.58**	0.54	**0.59**	0.47
11	0.50	**0.63**	**0.58**	0.56**	**0.58**	0.54*	**0.60**	0.50
12	0.50	**0.65**	**0.60**	**0.59**	0.55**	0.49	**0.59**	0.46
13	0.50	**0.63**	**0.62**	**0.61**	0.54*	0.47	**0.58**	0.46
14	0.52	**0.65**	**0.63**	**0.65**	0.56**	0.52	**0.60**	0.47
15	0.53	**0.66**	**0.65**	**0.65**	**0.58**	0.54	**0.59**	0.47
16	0.53	**0.63**	**0.67**	**0.67**	**0.58**	0.52	**0.59**	0.51
17	0.50	**0.63**	**0.64**	**0.65**	0.54**	0.52	**0.58**	0.44
18	0.52	**0.63**	**0.62**	**0.65**	0.54*	0.54*	**0.59**	0.48
19	0.52	**0.63**	**0.61**	**0.65**	0.53	0.51	**0.57**	0.47
20	0.52	**0.59**	**0.59**	0.57**	0.51	0.52	**0.57**	0.49
21	0.52	**0.57**	**0.62**	**0.60**	0.50	0.51	0.54**	0.50
22	0.53	**0.59**	**0.64**	**0.64**	0.51	0.53	0.55**	0.50
23	0.52	**0.60**	**0.65**	**0.61**	0.50	0.55**	0.53*	0.48
24	0.54	**0.59**	**0.63**	**0.60**	0.51	0.51	0.52	0.52
Average	0.51	**0.61**	0.57	0.56	0.56*	0.52	0.57**	0.48

Note: Bold values denote a significance level of P<0.01, ** and * 0.05 and 0.1, respectively based on the directional accuracy test by Pesaran and Timmermann (1995). The average across all 24 horizons is presented to assist the reader in summarizing the overall performance of the models and the average p-values should not be interpreted as anything other than a summary measure.

TABLE 2.14: Robustness check - Leave one out sensitivity analysis of the 4 model combination relative to the WTI benchmark

Horizon	Equal	Futures	Inventories	VAR	CRB
1	0.8028	−0.1472	0.0920	−0.0485	−0.0078
2	0.8565	−0.0539	0.0538	−0.0598	−0.0349
3	0.8635	−0.0360	0.0295	−0.0479	−0.0199
4	0.8914	−0.0310	0.0259	−0.0510	−0.0020
5	0.9278	−0.0343	0.0357	−0.0743	0.0176
6	0.9561	−0.0386	0.0446	−0.0913	0.0248
7	0.9524	−0.0363	0.0339	−0.0902	0.0302
8	0.9145	−0.0269	0.0075	−0.0775	0.0333
9	0.8711	−0.0190	−0.0204	−0.0609	0.0357
10	0.8328	−0.0109	−0.0398	−0.0449	0.0294
11	0.8076	−0.0117	−0.0492	−0.0352	0.0261
12	0.7934	−0.0161	−0.0504	−0.0312	0.0228
13	0.7883	−0.0246	−0.0516	−0.0306	0.0261
14	0.7869	−0.0311	−0.0511	−0.0316	0.0301
15	0.7901	−0.0385	−0.0491	−0.0337	0.0361
16	0.7983	−0.0452	−0.0459	−0.0370	0.0405
17	0.8126	−0.0474	−0.0356	−0.0401	0.0430
18	0.8330	−0.0555	−0.0252	−0.0486	0.0427
19	0.8503	−0.0625	−0.0220	−0.0565	0.0472
20	0.8571	−0.0644	−0.0246	−0.0614	0.0497
21	0.8574	−0.0632	−0.0293	−0.0646	0.0499
22	0.8509	−0.0609	−0.0322	−0.0643	0.0448
23	0.8492	−0.0598	−0.0283	−0.0660	0.0374
24	0.8573	−0.0615	−0.0202	−0.0692	0.0300
Average	0.8500	−0.0449	−0.0105	−0.0548	0.0264

Note: Positive values indicate a decrease in the forecast performance relative to the equal weighted combination of all 4 models in column 1 if the model is left out of the combination. Including a model with a negative value would have increased the forecast performance if included in the forecast combination. The average across all 24 horizons is presented to assist the reader in summarizing the overall performance of the models.

B.3 Alternative Benchmarks

TABLE 2.15: Recursive MSPE ratios relative to a benchmark computed using the average growth rate of the real price of Brent oil

Horizon	ARMA	Futures	Inventories OECD	VAR CLI	VAR Steel	CRB Index	Oil Stock
1	**0.9135** (0.1056)	**0.7534** (0.0004)	1.0729 (0.9945)	**0.8849** (0.1402)	**0.9516** (0.2965)	**0.9800** (0.4016)	1.0760 (0.9752)
2	**0.9413** (0.2157)	**0.9273** (0.0575)	1.0555 (0.9121)	**0.8576** (0.1471)	**0.9680** (0.1989)	**0.9263** (0.1845)	**0.9963** (0.0801)
3	**0.9575** (0.3002)	**0.9577** (0.1719)	1.0172 (0.6417)	**0.8543** (0.1735)	**0.9611** (0.1399)	**0.9584** (0.2885)	**0.9921** (0.2192)
4	**0.9712** (0.3722)	**0.9676** (0.2243)	1.0127 (0.6109)	**0.8869** (0.2606)	**0.9892** (0.3505)	1.0242 (0.6351)	**0.9847** (0.2344)
5	**0.9770** (0.4056)	**0.9697** (0.2415)	1.0337 (0.7973)	**0.9433** (0.3959)	1.0075 (0.6194)	1.1121 (0.9315)	**0.9940** (0.4674)
6	**0.9814** (0.4291)	**0.9619** (0.2008)	1.0480 (0.8733)	**0.9009** (0.3089)	1.0160 (0.7782)	1.1575 (0.9580)	**0.9747** (0.2698)
7	**0.9831** (0.4404)	**0.9471** (0.1312)	1.0297 (0.7908)	**0.8802** (0.2583)	1.0088 (0.6752)	1.1733 (0.9502)	**0.9695** (0.2684)
8	**0.9838** (0.4473)	**0.9289** (0.0829)	**0.9907** (0.3800)	**0.8704** (0.2251)	1.0039 (0.5817)	1.1615 (0.9276)	**0.9581** (0.2216)
9	**0.9880** (0.4636)	**0.9114** (0.0603)	**0.9464** (0.0955)	**0.8826** (0.2259)	1.0040 (0.5866)	1.1437 (0.8884)	**0.9505** (0.2011)
10	**0.9893** (0.4701)	**0.9098** (0.0767)	**0.9096** (0.0450)	**0.8996** (0.2465)	**0.9945** (0.3651)	1.1003 (0.7894)	**0.9395** (0.1742)
11	**0.9875** (0.4671)	**0.8809** (0.0453)	**0.8908** (0.0330)	**0.9197** (0.2848)	**0.9867** (0.1847)	1.0706 (0.6992)	**0.9254** (0.1596)
12	**0.9831** (0.4573)	**0.8292** (0.0078)	**0.8859** (0.0274)	**0.9331** (0.3175)	**0.9828** (0.1488)	1.0559 (0.6511)	**0.9205** (0.1560)
13	**0.9796** (0.4497)	**0.8113** (0.0065)	**0.8856** (0.0226)	**0.9443** (0.3453)	**0.9853** (0.1616)	1.0541 (0.6415)	**0.9160** (0.1541)
14	**0.9786** (0.4486)	**0.7946** (0.0068)	**0.8871** (0.0182)	**0.9510** (0.3629)	**0.9814** (0.1154)	1.0578 (0.6435)	**0.9112** (0.1599)
15	**0.9781** (0.4494)	**0.7855** (0.0105)	**0.8871** (0.0117)	**0.9608** (0.3902)	**0.9789** (0.0963)	1.0816 (0.6918)	**0.9101** (0.1681)
16	**0.9783** (0.4516)	**0.7754** (0.0142)	**0.8890** (0.0076)	**0.9713** (0.4195)	**0.9776** (0.0866)	1.1214 (0.7578)	**0.9049** (0.1632)
17	**0.9799** (0.4569)	**0.7769** (0.0219)	**0.8983** (0.0085)	**0.9832** (0.4529)	**0.9781** (0.0998)	1.1552 (0.7980)	**0.9069** (0.1698)
18	**0.9832** (0.4653)	**0.7729** (0.0278)	**0.9143** (0.0178)	**0.9937** (0.4821)	**0.9776** (0.1036)	1.1996 (0.8428)	**0.9045** (0.1728)
19	**0.9867** (0.4736)	**0.7730** (0.0381)	**0.9240** (0.0411)	1.0032 (0.5089)	**0.9777** (0.1183)	1.2492 (0.8727)	**0.8997** (0.1702)
20	**0.9888** (0.4787)	**0.7748** (0.0513)	**0.9279** (0.0687)	1.0117 (0.5323)	**0.9771** (0.1317)	1.2891 (0.8792)	**0.8955** (0.1656)
21	**0.9901** (0.4820)	**0.7778** (0.0662)	**0.9278** (0.0808)	1.0182 (0.5484)	**0.9749** (0.1305)	1.3299 (0.8789)	**0.9004** (0.1694)
22	**0.9880** (0.4789)	**0.7641** (0.0643)	**0.9274** (0.0875)	1.0259 (0.5659)	**0.9729** (0.1363)	1.3516 (0.8695)	**0.9005** (0.1747)
23	**0.9831** (0.4707)	**0.7555** (0.0696)	**0.9329** (0.1111)	1.0303 (0.5751)	**0.9720** (0.1412)	1.3749 (0.8631)	**0.8892** (0.1618)
24	**0.9769** (0.4604)	**0.7275** (0.0473)	**0.9418** (0.1513)	1.0355 (0.5864)	**0.9686** (0.1197)	1.4057 (0.8640)	**0.8856** (0.1607)
Average	**0.9770** (0.4225)	**0.8431** (0.0719)	**0.9515** (0.2845)	**0.9434** (0.3648)	**0.9832** (0.2653)	1.1473 (0.7462)	**0.9377** (0.2257)

Note: Bold values denote an improvement relative to the no-change benchmark. P-values in parenthesis are based on the test of Clark and West (2007). The average across all 24 horizons is presented to assist the reader in summarizing the overall performance of the models and the average p-values should not be interpreted as anything other than a summary measure.

TABLE 2.16: Recursive MSPE ratios relative to an AR Benchmark

Horizon	ARMA	Futures	Inventories OECD	VAR CLI	VAR Steel	CRB Index	Oil Stock
1	**0.9658** (0.1226)	**0.7965** (0.0261)	1.1344 (0.9147)	**0.9356** (0.0776)	1.0061 (0.5551)	**1.0361** (0.7124)	1.1377 (0.9286)
2	**0.9769** (0.2580)	**0.9623** (0.3485)	1.0953 (0.8164)	**0.8899** (0.0567)	1.0045 (0.5266)	**0.9612** (0.2820)	1.0339 (0.6517)
3	**0.9671** (0.2009)	**0.9672** (0.3734)	1.0273 (0.6202)	**0.8628** (0.0525)	**0.9706** (0.3370)	**0.9680** (0.3419)	1.0020 (0.5097)
4	**0.9478** (0.0906)	**0.9443** (0.2911)	**0.9883** (0.4346)	**0.8655** (0.1105)	**0.9654** (0.3389)	**0.9995** (0.4981)	**0.9610** (0.2946)
5	**0.9363** (0.0568)	**0.9294** (0.2505)	**0.9906** (0.4524)	**0.9041** (0.2666)	**0.9655** (0.3516)	1.0658 (0.6952)	**0.9526** (0.1350)
6	**0.9367** (0.0686)	**0.9180** (0.2244)	**1.0002** (0.5010)	**0.8598** (0.1501)	**0.9697** (0.3813)	1.1047 (0.7630)	**0.9302** (0.1258)
7	**0.9333** (0.0681)	**0.8992** (0.1730)	**0.9776** (0.4129)	**0.8356** (0.0882)	**0.9577** (0.3480)	1.1139 (0.7683)	**0.9204** (0.0865)
8	**0.9282** (0.0672)	**0.8764** (0.1235)	**0.9347** (0.2575)	**0.8212** (0.0544)	**0.9472** (0.3188)	1.0959 (0.7314)	**0.9040** (0.0466)
9	**0.9221** (0.0652)	**0.8507** (0.0843)	**0.8833** (0.1182)	**0.8237** (0.0379)	**0.9371** (0.2927)	1.0674 (0.6639)	**0.8871** (0.0271)
10	**0.9195** (0.0695)	**0.8456** (0.0863)	**0.8454** (0.0618)	**0.8361** (0.0351)	**0.9243** (0.2636)	1.0227 (0.5521)	**0.8732** (0.0203)
11	**0.9195** (0.0671)	**0.8202** (0.0674)	**0.8295** (0.0556)	**0.8563** (0.0419)	**0.9187** (0.2618)	**0.9969** (0.4936)	**0.8617** (0.0164)
12	**0.9224** (0.0585)	**0.7779** (0.0392)	**0.8312** (0.0756)	**0.8755** (0.0563)	**0.9221** (0.2859)	**0.9907** (0.4829)	**0.8637** (0.0271)
13	**0.9280** (0.0530)	**0.7685** (0.0429)	**0.8389** (0.1048)	**0.8945** (0.0731)	**0.9333** (0.3255)	**0.9985** (0.4975)	**0.8677** (0.0400)
14	**0.9330** (0.0446)	**0.7576** (0.0445)	**0.8458** (0.1365)	**0.9067** (0.0791)	**0.9357** (0.3413)	1.0086 (0.5137)	**0.8688** (0.0506)
15	**0.9366** (0.0400)	**0.7521** (0.0511)	**0.8494** (0.1641)	**0.9200** (0.0955)	**0.9373** (0.3545)	1.0357 (0.5558)	**0.8715** (0.0677)
16	**0.9390** (0.0363)	**0.7443** (0.0549)	**0.8533** (0.1886)	**0.9322** (0.1210)	**0.9383** (0.3647)	1.0763 (0.6176)	**0.8685** (0.0808)
17	**0.9401** (0.0329)	**0.7453** (0.0649)	**0.8618** (0.2215)	**0.9433** (0.1688)	**0.9384** (0.3724)	1.1083 (0.6633)	**0.8701** (0.1018)
18	**0.9403** (0.0321)	**0.7392** (0.0681)	**0.8744** (0.2602)	**0.9503** (0.2218)	**0.9349** (0.3722)	1.1473 (0.7146)	**0.8650** (0.1074)
19	**0.9394** (0.0308)	**0.7360** (0.0740)	**0.8798** (0.2859)	**0.9551** (0.2658)	**0.9308** (0.3710)	1.1894 (0.7633)	**0.8566** (0.1077)
20	**0.9381** (0.0298)	**0.7351** (0.0797)	**0.8803** (0.3012)	**0.9598** (0.3026)	**0.9270** (0.3700)	1.2230 (0.7962)	**0.8496** (0.1108)
21	**0.9379** (0.0291)	**0.7368** (0.0861)	**0.8789** (0.3110)	**0.9645** (0.3314)	**0.9235** (0.3697)	1.2597 (0.8244)	**0.8529** (0.1342)
22	**0.9363** (0.0270)	**0.7241** (0.0782)	**0.8788** (0.3197)	**0.9722** (0.3694)	**0.9219** (0.3724)	1.2808 (0.8338)	**0.8533** (0.1461)
23	**0.9357** (0.0254)	**0.7191** (0.0757)	**0.8879** (0.3379)	**0.9807** (0.4093)	**0.9252** (0.3807)	1.3086 (0.8460)	**0.8463** (0.1395)
24	**0.9358** (0.0250)	**0.6969** (0.0552)	**0.9022** (0.3613)	**0.9919** (0.4620)	**0.9279** (0.3871)	1.3466 (0.8623)	**0.8484** (0.1462)
Average	**0.9382** (0.0666)	**0.8101** (0.1193)	**0.9154** (0.3214)	**0.9057** (0.1637)	**0.9443** (0.3601)	1.1002 (0.6447)	**0.9019** (0.1709)

Note: Bold values denote an improvement relative to the no-change benchmark. P-values in parenthesis are based on the test of Clark and West (2007). The average across all 24 horizons is presented to assist the reader in summarizing the overall performance of the models and the average p-values should not be interpreted as anything other than a summary measure.

Chapter 3

Oil Price and Cost of Debt: Evidence from Loans and Corporate Bonds

The following chapter is based on the paper:

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Oil Price and Cost of Debt: Evidence from Loans and Corporate Bonds[1]

Christoph FUNK[2,3] Karol KEMPA[4] Johannes LIPS[5]

Abstract

This paper empirically analyses the relationship between oil price and the costs of debt of firms in the US oil industry, which we categorize according to their position in the oil industry's value chain. We collect data on (i) individual syndicated loans taken, (ii) bonds issued, and (iii) bond trades on the secondary markets and combine this data with information from these firms' corporate financial statements. OLS estimates indicate controlling for firms' characteristics – such as firm size, profitability and leverage/indebtedness – a positive impact of oil price on the cost of debt. For bonds at issuance, findings are rather mixed. When accounting for time-invariant firm heterogeneity, the results change notably: We find that the within-firm effect of oil price on the cost of debt is negative. This negative impact is particularly strong for upstream and support services firms. The difference of the OLS estimates might be driven by unobserved firm heterogeneity or selection effects. Higher oil price volatility means higher uncertainty on the oil market and, as a consequence, capital markets charge higher prices for debt raised by oil firms.

Keywords: Corporate Finance, Debt, Energy Economics, Leverage, Oil Industry

JEL classification: C33, C58, G01, G30, Q40

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3.1 Introduction

The effects of oil price shocks on the (world) economy have been extensively studied over the last decade (Hamilton 2009; Kilian 2009; Kilian and Vigfusson 2011; Ravazzolo and Rothman 2013). Most of these studies focus on the effect of oil prices on macroeconomic aggregates such as real GDP or real consumption expenditure. Yet comparably little is known of the effects of these shocks at the firm level in the oil industry, especially with respect to the cost of debt. This is, however, of high relevance in the sector as debt is the main external source of finance used for funding real investments and maintaining flexibility in operations (Valta 2012). This is particularly relevant for the capital-intensive oil industry. At the same time, oil price fluctuations and shocks are likely to have a high impact on firms' risks of default and thus on their costs of debt. This paper aims to fill this gap by empirically analysing the impact of oil prices on the spreads of bank loans and corporate bonds of oil firms in the US.

Falling oil prices and shocks have several implications for the oil industry. First, oil firm's revenues decrease, which could also increase uncertainty around future oil prices and earnings. The uncertainty could increase further when price volatility is high. Second, assets backing a firm's debt could lose value. The effects on firm production and investment, however, are not clear. Firms with relatively high costs could reduce production or shut down completely (Sengupta et al. 2017). At the same time, firms with capacities and efficiencies that are not fully utilized could increase production to make up for the downward pressure on revenues caused by low prices (Cakir Melek 2015). Moreover, highly leveraged oil producers are likely to cut down their investment and increase production to generate cash flows needed to fulfill their debt obligations, which were able to be absorbed in the aftermath of the 2014 oil price shock (Lehn and Zhu 2016; Lips 2019). Rodziewicz (2018) shows that investments in the energy sector fell dramatically and were a drag on aggregate investment in the US. The higher risk of default is also likely to lead to rising financing costs for oil firms (Domanski et al. 2015).

Despite these channels through which the oil price may affect a firm's risk of default and thus its costs of debt, there is almost no empirical evidence on this issue. Debt financing and its cost is, however, essential for firms in the US oil industry and its importance has become particularly pronounced in recent years. Azar (2017) argues that access to relatively cheap debt in the aftermath of the financial crisis was a key fact in enabling investments in new technologies facilitating the "shale oil revolution". In this period, the indebtedness of US oil firms increased substantially. We fill this gap by empirically examining the relationship between the oil price, its volatility and specific shocks, and the costs of debt of US oil firms.

We investigate whether oil prices, in addition to directly affecting oil firms' sales revenues, have an impact on the price a firm has to pay to raise new debt. In general, firms can choose to raise debt through bank loans or on the capital markets by issuing bonds. In our analysis, we consider both forms of debt financing, thus expanding upon previous studies, such as Sengupta et al. (2017). Hence, we capture both the corporate bond and the banking markets, which are both frequently used by US oil firms. This allows us to examine whether banks and the capital market evaluate the effect of oil prices on the creditworthiness of oil firms differently. Furthermore, we can explicitly check whether certain effects could be driven by the specifics of the banking sector or debt markets.

We collect data on (i) syndicated loans taken and (ii) bonds issued by US oil firms as well as (iii) bonds traded on the secondary market. We then combine this data with information from these firms' corporate financial statements. Thus, we can analyze how a firm's (financial) characteristics – e.g. firm size, profitability, or leverage/indebtedness – affect the credit spread of loans and bonds, i.e. the cost of debt. In addition to these firm characteristics proposed in the financial economics literature (Chava et al. 2009; L. Chen et al. 2007; Dennis et al. 2000; Goss and Roberts 2011; Valta 2012), we take the oil price, oil price volatility and the macroeconomic environment into consideration. Furthermore, we categorize firms according to their position in the oil industry's value chain.

OLS estimates indicate that, even after controlling for loan/bond and firm characteristics, oil prices have a positive effect on the credit spread of loans issued to oil firms. The results are rather mixed for corporate bonds at issuance. When accounting for time-invariant firm heterogeneity, the results change notably. We find that the within-firm effect of oil price on the cost of debt is negative. The between effects results show that this negative impact is particularly strong for upstream and support services firms. Overall, our findings indicate that higher oil price volatility seems to lead to higher uncertainty about the market environment of oil firms on the secondary market. Consequently, capital markets charge higher prices for debt. The difference between the OLS and the within-between estimates might be driven by two factors. First, non-observable firm characteristics, which are only controlled for in the fixed effects (FE) estimation, and a possible selection effect possibly affecting the OLS findings.

The remainder of the paper is organized as follows: Section 3.2 reviews the literature on the determinants of firms' costs of debt and presents the specifics of debt in the oil industry. In Section 3.3, we describe the data set in detail. Section 3.4 first provides an exploratory data analysis and then presents the estimation approaches and their results. Section 3.5 concludes.

3.2 Debt Financing and the Oil Industry

3.2.1 Determinants of Sources and Costs of Debt

Firms have two main ways of obtaining external debt: issuing corporate bonds or taking out (syndicated) bank loans. Previous studies have analyzed both the drivers for choosing between these types of debt and, more closely related to this paper, the determinants of the characteristics of these bonds and loans. In a perfect capital market, all firms would be able to obtain funding for all investments with a positive net present value. In a market with frictions, such as information asymmetry, potential lenders are not able to evaluate a firm's quality, at least not without incurring costs, which may lead to credit rationing (Stiglitz and Weiss 1981).

Becker and Ivashina (2014) investigate firms' decisions to substitute loans for bonds and vice versa to raise external funds. The results of their firm-level analysis indicate that substitution of loans for bonds is particularly pronounced in times of tight lending markets, poor performance of the banking sector, and tight monetary policy. When interpreting these results, it must be kept in mind that the sample of firms is comprised of large firms, which can tap public debt markets more easily. This is also highlighted by Lemmon and Roberts (2010) who, by analyzing an exogenous shock to the supply of below-investment-grade credit after 1989, only observe limited substitution away from bank debt. Boneva and Linton (2017) investigate how the costs of funding in the corporate bond markets affect issuance decisions and especially focus on the importance of the transmission mechanism of monetary policy. The authors ascertain that the negative relationship between corporate bond yields and their issuance is driven by firms with low credit ratings. This effect is particularly strong in the aftermath of the financial crisis, which may indicate that it was probably more difficult for firms to obtain loans and that the bond market offered a viable alternative for firms to fulfil their financing needs (Farrant et al. 2013).

Greenwood et al. (2010) explain the time variation in the maturity of corporate debt with changes in the maturity structure of government debt, arguing that firms absorb supply shocks initially caused by the maturity choices of the government. This theoretical consideration is empirically tested by Greenwood and Vayanos (2014) and Badoer and James (2016), where the latter are particularly interested in very long-term corporate borrowing of 20 years or more. In a closely related paper, Graham et al. (2014) analyse the relationship between the US Government's fiscal policy and corporate financing decisions. They also highlight the empirical observation that firms do not switch between different sources of funding, which is consistent with Faulkender and Petersen (2006) and Leary (2009), for example, and indicates a segmentation within financial markets.

Faulkender and Petersen (2006) provide evidence of restrictions for the substitution between private and public debt in the presence of market frictions. The authors show that firms with access to public debt markets, proxied by the presence of a credit rating, typically have higher leverage compared to firms that have to borrow from banks. Furthermore, firms with a credit rating seem to mainly issue public debt. However, ratings also appear to matter for private debt. According to Sufi (2009), the introduction of ratings for syndicated loans led to increased debt issuance and investment by riskier borrowers. This suggests that these ratings were effective in reducing the informational frictions that cause segmentation, as noted by Faulkender and Petersen (2006).

Several articles focus on the role of different lender types in loan syndicates. In the presence of information asymmetries, lead banks in loan syndicates retain a higher share of the loan (Sufi 2007). Ivashina (2005, 2009) find that, controlling for borrowers' characteristics, a higher retained share of the lead bank seems to function as a signalling device that mitigates the problem of information asymmetry and consequently lowers the loan spread. Furthermore, the inclusion of non-bank institutions in the syndicate increases the loan spread (Lim et al. 2014). The authors argue that these institutions have a higher required rate of return than banks. Additionally, non-bank premiums are larger if the borrowing firms are facing financial constraints and the capital supply from banks is curtailed.

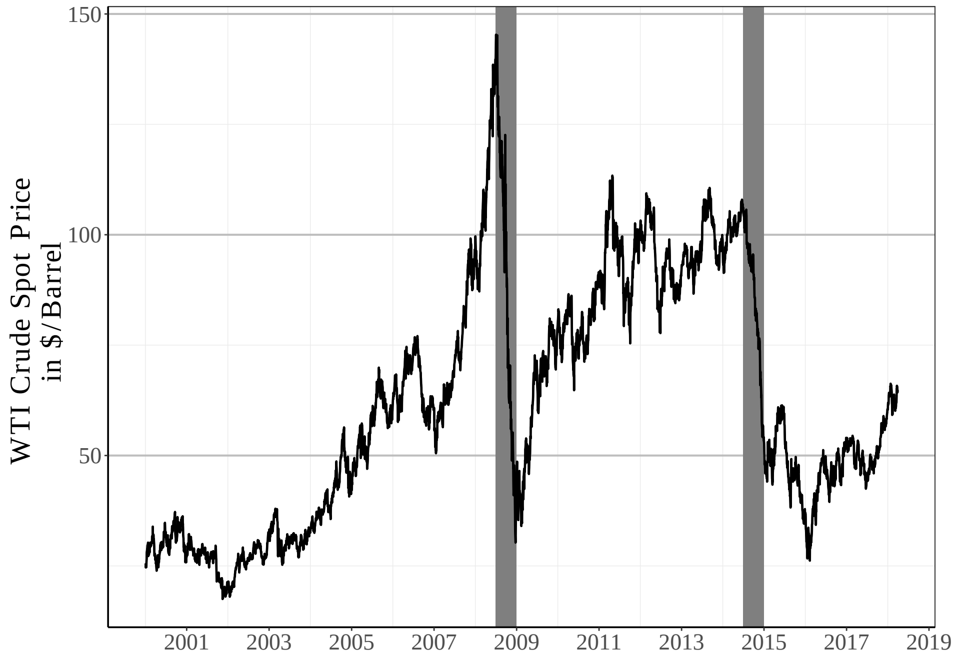
There is also evidence for the effect of equity risk on a firm's cost of debt. Campbell and Taksler (2003) identify a firm's equity volatility as a major factor, which explains a sizeable share of the cross-sectional variation in corporate bond yields. This relationship is based on Merton (1974)'s theoretical explanation that bond owners have issued put options to the equity holders and thus both idiosyncratic and market volatility affect the value of these put options. Campbell and Taksler (2003) provide evidence for the link between equity risk and a widening spread of corporate bonds relative to Treasury bonds. L. Chen et al. (2007) stress the importance of bond volatility for corporate yield spreads. The authors find that higher liquidity results in a lower spread, even when controlling for bond-specific, firm-specific, and macroeconomic variables affecting the default risk of the issuing firm. Dick-Nielsen et al. (2012) show that the effect of liquidity on corporate bond spreads increased substantially during the sub-prime crisis.

3.2.2 Specifics of the Oil Industry

In the past two decades, the US oil market has experienced substantial changes and dramatic events. After a long-lasting decline that began in the 1980s, oil production increased sharply following the financial crisis in 2008 (EIA 2017b), which was mainly driven by the so called "shale oil revolution" (Baumeister and Kilian 2016). The EIA estimates that, as of 2016, 48% of total US oil production is attributable to shale oil. Connected with this, Domanski et al. (2015) describe an interesting phenomenon: a contemporaneous increase in debt-driven investments in the oil sector since the start of the shale oil revolution. This growth in debt was driven by a macroeconomic environment with low interest rates and investors searching for profitable investments after the financial crisis. This was also reinforced by the impact that the Federal Reserve's Quantitative Easing (QE) had on the corporate bond market (A. Krishnamurthy and Vissing-Jorgensen 2011).

Between January 2011 and June 2014 in particular, the crude oil price experienced a comparatively stable sideways shift closely followed by a major decline until January 2015 (Figure 3.1).

FIGURE 3.1: Development of WTI crude oil spot price.



On the one hand, this event may be a supply shock based on the US shale oil boom and the refusal of the Organization of the Petroleum Exporting Countries (OPEC) to reduce supply quantities. On the other hand, there is evidence that the price depreciation was driven by a demand shock based on a slowdown of the world economy (Baumeister and Kilian 2016). In addition, the appreciation of the US dollar could have lowered demand even further as crude oil imports denominated in US dollars became more expensive (Baffes et al. 2015). Interestingly, supply increased even further despite the oil price decline in 2014. This seems to be counter-intuitive, as a cut in production, such as that observed following the oil price shock in the aftermath of the financial crisis in 2008, would be expected.

The oil price, its volatility, and oil price shocks are likely to affect firms' cost of debt. In general, the cost of debt should depend on the default risk of a firm and the costs that the bank would incur in the event of a default (Valta 2012). In the case of imperfect contracts and if there are transaction costs, liquidation values play a major role for financial contracts between borrowers and lenders (Bolton and Scharfstein 1996; Hart and Moore 1994). These values are important for the interest rate on a loan, since creditors have the right to possess the assets if a firm defaults on its debt payments: the lower the liquidation value, the higher the lender's costs if a firm defaults, which translates into higher costs of debt (Benmelech et al. 2005). As assets of oil firms are very specific, adverse oil price shocks directly affect their liquidation value and consequently the cost of debt. In light of the limited redeployability in the oil and gas extraction industry, an oil price shock affecting the whole upstream industry should increase the cost of debt for firms in this industry segment (Kim and Kung 2016). In cross-section and time-series tests, Ortiz-Molina and Phillips (2014) find that real asset illiquidity affects the cost of capital. Firms with less liquid real assets face higher cost of capital than firms with more liquid assets and the cost of capital also increases in periods with particularly illiquid real assets. Finally, Benmelech and Bergman (2011) show that bankruptcies of industry peers lead to a contagion effect by reducing the value of other firms' collateral and thereby increasing their cost of debt financing. This is likely to be more pronounced when focussing only on one part of the oil industry's value chain. As most assets are quite distinct for each part of the oil industry's value chain, distress should be largely contained within each part of the chain.

In addition to affecting the asset value and thus the lenders' costs in the event of default, oil price changes also affect an oil firm's probability of default by impacting, for example, firms' profits. Kinda et al. (2016) investigate the impact of commodity price shocks on financial sector fragility and find that negative price shocks increase the number of non-performing loans. The authors do not, however, analyse the effect of commodity price shocks on the loan spreads of individual loans. Such an analysis was conducted by Sengupta et al. (2017), who analyze the effect of oil price shocks on the credit spreads of syndicated loans to US oil firms and find increasing loan spreads for upstream and support services firms in the aftermath of the 2014 oil price shock.

Overall, theory and previous evidence suggest that oil prices are likely to be an important determinant of the oil firms' cost of debt. In the presence of information asymmetries in financial markets, a firm's decision and ability to raise private or public debt depends on its characteristics. Larger and listed firms are usually less informationally opaque and thus more likely to be able to tap capital markets in order to raise debt. Smaller and riskier firms are more likely to borrow from banks, which specialise in screening potential lenders prior to approving credits. By analysing both loans received and bonds issued by oil firms, we provide an initial comprehensive empirical examination of the determinants of oil firms' costs of debt.

3.3 Data Set and Variables

The data used in the empirical analysis can be split up into four categories: (i) characteristics of borrowing firms, (ii) bond and bank loan data, (iii) oil price data, and (iv) data on the macroeconomic conditions. This subsection presents all data sources and describes the construction of the variables used in the empirical analysis. Table 3.7 in Appendix C.2 contains the definitions of the variables used in the analysis.

3.3.1 Oil Firms

In order to analyse the whole value chain of the oil industry in the US, we identify oil firms and classify them according to their position the value chain: upstream, midstream, downstream, and support services. Firms might be differentially affected by the oil price given their different features that differ along the value chain. Upstream firms are engaged in the exploration and production of oil and gas resources. They identify possible oil fields, drill wells and extract the resources from the ground. As such, one can expect that upstream firms' revenues and their credit conditions would be most affected by changes in the crude oil price. Midstream firms link upstream with downstream entities by transporting the oil resources through pipelines and gathering systems. Their revenue streams are fee-based and typically tied to long-term contracts, which means that midstream firms should be less affected by oil price volatility in the short run (Sengupta et al. 2017). Downstream firms refine crude oil and are engaged in the marketing, distribution and sale of processed petroleum products (Rodziewicz 2018). Refiners face a double risk between the raw materials market and the petroleum products market, which determines their profitability to a large extent. Thus, downstream firms engage in hedging strategies to reduce their sensitivity to oil price fluctuations (Ji and Fan 2011). Support services firms are active in the whole supply chain. Although these firms derive mostly stable cash flows from midstream and upstream firms, they are closely connected to upstream entities as they provide oilfield services, equipment, and drilling site preparation (Rodziewicz 2018). Similar to the upstream industry, we expect their credit availability and profitability to react sensitively to changes in oil prices.

For this analysis, we first identify all relevant Standard Industrial Classification (SIC) and North American Industry Classification System (NAICS) classifications and assign each of them to one of the four categories along the value chain. The resulting 31 SIC and 22 NAICS codes (see Table 3.6 in Appendix C) were used to identify North American oil firms in the Compustat – Capital IQ database.[6] This database contains detailed quarterly financial data on publicly listed firms, which we use to control for firms' financial situations and risk of default as proposed in the literature (Chava et al. 2009; L. Chen et al. 2007; Dennis et al. 2000; Goss and Roberts 2011; Valta 2012). As a measure for firm size, we use the natural logarithm of a firm's total assets, *log(Total Assets)*. We further control for a firm's *Profitability*, measured as the EBITDA relative to total assets, and its *Leverage*, which is the sum of short-term and long-term debt divided by total assets.

To remove observations, which are most probably caused by errors in the data collection process or represent implausible values, an outlier detection and removal is applied to the dataset. We remove the observations for the smallest and largest 1% of calculated *Leverage* and *Profitability* and require these two measures to have finite values. Additionally, companies that are only observed in one quarter are also not considered in the analysis. This is in line with the most basic requirements for outlier removal as discussed in Adams et al. (2019).

3.3.2 Bank Loans and Bonds

The data on syndicated loans is obtained from the Thomson Reuters' Dealscan database. This database contains a comprehensive overview of the characteristics of syndicated loans, such as pricing, contract details and additional terms and conditions. Chava and Roberts (2008) provide a detailed introduction to the Dealscan data and also emphasise its good coverage of the US syndicated loan market. The costs of bank loans are measured using the log of the *Loan Credit Spread*, i.e. the Dealscan variable all-in-drawn spread (Chava 2014; Chava et al. 2009; Sengupta et al. 2017; Valta 2012). This variable measures the amount the borrowing firm pays in basis points over the London Interbank Offering Rate (LIBOR) or equivalent rate for each dollar drawn, including annual fees paid to the syndicate.[7]

Since syndicated loans represent only a relatively small part of corporate debt, we additionally use bond data obtained from the enhanced version of the Trade Reporting and Compliance Engine (TRACE) database provided by the Financial Industry Regulatory Authority (FINRA).[8] This database was introduced in 2001 to improve transparency in corporate bond markets. The initial phase of TRACE was implemented in July 2002, which is also the earliest date for which transaction data is available. All members of FINRA are obliged to report their over-the-counter (OTC) transactions of fixed-income securities. The monthly data on the constant maturity yields of US Treasury securities, which we use to calculate bond credit spreads, were obtained from the FRED database of the Federal Reserve Bank of St. Louis.[9] Besides data from the FRED database, the TRACE data is enhanced with base data from Bloomberg, which has additional information on the issuance of the loan. For example, this data provides information on the initial rating, the coupon rate, the maturity and the issued amount of the loan.

We use the bond data in two different ways. In a first approach, we only consider the costs of debt at the time of issuance. We calculate the *Bond Credit Spread at Issuance* as the difference between the coupon of the bond and the yield of a US Treasury bond with a similar or the closest matching maturity available. This approach makes the bond analysis very comparable to bank loans, where the price is also determined once at the time the loan is issued.

6 According to the data descriptions, this covers North American (US and Canada) firms that were publicly held and were active in the US over the period analyzed.

7 See Berg et al. (2016) for a discussion of the importance of fees for the costs of borrowing in the case of syndicated loans.

8 The different data sets were combined using the linking suite provided by Wharton Research Data Services (WRDS).

9 Board of Governors of the Federal Reserve System (2019) via the website: https://fred.stlouisfed.org/categories/115.

In a second approach, we exploit the fact that bonds, after their issuance, can be traded on secondary markets. These trades contain further information on the costs of debt and allow specific bonds to be tracked over time. The TRACE enhanced database contains detailed information of all fixed-income transactions on the secondary market. It is possible to see the price, volume and yield of the traded security. Thus, the information in this data set allows individual traded bonds to be tracked over time and thus the development of the cost of debt to be observed over the horizon of our analysis. In order to do that, it is necessary to adjust the data and remove reporting errors. We follow the procedures described in Dick-Nielsen (2009, 2014) and remove all trades that are subsequently cancelled and only keep the information concerning the last modification in the database. Following the procedure in Rossi (2014), the return reversals in the price and yield time series are removed as well. This means a trade is eliminated if its price or yield is preceded and followed by a price change of more than 50%. Additionally, a filter is applied, which is also proposed by Rossi (2014) and follows earlier work by Brownlees and Gallo (2006) on high-frequency trading data. To remove outliers, the smallest and largest 0.0001% of reported yields of individual trades were removed, which resulted in the removal of only 28 individual trades and should not affect the overall results of the analysis.

To calculate the cost of debt based on secondary market bond trades, we apply the methodologies employed by Bessembinder et al. (2009) and Li and Richie (2016), i.e. we aggregate the TRACE data per quarter. The aggregation of price and yield data is done using a weighted average with the reported trade volume as weights. Until November 2008, the reported yield of a transaction was calculated by the reporting firms. Since then, the calculations have been carried out by FINRA.[10] We calculate the *Bond Credit Spread on the Secondary Market* as the difference between the weighted bond yield from TRACE and US Treasury securities with the same time to maturity. If an exact match is not possible, we use the closest maturity available. This is in line with Gilchrist and Zakrajšek (2012), who use secondary market credit spreads to calculate the cost of capital.

The loan-level and bond-level data is matched to the firm-level data presented above. Matching the Dealscan loan data and the Compustat firm-level data was facilitated by using the matching table provided by Chava and Roberts (2008). The bond data is matched with the firm-level data based on the Committee on Uniform Security Identification Procedures (CUSIP), which is used as unique identifier in both TRACE and Compustat. Table 3.1 reports descriptive statistics of firm and bond or loan characteristics for all firms in the dataset.

TABLE 3.1: Summary statistics - Full sample for all firms

Full Sample	n	mean	sd	min	Q0.25	Q0.5	Q0.75	max
Total Assets	1647	7074.84	27568.61	-12.67	86.64	735.92	3711.92	419648.00
Total Debt	1647	1822.65	5884.23	0.00	9.2	200.00	1193.34	138237.00
Leverage	1647	0.31	0.33	0.00	0.13	0.27	0.39	4.91
Profitability	1647	0,00	0.17	-2.66	0.00	0.03	0.04	0.23
Loan Credit Spread	576	183.73	138.92	12.50	100.00	150.00	234.99	1325.00
Loan Amount	577	824.22	1377.81	2.00	200.00	400.00	925.00	29762.75
Loan Maturity	577	43.19	21.63	1.00	25.00	48.00	60.00	324.00
Bond Credit Spread	233	2.64	2.23	-10.66	1.31	2.12	3.67	11.55
Bond Amount	225	768.85	992.97	0.00	300.00	500.00	800.00	11000.00
Bond Maturity	234	190.73	99.93	37.50	112.00	174.71.	251.68	779.00

Note: All monetary variables are in million US dollars.

[10] For more details on the content and the data, please see http://www.finra.org/industry/trace/historic-file-layout for all data before 6th February 2012 and http://www.finra.org/industry/trace/historic-data-02062012 for all dates thereafter.

3.3.3 Oil Price

The oil price plays a crucial role for the revenues or costs of oil firms, depending on their position in the value chain, and thus directly influences the creditworthiness of oil firms. A higher volatility of the oil price means more uncertainty and hence can influence firms' investment decisions and affect the risk perception of financial markets concerning the oil industry. Gilchrist et al. (2014) show that changes in the level of uncertainty, measured as the standard deviation of the unforecastable daily excess stock return, have an impact on investment activity, mainly through changes in credit spreads. For the analysis, we use the and the corresponding average quarterly oil price volatility (*Oil Volatility*), measured as the coefficient of variation. In December 2015, the US lifted its ban on crude oil exports. Presumably, this may have had an impact on firms in the value chain of the oil industry. To control for this, we include the log of quarterly US crude oil exports. The data is taken from the EIA.[11]

3.3.4 Macroeconomic Environment

Next to the default risk of the firm itself, also the macroeconomic situation, such as the business cycle or liquidity in the market, are likely to affect credit spreads of loans and bonds (Beckworth et al. 2010; Krainer 2004; Thakor 2016). To capture the overall risk environment of the economy, we use two different interest rate spread variables. The first variable, denoted as *Credit Spread*, is the spread between the corporate bond yield for US firms rated as AAA and Baa by Moody's with maturities as close as possible to 30 years. A widening of this credit spread is also an indicator for current or expected poorer economic conditions (Moody's 2018). To control for the overall state of the economy, we include the *Term Spread* as the difference between the ten-year Treasury yield and the T-bill yield (Federal Reserve Bank of St. Louis 2018).

3.4 Empirical Analysis

3.4.1 Exploratory Data Analysis

The dataset we use for the empirical analysis consists of 1504 publicly held firms active in the North American (US and Canada) oil market between Q2 2000 to Q1 2018. The firms in our sample are not evenly distributed across the oil industry value chain. The majority of the firms are active in the midstream sector (743) followed by upstream firms & support services (554) and firms active in the downstream (207) segment. Figure 3.2 provides a comprehensive overview of the average firm size and indebtedness across the four different industry classifications. In the upper panel of the figure, it can be seen that the firms in the downstream industry are the largest in our sample in absolute terms, followed by midstream, upstream, and support services firms. This means that there are big differences in firm size between the different industry classifications. Figure 3.3 illustrates although firms' profitability in our sample are quite similar across sub-sectors, upstream & support services have fewer assets on average and are more evenly distributed in terms of their size. The lower panel of Figure 3.2 depicts the development of the overall debt-to-asset ratio, i.e. the indebtedness in the industry. The highest indebtedness can be observed for midstream firms, while the debt-to-asset ratios of upstream & support services firms increased the most between 2000 and 2017. This increase was most probably driven by increasing investment in shale oil projects. Firms active in the downstream part of the oil industry's value chain have the lowest debt-to-asset ratios, which, however, increased considerably following the financial crisis.

[11] Monthly volume of US Crude Oil Exports in thousand barrels per day was taken from the EIA website at: https://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=pet&s=mcrexus2&f=m.

FIGURE 3.2: Development of aggregate assets and debt in each part of the value chain and the resulting debt-to-asset ratios

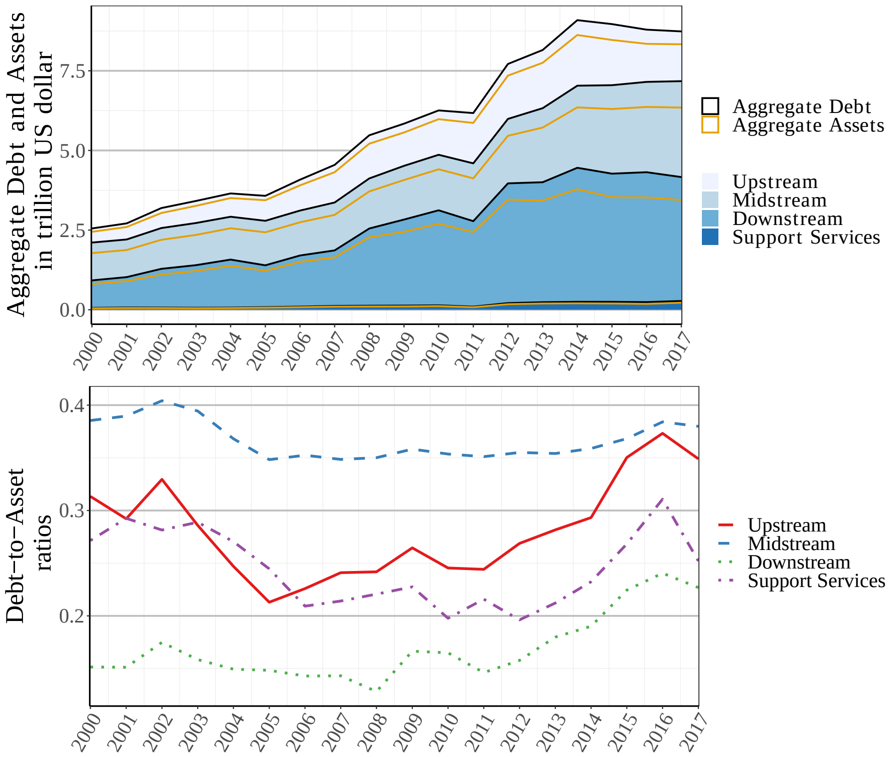
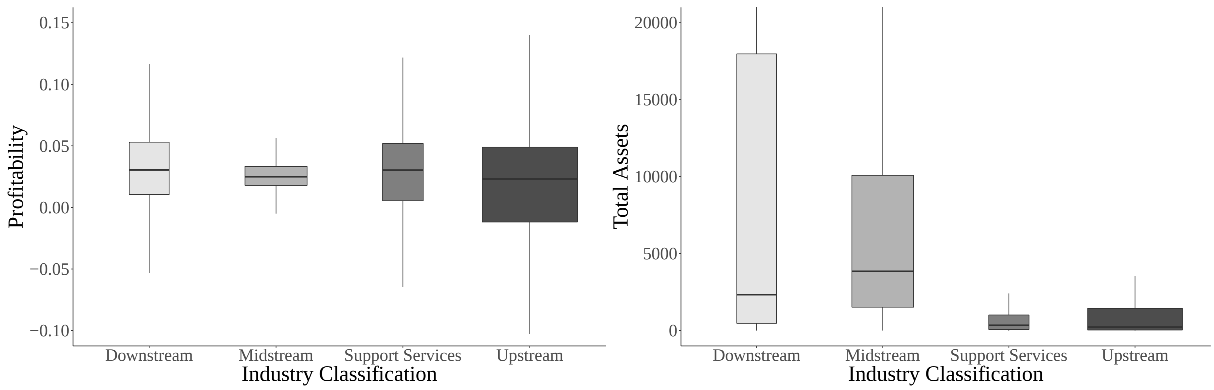


Figure 3.4 depicts the number of loans and bonds issued and reveals distinct differences between the bond market and the market for syndicated loans. First of all, the availability of syndicated loans seems to have tightened after the oil price declines during the financial crisis in 2008 and after the adverse oil price shock in 2014. This holds especially true for upstream and midstream entities, where a significant decrease in the number of loans issued can be observed (see Figure 3.7 in Appendix C.3). A similar pattern can be observed in the development of average loan amounts. As depicted in Figure 3.11 in Appendix C.3, the average loan size across the value chain dropped drastically after the oil price shocks in 2008 and 2014, while they show positive trends overall across the sample period.

The opposite can be observed for the bond market. Corporate bonds played a negligible role before the financial crisis. After 2010, however, the number of bonds issued by oil firms increased notably, peaking in 2014. The average volume of bonds issued behaved similarly in that time period (see Figure 3.12 in Appendix C.3). An explanation could be that firms substituted bank loans for public debt due to tightened credit conditions. The increase in bond issuance is particularly pronounced in the case of firms in the midstream and downstream sectors (see Figure 3.8 in Appendix C.3). This is unsurprising for two reasons. First, as discussed in Section 3.2, the larger sizes of midstream and downstream firms allow them to borrow money on the corporate bond market, while smaller upstream and support services firms are more dependent on bank lending. Second, given that the banking sector was in distress after the financial crisis, firms' access to credit was affected by changes in the financial conditions of their banks (Popov and Udell 2012).

Figure 3.5 depicts the credit spreads of syndicated loans and corporate bonds at issuance and reveals further differences between private and public debt markets. It can be seen that the spread for bonds at issuance exhibits much greater variation than the spread of syndicated loans. Over the whole time period under consideration, the spreads of the syndicated loans are much more concentrated around the mean and median, whereas the credit spread of bonds at

FIGURE 3.3: Boxplots of main firm characteristics



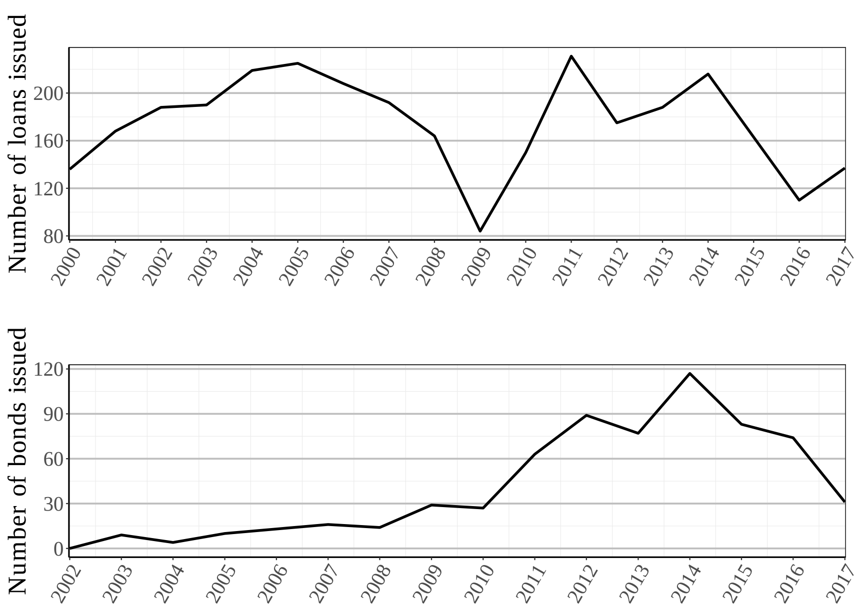
(a) Profitability

(b) Total Assets

issuance have a greater variance. Figures 3.9 and 3.10 in Appendix C.3 disentangle credit spread development for bonds and syndicated across industry classifications. There is a general trend of midstream firms paying the lowest spreads, followed by downstream, upstream and support services firms.

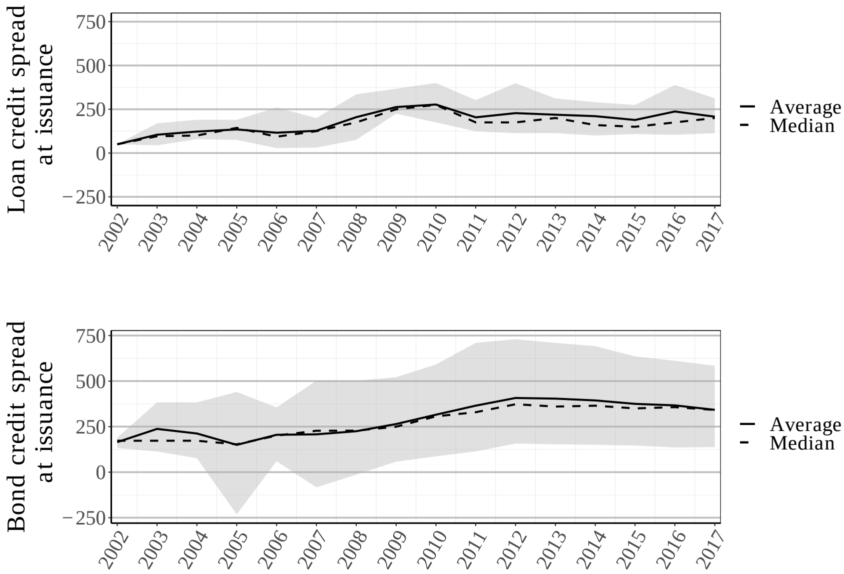
Figure 3.6 depicts the continuously calculated credit spread of bonds traded on the secondary market. These bond credit spreads seem to be affected more strongly by the financial crisis and, in particular, the adverse oil price shock in 2014. This effect is especially pronounced for downstream and support firms (see Figure 3.13 in Appendix C.3). This hints at the possibility of a selection effect in times of economic distress. In a difficult economic environment, some firms that were able to raise debt via bonds or, in particular, loans, may not receive debt in difficult times, as can be seen from the lower number of new loans during the financial crisis. This selection effect towards less risky firms may explain why the credit spreads of issued loans

FIGURE 3.4: Number of bonds and loans issued per year for all firms in the sample



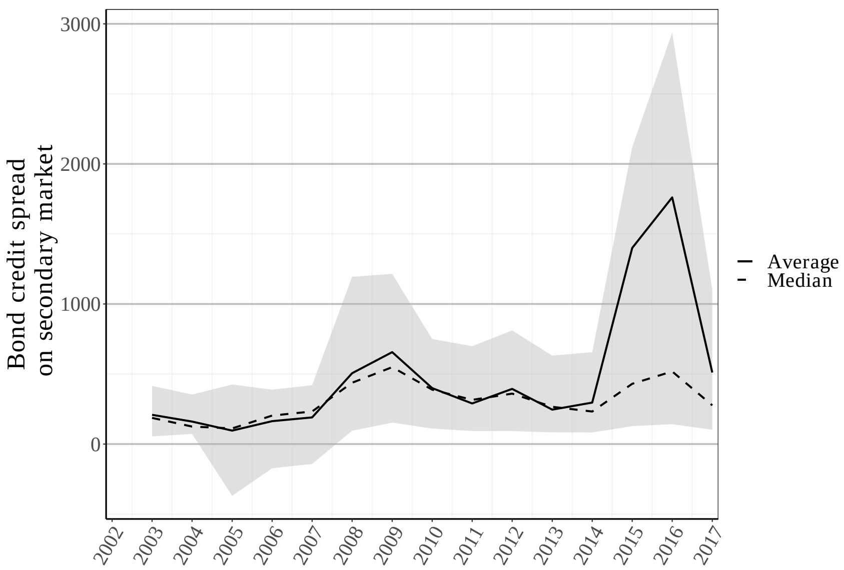
do not increase substantially during the financial crisis. The credit spread on the secondary market, however, is based on bonds issued in the past and thus exhibits a stronger reaction to market shocks and recessions or oil price shocks.

FIGURE 3.5: Loan and bond credit spreads at issuance



Note: Shaded areas indicate the upper (90%) and lower (10%) quantile of the credit spread.

FIGURE 3.6: Development of the average and median bond credit spread on the secondary market



Note: Shaded area indicates the upper (90%) and lower (10%) quantile of the credit spread.

Overall, there seem to be similar patterns between oil firms' debt (decisions) and the oil price. This seems to be particularly pronounced in the case of bank loans. In periods of rather high oil prices, oil firms seem to borrow more, i.e. the number and average size of loans are higher, at better conditions, i.e. the credit spreads of loans are relatively low. Most of these patterns can also be observed for corporate bonds, both at their issuance and for trades on the secondary market. One exception is the average volumes of newly issued bonds, which do not seem to decline as markedly as loan volumes in the aftermath of adverse oil price shocks.

Figure 3.9 and 3.10 provide information about the median credit spread development for TRACE bonds and the spread for syndicated loans from the Dealscan database. There is a general tendency of midstream firms paying the lowest spreads, followed by downstream, upstream and support services firms. The spreads peaked in both cases around the global financial crisis and oil price shock in 2008/09 and increased substantially after the oil price shock in 2014.

3.4.2 Estimation Approach

We employ two different empirical approaches to investigate the effect of oil prices on firms' costs of debt. The first approach focuses on the costs of debt of individual loans or bonds at issuance. This approach is similar to the one employed by Sengupta et al. (2017) for syndicated loans, upon which we expand by also applying it to corporate bonds issued by oil firms. The second approach utilises not only the credit spreads at issuance but also the fact that bonds are traded on the secondary market and includes this information on a firm's cost of debt after the issuance of the bond. One advantage of this is that it is possible to observe costs of debt during phases when bond issuance and loan supply may be curtailed. This presents an opportunity to estimate and analyse a possible selection effect. This selection effect might be especially pronounced during phases when credit markets dry up. Thus, this approach offers the opportunity to assess the extent of this selection effect.

3.4.2.1 Distributed Lag Model for Credit Spreads at Issuance

This first approach could be described as a variant of a distributed lag model, since only the lagged financial variables are included in the model. This is based on the assumption that credit spreads are based on the latest available financial statement of a firm. The initial approach at the loan and bond level is implemented using the following model for estimating credit spreads:

$$Y_{i,j,t} = \beta_0 + \beta_1 DEBT_{i,j,t} + \beta_2 FIRM_{i,t-1} + \beta_3 OIL_t + \beta_4 MACRO_t + \nu_t + \epsilon_{i,j,t}, \tag{3.1}$$

where $Y_{i,j,t}$ is the (average quarterly) credit spread of a syndicated loan received or a bond issued j by firm i at time t; $DEBT_{i,j,t}$ is a vector containing loan/bond characteristics, $FIRM_{i,t-1}$ contains firm characteristics at time $t-1$, OIL_t is a vector with the oil price, its volatility and the volume of crude oil exports, $MACRO_t$ includes control variables on the macroeconomic situation, and $\epsilon_{i,j,t}$ is the error term. Following the literature (Chava 2014; L. Chen et al. 2007; Ghouma et al. 2018; Sengupta et al. 2017; Valta 2012), we use firm information from the respective preceding quarter. This is the most recent information that is available to the bank or the capital markets for evaluating the firm trying to raise debt and the relevant market conditions. Additionally, this has the advantage that the likely endogeneity between the debt and the financial variables is averted by design. As mentioned above, we can distinguish between the firms' positions in the value chain of the oil industry. To investigate whether there are differences in the effects of oil prices and other controls on the cost of debt along the value chain, we estimate all models for the whole sample as well as separately for firms in the three sub-sectors of upstream and support services, midstream, and downstream.

3.4.2.2 Panel Data Methods for Continuous Credit Spreads

With the TRACE data, it is possible to continuously asses these costs of debt based on the development of bond prices and yields on the secondary market. This approach utilises the panel structure of the data by aggregating the high-frequency bond pricing data of TRACE and combining these data with the quarterly financial data from the Capital IQ database. This results in a larger sample compared to the first approach, since it observes the credit spread not only at the time of issuance, but also whenever trades are reported in the TRACE database.

The main advantage of the panel data approach is the possibility of assessing the different effects that oil prices have on a firm depending on its position in the oil industry's supply chain. In particular, we can estimate the model jointly for all oil firms and then test for differences across industry classifications compared to the first approach, where we estimate the models separately for the three sub-sectors. Since the industry classification of the individual firm is time-invariant, we cannot use the classical FE estimation to directly estimate the impact of the firms position in the oil industry's supply chain. To circumvent this methodological limitation, we utilize an approach that expands upon the basic random effects (RE) estimation method. Initially proposed by Mundlak (1978) and further developed by Bell and Jones (2015), this "within-between"approach has the advantage that it allows for the decomposing of the combined effect in the random effect models into between- and within-firm effects. Thus, it is possible to obtain separate estimates for the effect of an explanatory variable on the dependent variable between firms (between-firm estimator) and the effect within a particular higher-level group (within-firm estimator). The model can be expressed in its most general form as:

$$Y_{i,t} = \beta_{0,i} + \beta_1(X_{i,t} - \bar{X}_i) + \beta_2\bar{X}_i + \gamma Z_i + u_{0,i} + \epsilon_{i,t}, \tag{3.2}$$

where $Y_{i,t}$ is the dependent variable, $X_{i,t}$ are time-variant explanatory variables, and Z_i are time-invariant variables. The interpretation of β_1 is the same as in the FE model, because it measures the effects of within-firm deviations of X on the within-firm deviations of Y. β_2 then indicates how the impact varies with cross-sectional variation in the dependent variable, i.e. across industry classification in our model.[12]

We estimate the following within-between effects model for the determinants of the average quarterly credit spread of a firm:

$$\begin{aligned} Y_{i,t} = \beta_{0,i} &+ \beta_1 DEBT_{i,t} + \beta_2 FIRM_{i,t-1} + \beta_3 OIL_t + \beta_4 MACRO_t \\ &+ \beta_7 INTER_{i,t} + \gamma Z_i + u_{0,i} + \epsilon_{i,t}, \end{aligned} \tag{3.3}$$

where $Y_{i,t}$ is the (quarterly volume-weighted average) credit spread of outstanding bonds of firm i at time t, $DEBT_{i,t}$ is a vector containing bond characteristics, $FIRM_{i,t-1}$ contains firm characteristics in the previous quarter, OIL_t is a vector with oil price and export information, $MACRO_t$ includes control variables on the macroeconomic situation, $INTER_{i,t}$ is an interaction term between oil price development and the industry classification of a firm, $u_{0,i}$ are random errors of the model predicting $\beta_{0,i}$, and $\epsilon_{i,t}$ is the error term. Since it is not appropriate to include interaction terms in the model, we follow Giesselmann and Schmidt-Catran (2018) and use their "double-demeaned"estimator for the coefficient of the interaction terms. The estimation of the within-between model is carried out using R Core Team (2018) and the *panelr* package by Long (2019).

[12] A more detailed description of this model and how to arrive at this notation starting from the general RE model can be found in Bell and Jones (2015).

3.4.3 Estimation Results

3.4.3.1 Determinants of Credit Spreads at Issuance

In this subsection, we present the results of estimating equation (3.1), which is the model of credit spreads at issuance. Results for syndicated loans are displayed in Table 3.2, while Table 3.3 summarizes the regression results of the estimation at the individual bond level. In both tables, the first columns show the estimates for all firms, while the subsequent columns display the results for different sub-samples of firms depending on their position in the oil industry's value chain. The dependent variables in both the bond and the loan estimations are the natural logs of the respective credit spreads in basis points.

Overall, the effects firm characteristics on the credit spreads of loans and bonds at issuance are as to be expected. We find that higher indebted firms have higher cost of debt. For the full sample, an increase in *Leverage* by 0.1 increases the credit spread by 7 %. When comparing the effects across sub-sectors, the effect is strongest for firms in the midstream segment, at around 14 %, and weakest – and not significant – for downstream firms. The effect of indebtedness is quantitatively similar for bonds when considering the full sample. We find the credit spreads of bonds at issuance increase by 7.8 % if leverage increases by 0.1. As for syndicated loans, the effect of leverage is strongest for midstream firms. This finding is in line with the theory, as higher firm indebtedness increases the risk of default, which translates into a higher risk premium for further debt charged by banks and the capital market.

In the case of loans, we find the expected negative effect of profitability. The only exception are downstream firms for which we do not find any effect. For the full sample, the coefficient of *Profitability* indicates that a 0.1 increase in profitability leads to a reduction of the cost of debt by 9.3 %. When comparing the estimates for the sub-samples, it seems particularly beneficial for midstream firms to increase their profitability, as a 0.1 increase would decrease the bond credit spread by almost 37 %. In the bond credit spread model, *Profitability* has the expected sign, but is not significant for the full sample. Only in the case of midstream firms, we find a significant negative effect of firm profitability on credit spreads, which is, as in the case of loans, quite high.

In all models, we find highly significant negative effects of firm size, measured by *Total Assets*, on credit spreads at issuance. This means that larger firms face lower costs of debt on average. This effect remains robust across the whole supply chain, while it is quantitatively larger in the case of bonds. For the full sample, a 1% increase in total assets leads to a decrease in the bond credit spread by almost 0.3%, whereas the loan credit spread increases by about 0.14%. These results are not surprising, since more assets also translate into more potential collateral, which lowers the risk of complete financial loss for the banks.

In addition to the firm-level characteristics, we included bond-level and loan-level controls in the models. With respect to the volume of debt raised, we find that the loan amount has a negative effect on the credit spread for the full sample and the sub-samples with the exception of midstream firms. For bonds, however, the results indicate the opposite: the higher the amount raised by issuing a bond, the higher the bond credit spread. These differing results may be attributable to two opposite effects. On the one hand, a higher volume of debt means higher potential losses for the lender in the event of default, which should translate into higher costs. On the other hand, higher volumes of debt are likely to be raised by firms that are larger on average, which are likely to be more creditworthy and receive better credit conditions. Thus, the former might be stronger in the case of corporate bonds, while the latter might be more important in the case of syndicated loans. A longer maturity is expected to lead to higher costs of debt, as it increases the debt exposure of the lender. We find this relationship for syndicated loans: an increase of the loan maturity by one month results in an increase of the loan credit spread by 0.3%. This effect is robust across all sub-sectors. In the case of bonds, there is some

TABLE 3.2: Determinants of the loan credit spread at issuance.

	Dependent variable: log(Loan Credit Spread)$_t$			
	Full Sample	Upstream & Support Services	Midstream	Downstream
Leverage$_{t-1}$	0.6812***	0.6596***	1.4373***	0.1994
	(0.0628)	(0.0678)	(0.1453)	(0.1782)
Profitability$_{t-1}$	−0.9291***	−1.0215***	−3.6964***	1.0056
	(0.2462)	(0.2537)	(0.5987)	(0.8264)
log(Total Assets)$_{t-1}$	−0.1379***	−0.1521***	−0.0687***	−0.0841***
	(0.0076)	(0.0104)	(0.0153)	(0.0165)
log(Loan Amount)$_t$	−0.1022***	−0.1118***	−0.0502***	−0.2195***
	(0.0105)	(0.0132)	(0.0186)	(0.0245)
Maturity$_t$	0.0034***	0.0023***	0.0033***	0.0054***
	(0.0005)	(0.0007)	(0.0008)	(0.0009)
Credit Spread$_t$	0.3413***	0.3078***	0.2055***	0.4244***
	(0.0393)	(0.0482)	(0.0642)	(0.1130)
Term Spread$_t$	0.1560***	0.0959***	0.2211***	0.1768***
	(0.0092)	(0.0116)	(0.0148)	(0.0240)
Oil volatility$_t$	−1.5934***	−1.1139**	−0.7415	−2.2896**
	(0.3785)	(0.4888)	(0.5993)	(0.9386)
log(Oil Price)$_t$	0.2353***	0.2613***	0.1496***	0.2038***
	(0.0243)	(0.0298)	(0.0412)	(0.0617)
log(Oil Exports)$_t$	0.1483***	0.1853***	0.1059***	0.1234***
	(0.0084)	(0.0110)	(0.0132)	(0.0216)
Constant	3.5949***	3.6272***	2.9223***	4.2674***
	(0.1118)	(0.1405)	(0.1882)	(0.3077)
Observations	3848	1860	1498	490
R^2	0.3463	0.4367	0.2779	0.4231
Adjusted R^2	0.3446	0.4337	0.2730	0.4110
F-Statistic	203.2854***	143.3645***	57.2198***	35.1278***
	(df = 10; 3837)	(df = 10; 1849)	(df = 10; 1487)	(df = 10; 479)

Note: *p<0.1; **p<0.05; ***p<0.01; Standard errors in parentheses.

evidence that maturity has a positive effect on credit spreads for downstream and midstream firms, while the coefficient of *Maturity* is not significant for the full sample.

The variables measuring the overall macroeconomic risk environment have the expected effects on the credit spread of newly issued loans. Both the *Credit Spread* and the *Term Spread* have a positive and highly significant effects. In the corporate bond models, a higher *Credit Spread* also leads to higher credit spreads faced by firms in the oil industry. The term spread, however, only increases the credit spreads of bonds issued by downstream firms.

We now turn to the variables of interest in the models, i.e. various measures of oil prices. As the oil price is expressed in logs, the coefficients can be interpreted as elasticities. The results for the oil price itself are qualitatively the same in the bond and the loan models: in both cases we find that positive and significant coefficients of *log(Oil Price)* across all specifications. For the whole sample, we find that a 1% increase in the WTI spot price yields a 0.24% increase in the loan credit spread. This effect is robust across all sub-samples and quantitatively the highest for upstream firms. The findings for bonds at issuance are very similar, whereas the effects are marginally smaller. When considering all firms, the credit spread of bonds at issuance increase by 0.2% if the oil price increases by 1%. These findings are intuitively plausible in the case of midstream and downstream firms. As crude oil is most likely an input for these firms, higher oil prices mean higher costs for these firms. Hence, their default probability increases, which results in higher premiums on the price of debt charged by banks and the capital market.

TABLE 3.3: Determinants of the bond credit spread at issuance.

	Dependent variable: log(Bond Credit Spread)$_t$			
	Full Sample	Upstream & Support Services	Midstream	Downstream
Leverage$_{t-1}$	0.7776***	0.8875***	1.5219***	0.9832***
	(0.1101)	(0.1436)	(0.2003)	(0.3333)
Profitability$_{t-1}$	−0.6298	−0.3772	−4.0477***	0.9966
	(0.4284)	(0.4628)	(1.3453)	(1.6791)
log(Total Assets)$_{t-1}$	−0.2931***	−0.2856***	−0.1528***	−0.3100***
	(0.0118)	(0.0215)	(0.0185)	(0.0386)
log(Bond Amount)$_t$	0.2238***	0.1513***	0.1352***	0.2757***
	(0.0185)	(0.0384)	(0.0212)	(0.0885)
Maturity$_t$	−0.0002	0.0000	0.0003**	0.0007*
	(0.0001)	(0.0003)	(0.0002)	(0.0003)
Credit Spread$_t$	0.5865***	0.5938***	0.5607***	0.7147***
	(0.0453)	(0.0706)	(0.0577)	(0.1231)
Term Spread$_t$	0.0105	−0.0108	−0.0027	0.1474***
	(0.0168)	(0.0263)	(0.0205)	(0.0560)
Oil volatility$_t$	0.0958	0.0688	1.2259**	−2.6959*
	(0.5077)	(0.8338)	(0.6224)	(1.4633)
log(Oil Price)$_t$	0.2080***	0.2393***	0.1883***	0.1456
	(0.0392)	(0.0682)	(0.0470)	(0.1220)
log(Oil Exports)$_t$	0.0850***	0.1450***	0.0047	0.1488***
	(0.0126)	(0.0214)	(0.0153)	(0.0406)
Constant	1.0579	1.8984**	1.7191***	−0.4880
	(0.3730)	(0.7674)	(0.4286)	(1.5529)
Observations	1504	554	743	207
R^2	0.4670	0.4844	0.3898	0.5416
Adjusted R^2	0.4634	0.4749	0.3815	0.5183
F-Statistic	130.8218***	51.0071***	46.7586***	23.1609***
	(df = 10; 1493)	(df = 10; 543)	(df = 10; 732)	(df = 10; 196)

Note: *p<0.1; **p<0.05; ***p<0.01; Standard errors in parentheses.

The results regarding the volatility of oil prices, however, are less robust across industry classifications and sources of debt. We find that the credit spreads of loans decreases with the volatility of the oil price when considering the full samples of firms, while we find no significant effect for bonds at issuance. When looking at the sub-sectors, the impact of price volatility on credit spreads remains robust (although not significant for midstream firms). For the bonds at issuance, we find a significant positive effect for midstream firms, while the effect is negative (and marginally significant) for downstream firms. Overall, the results for loans indicate that a higher price volatility would not translates into higher uncertainty about oil prices and thus the economic environment of oil firms. This is a surprising result as one would expect banks to charge higher prices for debt in such periods. Finally, we find that the possibility to export to other markets, which was banned until 2015, seems to induce higher costs of debt.

3.4.3.2 Determinants of Credit Spreads on the Secondary Market

This subsection discusses the results of the second empirical approach using data on bond credit spreads on the secondary market. The results of the within-between effects estimation of the model in Equation (3.3) is presented in Table 3.4. The within effects reported in the upper part of the table can be interpreted as the coefficients of a FE estimation. The coefficients capture the impact of the within-firm variation of the independent variables on the variation of the firms' bond credit spreads. In contrast, the between effects displayed below measure how cross-sectional variation in the variables, i.e. differences between firms, affect the credit spreads.

With respect to the firm-specific financial variables, the within effects support the previous OLS estimates, i.e. a positive effect of *Leverage* and negative effects of *Profitability* and *log(Total Assets)*. The latter measure for firm size, however, is statistically not significant. The between effect of *log(Total Assets)*, however, is negative and significant, which indicates that difference in firms sizes between firms seem to affect the cost of debt in contrast to (within-firm) changes of size. The controls for the macroeconomic environment have opposing directions. While the term spread has the expected positive impact on the calculated bond credit spread, the term spread has the opposite and considerably smaller effect. Thus, an overall increase in the perceived macroeconomic risk also increases the risk premium the market implicitly assigns to firms in the oil industry.

The impact of the oil price and its volatility is also statistically significant, however different from the OLS estimates presented above. When accounting for time-invariant firm heterogeneity, within-between effects estimates indicate that a higher oil price leads to lower financing costs for the firms. Thus, the within-firm effect of oil prices on the cost of debt has the opposite direction compared to the pooled OLS estimate. The same is true for the effect of oil price

TABLE 3.4: Within-between effects estimation of the determinants of the bond credit spread on the secondary market for the full sample.

	Dependent variable:				
	log(Bond Credit Spread)$_t$				
	est.	std. error	t-val.	d.f.	p-val.
Within Effects					
Leverage$_{t-1}$	1.18	0.06	20.99	6435	0.00
Profitability$_{t-1}$	−0.82	0.11	−7.31	6302	0.00
log(Total Assets)$_{t-1}$	−0.03	0.02	−1.23	6386	0.22
Avg. Months-to-Maturity	0.00	0.00	−0.99	6283	0.32
Credit Spread	0.50	0.02	22.28	6258	0.00
Term Spread	−0.17	0.01	−22.20	6276	0.00
Oil Volatility	1.33	0.24	5.45	6243	0.00
log(Oil Price)	−0.07	0.03	−2.24	6291	0.03
log(Oil Exports)	0.01	0.01	0.65	6396	0.52
Between Effects					
(Intercept)	4.88	1.31	3.72	233	0.00
Leverage$_{t-1}$	1.21	0.23	5.18	211	0.00
Profitability$_{t-1}$	−2.44	0.95	−2.55	224	0.01
log(Total Assets)$_{t-1}$	−0.15	0.03	−5.82	201	0.00
Avg. Months-to-Maturity	0.00	0.00	−5.79	199	0.00
Credit Spread	0.00	1.32	0.00	256	1.00
Term Spread	−0.02	0.24	−0.07	225	0.95
Oil Volatility	13.94	17.51	0.80	260	0.43
log(Oil Price)	0.28	0.46	0.61	241	0.54
log(Oil Exports)	−0.01	0.10	−0.15	240	0.88
Upstream & Support Services	0.43	0.08	5.53	195	0.00
Downstream	0.38	0.10	3.69	194	0.00
Cross-Level Interactions					
log(Oil Price)*Upstream & Support Services	−0.31	0.04	−7.44	6352	0.00
log(Oil Price)*Downstream	0.08	0.06	1.36	6376	0.17
Random Effects					
Group	Parameter	Std. Dev.			
Firm ID	(Intercept)	0.44			
Residual		0.54			

Notes: p-values calculated using Satterthwaite d.f.

TABLE 3.5: Information on the estimated within-between model.

Model Info & Fit:			
Firms	230	Quarters	11-70
Type	Linear mixed effects	Specification	within-between
AIC	11185.42	BIC	11354.85
Pseudo-R^2 (fixed effects)	0.51	Pseudo-R^2 (total)	0.7
Entity ICC	0.4		

volatility. In contrast to the OLS estimates based on syndicated loans, we find that rising uncertainty, i.e. higher volatility, within-firm increases of the cost of debt. In contrast to our previous results, we do not find a significant effect for the possibility of exporting to other markets.

The between effects reveal significant differences between the costs of debt for firms in the different industry categories. Both the upstream and support services and the downstream sectors indeed face significantly higher financing costs on average – 43% and 38% respectively – compared to midstream firms. Moreover, the interaction effects between the industry classifications and the oil price show that the impact of the oil price on financing costs varies with the industry classification of the firms. The results indicate that the negative impact of an oil price increase on the bond credit spread is much stronger for upstream and support service firms than for midstream firms. By contrast, downstream firms are affected to the same extent. This is in line with our initial expectation: as the oil price affects the revenues and in the upstream sector, it is not surprising that oil price increases reduce the cost of debt of firms active in that sector.

3.5 Conclusion

This paper provides an empirical analysis of the effect of oil prices on the costs of debt in the oil industry. For this analysis, we combine data on syndicated loans and issued bonds with firm-level financial data of firms in the US oil industry. In the case of bonds, we additionally use data on bond trades on the secondary market. We thereby capture both the banking sector and the bond market, which are both frequently used by oil firms in the US to raise debt. This allows us to investigate whether banks and the capital market evaluate the effect of oil prices on the creditworthiness of oil firms differently. Furthermore, we can explicitly check whether certain effects may be driven by specifics attributes of the banking sector or debt markets. Controlling for other factors, such as macroeconomic, we find that oil prices, and their volatility in particular, significantly affect the cost of debt of US oil firms.

For the firm characteristics, we confirm the findings of previous studies on various sectors. We find that larger firms have lower costs of debt, while the premium a firm has to pay on its debt increases with its indebtedness. As one would expect, we find that the credit spread for loans increases with their maturity. Furthermore, we find that the cost of debt in the oil industry increases with the perceived credit risk in the general economy.

With respect to oil prices, OLS estimates based on syndicated loans indicate that, even after controlling for loan, bond and firm characteristics, oil prices have a positive effect on oil firms' costs of debt. These findings seem plausible for midstream and, in particular, downstream firms that use crude oil as input. A higher prices indicates higher costs and thus a possibly higher probability of default. As a consequence, banks charge a risk premium on loans. The results are rather mixed for corporate bonds at issuance. When time-invariant firm heterogeneity is taken into account, the results change notably. The within-between effects estimation further reveals that the within-firm effect of oil price on the cost of debt is negative. Furthermore, the between effects results show that the effect of oil prices differ across sub-sectors. The negative impact of oil price on the cost of debt is particularly strong for upstream & support services firms. These firms' revenues decline if the oil price drops, which is penalized capital market charging a price mark-up on the provided debt. Overall, our findings indicate that higher oil price volatility seems to lead to higher uncertainty about the market environment of oil firms on the secondary market. As a consequence, capital markets charge higher prices for debt.

The difference of the OLS estimates might be driven might driven by two factors. First, non-observable firm characteristics, which are only controlled for in the FE estimation, might bias the OLS estimates for loans and bonds at issuance. Second, the differences, in particular with respect to the loan credit spreads, might be driven by a selection effect. As depicted in Figure 3.4, development of the number of issued loans shows a similar pattern as the oil price: in times of very low oil prices, only very few syndicated loans were issued to oil firms. Thus, there might be a selection effect, i.e. only a small number of very low-risk firms received loans, while others were not able to raise debt. Low oil prices and oil price shocks seem to rather lead to credit rationing instead of higher spreads, while in times of high oil prices also less productive firms apply for bank loans and possibly get charged rather high rates. The advantage of our analysis of bonds on the secondary market is that we can observe issued bonds over a longer time period, which allows to analyze how their price is affected by changes in the oil price without such selection effects.

Overall, our results emphasize the link between commodity prices and the costs of debt faced by producers of these commodities. Potential areas for further research could be other industries. In this paper, we only consider the oil industry and it thus might be fruitful to examine the coal or natural gas sectors, for example. Furthermore, our results indicate that the effects differ between bank loans and corporate bonds. Thus, a deeper investigation into developments in the banking sector, its regulation and changes in the market for corporate bonds may provide explanations for the differences we find.

C Appendix to Chapter 3

C.1 Classification of SIC and NAICS Codes

TABLE 3.6: Recursive success ratios relative to the no-change benchmark

SIC	NAICS	Industry Classification
1311	211111	Upstream
1321	211112	Downstream
1381	213111	Upstream
1382	213112	Support Services
1382	541360	Support Services
1389	213112	Support Services
1389	237120	Support Services
1389	238910	Support Services
1623	237120	Support Services
1629	237120	Support Services
2819	211112	Upstream
2865	325110	Downstream
2869	325110	Downstream
2911	324110	Downstream
2990	–	Downstream
2992	324191	Downstream
2999	324199	Downstream
3533	333132	Support Services
4612	486110	Midstream
4613	486910	Midstream
4619	486990	Midstream
4922	486210	Midstream
4923	221210	Midstream
4923	486210	Midstream
4924	221210	Midstream
4925	221210	Midstream
4931	221210	Midstream
4932	221210	Midstream
4939	221210	Midstream
5171	424710	Downstream
5171	454310	Downstream
5172	424720	Downstream
5900	–	Downstream
5983	454310	Downstream
5984	454310	Downstream
5989	454310	Downstream
6792	523910	Downstream
6792	533110	Downstream
7373	–	Support Services
8741	237120	Support Services

Note: SIC and NAICS codes are used to query firms' information from the Compustat Capital IQ database and their categorization within the oil industry's value chain.

C.2 Definition of Variables

Based on the data from the Capital IQ database, additional variables that are commonly used in the empirical corporate finance literature can be calculated.

TABLE 3.7: Definition of variables used in the empirical analysis.

Variable	Description
Leverage	Debt to Asset ratio of firms
Profitability	Ratio of EBITDA to Total Assets
Total Assets	Borrowers total amount of assets measured in million USD
Loan Credit Spread	Spread in base points over benchmark interest rate, LIBOR or EURIBOR
Loan Amount	Issued loan facility amount measured in million USD
Loan Maturity	Loan term measured in months
Bond Credit Spread (at Issuance)	Spread between the coupon rate of the issued bond and the interest rate of a US treasury bond with matching maturities
Bond Amount	Bond amount measured in million USD at issuance
Bond Maturity	Bond term measured in months at issuance
Bond Credit Spread (continuous)	Spread between calculated bond yield, based on secondary market transactions, and the interest rate of a US treasury bond with matching maturities
Avg. Months-to-Maturity (continuous)	Remaining average months to maturity measured continuously
Oil Price	Last available WTI oil spot price per quarter
Oil Volatility	Quarterly coefficient of variation of the WTI spot price
Oil Exports	Logarithm of quarterly US crude oil exports measured in thousand barrels
Credit spread	Difference between Aaa and Baa corporate bond yield by Moody's obtained from https://fred.stlouisfed.org/graph/?g=D9J.
Term spread	Difference between the ten-year Treasury yield and the three-month T-bill yield.

C.3 Exploratory Data Analysis

FIGURE 3.7: Number of loans issued per industry classification per year

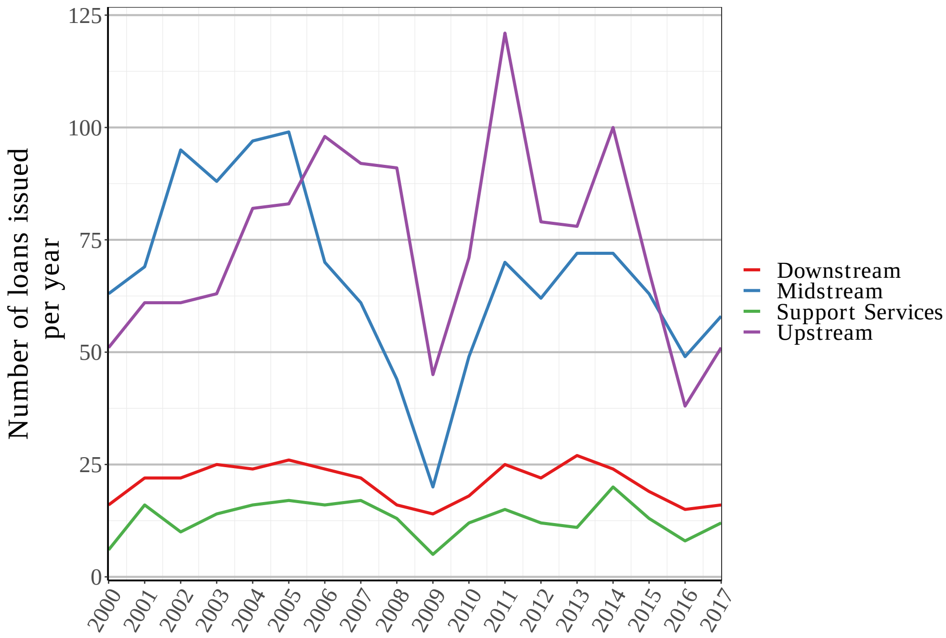


FIGURE 3.8: Number of bonds issued per industry classification per year

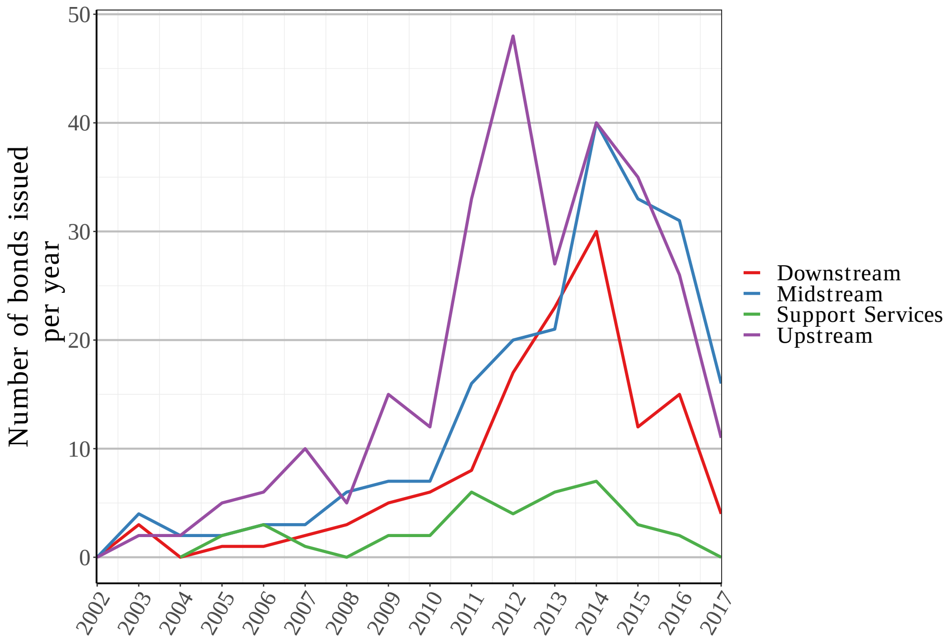


FIGURE 3.9: Median bond credit spread at issuance bonds per industry classification per year

FIGURE 3.10: Average loan credit spread at issuance and average maturity of loan facilities per industry classification per year

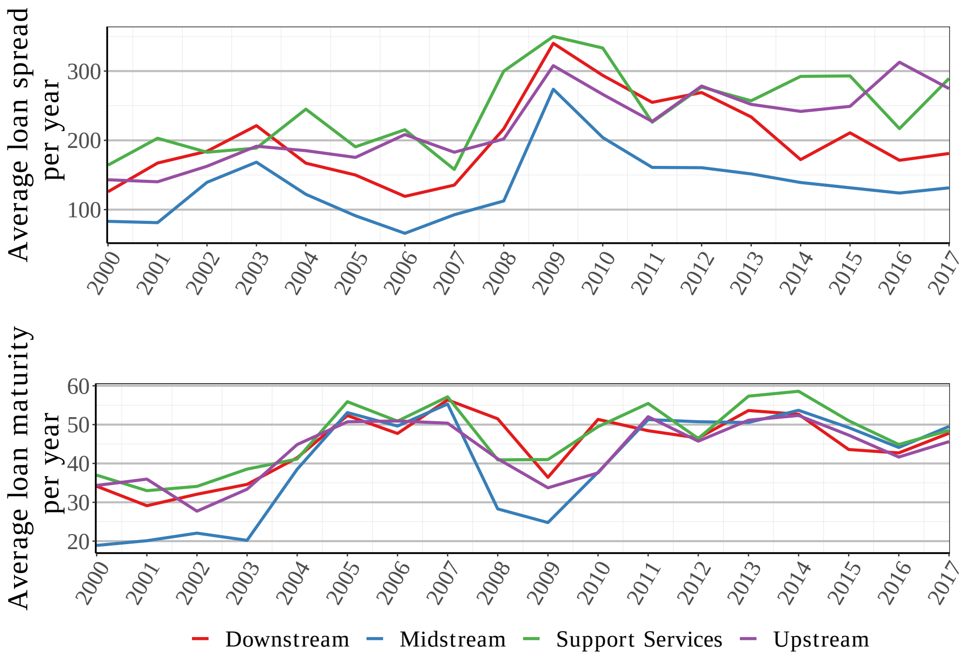


FIGURE 3.11: Average volume of loans issued per industry classification per year

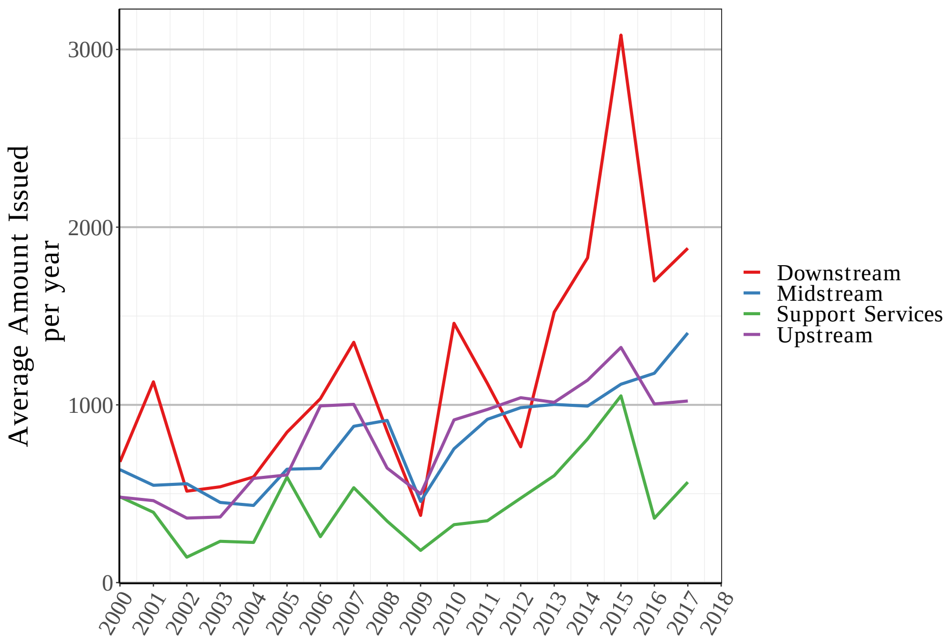


FIGURE 3.12: Average volume of bonds issued per industry classification per year

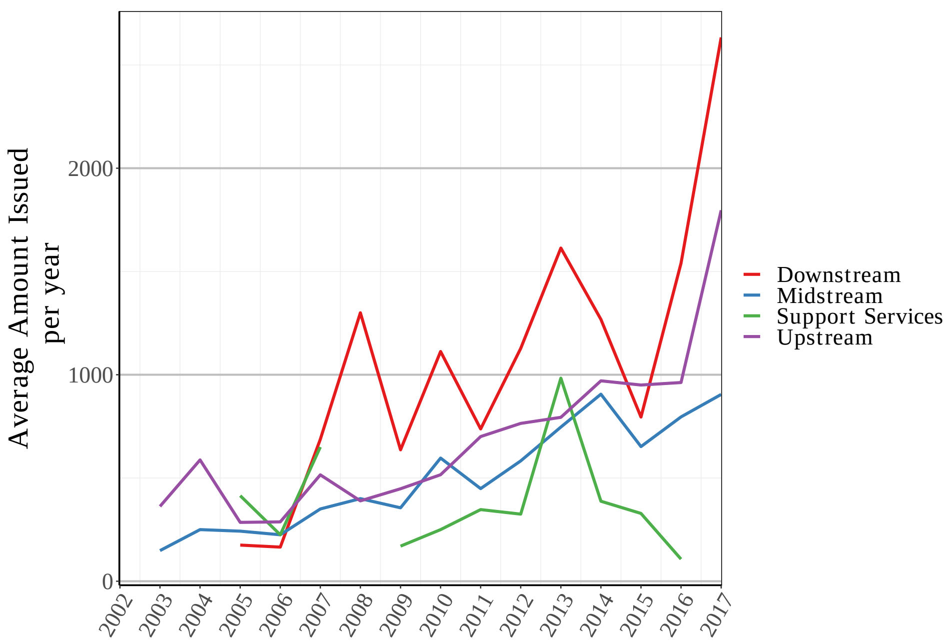
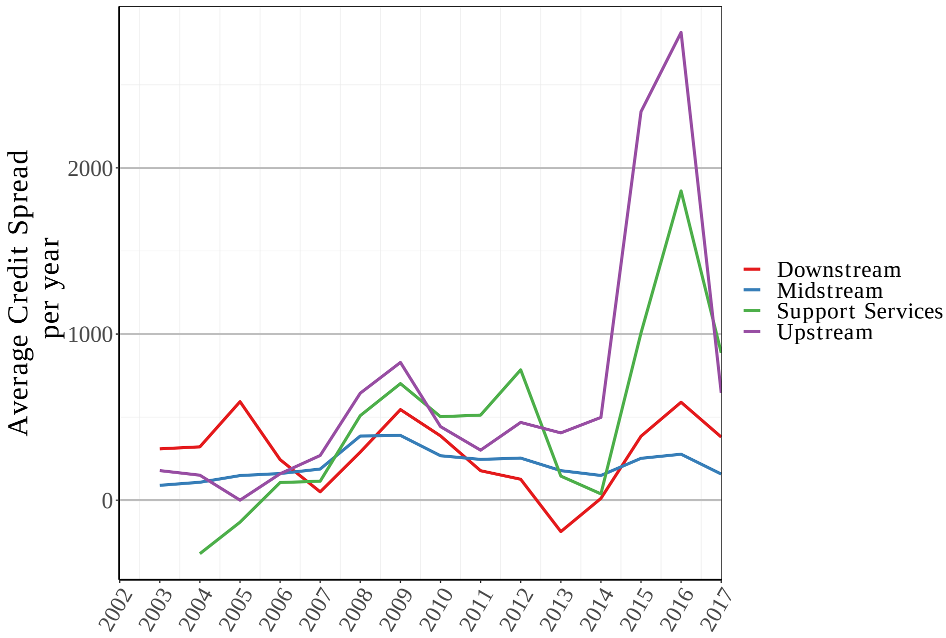


FIGURE 3.13: Average credit spread of bonds traded on the secondary market per industry classification per year



Part III

Climate Change: Vulnerability and Adaptation Strategies

Chapter 4

Climate Vulnerability in Rainfed Farming: Analysis from Indian Watersheds

The following chapter is based on the paper:

Title:	Climate Vulnerability in Rainfed Farming: Analysis from Indian Watersheds
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Climate Vulnerability in Rainfed Farming: Analysis from Indian Watersheds[1]

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Abstract

India ranks first among the rainfed agricultural countries in the world. The impact of changing climate threatens rainfed food production as well as the food security of millions of people in the tropics and subtropics. The Government of India initiated WDPs for the overall development of these areas. We, therefore, established a comprehensive, location-specific, bottom-up tool to analyze and compare the climate vulnerability of watershed areas. For this, we deducted a new CVI^{RFT} to evaluate the potential effectiveness of programs to adapt to climate change impacts. The CVI^{RFT} comprises of three dimensions of vulnerability, i.e., *adaptive capacity*, *exposure* and *sensitivity*. These dimensions consist of ten major components and 59 indicators with emphasis on rainfed farming and WDP interventions. To test the tool, we collected primary data through household surveys (n = 215, split among three watershed communities) in Kerala. We show that there were strong variations in the *exposure* dimension, moderate in *sensitivity* and negligible in *adaptive capacity* across the watersheds. After analyzing the major components under the dimensions, we suggest focusing on policy orientation towards redesigning of the WDPs with emphasis to economic diversification, livelihood strategies, social networking coupled with stakeholder participation, natural resource management and risk spread through credit and insurance flexibility. The CVI^{RFT} is replicable to similar physio-geographic areas of rainfed farming, with the refinement of indicators suited to the locality.

Keywords: Adaptive capacity, Climate vulnerability, Exposure, Rainfed farming, Sensitivity, Watershed development program

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4.1 Introduction

Rainfed agricultural systems dominate much of tropical agriculture, and are extremely vulnerable to projected climate change. Nearly 80% of the global agriculture is based on rainfed farming (Wani et al. 2009). Rural communities across the world report that rainfall has become more erratic, shorter and heavier within seasons, and that 'unseasonal' events such as heavier rains, drier spells, unusual storms and temperature fluctuations have increased (Devereux et al. 2012). Dependence on climate-sensitive activities, pessimistic projections for agricultural yield, falling production, poverty, food insecurity and limited capacity to adapt, exacerbate the vulnerability situation of rainfed farmers (Fischer et al. 2005; Gebrehiwot and van der Veen 2013; Idrisa et al. 2012; P. K. Krishnamurthy et al. 2012; Lobo et al. 2017). Moreover, tropical countries have large populations of poor smallholders (Harvey et al. 2014) who live in a 'complex, diverse and risk-prone' system (Chambers 1989) which adds to their vulnerability (Jarvis et al. 2011).

India stands first among the rainfed agricultural countries of the world, with 66% of its total cropped area (Planning Commission 2012). It is the second-largest producer of rice and wheat, staple food for millions of the world, while half of India's production is under rainfed (FAO 2018). In the past century, all over India, severe climatic changes were already observable: the surface temperature has increased by about 0.4 °C, and monsoon rainfalls were decreasing by 6–8% over north eastern India, Gujarat and Kerala (Government of India 2008). The monsoon rainfall variations include delay in onset, long dry spells and early withdrawal, which strongly affect productivity in rainfed farming (Venkateswarlu and Singh 2015). Moreover, it has been projected that unless people adapt their farming behavior, there is a probability of 10–40% loss in crop production by 2080–2100, due to global warming (Aggarwal and Sivakumar 2011). Climate change will act as a hunger risk multiplier by negatively affecting food security, food stability, rural income, food prices and crop yields (P. K. Krishnamurthy et al. 2012). Thus, climate change vulnerability assessment in rainfed farming systems is an important tool in adaptation planning and decision-making to reduce the detrimental effects of climate change on the most vulnerable people.

Millions of the rainfed smallholder farmers will experience immediate hardship and hunger as a consequence of climate change, since they will be less able to make adequate decisions about when to sow, what to grow, and how to time inputs (National Intelligence Council 2009) along with having a low adaptive capacity (Burnham and Ma 2017). As climate change impacts are increasingly observed and felt by smallholder farmers, there is an urgent need to identify approaches which enhance the adaptive capacity of farmers, their households and communities (Frank and Penrose-Buckley 2012; Harvey et al. 2014). It is here that the importance of watershed level planning and development comes into play, by which the communities can better track and understand the importance and impacts of climate change and natural resource management in accordance with the local social system, compared to analysis of larger systems on regional or even country scale. This is why WDPs in India are potential tools to make a significant contribution to reduce vulnerability, enhance resilience and build adaptive capacities of rain fed farming communities to climate-induced shocks. Watershed development is a multi-sectoral intervention that aims at enhancing the potential of ecosystem resources and the socio-economic situation of the community in a specific natural landscape unit (Samuel et al. 2015). It refers to the conservation, regeneration and the judicious use of all the resources (natural and human) within the watershed area. Different studies revealed that WDPs have the capacity to reduce the risk associated with rainfed agriculture and to act as tools for disaster management (Gandhi and Crase 2012; Kelkar et al. 2008). Moreover, they are also valued as one of the best practices contributing to adaptation and mitigation (Venkateswarlu and Singh 2015). Accordingly, climate change vulnerability assessments are necessary in watersheds to better understand structural weaknesses, improve the allocation of those resources that make a system vulnerable, better decision making and to monitor the effects of adaptation measures (Eriksen and Kelly 2007; Tonmoy et al. 2014).

Several studies have examined climate change vulnerability in terms of specific climatic issues, contexts, social groups or ecosystems worldwide (Berger et al. 2017; Debela et al. 2015; Le Phuong et al. 2018; Touch et al. 2017). Indicator development is one of the methodologies to encapsulate complex reality of climate vulnerability for generating more scope and opportunities in terms of policy interventions (Wiréhn et al. 2015). Moreover, indicators provide information on matters of wider significance than what is actually measured or what can be made perceptible as a trend or phenomenon that is not immediately detectable (Hammond et al. 1995). Several indices have been developed to quantify vulnerability to climate change (Chaliha et al. 2012; Pandey and Jha 2012; Pandey and Bardsley 2015; Piya et al. 2012; Upgupta et al. 2015). But there are very limited studies on climate change vulnerability among rainfed smallholders (Alemaw and Simalenga 2015; Asha latha et al. 2012; Harvey et al. 2014; Mongi et al. 2010) or at watershed level, especially in the Indian context (Venkateswarlu and Singh 2015). The existing studies in India focus on the vulnerability of farmers towards flood (Chaliha et al. 2012) or compared the vulnerability of rural indigenous mountainous communities (Pandey and Jha 2012). Upgupta et al. (2015) investigated the vulnerability of forests under the current climate, but excluded socio-economic aspects of the forest dependent communities. In addition, previous studies on climate change in watersheds have mainly focused on the biophysical aspects (Jose et al. 1996), geophysical vulnerability (Tiburan et al. 2013), ecosystem vulnerability (Rice et al. 2017), but less on the people living there. Gender dimensions of climate change (Jost et al. 2016) have almost always been neglected. However, women represent a disproportionate share of the poor and are thus highly vulnerable to climate change (Eastin 2018). They are hindered from fully exploiting their potential due to lack of power, limited market opportunities, lack of knowledge and access to financial resources. Eastin (2018) also found that increasing climatological disasters and shocks are associated with decline in women's socioeconomic rights. Moreover, more women die in natural calamities than men, especially in countries such as India, Indonesia, Sri Lanka and Bangladesh, where they are socio-economically disadvantaged (Arora-Jonsson 2011). Therefore, it is also necessary to examine location-specific gender vulnerability and discrimination to enhance the adaptive capacity of women to respond effectively.

It is difficult to formulate one-size-fits-all solution for all vulnerability assessment (Hinkel 2011). Moreover, it is widely accepted that climate vulnerability studies should explore the socio-economic and institutional factors in depth (Gbetibouo et al. 2010) and at bottom level (Vincent and Cull 2010). Bottom up approaches offer opportunities for fine grained assessment (Kuriakose et al. 2012) by integrating climate change considerations into existing decision making and management decisions. The impacts of climate change effects on smallholders will be locally specific and difficult to measure because of the complexity of farming systems, the complexity of agricultural and non-agricultural livelihood activities (Touch et al. 2017). Hence, the main objectives of our study are (1) to develop and apply the CVI^{RFT}; and (2) to test the new CVI^{RFT} for comparing the vulnerability of three watersheds in India that are characterized by the implementation of WDPs by different agencies. The methodology was developed and pilot tested in one of the watersheds (Raghavan Sathyan et al. 2016) before extending it to the comparative application level presented here.

4.2 Materials and Methods

4.2.1 Climate Vulnerability Assessment Concepts

According to Chambers et al. (1989), vulnerability has two sides: an external side of risks, shocks and stress to which an individual or household is exposed and an internal side, which is defenselessness. In climate change vulnerability assessment, the most vulnerable are considered to be those who are most exposed to hazards, who possess limited resources to cope, who are heavily dependent on subsistence activities involving the extraction natural resources and who have the least resilience to climate shocks (Bohle et al. 1994). The Government of India has started preparing an Action Plan on Climate Change since 2007, after the publication of Intergovernmental Panel on Climate Change Fourth Assessment Report (IPCC AR4). The following definitions act as the principles for the basis of national and state level strategic action plans.

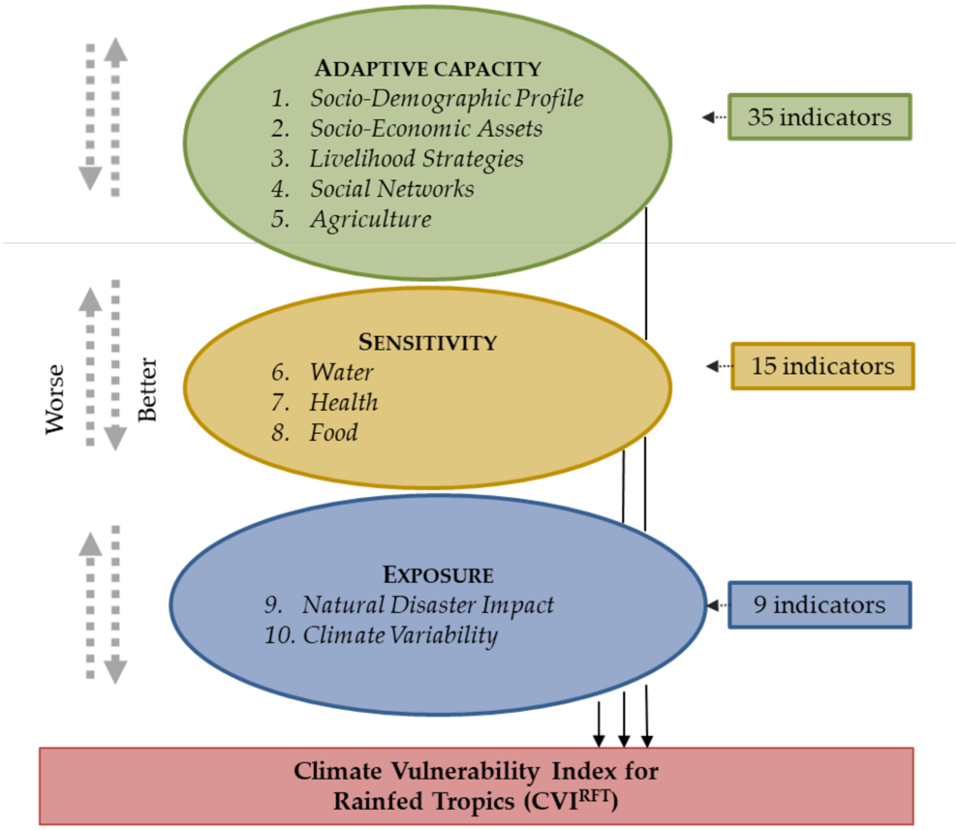
A system is vulnerable or susceptible if it is exposed and sensitive to the effects of climate change and at the same time, only has limited capacity to adapt (Mearns and Norton 2012) and vice versa (Smit and Wandel 2006). Thus, building adaptive capacity enables communities to mobilize resources needed to reduce vulnerability (D. R. Nelson et al. 2007). A widely accepted definition is that vulnerability is a function of *exposure*, *sensitivity* and *adaptive capacity* (Adger 2006; Chishakwe et al. 2012; Mikulewicz 2018).

Here, *exposure* is defined as the nature and degree to which the system is exposed to climatic variations (McCarty et al. 2001) and *sensitivity* is the degree to which a system is affected, either adversely or beneficially, by climate-related stimuli (McCarty et al. 2001). *Adaptive capacity* is crucial to modify *exposure* to the risks, to absorb and to recover from the losses stemming from climate change (Vincent and Cull 2010). *Adaptive capacity* is defined as the propensity or predisposition to be adversely affected (Preston et al. 2011). The vulnerability research has emphasized social vulnerability, which concerns the social and economic determinants of the risks of undergoing climatic stress. Thus, efforts to reduce vulnerability stress the importance of decreasing the *sensitivity* and strengthening the *adaptive capacity* of local communities (Adger et al. 2005). As the adaptive capacity varies between different contexts and systems (Soemarwoto 1987), it is important to identify what builds *adaptive capacity* or what functions as barriers or limits to adaptation (Adger et al. 2009). Therefore, the possibility of creating anticipatory *adaptive capacity* in advance of the *exposure* is required to reduce the impacts of future climate change. Moreover, it is closely linked with infrastructural, institutional, community, social, political, demographic, economic, educational, health, technological, and cognitive factors in influencing the capacity of communities to adapt to adverse climate effects (Adger et al. 2007; Esham and Garforth 2013; Pelling 2011; Sovacool 2011).

4.2.2 Climate Vulnerability Index

We modified well-established approaches for estimating climate vulnerability and the existing indices according to local situations, addressing rain fed farming systems in particular (Hahn et al. 2009; Pandey and Jha 2012; Pandey and Bardsley 2015; K. J. Richardson et al. 2018). The CVI^{RFT} developed here is based on the framework shown in Figure 4.1. It concentrates on the three aforementioned dimensions of vulnerability i.e., *adaptive capacity*, *sensitivity* and *exposure* (Table 4.1). For the development of the CVI^{RFT}, the three dimensions are subdivided into its major components. The *adaptive capacity* dimension comprises of five major components: Socio-Demographic Profile, Socio-Economic Assets, Livelihood Strategies, Agriculture and Social Networks. The second dimension is *sensitivity* with three major components: Water, Food and Health. The *exposure* dimension integrates two major components: 'Natural Disaster and Impact as well as Climate Variability. Each of these major components is subdivided into

FIGURE 4.1: The composition of the CVI^{RFT}



Note: The CVI^{RFT} consists of the three dimensions *adaptive capacity*, *sensitivity* and *exposure*. Each dimension is made up of two to five major components (1-10). Overall, 59 indicators are used to determine the major components.

specific indicators. The major components and overall 59 indicators have been selected to capture the theoretical determinants of vulnerability based on literature, local situation and expert opinion at watershed level. After calculating the overall index, we assess dimensional vulnerability at the watershed level. A detailed description of the indicators under major components can be found in Table 4.6.

The dotted gray arrows in Figure 4.1 indicate the direction of change in the dimensions and the resulting vulnerability situation. For example, a better *adaptive capacity* with a lower level of *sensitivity* and *exposure* contributes to a lower vulnerability situation, and vice versa. A brief description about the definition of the major components and the associated indicators can be found in the results section.

The variables used for indicator development were tested for correlations at a 99% confidence interval. The significant levels of these variables are plotted in Figure 4.5. Out of the 59 variables, on an average 13 variables per watershed showed correlations above 0.7. We found no typical pattern for a single watershed, but rather, mixed results across all watersheds. Apart from this general finding, we identified three pairs of variables that showed positive correlations (0.7) in all three of the watersheds for certain major components: Socio-Economic Assets (variables: area owned & area sown), Livelihood Strategies (new activity, and change in livelihood strategies) and Climate Variability (perception about erratic rain fall, and increase in rain fall and decrease in rainfall). We decided to include these variables despite their potential correlation in the composite index, as they are crucial for assessing the vulnerability index value under the respective major components and dimensions.

TABLE 4.1: Dimensions of Vulnerability, their ten major components and the 59 indicators involved for estimation of the CVI^{RFT}

Dimension of vulnerability	Major component	Indicator
Adaptive capacity	1. Socio-Demographic Profile	1. Family dependency 2. House type diversity 3. Family decision 4. Poverty 5. Indebtedness 6. High income households 7. Male-headed households 8. Religious diversity
	2. Socio-Economic Assets	9. House hold asset possession 10. Farm asset possession 11. Average farm holding size 12. Water access
	3. Livelihood Strategies	13. Migration 14. New crop 15. Dependency on agriculture 16. Farm diversification 17. New livelihood strategies 18. Introduced livestock
	4. Agriculture	19. Rainfed farming 20. Net sown area 21. Crop diversification 22. Adoption of new varieties 23. Decline in farm production 24. Soil erosion perception 25. Non adoption of soil and water conservation (SWC) works 26. Households with 0.2 ha of land
	5. Social Networks	27. Percent of beneficiaries 28. Cooperation 29. Membership in co-operative institutions 30. Help from others 31. Watershed committee (WC) membership 32. No beneficiary contribution 33. Lack of ICT access 34. Grass root planning 35. Trainings
Sensitivity	6. Water	36. Water scarcity 37. Dependency on water resources 38. Public water sources 39. Groundwater decline 40. Gender inequality 41. Decreased water availability 42. Water resource depletion
	7. Health	43. Waterborne diseases 44. New disease incidence 45. Poor quality drinking water 46. Sunburn 47. Death due to climatic variability
	8. Food	48. Off-farm dependency 49. Food insufficiency 50. Poor governmental support

TABLE 4.1 (cont.)

Dimension of vulnerability	**Major component**	**Indicator**
Exposure	9. Natural Disaster Impact	51. Death or injury due to natural disaster 52. Crop loss 53. Property damage 54. Heavy wind
	0. Climate Variability	55. Temperature increase perception 56. Hot months increase perception 57. Erratic rainfall perception 58. Less rainy days perception 59. Extreme climate events

The indicators were measured on different scales, e.g., some of them are numbers or percentages, and others are indices. Therefore, they were normalized to a range between 0 and 1 as suggested by Hahn et al. (2009). Before that, the functional relationship of each indicator to vulnerability is considered whether it contributes to an increase or a decrease in the overall vulnerability. For indicators which decrease the vulnerability, the values were transferred so that we derived a positive (hypothetical) value from the actual value (e.g., 100 minus the indicator value in case of percentage units) (see Table 4.7) which contributes to increase in vulnerability.

For calculating the CVI^{RFT}, each major component contributes equally to the overall index (Hahn et al. 2009; Raghavan Sathyan et al. 2016). The index scores for the major components are calculated by taking the simple average of the normalized indicators. Initially, the values of each indicator were normalized to form an index value using equation 1:

$$Index_{sw} = \frac{S_w - S_{min}}{S_{max} - S_{min}}, \tag{1}$$

where S_w is the original indicator value for the watershed community, and S_{min} and S_{max} are the minimum and maximum values, respectively. The next step after the normalization is the calculation of the index score for the major components. For that, each indicator is averaged (equation (2)):

$$M_w = \frac{\sum_{i=1}^{n} Index_{swi}}{n}, \tag{2}$$

where M_w is one of the major components under the three dimensions of vulnerability, the $Index_{swi}$ is the indexed indicator value of the watershed community, and n is the number of indicators under each major component.

After calculating the index for each major component, the next step was assigning the weights. The balanced weighted approach (Hahn et al. 2009; Sullivan and Meigh 2005) is used in this study, where the number of indicators in each major component has been taken as the weight for calculating the CVI^{RFT}. In our study, the indicators are given equal weights because all the dimensions included in the CVI^{RFT} are equally important and desirable in their own right for assessing the three dimensions of vulnerability i.e., *adaptive capacity*, *sensitivity* and *exposure*. According to Chowdhury (2005), 'the a priori decision to adopt the technique of equal weighting for methodological purposes is often believed to make the choice of weights less subjective' and 'giving equal importance to all the variables is perfectly acceptable when there is no reason to do otherwise'. The weighted scores of the major components are averaged to calculate the final CVI^{RFT} for each watershed. The overall CVI^{RFT} for vulnerability (Raghavan Sathyan et al. 2016) can then be expressed as

$$CVI^{RFT} = \frac{\sum_{i=1}^{10} W_{mi} M_{wi}}{\sum_{i=1}^{10} W_{mi}}, \tag{3}$$

where, W_{mi} is the weight and M_{wi} is the average value of each major component. The CVI^{RFT} is scaled from 0 to 1, i.e., from the least vulnerable to the most vulnerable. The calculation of *adaptive capacity*, *sensitivity* and *exposure* helps to compare and analyze the dimensional vulnerability of the three watersheds. *adaptive capacity*, *sensitivity* and *exposure* are calculated according to equations 4-6:

$$Adaptive\_capacity = \frac{W_{a1}SD + W_{a2}SE + W_{a3}LS + W_{a4}A + W_{a5}SN}{W_{a1} + W_{a2} + W_{a3} + W_{a4} + W_{a5}}, \tag{4}$$

where W_a1, W_a2, W_a3, W_a4, W_a5 are the weights for the Socio-Demographic Profile (SD), Socio-Economic Assets (SE), Livelihood Strategies (LS), Agriculture (A) and Social Network (SN), respectively.

$$Sensitivity = \frac{W_{s1}H + W_{s2}F + W_{s3}Wa}{W_{s1} + W_{s2} + W_{s3}}, \tag{5}$$

where W_{s1}, W_{s2}, and W_{s3} are the weights for the components Health (H), Food (F), and Water (W), respectively.

$$Exposure = \frac{W_{e1}ND + W_{e2}CV}{W_{e1} + W_{e2}}, \tag{6}$$

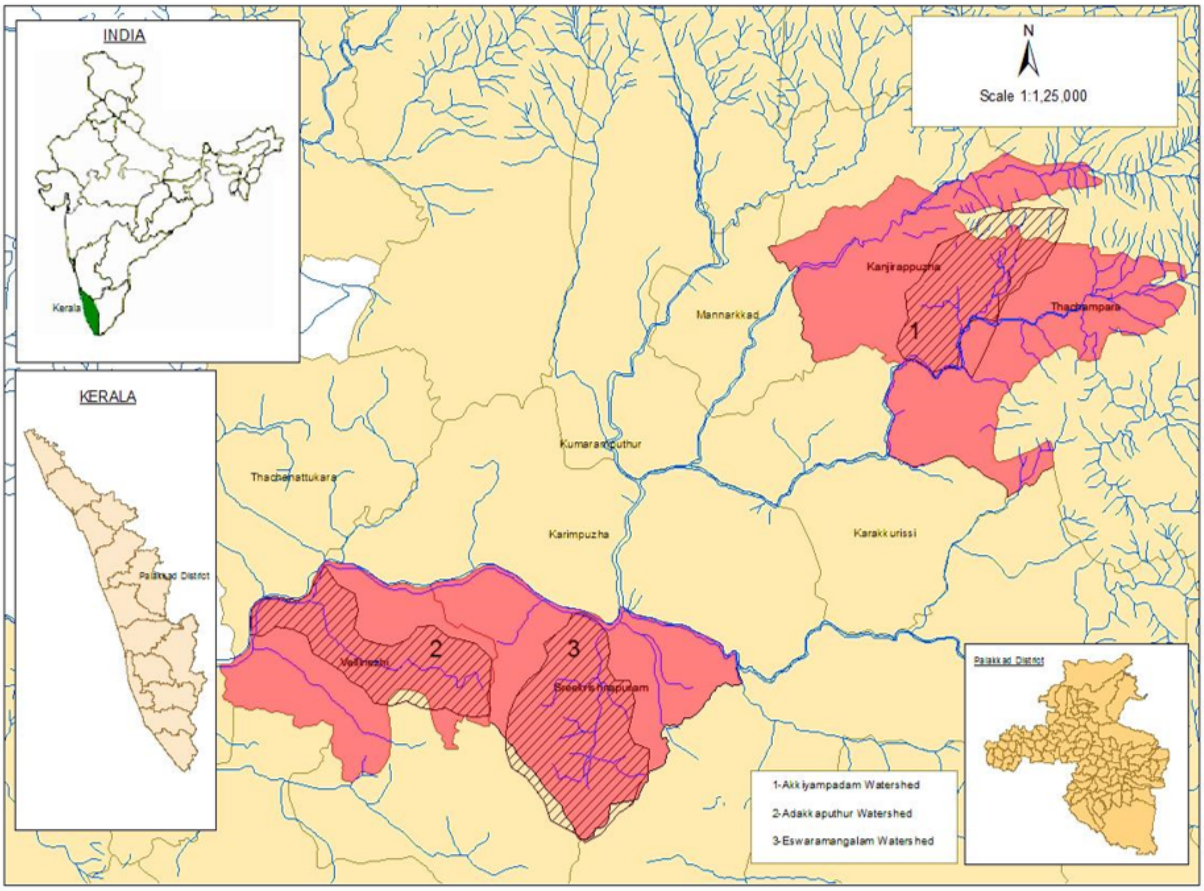
where W_{e1} and W_{e2} are the weights for Natural Disaster Impact (ND) and Climate Variability (CV), respectively. The dimensional vulnerability value varies between 0 and 1, where a higher value indicates greater vulnerability.

4.2.3 Study Area

Field data was collected from Kerala state to estimate the 59 indicators and to calculate the 10 major components, the three dimensions of vulnerability and finally the CVI^{RFT}. Kerala, located in the southwest tip of India between the Arabian Sea in the west and the Western Ghats mountains in the east (Figure 4.2), covers around 1.18% of the Indian landmass. It has a tropical monsoon climate with heavy annual rainfall of up to 3000 mm as it lies in the western windward slopes of the Western Ghats. Spatial and temporal variations in monsoon rainfall make the state extremely vulnerable to climate change (Nair et al. 2014). The state faced 64 intense and short term droughts (Krishnakumar et al. 2009) during the past 100 years period even with the highest annual rainfall in India The temperature reaches up to 32 °C during March to April with a relative humidity of 73–89%. Subsistence homestead farming is a key feature of the land use in this area. Out of the net cropped area of the state, 81% is rainfed (Government of Kerala 2014). Moreover, 40% of the total cropped area is prone to soil erosion (Government of Kerala 2014). With this background, we selected the Kerala state for the climate vulnerability assessment among rainfed smallholders.

Palakkad district, the study area, is listed as one of the highly vulnerable districts to climate change due to its specific geographic location, humid climate, high percentage of population, dependence on agriculture, a low ranking in the human development index, high social deprivation and a high degree of vulnerability to natural hazards like floods and droughts (Government of Kerala 2014). The district is known as the 'Granary of Kerala' as it is the highest producer of rice in the state. Moreover, 90% of the rice production comes from rainfed farming (Krishnakumar et al. 2009). At the same time, the annual rainfall in this region is the lowest (1600 mm) among the districts of Kerala (Nair et al. 2014) due to the peculiar geographic conditions of the area coming under the Palakkad gap with landlocked physiography. The Palakkad Gap also moderates the summer temperatures of the district (Nikhil Raj and Azeez 2012) where the daytime temperature often exceeds 40 °C while the maximum mean annual temperature of the state is 32 °C.

FIGURE 4.2: Location of the study area in Kerala, India



4.2.4 Watershed Development Programs

The newly developed CVI^{RFT} was tested in three different settings. The three watersheds selected for the study are shown in Figure 4.2 and further described in Table 4.2. The respective WDPs in these watersheds have been implemented by three different agencies, i.e., Soil Survey and Conservation department that represents the State Government (SG), Non-Governmental Organisation (NGO) and a Local-Self Government (LG). In recent years, three main activities of the WDPs have been implemented in these watersheds: natural resource management, production system enhancement and livelihood support system activities. The natural resource management activities include construction of small check dams, farm ponds, contour bunding, river bank protection walls, moisture conservation pits and protection of wells. The production system enhancement included the distribution of new fruits, medical plants, crops and varieties as well as organic manure. The livelihood support system activities were concentrated on the women and landless in the area by mobilizing self-help groups. The main livelihood activities introduced were rabbit rearing, livestock and poultry units. An overview of the watersheds described above is given in Table 4.2.

4.2.5 House Hold Surveys

The household interviews were conducted during the period August–November 2015. In all watersheds, the WDP activities were completed before 2014. The cluster sampling method was used for the selection of farm households. The farmers were grouped into small, marginal,

TABLE 4.2: Socio-economic and physical characteristics of the selected watersheds and the implemented WDPs

Criteria	Watersheds		
Name	**Adakkaputhur**	**Akkiyampadam**	**Eswaramangalam**
Project implementing agency	SG	NGO	LG
Grama Panchayat	Vellinezhi	Kanjirampuzha	Sreekrishnapuram
Project period	2003-2008	2009-2013	2007-2012
Project fund	26,485 US$	57,920 US$	82,456 US$
Soil	Gravelly clay and sandy clay	Laterite	Laterite and alluvial
Population	5,742	7,399	6,469
Households	1,243	1,482	1,198
Literacy (%)	87.3	98	98.9
Farm size <1ha (%)	81	92	71
Major crops	Rubber, paddy, arecanut, coconut, vegetables	Coconut, cashew, arecanut, rubber, tapioca, vegetables	Rubber, coconut, arecanut, banana, vegetables

Source: Detailed project reports of Adakkaputhur, Akkiyampadam (People Service Society 2009) and Eswaramangalam watersheds (Integrated Rural Technology Center 2009).

medium and large based on their landholding size. A farmer owning less than 2 ha of land is considered to be a smallholder farmer, which is the case for more than 80% of the farmers in the three selected watersheds. Out of the total 215 smallholder households covered in the field survey, 70 households were located each in SG and NGO, and 75 households in LG watershed. Interviews were conducted in Malayalam (local language) with the support of a local assistant. The interview schedule consisted of four broad sections: (i) basic information about the households; (ii) perception on *exposure* to climate change; (iii) perception on *sensitivity* to climate change; and (iv) present *adaptive capacity* to climate change.

4.3 Results and Discussion

4.3.1 Dimensions of Vulnerability and the Climate Vulnerability Index

According to the CVI^{RFT}, the differences between the LG, SG and NGO managed watershed are negligible (Figure 4.3). Nevertheless, a closer look into the three dimensions of vulnerability *adaptive capacity*, *sensitivity* and *exposure* reveal some interesting differences. The highest *sensitivity* towards climate variability can be found for SG, while it was the lowest for LG. Water and Food components contribute to the high vulnerability values, and thus, to the highest *sensitivity* (Figure 4.4). The largest difference between the watersheds was reported for *exposure*. *Exposure* was more pronounced and on a similar level in LG and NGO, while SG depicted a substantially lower index value. Both, Natural Disasters and Climate Variability components account for these differences (Figure 4.4). Overall, *adaptive capacity* has the lowest variation among the watersheds, *sensitivity* has moderate and *exposure* the highest variability. The following analysis of the major components, and the contributing indicators of the dimensions of vulnerability will help to identify the key areas to be considered in restructuring of WDP planning, decision making and implementation.

FIGURE 4.3: Dimensions of Vulnerability and the resulting CVI^{RFT} of the three watersheds

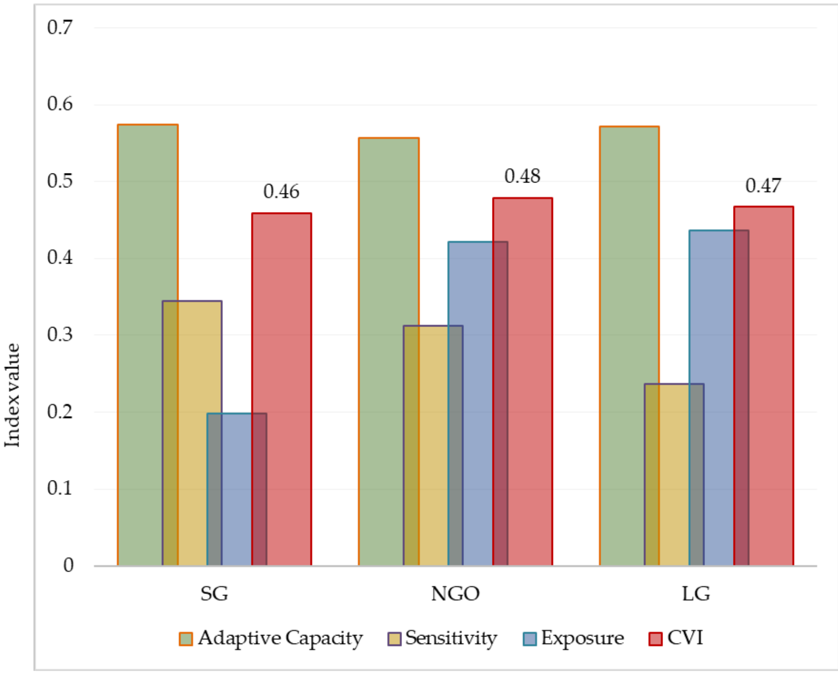
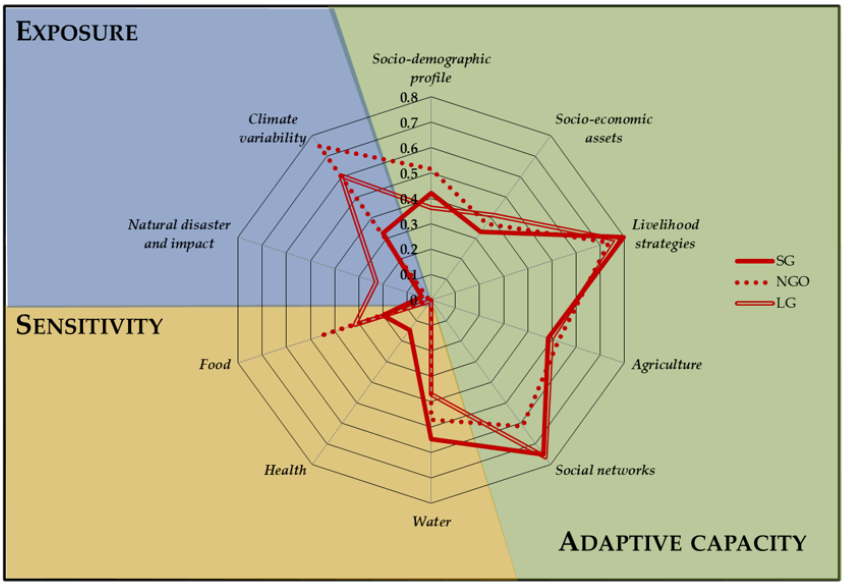


FIGURE 4.4: Comparison of average values of the ten major components for the three watersheds



4.3.2 Major Components and Indicators

4.3.2.1 Adaptive Capacity

Livelihood Strategies and Social Networks are the major components of *adaptive capacity*, which exhibit relatively high values in all the three watersheds (Table 4.3). However, the indicators contribute in different proportions in the three regions (Table 4.8). Livelihood Strategies

TABLE 4.3: Indexed values for the major components of *adaptive capacity*

Major components	SG	NGO	LG
1. Socio-Demographic Profile	0.42	0.48	0.37
2. Socio-Economic Assets	0.33	0.37	0.41
3. Livelihood Strategies	0.80	0.74	0.77
4. Agriculture	0.48	0.52	0.50
5. Social Networks	0.75	0.61	0.76

are the choices and activities that people make and undertake in pursuit of income, security, well-being, and other productive and reproductive goals (Department for International Development 1999). Livelihood decisions may vary according to opportunities for access to, control over and use of local assets along with their capacity to make use of them for subsistence and/or income generating purposes (Walker et al. 2001). The Livelihood Strategies of SG were the least diversified which contributed to a lesser *adaptive capacity* (Table 4.3, Figure 4.4). Not even a single household tried to introduce livestock in their farming (1.00, Table 4.8). The NGO households had somewhat more opportunities and accessibilities for diversification as the WDP intervened with poultry and cattle units for their beneficiaries and hold comparatively a lower vulnerability value. Venkateswarlu and Singh (2015) also emphasized the importance of policy initiatives for economic diversification, diverse livelihood strategies and migration possibilities for strengthening the adaptive capacities of rainfed farmers in India.

Marshalling and extending of social networks and relationships is also very important in increasing *adaptive capacity* (Walker et al. 2001). Here, LG has the highest Social Networks vulnerability. 98.7% of the people complained that they never received any help from neighbors or government institutions during the crisis of the heavy storm in 2015. Moreover, only 28% of the households received benefits from the WDP and thus contributed to a higher vulnerability value (0.72, Table 4.8). The local credit institutions coupled with private institutions should be promoted to create *adaptive capacity* (Venkateswarlu and Singh 2015). It is necessary to engage a diverse set of stakeholders operating at different levels and scales in networks to mobilize and facilitate information flows as a means to reduce vulnerability (Hochman et al. 2017; Olsson et al. 2004). Thus, policy implications are essential in diversifying the livelihood strategies, to create financial mechanisms such as access to credit institutions, disaster insurance services and information services to tackle the envisaged climate change scenario (Venkateswarlu and Singh 2015). These results are in line with the findings of Moench and A. Dixit (2004) who conducted a study in South Asia on *adaptive capacity* and livelihood resilience.

NGO is the highest vulnerable watershed in terms of Agriculture. In this region, we found less crop diversification (0.36, Table 4.8) and farmers were complaining about the low productivity due to soil erosion. Even then, only 25% of the households adopted soil and water conservation works (0.76, Table 4.8) offered by the WDP. In a nutshell, a majority of the farmers adopt no strategies for conserving soil and water to cope with potential climate change impacts, which stands in line with the findings of Touch et al. (2017) for smallholder farmers in North-West Cambodia. Documentation of indigenous practices, existing best practices for production system along with long term strategic research and planning (Venkateswarlu and Singh 2015), the introduction of new crop varieties and natural resource management are essential practices to be considered for creating better *adaptive capacity* in the agriculture component.

Socio-economic factors play a key role in enhancing or constraining the existing *adaptive capacity* of farmers to cope with climate change (Venkateswarlu and Singh 2015). Socio-Demographic Profile and Socio-Economic Assets hold lower vulnerability values in all three watersheds. Among the three watersheds, the NGO exhibited relatively higher Socio-Demographic vulnerability. A high religious diversity index (0.63) and family dependency ratio (0.51, see

Table 4.8) contribute to the highest value of vulnerability when compared to the other two watersheds. The previous research with regard to religion and climate change perceptions shows that there is an attitudinal difference to climate change and climate change policy across various religious groups (Morrison et al. 2015; C. Murphy et al. 2016; N. Smith and Leiserowitz 2013).

Religious beliefs have a direct impact on how to deal with threats, either it is on the short-term (e.g., famine, water access) or long-term (climate change, land ownership). Thus, adaptation planning must aim to integrate cultural values to facilitate interventions that redress power imbalances and empower individuals to help themselves through religious organizations (Idrisa et al. 2012). We, therefore, included religious diversity as one of the indicators. Moreover, the watershed inhabitants are from three major religious groups, i.e., Hindu, Muslim and Christian.

In LG, household asset possession (0.36) and farm asset possession (0.35) indices contribute to relatively higher value of Socio-Economic vulnerability (0.41) when compared to the other two watersheds (Tables 4.3 and 4.8). 96% of the households own less than 0.2 ha of land and have fewer opportunities for farm expansion. Thus, the lack of financial assets is one of the main factors inhibiting choices to climate change adaptation (Gebrehiwot and van der Veen 2013).

WDPs are one of the best tools to build *adaptive capacity* because of their interventions to promote livelihood, production system improvement, and natural resource management. Even then, there is an urgent need to bring out technological, institutional and operational changes at policy and practice level (Samuel et al. 2015). Nevertheless, people in our studied watersheds were reluctant to adopt new livelihood activities, especially to introduce livestock into their ongoing farm activities. Moreover, they were skeptical towards new crops and varieties despite having suitable soils and climatic conditions. It will be advantageous to intervene with on-farm trials, farmer field schools, climate smart extension strategies (Touch et al. 2017), field demonstration to promote new crops and drought resistant varieties, awareness creation on adjusting planting time (Poulton et al. 2016), and diversification of farm and livelihoods for better preparing the local people for climate change impacts.

4.3.2.2 Sensitivity

Under the *sensitivity* dimension, three major components were analyzed, i.e.,Water, Health and Food, which are very basic and essential elements for any community (Table 4.4). The three watersheds exhibited relatively low indicator values for Health and Food components. This shows a positive sign towards reduced *sensitivity* to climate change (Figure 4.4). SG displays the highest vulnerability towards the component Water. Water scarcity was a serious problem in the watershed due to a strong groundwater decline (0.69, Table 4.8) and a decreased availability of drinking water compared to previous years. In total, 17% of the households were solely depending on public water sources for the daily routine. Pandey and Bardsley (2015) also observed that water vulnerability of rural households in Uttarakhand was mainly due to the water scarcity and high dependency on agriculture and natural resources for their living. The WDP further aims at soil and water conservation measures, which are one of the important adaptation measures (N. Smith and Leiserowitz 2013; Venkateswarlu and Singh 2015). Only 3%

TABLE 4.4: Indexed values for the major components of *sensitivity*

Major Components	SG	NGO	LG
6. Water	0.55	0.47	0.37
7. Health	0.15	0.00	0.00
8. Food	0.20	0.46	0.32

of the farmers adopted any kind of soil and water conservation activities in their field. Out of these 3%, 12% of the strategies were stone pitched contour bunds and moisture conservation pit offered through the WDP. As these strategies were expensive, the WDP have subsidized these interventions up to 90%. Nevertheless, only a minor fraction of farmers adopted one of these strategies.

During the field survey, one of the farmers expressed that 'we were not informed about soil and water conservation works and the committee has special concerns to some of the big farmers'. This can be addressed through public awareness campaigns about WDP activities, as well as the creation of Water Users Societies and women Self Help Groups, to strengthen effective water management through the community involvement (Banerjee 2015). Another reason for not adopting conservation efforts is resulting from small fragmented land holdings.

Groundwater decline and increased drinking water shortage were other major concerns. The paddy fields are reclaimed for either cash crops or construction purposes, because of agricultural labor shortage, increased labor charges and input price hikes. Improvements could be addressed via the state government by formulating strict rules and regulations, against paddy field conversion for non-agricultural purposes with support from competent local institutions responsible for enactment.

Regarding the Health component, there are many prevalent human diseases, which are linked to climate variabilities such as respiratory illnesses, altered transmission of infectious diseases such as cholera, malaria, and even malnutrition due to crop failures (P. K. Krishnamurthy et al. 2012; Patz et al. 2005). The Health components showed low vulnerability values in all the three watersheds except for the case of sunburns. The sunburn incidence is common in the Palakkad district and it happens because of a peculiar geographic condition called the Palakkad gap, i.e., a low mountain pass in the Western Ghats between Tamil Nadu and Kerala states. It is the only break in the Western Ghats, the rain shadow barrier, and the rain clouds are blown away making the district one of the most drought prone districts of Kerala. In the SG, people opined that there were an increasing influence of heat waves and sunburn incidence since the past two years which reduce their working hours outside during the day time. There were reports of sunburn in 2010 (Gopakumar 2011) as well as deaths in 2016 resulting from heat waves and associated dehydration. All these factors enhanced the climate vulnerability of the district.

There was a wider variation in the Food component vulnerability between the watersheds (Table 4.3). Climate variability and disasters can worsen the situation of vulnerable people during food and nutrition crisis. The NGO had the highest Food vulnerability value, because people opined that there was no improvement in the support from the government (0.94, Table 4.8) to achieve food security. Almost half of the households depended on off-farm sources for their daily needs, which show insufficient food from farm due to either low availability of agricultural land or due to dependency on other income sources. Here the NGO watershed is highly vulnerable because 67% of the households depend on off-farm food sources while in SG it is only 43%.

4.3.2.3 Exposure

The dimension *exposure* comprises of two major components, i.e., Natural Disaster Impact and Climate Variability (Table 4.5). Impacts of natural disasters such as floods, droughts, or earthquakes are partly dependent on the social system where they occur (Dayton-Johnson 2006). Reports on the occurrence of such disasters for the past ten years were obtained in the household surveys. Here, the LG depicts the highest value towards natural disasters because this watershed was affected by heavy wind in 2015, with severe crop losses and property damages (Table 4.8). Nevertheless, the indicator values of Natural Disaster Impact were comparatively low, likely due to the fact that no larger, life-threatening disasters occurred in the past decade.

TABLE 4.5: Indexed values for the major components of *exposure*

Major Components	SG	NGO	LG
9. Natural Disaster Impact	0.04	0.01	0.23
10. Climate Variability	0.33	0.75	0.61

In contrast, values for Climate Variability score are substantially higher (Table 4.5). More than 60% of the crop yield variability, mainly of maize, wheat, soybean and rice can be explained by Climate Variability (Ray et al. 2015). Farmers do perceive the climatic variations and try to adapt through local adaptation strategies (Ogalleh et al. 2012). As part of this major component, we considered the perception of people about an increase in temperature, hot months, the incidence of erratic rainfall and a decrease in rainy days during the last ten years (Table 4.8). We find that Climate Variability perceptions were more pronounced in NGO as compared to the other two watersheds. The households were much more concerned about the rise in temperature (0.94), hot months (0.93) and decrease in rainy days (0.91, Table 4.8) compared to the other two watersheds. Smallholders were worried about a decline in production due to erratic rainfall with high temperatures and the occurrence of persistent droughts. Similar findings from North-West Cambodia (Touch et al. 2017) and Telangana region of India (Nidumolu et al. 2015) indicated that farmers perceive erratic rainfall, dry spells and drought affect the crop yield. In LG, 50% of the households faced drought and water scarcity of about 3–6 months during the summer season.

People opined less physical and financial assistance during disaster emergencies. One of the solutions for this might be strengthening and equipping the local institutions and informal associations to tackle natural disasters. Residents participating in community-based adaptation actions are both knowledge holders and users. So, flexibility in key institutions that make up a local knowledge system is necessary for learning (Lebel 2013; Nidumolu et al. 2015). By working together in such kind of groups, people will be able to spread and share the risks and knowledge (Bapna et al. 2009) along with proper channeled collective action to address the situation (Pandey and Jha 2012).

4.3.2.4 Comparison of Major Components

The major components for the three watersheds are compared in Figure 4.4. We found that the major component indices for Livelihood Strategies, Socio-Economic Assets and Agriculture were almost similar (<0.1 difference) in the three watersheds while there were stronger differences (between 0.1 and 0.2) in Socio-Demographic Profile, Social Networks,Water and Health. The strongest difference (>0.2) can be depicted for the components Climate Variability, Natural Disaster and Food.

The reason for the strong variations in Climate Variability and Natural Disaster is the varying perception of people about an increase in temperature (Table 4.8) and hot months as well as the occurrence of less rainy days and erratic rainfall. People do strongly perceive climate variability and incidence of natural disasters but neither in the same intensity nor climatic parameter. Another concern is Food, where the NGO watershed exhibited strong variation because of poor government support to ensure food security in the area through Public Distribution System. This result is different from Pandey and Jha (2012) where the people complained about low availability of agriculture land and productivity as a reason for Food vulnerability.

Overall, it would be interesting to study the performance of the CVI^{RFT}, its dimensions, major components and indicators across a wide range of socioeconomic and physio-geographic conditions. Knowledge about the average performance of watersheds with regard to these indices would allow detecting watershed types of particular vulnerability to climate change.

However, in this study, we mainly introduced the concept of the CVI^{RFT} and showed the functionality of the concept to investigate three WDPs in India.

4.4 Conclusion

The new CVI^{RFT} provides a straight forward approach to investigate the vulnerability of spatial entities to climate changes in a human dimension. It can be used as an effective tool in evaluating the vulnerability of rainfed regions in general with modification of contributing indicators according to the context and locality.

Since the derived CVI^{RFT} values for the three watersheds are almost identical, an in-depth qualitative data analysis is proposed to identify the differences in performance of the considered implementing agencies. For example, focus group discussions and key informant interviews with emphasis on participatory approaches would provide unbiased detailed information on the functioning of WDPs. Furthermore, future research could focus on comparative vulnerability assessment of WDP communities with communities that are not supported by WDPs. Another issue that should be addressed in any survey-based index assessment is the issue of uncertainty and sensitivity. For the CVI^{RFT}, we were able to show the statistical significance of differences between dimensions and identify the main influencing major components that led to these differences (Raghavan Sathyan et al. 2018a).

High values of dimensions or major components indicate a neglect of the respective topic area in the design of WDPs. This can provide stakeholders and politicians with relevant information to act and address the identified deficiencies. The policy implications are crucial in restructuring the existing WDPs through concerted research and development efforts for novel location specific adaption strategies, documenting indigenous adaptation strategies, promoting the adoption of existing interventions and mobilizing marginalized sections. For example, emphasis on adoption of new crops and resistant varieties suited to agro-climatic conditions and diversification of farm and livelihoods is needed while formulating action plans for implementation of the WDPs. Moreover, a timely and accurate weather forecasting system, an effective disaster management and awareness campaigns on natural resource management seem to be emergent needs of the communities. Criticism in the selection of our indicators could be the subjectivity in their definition. However, as we analyzed 59 indicators in total, we are convinced that we span a large range of potentially relevant information. Further, the direction of the relationship between the indicators and vulnerability is subjective and could be interpreted differently. We used an equal weighting approach in constructing the composite index CVI^{RFT}. Future research on indicator development may concentrate on applying different weighting schemes and refinement of contributing indicators based on the location and the target group coupled with qualitative data analysis. Nevertheless, we discussed our framework in many workshops and think that the direction we identified is plausible. Finally, data evaluation obtained from questionnaires is prone to errors and false information given by the farmers, a feature that should be considered in the assessment of uncertainty of complex indicator systems such as the CVI^{RFT}.

D Appendix to Chapter 4

TABLE 4.6: List of indicators, their explanation and sources

Indicator	Explanation (Unit)	Relationship to vulnerability	Source
1. Family dependency	Ratio of population between 0-14 years and population of 60 years & above to the population between 15-59 years [-]	Increase	Sadhak (2013)
2. House type diversity	Simpson's diversity index $(1-D)^a$ based on the type of house roof such as tiled or concrete [-]	Increase	New[d]
3. Family decision	Literate household head [%]	Decrease	Pandey and Jha (2012)
4. Poverty	Families below poverty line [%]	Increase	New
5. Indebtedness[b]	Families with debt [%]	Increase	New
6. High income households[c]	Households with income >2250 $/year [%]	Decrease	National Intelligence Council (2009)
7. Male headed households	Households with male as head of family [%]	Decrease	Pandey and Jha (2012)
8. Religious diversity	Simpson's diversity index $(1-D)^a$ based on the religious belief of the family (Hindu, Muslim or Christian) [-]	Increase	New
9. Household asset possession	Inverse of (no of household asset+1) [-]	Decrease	New
10. Farm asset possession	Inverse of (no of farm asset +1) [-]	Decrease	New
11. Average farm holding size	Inverse of (land holding size +1) [-]	Decrease	New
12. Water access	Households with at least one water (well/pond) resource at home [%]	Decrease	New
13. Migration	Households in which at least one member migrated for better income since last ten years [%]	Decrease	Pandey and Jha (2012)
14. New crops	Households introduced at least one new crop in the homestead /farming [%]	Decrease	Pandey and Jha (2012)
15. Dependence on agriculture	Households with agriculture as the only source of income [%]	Increase	World Bank (1997)
16. Farm diversification	Inverse of (types of enterprises+1) [-]	Increase	World Bank (1997)
17. New livelihood strategies	Households which adopted new livelihood strategies since the start of WDPs [%]	Decrease	New
18. Introduced livestock	Households which adopted livestock in farming since the start of WDPs [%]	Decrease	New
19. Rainfed farming	Households which has not following any irrigation methods [%]	Increase	New
20. Net sown area	Cultivated land area [%]	Decrease	New
21. Crop diversification	Inverse of (types of crops+1) [-]	Decrease	Hahn et al. (2009) and World Bank (1997)
22. Adoption of new varieties	Households which introduced new varieties in farming since the start of WDPs [%]	Decrease	New
23. Decline in farm production	Households reported decreasing trend in farm production [%]	Increase	Pandey and Jha (2012)
24. Soil erosion perception	Households opined moderate to severe soil erosion in their land [%]	Increase	New
25. Non adoption of SWC works	Households where farmers not adopted any SWC works [%]	Increase	New

TABLE 4.6 (cont.)

Indicator	Explanation (Unit)	Relationship to vulnerability	Source
26. Households with <0.2 ha of land	Households with less than .2 ha of land [%]	Increase	New
27. Percent of beneficiaries	Households received benefits from the WDPs [%]	Decrease	New
28. Cooperation	Households which provided help to others during distress [%]	Decrease	Pandey and Jha (2012)
29. Membership in co-operative institution	Households which has membership in co-operative institutions [%]	Decrease	New
30. Help from others	Households which received assistance during distress [%]	Decrease	Pandey and Jha (2012)
31. WC Membership	Households with members in WC [%]	Decrease	New
32. No beneficiary contribution	Households that did not contribute any beneficiary share [%]	Increase	New
33. Households lack ICT access	Households with no access to Information Communication Technology [%]	Increase	New
34. Grass root planning	Households that participated in grass root planning [%]	Decrease	New
35. Trainings	Households that received training on climate change [%]	Decrease	New
36. Water scarcity	Households with problems of drinking water during summer [%]	Increase	
37. Dependency on water resources	Households depend on other's water resources [%]	Increase	New
38. Public water sources	Households depend on public tap for drinking water [%]	Increase	World Bank (1997)
39. Groundwater decline	Households reported decrease in ground water [%]	Increase	New
40. Gender inequality	Households where female fetch potable water [%]	Increase	New
41. Decreased water availability	Households reported decreased availability of water [%]	Increase	Panthi et al. (2016)
42. Water resource depletion	Households reported severe depletion of water resources [%]	Increase	New
43. Waterborne diseases	Households reported waterborne diseases to the family [%]	Increase	Pandey et al. (2015)
44. New disease incidence	Households reported with new disease [%]	Increase	Pandey and Jha (2012)
45. Poor quality drinking water	Households reported decreased quality of drinking water [%]	Increase	New
46. Sunburn	Households reported sun burn problems [%]	Increase	New
47. Death due to climatic variability	Households with death due to climate variations especially heat waves and dehydration [%]	Increase	Hahn et al. (2009)
48. Off-farm dependency	Households depend on off-farm supply for food [%]	Increase	Hahn et al. (2009)
49. Food insufficiency	Households reported food insufficiency [%]	Increase	World Bank (1997)

TABLE 4.6 (cont.)

Indicator	Explanation (Unit)	Relationship to vulnerability	Source
50. Poor governmental support	Households reported poor support from Govt. through Public Distribution System (a network of fair price shops) [%]	Increase	New
51. Death or injury due to natural disaster	Households with death or injury due to natural disasters, e.g storm, flood, cyclone [%]	Increase	Pandey and Jha (2012)
52. Crop loss	Households reported crop loss [%]	Increase	Pandey and Jha (2012)
53. Property damage	Households reported housing or property damage [%]	Increase	Pandey and Jha (2012)
54. Heavy wind	Households reported heavy wind [%]	Increase	New
55. Temperature increase perception	Households reported very high temperature increase [%]	Increase	New
56. Hot months increase perception	Households reported hot months increase [%]	Increase	New
57. Erratic rainfall perception	Households reported erratic rainfall [%]	Increase	New
58. Less rainy days perception	Households reported less rainy days [%]	Increase	New
59. Extreme climate events	Households reported at least one extreme climate event [%]	Increase	New

[a] $(1 - D))$, where $D = \sum n(n-1)/N(N-1)$ and n = the number of households under different religion, N = total households; [b] Considered the worst case (i.e., indebted) situation for respondents who did not give information on debt status. [c] According to the Planning Commission of India a household that earns $> 2250\$/year$ is classified a high-income class; [d] New = developed for this study.

TABLE 4.7: Indicators of major components with its actual (A) and hypothesised (H) values for the watersheds.

Indicator	SG		NGO		LG	
	A	H	A	H	A	H
1. Family dependency	0.40	0.40	0.50	0.50	0.28	0.28
2. House type diversity	0.51	0.51	0.58	0.58	0.52	0.52
3. Family decision	91.43	8.57	90.00	10.00	92.00	8.00
4. Poverty	41.43	41.43	37.14	37.14	0.48	0.48
5. Indebtedness	80.00	80.00	65.71	65.71	58.67	58.67
6. High income households	0.00	100.00	11.40	88.60	21.33	78.67
7. Male headed households	85.71	14.29	87.14	12.86	89.33	10.67
8. Religious diversity	0.00	0.00	0.63	0.63	0.08	0.08
9. Household asset possession	0.14	0.14	0.16	0.16	0.13	0.13
10. Farm asset possession	0.44	0.44	0.47	0.47	0.51	0.51
11. Average farm holding size	0.81	0.81	0.82	0.82	0.86	0.86
12. Water access	82.86	17.14	90.00	10.00	85.33	14.67
13. Migration	0.00	100.00	2.86	97.14	4.00	96.00
14. New crops	4.29	95.71	5.71	94.29	1.00	99.00
15. Dependence on agriculture	12.86	12.86	5.71	5.71	7.00	7.00
16. Farm diversification	0.74	0.74	0.69	0.69	0.75	0.75
17. New livelihood strategies	4.29	95.71	12.86	87.14	3.00	97.00
18. Introduced livestock	0.00	100.00	11.43	88.57	4.00	96.00
19. Rainfed farming	20.00	20.00	42.90	42.90	28.00	28.00
20. Net sown area	59.63	40.37	55.47	44.53	39.81	60.19
21. Crop diversification	0.38	0.38	0.42	0.42	0.33	0.33
22. Adoption of new varieties	1.43	98.57	1.43	98.57	1.33	98.67
23. Decline in farm production	5.70	5.70	8.60	8.60	9.30	9.30
24. Soil erosion perception	97.14	97.14	44.29	44.29	12.00	12.00
25. Non adoption of SWC works	45.71	45.71	75.71	75.71	89.33	89.33
26. Households with <0.2 ha of land	51.43	51.43	68.57	68.57	72.00	72.00
27. Percent of beneficiaries	65.71	34.29	45.71	54.29	28.00	72.00
28. Cooperation	2.86	97.14	12.86	87.14	1.33	98.67
29. Membership in co-operative institutions	17.14	82.86	80.00	20.00	38.70	61.30
30. Help from others	2.86	97.14	5.71	94.29	1.33	98.67
31. WC Membership	7.14	92.86	5.71	94.29	6.70	93.30
32. No beneficiary contribution	68.42	68.42	3.03	3.03	28.57	28.57
33. Households lack ICT access	11.43	11.43	91.43	8.57	46.67	46.67
34. Grass root planning	2.86	97.14	7.14	92.86	5.30	94.70
35. Trainings	5.71	94.29	1.43	98.57	6.70	93.30
36. Water scarcity	35.71	35.71	40.00	40.00	41.33	41.33
37. Dependency on water resources	0.00	0.00	10.00	10.00	16.00	16.00
38. Public water sources	17.14	17.14	2.86	2.86	10.66	10.66
39. Groundwater decline	68.60	68.60	54.30	54.30	29.30	29.30
40. Gender inequality	100.00	100.00	100.00	100.00	41.33	41.33
41. Decreased water availability	70.00	70.00	25.70	25.70	29.30	29.30
42. Water resource depletion	92.86	92.86	97.14	97.14	92.00	92.00
43. Waterborne diseases	0.00	0.00	0.00	0.00	0.00	0.00
44. New disease incidence	0.00	0.00	0.00	0.00	0.00	0.00
45. Poor quality drinking water	1.43	1.43	0.00	0.00	0.00	0.00
46. Sunburn	71.43	71.43	0.00	0.00	1.33	1.33
47. Death due to climatic variability	0.00	0.00	0.00	0.00	0.00	0.00
48. Off-farm dependency	52.86	52.86	42.86	42.86	66.67	66.67
49. Food insufficiency	1.43	1.43	1.43	1.43	2.66	2.66

TABLE 4.7 (cont.)

Indicator	SG		NGO		LG	
	A	H	A	H	A	H
50. Poor governmental support	5.71	5.71	94.30	94.30	25.30	25.30
51. Death or injury due to natural disaster	0.00	0.00	0.00	0.00	0.00	0.00
52. Crop loss	11.43	11.43	4.29	4.29	21.33	21.33
53. Property damage	0.00	0.00	0.00	0.00	13.33	13.33
54. Heavy wind	2.86	2.86	0.00	0.00	56.00	56.00
55. Temperature increase perception	60.00	60.00	94.30	94.30	98.70	98.70
56. Hot months increase perception	58.50	58.50	92.90	92.90	97.30	97.30
57. Erratic rainfall perception	15.70	15.70	91.40	91.40	24.00	24.00
58. Less rainy days perception	17.10	17.10	91.40	91.40	25.40	25.40
59. Extreme climate events	11.43	11.43	0.29	0.29	7.33	7.33

TABLE 4.8: Indexed values for the indicators under the dimensions

Dimension	Indicator	Indexed value for		
		LG	SG	NGO
	1. Family dependency	0.40	0.50	0.28
	2. House type diversity	0.51	0.58	0.52
	3. Family decision	0.09	0.10	0.08
	4. Poverty	0.41	0.37	0.48
	5. Indebtedness	0.80	0.66	0.59
	6. High income households	1.00	0.89	0.79
	7. Male headed households	0.14	0.13	0.11
	8. Religious diversity	0.00	0.63	0.05
	9. Household asset possession	0.27	0.28	0.36
	10. Farm asset possession	0.17	0.34	0.35
	11. Average farm holding size	0.72	0.77	0.81
	12. Water access	0.17	0.10	0.10
	13. Migration	1.00	0.97	0.96
	14. New crops	0.96	0.94	0.99
	15. Dependence on agriculture	0.13	0.06	0.07
	16. Farm diversification	0.74	0.69	0.67
	17. New livelihood strategies	0.96	0.87	0.97
1. Adaptive capacity	18. Introduced livestock	1.00	0.89	0.96
	19. Rainfed farming	0.20	0.43	0.28
	20. Net sown area	0.40	0.45	0.40
	21. Crop diversification	0.25	0.36	0.24
	22. Adoption of new varieties	0.99	0.99	0.99
	23.Decline in farm production	0.06	0.09	0.09
	24. Soil erosion perception	0.97	0.44	0.12
	25. Non adoption of SWC works	0.46	0.76	0.89
	26. Households with <0.2 ha of land	0.51	0.69	0.96
	27. Percent of beneficiaries	0.34	0.54	0.72
	28. Cooperation	0.97	0.87	0.99
	29. Membership in co-operative institutions	0.83	0.20	0.61
	30. Help from others	0.97	0.94	0.99
	31. WC Membership	0.93	0.94	0.93
	32. No beneficiary contribution	0.68	0.03	0.29
	33. Households lack ICT access	0.11	0.09	0.47
	34. Grass root planning	0.97	0.93	0.95
	35. Trainings	0.94	0.99	0.93

TABLE 4.8 (cont.)

Dimension	Indicator	Indexed value for		
		LG	SG	NGO
2. Sensitivity	36. Water scarcity	0.36	0.40	0.41
	37. Dependency on water resources	0.00	0.10	0.16
	38. Public water sources	0.17	0.03	0.11
	39. Groundwater decline	0.69	0.54	0.29
	40. Gender inequality	1.00	1.00	0.41
	41. Decreased water availability	0.70	0.26	0.29
	42. Water resource depletion	0.93	0.97	0.92
	43. Waterborne diseases	0.00	0.00	0.00
	44. New disease incidence	0.00	0.00	0.00
	45. Poor quality drinking water	0.01	0.00	0.00
	46. Sunburn	0.71	0.00	0.01
	47. Death due to climatic variability	0.00	0.00	0.00
	48. Off-farm dependency	0.53	0.43	0.67
	49. Food insufficiency	0.01	0.01	0.03
3. Exposure	50. Poor governmental support	0.06	0.94	0.25
	51. Death or injury due to natural disaster	0.00	0.00	0.00
	52. Crop loss	0.11	0.04	0.21
	53. Property damage	0.00	0.00	0.13
	54. Heavy wind	0.03	0.00	0.56
	55. Temperature increase perception	0.60	0.94	0.99
	56. Hot months increase perception	0.59	0.93	0.97
	57. Erratic rainfall perception	0.16	0.91	0.24
	58. Less rainy days perception	0.17	0.91	0.25
	59. Extreme climate events	0.11	0.04	0.57

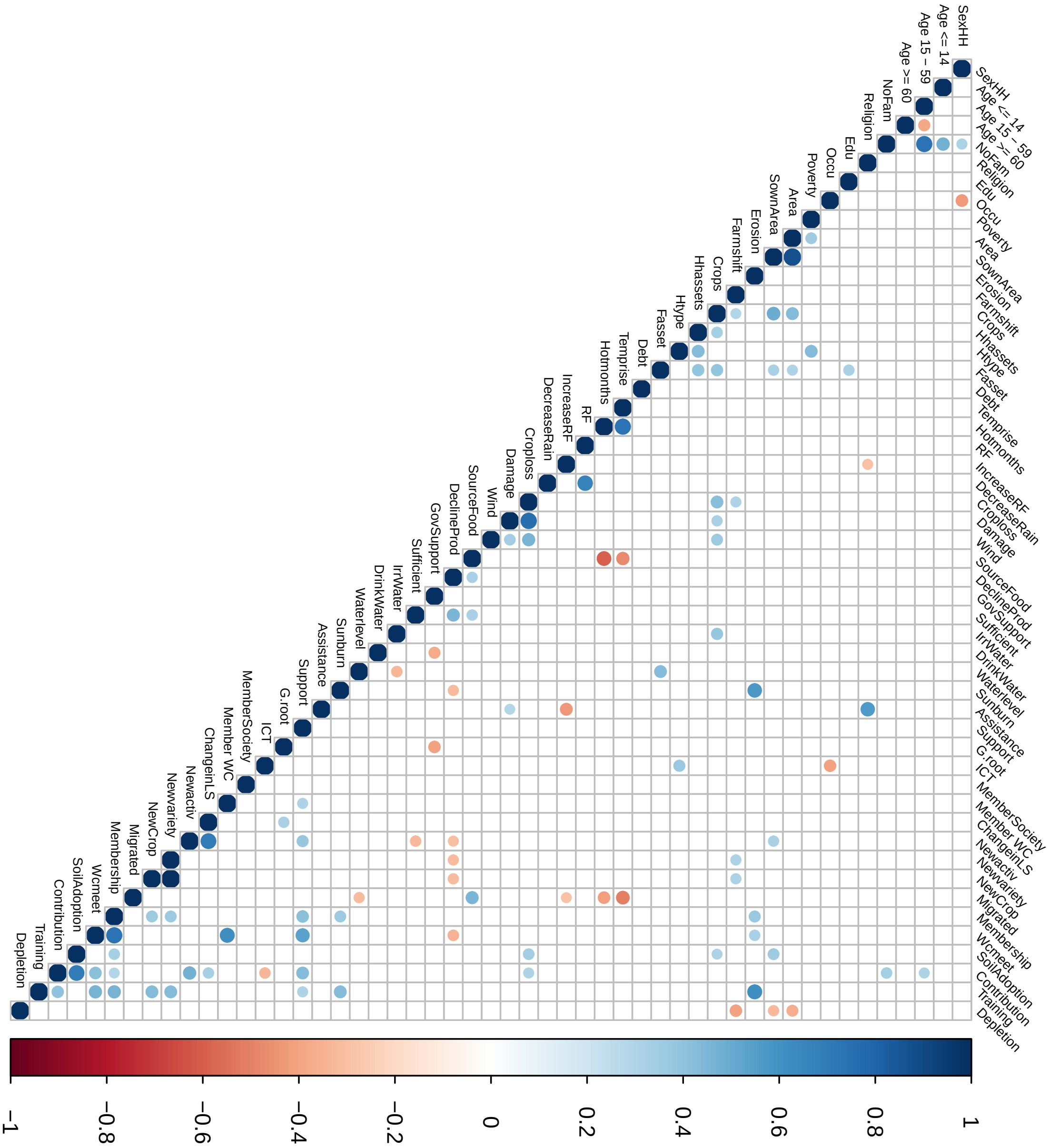


FIGURE 4.5: Correlation analysis of the 59 variables

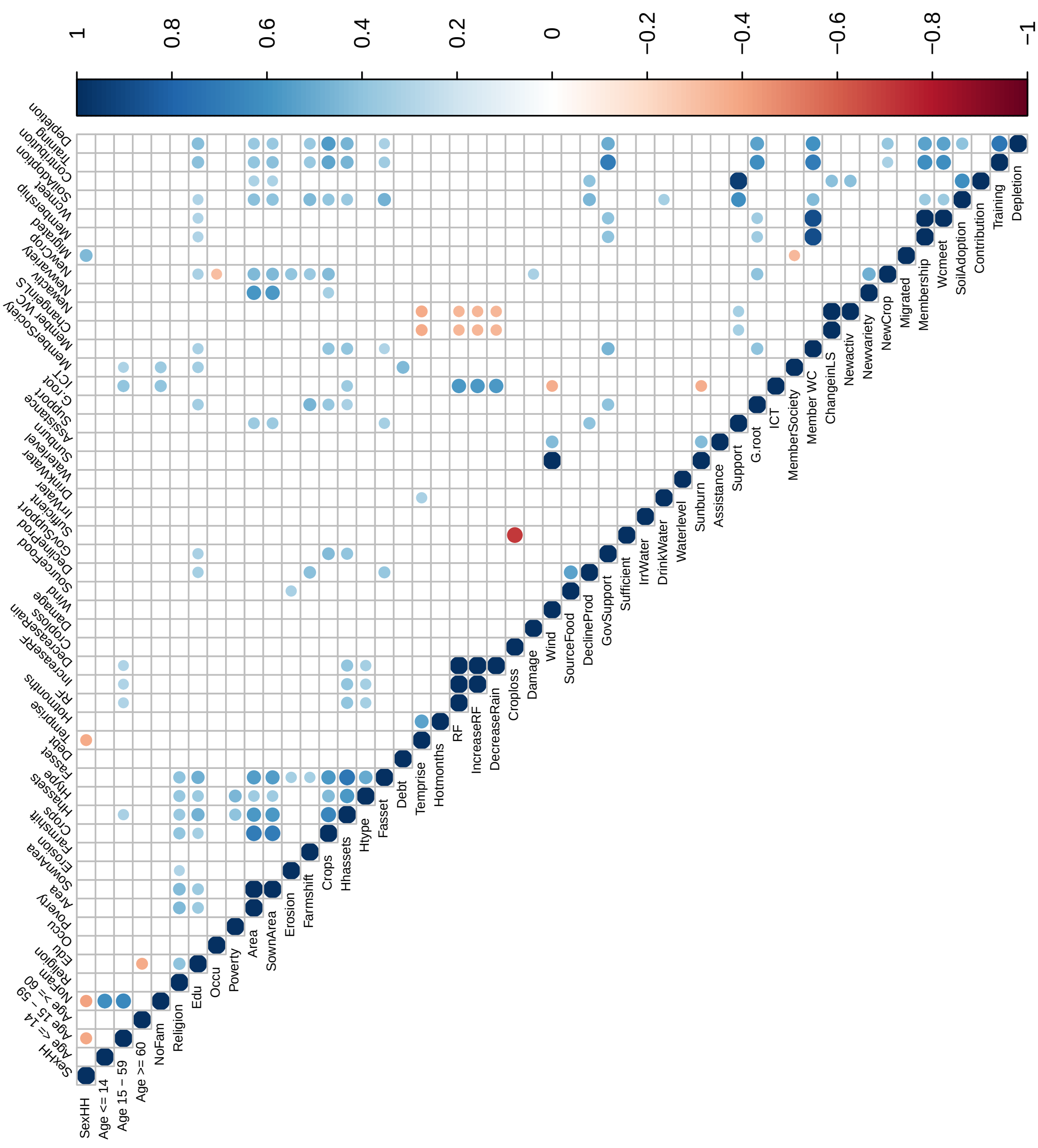
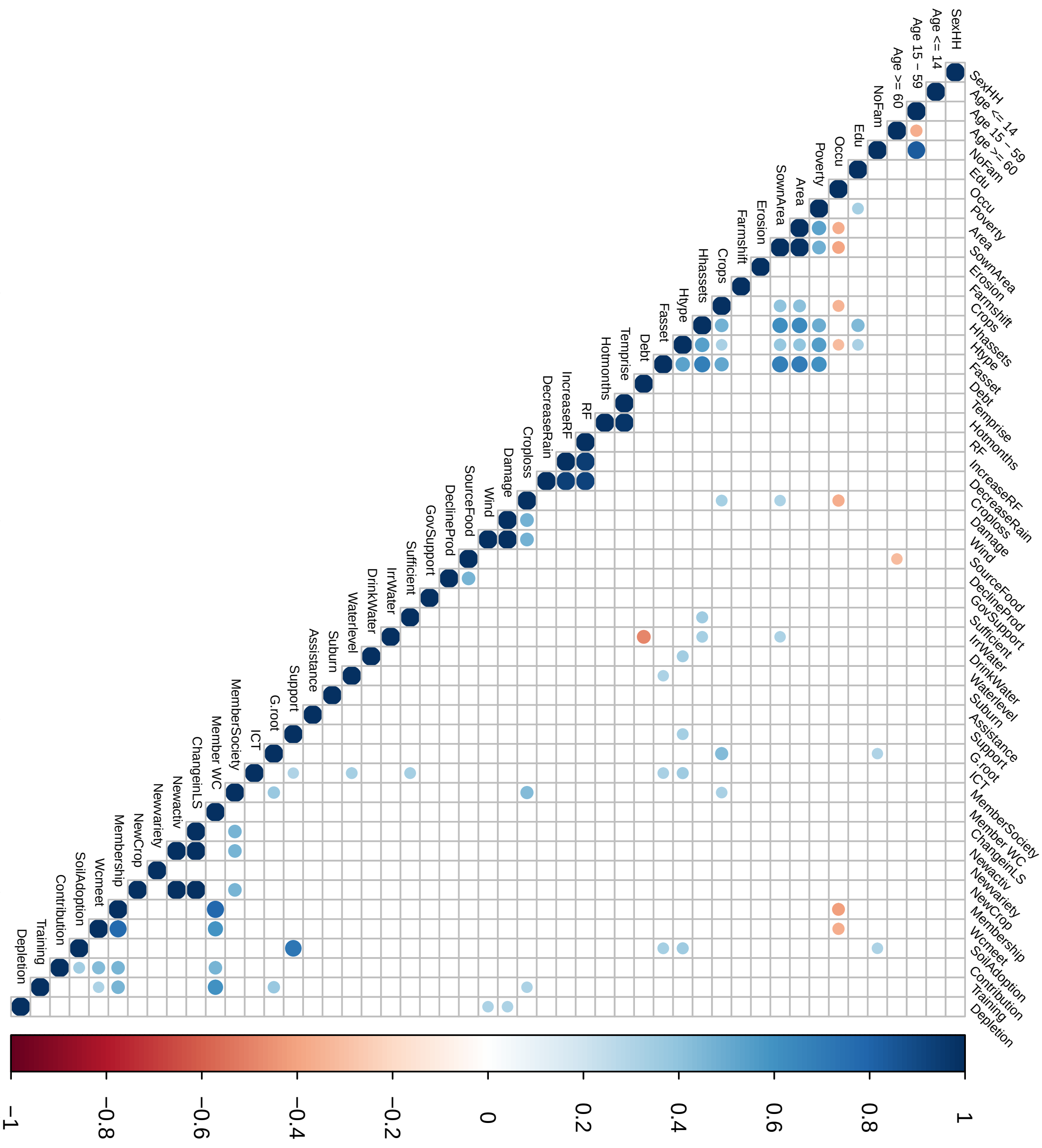


FIGURE 4.5 (cont.)

FIGURE 4.5 (cont.)



Note: Correlation analysis of the 59 variables used for the calculation of indicators, significance at the 1% level for LG, NGO and SG.

Chapter 5

Changing Climate - Changing Livelihood: Smallholder’s Perceptions and Adaptation Strategies

The following chapter is based on the paper:

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Authors:	Christoph FUNK (contribution: 50%), Archana RAGHAVAN SATHYAN (contribution: 30%), Peter WINKER (contribution: 10%) and Lutz BREUER (contribution: 10%)
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Changing Climate - Changing Livelihood: Smallholder's Perceptions and Adaptation Strategies[1]

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Abstract

Experts expect that climate change will soon have a severe impact on the lives of farmers in the region surrounding Kerala, India. This region, which is known for its monsoon climate (which involves a distinct temporal and spatial variation in rainfall), has experienced a decrease in annual rainfall over the last century. This study is aimed at investigating how smallholder farmers perceive climate change and at identifying the methods that these smallholders use to adapt to climate change. We use data collected from a survey of 215 households to compare the climate vulnerability of three watershed communities in Kerala. We find that the farmers perceive substantial increases in both temperature and the unpredictability of monsoons; this is in accordance with actual observed weather trends. The selection of effective adaptation strategies is one of the key challenges that smallholders face as they seek to reduce their vulnerability. The surveyed households simultaneously use various adaptation methods, including information and communication technology, crop and farm diversification, social networking through cooperatives, and soil and water conservation measures. The results of a binary regression model reveal that the household head's age, education and gender, as well as the farm's size and the household's size, assets, livestock ownership, poverty status and use of extension services, are all significantly correlated with the households' choices regarding adaptations to cope with climate change.

Keywords: Smallholders, watershed, climate change, perception, adaptation strategy

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5.1 Introduction

Climate change is one of the most important challenges of the current era. This holds especially true for developing countries in the tropics and subtropics, which are expected to be hit hardest by climate change (Burney et al. 2014; Hertel and Rosch 2010). The potential negative implications of climate change include declining agricultural production (Frank and Penrose-Buckley 2012), lack of access to safe water, increased livelihood insecurity and downward spirals in various human-development dimensions (IPCC 2007).

Moreover, most tropical developing countries have a large share of poor smallholder farmers (Harvey et al. 2014); the World Bank (2003) defines this group as farmers who have low asset bases and who operate on less than 2ha of cropland. Estimates indicate that individuals, small groups or households run at least 90% of the more than 570 million farms in the world (Lowder et al. 2016). Roughly 2.5 billion of the 3 billion people who live in rural areas rely on farming as their main source of income (FAO 2013), and smallholders comprise 84% of that group (Lowder et al. 2016). Climate change is particularly problematic for smallholders because their limited resources prevent them from coping with climate-induced shocks (Frank and Penrose-Buckley 2012; Harvey et al. 2014), which adds to these farmers' vulnerability (Jarvis et al. 2011).

The phenomenon of smallholder farming is especially pronounced in Asia, and India ranks second on that continent with 78% of its farmers being smallholders. A majority of these farmers live in rain-fed areas that are characterized by rainfall variability, temperature fluctuations and frequent droughts. As a consequence of these farmers' limited access to the climate-related information that they need to make adequate decisions about when to sow, what to grow and how to time various inputs, climate change will cause millions to experience immediate hardship and hunger (National Intelligence Council 2009). However, these impacts are locally specific and hard to predict (Morton 2007). Because smallholder farmers are increasingly perceiving and experiencing climate change's impacts (Amare and Simane 2017; Yila and Resurreccion 2013), there is an urgent need to identify approaches and strategies that can enhance the adaptive capacity of these farmers, their households and their communities (Frank and Penrose-Buckley 2012; Harvey et al. 2014). Thus, it is necessary to understand both how farmers perceive various climatic changes and how these perceptions affect their selection of strategies and, ultimately, their ability to adapt.

Many studies, from various countries, deal with farmers' perceptions of climate change (Banerjee 2015; Juana et al. 2013; Mamba et al. 2015; Uddin et al. 2017; Udmale et al. 2014), the determinants of farmers' adaptation strategies (Banerjee 2015; Benson et al. 2015; Bryan et al. 2009; Burney et al. 2014; Gbetibouo 2009; Mamba et al. 2015; Ndamani and Watanabe 2016; Yila and Resurreccion 2013) and the barriers to those adaptation strategies (Alemayehu and Bewket 2017). However, little is known about the perceptions and adaptation strategies of smallholder farmers in rain-fed tropical areas.

Moreover, Grothmann and Patt (2005) argue that, to explain adaptive behavior, models of adaptation and adaptive capacity should include socio-cognitive indicators such as perceived adaptive capacity. These factors are relevant because farmers' adaptation decisions take place at the local level and depend on various perceived socio-environmental contexts. For instance, social and institutional support, cultural values and norms, regional characteristics and climate-related trigger events (Grothmann and Patt 2005; Mitter et al. 2019) all affect farmers' adaptation decisions. In addition, Sanderson and Curtis (2016) show that cultural factors influence farmers' perceptions of climate- change risk; these factors also provide important insight into the farmers' environmental attitudes, which, in turn, can be used to foster agricultural adaptation (Mitter et al. 2019).

Adaptation is a complex process that includes interactions with resources, institutions and the environment (Adger 2006). Farmers must recognize that the climate is changing if they are to identify and implement climate-change adaptation strategies (Maddison 2007). Perception is the process of receiving external stimuli and converting them into psychological responses based on past events and the present situation (van den Ban and Hawkins 1996). When faced with climate vulnerability, farmers must perceive specific weather parameters such as the onset of a monsoon, an increase in temperature, an intense summer or unpredictable seasons. The distribution, periodicity and effectiveness of rainfall, combined with fluctuations in temperature, affect farmers' crop decisions – and thus, the success of their farming. Various studies of farmers in dry areas of north India and Tamil Nadu describe perceptions of declining rainfall, erratic monsoon onsets, increasingly intense rainfall and heat (Banerjee 2015; Kelkar et al. 2008) and increasingly severe dry spells (Varadan and Kumar 2014).

Vulnerability, in general, is an individual or group's reduced capacity to cope with, resist and recover from the impacts of a natural or human-made hazard (Birkmann 2007). The biophysical, economic and social contexts of agricultural production are increasingly unpredictable and volatile (J. Thompson and Scoones 2009) because such production is becoming more driven by complex and interrelated contextual changes, including increases in natural-resource scarcity, climate change, food demand and administrative regulation. The vulnerability of any system (at any scale) is a function of that system's exposure and sensitivity to a range of hazards, as well as its capacity to cope with, adapt to or recover from the effects of such conditions (Smit and Wandel 2006).

Without adaptation, farmers' livelihoods are under threat – especially those of smallholders who depend solely on farming and natural resources. Thus, "adaptation in agriculture is rather the norm than the exception" (Rosenzweig and Tubiello 2007). Previous studies show that farmers adapt according to their agricultural systems, location (Rosenzweig and Tubiello 2007) and perceptions of changing climatic conditions (Mamba et al. 2015; Uddin et al. 2017). At the same time, the access to technologies, support from institutions, and both local and community involvement (Banerjee 2015) are vital to the adaptation process.

The available studies indicate that farmers adapt to existing climate change in various ways, such as by selecting new crops and varieties (Dhanya and Ramachandran 2015; Hassan and Nhemachena 2008; Ndambiri et al. 2013) , adjusting their sowing and planting dates (Deressa et al. 2009; Mengistu 2011; Ravi Shankar et al. 2013), shifting their cropping patterns (Banerjee 2015), introducing livestock (Ndambiri et al. 2013; Yila and Resurreccion 2013), improving their water-management practices (Banerjee 2015; Burney et al. 2014), changing their soil-conservation measures (Deressa et al. 2009), and migrating to less vulnerable regions (Ravi Shankar et al. 2013).

Many of the studies undertaken in India include the perceptions of climate change and adaptation strategies of farmers from the semiarid tropics of south India (Dhanya and Ramachandran 2015); others focus on how climate change impacts the semiarid tropics of Maharastra and Andhra Pradesh (Banerjee 2015). Banerjee (2015) also discusses adoption decisions and perceived capacity, specifically regarding improved water management, for village farmers in Maharastra and Andhra Pradesh. Such studies on the perceptions of climate change and adaptation strategies among farmers in semiarid regions of India reveal the limited availability of important, locally specific adaptation strategies (Banerjee 2015; Dhanya and Ramachandran 2015), as well as policies that address farmers' concerns regarding (and responses to) climate variability. These studies can help policymakers, donors and researchers to better understand these farmers' situations and can thus spur efforts to reduce climate change's adverse effects and the resulting vulnerability. However, in the case of India, limited information is available in this regard, especially at the watershed level.

In this research, we not only investigate how households perceive climate change but also determine the main drivers that influence the selection of adaptation strategies for the specific case of WDPs in Kerala, India. The government of India initiated these WDPs to enhance semiarid ecosystems' resources and the surrounding communities' socioeconomic situations. Watershed development affects multiple sectors and is specifically designed to reduce the risks of rain-fed farming; thus, it also acts as a tool for disaster management (Eriksen and Kelly 2007; Kerr 2007) . Even though WDPs have been successfully implemented in the past and are known to be one of the best disaster-management tools, there exist (to the best of our knowledge) no specific studies on the perceptions and adaptation strategies of smallholders who operate rain-fed farms at the watershed level in India. This study contributes to the existing literature by filling this gap regarding farmers' climate-change perceptions and adaptation strategies.

This study is based on three watersheds where WDPs have been implemented. We use data from previous works that focused on the establishment of a Climate Vulnerability Index for Rain-fed Tropical Agriculture (Raghavan Sathyan et al. 2016, 2018a,b). These previous studies are based on the IPCC's climate-vulnerability framework and together comprise the theoretical foundation of this work. The index used in those studies is based on data collected through household surveys, and we use it to compare the climate vulnerability of three watershed communities in Kerala. The index provides an overall picture of the levels of vulnerability, but an in-depth analysis of the stressors and of the factors that promote adaptation strategies is beyond its scope. Therefore, we focus on how smallholder households perceive climate change and on the main drivers or determinants in the households' choices regarding adaptation measures. Thus, we aim to use binary logistic regression modeling to quantify the impact that various explanatory variables have on smallholder farmers' adaptation strategies.

This paper is organized as follows. Section 5.2 gives a brief overview of the underlying concepts, the study area, the collected data, the empirical approach and the regression model's explanatory variables. Section 5.3 describes the adaptation strategies and the empirical results. Section 5.4 then contains the concluding remarks and the policy implications.

5.2 Methodology

5.2.1 Description of the study area

Kerala is the long strip of land on the southwestern tip of India; the Arabian Sea is located to the west, and the Western Ghats mountains are to the east. The state is divided into three physiographically distinct regions: the eastern highlands (600 m and above), the central midlands (300–600 m) and the western lowlands (below 300 m). The state ranks the highest in India with regard to certain dimensions of the Human Development Index, including literacy rate (93%), urbanization and various health indicators (Government of Kerala 2016). Farming in Kerala is unique in that it is based on homesteads, a system in which farmers produce subsistence crops for their families and then may or may not opt to produce any additional crops (Soemarwoto 1987).

These farms produce a large number of food crops, including plantation trees, fruits, vegetables and tuber crops; the crops are grown with livestock and mainly serve to satisfy the basic needs of the farmers and their families. Moreover, 63% of the farms' total cultivated area contains cash crops such as cashews, rubber, pepper, coconuts, cardamom, tea and coffee, whereas 10% contains food crops such as rice and pulses (Government of Kerala 2017). Around 16% of the total cropped area is irrigated (Government of Kerala 2017).

In Kerala, the land reforms of the 1960s gave title ownership to 1.5 million tenants. These reforms also inhibited the formation of free capital in the agricultural sector and restricted the scope of large-scale farming. The successive subdivision of families' inherited land has since led to the emergence of a large number of small, marginal holdings (Mahesh 2000). As a result, these marginal holdings dominate Kerala's agrarian structure, comprising 99% of farms and 77% of the farming area (Government of Kerala 2014). In addition, 94% of these marginal holdings have an average size of 0.16 ha. Kerala's agricultural income per hectare is too low for farming families to subsist on. Kerala's alarming number of smallholders, who are highly dependent on monsoons and natural resources, reduces the region's ability to adapt to socioeconomic and environmental adversity.

Kerala has a tropical monsoon climate with the highest annual rainfall rate (3000 mm) of any state in India. It is known as the "Gateway of summer monsoon" (Krishnakumar et al. 2009). Spatial and temporal variations in monsoon rainfall make the state extremely vulnerable to climate change (Nair et al. 2014). The state has already experienced a significant decrease in annual rainfall together with both a decrease in the southwest monsoon (Government of Kerala 2014; Krishnakumar et al. 2009; Nair et al. 2014; Thomas and Prasannakumar 2016) and an increase in the northeast monsoon (Guhathakurta and Rajeevan 2008). High temperatures of 40° C and above have been recorded in March and April. A wide range of thermosensitive crops are grown all over the state, which makes Kerala highly vulnerable to any change in climatic conditions (Krishnakumar et al. 2009). In recent years, the state has faced a deterioration of its natural resources, as well as increased landslide frequency, severe forest and biodiversity degradation, decreased river-water quality, paddy-land conversion, increased water scarcity and decreased productivity. Climate change's impacts have accelerated these changes. Moreover, 40% of the total cropped area in Kerala is prone to soil erosion. Recently, the state suffered its worst monsoon flooding in a century, causing around 400 deaths and the displacement of about one million people.

5.2.2 Development of the Database and Empirical Model

We use data from 215 households, collected between August and November 2015. Out of these households, 70 are located in each the Adakkaputhur or Akkiyampadam watersheds, and the other 75 are in the Eswaramangalam watershed (all of which are located in Kerala). The household surveys took place in Malayalam (local language) on a pretested schedule. We used multistage sampling to select the sample households from the three watershed regions. Both the full survey and the data are described in more detail in Raghavan Sathyan et al. (2018a). For the data analysis, we used SPSS, R and MATLAB. We collected quantitative data for 59 indicators, 10 major components and three dimensions of vulnerability. The household survey consisted of three broad parts: (i) basic information about the households, (ii) information on their adaptive capacity, adaptation strategies and sensitivity; and (iii) their perceptions of natural disasters and climate variability.

In this study, we use a binary logistic model (logit) to quantify the impact of various explanatory variables that affect households' choices of adaptation strategies in the three study areas. We thereby focus on the strategies that households can use to cope with the possible negative impacts of climate change. Following previous scholars, we assume that the households will implement climate-change adaptation strategies only if doing so increases their expected net farm benefits or reduces the perceived risk to their crop production (Abid et al. 2015; Bryan et al. 2009, 2013; Kato et al. 2011; Mendelsohn 2000). Consider the following model:

$$Y^*_{i,j} = X_{i,j}\beta_j + \varepsilon_{i,j}, \tag{1}$$

where $Y^*_{i,j}$ is the unobserved, or latent, variable for household i, which is adapting strategy j. In addition, $X_{i,j}$ denotes a matrix of k explanatory variables that influence a household's perceptions of and adaptation to climate change, as summarized in Table 5.1. A correlation table of these variables is located in the Appendix (Figure 5.6). Next, β_j is a vector of coefficients (including a constant) of the binary regression model, and $\varepsilon_{i,j}$ is the corresponding error term for model , which follows a standardized logistic distribution with a mean of 0 and a variance of $\pi^2/3$. We do not observe the net benefit of adapting directly; rather, we use $Y_{i,j}$, which takes on values of 0 or 1 according to the following rule:

$$Y_{i,j} = \begin{cases} 1 & \text{if } Y^*_{i,j} > 0 \\ 0 & \text{if } Y^*_{i,j} \leq 0. \end{cases} \tag{2}$$

Thus, household i will chose strategy j to adapt to climate change $(Y_{i,j} = 1)$ if that strategy is expected to benefit the household $Y^*_{i,j} > 0$. The conditional probability that $Y_{i,j}$ equals 1 is

$$\begin{aligned} prob(y_{i,j} = 1|x) &= prob(y^*_{i,j} > 0|x) \\ &= prob(\varepsilon_{i,j} < X_{i,j}\beta_j|x) \\ &= \frac{exp(X_{i,j}\beta_j)}{1 + exp(X_{i,j}\beta_j)} \\ &= \Lambda(X_{i,j}\beta_j) \end{aligned} \tag{3}$$

where $\Lambda(\dot{)}$ is the cumulative distribution function of the logistic distribution. One of the limitations of the logit approach is that the only aspects that can be directly interpreted in a meaningful way are the signs and significance of the coefficients reported in the resulting regression. However, we can compute the marginal effects for the continuous variables using the coefficients by taking the derivative of the probability with respect to one element, k, of X:

$$\frac{\partial E(y_{i,j})}{\partial X_k} = \frac{exp(X_{i,j}\beta_j)}{(1 + exp(X_{i,j}))^2}\beta_k \tag{4}$$

Thus, the marginal effect varies with the values of X. The marginal effects can be reported either as the data's sample mean or as the mean of the marginal effects across all observations. As most of the literature is focused on marginal effects rather than odds ratios, we also enable comparisons by reporting the marginal effects in the Appendix (Table 5.5 and 5.6). In addition, reporting marginal effects for the dummy variables is not appropriate because the derivative with respect to such small changes do not apply to changes of state in dummy variables (Greene 2012). In this situation, group comparisons are more appropriate. Nevertheless, the logit approach (which we use here) allows for another common way of interpreting the coefficients. We interpret the coefficients in terms of their marginal effects on odds ratios rather than on probabilities. Using $p = \frac{exp(X_{i,j}\beta_j)}{1+exp(X_{i,j}\beta_j)}$, we calculate an odds ratio as

$$\frac{p}{1-p} = exp(X_{i,j}\beta_j) \rightarrow ln\frac{p}{1-p} = X_{i,j}\beta_j. \tag{5}$$

where $\frac{p}{1-p}$ measures the probability that $y_{i,j} = 1$, relative to the probability that $y_{i,j} = 0$. This allows for an intuitive interpretation of the logit model, as the log-odds ratio is linear in the regressors.

Many researchers empirically investigate the factors that influence adaptations in response to perceptions of climate change (Alauddin and Sarker 2014; Arunrat et al. 2017; Deressa et al. 2009; Gbetibouo 2009; Hassan and Nhemachena 2008; Hisali et al. 2011; Ndamani and Watanabe 2016; Seo and Mendelsohn 2008), typically using a binomial or a multinomial logit approach. Most of the literature is focused on the multinomial approach, but that approach is inappropriate for this study. First, most of the surveyed households in this study adopted more than one adaptation strategy simultaneously, such that the multinomial logit approach is not feasible (as that model assumes that choices are mutually exclusive). In addition, we follow Abid et al. (2015) and Bryan et al. (2013) by not combining similar adaptation strategies into self-defined categories, as doing so might prevent a meaningful analysis of the adaptation strategies. For these reasons, we use the bivariate logit model to examine the factors that influence the households' decisions regarding the adoption of specific adaptation strategies. We validate the empirical models before discussing this study's results in more detail. Therefore, we examine all of the estimates by testing the overall significance of this study's approaches, as well as their goodness of fit. In addition, we use the receiver operating characteristic (ROC) curve and out-of-sample predictions to check the accuracy of the models.

To validate this study's models, we have to use a general hypothesis test, as the logit approach uses a nonlinear regression. We use the likelihood- ratio test to check the overall significance of the models. The null hypothesis is that all parameters other than the constant are equal to 0, and we test the model against this restricted version (which only includes a constant). This test follows an asymptotic chi-squared distribution with degrees of freedom equal to the difference between the two models' number of estimated parameters.

Moreover, we evaluate the models using ROC curves. This allows for a graphical inspection of the models' performance because it plots the fraction of correctly classified adapting households versus the incorrectly classified households (which are not actually adapting to climate change). Thus, a ROC curve illustrates the tradeoff between the sensitivity (i.e., the true-positive rate) and that value subtracted from 1 (i.e., the false-positive rate), as the threshold (c) varies between 0 and 1. Two corner cases are of interest. First, for $c = 1$, all households are predicted to adapt to climate change, so all of the households that effectively adapt are correctly specified; on the other hand, all households that do not adapt are incorrectly specified. Thus, the ROC curve takes on the value $(0, 100)$. Following the same logic, the ROC curve takes on the value $(100, 0)$ for $c = 0$. Thus, if a model has no predictive ability, its ROC curve is a straight line between these two points (Cameron and Trivedi 2005). Therefore, when the area under the curve (AUC) for a model's ROC is greater than the area under that line, the model has better- than-random predictive ability.

Although one can compute the ROC curves for in-sample predictability, we evaluate the performance of this study's models by computing out-of-sample predictions. Therefore, we split the dataset randomly into two groups. We use two-thirds of the full dataset as a training set to estimate the logit models, but we retain the remaining one third for testing the out-of-sample performance. This allows us to use bootstrap replications to compute confidence intervals for the ROC curves, as well as the AUC.

5.2.3 Choice of Explanatory Variables

Our selection of explanatory variables is based on an extensive literature review but is limited by data availability. As such, some factors that we have not accounted for in this analysis could alter its results. However, the explanatory variables cover a broad spectrum of factors that researchers widely accept as influencing adaptation to climate change. The explanatory variables are summarized in Table 5.1, and they include

- household characteristics such as the age, education and gender of the household head, as well as the household size;
- monetary aspects such as farm income, livestock ownership, household assets and poverty status;
- physical characteristics such as farm size, well ownership and the use of extension services;
- climate-change awareness, as measured by perceptions regarding a decrease in rainy days and increases in soil erosion, temperature and water depletion.

In addition, we use region fixed effects to control for institutional and climatic differences, as well as for any other unobservable differences among the three watersheds.

Age of household head can be used as a proxy for farming experience. The literature shows mixed evidence regarding the sign and size of age's effect on the use of adaptation strategies. Several studies show at least a partially significant negative relationship between age and adaptation (Deressa et al. 2009; Hassan and Nhemachena 2008; Jiri et al. 2017), but others indicate that age positively influences adaptation to climate change (Hassan and Nhemachena 2008; Maddison 2007; Nhemachena et al. 2014). Some scholars even detect no significant relationship at all (Di Falco et al. 2012; Esham and Garforth 2013). Hence, one could argue that older (and thus more experienced) farmers are more likely than younger ones to adapt their farming behaviors to changes in climatic conditions; however, older farmers might also be more risk-averse and less flexible than younger farmers. Based on these findings, we conclude that the relationship between age and adaptation strategies is nonlinear. Thus, we add the square of the household head's age to the regression. Nevertheless, we expect the sign to be inconclusive.

Education of household head is hypothesized to be positively correlated with the application of new agricultural technologies and the adaptation to climate change. Better-educated farmers are expected to have better knowledge and more information about climate change. Thus, they should be able to use their knowledge to react to perceived changes by applying improved farming methods. We find this to be the conventional wisdom in the literature; for example, Abid et al. (2015), Anley et al. (2007), Bryan et al. (2013), Deressa et al. (2009), Dolisca et al. (2006), and Hassan and Nhemachena (2008)all find a positive and significant relationship, thus supporting this argument.

Gender of household head is hypothesized to influence decisions regarding adaptation to climate change. Nhemachena et al. (2014) argue that, as compared to male-headed households, female-headed ones are more likely to use adaptation methods, as women are more involved than men in agricultural work and thus are more experienced in farm management. In addition, scholars such asBayard et al. (2007) and Dolisca et al. (2006) provide supporting evidence for this argument because they find a positive relationship between female-headed households and adaptation. Nevertheless, there is also evidence that male-headed households are more likely than female-headed ones to get information about new technologies and farming practices (Deressa et al. 2009), which can positively influence the adaptation process (Hassan and Nhemachena 2008; Hisali et al. 2011). Other evidence is mixed, as researchers such as Bryan et al. (2013), Di Falco et al. (2012), and Ndamani and Watanabe (2016) find that the gender of the household head has no influence on adaptation to climate change.

Household size is hypothesized to impact the adaptation process. As Deressa et al. (2009) and Gbetibouo (2009) argue, this issue can be seen from two angles. On the one hand, household size (as a proxy for labor endowment) should be positively related to adaptation because a larger household means more available workers and, thus, higher adaptation capability Jiri et al. (2017). On the other hand, larger families might require more off-farm activities in order to secure more income and decrease their consumption pressure. However, the empirical findings support the former reasoning.

Farm income, *livestock ownership*, *household assets* and *poverty status* represent various aspects of wealth. Although farm income provides information about whether a household is solely dependent on farming to pay for the family members' living, livestock and household assets can be seen as accumulated wealth. It is hypothesized that a higher level of wealth and financial wellbeing is positively related to use of adaptation strategies (Jiri et al. 2017; Knowler and Bradshaw 2007). In addition, we use the poverty status of a household to cover a wide range of wealth aspects that we cannot explicitly control for otherwise.

Farm size measures the total land size that a household holds in hectares and can be seen as a proxy for wealth Abid et al. (2015). In addition, Alauddin and Sarker (2014), Chengappa et al. (2017), and Gbetibouo (2009) argue that households with larger farm sizes are more likely

TABLE 5.1: Description of the variables

Explanatory Variable	Mean	Standard Deviation	Description	Expected Sign
Age of household head	54.7163	13.0701	Continuous	(+) / (-)
Age of household head squared	3164.6977	1462.8538	Continuous	(+) / (-)
Education of household head	0.8698	0.5568	Dummy: 2 if high school, graduate or post-graduate degree; 1 if primary, middle or secondary school; 0 if no schooling	(+)
Gender of household head	0.7953	0.4034	Dummy: 1 if male, 0 otherwise	(+) / (-)
Household size	4.0000	1.5004	Continuous	(+)
Farm income (as only source)	0.0837	0.2770	Dummy: 1 if yes, 0 otherwise	(+)
Household assets	6.3488	1.5323	Continuous	(+)
Livestock ownership	0.4884	0.4999	Dummy: 1 if owned, 0 otherwise	(+)
Household poverty status	0.5767	0.4941	Dummy: 1 if above poverty line, 0 otherwise	(+)
Farm size in hectares	0.2858	0.4536	Continuous	(+)
Well ownership	0.0651	0.2467	Dummy: 1 if owned, 0 otherwise	(-)
Extension services	0.0930	0.2905	Dummy: 1 if received, 0 otherwise	(+)
Rainy days	0.4419	0.4978	Dummy: 1 if medium, high or very high; 0 if negligible or low	(+) / (-)
Soil erosion	0.5023	0.5012	Dummy: 1 if moderate or high, 0 if undetectable	(+) / (-)
Temperature rise	0.8556	0.3521	Dummy: 1 if medium, high or very high; 0 if negligible or low	(+) / (-)
Water depletion	0.9442	0.2301	Dummy: 1 if seasonal, considerable or almost complete; 0 if irregular or not problematic	(+) / (-)

to adopt inventions earlier compared with smaller farms, as adaptation processes typically involve large transaction and information costs. We follow this argument and hypothesize a positive relationship between adaptation to climate change and farm size.

Well ownership allows for controlling for an adequate supply of water. If a household does not have enough water for the irrigation of crops, we hypothesize that households are more likely to engage in an adaptation process.

Extension services influence the adaptation decision. They provide assistance and information about climate change, which is required to make an adaptation decision (Deressa et al. 2009). Various studies have found a positive relationship between extension services and households' adoption behavior (Deressa et al. 2009; Gbetibouo 2009; Maddison 2007; Nhemachena et al. 2014).

Climate-change awareness is an important factor in determining adaptation strategies. We explicitly control for this using the variables rainy days, soil erosion, temperature rise and water depletion. We measure the perceived existence of a substantial decrease in rainy days, the presence of soil erosion, the possible depletion of water and a considerable rise in temperature over the past few years. Especially, soil fertility has been found to be positively correlated to the decision of using soil-conservation methods (Di Falco et al. 2012; Gbetibouo 2009). In addition, awareness of changes in temperature and precipitation are important to adaptation decisions and the success of those decisions (Deressa et al. 2009; Maddison 2007; Nhemachena et al. 2014). We expect that a farmer who is aware of a change in the climatic condition will increase the adoption of specific adaptation strategies that will help him in his situation. At the same time, however, farmers will eliminate the strategies that do not work specifically for their situations, are too expensive or address other risks. Thus, we expect the sign to be inconclusive.

5.3 Results and Discussion

5.3.1 Perception of and Adaptation Strategies to Climate Change

We are interested in the adaptation strategies that farmers use in response to perceptions of climate change. Nevertheless, a distinct difference exists between such perceptions and the actual use of adaptation strategies in the farming process.

This study's descriptive findings are in line with the assumptions of its empirical approach. Figure 5.1 summarizes the results related to if a household perceives climate change based on five questions:

1. Did the household perceive a considerable rise in temperature over the past few years?
2. Did the household perceive a substantial increase in hot months?
3. Did the household perceive erratic rainfall during the past few years?
4. Did the household perceive an increase in rainfall?
5. Did the household notice a substantial decrease in rainy days?

The vast majority of the households have at least medium to high levels of perception of the situations highlighted in the five questions. For example, more than 97% of the survey participants recognize a considerable rise in temperature, an increase in hot months and an increase in rainfall. At the same time, 87.5% of the households perceive low to medium levels of erratic rainfall, whereas almost 90% recognize a substantial decrease in rainy days.

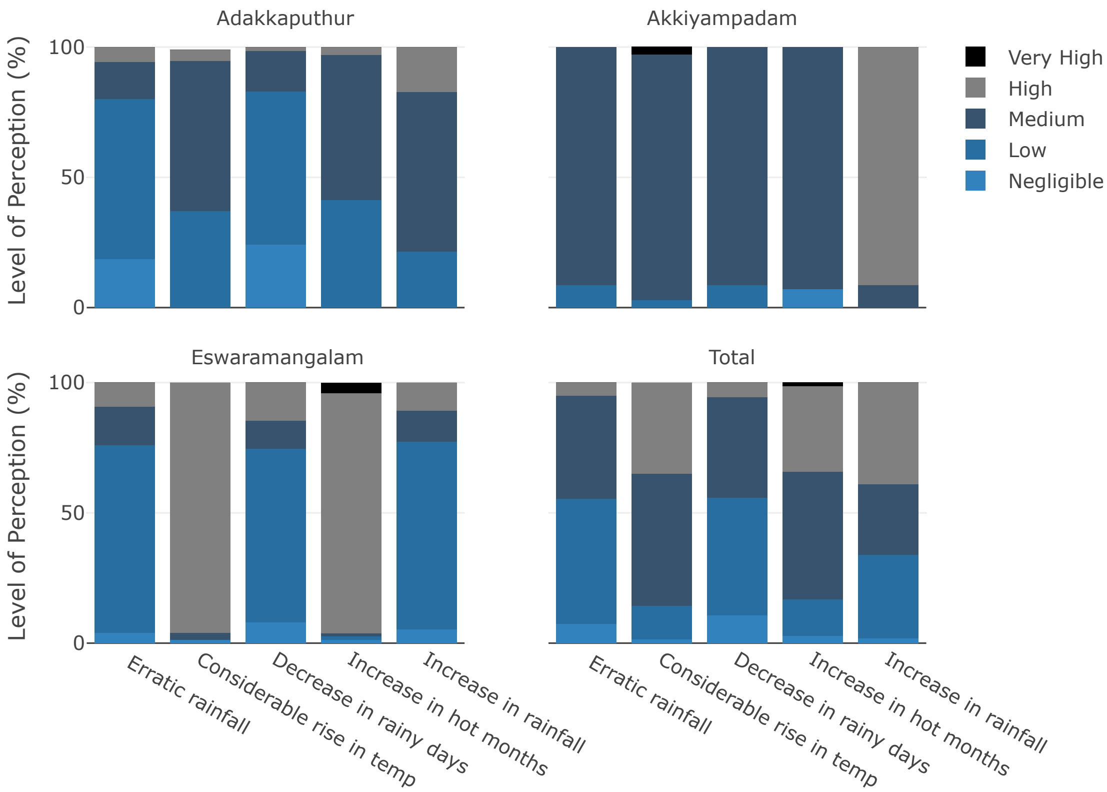
Farmers perceive medium to high levels of "considerable rise in temperature" and "increase in hot months". Similar results are reported in the Bundi district of Rajasthan (Dhaka et al. 2010) and in Maharastra and Andhra Pradesh (Banerjee 2015; Ravi Shankar et al. 2013). It is notable that the perceptions of the farmers are similar in various parts of the world, for example, for Ethiopia (Mengistu 2011) and South Africa (Bryan et al. 2013), irrespective of place and season.

More than 66% of the households opine medium to high levels of perception regarding the "increase in rainfall" parameter, and 87% have experienced low to medium levels of erratic monsoon incidences. Other studies demonstrate similar results; for example, farmers in Andhra Pradesh discern a general decrease in rainfall even when facing heavy, irregular and unpredictable rains (Banerjee 2015; Mengistu 2011; Ravi Shankar et al. 2013).

To compare perceptions of climate change with its actual effects, we use high-spatial-resolution and time-varying data from TerraClimate (Abatzoglou et al. 2018). This dataset provides a monthly temporal resolution and an approximately 4 km (1/24th degree) spatial resolution. We use a rectangle with a latitude bound between 10.8° N and 11.3° N, as well as a longitude bound between 76.2° E and 76.4° E for the data extraction. Figure 5.2 summarizes the annual and seasonal average maximum temperatures, as well as the seasonal and annual rainfall in the lower panel between 1958 and 2017. Two main things are prominent in these data. First, a clear upward moving trend exists in the mean maximum temperature over the past century for the studied region. Second, Kerala is known for its monsoon climate, showing a distinct temporal variation and a decrease in annual rainfall. Both of these phenomena are clearly visible in the lower panel. Thus, the households' perceptions of climate change seem to be in accordance with the observed trends in Figure 5.2.

Nevertheless, the question is how households can react if they recognize that climatic conditions have changed over time. Households use a broad variety of possible adaptation strategies to cope with such perceptions of climate change. Based on a review of climate-change adaptation strategies, Below et al. (2010) find 104 relevant practices covering data from 17 studies and more than 16 countries in Africa, America, Europe and Asia. A major part of the literature,

FIGURE 5.1: Households' perceptions of climate change

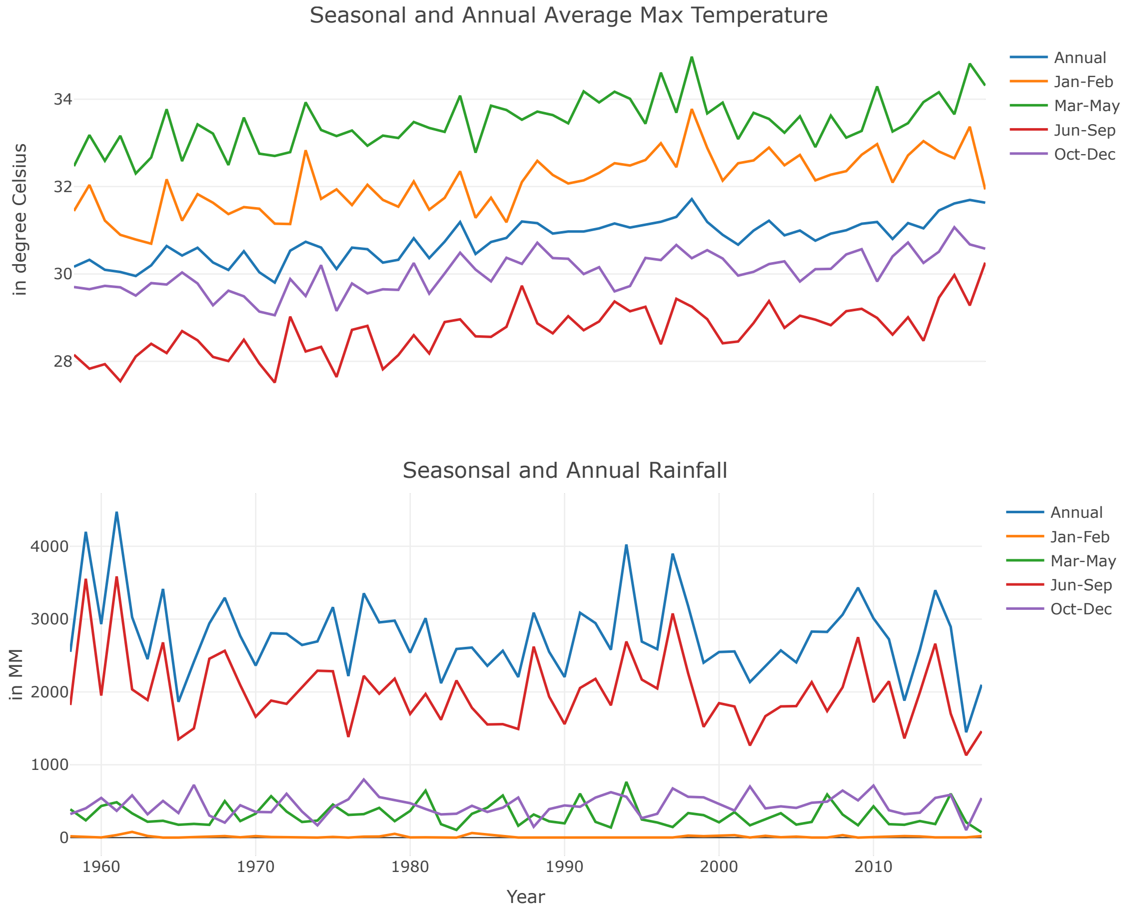


which examines adaptation strategies and perceptions of climate change, is focused on countries in Africa (Bryan et al. 2013; Deressa et al. 2009; Gbetibouo 2009; Hassan and Nhemachena 2008; Hisali et al. 2011; Ndamani and Watanabe 2016). The most common adaptation strategies include changing the crop variety to more drought- and heat-tolerant crops, changing the planting dates, irrigation, the planting of shade trees (agroforestry), soil and water conservation, and crop diversification.

However, we examine the relationship between perceptions of climate change and adaptation strategies specifically for the case of rain-fed smallholders at the watershed level in India. This is why (unlike in the micro-level studies mentioned above for Africa) this study shows that certain adaptation strategies are used more frequently than others. Figure 5.3 summarizes the 10 most frequently named strategies.

Information and communication technology facilitates public awareness and efficiency in communication, particularly when it comes to changing climatic parameters and adaptation to climate change (Aleke and Nhamo 2016). The households depend mainly on the internet and on mobile phones for climate-related information. Livestock introduction and crop diversification in farming reduce households' sensitivity to extreme events, drought and erratic monsoons by providing ensured additional sources of income Ndambiri et al. (2013) and Yila and Resurreccion (2013). In this case, most of the households introduced poultry, goat, rabbit or cattle to their farming systems. Cooperatives and self-help group activities enhance their collection action, spread the risk among their members and render support to households in terms of cash or inputs at minimal interest rates.

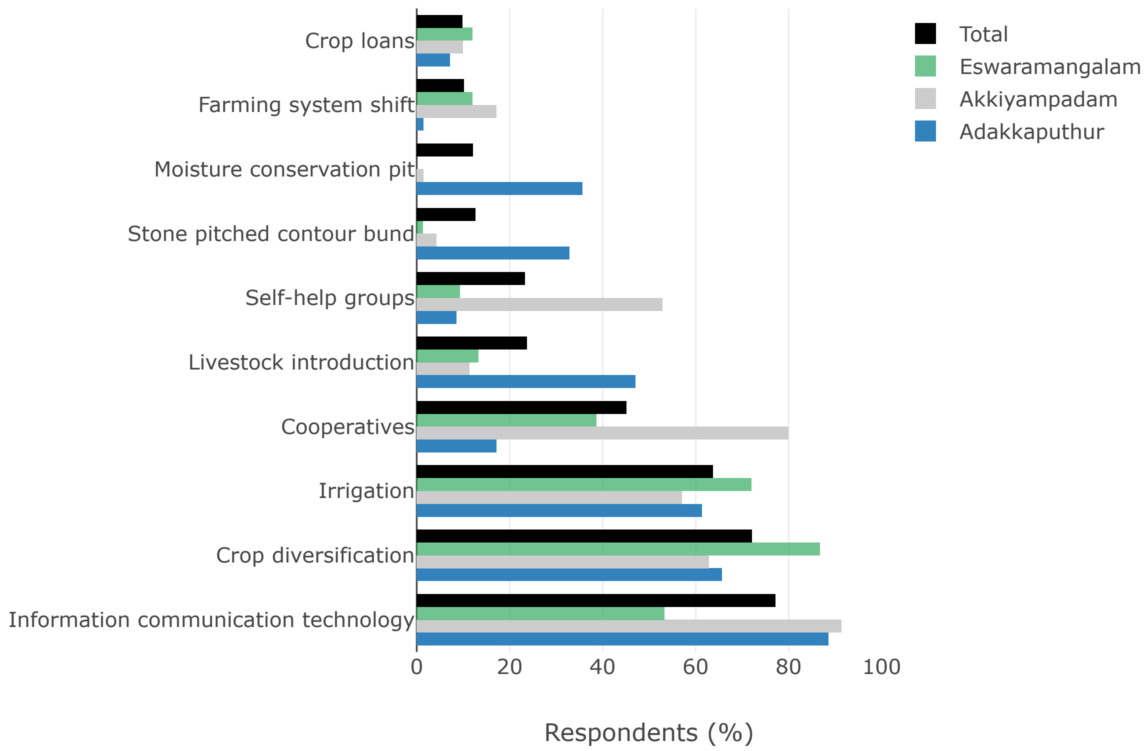
FIGURE 5.2: Seasonal and annual temperature and rainfall



Furthermore, stone pitched contour bunds and moisture-conservation pits are mechanical measures constructed in the slope regions to reduce soil erosion and run off, as well as increase the infiltration of water deeper into the soil.

The three watersheds are considerably different when it comes to the actual use of adaptation strategies. For instance, crop diversifica tion and irrigation are used relatively more often in Eswaramangalam than in Adakkaputhur and Akkiyampadam. This is not surprising given that the vast majority of households perceive a high rise in temperature and a large increase in hot months in the Eswaramangalam watershed. Admittedly, this is only one possible explanation. The differences among the watersheds could also be explained by other factors than perceiving the risk of higher temperatures, which we do not observe tershed focuses more attention on the adaptation strategies involving social dimensions. As a result, information and communication technology, cooperatives and self-help groups are far more important in the Akkiyampadam watershed than in the Adakkaputhur and Eswaramangalam watersheds. Given that we find that the majority of households perceive low to medium changes in all five categories for the Adakkaputhur and Akkiyampadam watersheds (Figure 5.3), it is not surprising that we identify a higher diversification of the adaptation strategies that the households use. This is why at least 30% of the households in the Adakkaputhur watershed use six strategies, those in the Akkiyampadam watershed use five strategies, and those in the Eswaramangalam watershed use four strategies. Thus, our household survey results reveal that the households generally use various adaptation methods simultaneously.

FIGURE 5.3: Households' adaptation strategies



5.3.2 Model Significance and Goodness of Fit

Table 5.2 summarizes the results for the model significance tests and the goodness of fit. The results indicate that we can reject our null hypotheses that none of the considered factors has any influence on the outcome variable for all of the estimated models at the 1% level. Furthermore, we calculate the goodness of fit by using McFadden's R-squared. The value for the pseudo-R-squared ranges from 0.20 to 0.53, indicating a good fit compared with the null model, using only a constant as regressor. In addition, we measure the in-sample model correctness for the estimated models. These are computed by using an optimal threshold for the predictions of our logit models. The optimal threshold varies between 0.29 and 0.57 for the various models. However, similar results have been obtained by using a fixed cutoff value of 0.5. We measure the accuracy of our models by comparing the predicted values of our models with the actual responses from the households. If a predicted value is above the threshold, it is considered to be 1 (e.g., a household adopts a technology); otherwise, the prediction is deemed 0 (e.g., a household does not adopt). The model correctness then reflects the proportion of correctly estimated positive and negative events out of the total number of events – 215 in this case. Thus, all of our models are able to predict with a success rate of more than 77% if a household does or does not adapt to climate change.

Moreover, we evaluate our models by ROC curves, which are plotted for the 10 logit models in Figure 5.4 The blue shaded areas represent the 95% confidence interval for the ROC curves estimated by using 2000 bootstrap replications. We also depict the confidence interval for the AUCs. The results indicate that models (a) – (h) show a good out-of-sample performance with mean values for the AUC well above 75%, whereas models (i) and (j) seem to be less suited for out-of-sample predictions. One reason for this is that only a small percentage of households have used farming-system shifts and crop loans as strategies. Thus, it is not surprising that the confidence bands for these two models are wider compared with the other eight models. The

TABLE 5.2: The models' significance and goodness of fit

Model	Chi-squared	P-value	Log likelihood	AIC	McFadden R-squared	Model correctness (%)
Information and communication technology	90.1	<0.0001	-70.347	180.695	0.39	85.1
Crop diversification	59.62	<0.0001	-97.488	234.976	0.23	82.3
Irrigation	55.7	<0.0001	-112.999	265.999	0.20	77.2
Cooperatives	106.04	<0.0001	-94.98	229.960	0.36	82.8
Livestock introduction	125.22	<0.0001	-55.174	150.348	0.53	94
Self-help groups	85.38	<0.0001	-73.913	187.825	0.37	85.1
Stone-pitched contour bunds	62.08	<0.0001	-50.21	140.42	0.38	90.7
Moisture-conservation pits	81.04	<0.0001	-38.768	117.535	0.51	93.5
Farming-system shifts	43.74	0.0010	-49.114	138.228	0.31	92.1
Crop loans	56.85	<0.0001	-40.361	120.723	0.41	94

low AUCs and confidence bands, including the 50%, lead us to conclude that the latter two models are inadequate for any further analysis.

5.3.2.1 Factors Affecting the Choice of Adaptation Strategies

We are interested in quantifying the impact of the explanatory variables that affect a farmers' choice of adaptation methods. Table 5.3 summarizes the regression results of the eight remaining adaptation strategies. A full regression table and a coefficient plot can be found in the Appendix (Table 5.4 and Figure 5.5)Here, we use odds ratios, which allow for a simple and intuitive interpretation of the coefficients. The following subsections discuss the results for our various explanatory variables based on the probability of adopting the respective adaptation strategy.

5.3.2.2 Age of household head

The odds ratio for age of the household head is in most cases smaller than one, which indicates a negative relationship for most of the adaptation strategies. Nevertheless, we find only one significant value. Thus, a greater age of the household head significantly decreases the odds of using cooperatives as an adaptation strategy. In addition, this effect seems to increase with age. This is more or less in line with our expectation that the sign of the relationship between the age of the household head and the adaptation strategies is inconclusive.

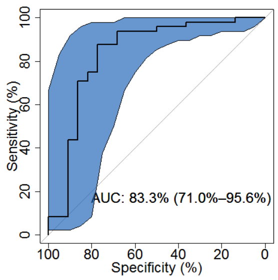
5.3.2.3 Education of household head

We expect a well-educated farmer to be more aware of climate change and the usefulness of adaptation strategies. However, we solely find a significantly positive relationship for the use of cooperatives as an adaptation strategy. Having a household head with a primary, middle or secondary school degree increases the odds by 200% compared with a household head with no degree or only a primary school degree. In addition, the odds are almost 10 times greater for a household head with a high school or university degree than for one in the base category.

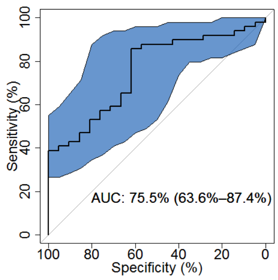
5.3.2.4 Gender of household head

This study's results suggest that the odds for a male-headed household to use information and communication technologies are almost 7.2 times greater than the same odds for female-headed households. This is in line with the findings in Deressa et al. (2009) that male-headed households are more likely to engage in new technologies and farming practices. Moreover, we

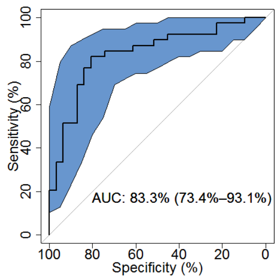
FIGURE 5.4: ROC curves for out-of-sample predictions



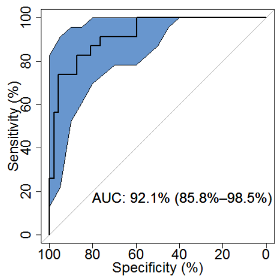
(a) *Information communication technology*



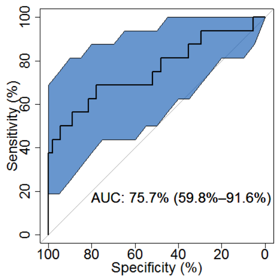
(b) *Crop diversification*



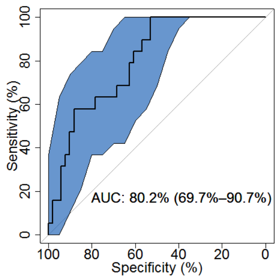
(c) *Cooperatives*



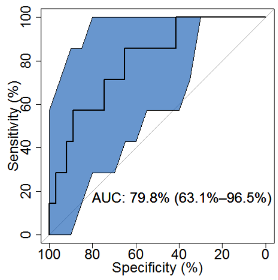
(d) *Irrigation*



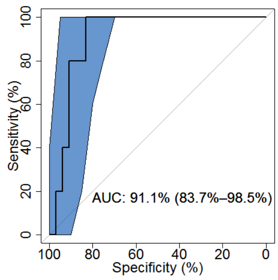
(e) *Livestock introduction*



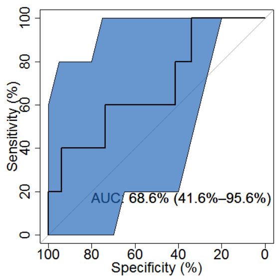
(f) *Self-help groups*



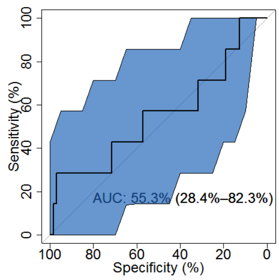
(g) *Stone pitched contour bund*



(h) *Moisture conservation pit*



(i) *Farming system shift*



(j) *Crop loans*

Note: The graphs have been computed using the R package pROC by Robin et al. (2011).

find the opposite relationship for the use of self-help groups and stone-pitched contour bunds as adaptation strategies. Here, male-headed households are almost 66% (78%) less likely to use self-help groups (stone pitched contour bunds) than female-headed households. Dolisca et al. (2006) find a similar result – that women's participation in social activities and their attendance of meetings are more likely. One might argue that the gender effect we measure here is at least partially superimposed by a wealth effect. Male-headed households are likely to be wealthier, and the odds ratios we observe are picking up this relationship. However, we explicitly control for various aspects of wealth, which – apart from other omitted variables – should at least partially reduce this wealth effect.

TABLE 5.3: Regression results – Odds ratios

	Information and communication technology	Crop diversification	Irrigation	Cooperatives	Livestock introduction	Self-help group	Stone-pitched contour bunds	Moisture conservation pits
Age	0.902	0.975	0.934	**0.771****	0.905	0.997	1.087	1.276
Age squared	1.001	1.001	1.001	**1.002****	1.001	1.000	0.999	0.998
Education1	0.909	1.942	0.686	**3.025****	0.692	1.281	1.104	0.978
Education2	3.604	4.131	1.774	**9.771*****	0.212	0.399	0.000	7.761
Gender	**7.155*****	1.651	1.497	1.665	0.734	**0.339***	**0.220***	0.541
Household size	0.855	1.038	0.910	1.222	**1.443***	**1.349***	1.215	1.508
Farm Income	1.989	2.972	1.587	1.978	1.143	0.942	0.840	0.921
Household assets	**1.751*****	**1.848*****	**1.520****	1.061	**0.542****	0.797	**1.928****	1.185
Livestock	2.109	1.259	1.273	**3.585*****	**85.446*****	2.009	0.719	0.700
Poverty status	**2.709***	1.318	**1.827***	0.570	0.642	**0.338****	1.986	**8.081****
Farm size	0.822	1.154	1.564	**3.188****	2.055	0.851	0.874	0.905
Well ownership	0.178	1.340	3.360	0.223	0.594	0.951	0.424	1.142
Extension service	2.400	1.512	**10.323****	1.984	0.509	**6.594****	2.112	2.796
Rainy days	**5.255*****	0.463	0.673	1.778	**0.189****	1.872	0.342	0.221
Soil erosion	0.300	1.700	**2.303***	0.933	1.570	**3.172****	1.914	1.513
Temp rise	**0.130****	0.827	1.459	0.684	0.763	2.284	0.912	1.163
Water depletion	1.236	1.987	2.655	0.599	0.594	1.615	3.526	7.236
Akkiyampadam	0.491	**4.120****	2.731	**17.481*****	**0.039*****	**16.144*****	0.314	**0.030****
Eswaramangalam	**0.031*****	**8.295*****	**3.918****	3.103	**0.052*****	1.459	**0.011*****	0.000
Constant	10.005	**0.002***	0.058	26.470	138.065	0.091	0.000	0.000

Note: *p<0.1; **p<0.05; ***p<0.01, significance is indicated by bold values.

5.3.2.5 Household size

An odds ratio greater than one for the household size indicates a positive relationship between the household size and the probability of adaptation to climate change. We find that increasing the household size by one person leads to a 44% increase in the odds of using livestock introduction and a 35% increase in the use of self-help groups. This is in line with our expectations that the household size (and thus the labor endowment) is positively related to the adaptation process.

5.3.2.6 Various aspects of wealth

We use income, livestock ownership, household assets and poverty status to measure various aspects of wealth. Although we find no significant relationship between the farm's income as the only source of a household's income, the latter three measures of wealth seem to be of great importance for the use of adaptation strategies. We find a significantly positive relationship between cooperatives and livestock ownership. Thus, a household is more than 250% more likely to engage in cooperatives if it owns livestock. Furthermore, the odds of introducing further livestock as an adaptation strategy are 85 times greater for a household that already owns livestock. This might be due to the fact that these households already have prior experience with the challenges of animal husbandry.

Moreover, we find a mostly positive relationship between household assets and various adaptation strategies. Thus, the odds of using information and communication technology, crop diversification, irrigation or stone-pitched contour bunds as adaptation strategies increase significantly with household assets. This meets our expectations. However, we also find a negative relationship for the use of livestock introduction. Here, households are 46% less likely, with respect to odds, to introduce livestock to cope with climate change.

In addition, we find that households that are above the poverty status are 170% more likely to use information and communication technology as a strategy, have seven times greater odds of using moisture- conservation pits and are more than 80% more likely to use irrigation compared with households that are considered to be poor. The opposite is true for involvement in self-help groups. Here, households above the poverty level are more than 66% less likely to make use of this adaptation strategy to face climate change.

5.3.2.7 Farm size in hectares

The farm size of a household might be seen as a proxy for wealth, which makes it easier for a family to adapt to climate change, as adaptation processes typically are often associated with high transaction costs. We find a significantly positive relationship between farm size and engagement in cooperatives. Thus, increasing the farm size by 1ha increases the odds of using cooperatives by a factor of three.

5.3.2.8 Well ownership

Not owning a well indicates an inadequate supply of ground water and is considered to be positively associated with the use of adaptation strategies. Nevertheless, we do not find a significant relationship between owning a well and the use of such strategies.

5.3.2.9 Extension services

The use of extension services is hypothesized to have a positive relationship with the use of adaptation strategies (Jiri et al. 2017). We find a positive relationship between extension services and the use of irrigation and self-help groups as adaptation strategies. A household's odds of using irrigation are almost 10.5 times higher than those for households that are not provided with extension services. In addition, the odds of using self-help groups are 6.5 times higher when the household is provided with extension services. Thus, we can conclude that extension services that provide households with assistance and information about climate change are very important for the use of adaptation strategies.

5.3.2.10 Climate-change awareness

We expect the sign between climate-change awareness and various adaptation strategies to be inconclusive. However, we find a significantly positive relationship between rainy days and Information communication technology. Furthermore, the introduction of livestock is 81% less likely, with respect to odds, if the household perceives an increase in rainy days. Although not significant, the odds are smaller 1 among crop diversification, irrigation, stone pitched contour bunds, moisture-conservation pits and a perceived increase in rainy days, and this is not surprising, as one could expect these strategies to be used for decreased precipitation.

We find a significant relationship between soil erosion and the use of irrigation and self-help groups. Thus, a household is 150% more likely to use irrigation and more than 200% more likely to engage in self-help groups if households are aware of soil erosion. In addition, we find that households that perceive an increase in temperature are 87% less likely to use information communication technology as a strategy, although we do not find any significant effect for the other adaptation strategies.

Being aware of water depletion has no significant effect on any of the adaptation strategies. However, the signs for crop diversification, irrigation, stone-pitched contour bunds and moisture conservation especially are in alignment with our expectations, as these strategies are particularly useful for coping with a water shortage.

5.4 Conclusion and Policy Implications

Climate change is expected to have a severe impact on the lives of farmers in the Kerala region in the near future. Already today, one can observe a substantial spatial and temporal variation in monsoon rainfall (Nikhil Raj and Azeez 2012) combined with an increase in short-term droughts (Thomas and Prasannakumar 2016). Hence, this study is aimed at not only investigating how households perceive climate change but also observing which strategies are most common and which drivers most influence households' choices regarding the adoption of such strategies in rain-fed watershed areas in Kerala. We find that the vast majority of the households in the three study areas perceive at least medium to high levels of a rise in average temperature and an increase in hot months. In addition, we find that almost all (>98%) of the survey participants recognize an increase in rainfall in all three watersheds. However, the three examined watersheds differ considerably in terms of the quantity and the selection of the adaptation strategy that the farmers use to cope with perceptions of climate change.

This study's results also reveal that various factors are significantly correlated with the adaptation strategies that the households use. For instance, more experienced farmers are less likely to seek social assistance and are also less likely to use irrigation methods. In addition, male-headed households are found to be more engaged in using new technologies and farming practices, whereas women's participation in social activities and attendance of meetings are more likely. Furthermore, education, farm size and owning livestock can be seen as three important factors for a household to engage in cooperatives. Thus, we conclude that farmers in the WDPs are well aware of the fact that the climatic conditions are changing, and measures should be and partially have been undertaken to overcome the potential negative effects.

Some of the determinants of adaptation strategies are institutional in nature (e.g., educational status and extension services). First, extension services are an effective tool for educating farmers about adaptation strategies and about how to implement practically. Thus, the expansion of extension services could significantly affect the rate of the adoption of strategies to cope with climate change, especially among the poorest households.

Another concern is the socioeconomic statuses of the households, with an emphasis on wealth assets. This study's results strongly support this statement, as we mostly find a positive relationship between household assets and various adaptation strategies. Furthermore, it is widely accepted in the literature that the poorest ones are the least equipped when it comes to dealing with long-term climate change to maintain their current livelihoods (Bryan et al. 2013; Hahn et al. 2009; Jiri et al. 2017). By contrast, households with high levels of assets are innovative and are keen to access information related to weather and climatic parameters; social-networking institutions, such as cooperatives and self-help groups; and modern technologies for irrigation and for soil and water conservation.

We conclude that the services that the WDPs render are not sufficiently effective adaptation processes for populations with no access (or only limited access) to them. The vertical and horizontal integration of these institutions, as well as effective public–private partnerships and community involvement, are necessary for combining adaptation processes at various levels. Even though WDPs are focused particularly on natural-resource management and production-system enhancement, very few households have adopted soil and water conservation strategies, such as the use of stone-pitched contour bunds and moisture-conservation pits, the introduction of livestock and the diversification of existing farming practices. Moreover, a closer look at the indigenous adaptation strategies is necessary for facilitating the adoption process and future location-specific research developments. Future researchers may also concentrate on completing an in-depth qualitative analysis of the barriers to adoption processes in rain-fed agricultural areas in the tropics.

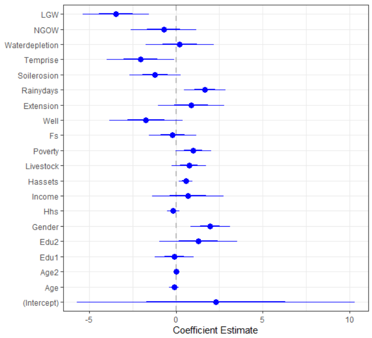
E Appendix to Chapter 5

TABLE 5.4: Regression results – Odds ratios (full table)

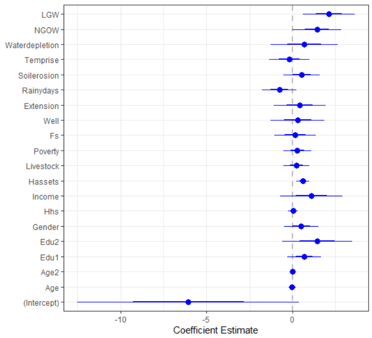
	Information communication technology	Crop diversification	Irrigation	Cooperatives	Livestock introduction	Self-help groups	Stone pitched contour bund	Moisture conservation pits
Age	0.902	0.975	0.934	**0.771****	0.905	0.997	1.087	1.276
	z = -0.743	z = -0.235	z= -0.692	z = -2.267	z = -0.606	z = -0.026	z = 0.390	z = 0.831
Age squared	1.001	1.001	1.001	**1.002****	1.001	1.000	0.999	0.998
	z = 0.702	z = 0.546	z= 0.585	z = 2.123	z = 0.459	z = -0.347	z = -0.331	z = -0.838
Education1	0.909	1.942	0.686	**3.025****	0.692	1.281	1.104	0.978
	z = -0.167	z = 1.355	z= -0.311	z = 2.134	z = -0.575	z = 0.410	z = 0.136	z = -0.025
Education2	3.604	4.131	1.774	**9.771*****	0.212	0.399	0.00000	7.761
	z = 1.147	z = 1.392	z= 0.672	z = 2.748	z = -1.026	z = -0.806	z = -0.013	z = 1.222
Gender	**7.155*****	1.651	1.497	1.665	0.734	**0.339***	**0.220***	0.541
	z = 3.438	z = 0.998	z= 0.903	z = 1.023	z = -0.451	z = -1.725	z = -1.856	z = -0.558
Household size	0.855	1.038	0.910	1.222	**1.443***	**1.349***	1.215	1.508
	z = -0.863	z = 0.264	z= -0.742	z = 1.352	z = 1.845	z = 1.823	z = 1.006	z = 1.558
Farm Income	1.989	2.972	1.587	1.978	1.143	0.942	0.840	0.921
	z = 0.665	z = 1.206	z= 0.646	z = 0.956	z = 0.154	z = -0.054	z = -0.202	z = -0.089
Household assets	**1.751*****	**1.848*****	**1.520****	1.061	**0.542****	0.797	**1.928****	1.185
	z = 2.777	z = 3.214	z= 2.573	z = 0.368	z = -2.380	z = -1.081	z = 2.077	z = 0.445
Livestock	2.109	1.259	1.273	**3.585*****	**85.446*****	2.009	0.719	0.700
	z = 1.495	z = 0.610	z= 0.698	z = 3.097	z = 5.464	z = 1.558	z = -0.572	z = -0.514
Poverty status	**2.709***	1.318	**1.827***	0.570	0.642	**0.338****	1.986	**8.081****
	z = 1.941	z = 0.687	z = 1.657	z = -1.316	z = -0.797	z = -2.171	z = 1.024	z = 2.529
Farm size	0.822	1.154	1.564	**3.188****	2.055	0.851	0.874	0.905
	z = -0.288	z = 0.237	z = 0.862	z = 2.269	z = 1.405	z = -0.347	z = -0.246	z = -0.125
Well ownership	0.178	1.340	3.360	0.223	0.594	0.951	0.424	1.142
	z = -1.633	z = 0.373	z = 1.538	z = -1.151	z = -0.423	z = -0.038	z = -1.027	z = 0.152
Extension service	2.400	1.512	**10.323****	1.984	0.509	**6.594****	2.112	2.796
	z = 0.916	z = 0.544	z = 2.134	z = 1.028	z = -0.634	z = 2.423	z = 1.083	z = 1.488
Rainy days	**5.255*****	0.463	0.673	1.778	**0.189****	1.872	0.342	0.221
	z = 2.790	z = -1.565	z = -0.901	z = 1.209	z = -1.990	z = 1.001	z = -1.310	z = -1.490
Soil erosion	0.300	1.700	**2.303***	0.933	1.570	**3.172****	1.914	1.513
	z = -1.643	z = 0.997	z = 1.664	z = -0.124	z = 0.559	z = 2.109	z = 0.618	z = 0.283
Temp rise	**0.130****	0.827	1.459	0.684	0.763	2.284	0.912	1.163
	z = -2.107	z = -0.323	z = 0.667	z = -0.559	z = -0.343	z = 0.989	z = -0.148	z = 0.221
Water depletion	1.236	1.987	2.655	0.599	0.594	1.615	3.526	7.236
	z = 0.215	z = 0.704	z = 1.148	z = -0.638	z = -0.396	z = 0.355	z = 0.935	z = 1.407
Akkiyampadam	0.491	**4.120****	2.731	**17.481*****	**0.039*****	**16.144*****	0.314	**0.030****
	z = -0.752	z = 1.996	z = 1.515	z = 3.735	z = -2.757	z = 3.203	z = -0.981	z = -2.131
Eswaramangalam	**0.031*****	**8.295*****	**3.918****	3.103	**0.052*****	1.459	**0.011*****	0.000
	z = -3.610	z = 2.830	z = 2.075	z = 1.594	z = -2.703	z = 0.448	z = -2.756	z = -0.011

Note: *p<0.1; **p<0.05; ***p<0.01, significance is indicated by bold values.

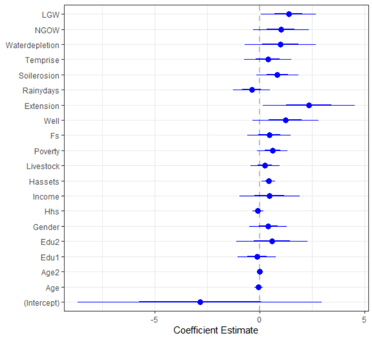
FIGURE 5.5: Coefficient plot for the regression results of table A.1.



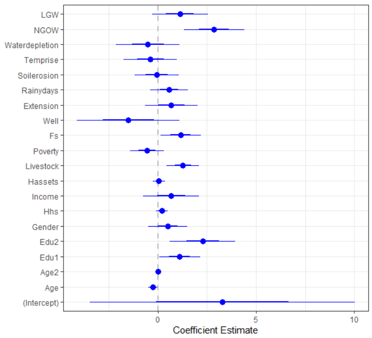
(a) *Information communication technology*



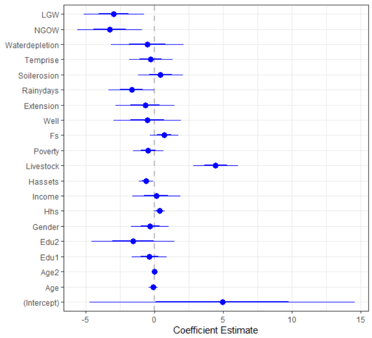
(b) *Crop diversification*



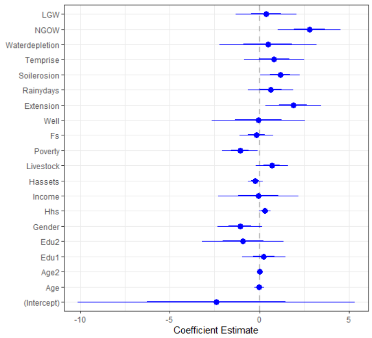
(c) *Irrigation*



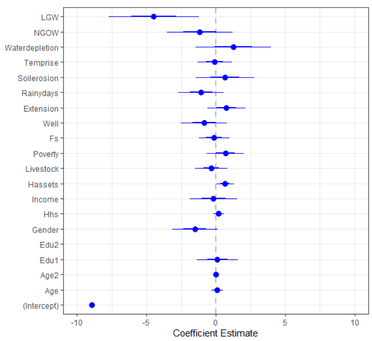
(d) *Cooperatives*



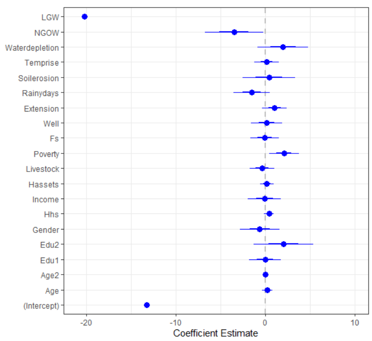
(e) *Livestock introduction*



(f) *Self-help groups*



(g) *Stone pitched contour bund*



(h) *Moisture conservation pit*

FIGURE 5.6: Correlation table for variables of Table 5.1

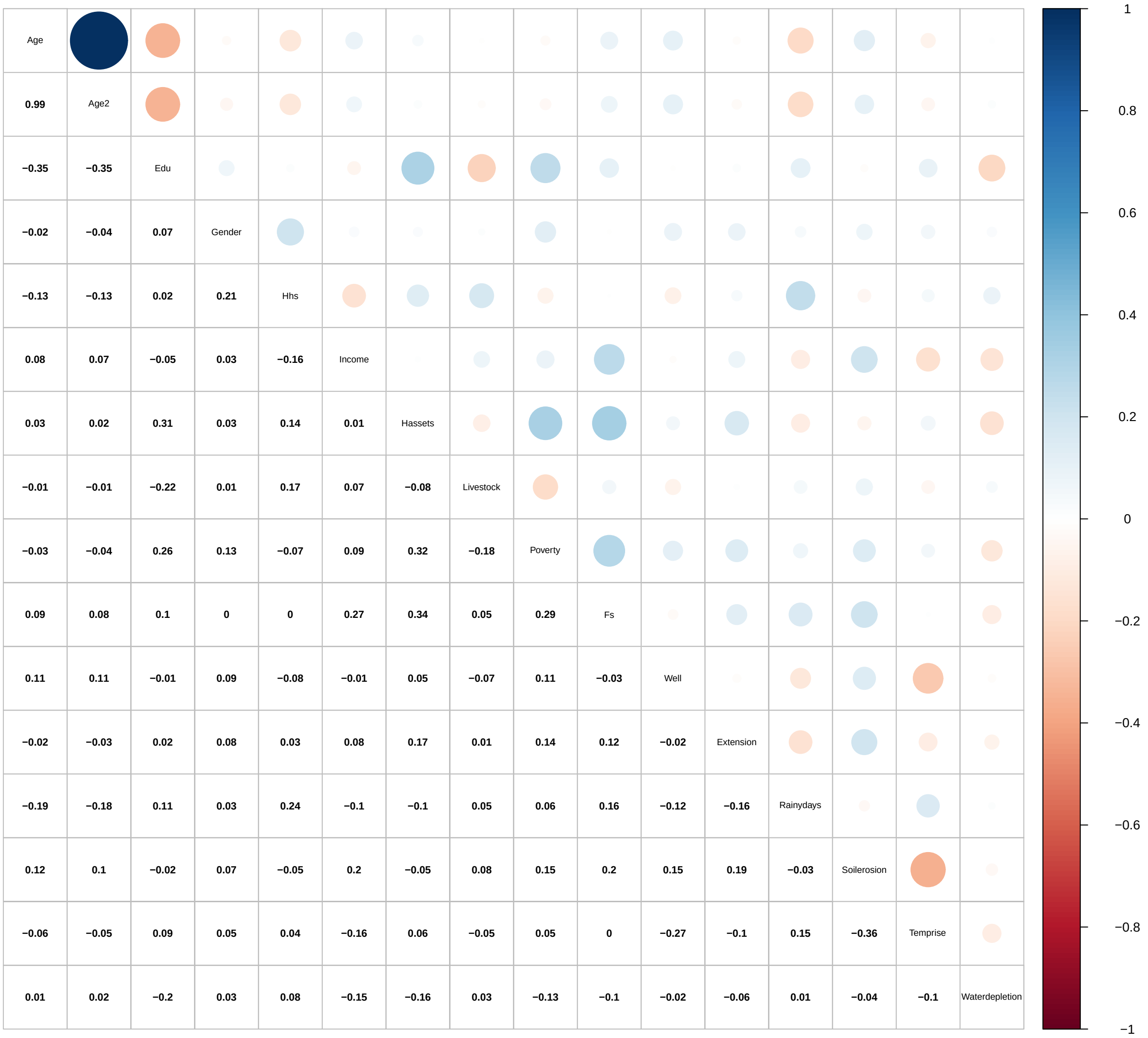


TABLE 5.5: Regression results – Marginal effects reported as the data's sample mean

	Information communication technology	Crop diversification	Irrigation	Cooperatives	Livestock introduction	Self-help groups	Stone pitched contour bund	Moisture conservation pits
Age	-0.010	-0.004	-0.015	-0.064**	-0.005	-0.0003	0.001	0.00002
	t = -0.743	t = -0.235	z = -0.692	t = -2.254	t = -0.613	t = -0.026	t = 0.008	t = 0.002
Age squared	0.0001	0.0001	0.0001	0.001**	0.00004	-0.00004	-0.00000	-0.00000
	t = 0.701	t = 0.547	z = 0.586	t = 2.112	t = 0.464	t = -0.351	t = -0.008	t = -0.002
Education1	-0.009	0.115	-0.030	0.259**	-0.022	0.023	0.001	-0.00000
	t = -0.170	t = 1.270	z = -0.314	t = 2.315	t = -0.531	t = 0.421	t = 0.008	t = -0.002
Education2	0.083*	0.160**	0.110	0.473***	-0.052*	-0.067	-0.038*	0.0004
	t = 1.708	t = 2.146	z = 0.759	t = 4.267	t = -1.683	t = -1.098	t = -1.907	t = 0.002
Gender	0.291***	0.088	0.089	0.122	-0.019	-0.134	-0.020	-0.00005
	t = 2.693	t = 0.929	z = 0.872	t = 1.063	t = -0.411	t = -1.461	t = -0.009	t = -0.002
Household size	-0.015	0.006	-0.020	0.049	0.020*	0.029*	0.002	0.00003
	t = -0.863	t = 0.264	z = -0.743	t = 1.351	t = 1.795	t = 1.838	t = 0.008	t = 0.002
Farm Income	0.053	0.132*	0.090	0.169	0.008	-0.006	-0.001	-0.00001
	t = 0.839	t = 1.696	z = 0.710	t = 0.982	t = 0.146	t = -0.055	t = -0.008	t = -0.002
Household assets	0.054***	0.099***	0.089***	0.015	-0.034**	-0.022	0.005	0.00001
	t = 2.712	t = 3.317	z = 2.579	t = 0.368	t = -2.203	t = -1.086	t = 0.008	t = 0.002
Livestock	0.072	0.037	0.051	0.306***	0.370***	0.068	-0.003	-0.00002
	t = 1.496	t = 0.610	z = 0.699	t = 3.304	t = 5.067	t = 1.532	t = -0.008	t = -0.002
Poverty status	0.103*	0.045	0.130	-0.138	-0.025	-0.114**	0.005	0.0001
	t = 1.792	t = 0.677	z = 1.638	t = -1.328	t = -0.744	t = -2.041	t = 0.008	t = 0.002
Farm size	-0.019	0.023	0.095	0.286**	0.040	-0.015	-0.001	-0.00001
	t = -0.286	t = 0.238	z = 0.869	t = 2.256	t = 1.354	t = -0.345	t = -0.008	t = -0.002
Well ownership	-0.279	0.044	0.199**	-0.303*	-0.024	-0.005	-0.005	0.00001
	t = -1.205	t = 0.404	z = 2.151	t = -1.656	t = -0.514	t = -0.039	t = -0.008	t = 0.002
Extension service	0.064	0.060	0.304***	0.170	-0.030	0.309*	0.008	0.0001
	t = 1.226	t = 0.610	z = 4.632	t = 1.055	t = -0.819	t = 1.880	t = 0.008	t = 0.002
Rainy days	0.155***	-0.128	-0.085	0.142	-0.091*	0.063	-0.008	-0.0001
	t = 2.652	t = -1.537	z = -0.896	t = 1.222	t = -1.812	t = 0.974	t = -0.008	t = -0.002
Soil erosion	-0.118	0.086	0.176*	-0.017	0.025	0.113*	0.005	0.00003
	t = -1.568	t = 0.994	z = 1.689	t = -0.124	t = 0.549	t = 1.937	t = 0.008	t = 0.002
Temp rise	-0.118***	-0.029	0.084	-0.094	-0.016	0.064	-0.001	0.00001
	t = -3.130	t = -0.337	z = 0.641	t = -0.559	t = -0.314	t = 1.262	t = -0.008	t = 0.002
Water depletion	0.022	0.131	0.231	-0.128	-0.035	0.039	0.006	0.0001
	t = 0.200	t = 0.617	z = 1.103	t = -0.644	t = -0.326	t = 0.426	t = 0.008	t = 0.002
Akkiyampadam	-0.076	0.198**	0.197*	0.607***	-0.145**	0.395***	-0.008	-0.0002
	t = -0.676	t = 2.320	z = 1.675	t = 5.342	t = -2.278	t = 2.585	t = -0.008	t = -0.002
Eswaramangalam	-0.499***	0.287***	0.262**	0.276*	-0.139**	0.038	-0.036	-0.072
	t = -3.222	t = 3.365	z = 2.345	t = 1.673	t = -2.188	t = 0.424	t = -0.009	t = -1.371

Note: *p<0.1; **p<0.05; ***p<0.01, significance is indicated by bold values.

TABLE 5.6: Regression results – Marginal effects ereported as the mean of the marginal effects across all observations

	Information communication technology	Crop diversification	Irrigation	Cooperatives	Livestock introduction	Self-help groups	Stone pitched contour bund	Moisture conservation pits
Age	-0.011	-0.004	-0.012	**-0.037****	-0.008	-0.0004	0.006	0.014
	t = -0.735	t = -0.235	z = -0.688	t = -2.107	t = -0.601	t = -0.026	t = 0.389	t = 0.813
Age squared	0.0001	0.0001	0.0001	**0.0003****	0.0001	-0.00005	-0.00004	-0.0001
	t = 0.695	t = 0.543	z = 0.583	t = 1.989	t = 0.458	t = -0.346	t = -0.330	t = -0.819
Education1	-0.010	0.103	-0.025	**0.156****	-0.030	0.027	0.007	-0.001
	t = -0.168	t = 1.328	z = -0.313	t = 2.276	t = -0.561	t = 0.413	t = 0.137	t = -0.025
Education2	0.114	**0.173***	0.098	**0.323*****	-0.102	-0.090	**-0.135*****	0.122
	t = 1.400	t = 1.850	z = 0.708	t = 3.265	t = -1.222	t = -0.919	t = -6.290	t = 1.289
Gender	**0.240*****	0.077	0.073	0.072	-0.025	**-0.121***	**-0.125***	-0.037
	t = 3.263	t = 0.973	z = 0.894	t = 1.045	t = -0.440	t = -1.747	t = -1.803	t = -0.552
Household size	-0.016	0.006	-0.017	0.029	**0.029***	**0.033***	0.014	0.024
	t = -0.849	t = 0.264	z = -0.737	t = 1.315	t = 1.701	t = 1.716	t = 0.982	t = 1.445
Farm Income	0.065	0.140	0.079	0.100	0.011	-0.006	-0.012	-0.005
	t = 0.731	t = 1.473	z = 0.675	t = 0.954	t = 0.152	t = -0.054	t = -0.208	t = -0.089
Household assets	**0.057****	**0.091*****	**0.074****	0.008	**-0.048****	-0.025	**0.048***	0.010
	t = 2.406	t = 2.810	z = 2.375	t = 0.367	t = -2.065	t = -1.059	t = 1.877	t = 0.443
Livestock	0.074	0.034	0.043	**0.184*****	**0.377*****	0.076	-0.024	-0.021
	t = 1.567	t = 0.612	z = 0.701	t = 3.330	t = 8.639	t = 1.596	t = -0.576	t = -0.513
Poverty status	**0.106***	0.042	0.111	-0.080	-0.035	**-0.116****	0.048	**0.118*****
	t = 1.927	t = 0.680	z = 1.621	t = -1.337	t = -0.789	t = -2.305	t = 1.073	t = 3.069
Farm size	-0.020	0.021	0.079	**0.166****	0.057	-0.018	-0.010	-0.006
	t = -0.287	t = 0.237	z = 0.855	t = 2.106	t = 1.328	t = -0.346	t = -0.245	t = -0.125
Well ownership	-0.199	0.042	**0.190***	-0.196	-0.039	-0.005	-0.055	0.008
	t = -1.555	t = 0.387	z = 1.866	t = -1.337	t = -0.450	t = -0.039	t = -1.191	t = 0.151
Extension service	0.082	0.059	**0.306*****	0.099	-0.049	**0.226****	0.061	0.064
	t = 1.034	t = 0.575	z = 3.829	t = 1.039	t = -0.693	t = 2.465	t = 0.987	t = 1.424
Rainy days	**0.172*****	-0.116	-0.071	0.089	**-0.139****	0.071	-0.077	**-0.085***
	t = 2.898	t = -1.571	z = -0.900	t = 1.151	t = -2.035	t = 0.978	t = -1.354	t = -1.651
Soil erosion	**-0.117***	0.078	**0.145***	-0.010	0.036	**0.126****	0.045	0.023
	t = -1.800	t = 1.009	z = 1.747	t = -0.123	t = 0.544	t = 2.170	t = 0.664	t = 0.293
Temp rise	**-0.169*****	-0.028	0.068	-0.055	-0.022	0.083	-0.007	0.009
	t = -2.971	t = -0.329	z = 0.658	t = -0.562	t = -0.333	t = 1.097	t = -0.147	t = 0.223
Water depletion	0.022	0.109	0.177	-0.075	-0.044	0.049	0.072	**0.091****
	t = 0.210	t = 0.671	z = 1.172	t = -0.633	t = -0.374	t = 0.377	t = 1.271	t = 2.124
Akkiyampadam	-0.074	**0.180****	**0.162***	**0.473*****	**-0.251*****	**0.371*****	-0.079	**-0.165*****
	t = -0.757	t = 2.475	z = 1.741	t = 4.656	t = -3.523	t = 3.190	t = -1.068	t = -2.792
Eswaramangalam	**-0.432*****	**0.282*****	**0.233****	**0.153***	**-0.226*****	0.041	**-0.218*****	**-0.230*****
	t = -3.850	t = 3.512	z = 2.344	t = 1.749	t = -3.393	t = 0.454	t = -3.611	t = -2.848

Note: *p<0.1; **p<0.05; ***p<0.01, significance is indicated by bold values.

Part IV

Climate Change: Coastal Adaptation and Wave Power

Chapter 6

Project Valuation for Coastal Adaptation – A Literature Review

The following chapter is based on the paper:

Title:	Project Valuation for Coastal Adaptation – A Literature Review
Authors:	Chi TRUONG, Stefan TRÜCK, Supriya MATHEW and Christoph FUNK (contribution: 25%)
Status:	*Working Paper*

Project Valuation for Coastal Adaptation – A Literature Review[1]

Chi TRUONG[2] Stefan TRÜCK[1] Supriya MATHEW[3] Christoph FUNK[4,1]

Abstract

This work presents a review of various valuation methods that can be used to evaluate coastal adaptation projects. We also provide a guide for policy makers on how to evaluate and choose between potential strategies for the management of coastal regions. We discuss and review a number of widely used methodologies in detail and provide examples for the practical application of these methods. The main methods discussed include cost benefit analysis, cost effective analysis, cost utility analysis and multi-criteria analysis. In addition, we provide an overview of studies that have evaluated coastal adaptation projects using cost benefit and optimal timing approaches to highlight methodological issues in this area of research.

Keywords: Literature review, Coastal adaptation, Project valuation, CBA, CEA, CUA, MCA, Real options

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6.1 Introduction

Global sea-levels have risen substantially over the last century and will continue to do so during the 21st century (Church et al. 2013; Dawson et al. 2018). This puts coastal regions under particular risk by virtue of their geographical location. Coastal areas are not only considered the most attractive areas for people to live in (Kron 2013) but also typically have a significantly higher population (Balk et al. 2009). As of today, around 10% of the world's population is already living in low-elevation coastal zones (Lichter et al. 2011). Moreover, the expansion rates have been significantly higher in coastal areas compared to the non-coastal hinterlands in the past, and this trend is likely to continue over the next century (Anderson and Hsiao 1982; Calil et al. 2017; Neumann et al. 2015; Peduzzi et al. 2012). This makes sea level rise an important scenario to consider for further policy analysis (Nicholls 2004), especially when taking into account that the risk of losses from natural hazards increases with population and the value of assets and infrastructure in risk-prone areas (Kron 2013).

Hallegatte et al. (2013) estimated the cost of flood damage in coastal areas to exceed $1 trillion a year by 2050. In addition, it is likely that the growth rate in coastal populations will outperform the possible progress in risk reduction worldwide over the same time (Peduzzi et al. 2012). In fact, Reguero et al. (2018) conclude that the annualized risk will more than double between 2030 and 2050, given the increase of climate change risk and the concentration of assets in coastal areas for the gulf coast of the United States. It is apparent that adaptation options should be given a high priority in managing the risk associated with these changing climatic conditions. Therefore, the valuation of adaptation options is crucial to appropriate adaptation decision-making when dealing with the management of coastal erosion. One major requirement in the evaluation of adaptation options is dealing with uncertainty. This uncertainty is not limited to climate projections but extends to a range of unknown variables in the future such as economic uncertainty (Adger et al. 2009). In this study, we aim to provide a review of possible project valuation methods used specifically for the case of coastal adaptation.

A wide range of valuation methods are available, including CBA, CEA, CUA and MCA. Often, it is difficult for stakeholders to understand the contexts in which these various valuation methods should be applied. This review can be seen as a guide for local government decision makers as it highlights various valuation methods by giving examples on how they have been applied in practical applications.

The remainder of the paper is organized as follows. In Section 6.2, we provide an overview of methods that can be used for the evaluation of adaptation projects in coastal areas. This includes CBA, CEA, CUA and MCA. A block diagram of various valuation methods with sign posts indicating when to apply each method is provided to guide stakeholders. In Section 6.3, we examine CBA and MCA methods in detail. In particular, we analyze the determination of discount rates, methods to estimate non-market values (e.g., revealed preference method, stated preference method, statistical methods, benefit transfer methods), linear utility MCA, PROMETHEE II MCA (Brans 1982; Brans and Vincke 1985) and methods applied to elicit criteria weights. Section 6.4 reviews studies that have evaluated coastal adaptation projects to highlight the issues that are important in this area of research. These include cost benefit and optimal timing studies as well as recent research on the real options that allow professionals to incorporate investment flexibility into the analysis adaptation projects. The concluding remarks are provided in Section 6.5.

6.2 Overview of Valuation Methods

Valuation methods that are commonly used in project assessment and have also become popular for coastal adaptation evaluation include CBA, CEA, CUA and MCA (Persson 2010).[5] CBA is used when it is possible to value all costs and benefits associated with a considered policy or project in monetary terms. The policy or the project is recommended when the net present value of the benefits exceeds the costs.[6] CBA has been a dominant valuation method in general and a much used method in coastal adaptation in particular. For example, Mendelsohn and Olmstead (2009) use CBA to determine whether Singapore should construct a seawall to protect against flooding due to sea-level rise, while Turner et al. (2007) conduct CBA to analyze whether the UK should implement retreat. Duke et al. (2013) discuss cost-effective conservation planning as an alternative method to CBA. Here, costs and benefits are also measured in monetary terms, but the goal is to maximize conservation relative to a given budget constraint. However, this method is far less common in practical applications, which is why it will not be discussed in further detail in this work.

CEA can be used when the benefits of different policies or options cannot be valued in monetary terms but can be measured in alternative output units such as tons of carbon sequestered. In CEA, the option with the lowest cost per unit of output is selected. Wintle et al. (2011) provide an example of using CEA to find the least costly adaptation option to conserve a given area of habitat for species that are vulnerable to climate change. Taborda et al. (2005) compare and evaluate the cost-effectiveness of beach nourishment[7] and the construction of groin fields, while Chu et al. (2014) use a simulation approach to generate risk contours that allow for an assessment of the costs and benefits of different beach nourishment scenarios. When benefits are measured in more than one output unit and all costs are measured in monetary units, then CUA can be used to select the option that helps to achieve a desired level of utility at the least cost. For example, Marinoni et al. (2011) use CUA to find an optimal portfolio of intervention sites for treating water pollution in a river catchment that maximizes the community's utility subject to a budget constraint. Outputs in their model include various water quality measures, as well as ecological outputs. Applying MCA, the authors calculate utility scores for each intervention measure and then use these scores together with allocated costs to obtain a benefit cost ratio. The benefit cost ratio then provides a measure that reflects how much benefit is obtained for each dollar spent or how effectively the expenditure is allocated.

When benefits are measured in more than one output unit and not all costs are measured in monetary units, MCA can be used. MCA involves determining the performance of alternative policies or options against selected criteria. The method also provides an opportunity to provide different weights to each criterion. The option that has the highest overall score based on the determined criteria and weights is then selected as the optimal one.

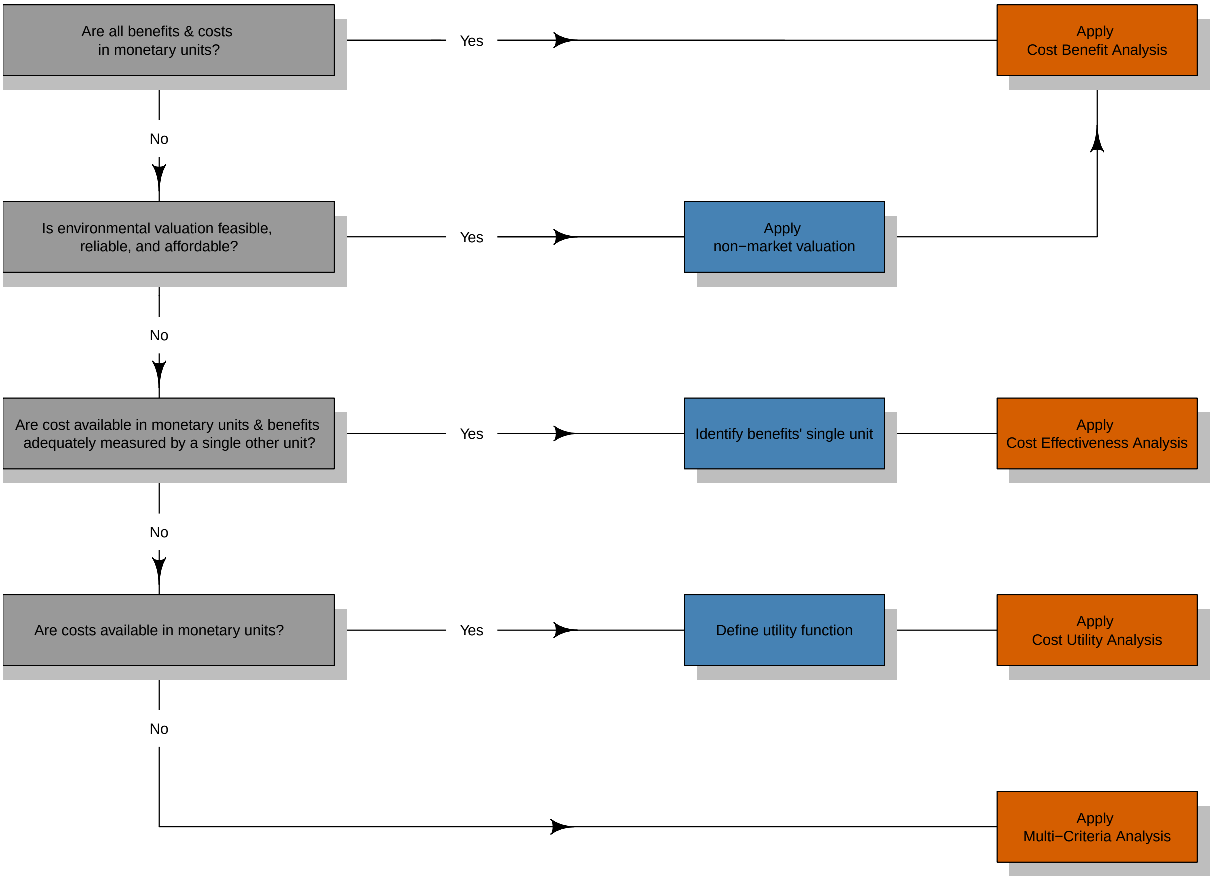
Some guidance on method selection is provided in Figure 6.1, following Hajkowicz (2008). CBA is often preferred, since it is typically based on actual data and is therefore more objective compared to MCA. Furthermore, the method applies quantitative data, such that results from CBA are also helpful when stakeholders are required to choose an optimal selection of projects under budget constraints. CBA is, however, only applicable when all costs and benefits can be monetized. When other criteria such as social and distributional effects are also important, or

[5] While we use a broad classification of evaluation methods for coastal adaptation strategies, it is worth pointing out that there exists a variety of alternative classifications and valuation schemes that could be used for climate change adaptation in a broader sense. The interested reader may find alternative classifications of valuation methods, e.g., in Dittrich et al. (2016) or Lazarow and Capon (2016).

[6] To obtain the net present value of the costs and benefits, future cash flows need to be discounted at an appropriate rate. The choice of the discount rate is discussed in Section 6.3.

[7] Cooke et al. (2012) provide a comprehensive review of the frequency and scale of beach nourishment practices in Australia and discuss the determinants of adopting such adaptation strategies.

FIGURE 6.1: Selecting appropriate tools to evaluate climate change adaptation options



Source: Own representation based on Hajkowicz (2008).

when some benefits cannot be quantified and valued (such as the benefits of preserving biodiversity), then MCA may be a preferred valuation method. However, note that the selection of methods need not be mutually exclusive. For example, the outcomes of CBA can be incorporated into MCA to make a hybrid analysis (Mathew 2012).

All of the above approaches involve stakeholders at numerous points within the appraisal process. Stakeholders could, for example, be involved in setting management objectives or determining values. It is important to understand that deciding how stakeholders should be involved may influence the choice of the valuation approach (Gamper and Turcanu 2007).

CBA is recognized as the main decision tool for adaptation in coastal areas in many countries. The UK and Holland governments have developed a CBA model for funding prioritization between projects (Persson 2010). The UK government's guidance on CBA emphasizes the need to consider a reasonably long-time horizon and to include as many benefits and costs (market and non-market) as is feasible with a money metric and existing knowledge (Turner et al. 2007).

In the US, CBA is also used as a primary tool for regulatory impact analysis. Circular A-4, issued by the Office of Information and Regulatory Affairs (2016), outlines the analytical considerations and best practices for regulatory CBA, including development of baselines, methods for obtaining costs and benefits, choice of discount rates and treatments of uncertainty. In contrast, MCA is rarely required by law. It is, however, indirectly required through the environmental impact assessments, where conflicts, equity and distributional issues need to be recognized (Gamper and Turcanu 2007). The potential of MCA is highlighted in situations involving multiple value systems and objectives that cannot be easily quantified (e.g., environmental issues) or, even less, translated in monetary terms due to their intangible nature (e.g., social, cultural or psychological issues). MCA can also structure and facilitate stakeholders' involvement in the decision-making processes. The analysis, the questions raised, and the reasoning in the process of a MCA can have a positive impact on the decision-making process such that preferences are revealed and can be considered by the final decision maker. The added value of MCA for public decision- making lies in its ability to reveal preferences in a more direct and practical way than other decision support tools. Affected stakeholder groups are asked, as a minimum, to ascribe their preferred options and respective criteria weights, and they might even be involved in creating these from an early stage of the decision-making process (Gamper and Turcanu 2007).

6.3 Review of Relevant Concepts and Methods

6.3.1 The Discount Rate

Investment projects usually have investment costs that occur at or near the investment time and benefits that spread over a long period of time. Due to the time preference of money (i.e., people often prefer to have money now rather than at a future time) one dollar that is obtained in a future period is typically considered to be worth less than a dollar that is obtained today. To make investment benefits that occur in the future comparable with investment costs that occur today or at an earlier point in time, an appropriate discount rate needs to be identified to convert all cash flows of a project to present value dollars. Once this is done, project costs can be deducted from project benefits to obtain the net present value (NPV) of the project. According to the NPV rule, one would consider an investment to be made if the associated NPV of the project is positive, while a negative NPV would suggest that the project should not be invested in. The choice of an appropriate discount rate for long-lasting projects is, however, highly controversial.[8] Some studies such as Stern (2007) and Garnaut et al. (2008) suggest that, for projects spanning more than one generation, the discount rate should reflect not only the consumption-saving preference of the current generation, but also that of future generations to ensure intergenerational equity. They propose using an optimal growth rate model to determine the discount rate. Determining discount rates based on optimal growth rate models, however, requires a social value judgment about intergenerational equality, which may be subjective and difficult. Other studies including Newell and Pizer (2003), Nordhaus (2007), and Quiggin (2008) suggest determining the discount rate based on the observed market interest rates. The discount rate has a significant impact on the NPV of adaptation projects and therefore on the valuation results. For example, the difference between Cline (1992) and Stern (2007) arguing for an immediate intervention and Nordhaus (2007) being in favor of a more moderate response to climate change is based on the different choices of discount rates (Dasgupta 2008).[9] Based on the computations in Dasgupta (2008), the proposed discount rates amount to 1.4% for Stern, 2.05% for Cline, and 4.3% per year for Nordhaus. In practice, this would mean that a cash flow of $1,000,000 in 50 years has a NPV of $499,002 (Stern 2007), $362,535 (Cline 1992) or

8 A summary of methods used for the implementation of discounting operations can be found in Bottero et al. (2013).

9 Moreover, the elasticity of marginal utility with respect to income is another important factor in models for climate economics. A more detailed discussion on the importance of discount rates and elasticities in this context can be found in Hampicke (2011) and Dasgupta (2008).

$121839 (Nordhaus 2007). Apparently, even small differences in the discount rate will lead to significant differences for large time horizons and thus affect the choice of investment projects.

The literature review of studies on adaptation to reduce catastrophic risk shows that the assumed discount rates vary across these studies and are usually not explicitly justified (Truong and Trück 2016a). An exception to this rule is the study by Michael (2007), which uses discount rates provided by Newell and Pizer (2003). Truong and Trück (2016a) use historical long-term government bond rates from 1970-2010 to determine the appropriate discount rate for investment valuation in Australia. Since the prices of government bonds vary stochastically over time, risk-free interest rates are also stochastic, and the authors estimate the model originally proposed by Cox et al. (1985) to describe the dynamics of long-term interest rates. They found that Australian interest rates have a quite low persistent coefficient, and the estimated certainty equivalent discount rate converges quickly to a long-term level of 4.5%.

6.3.2 Estimation of Non-Market Values

CBA is often conducted based on a total economic value model, where the value of environmental goods and services can be categorized into use and non-use values. Figure 6.2 gives an overview of the valuation techniques discussed in the following sections. Use values include the values obtained from actual usage or consumption of the environmental good, whereas non-use values are the values that arise from improving the well-being of people, even though no environmental good is consumed. Use values can include direct values, such as timber harvest, and indirect use values such as clean air from trees. Direct values can be divided into consumptive values such as timber harvest or non-consumptive values such as forest visual amenity (Tapsuwan et al. 2009).

Non-use values may be existence, bequest or option values. The existence value is the value that people place on knowing that something is there, such as knowing that a rare species still exists. The bequest value is the value that is gained from being able to conserve something for future generations. The option value is the value that an individual is willing to pay to ensure that a resource is available to him or her in the future.

In general, use values are easier to estimate, since the values are reflected in the marketplace. For example, the value of timber can be measured by the dollar amount for which the timber can be sold. The value of a beach can be measured by the amount that people pay to visit the beach. Non-use values are more difficult to measure due to the lack of a market for such services. For example, it is difficult to determine the benefit in dollar terms of preserving a wildlife species (Tapsuwan et al. 2009).

A number of techniques have been developed to estimate use and non-use values of environmental goods in the absence of explicit markets. These methods belong to two broad classes: behavioral (revealed preference) and attitudinal (stated preference) methods. Revealed preference methods aim to find the value people place on a good from observed behavior in markets for related goods, while stated preference methods ask consumers how much they value environmental goods and services in carefully structured surveys (Mendelsohn and Olmstead 2009).

The two most commonly used revealed preference methods are the travel cost method and the hedonic pricing method. The travel cost method estimates the recreational value of an environmental good such as wetland and beach, based on the costs that people incur to travel to the recreational site. Hedonic pricing methods use the market price of related goods to infer the value of an environmental resource. For example, the price of a house depends on the intrinsic characteristics of the house (e.g., number of bedrooms, number of bathroom, land area) as well as the environmental amenity such as beach view. Hedonic property models collect data on the prices of home sales and housing characteristics and then estimate the marginal implicit prices of the characteristics of interest. Two main methods of stated preference are contingent valuation and choice modeling. In contingent valuation, people are asked about their willingness to pay to prevent the loss of an environmental asset or their willingness to accept (a compensation) to let go of or lose the environmental asset (Carson et al. 2003; L. Richardson et al. 2015; S. A. Richardson and Sloan 2003). Choice modeling is similar to contingent valuation but the environmental good in question is described in terms of its attributes, and the levels of the attributes and respondents are required to choose between various attribute packages. Thus, the willingness to pay or to accept can be broken down into the willingness to pay/accept for each attribute (see, e.g., Hoyos (2010) or Bueren and Bennett (2004)).

For revealed preference methods - because experiments are not randomized - the methodologies must control undesired variation using a combination of carefully constructed experiments and more efficient statistical techniques minimizing the errors. Stated preference methods have the appealing feature that they can be used to value any environmental good or service as long as the good can be described. However, in practice, survey methods are more difficult than they appear. What people say they would do and what they actually do may differ. In this context, Rakotonarivo et al. (2016) review the reliability and validity of stated preference and discrete choice experiments in valuing non-market environmental goods. As such, Rakotonarivo et al. (2016) find mixed evidence for the reliability of discrete choice experiments and suggest considerable caution for their usage. Thus, economists generally rely primarily on revealed preference methods to estimate use value and reserve stated preference methods for non-use value. Moreover, they assess peoples' value for states of the world that do not exist (e.g., estimating the value of a piped water connection where there currently is none) (Mendelsohn and Olmstead 2009).

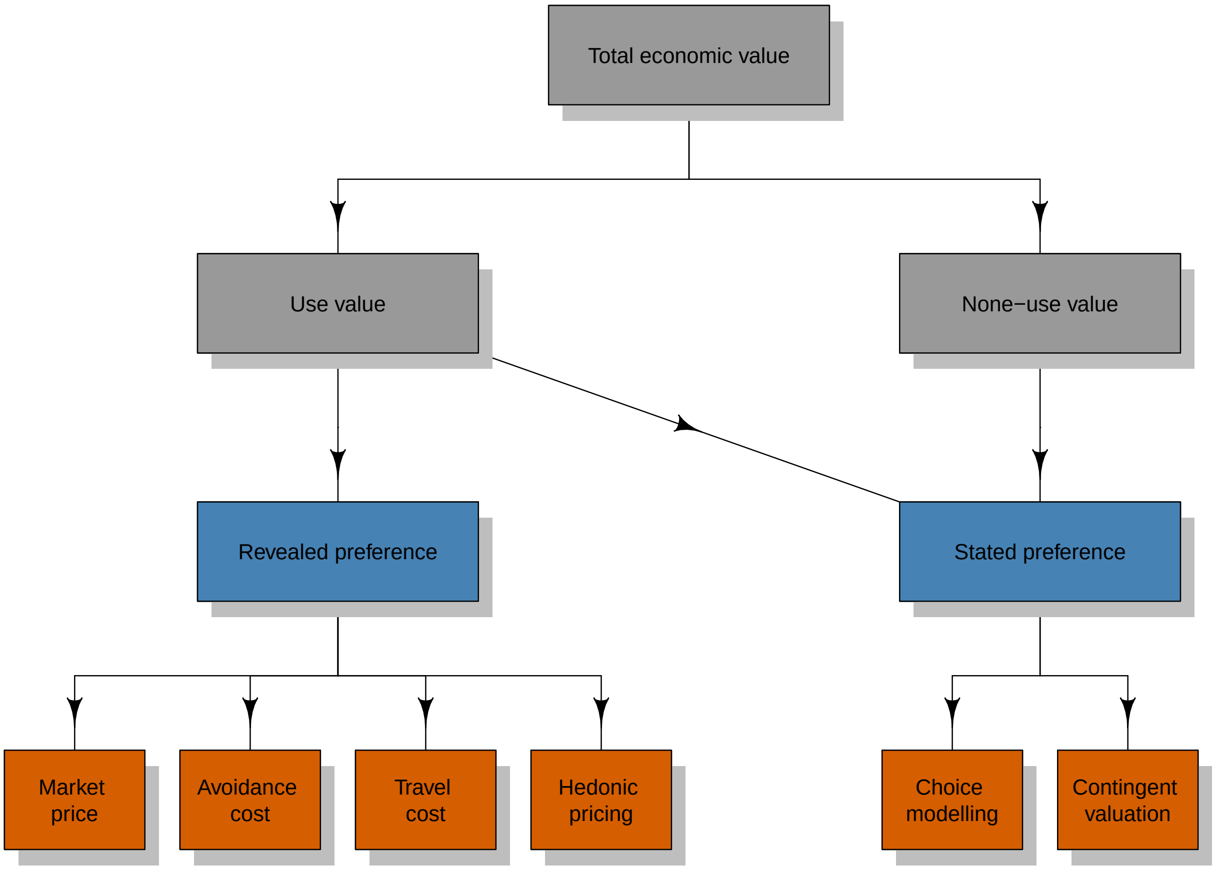
6.3.2.1 Revealed Preference Methods

Revealed preference methods are valuable tools for the estimation of use and non-use values of environmental goods, with travel cost and hedonic pricing are most commonly used. Travel cost models are among the most widely applied valuation methods, which have become very useful tools for estimating recreational demand. These methods, however, are vulnerable to the possibility that important factors have been omitted, which could bias the results. In addition, actual travel cost or some portion of it may be unobservable. One key unobserved cost is the opportunity cost of travel time. Wage rates may be assigned to value time, but empirical evidence suggests that people enjoy traveling, and the opportunity cost of travel time can be lower than the value implied by the wage rate (Cesario 1976). Another important issue concerns multipurpose trips. For trips with multiple purposes, an individual recreation site represents only a portion of the trip's value. If the analyst excludes multipurpose trips from the sample, so that all trips are single purpose, it will negatively affect the site's value. Assigning proportional values to each destination or purpose is unfortunately arbitrary (Mendelsohn and Olmstead 2009).

Many of the assumptions of travel cost models can be dealt with through sensitivity analysis. Researchers can make a range of assumptions about the opportunity cost of time, which travel expenditures to include and what portion of costs for a multipurpose trip should be attributed to an individual site. They can then observe how the recreational value of a site changes with these changes in assumption (Haab and McConnell 2002; Mendelsohn and Olmstead 2009).

Hedonic pricing models infer the marginal value of an environmental amenity from observed market values such as house prices. Although house prices are the main environmental application for hedonic pricing models, they could also be used to model the willingness to pay to avoid risk (Haab and McConnell 2002). Hedonic models have been used to estimate the economic value of air quality, proximity to wetlands and open space, and "disamenities"

FIGURE 6.2: Valuation techniques for use and non-use values



Source: Own representation based on Figure 1.3 and 1.4 of Bateman et al. (2002).

such as hazardous waste sites and airport noise. However, hedonic models have some limitations. First, it is assumed that buyers and sellers have good information on the characteristics of all housing alternatives. This assumption may not hold if, for example, the level of pollution produced by a nearby industrial site is only known with significant delays (Freeman et al. 2014). Second, the housing market is assumed to be in equilibrium, which implies that there are no further gains from trade and that the market clears at all times (Hanley and Barbier 2009). In reality, housing bubbles are often observed, which suggests that market prices may deviate from the equilibrium for some time before they are recorrected. Third, the models assume that residential properties are available in continuity and people can choose the properties best suited to their preferences (Mendelsohn and Olmstead 2009). In some cases, unobserved characteristics of housing consumers cause people to self-sort into neighborhoods on the basis of their preferences for environmental quality. For example, higher levels of air pollution may be observed in urban areas that also have more jobs. More jobs can in turn increase housing values. If there is a failure to adequately control for such factors, then there may be an over- or under-estimation of the price of air pollution (Mendelsohn and Olmstead 2009).

6.3.2.2 Stated Preference Methods

Stated preference methods use carefully designed surveys that ask consumers how much they value environmental goods and services. The survey creates a hypothetical market for the amenity so that responses can be evaluated in a manner similar to behavior observed in markets. The basic architecture of a contingent valuation survey is: (a) a description of the service/amenity to be valued and the conditions under which the policy change is being suggested, (b) a set of choice questions that ask the respondent to place a value on the service/amenity, and (c) a set of questions assessing the socioeconomic characteristics of the respondent that will help with determining what factors may shift that value (Mendelsohn and Olmstead 2009).

In early surveys, researchers simply asked people open-ended questions, such as how much they were willing to pay for each amenity. However, such open-ended questions are limited in their ability to provide accurate results. Closed-ended, discrete choice questions are questions in which respondents offer a "yes" or "no" responses when offered one or more specified prices for a good. A possible problem with stated preference surveys is that the responses to being willing to accept questions have generally been many times greater than the responses to being willing to provide questions. This is especially true for non-use values. The factors that cause these large differences are still an active topic of research. Mendelsohn and Olmstead (2009) suggest that these differences are measurement problems, whereas Flachaire et al. (2013) find that they can be due to so-called "protest behavior", for example, many respondents refuse to pay at all.

6.3.3 Benefit Transfer Methods

The primary valuation of an ecosystem service is time and money intensive. Benefit transfer in general refers to the practice of using nonmarket values estimated by previous studies by applying and adjusting them to the specific context of interest (Freeman et al. 2014). A low-cost method of valuation is the value transfer method, which is the procedure of estimating the value of an ecosystem by assigning an existing valuation estimate to a similar ecosystem. Typically, the literature distinguishes among three value transfer methods (see, e.g., Brander et al. (2012)): (1) unit value transfer, where the value estimated for study sites (sites that we have values for) is used without adjustment, or with adjustment for income only, for policy sites (sites that require valuation); (2) value function transfer (using an estimated value function from an individual primary study); and (3) meta-analytic function transfer (using a value function estimated from the results of multiple primary studies).

However, one of the main concerns with benefit transfer methods might be the questions of the validity when applying the values of previous studies to substitute original valuation research (Freeman et al. 2014). In particular, the heterogeneity of nonmarket environmental goods can be a challenge when one is gathering sufficient data (Boutwell and Westra 2013). Marginal unit values for ecosystem services are likely to vary with the characteristics of the ecosystem site (area, integrity, type of ecosystem), beneficiaries (number, income, preferences) and context (availability of substitute, and complementary sites and services). The transfer of values to an individual ecosystem site needs to account for variation in these characteristics between study sites (sites that we have values for) and policy sites (sites that need valuation); otherwise, the transfer error will possibly be large (Brander et al. 2012). The interested reader may find a comprehensive overview of benefit transfer methods, issues, challenges and applications that are relevant to both researchers and practitioners in Boutwell and Westra (2013) and R. J. Johnston et al. (2015), as well as reviews of various studies on benefit transfer methods in R. J. Johnston and Rosenberger (2009) and R. J. Johnston et al. (2018).

6.3.4 Multi-Criteria Analysis

MCA is a powerful valuation method for cases where it is not possible, time consuming or beyond a project's budget to monetize all project outputs. In many adaptation studies, one needs to incorporate the value of the flexibility of adaptation options, the social costs induced by the distributional effects of adaptation and the aesthetic impact of adaptation strategies. MCA is a commonly used analytical tool and can help with integrating all of these aspects in a single decision-making framework in a meaningful way (Lawrence et al. 2019). MCA has the advantage of offering decision-makers a direct way of incorporating qualitative and quantitative information into their decision processes (Preston et al. 2013). However, there exists a broad variety of approaches to MCA with different degrees of complexity. A useful starting point for a detailed general introduction and review of MCA methods in natural resource management and climate planning can be found in multiple sources (de Bruin et al. 2009; Ellen et al. 2016; Greco et al. 2016; Mendoza and Martins 2006). Moreover, the UK government provides a highly used manual for MCA techniques (Department for Communities and Local Government 2009).

6.3.4.1 General Framework and Applications of MCA

Many MCA methods have been proposed in the literature, several of which may be quite complex and can be considered as a "black box" by decision-makers. Various MCA methods have been reviewed by Govindan and Jepsen (2016). In conducting an MCA to evaluate dairy effluent management options in Australia, Hajkowicz and Wheeler (2008) explicitly avoided "black box" methods and instead used the weighted summation with linear transformation MCA method. This method is also called the linear utility MCA method as proposed by Prato (2003). Hajkowicz and Wheeler (2008) also carried out the analysis with another method known as PROMETHEE II, which is an outranking method, to check the robustness of the results. Additionally, an overview and discussion of various other multi-criteria decision-making methods for the case of flood risk management can be found in de Brito and Evers (2016).

Prato (2003) has used the weighted summation approach to rank five water management alternatives for the Missouri River system. However, instead of using standardized scores (as in the case of Hajkowicz and Wheeler (2008)), Prato (2003) used relative scores, where an alternative (usually the current management scheme) is selected as a base alternative, and the performance of other alternatives is evaluated relative to the base alternative. Relative scores provide a sense of how different alternatives perform compared with a system that may be familiar to the decision-maker (e.g., a system that is currently implemented), and how relative scores may be more intuitive than standardized scores are. Using relative scores, alternatives that have an overall performance score of 0 are considered to be as desirable as the base alternative, whereas those with positive scores are more desirable. The advantage of relative scores is that the ranking of alternatives does not change when additional alternatives are considered. Prato (2003) also outlines a non-linear utility using the square root functional form to model diminishing marginal utility. However, because the relative scores can be negative, in which case the square root utility does not exist, the author did not use the non-linear utility function in his empirical evaluation.

MCA has been successfully applied in various contexts of assessing the vulnerability of the coastal infrastructure and the project evaluation of coastal adaptation. Preston et al. (2011) provide a comprehensive overview of the applications and challenges of MCA methods for coastal adaptation options. Various case studies are applied in conjunction with local governments in three regions in Australia to prioritize coastal adaptation and development options. A. Johnston et al. (2014) use a simple MCA method for ranking potential consequences of infrastructure loss through flooding in Scarborough, Maine (USA). The authors build a Flood Consequence Score using a four-tier scoring approach based on economic impacts, social impacts, health and safety impacts, and environmental impacts. Rizzi et al. (2016) developed a regional risk assessment for the Tunisian coastal zone of the Gulf of Gabes. This approach is based on MCA and on geographical information to prioritize adaptation strategies. Local experts are asked to assign relative scores based on the four susceptibility factors identified in the vulnerability matrix:

vegetation cover, coastal slope (°), wetland extension (in Km^2), and percentage of urbanization. Lawrence et al. (2019) use an MCA combined with dynamic adaptive pathway planning using real options analysis (ROA) to develop a 100-year coastal adaptation strategy in Hawke's Bay, New Zealand.

6.3.4.2 Criteria Weight Selection and Elicitation

The selection of a set of criteria and key variables is an important factor for implementing an MCA. The criteria should be selected specifically for the implementation and require a substantial literature review to identify the most important factors. For example, when it comes to coastal disaster risk reduction, multiple factors, such as social acceptance, political will, the availability of financial resources and technological know-how, can play a major role in investment decisions (Barquet and Cumiskey 2018; I. Davis et al. 2015). An empirical MCA framework suggested in the Resilience-Increasing Strategies for Coasts – toolKIT (van Dongeren et al. 2014)– an EU-funded project with the aim of developing the risk management tools of feasibility, acceptability, and sustainability– were selected as the three main categories of criteria (Barquet and Cumiskey 2018). Alternatively, Preston et al. (2013) provide a guideline for prioritizing coastal adaptation and development options, and they categorize the criteria into four groups, namely governance, financial, social and environmental. Rouillard et al. (2016) provide an overview of non-monetary criteria based on a literature review with 40 publications in various policy areas, including water management and coastal protection. No regret, urgency, climate mitigation potential, extreme events, robustness, flexibility and the level of autonomy have been identified as additional indicators used for adaptation processes. Regarding criteria selection for flood management, a summary of criteria used in ranking flood management alternatives in previous studies is provided by Chitsaz and Banihabib (2015). They indicated that the expected annual damage is the most common criterion, followed by the protection of wildlife habitats, the expected average number of casualties per year, and technical feasibility and construction speed. Additionally, a review of MCA applications for the case of flood risk management can be found in de Brito and Evers (2016).

In conducting an MCA, criteria weights play an important role, and it is important to obtain an accurate evaluation of these weights. In environmental economics studies, criteria weights are obtained by asking decision-makers direct questions about these weights (Prato 2003). It is often quite difficult for decision-makers to come up with criteria weights in that context. As suggested by Xia and Wu (2007), the weights obtained using this approach are often biased, and the MCA results may be considered to be unreliable. Alternatively, Félix et al. (2012) discuss the usage of a stochastic multi-criteria acceptability approach to take into account the uncertainty of decision-makers' preferences.

De Almeida et al. (2016) present two methods for eliciting the criteria weights. The first method, called "exact weight", involves comparing an alternative with known performance scores in all criteria with another alternative that has the performance score in one criterion left unspecified. The decision-maker is then asked to specify the missing performance score for the second alternative so that they are indifferent between the two alternatives. This information is then used to calculate the weights.

The second method is called "flexible weight". In this method, the decision-maker is presented with two hypothetical alternatives whose performance scores are all specified. The decision-maker is then asked to select the preferred alternative. The observed decision is used in a linear programming problem to infer the criteria weights. Moreover, the weight could also be derived using consistency or consensus weights. In the former case, the weights are determined based on the idea of how consistent scores are between multiple rounds of ranking or scoring analysis (Beroggi and Waliace 2000; Tsiporkova and Boeva 2006). Thus, experts will be considered to be more reliable if they do not change their scores drastically between rounds and are ultimately given more weight in the aggregation. In the latter case, each expert's score is compared with the dominant score and then weighted based on its proximity to that central score (Mathew 2012).

6.4 Review of Climate Adaptation Studies in Coastal Areas

With climate change, sea-level is projected to rise, and the severity of storm surges is projected to increase (Bernier and K. R. Thompson 2006). These environmental changes may lead to the aggravated problems of coastal erosion, surface salinity and flooding damage in coastal areas. Therefore, timing has been found to be an important aspect of CBA. The insight is that even though investing now may generate a positive net present value, deferring investment to a future time may provide an even higher net present value. For example, assume that the annual cost of the project, which includes interest expense on the investment capital and maintenance cost, is constant over time. In the years when the annual benefit is lower than the annual cost, the project is not beneficial, and it is best to time the investment to avoid these years. If the NPV of the project is positive but the current annual benefit is lower than the current annual cost, then the NPV of the project can be increased by deferring the investment to a future year. The optimal time to invest is when the annual benefit is equal to the annual cost. When the annual benefit is higher than the annual cost, it is optimal to invest immediately.

In recent years, there has been an increasing amount of research done using ROA to find the optimal timing for climate adaptation investments. Previous studies have examined the issues of whether to invest in hard protection measures, such as dykes or sea walls, and what the optimal time to invest is (Hino and Hall 2017; Jonkman et al. 2009; Kim and Kung 2016; Lickley et al. 2014; Linquiti and Vonoratas 2012; K. U. Shah and Dulal 2015; Tsvetanov and F. A. Shah 2013; van der Pol et al. 2014; Woodward et al. 2011; Woodward et al. 2014). Such measures may be more appropriate for developed regions, where expensive buildings and infrastructures have been constructed; however, in less developed regions, soft protection measures, such as wetland restoration or retreats, may be a better option. Soft protection measures have been evaluated by multiple authors (Cardoso and Benhin 2011; Luisetti et al. 2011; Martínez-Paz et al. 2013; Turner et al. 2007). In addition, the problem of alleviating coastal erosion has been examined by several other authors (Arias et al. 2015; Roebeling et al. 2011; M. D. Smith et al. 2009; van Vuren et al. 2004; Yohe et al. 1995). Here, we provide a detailed review of some important studies published as journal articles to highlight the methods that have been used, as well as the issues that are encountered in conducting a project valuation for coastal adaptation. We have classified the studies by the applied methods, for example, CBA versus optimal timing, to focus on the methodological issues.

6.4.1 CBA Studies

Turner et al. (2007) have provided a CBA for managed realignment (retreat) scenarios as well as a holding-the-line strategy (maintain the position of the shoreline with protection strategies) for the Humber estuary in Northeast England. The construction of sea walls in the past effectively stopped the natural and adaptive migration of ecosystems at the land-sea interface. In response to rising sea-levels, a modified coast is unable to adapt by migrating landwards, and valuable intertidal habitats are eventually lost through inundation and it erosion. The loss of wetland reduces the ability of the intertidal zone to absorb energy and water, and reduces its ability to defend against waves and tides, especially during the storm conditions. It also results in increased capital and maintenance costs for engineered defenses. The loss of wetland also means the loss of a number of the ecosystem services it provides. Wetland represents significant reservoirs of biodiversity and attracts a range of conservation designations. Under the EU Water Framework Directive, the loss of a conservation area must be compensated for on a "like-for-like" basis. A managed retreat seems to offer a way of mitigating this problem by deliberately breaking defenses, allowing the coastline to recede and the intertidal zone to expand.

Turner et al. (2007) deliberately selected a study site to avoid a trade-off between realignments and people, property assets and nature conservation designation sites to avoid the use of a mixed approach to coastal management. They suggested that if the policy appraisal involves complex social justice/nature conservation and ethical concerns, CBA will not be decisive, and MCA should be preferred.

Luisetti et al. (2011) have provided a CBA of realigning (retreating) the defense line for the east coast of England, where flooding exacerbated by a storm surge and rise in sea-level is a major issue. Existing sea walls help to protect buildings and the infrastructure (including road and car parks), but they also obstruct the migration of wetland that adapts to sea-level rise. The status quo of maintaining existing sea walls would result in the gradual loss of wetland, whereas a managed realignment that moves the sea walls landward to maintain the wetland would result in the loss of agricultural land. Along the English east coast, coastal squeeze has resulted in the complete loss of wetland, but managed realignment can either create or restore wetland. The created or restored saltmarshes dissipate wave energy and provide a soft and more sustainable flood defense. They also provide ecosystem services, including carbon storage benefits, fishery productivity, recreation and amenity benefits (e.g., bird watching), existence value benefits (e.g., biodiversity maintenance) and the reduction of maintenance costs for sea walls. Luisetti et al. (2011) used market data to estimate the maintenance cost savings on hard defenses and the benefit of fish production. They used the damage-cost-avoided method to value the carbon storage benefits of wetland. For the recreation and amenity benefits of wetland, they used the stated preference method. Stated preference techniques are survey-based studies, in which respondents are asked to state their willingness to pay for a policy against a status quo policy. This technique may provide more accurate estimates of the regional specific values compared with the benefit transfer method when appropriately designed.

Roebeling et al. (2011) provide a CBA for various adaptation measures, including the construction of new groins, artificial nourishments, the extension of existing groins and the construction of longitudinal revetments to reduce coastal erosion. The benefits transfer approach is used to value coastal ecosystems, and the wave climate is assumed to be constant. It is found that constructing new groins is not attractive, whereas artificial nourishments, the extension of existing groins and the construction of longitudinal revetments provide positive returns on investment.

Hinkel et al. (2013) provide a CBA for the status quo of no protection and beach nourishment to deal with coastal erosion. In the status quo, if land for more valuable uses, such as housing or industry, is lost to erosion, then those activities would be relocated elsewhere at the expense of the dominant agricultural or lower value land. The number of people forced to migrate is calculated as the product of the land area eroded and the average population density per segment, assuming that the population is spread evenly over the area. Emigration is guessed using three times the per capita income. Buildings and infrastructure are assumed to be fully depreciated before being swallowed by the sea, based on the argument that erosion due to sea-level rise is a slow process and the losses can be anticipated. Hinkel et al. (2013) assume that tourism income increases with population and regional income. This may be reasonable because tourists are often attracted to regions with more available recreational activities and services. This is consistent with the findings by Ghermandi and Nunes (2013), who conclude that the visit frequency by tourists is positively correlated to the region's population and income. Therefore, as the region's land erodes, there is a decline in the population and in the income from tourism. In determining the level of nourishment, Ghermandi and Nunes (2013) assume that the marginal benefit of nourishment consists of only the land that is otherwise lost, and the marginal cost is the cost of nourishing sand. As a result, the optimal level of nourishment is binary, taking a value of zero if the nourishment cost exceeds the land value, and a value equal to erosion level otherwise.

Martino and Amos (2015) used a CBA for an ex-post evaluation of a beach nourishment project for Tarquinia Lido beach, Italy. This analysis can be used as a policy advisory tool for coastal managers by addressing the value of the benefits resulting from beach nourishment and how these values are distributed among different stakeholders. In addition, Martino and Amos (2015) address the problem of free riding, which emerges due to the public supply of coastal protection, and they discuss how this can be removed (at least partially) by charging local fees to internalize the benefits resulting from the adaptation project to beach users and property owners. As such, it is necessary for coastal communities that profit from beach enlargement to be charged with the real costs as a proportion of the benefits they receive to reduce the burden of those not benefiting.

Alexandrakis et al. (2015) used a CBA to evaluate the effects of beach erosion for the coastal city of Rethymnon on the island of Crete. Thus, they discussed various cost-benefit scenarios for planning coastal protection measures by relating the beach erosion vulnerability to the expected land loss, as well as the value of properties and the revenue losses arising from tourism and other economic activities. The evaluation was based on a multidisciplinary approach combining the environmental characteristics of the study site with economic data. The former was used to estimate the erosion vulnerability and the shoreline retreat that will stem from an expected sea-level rise over the next 30 years. The economic data, however, were used for the implementation of a hedonic pricing model to evaluate the value of the beach in terms of accommodation facilities, coastal businesses, tourism area and beach width using a two-stage least squares estimation. It turned out that the beach width in this application was endogenous and was instrumented using the distance to the closure depth, the presence of the coastal road on the boundary of the beach and the sector length. The risk assessment was then based on evaluating the vulnerability of the beach to erosion by its exposure (estimated revenue loss) estimated by the hedonic pricing model.

Coelho et al. (2016) discussed the costs and benefits of longitudinal revetments as an applied mitigation measure used to fix the existing shoreline position. They provided a statistical analysis that allowed for the comparison of different types of longitudinal revetments in terms of their effectiveness, costs and benefits to protect the waterfronts from erosion and overtopping. Coelho et al. (2016) compared crest elevation, artificial beach profile nourishment, and the construction of an intermediate berm as three possible solutions for reducing the frequency of overtopping. Therefore, the cost for additional investment and the maintenance of these types was compared with the benefits of the corresponding avoided flood damages. The frequency of overtopping was related to the geometrical characteristics and the wave climate, as well as the seabed profile in front of the structure. The approach was applied to a case study for Furadouro beach in Portugal, with the result being that further investments in the longitudinal revetments are economically justified in the mid term, particularly if one assumes an increase in the overtopping frequency over time.

Roebeling et al. (2018) argued that although studies had focused on adaptation strategies on a locale scale, they were not yet taking into account the fact that the costs and benefits of coastal erosion adaptation measures were determined by their suitability on a landscape scale. Hence, they developed a coastal erosion adaptation strategies (CEAS) approach that combined a shoreline evolution model together with a CBA, as well as a combinatorial optimization method to identify efficient coastal erosion adaptation strategies on a landscape scale. The shoreline evolution model was used to simulate the impact of various adaptation strategies on the shoreline evolution patterns over the next 10 to 50 years. The CEAS approach was then applied to a groin system in Central Portugal comparing a baseline scenario (without the use of groin systems) with various scenario simulations (with and without budget constraints), and a sensitivity analysis was conducted that took into account different variations of costs, benefits and discount rates. Roebeling et al. (2018) found that if budget constraints are in place, the gains of the protection of urban areas outweigh the loss of natural areas.

6.4.2 Timing Studies

Van Vuren et al. (2004) provide a framework to optimize beach nourishment timing for the Netherlands. The beach is assumed to erode at a linear rate due to sea-level rise and storm surges. Erosion causes damage to the coastal area in terms of land and building structures such as restaurants, hotels, holiday resorts, etc. Damage by erosion is summarized by a damage function that takes recession level as the independent variable. Van Vuren et al. (2004) consider nourishment as an erosion mitigation option. Nourishment has a fixed and a variable cost. The model provides the optimal times to renourish the beach and the corresponding nourishment cost.

M. D. Smith et al. (2009) provide a similar framework to optimize beach nourishment time for the US In contrast to van Vuren et al. (2004) , they argue that with nourishment, the beach erodes not only linearly due to the influence of sea-level rise but also exponentially due to the impact of nourishment that makes the facial profile of the beach steeper. M. D. Smith et al.'s (2009) model provides the optimal times to renourish the beach as well as the optimal beach width to be nourished.

McNamara et al. (2015) extend the model of M. D. Smith et al. (2009) to allow for storm surge risk. Both M. D. Smith et al. (2009) and McNamara et al. (2015) adjust the models developed in forestry economics using a comparison between nourishment and forest production: the nourishment cycle is similar to the tree harvest cycle, and storm surge risk is similar to fire risk. Erosion due to storm surge is often called short-term erosion. It is often argued that rapid short-term accretion usually follows short-term erosion so that the net change is often negligible; see for example, Hinkel et al. (2013).

Woodward et al. (2011) provide a real options framework to take into account climate change uncertainty and the value of investment flexibility in flood risk management.[10] In their study region, the flood defense system is due for refurbishment, and rebuilding it to the existing height does not offer further protection if water levels increase in the future. Raising the crest level to the maximum height offers only limited protection since the base of the system is small and the maximal height is limited. Another alternative is to widen the base so that the height can be increased now or at a future time. Increasing the height now offers higher protection, but if the water level remains unchanged in the future, investment in height may not justify the investment cost. A more flexible strategy is to leave the investment in height to a future time. Other alternatives to reduce flood risk include setting back defenses (managed retreat), flood proofing properties and improving the flood warning system. Woodward et al. (2011) evaluate three adaptation strategies for the Thames Estuary: refurbishing defenses, widening the base of the defense and raising the crest level according to the expected rise in sea-level. The time horizon is 100 years, and these adaptation strategies can be implemented in 2010 or 2040 only. Using different discount rates, Woodward et al. (2011) present the NPV of different adaptation strategies and find that real options have potential to provide significant economic benefits to long-term flood risk management.

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[10] Although Woodward et al. (2011) are not specific in how they model real options, a good reference on the standard real options model can be found in A. K. Dixit and Pindyck (1994). When the benefit of the investment project is uncertain and investment is irreversible, the decision to invest is similar to the decision to exercise an American call option. The optimal investment decision can be determined in the same way as for the call option. In addition, R. Nelson et al. (2013) briefly review the origins of real options and illustrate their utility to natural resource managers and decision makers.

Jonkman et al. (2009) examine the optimal level of flood protection for New Orleans. In their model, each dike height corresponds to a certain probability of flooding. Increasing the height of the dike reduces the probability of flooding and therefore the expected damage. When the dike is already very high, the benefit of an additional increase in the dike height (in terms of flood risk reduction) is low, while the (construction) cost is high. Conversely, when the dike is low, increasing the dike height by one unit will have a large impact on flood risk with only a small marginal construction cost. The total cost of expected flood damage and dike construction cost, therefore, can be optimized with the dike height. Jonkman et al. (2009) assume that damage increases at the rate of 1% per year due to economic growth. Moreover, the flood probability increases by 1% per year as a result of sea-level rise. To find the optimal level of protection, they consider safety levels of 1/100 (i.e., 1 in 100 years, or more frequent events result in no damage), 1/500, 1/1000, 1/5000, 1/10,000, 1/100,000. The damages at these safety levels are obtained by using the corresponding storm surge level in a hydraulic simulation model. Jonkman et al. (2009) find that the optimal protection level is 1/1000, which is substantially higher than the level 1/100 often assumed as an engineering standard. The high protection level is attributed to the highly populated and therefore highly exposed area of New Orleans.

Lickley et al. (2014) examine the optimal protection strategy over time to reduce the damage from flooding and sea-level rise in a region. In their framework, for each time period and level of protection in place, the decision maker determines the additional level of protection to be developed (doing nothing is equal to zero additional protection). Lickley et al. (2014) estimate flood risk by using climatic conditions from global climate models together with a statistical-deterministic hurricane model by Emanuel et al. (2006) to simulate a large set of synthetic hurricanes. Simulated storm data are then used in a hydrodynamic model (Overland Surges from Hurricane model by Jelesnianski et al. (1992)) to generate storm surges. Sea-level rise is modeled to shift the loss distribution over time. The framework is used in a case study to determine the optimal heights of the considered levee in each decade of the period 2010-2100.

Tsvetanov and F. A. Shah (2013) examine the value of the option to delay investment in hard protection measures such as sea walls or levees to reduce damages from coastal floods. They use the HAZUS-MH MR4 risk assessment software developed by the Federal Emergency Management Agency to simulate floods and damages. The HAZUS model uses 100-year flood still-water elevation to compute the wave height at the shoreline. Wave height is then used in combination with wave peak periods and the average slope to calculate the so-called "wave run-up", which is the height above the still-water level reached by waves after breaking. Wave height and wave run-up, together with loss exposure obtained from census data, are then used to determine flood damages. To incorporate the impact of sea-level rise, still-water elevations in future years are assumed to be the current elevation plus the sea-level rise. Sea-level rise is assumed to be linear in time. However, the authors use different rates of sea-level rise to account for an accelerating rate over time. Flood damages include (i) repair and replacement costs for damaged buildings, (ii) building content losses, (iii) building inventory losses, (iv) reallocation expenses for businesses and institutions, (v) capital-related income losses, (vi) wage losses and (vii) rental income losses to building owners. However, the authors have made some implications by, for instance, not including loss of life and health effects, zoning restrictions or changes in human behavior.

Tsvetanov and F. A. Shah (2013) assume that the sea barrier is constructed and expanded to protect the region against a 100-year flood or an event of smaller magnitude at all times. The cost of constructing sea barriers includes construction and maintenance costs, costs of future retrofitting and social costs (loss of wetlands, ocean view or recreational space, as well as shoreline erosion). Loss of recreational space and view can be accounted for as part of the initial costs and the cost of expanding the structure. Erosion and loss of wetland are generally a slow and continuous process and can be viewed as a variable cost component. Tsvetanov and F. A. Shah (2013), however, do not provide details on social costs or how they are obtained.

Mills et al. (2014) provide a framework to determine land use policy in a coastal area under the uncertainty of sea-level rise. They consider a coastline with a wetland that is threatened by sea-level rise and seek to decide how much land should be set aside to allow the wetland to migrate as the sea-level rises. If the wetland's migration is obstructed by developed structures, the obstructed part of the wetland is lost. How high the sea-level will rise is uncertain. The wetland migration distance that maximizes the expected value and development of the wetland is the optimum. The authors show that the optimal distance leads to significant increases in development benefits (by 119%, 99% and 64% for sea-level rise of 0.7, 0.95 and 1.2 m, respectively) and only a small decrease in the expected conservation benefit (by 2%) compared to the maximum distance that leaves the wetland unaffected by development.

Truong and Trück (2016b) use the framework of Mills et al. (2014) to analyze the principal-agent problem that may arise in the context of coastal development under sea-level rise uncertainty. They suggest that the principal-agent problem (i.e., the mismatch of incentives to achieve the maximal social benefits due to development benefits accruing to property developers and property losses and conservation benefits accruing to the society at large) may result in a suboptimal removal of flexibility that can help society cope with the uncertainty of sea-level rise. A more serious consequence is that coastal regions developed with permanent structures (rather than socially optimal transportable structures) are likely to be protected in the case of high sea-level rise and the loss of environmental assets, due to the strong political power of coastal property owners. To overcome the principal-agent problem, Truong and Trück (2016b) suggest insisting upfront on the development of socially optimal structures in areas at risk of inundation. For example, the use of removable properties has been incorporated into the planned retreat policy of Byron Shire Council, NSW, Australia (Niven and Bardsley 2013). The policy states that for the development to be approved, owners need to accept that the structure must be relocated or removed when the erosion escarpment advances within 20 m of the structure. Arguably, this policy might not be time-consistent however, if policy makers will not enforce it due to potential increased public pressure. However, the use of removable structures reduces the social cost of purchasing costly permanent properties in high sea-level rise scenarios and provides the means to make full use of land in at-risk regions for development benefits. It is also a way to overcome the uncertainty posed by sea-level rise in development decision-making.

Van der Pol et al. (2017) discussed two types of probabilistic extensions of the CBA framework used for the welfare maximization of flood risk management strategies under climate change. The impacts of climate change based on hydrologic uncertainty are implemented by using probability-weighted climate scenarios. In addition, new information about climate change impacts are used to extend the CBA analysis. New information can take the form of scientific progress, which can be seen as a reduction of epistemic uncertainty for the impacts of climate change. Alternatively, the arrival of new data allows for a Bayesian believe update of the distributional estimates. Van der Pol et al. (2017) argued that the efficiency of decisions on flood risk management options is increased by taking into account climate change signals on the likelihood of investment responses.

Policy makers are typically confronted with a series of possible adaptation strategies and uncertainty about future climate change. In order to find the optimal selection of investment projects as well as the optimal investment sequence, Truong et al. (2018) extend the framework established in Truong and Trück (2016a). In addition, the impact of climate change uncertainty is incorporated into the investment decision of adaptation projects in this framework by using a doubly stochastic Poisson process. Truong et al. (2018) also showed that investment flexibility increased the value of adaptation investments and could be increased even further by considering the optimal sequence of projects. Therefore, it is advisable to preserve flexibility of investment decisions under climate change uncertainty for times when catastrophic risks are higher by focusing on projects with low sunk costs first before investing in ones with higher sunk costs. Thus, the framework allows for a significant increase in the value of adaptation investments above the current NPV by allowing for investment flexibility.

Although ROAs provide a great deal of flexibility and are useful in guiding investments decisions for climate change adaptation, the approach itself comes at the cost of being complicated to implement in practical applications, as argued by Dittrich et al. (2019). The authors thus address some of these challenges for policy makers when using ROA and provide a more simplistic approach. The implementation is done using a spreadsheet format with backward induction for the case of afforestation as a flood management measure in a rural catchment in Scotland. Using an exceedance probability of 5%, the goal accordingly is to minimize the life cycle cost and to prevent flooding. The derivation of the transition probabilities is obtained by slicing potential climate change paths –here the expected change in rainfall intensity– into quartiles. The mean return level estimate of each quartile represents then the event nodes used in the decision tree used for the real options approach.

There is an ongoing debate in the literature about the usefulness of the ROA for climate change adaptation. On the one hand Kwakkel (2020) argues that the ROA approach is not free from criticism. In particular, the underlying assumptions of estimating the value of an option for a flexible climate change adaptation strategy can be seen as problematic. For once, the ROA requires the choice of a baseline scenario against which the option value is to be estimated. This choice might not be obvious, and changing it might substantially change the option value itself. Additionally, one could argue that the typically long time horizons for climate adaptation strategies render the probabilities and weights assigned for scenarios a meaningless task, given the uncertainty and dynamic nature of future scenarios.

On the other hand, Wreford et al. (2020) argue that ROAs can help make investment decisions more efficient when considering uncertainty and new information simultaneously, as this situation reflects real-world characteristics. Moreover, they discuss the differences between traditional ROAs – originating from financial literature designed to determine option values – and scenario-based ROAs and their potential use for climate adaptation decisions. According to authors, scenario-based ROA especially seem to be a logical extension when the CBA is used in the same manner and might help overcome some of the limitations of traditional ROA approaches. However, further development and cooperation between researchers and policy makers is required to improve the implementation of ROAs for adaptation decisions.

6.5 Conclusion

Given the apparent increase in climate change-related risks for coastal regions, the use of suitable adaptation strategies has grown in importance over the last decade. Our work can be seen as a guide for policy makers on how to evaluate and choose between potential strategies for the management of coastal regions. Accordingly, we discuss and review a number of different widely used methodologies in detail and provide examples of practical applications of these methods. The CBA can be carried out with limited technical resources, and because the results are easy to communicate to the public (Dittrich et al. 2016), it is the dominant valuation method. However, for CBA analysis, all the costs and benefits of projects need to be estimated, which requires not only a reliable data set but also the evaluation of marketed or non-marketed goods. If it is possible to value the benefits of different policy options not in monetary terms but in different output units, CEA provides an alternative to CBA. CEA is straightforward in terms of the optimization procedure. As a result, the option with the minimum costs per unit of output is selected. As in the case of CBA, CUA requires the costs to be valued in monetary units, although the benefits are measured in more than one output unit. The selection of the project is then based on the option that achieves a desired level of utility at the least cost. MCA is applied in situations where it is not possible to monetize all project outputs. MCA provides a decision tool to policy makers by ranking adaptation options based on criteria weights. This allows for flexibility to integrate adaptation options, the social costs induced by distributional effects of adaptation, and the aesthetic impact of adaptation strategies in a meaningful way. These presented methods are, however, not mutually exclusive and can be combined with hybrid analysis. Although these methods have a long record of successful evaluation of climate change adaptation projects, policy makers have to make decisions under uncertainty . This might put a strain on the validity of the results obtained by traditional methods and requires more robust approaches by integrating a broad range of climate change scenarios (Dittrich et al. 2016).

One possible solution would be to use a robust decision-making strategy that allows for a (not necessarily optimal) decision between multiple scenarios by finding the least vulnerable strategy (Batouli and Mostafavi 2016; Lazarow and Capon 2016). Moreover, a real options framework can be used to take climate change uncertainty into account, as well as to consider the value of flexibility of investments for coastal adaptation projects. A ROA as such should be preferred over CBA or using a simple NPV rule, as it allows for optimization of the timing of an investment by incorporating the uncertainty associated with climate change.

Given that coastal areas are particularly at risk due to rising global sea-levels, and that natural hazard losses are likely to increase in the near future, adaptation strategies play a crucial role in the management of coastal regions. This work has presented a broad range of existing valuation methods by describing the methods and their possible drawbacks and providing examples of practical applications. Further research should concentrate on improving the existing valuation methods in terms of their complexity and flexibility across climate change scenarios.

Chapter 7

Long-Term Trends in the Australian Wave Climate

The following chapter is based on the paper:

Title:	Long-Term Trends in the Australian Wave Climate
Authors:	Christoph FUNK (contribution: 80%) and
	Stefan TRÜCK (contribution: 20%)
Status:	*Working Paper*

Long-Term Trends in the Australian Wave Climate

Christoph FUNK[1,2] Stefan TRÜCK[7]

Abstract

Global mean sea levels have risen substantially over the last century. This has important implications for low-elevation coastal regions around the world, as they are particularly vulnerable to rising sea levels. In our analysis we focus on the wave power (WP) as climate change indicator for coastal regions. WP, the energy transmitted in the direction of wave propagation, can potentially characterize the long-term behavior of the global wave conditions better than wave heights (Reguero et al. 2019). Our contributions to the literature are twofold. First, we investigate long-term trends in WP and wave height at the local scale, using a comprehensive data set consisting of 18 wave rider buoys along Australia's eastern and southeast coasts. Second, we introduce Laplacian embedding as a potential tool for investigate temporal and spatial variation in the wave climate between and within different locations. This allows us to compare the distribution of the WP over time and to get new insights on the wave climate along the Australian coast. Our results suggest that the WP along the Central Australian Coast seems to have a different behavior than those of the WP measured for the northern and southern parts of Australia. In addition, we find several potential decadal changes in the WP distribution for the median, 90th and 99th percentiles throughout the last 40 years. Results from the latest decades confirm that extreme values seem to have increased for the northern and southern parts of the Australian east coast, whereas they have decreased for central parts of the eastern coastline. Moreover, we find an increase in the yearly mean WP in Brisbane, Tweed Heads, Coffs Harbour, and Port Kembla, we also find an alarming increase in the 99th percentile, or the maximum, over the evaluation period for seven out of the 18 locations. A failure to take into account such trends will lead to an under- or overestimation of the potential risk posed by maximum WP and wave height.

Keywords: Wave climate, Wave power, Long-term trends, Laplacian embedding, Decadal change

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7.1 Introduction

The global climate has changed relative to the pre-industrial period and, moreover, is already affecting ecosystems and livelihoods worldwide (IPCC 2018). Climate change has been attributed, among other things, to an increase in both land and ocean temperature; the frequency and intensity of weather extremes, such as extreme temperatures, and heavy precipitation, droughts and the frequency and duration of marine heatwaves (IPCC 2018, 2019). Moreover, the global mean sea level (GMSL) has risen substantially since the 19th century and will continue to do so during the 21st century (Church et al. 2013). It is likely that the rate at which the GMSL is rising has also been increasing over the past century. Tide gauge and satellite observations suggest that the GMSL has increased from 1.4 mm/yr over the period 1901–1990 to 3.6 mm/yr over the period 2006–2015 (Oppenheimer et al. 2019). Furthermore, an increase in the temperature in the global average sea surface temperature has been observed over the same time period. The increase has amounted to 0.65°C, 0.41°C, and 0.31°C, for the Indian, Atlantic, and Pacific Oceans, respectively, over the period 1950–2009 (Hoegh-Guldberg et al. 2014). Consistent with the change in temperature, the frequency and duration of marine heatwaves has also been increasing, resulting in a 54% increase in annual marine heatwave days globally between 1925 and 2016 (Oliver et al. 2018). As a consequence, extreme-climate events, such as intense storms, increases in maximum wind speed and wave height, and greater rates of inundation possibly have highly destructive impacts on ocean and coastal ecosystems (Hoegh-Guldberg et al. 2014). This is especially problematic for low-elevation coastal regions, as they are particularly vulnerable to rising sea levels. Moreover, these regions are not only the most attractive regions to live (Kron 2013) but are also characterized by significantly higher populations (Balk et al. 2009) and high values of assets and infrastructure. Thus, it is expected that coastal flood damages will increase significantly during the 21st century (Hinkel et al. 2014) and are projected to exceed $1 trillion per year by 2050 in major coastal cities without any upgrade to current adaptation measures (Hallegatte et al. 2013).

Sea levels vary over temporal and spatial dimensions and can be divided into global mean sea levels and regional variations, which are associated with glacier and ice sheet loss and ocean thermal expansion (Melet et al. 2018). However, variations in the local sea level, such as in coastal regions, and the occurrence of sea-level extremes are associated with storm surges, tides, and waves (IPCC 2018). In particular, surface gravity waves generated by winds play an important role for creating extreme sea levels in coastal regions (Reguero et al. 2019), and wave characteristics (height, direction, and period) are affected by climate change (Fan et al. 2013; X. L. Wang and Swail 2006). Increases in wave height (and period) are important contributors to extreme events such as coastal flooding and erosion (Serafin et al. 2017; Vitousek et al. 2017) and might even be more important than rising GMSL (Ruggiero 2013). Thus, it is important to understand how waves and extremes change over the long-term in order to assess the impacts of climate change. Church et al. (2013) concluded that these extreme events are very likely caused by rises in relative sea level. However, only a limited number of studies are available on a regional level that analyzed the impacts of long-term sea-level changes (Melet et al. 2018), which provides low confidence for projections on a local scale (Oppenheimer et al. 2019). This is of particular interest from a risk-management perceptive and amplifies the importance of location-specific coastal adaptation strategies.

The literature on global wave climate so far has mainly focused on identifying historical trends in mean and extreme values of wave characteristics such as the wave height and period (Reguero et al. 2019). Overall, results seem to suggest that wave heights have been increasing over the last decades around the globe, particularly at the high latitudes of both hemispheres (Melet et al. 2018; Oppenheimer et al. 2019). Moreover, wave height extremes seem to have been increasing more quickly than the GMSL has. For example, Wahl and Plant (2015) found a 30% increase in the erosion/flood risk at the northern Gulf of Mexico since the 1980s and a significant change in the seasonal cycle of sea level and significant wave height. Wahl et al. (2014) found that seasonal sea-level changes since the 1990s along the US Gulf coastline have doubled the risk of hurricane-induced flooding associated with sea level rise. Comparable results have been found by Ruggiero (2013) for the U.S. Pacific Northwest coast, where wave height (and period) increases played a more significant role in flooding and erosion than the mean sea level rise did over a period of 30 years. Mendez et al. (2010) confirmed these results for the eastern North Pacific and found significant long-term trends of extreme significant wave heights using two time-dependent extreme value models. On a global scale, Young et al. (2011) find increases in the wind speed and significant wave height, which were greater for extreme events compared to the mean sea level rise. In addition, Melet et al. (2018) found for the time period 1993-2015 that wave contributions can strongly dampen or enhance water-level changes at the coastline for the case for interannual to multidecade timescales. In addition, there is consensus in the literature that annual and seasonal mean and extreme significant wave height are projected to increase in the Southern Ocean but expected to decrease over the northeastern Atlantic and Mediterranean Sea (Oppenheimer et al. 2019).

In contrast to the studies mentioned above, we will use WP as an alternative climate change indicator for coastal regions. WP is the energy transmitted in the direction of wave propagation and can be expressed in kilowatts per meter of wave crest length (Pecher and Kofoed 2017). WP is a non-linear combination of wave period and wave height (see Section 7.2.1)]. Wave energy has not been a focus of attention in the context of climate change (Reguero et al. 2015). However, as argued by Arns et al. (2017), increasing sea levels will also increase the amount of energy impinging on coastal defenses due to relaxed depth limitation of waves, resulting in waves with larger periods, greater amplitudes, and higher run-up. Thus, assessing the WP is also crucial for the adaptation of coastal defenses. Moreover, we follow the argumentation made by Reguero et al. (2019) that the WP can potentially characterize the long-term behavior of the global wave conditions better than wave heights. Thus, assessing long-term trends in WP at the local and regional level will provide additional insights into the wave climate in the context of climate change.

We contribute to the literature by assessing the long-term trends in WP and wave height at the local scale along the Australian eastern and southeastern coasts. We focus on Australia mainly for two reasons. First, we require long time series to investigate the long-term trends in WP. The stations in New South Wales (NSW) and Queensland not only fulfill this criteria but, especially for NSW, represent one of the most comprehensive wave climate data sets available (Kulmar et al. 2013). Second, approximately 80% of Australia's population lives in or near the coastal zone (McInnes et al. 2016). Thus, a critical assessment of the wave climate is not only important from an environmental point of view but also from an economic and social perspective.

We introduce Laplacian embedding as a potential tool for investigating temporal and spatial variation in the wave climate between and within different locations. This allows us to compare the distribution of the WP over time and to get new insights on the wave climate in Australia. Through this, we find that stations within a close proximity seem to share similar behavior in terms of their WP distributions. Thus, the WP along the Central Australian Coast seems to have a different behavior than those of the WP measured for the northern and southern parts of Australia. In addition, we find potential decadal changes in the distribution, which we further address using bootstrap tests to identify significant differences. Our results indicate various decadal changes in the median as well as the 90th and 99th percentiles.

In order to investigate our research question, we use a comprehensive data set consisting of 18 wave rider buoys along Australia's eastern and southeastern coasts. We chose this particular network of wave buoys based on its data availability, ranging between 17 effective record years (product of record years and coverage) for Cape du Couedic in Tasmania and 42 years for Cairns in Far North Queensland. This allows us to focus on the long-term trends in WP and wave height as well as on extreme values at the regional level. We find an increase in the yearly mean WP in Brisbane, Tweed Heads, Coffs Harbour, and Port Kembla. We also find an alarming increase in the 99th percentile, or the maximum, over the evaluation period for seven out of the 18 locations. This is of particular interest from a risk-management perceptive and underlines the importance of location-specific adaptation measures.

The remainder of the paper is organized as follows. In Section 7.2, we provide an overview of the wave ryder buoy system along the Australian eastern and southeastern coast. This includes a characterization of ocean wave parameters, significant wave height (Hs), peak energy wave period (Tp), the derivation of the WP and an overview of their descriptive statistics. In Section 7.3, we provide the methodology for the Laplacian embedding and discuss our findings after comparing the distributions of WP for our data set. Section 7.4 examines the long-term trends in the annual WP in terms of their mean, the 90th and 99th percentiles and the maximum. Section 7.5 investigates possible decadal changes in the annual WP using a Tukey difference-in-mean test and using bootstrapping for the median and the 90th and 99th percentiles of all individual locations. The concluding remarks are provided in Section 7.6.

7.2 Data and Descriptive Statistics

FIGURE 7.1: Locations of wave measuring buoys

TABLE 7.1: Descriptive statistics of the available data set

	Last Location	Water Depth (m)	Date Range	Observations	Coverage (%)	Missing Days (%)	Missing Month (%)	Effective Record Length (years)
Cairns	16°26′18"S 145°25′45"E	12	4/05/1975 - 31/12/2019	397,302	95.31	9.02	2.24	42.56
Townsville	19°05′44"S 147°02′08"E	17	20/11/1975 - 31/12/2019	387,310	89.54	8.48	1.89	39.50
Mackay	21°03′39"S 149°09′17"E	12	19/09/1975 - 31/01/2018	312,003	71.13	14.00	6.29	30.14
Hay Point	21°09′47"S 149°11′14"E	10	24/03/1977 - 31/12/2019	411,304	87.02	16.10	13.80	37.22
Emu Park	23°10′59"S 151°02′34"E	19	24/07/1996 - 31/12/2019	342,220	94.04	3.18	0.36	22.04
Mooloolaba	26°20′23"S 153°06′31"E	32	20/04/2000 - 31/12/2019	322,988	93.52	3.70	2.53	18.42
Brisbane	27°17′32"S 153°22′44"E	70	31/10/1976 - 30/06/2019	398,682	94.37	6.89	0.20	40.27
Gold Coast	27°34′45"S 153°15′56"E	17	21/02/1987 - 31/12/2019	410,306	89.10	4.58	0.00	29.28
Tweed Heads	28°06′24"S 153°20′45"E	22	13/01/1995 - 30/06/2019	371,006	86.65	0.72	0.00	21.20
Byron Bay	28°52′14"S 153°41′39"E	62	14/10/1976 - 31/12/2018	245,042	77.77	17.00	4.73	32.83
Coffs Harbour	30°21′45"S 153°16′09"E	72	26/05/1976 - 31/12/2018	273,445	86.90	10.50	1.56	37.02
Crowdy Head	31°48′50"S 152°51′22"E	79	10/10/1985 - 31/12/2018	254,542	87.01	9.01	0.50	28.91
Sydney	33°46′26"S 151°24′42"E	90	3/03/1992 - 31/12/2018	199,534	84.37	7.24	1.86	22.64
Port Kembla	34°28′35"S 151°01′33"E	80	7/02/1974 - 31/12/2018	272,974	85.50	11.80	3.53	38.39
Batemans Bay	35°42′11"S 150°20′38"E	73	27/05/1986 - 31/12/2018	257,469	89.70	7.65	1.02	29.24
Eden	37°15′57"S 150°11′36"E	100	08/02/1978 - 31/12/2018	261,554	84.16	11.00	3.26	34.42
Cape du Couedic	36°04′12"S 136°36′36"E	80	29/11/2000 - 31/12/2019	688,623	89.34	7.43	3.04	17.05
Cape Sorell	42°07′12"S 145°01′48"E	100	7/01/1998 - 31/12/2019	658,752	94.11	4.18	0.76	20.69

Our goal is to investigate and compare long-term trends in the wave climate along Australia's eastern and southeastern coast. For this, we use 18 wave rider buoys, of which nine are located in Queensland, seven in NSW and one each in South Australia and Tasmania. Figure 7.1 provides an overview of the particular locations of the buoys used in this work. Table 7.1 presents a detailed overview of the wave buoy locations, information about their water depths and information about the dataset, including the date range and coverage.

The data for the buoys in Queensland are publicly available and have been downloaded from the Open Data Portal of the Queensland Government. The data on the buoys of Cape du Couedic and Cape Sorell have been downloaded from the Australian Ocean Data Network. The stations in NSW are recorded by the NSW Office of Environment and Heritage. We would like to thank Mark Kulmar and the Manly Hydraulics Laboratory for providing us with the data on these buoys.

We have chosen this particular network of wave buoys based on data availability ranging from 17 effective record years (product of record years and coverage) for Cape du Couedic in Tasmania and 42 years for Cairns in Far North Queensland. Data have been captured by the waverider buoys with various minimal intervals ranging from 12 and 6 hours in the 1970s and

1980s, to hourly or half-hourly intervals for later periods. Since 1984, all wave buoys in NSW have captured data at 1-hour intervals. For Queensland, 1-hour intervals have been recorded in our dataset since 1991 in Gold Coast and Townsville, whereas by 1994, all stations are record in this frequency. For the two buoys in South Australia and Tasmania, we even have partially minimum intervals of 15 min, which is why we have more than 650,000 recorded observations – considerably more than for the other stations. Data quality and coverage varies among the locations from 78% in Byron Bay to 95% in Cairns. Figures 7.9 and 7.10 in Appendix G provide a graphical analysis of the gaps and missing data for all buoys over time.

To avoid distorting seasonal effects for our trend analysis and the Laplacian embedding in the following section, we restrict our analysis to full record years at the beginning and end of our data sets. Thus, for example, we limit our analysis to the period January 1977 and December 2018 for Brisbane. Two exceptions to this rule are the buoys in Mackay and Port Kembla. In Mackay, the beginning and end of our records have multiple missing months in a row, which is why we restrict the analysis to the year range of 1978 to 2016. In Port Kembla, we have multiple missing months at the beginning of the record and thus start our analysis in 1976.

7.2.1 Characterization of Parameters

Ocean waves are produced by wind blowing over the sea surface. The surface is composed of various random waves with different lengths, periods and directions. The distribution of wave energy with variations in the wave frequency and wave length on the sea surface is described by the wave spectrum (Stewart 2008). A not fully developed sea state is commonly represented by the spectrum that resulted from research by Hasselmann et al. (1973) in the Joint North Sea Wave Observation Project (JONSWAP). According to this, the JONSWAP spectrum can be described as:

$$S(\omega) = \frac{\alpha g^2}{\omega^5} e^{[-\frac{5}{4}(\frac{\omega_p}{\omega})^4]} \gamma^{e^{[-\frac{(\omega-\omega_p)^2}{2\sigma^2\omega_p^2}]}}, \tag{7.1}$$

$$\alpha = 0.076(\frac{U_{10}^2}{Fg})^{0.22}, \tag{7.1a}$$

$$\omega_p = 22(\frac{g^2}{U_{10}F})^{\frac{1}{3}}, \tag{7.1b}$$

$$\gamma = 3.3, \tag{7.1c}$$

$$\sigma = \begin{cases} 0.07 & \omega \leq \omega_p \\ 0.09 & \omega > \omega_p \end{cases}, \tag{7.1d}$$

where $S(\omega)$ is the spectral variance density, ω_p denotes the peak frequency, g the gravitational acceleration, U_{10} the wind speed at a height of 10 m, F is the distance from a lee shore (fetch), or the distance over which the wind blows with constant velocity and ω is the wave component frequency. Moreover, γ is called the peak enhancement factor.[3] The spectral moments can then be used to define other characteristics of a sea-state, such as the significant wave height and

[3] Note: The spectral shape of the JONSWAP is an extension of the Pierson-Moskowitz (Pierson and Moskowitz 1964) spectrum multiplied by peak enhancement factor γ to allow for a more pronounced peak in the spectrum.

average zero-crossing period. Thereby, the nth-order moment, m_n, of the spectrum is defined as:

$$m_n = \int_0^{\inf} S(\omega)\omega^n d\omega. \tag{7.2}$$

The wave height can be computed from the zero-order moment, m_0, as follows:

$$H_{m0} = 4\sqrt{m_0}. \tag{7.3}$$

H_{m0} is similar to the significant wave height represented as the average height of the highest one-third of waves, which is another commonly used method in wave buoy records. Given our data, we will use the latter definition and refer to the significant wave height as H_s throughout the manuscript. Moreover, one can further define the mean zero-crossing period of the waves T_z as:

$$T_z = \sqrt{\frac{m_0}{m_2}}. \tag{7.4}$$

Given the JONSWAP spectrum with a peak enhancement factor of $\gamma = 3.3$, one can relate T_z to two other commonly used measures of the wave period, namely the peak period, T_p (the wave period of those waves producing the most energy in a wave record) and the wave energy period, T_e (defined as the ratio of the first negative moment to the zero-order moment of the wave spectrum ($\frac{m_{-1}}{m_0}$)), as follows (Pecher and Kofoed 2017):

$$1.12T_e = 1.29T_z = T_p. \tag{7.5}$$

Consequently, omnidirectional WP in deep water can be estimated from the spectral parameters defined above as:

$$WP = \frac{pg}{64\pi} T_e (H_s)^2. \tag{7.6}$$

This is the rate at which wave energy is transmitted in the direction of wave propagation. It is normally expressed in kilowatts per meter of wave crest length, where WP is expressed in kW/m of the wave front, p is the sea water density (1025.9 kg/m^3 at 15 °C) and g is the gravitational acceleration (9.8 m/s^2). We will use T_p for calculating WP for our further analysis.

7.2.2 Descriptive Statistics

Table 7.2 presents a full summary of the descriptive statistics for the WP of our 18 locations. Wave buoys in Queensland exhibit a mean significant WP ranging from between 0.63 kW/m in Cairns to 13.51 kW/m in Brisbane. The WP in NSW seems to be more grouped together in the range of 12.93 to 14.12 kW/m with the exception of Batemans Bay with a reduced mean WP of 10.42 kW/m.[4] The mean WP in Cape du Couedic and Cape Sorell is considerably higher than for the buoys in NSW and Queensland.[5] Similar statements can be made for the other parameters. There seems to be a general tendency of buoys in NSW being grouped closer together than in Queensland when considering the median, the 90th and 99th percentiles, as well as the maximum. Additionally, this can be seen graphically from the exceedance Hs plotted in Figure 7.2, and it seems to hold true throughout the set of exceedance probabilities. Moreover, all stations exhibit a positive skewness and high excess kurtosis.

[4] The reduced wave climate can be explained by coastal orientation and land-mass sheltering from Victoria, Tasmania and New Zealand (Coghlan et al. 2011).

[5] This can be explained by wind-waves generated by extra-tropical cyclones of the Southern Ocean. These waves can travel long distances without loosing much of its energy until shoaling near the coast of Western Australia and the southern Tip of Tasmania (McInnes et al. 2016).

FIGURE 7.2: WP exceedance

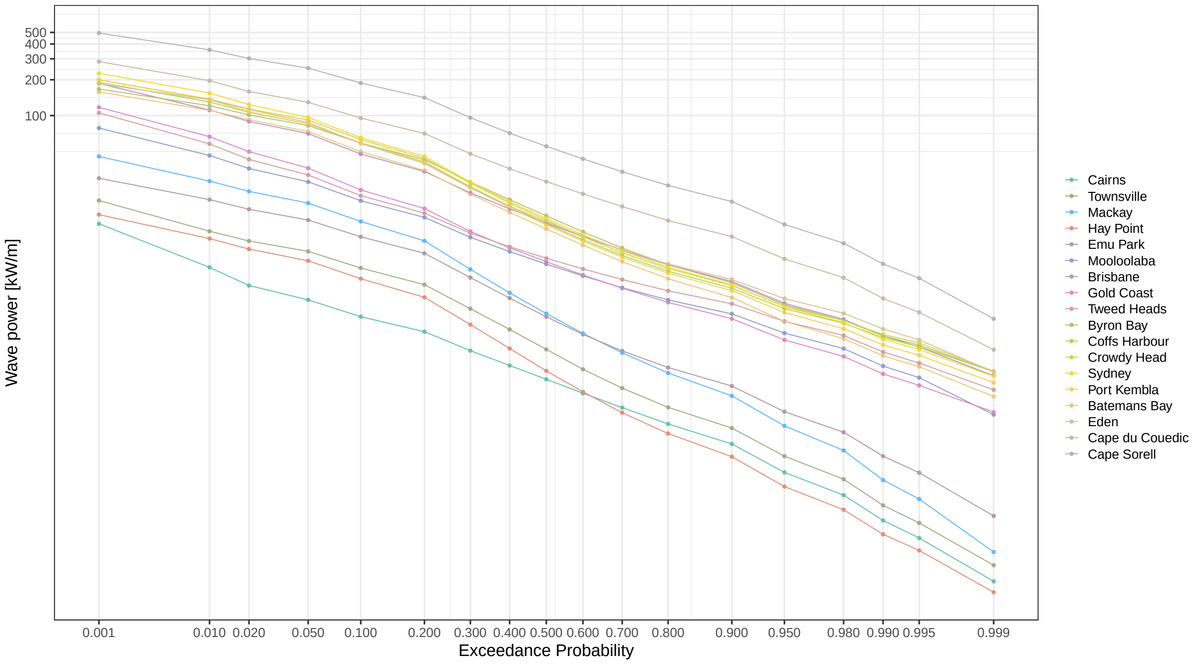


TABLE 7.2: Descriptive statistics for WP

WP (kW/m)	Mean	Median	90% Quantile	99% Quantile	Maximum	Standard Deviation	Skewness	Excess Kurtosis
Cairns	0.63	0.45	1.34	2.79	38.10	0.75	9.64	230.86
Townsville	1.32	0.70	3.28	7.38	141.13	1.78	9.96	420.45
Mackay	2.87	1.32	7.38	19.36	143.62	4.22	4.73	54.82
Hay Point	1.11	0.47	2.95	7.52	63.77	1.71	5.74	92.53
Emu Park	2.52	1.37	6.19	14.34	62.32	3.09	3.30	23.62
Mooloolaba	6.69	4.49	13.92	35.88	183.10	7.51	4.79	47.60
Brisbane	13.51	8.76	28.50	77.39	301.21	15.64	4.43	37.53
Gold Coast	6.43	4.16	12.98	38.41	286.84	8.32	6.65	84.14
Tweed Heads	7.60	5.13	15.12	42.81	319.07	9.17	6.80	97.28
Byron Bay	14.12	9.33	29.96	76.28	331.07	15.14	3.63	26.00
Coffs Harbour	12.93	8.31	27.05	74.88	266.48	14.92	4.29	34.05
Crowdy Head	13.56	8.61	28.36	81.37	341.07	15.90	4.38	35.32
Sydney	14.11	8.69	29.69	87.82	421.78	17.73	4.99	47.69
Port Kembla	12.93	8.20	27.22	77.11	397.68	15.48	4.71	43.21
Batemans Bay	10.42	6.68	21.54	63.29	275.95	12.39	4.57	38.13
Eden	13.49	9.18	26.64	78.46	392.72	15.06	4.64	38.79
Cape du Couedic	32.22	22.06	69.24	163.87	522.46	32.93	3.09	18.96
Cape Sorell	59.10	41.91	125.77	271.29	815.18	55.67	2.64	14.54

Additionally, a summary of the Hs and Tp for the different locations can be found in the Appendix in Tables 7.6 and 7.7. The statements made for the WP in terms of the parameters in NSW being more grouped together are supported by the patterns emerging for Hs. Occurrences of Tp in NSW as well as Mooloolaba, Brisbane, the Gold Coast, Tweed Heads and Cape du Couedic display a similar pattern with mean values of around 9 to 10 seconds. This is tantamount with the vast dominance of ocean swell (Tp > 6s) along these locations. The remaining locations in Queensland display a noticeably lower mean period, whereas Cape Sorell has with 12.38 seconds the highest mean Tp value. The sea state, a combination of Hs and Tp, can be described via Scatterplots and can be found in Figures 7.11 and 7.12. In these graphs the aforementioned differences become particularly visible when one is comparing the patterns. Especially, the buoys in Cairns and Hay Point have seemingly higher amounts of combinations of lower Hs and comparably high amounts of Hs. This also explains the big difference in the excess kurtosis of their WP compared with the other locations, as the WP is a non-linear function of these two parameters.

7.3 Laplacian Embedding

Descriptive statistics alone provide only a summary measure and thus no description of temporal and spatial variation in the wave climate between and within different locations. Therefore, in the following we will compare the distribution of the WP for each location and buoy over time to get a different picture of the wave climate in Australia.[6] Our goal it to visualize each year for each location by converting it to a single two-dimensional (2D) point that we can then plot in a scatter plot. This allows us to get an idea of which station and/or year is unusual, which locations share a behavior (are clustered together) and if other potentially interesting patterns emerge.

Our first step in this analysis is to compute percentiles with probabilities in the range of 1%, 2%, ... 99% for each year and each location.[7] Thus, the probabilistic distribution of each year is described by 99 percentiles. Figures 7.13 and 7.14 display the profiles as a continuous rainbow plot for each of the 18 locations used in this work. In total, this gives us 603 x 99 percentiles (18 locations with an average length of 33.5 years).

In a second step, we compute the pairwise distances of the probability distributions for the 603 profiles using the Jensen–Shannon divergence (JSD). The JSD is a method to quantify the similarity between two probability distributions P and Q and can be calculated as follows (K. P. Murphy 2013):

$$JSD(P||Q) = \frac{1}{2}KL(P||M) + \frac{1}{2}KL(Q||M), \tag{7.7}$$

where $M = 0.5(P + Q)$ and KL is the Kullback-Leibler divergence or relative entropy between P and Q given as:

$$KL(P||Q) = \sum_{k=1}^{K} P_k log \frac{P_k}{Q_k}. \tag{7.8}$$

[6] The idea for this approach is based on a work by Hyndman et al. (2018) and https://github.com/robjhyndman/ftsviz, who use a similar approach to compare the electricity demand of households using smart-meter data.

[7] Note: In principle, depending on the question and the available data, one could compute the percentiles on a lower frequency, such as on a daily, weekly or monthly basis, and average them over the location to generate a different profile, taking into account possible seasonality. However, we decided not to follow this approach for two reasons. First, we are mainly interested in the long-term behavior of the wave climate in Australia, and second, due to limited data availability and gaps in our data (see Figure 7.9 and 7.10), it is in a few instances not possible to construct continuous profiles for each year.

Intuitively, this means that we find a large divergence if the probability for an event from P is large but the probability for Q is small, and vice versa. In our case, we use a discretized probability distribution with $K = 99$ events. The JSD score is bound between 0 (identical) and 1 (maximally different) when using the base 2 logarithm. Taking the square root of JSD then yields a metric distance (Nielsen 2019). Having computed the pairwise distances among the 603 profiles, we can finally project them into a 2D space to visualize them using Laplacian embedding. Thus, we reduce each vector from a K = 99 dimensional to a 2D space, keeping the most similar points in the k-dimensional space as close as possible in the 2D space (Belkin and Niyogi 2002; Hyndman et al. 2018). Therefore, we construct a similarity matrix (or heat Kernel) for each of the pairs of i and j using:

$$W_{ij} = e^{-\frac{JSD^2}{t}}, \tag{7.9}$$

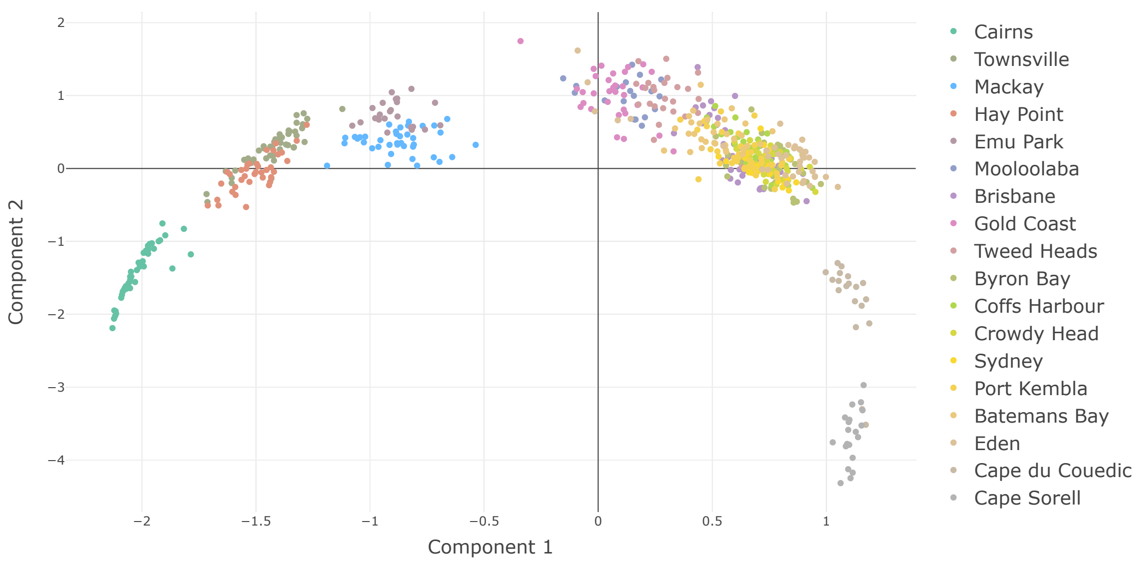
where we choose t to be the median of all distances[8]. We can then compute the eigenvectors and eigenvalues for a generalized eigenvector problem given by Belkin and Niyogi (2002):

$$L\lambda = \lambda D y, \tag{7.10}$$

where D is a diagonal weight matrix constructed with entries being the sums of W, $D_{ii} = \sum_{j=1} = W_{ji.}$ and $L = D - W$ being the Laplacian matrix. The solution of equation 7.10 is given by $y_0, ..., y_k$ ordered according to their eigenvalues, with y_0 having the smallest number. As $y_0 = 0$, eigenvectors $y_1(i)$ and $y_2(i)$ give the embedding into the 2D space of i (see Belkin and Niyogi (2002) for a detailed justification). The two eigenvalues are denoted with Component 1 and Component 2 on the axis in Figures 7.3-7.5.

Figures 7.13 and 7.14 depict the percentiles ranging from 1 to 99 per year over time for our 18 stations. It is already evident that the WP is subject to temporal variations and shows considerable differences between the locations. However, to compare all locations with one another, Figure 7.3 shows the results for the comparison of all 603 profiles, from which we can infer two main things. First, the distances among the 18 stations are clearly visible and fit to the

FIGURE 7.3: Laplacian embedding of all stations



[8] Note: The choice of t is not obvious and debatable. The simplest form to avoid a choice is to set $t = \infty$ so that $W_{ij} = 1$ if and only if i and i are connected by an edge (Belkin and Niyogi 2002).

their locations from north to south along the coast. The stations are bounded between Cairns in the north (Quadrant III) and Cape Sorell (Quadrant IV) in the south. Second, stations within close proximity seem to share similar behaviors in terms of their WP distributions. Especially the stations in NSW appear to be clumped together, which confirms the statements suggested by the descriptive statistics in the previous section. Thus, it is evident that the wave climate shows considerable variation among the Australian coastline.

FIGURE 7.4: Laplacian embedding of all Stations per year

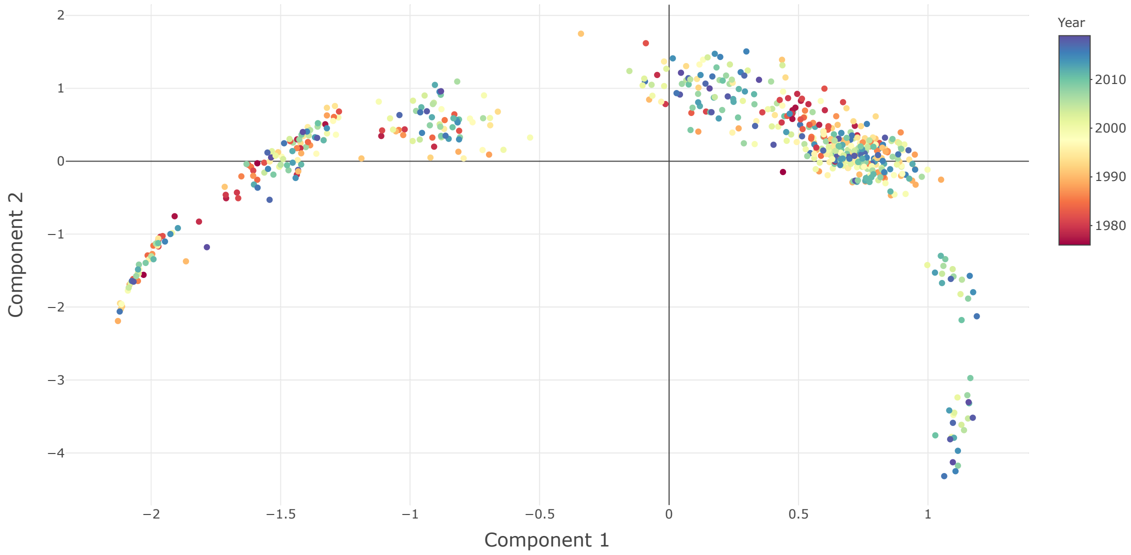
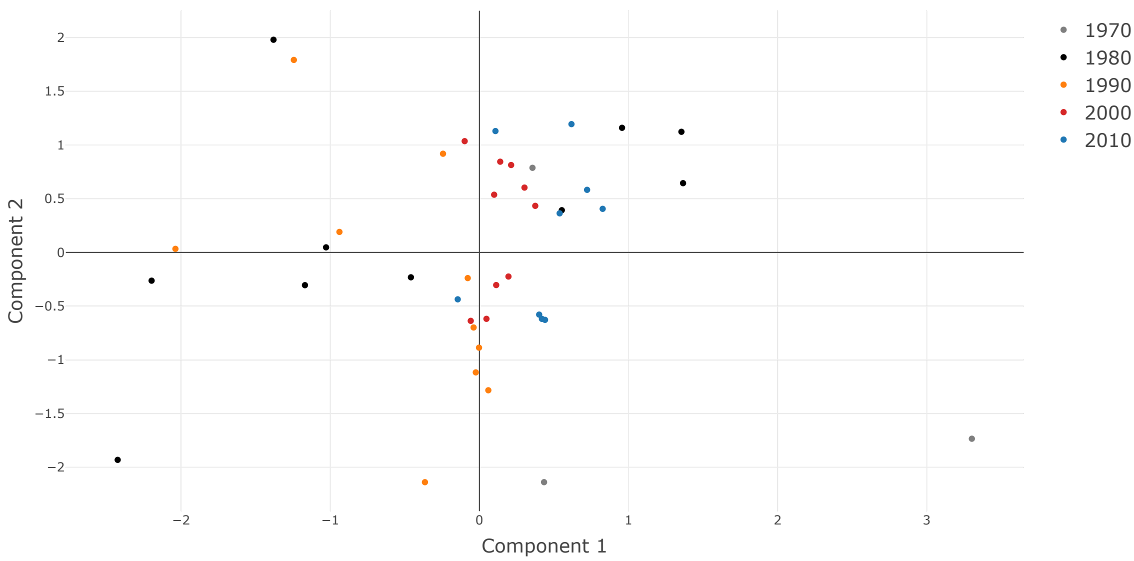


FIGURE 7.5: Laplacian embedding of all stations as averages per year



Moreover, Figure 7.4 provides additional information on the stations by assessing the temporal variation of the different stations. At first, one could argue that the spatial dimension dominates the time serial component for the different locations. However, it seems to be the case that the 1970s and 1980s are somewhat different from the the remaining years (especially for the stations in NSW in Quadrant I). This is further illustrated by Figure 7.5 . Here, the average WP distributions per year over all stations have been computed, and the resulting 42 distributions (one for each year) embedded in a 2D space are grouped by decades. It is evident that the distances in the 1970s and 1980s are notably different from those of the 1990s, 2000s and 2010s. We will follow up on this in more detail in Section 7.5.

7.4 Long-Term Trends in Wave Power

We are also interested in assessing long-term trends in the WP and wave height for our 18 locations. In principle, there are multiple ways of performing trend calculations, such as, ordinary least squares, maximum likelihood or pre-whitening (a comparison of methods can be found in Hartmann et al. (2013)). We use the non-parametric Mann-Kendall test (Kendall 1948; Mann 1945) to check the significance of the linear trends in this work. However, the Mann-Kendall test requires the time series to be serially uncorrelated. Thus, we follow the recommendation by X. Zhang and Zwiers (2004) for small samples and take into account possible autocorrelation by using the iterative method proposed by X. L. Wang and Swail (2001). The 95% confidence intervals for the trend and slope parameter are estimated using Sen's slope (Sen 1968), and Kendall's rank correlation test is used to test for significance.[9] Consider the following time series, Y_t, for which we would like to estimate the trend component using the following model:

$$Y_t = a + bt + X_t, \tag{7.11}$$

where a is the intercept, b is the slope parameter of Y_t and X_t follows an AR(1) process with autocorrelation parameter c and white noise error ε:

$$X_t = cX_{t-1} + \varepsilon_t. \tag{7.12}$$

Given that one can compute a pre-whitened time series, W_t, that has the same trend as Y_t and takes into account autocorrelation:

$$W_t = \frac{Y_t - cY_{t-1}}{1-c}. \tag{7.13}$$

X. L. Wang and Swail (2001) propose a three-step procedure for estimating b and c:

1. Compute $\hat{c_0}$ of time series Y_t. If the estimate is smaller than 0.05, autocorrelation is negligible, and the Mann-Kendall test can be used without further adaptation to obtain b. However, if autocorrelation is present, the process will be pre-whitened (equation 7.13) using $\hat{c_0}$ to compute first estimate $\hat{b_0}$.

2. Remove the trend from Y_t ($Y_t - \hat{b_0}t$), and re-estimate c, namely $\hat{c_1}$. If $\hat{c_1} < 0.05$, $\hat{b_0}t$ and $\hat{c_0}t$ are the final estimates. Otherwise, a new estimate of b, $\hat{b_1}t$ will be obtained from pre-whitened process $W_t = \frac{Y_t - \hat{c_1}Y_{t-1}}{1-\hat{c_1}}$.

3. If the difference between $|\hat{c_1} - \hat{c_0}|$ and $|\hat{b_1} - \hat{b_0}|$ is larger than 1%, steps 2 and 3 will be repeated, which will ultimately lead to final estimates $\hat{c}$ and $\hat{b}$. These will then be used to conclude the trend analysis using the Mann-Kendall test on pre-whitened time series $W_t = \frac{Y_t - \hat{c}Y_{t-1}}{1-\hat{c}}$.

[9] The application of this test procedure has been conducted using the R package "zyp"(https://cran.r-project.org/web/packages/zyp/zyp.pdf).

Figures 7.15 and 7.16 represent the mean, 90th and 99th percentiles of the annual WP for the 18 locations and their linear trend lines. An initial view on the graphical representation suggests that there is no common pattern emerging for all locations. Although we find, especially in the 99th percentile, notable increases in the annual WP (for e.g., Hay Point and Brisbane), we also find seemingly downward sloping trends, for example, in Emu Park and Crowdy Head.

Tables 7.3 and 7.4 summarize the results for the trend analysis, including the estimated trends, the 95% confidence interval, Kendall's tau and the p-value, as well as the cumulative trend over the complete location-specific horizon. Additionally, we added here the maximum WP of each year in the trend analysis. As to be expected, we find mixed results for the different locations.[10] Although we find an increase in the yearly mean WP in Brisbane, Tweed Heads, Coffs Harbour and Port Kembla, we also find an alarming increase in the 99th percentile, or the maximum, over the evaluation period for seven out of the 18 locations. One exception to this is Tweed Heads, where we find a significant decrease for the trend. In the remaining seven of our 18 locations, we find no significant increase in either of the four trends analyzed.

Only a limited amount of studies have investigated the wave climate in Australia at the local scale.[11] For example, Shand et al. (2011a) have investigated coastal storms and extreme waves in NSW and found a slight increase in yearly storms during the late 1990s. Moreover, they find that the mid NSW coast exhibits the highest extreme wave climate for a one in 100 year event with one hour exceedance height of 9.0 m at Sydney and 9.1 m at Botany Bay. Kinsela et al. (2014) find a similar magnitude for this region and in addition, that the wave climate of northern NSW is more extreme than the southern part with the exception of Eden which is exposed to storms from the southern Tasman Sea. Shand et al. (2011b) use a seasonal Kendall trend test to find temporal trends in the monthly mean Hs. They find significant increases at Coffs Harbour (4.6 mm/year) and significant decreases at Crowdy Head (-4.0 mm/year) and Batemans Bay (-6.1 mm/year) for the mean. In addition, Coffs Harbour and Byron Bay show significant increases in the 90th and 99th percentile, Port Kembla in the 99th percentile and Batemans Bay decreases significantly in the 90th percentile. Similar results have been obtained by us in terms of the sign of the trend, however not significant using annual Hs series (Table 7.9).

Our results suggest that Brisbane, in particular, should be monitored more closely, as we find a cumulative increase of more than 114 kW/m of crest. This corresponds to a cumulative increase in the annual maximum Hs of about 1.67 m since 1977 (Table 7.8). A failure to take into account such trends will lead to an underestimation of the potential risk posed by maximum WP and wave heights. This is particularly important when it comes to the appropriate adaptation decision-making about coastal defenses and managing the risk associated with changing climatic conditions.

[10] We find similar results for a trend analysis of the annual Hs. The results can be found in Tables 7.8 and 7.9 in Appendix G.

[11] Other studies that use satellite altimer-derived estimates that investigate trends in wave height on a global scale and for the southern hemisphere include for example, Hemer et al. (2010), Izaguirre et al. (2011), White et al. (2014), and Young et al. (2011). The interested reader may find additional information about past and future changes in sea level and coastal extremes in Australia in a review provided by (McInnes et al. 2016).

TABLE 7.3: Trend analysis for Queensland of annual WP

		Trend	95% Confidence Interval		Kendall's Tau	Kendall's p-value	Cumulative Trend
Cairns	Mean	−0.0007	−0.0032	0.0023	−0.0520	0.6302	−0.0304
	90% Quantile	−0.0031	−0.0091	0.0038	−0.0831	0.4387	−0.1365
	99% Quantile	0.0027	−0.0120	0.0159	0.0233	0.8318	0.1207
	Maximum	0.1335	0.0434	0.2249	0.2935	**0.0057*****	5.8725
Townsville	Mean	0.0007	−0.0057	0.0074	0.0277	0.8017	0.0297
	90% Quantile	−0.0005	−0.0134	0.0146	−0.0033	0.9833	−0.0205
	99% Quantile	0.0119	−0.0319	0.0451	0.0543	0.6154	0.5238
	Maximum	0.1705	0.0384	0.3662	0.2625	**0.0135*****	7.5005
Mackay	Mean	0.0060	−0.0162	0.0277	0.0526	0.6508	0.2337
	90% Quantile	0.0106	−0.0464	0.0649	0.0441	0.7061	0.4121
	99% Quantile	0.0954	−0.0120	0.1973	0.2006	**0.0784***	3.7196
	Maximum	0.5441	0.3120	0.8526	0.4035	**0.0003*****	21.2208
Hay Point	Mean	0.0004	−0.0069	0.0076	0.0159	0.9024	0.0165
	90% Quantile	0.0004	−0.0192	0.0188	0.0063	0.9674	0.0156
	99% Quantile	0.0597	0.0107	0.1025	0.2794	**0.0171****	2.2082
	Maximum	0.2094	0.0436	0.4131	0.2853	**0.0134****	7.7495
Emu Park	Mean	−0.0038	−0.0282	0.0244	−0.0649	0.6930	−0.0863
	90% Quantile	0.0175	−0.0491	0.0574	0.1429	0.3669	0.4035
	99% Quantile	−0.0931	−0.3023	0.0682	−0.1700	0.2673	−2.1413
	Maximum	0.6430	−0.5538	1.9109	0.1515	0.3377	14.7894
Mooloolaba	Mean	0.0696	−0.0520	0.1884	0.1895	0.2889	1.3221
	90% Quantile	0.2057	−0.0091	0.4398	0.3203	**0.0690***	3.9084
	99% Quantile	0.0520	−0.9564	0.8163	0.0065	1.0000	0.9876
	Maximum	1.0553	−2.7776	4.2984	0.1111	0.5289	20.0508
Brisbane	Mean	0.1330	0.0472	0.2017	0.3024	**0.0055*****	5.5861
	90% Quantile	0.2883	0.1217	0.4376	0.3220	**0.0031*****	12.1099
	99% Quantile	0.8410	0.2726	1.4637	0.3000	**0.0059*****	35.3240
	Maximum	2.7244	1.0139	4.1050	0.3220	**0.0031*****	114.4263
Gold Coast	Mean	0.0093	−0.0285	0.0466	0.0538	0.6833	0.2975
	90% Quantile	0.0492	−0.0387	0.1453	0.1570	0.2210	1.5751
	99% Quantile	−0.1192	−0.6584	0.2930	−0.0605	0.6382	−3.8149
	Maximum	1.1967	−0.7558	2.6245	0.1613	0.2002	38.2954
Tweed Heads	Mean	−0.0700	−0.1510	−0.0204	−0.4203	**0.0043*****	−1.7499
	90% Quantile	−0.1971	−0.3488	−0.0542	−0.3841	**0.0092*****	−4.9279
	99% Quantile	−0.7630	−1.5599	0.0775	−0.2536	**0.0870***	−19.0752
	Maximum	−0.5430	−3.8952	2.1550	−0.0333	0.8335	−13.5755

Bold values denote a significance level of P<0.01, ** and * 0.05 and 0.1, respectively.

TABLE 7.4: Trend Analysis for NSW, South Australia and Tasmania of annual WP

		Trend	95% Confidence Interval		Kendall's Tau	Kendall's p-value	Cumulative Trend
Byron Bay	Mean	0.0442	−0.0187	0.1100	0.1561	0.1537	1.8584
	90% Quantile	0.1377	−0.0271	0.2888	0.1659	0.1294	5.7835
	99% Quantile	0.0855	−0.2806	0.5838	0.0634	0.5668	3.5898
	Maximum	0.7068	−0.4723	2.0862	0.1243	0.2507	29.6861
Coffs Harbour	Mean	0.0521	−0.0060	0.1152	0.1854	**0.0899***	2.1884
	90% Quantile	0.1621	0.0150	0.2866	0.2317	**0.0338****	6.8085
	99% Quantile	0.4127	−0.1439	0.8196	0.1805	**0.0987***	17.3326
	Maximum	1.1876	−0.4568	2.9654	0.1488	0.1741	49.8807
Crowdy Head	Mean	−0.0341	−0.0894	0.0256	−0.1174	0.3446	−1.1263
	90% Quantile	−0.0146	−0.1685	0.1187	−0.0341	0.7922	−0.4806
	99% Quantile	−0.1576	−0.8333	0.4943	−0.0682	0.5876	−5.1993
	Maximum	−1.0825	−2.8297	1.1088	−0.0853	0.4953	−35.7215
Sydney	Mean	0.0186	−0.0569	0.1218	0.0462	0.7576	0.4847
	90% Quantile	0.1795	−0.0835	0.3783	0.1692	0.2340	4.6679
	99% Quantile	−0.1514	−1.4098	0.8411	−0.0733	0.6238	−3.9372
	Maximum	0.4319	−2.4598	3.9666	0.0400	0.7914	11.2304
Port Kembla	Mean	0.0374	−0.0092	0.0877	0.1783	**0.0940***	1.6093
	90% Quantile	0.1185	−0.0031	0.2228	0.1982	**0.0625***	5.0936
	99% Quantile	0.1794	−0.3590	0.5674	0.0698	0.5164	7.7148
	Maximum	0.9444	−1.0808	2.8794	0.1127	0.2982	40.6093
Batemans Bay	Mean	−0.0099	−0.0771	0.0618	−0.0323	0.8119	−0.3176
	90% Quantile	0.0344	−0.1175	0.1942	0.0323	0.8119	1.1005
	99% Quantile	−0.0668	−0.6928	0.6147	−0.0237	0.8650	−2.1379
	Maximum	−0.1114	−1.9404	1.3905	−0.0121	0.9354	−3.5656
Eden	Mean	0.0526	−0.1381	0.1211	0.0553	0.6285	2.1021
	90% Quantile	0.1027	−0.1396	0.3011	0.0742	0.5136	4.1066
	99% Quantile	0.4780	−0.0933	1.0619	0.1822	0.1050	19.1197
	Maximum	2.6519	0.8136	4.6105	0.3306	**0.0032*****	106.0748
Cape du Couedic	Mean	0.0009	−0.0041	0.0077	0.0994	0.5756	0.0171
	90% Quantile	0.0195	0.0021	0.0358	0.3801	**0.0252****	0.3898
	99% Quantile	0.0058	−0.0165	0.0265	0.0526	0.7796	0.1158
	Maximum	−0.0036	−0.0184	0.0103	−0.1158	0.4957	−0.0717
Cape Sorell	Mean	−0.0319	−0.0914	0.0277	−0.1684	0.3145	−0.7016
	90% Quantile	−0.0050	−0.0847	0.0876	−0.0043	1.0000	−0.1100
	99% Quantile	0.0706	−0.0348	0.1586	0.2421	0.1443	1.5536
	Maximum	−0.0428	−0.1550	0.0558	−0.1429	0.3812	−0.9422

Bold values denote a significance level of P<0.01, ** and * 0.05 and 0.1, respectively.

7.5 Decadal Change

To address the potential difference between the decades we found in our analysis using the Laplacian embedding in more detail, we test for significant differences between them. To do so, we split our data set into the five different decades (1970s to 2010s). Thus, the label of 1970 in this section denotes all observations earlier than or equal to 31. Dec 1979. The label of 1980 denotes all observations between 1 Jan 1980 and 31 Dec 1989, while the same procedure applies to the labels 1990, 2000 and 2010.

To get an overview of change over the decades, we use a Tukey difference in the mean test first to assess the overall change in the mean level between the decades for all stations together as well as separately for NSW, Queensland and the two southern locations. Here, Tukey's test compares the means of all decades with the mean of every other mean value by pairwise comparison using studentized range statistics that corrects for multiple comparisons. Table 7.5 summarizes the results of the Tukey test on the differences between the means of the various decades and their adjusted p-values. By averaging all stations, we find that the mean values increased significantly between the 1970s and all other decades. Except for the difference between the 1990s and 1980s, as well as the 2000s and 1980s, we find significant increases over the remaining decades. However, the differences between the locations in Queensland and NSW are apparent. Although the differences between the 1970s and all other decades are positive in NSW, we find a contrary behavior for Queensland. The contrasting signs in decadal trends remain unaltered for the differences among 1990, 2000 and 2010.

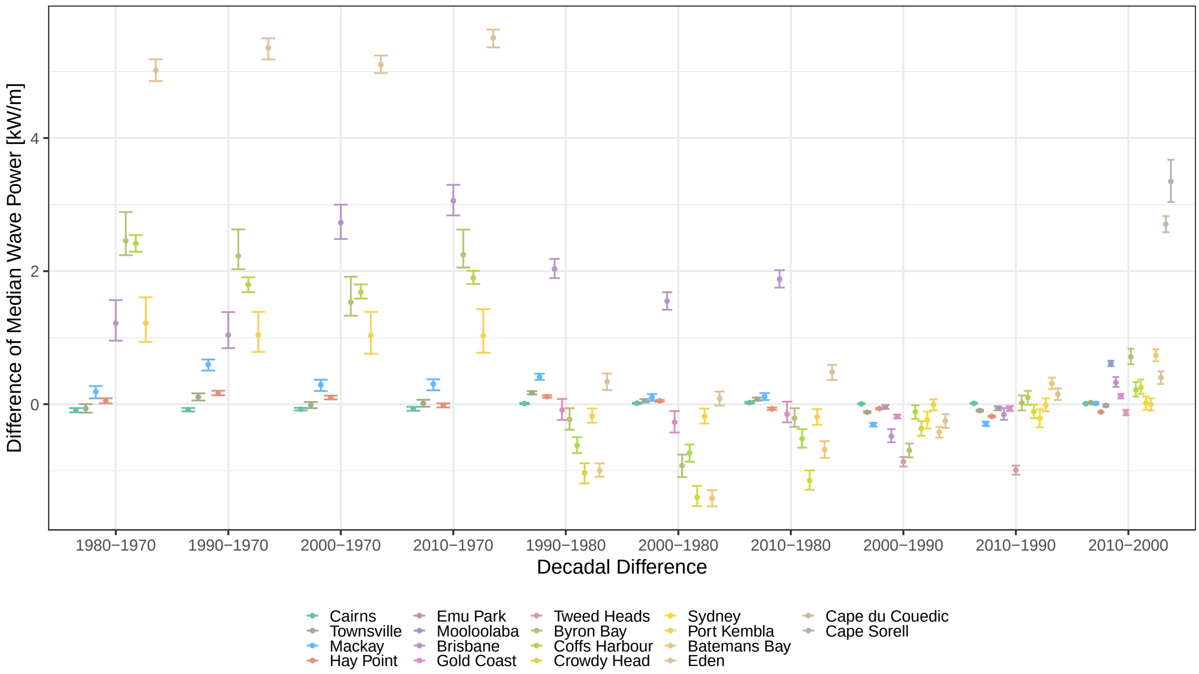
However, as we have found considerable differences among the particular locations, we will address this by comparing the decades for each station separately. Subsequently, as we are mostly interested in assessing the change in WP from a risk-management perspective, we additionally investigate the 99th percentile of the distributions for the different decades. Similarly to the Tukey test, we split the datatset for each location into the different decades. Next, we compute the median, 90th and 99th percentiles, and we use a general quantile comparison across the decades using the quantile estimator proposed by Harrell and C. E. Davis (1982). The confidence intervals for the p-values are determined using 1000 bootstrap replications. Additionally, the p-values are adjusted using Hochberg's method to take into account the multi-comparison problem on a 5% significance level.[12]

TABLE 7.5: Tukey difference-in-mean test

	All		**Queensland**		**NSW**		**South**	
	Difference	Adjusted p-value	Difference	Adjusted p-value	Difference	Adjusted p-value	Difference	Adjusted p-value
1980-1970	4.2775	0.0000	1.9393	0.0000	2.8037	0.0000		
1990-1970	3.5805	0.0000	0.8104	0.0429	2.2095	0.0000		
2000-1970	5.3733	0.0000	6.6249	0.0000	2.2954	0.0000		
2010-1970	12.4860	0.0000	3.6449	0.0000	2.5323	0.0000		
1990-1980	-0.6971	0.0000	-1.1289	0.0000	-0.5942	0.0000		
2000-1980	1.0957	0.0000	4.6856	0.0000	-0.5083	0.0000		
2010-1980	8.2085	0.0000	1.7056	0.0000	-0.2714	0.0000		
2000-1990	1.7928	0.0000	5.8145	0.0000	0.0859	0.0339		
2010-1990	8.9056	0.0000	2.8345	0.0000	0.3228	0.0000		
2010-2000	7.1128	0.0000	-2.9800	0.0000	0.2369	0.0000	6.0322	0.0000

[12] The implementation in R is done using the WRS2-package (https://cran.r-project.org/web/packages/WRS2/WRS2.pdf).

FIGURE 7.6: Difference in median decadal WP



Figures 7.6 to 7.8 provide the results for the median, 90th and 99th percentiles, including their confidence intervals. As to be expected, we find a considerable variation among the locations. We mostly find a significant increase in the median decadal WP between the 1970s and all other decades except for in the areas of Cairns, Townsville and Hay Point. Since the 1980s, this seems to have shifted in the other direction for most of the locations. Thus, we typically find a decrease between the 1980s and later decades, as well as between the 1990s and later decades. This trend reverses again, and we find an increase in the median WP between the last and the current decade. These results hold true for the 90% and 99% quantiles as well, although we can observe here that the variation and thus the confidence intervals seemingly increased for the locations and the quantiles. Although we have multiple insignificant results, we still find an increase between the 1970s and later decades for Mackay, Byron Bay, Coffs Harbour and Brisbane. In addition, we find that for the central coast in NSW, extreme values seems to have decreased while they have increased for northern Queensland (Cairns, Townsville, Hay Point and Mooloolaba) and southern Australia (Batemans Bay, Eden, Cape du Couedic and Cape Sorell) between the 2000s and 2010s.

FIGURE 7.7: Difference in 90% quantiles decadal WP

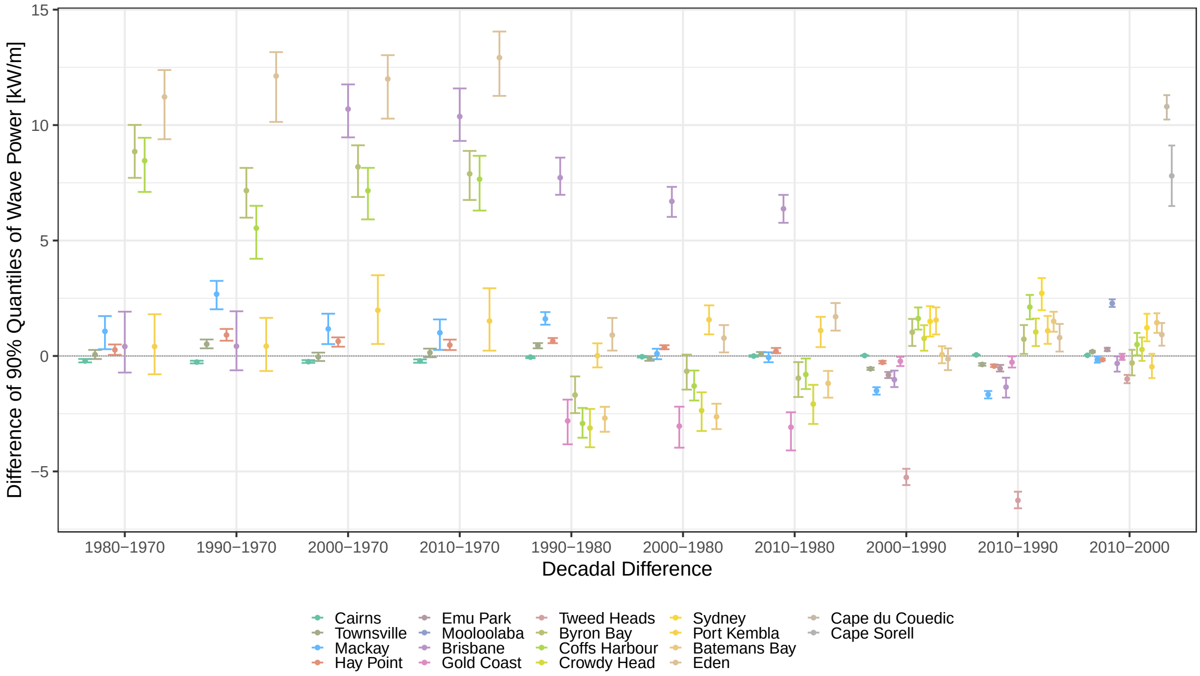
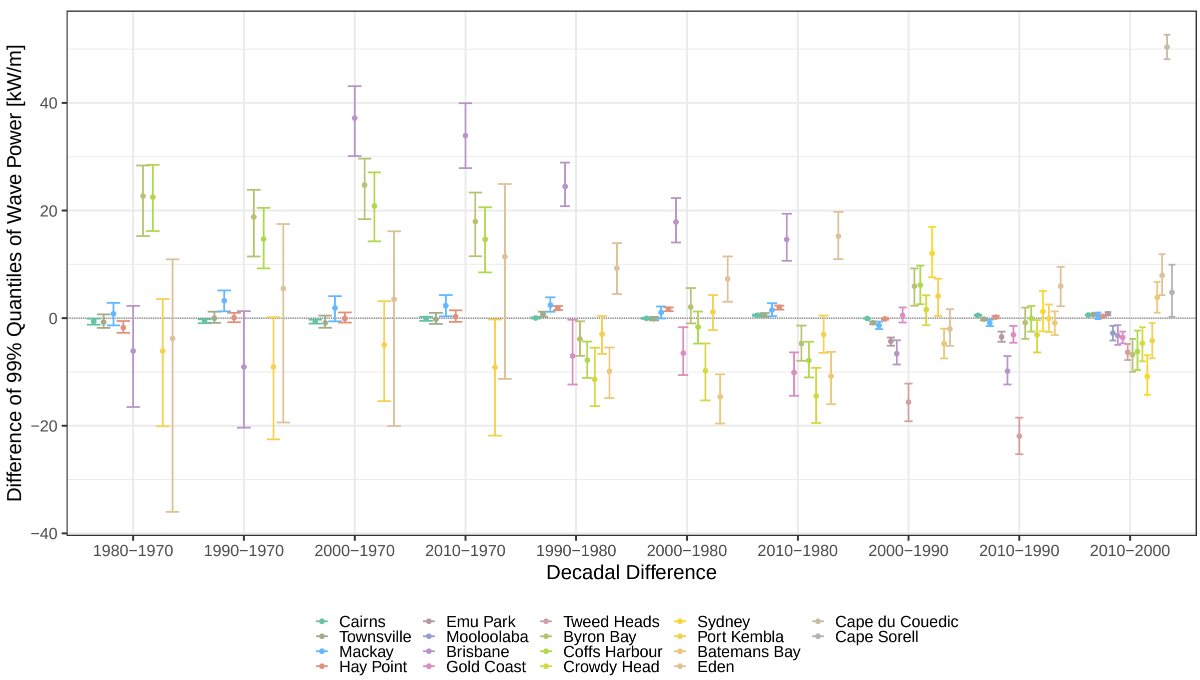


FIGURE 7.8: Difference in 99% quantiles of decadal WP



7.6 Conclusion

Climate change is a global phenomenon and one of the greatest challenges humankind faces in the current era. According to the IPCC (2018), the global climate has changed relative to the pre-industrial period and, moreover, is already affecting ecosystems and livelihoods worldwide. The GMSL have risen substantially over the last century and will continue to do so during the 21st century (Church et al. 2013; Dawson et al. 2018). Furthermore, an increase in the global average sea surface temperature has been observed over the same time period. This has important implications for low-elevation coastal regions around the world, as they are particularly vulnerable to rising sea levels.

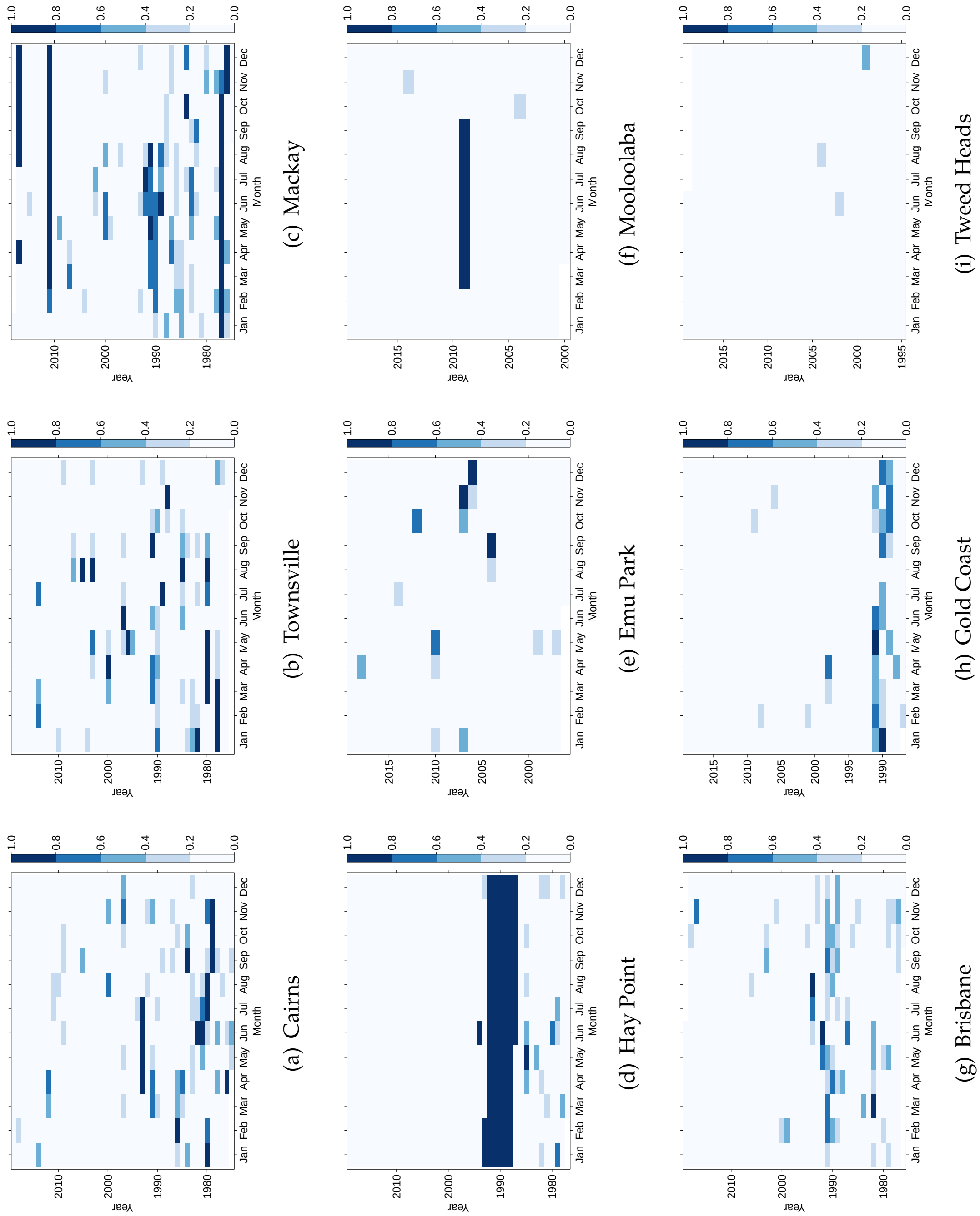
Also wave characteristics such as wave height, direction, and period are affected by changing climate conditions (Fan et al. 2013; X. L. Wang and Swail 2006). Increases in wave height and period are important contributors to extreme events such as coastal flooding and erosion (Serafin et al. 2017; Vitousek et al. 2017) and might even be more important than rising GMSL (Ruggiero 2013). These wave effects play an important role in coastal adaptation strategies and planning (Isobe 2013). For example, Vousdoukas et al. (2017) estimated that changes in storm surges and waves have enhanced the relative sea level rise locally by up to 40% along the Northern European coasts. Moreover, Vitousek et al. (2017) projected that an increase of 10 to 20 cm of GMSL will double the flood risk in the Tropics. Thus, this is of particular interest from a risk-management perceptive and underlines the importance of location-specific adaptation measures.

In contrast to the conventional literature on global wave climate which has mainly focused on identifying historical trends in mean and extreme wave heights or period, we used WP as an alternative climate change indicator for coastal regions. WP describes the energy that is transmitted in the direction of wave propagation and plays an important role for coastal defenses, since with rising sea levels the amount of energy impinging on coastal defenses will increase (Arns et al. 2017). Thus, investigating long-term trends in the WP at local and regional scales will provide additional insights on the wave climate in the context of climate change.

Our contributions to the literature are twofold. First, we have examined long-term trends in WP (and wave height) at the a local level along the Australian eastern and southeastern coasts. Second, we compared the distributions of WP by using the Jensen-Shannon divergence and Laplacian embedding simultaneously, which allowed us to draw conclusions about the temporal and spatial variations of the wave climate between and within different locations. This allowed us to compare the distribution of WP over time and to gain new insights about the wave climate in Australia.

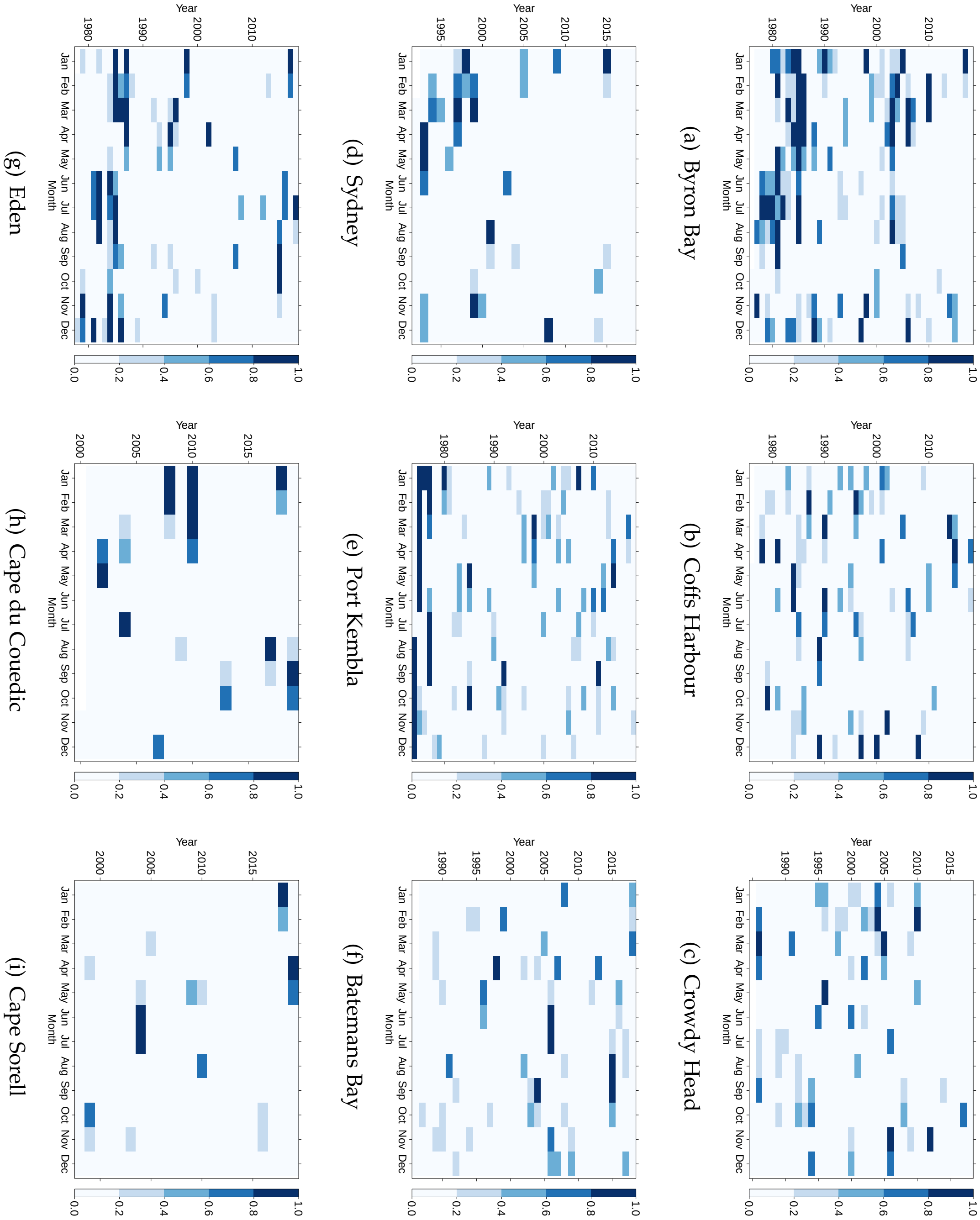
Our results suggest that the WP along the central Australian coast seems to have a different behavior than the WP measured for the northern and southern parts of Australia. In addition, we found several potential decadal changes in the WP distribution for the median, 90th and 99th percentiles throughout the last 40 years. Results from the latest decades confirm that extreme values seem to have increased for the northern and southern parts of the Australian east coast, whereas they have decreased for central parts of the eastern coastline. Moreover, in order to assess the long-term trends in WP, we used the non-parametric Mann-Kendall test by taking into account possible autocorrelation using the iterative method proposed by X. L. Wang and Swail (2001). We found an increase in the yearly mean WP in Brisbane, Tweed Heads, Coffs Harbour, and Port Kembla. We also found an alarming increase in the 99th percentile, or the maximum, over the evaluation period for seven out of the 18 locations. A failure to take into account such trends will lead to an under- or overestimation of the potential risk posed by maximum WP (and wave heights). Our results suggest that Brisbane, in particular, should be monitored more closely, as we found a cumulative increase of more than 114 kW/m of crest. This corresponds to a cumulative increase in the annual maximum Hs of about 1.67 m since 1977. This is particularly important from a risk-management perspective. Thus, future research should concentrate more on the risk associated with changing wave climate for appropriate adaptation decision-making about coastal defenses and managing the risk associated with changing climatic conditions. A limitation of this study is that we have ignored any possible changes in wave buoy position and exposure over time. This spatial variation might have introduced spurious trend and possible altered our estimates. This should be investigated further and possibly validated using satellite observations. Additionally, it would be worthwhile to check for seasonal variation in the trend components to allow for better adaptation planning from a risk-management perspective.

G Appendix to Chapter 7



(a) Cairns (b) Townsville (c) Mackay
(d) Hay Point (e) Emu Park (f) Mooloolaba
(g) Brisbane (h) Gold Coast (i) Tweed Heads

FIGURE 7.9: Gaps in daily data for buoys in Queensland



(a) Byron Bay

(b) Coffs Harbour

(c) Crowdy Head

(d) Sydney

(e) Port Kembla

(f) Batemans Bay

(g) Eden

(h) Cape du Couedic

(i) Cape Sorell

FIGURE 7.10: Gaps in daily data for buoys in NSW, South Australia and Tasmania

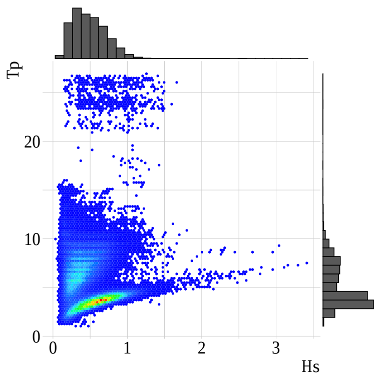
TABLE 7.6: Descriptive statistics for the Hs

Hs (m)	Mean	Median	90% Quantile	99% Quantile	Maximum	Standard Deviation	Skewness	Excess Kurtosis
Cairns	0.49	0.46	0.80	1.07	3.43	0.22	0.74	1.23
Townsville	0.66	0.60	1.15	1.62	5.46	0.35	0.98	1.87
Mackay	0.87	0.72	1.64	2.45	5.67	0.53	1.16	1.46
Hay Point	0.60	0.50	1.14	1.69	3.95	0.38	1.10	1.33
Emu Park	0.85	0.73	1.50	2.16	4.03	0.45	1.06	1.05
Mooloolaba	1.19	1.09	1.86	2.83	5.89	0.51	1.36	3.42
Brisbane	1.65	1.49	2.58	4.03	7.36	0.72	1.42	3.40
Gold Coast	1.12	1.02	1.72	2.83	7.05	0.49	1.88	7.11
Tweed Heads	1.23	1.14	1.85	2.98	7.52	0.51	1.83	7.11
Byron Bay	1.66	1.50	2.58	3.91	7.64	0.69	1.32	2.53
Coffs Harbour	1.58	1.42	2.44	3.84	7.37	0.67	1.55	3.80
Crowdy Head	1.60	1.44	2.47	3.96	7.35	0.68	1.60	4.03
Sydney	1.62	1.45	2.56	4.19	8.43	0.74	1.70	4.72
Port Kembla	1.57	1.42	2.47	3.93	8.43	0.69	1.58	4.09
Batemans Bay	1.44	1.30	2.23	3.57	7.19	0.62	1.54	4.00
Eden	1.65	1.52	2.44	3.98	8.49	0.65	1.72	5.40
Cape du Couedic	2.67	2.50	4.09	5.82	9.26	1.04	0.99	4.26
Cape Sorell	3.00	2.80	4.64	6.56	10.41	1.20	0.93	4.13

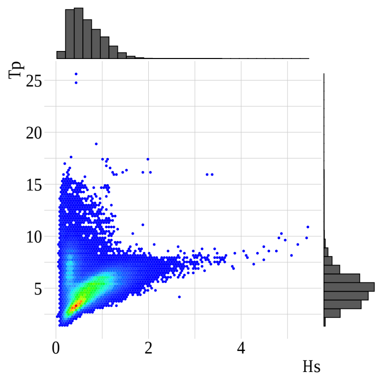
TABLE 7.7: Descriptive statistics for Tp

Tp (s)	Mean	Median	90% Quantile	99% Quantile	Maximum	Standard Deviation	Skewness	Excess Kurtosis
Cairns	5.17	4.23	8.42	10.78	26.84	2.30	1.81	9.01
Townsville	4.93	4.84	6.77	9.15	25.63	1.50	0.98	3.13
Mackay	6.26	5.74	9.86	12.89	23.51	2.42	0.84	0.20
Hay Point	4.99	4.29	8.90	13.88	19.13	2.53	2.15	4.30
Emu Park	6.19	5.66	9.62	13.81	17.68	2.36	1.21	1.61
Mooloolaba	8.97	8.84	12.35	14.75	21.12	2.49	0.22	-0.42
Brisbane	9.23	9.26	12.15	14.70	21.10	2.28	0.08	-0.13
Gold Coast	9.50	9.40	12.88	15.99	22.04	2.54	0.32	0.18
Tweed Heads	9.40	9.37	12.23	14.94	21.19	2.32	0.16	0.08
Byron Bay	9.63	9.50	12.20	15.10	19.70	2.22	0.10	0.15
Coffs Harbour	9.64	9.50	12.20	15.10	19.79	2.25	0.08	0.18
Crowdy Head	9.78	9.50	12.93	15.10	19.79	2.28	0.21	0.23
Sydney	9.82	9.77	12.93	15.38	21.12	2.40	0.12	-0.03
Port Kembla	9.63	9.50	12.23	15.10	19.70	2.38	0.07	0.02
Batemans Bay	9.41	9.40	12.20	15.00	19.70	2.28	0.16	-0.17
Eden	9.46	9.50	12.23	15.10	19.79	2.35	0.18	-0.19
Cape du Couedic	8.34	7.93	11.42	15.30	22.20	2.21	1.29	5.03
Cape Sorell	12.38	12.50	14.91	17.56	28.95	1.97	-0.30	4.58

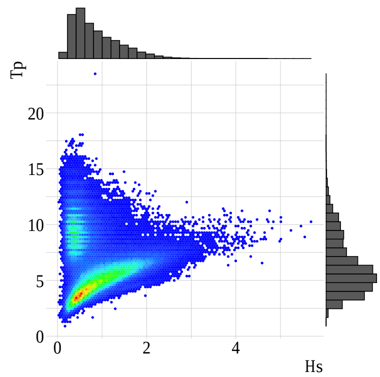
FIGURE 7.11: Scatterplots between Hs and Tp for Buoys in Queensland



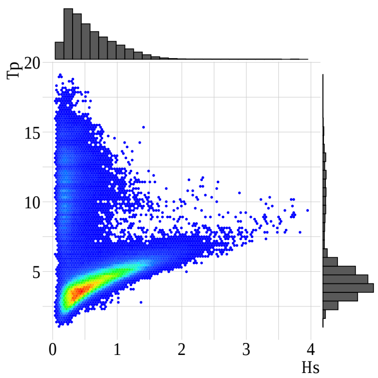
(a) Cairns



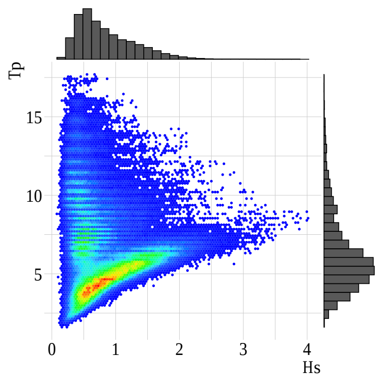
(b) Townsville



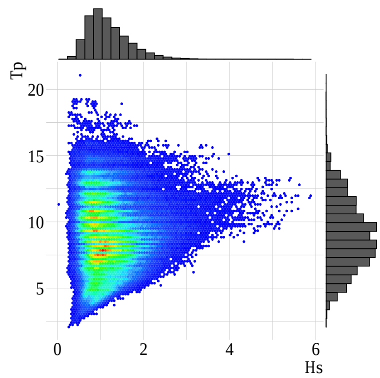
(c) Mackay



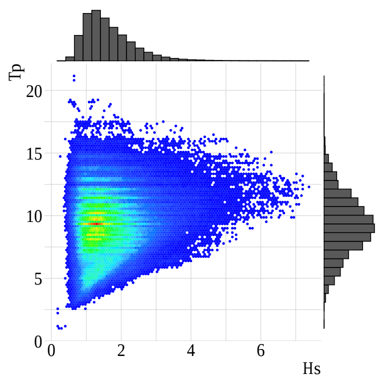
(d) Hay Point



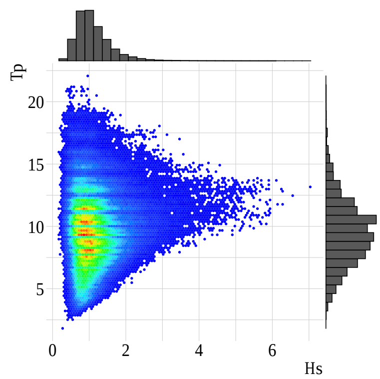
(e) Emu Park



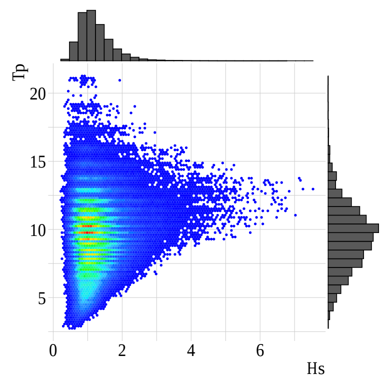
(f) Mooloolaba



(g) Brisbane

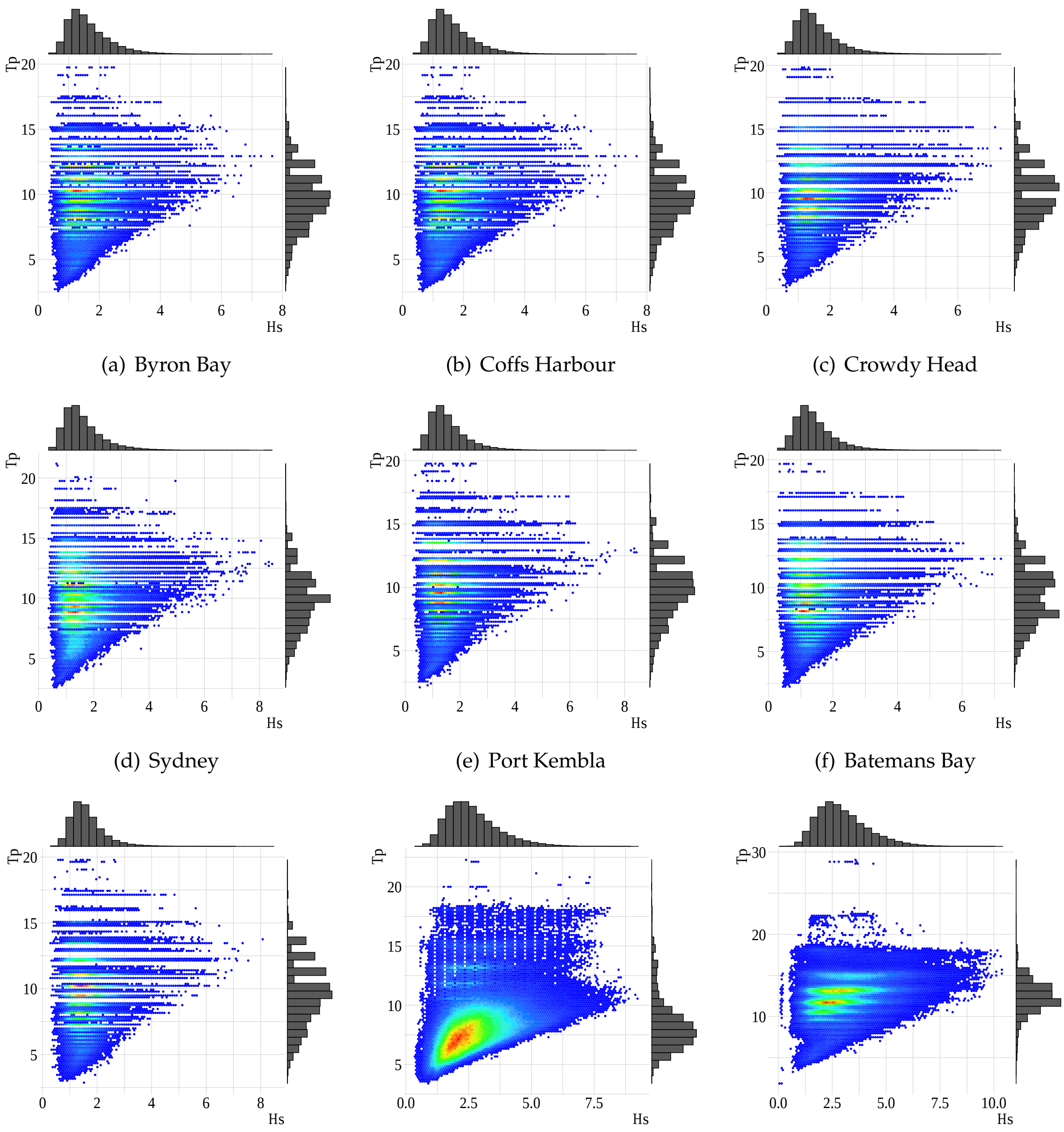


(h) Gold Coast



(i) Tweed Heads

FIGURE 7.12: Scatterplots between Hs and Tp for Buoys in NSW, South Australia and Tasmania

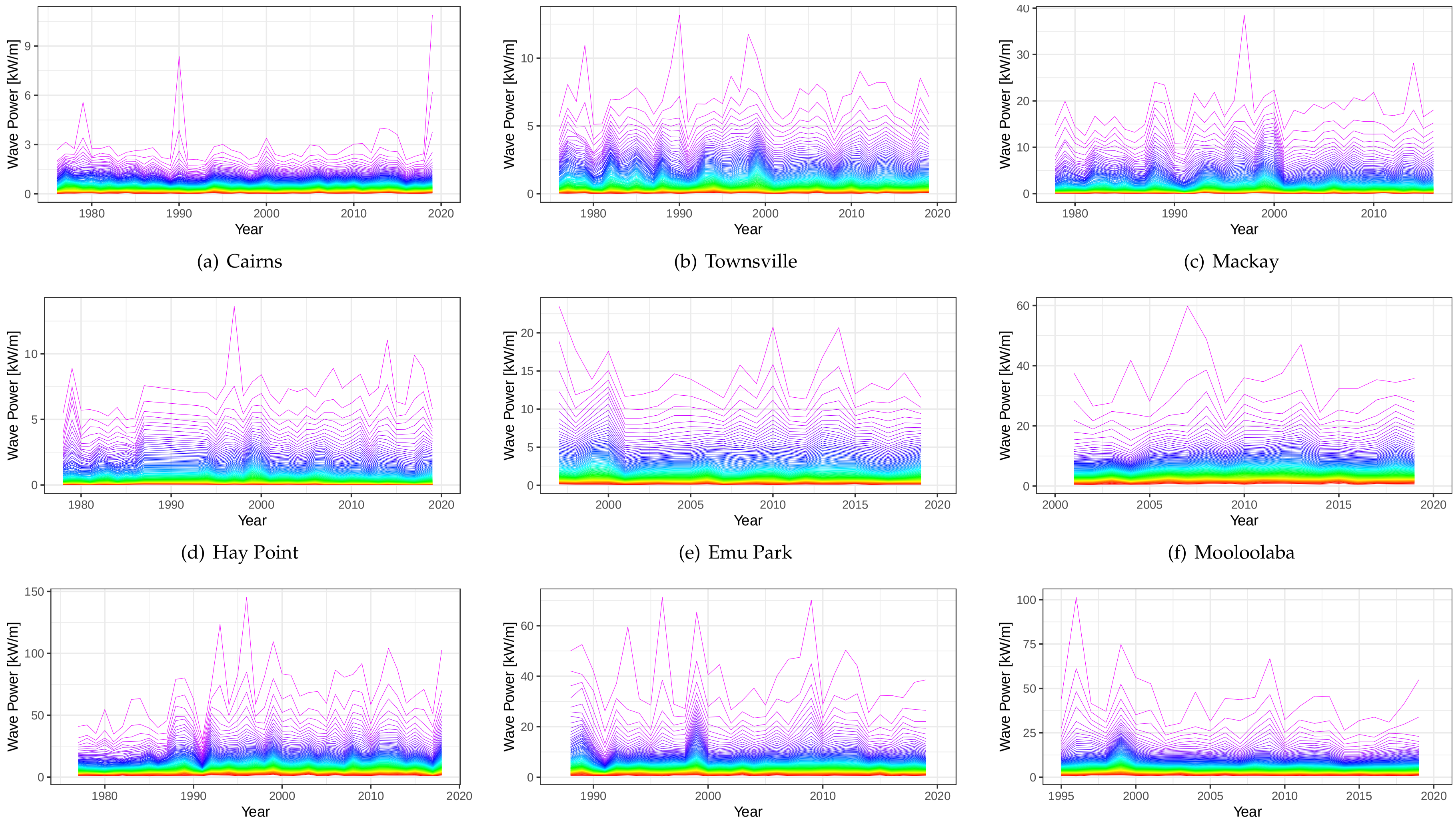


(a) Byron Bay (b) Coffs Harbour (c) Crowdy Head

(d) Sydney (e) Port Kembla (f) Batemans Bay

(g) Eden (h) Cape du Couedic (i) Cape Sorell

FIGURE 7.13: Rainbow plots of WP for Queensland



(a) Cairns (b) Townsville (c) Mackay

(d) Hay Point (e) Emu Park (f) Mooloolaba

(g) Brisbane (h) Gold Coast (i) Tweed Heads

Note: Lines represent the 1st to 99th percentiles of annual WP over time.

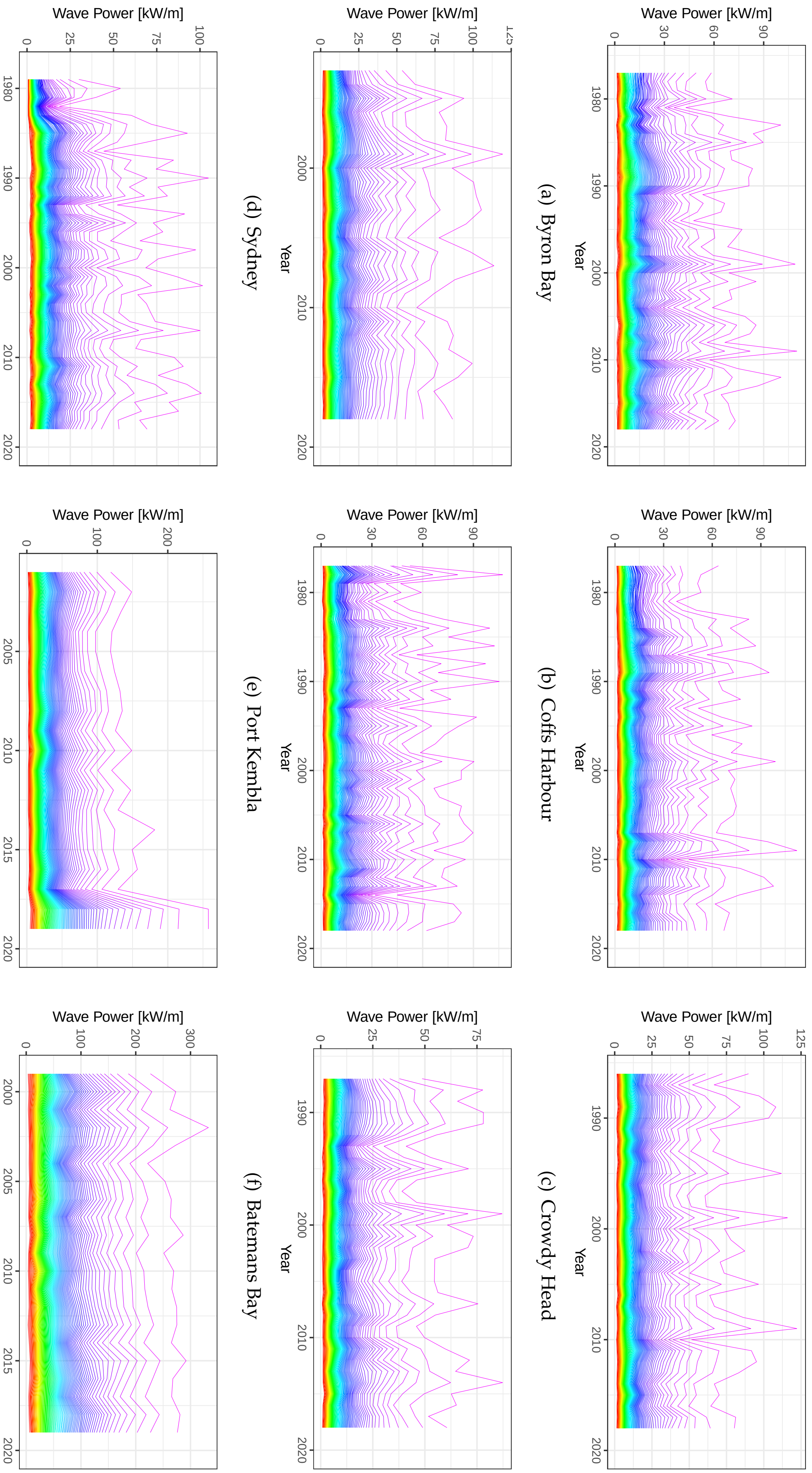


FIGURE 7.14: Rainbow plots of WP for NSW, South Australia and Tasmania

Note: Lines represent the 1st to 99th percentiles of annual WP over time.

FIGURE 7.15: Trend in annual WP of buoys in Queensland

(a) Cairns (b) Townsville (c) Mackay

(d) Hay Point (e) Emu Park (f) Mooloolaba

(g) Brisbane (h) Gold Coast (i) Tweed Heads

Note: Blue line represents the mean annual WP, yellow line represents the annual 90% quantile and the red line represents the annual 99% quantile. Dashed lines inside the plots indicate linear trend lines.

FIGURE 7.16: Trend in annual WP of buoys in NSW, South Australia and Tasmania

Note: Blue line represents the mean annual WP, yellow line represents the annual 90% quantile and the red line represents the annual 99% quantile. Dashed lines inside the plots indicate linear trend lines.

TABLE 7.8: Trend analysis for Queensland of annual Hs

		Trend	95% Confidence Interval		Kendall's Tau	Kendall's p-value	Cumulative Trend
Cairns	Mean	−0.0006	−0.0018	0.0007	−0.0963	0.3681	−0.0250
	90% Quantile	−0.0017	−0.0035	0.0010	−0.1352	0.2054	−0.0743
	99% Quantile	−0.0014	−0.0036	0.0008	−0.1274	0.2328	−0.0616
	Maximum	0.0069	0.0000	0.0143	0.2093	**0.0491****	0.3050
Townsville	Mean	0.0002	−0.0015	0.0016	0.0321	0.7695	0.0093
	90% Quantile	−0.0005	−0.0025	0.0015	−0.0443	0.6831	−0.0216
	99% Quantile	−0.0015	−0.0053	0.0020	−0.0853	0.4264	−0.0682
	Maximum	0.0093	−0.0012	0.0252	0.1938	**0.0686***	0.4078
Mackay	Mean	−0.0002	−0.0033	0.0026	−0.0100	0.9399	−0.0072
	90% Quantile	0.0003	−0.0051	0.0052	0.0327	0.7821	0.0100
	99% Quantile	0.0044	−0.0003	0.0098	0.2063	**0.0702***	0.1723
	Maximum	0.0218	0.0100	0.0322	0.3775	**0.0008*****	0.8488
Hay Point	Mean	−0.0018	−0.0037	0.0000	−0.2222	**0.0583***	−0.0655
	90% Quantile	−0.0007	−0.0038	0.0023	−0.0540	0.6531	−0.0251
	99% Quantile	0.0048	0.0003	0.0085	0.2413	**0.0397****	0.1780
	Maximum	0.0169	0.0079	0.0280	0.4222	**0.0003*****	0.6236
Emu Park	Mean	−0.0005	−0.0044	0.0028	−0.0649	0.6930	−0.0110
	90% Quantile	0.0017	−0.0067	0.0078	0.0736	0.6519	0.0396
	99% Quantile	−0.0030	−0.0160	0.0091	−0.1169	0.4635	−0.0693
	Maximum	0.0313	−0.0181	0.0751	0.2035	0.1946	0.7194
Mooloolaba	Mean	0.0004	−0.0102	0.0112	0.0327	0.8796	0.0072
	90% Quantile	0.0106	−0.0019	0.0261	0.2941	**0.0956***	0.2011
	99% Quantile	−0.0100	−0.0396	0.0314	−0.0458	0.8202	−0.1905
	Maximum	0.0162	−0.0772	0.0792	0.0409	0.8337	0.3075
Brisbane	Mean	0.0070	0.0028	0.0101	0.3488	**0.0014*****	0.2954
	90% Quantile	0.0115	0.0046	0.0164	0.3136	**0.0040*****	0.4839
	99% Quantile	0.0204	0.0051	0.0351	0.2634	**0.0157*****	0.8584
	Maximum	0.0399	0.0161	0.0622	0.3512	**0.0013*****	1.6776
Gold Coast	Mean	0.0005	−0.0026	0.0033	0.0409	0.7597	0.0157
	90% Quantile	0.0016	−0.0045	0.0086	0.0710	0.5865	0.0518
	99% Quantile	−0.0067	−0.0250	0.0091	−0.1070	0.3990	−0.2152
	Maximum	0.0239	−0.0253	0.0606	0.1271	0.3146	0.7640
Tweed Heads	Mean	−0.0046	−0.0094	−0.0012	−0.3841	**0.0092*****	−0.1159
	90% Quantile	−0.0105	−0.0222	0.0003	−0.2754	**0.0628***	−0.2630
	99% Quantile	−0.0200	−0.0479	0.0061	−0.2101	0.1574	−0.4999
	Maximum	−0.0040	−0.0679	0.0511	−0.0467	0.7614	−0.0990

Bold values denote a significance level of P<0.01, ** and * 0.05 and 0.1, respectively.

TABLE 7.9: Trend analysis for NSW, South Australia and Tasmania of annual Hs

		Trend	95% Confidence Interval		Kendall's Tau	Kendall's p-value	Cumulative Trend
Byron Bay	Mean	0.0022	−0.0015	0.0061	0.1537	0.1603	0.0924
	90% Quantile	0.0058	−0.0003	0.0119	0.1902	**0.0817***	0.2418
	99% Quantile	0.0064	−0.0034	0.0166	0.1439	0.1888	0.2697
	Maximum	0.0110	−0.0066	0.0300	0.1477	0.1720	0.4604
Coffs Harbour	Mean	0.0023	−0.0010	0.0056	0.1561	0.1537	0.0978
	90% Quantile	0.0068	0.0001	0.0116	0.2171	**0.0468****	0.2867
	99% Quantile	0.0107	0.0000	0.0213	0.2146	**0.0493****	0.4486
	Maximum	0.0149	−0.0112	0.0452	0.1220	0.2662	0.6257
Crowdy Head	Mean	−0.0026	−0.0051	0.0006	−0.1976	0.1157	−0.0865
	90% Quantile	−0.0017	−0.0086	0.0043	−0.0758	0.5457	−0.0566
	99% Quantile	−0.0037	−0.0188	0.0100	−0.0455	0.7216	−0.1230
	Maximum	−0.0100	−0.0394	0.0189	−0.1005	0.4204	−0.3294
Sydney	Mean	0.0018	−0.0033	0.0062	0.0523	0.7243	0.0460
	90% Quantile	0.0037	−0.0028	0.0155	0.1077	0.4536	0.0953
	99% Quantile	−0.0060	−0.0285	0.0201	−0.0467	0.7614	−0.1573
	Maximum	0.0206	−0.0171	0.0685	0.1754	0.2171	0.5365
Port Kembla	Mean	0.0015	−0.0013	0.0045	0.1452	0.1790	0.0656
	90% Quantile	0.0042	−0.0005	0.0087	0.1893	**0.0791***	0.1821
	99% Quantile	0.0036	−0.0071	0.0142	0.0676	0.5301	0.1565
	Maximum	0.0093	−0.0245	0.0381	0.0592	0.5879	0.3997
Batemans Bay	Mean	−0.0015	−0.0052	0.0025	−0.1011	0.4343	−0.0488
	90% Quantile	0.0003	−0.0081	0.0065	0.0022	1.0000	0.0094
	99% Quantile	−0.0013	−0.0173	0.0156	−0.0194	0.8918	−0.0419
	Maximum	0.0066	−0.0221	0.0411	0.0626	0.6266	0.2127
Eden	Mean	−0.0008	−0.0128	0.0099	−0.0256	0.8276	−0.0328
	90% Quantile	0.0028	−0.0072	0.0131	0.0796	0.4829	0.1132
	99% Quantile	0.0130	−0.0075	0.0307	0.1336	0.2358	0.5205
	Maximum	0.0513	0.0175	0.0813	0.3252	**0.0037*****	2.0530
Cape du Couedic	Mean	0.0009	−0.0041	0.0077	0.0994	0.5756	0.0171
	90% Quantile	0.0195	0.0021	0.0358	0.3801	**0.0252****	0.3898
	99% Quantile	0.0058	−0.0165	0.0265	0.0526	0.7796	0.1158
	Maximum	−0.0036	−0.0184	0.0103	−0.1158	0.4957	−0.0717
Cape Sorell	Mean	−0.0319	−0.0914	0.0277	−0.1684	0.3145	−0.7016
	90% Quantile	−0.0050	−0.0847	0.0876	−0.0043	1.0000	−0.1100
	99% Quantile	0.0706	−0.0348	0.1586	0.2421	0.1443	1.5536
	Maximum	−0.0428	−0.1550	0.0558	−0.1429	0.3812	−0.9422

Bold values denote a significance level of $P<0.01$, ** and * 0.05 and 0.1, respectively.

Part V

Conclusion

Chapter 7

Conclusion

This PhD thesis consists of three parts. The first part is dedicated to the econometric analysis of the oil market, the second part contributes to the literature on climate vulnerability and adaptation strategies, and the third part investigates the impacts of climate change on coastal regions. The following section briefly summarizes the main results of each chapter, outlining contributions to the literature and providing an outlook on further research avenues that are related to the work conducted in this thesis.

Chapter 2 – *Forecasting the Real Price of Oil – Time-Variation and Forecast Combination*
This chapter examines, whether it is possible to generate reliable long-term forecasts of the real price of Brent crude oil on a monthly basis and how these can be improved using forecast combination. The contribution to the literature is twofold. First, this work provides an overview of existing models and their performance, and it extends some of them by either introducing more suitable real-time measures for the Brent crude oil price or by using various measures for economic activity. Second, the work provides insights into the uncertainty associated with point forecasts based on the examined models.

The results show that it is possible to construct better forecasts compared with a no-change benchmark for horizons up to 24 months. The 'Futures' model provides substantial gains in terms of lowering the MSPE ratio by up to 25%. In addition, the newly introduced model variations of the classic inventories model provides better forecasts over the medium and long run. Additionally, despite having higher MSPE ratios in the long run, a combination of four models typically outperforms the best individual model over the medium run, whereas the overall time performance is less volatile. Moreover, the forecast interval of the real price of oil has been estimated by means of the quantiles of the distribution of previous out-of-sample forecast errors and a quantile regression approach. The latter improves the failure rate and is able to capture the uncertainty of oil price substantially better. However, the uncertainty analysis clearly reveals the limitations of these models and leaves room for further research opportunities. For one, it would be worthwhile to investigate the forecast uncertainty in greater detail. Although the MSPE ratio could be improved by a substantial amount, the models presented here have considerably wide confidence bands. In this context, it would be interesting to evaluate not only point forecasts but also forecast paths, which could, for example, be interesting for central banks for better policy planning. Second, oil and its derivatives are traded on a daily basis. Thus, it would be interesting to exploit different frequencies by using daily, weekly, monthly and quarterly data in a joint approach using, for example, a mixed frequency VAR or a heterogeneous autoregressive (HAR) model for long-term forecasts. Additionally, the derived models so far seem to capture the dynamics of the US oil market better than the world market of oil measured by the real price of Brent crude oil. This leaves room for optimization and further research in this field as well.

Chapter 3 – *Oil Price and Cost of Debt: Evidence from Loans and Corporate Bonds*
This chapter investigates the effect of oil price fluctuations on the cost of debt of US oil firms. This work contributes to the literature by empirically analyzing the relationship between the oil price, its volatility, and the cost of debt in the US oil industry. To answer our research question, we combine data on syndicated loans and issued bonds with the firm-level financial data of firms in the US oil industry. We estimate the credit spread of the loan and bond level at issuance via a distributed lag model, as well as the bond spread traded on the secondary market using a panel data "within-between"approach. The latter approach allows us to estimate the model jointly for all oil firms and then test for differences across industry classifications.

Our main findings can be summarized as follows. We find that firm characteristics, such as leverage, profitability and total assets, have a significant impact on the loan and credit spread that a firm has to pay. Although the credit spread increases with the leverage, it decreases with the profitability and the total assets. This is in alignment with previous findings in the literature. Moreover, we find that a higher risk in the macroeconomic environment also leads to a higher cost of debt in the oil industry. Additionally, as to be expected, we find that longer maturities also increase the costs of debt.

With respect to the oil price, we find a positive and significant coefficient for syndicated loans and bonds at issuance. Thus, the premiums on the price of debt charged by banks and the capital market increases with the oil price. The results regarding the volatility of oil prices, however, are less robust across industry classifications and sources of debt. We find that the credit spreads of loans decrease with the volatility of the oil price when considering the full samples of firms, whereas we find no significant effect for bonds at issuance.

When accounting for time-invariant firm heterogeneity, the results change notably. Within-between effects estimates for bonds traded on the secondary market indicate that higher oil price leads to lower financing costs for firms, whereas higher volatility increases the cost of debt. Overall, the bond market seems to consider high price volatility as a risk that increases uncertainty and thus reduces the creditworthiness of oil firms.

The difference between OLS estimates and within-between effects might be driven by unobserved firm heterogeneity or selection effects and provides an opportunity for further research. For one, non-observable firm characteristics, which are only controlled for in the FE estimation, might bias the OLS estimates for loans and bonds at issuance. Moreover, in times of very low oil prices, only very few syndicated loans were issued to oil firms. This indicates a possible selection effect as only a small number of very low-risk firms received loans, while others were not able to raise debt through this channel.

Our results suggest, however, that the oil price and its volatility are important drivers of the cost of debt in the US oil industry. Naturally, one would have to verify this result for other OECD countries and OPEC states. However, the latter would be difficult in terms of reliable data availability for publicly held firms. Moreover, the link between commodity prices and the costs of debt faced by the producers of other commodities, such as coal and gas producers, have potential for further research. Furthermore, our results indicate that the effects differ between syndicated loans and corporate bonds on the secondary market. This will require a deeper investigation to explain the differences we have found in this work. Moreover, as the energy sector as a whole is in a state of transition, it seems plausible to examine the possible impact of renewable energy resources on the energy sector as well as the possible consequences for the oil price and thus the cost of debt. In addition, recent developments in the economy due to the COVID-19 virus and the associated impact on the demand side (slow down in the economy) and supply side (limitation of storage capacity due to refusal of OPEC states to decrease supply quantities) will have a lasting effect on the US and world oil industries. This might lead to an increase in corporate debt, possibly cause bankruptcies, affect the bond market and provide many areas for future research.

Chapter 4 – *Climate Change Vulnerability and Adaptation Strategies – Analysis from Indian Watershed Development Programmes*
This chapter investigates how the climate vulnerability of rainfed farming can be measured and compared. This work contributes to the literature by developing a new kind of CVI^{RFT} that is specifically designed for this purpose. In addition to being theoretically conceptualized, the index is tested to compare the climate vulnerability of three watershed communities in Kerala, India. This allows for the evaluation of the potential effectiveness of WDPs to adapt to climate change impacts. The CVI^{RFT} consists of three dimensions of vulnerability; *adaptive capacity*, *exposure* and *sensitivity*. Although we do not find strong variation among the index values for the three watersheds, we find substantial variation in the three dimensions. There are strong variations in the *exposure* dimension; there is moderate variation in *sensitivity* and negligible in *adaptive capacity* across the watersheds. Given these results, we propose focusing on a policy orientation toward redesigning of the WDPs with an emphasis on economic diversification, livelihood strategies and social networking coupled with stakeholder participation, natural resource management and risk spread through credit and insurance flexibility.

The presented framework can be seen as an initial approach to evaluating the vulnerability of rainfed regions and can guide the framing of policy suggestions and help with restructuring WDPs. The index is replicable to similar physio-geographic areas of rainfed farming provided that the the indicators are refined to suit the specific locality. Further research should concentrate on the different steps involved in the indicator development. Possible areas include the indicator selection itself, weighting and the aggregation of the indices. For example, we have chosen a weighted average of the 59 indicators. Although this is a straightforward approach, it is not obvious that this is the appropriate choice for weighting the relative importance of the indicators. Thus, although not entirely avoidable, it is possible that combining variables with a high degree of correlation would lead to an overstating of the specific aspect they are measuring. We have checked the correlation of the indicators and identified three pairs of variables that showed positive correlations in all three of the watersheds. Thus, in a consecutive step, one could try other weighting schemes, such as, for example, principle component analysis or factor analysis, which would allow for a grouping of indicators according to their degrees of correlation (OECD 2008). Moreover, an uncertainty and sensitivity analysis of these indicators would also be an important additional step to ensure their quality and robustness. A first step in this direction has been completed by demonstrating the statistical significance of differences between dimensions using bootstrapping (Raghavan Sathyan et al. 2018a). However, this leaves further room for improvement, as one could add multiple sources of uncertainty simultaneously by, for example, including or leaving out individual indicators, using alternative normalization methods (min-max, standardization, etc.) or other aggregation methods (OECD 2008). Additionally, it would be interesting to increase the number of study sites, as we have used three WDPs in a single district and three implementing agencies only. Thus, the study should be conducted in multiple other regions in India. This would allow for a comparison on watershed-specific issues and their spatial dimensions, as well as help to improve climate change adaptation planning. Moreover, this would allow for a detailed investigation of the effectiveness of the different agencies.

Chapter 5 – *Changing Climate - Changing Livelihood: Smallholder's Perceptions and Adaptation Strategies*
This chapter discusses how smallholder households perceive climate change, how they adapt their behavior in response to perceived changes in the climate, and what factors influence their choices of adaption measures. This work offers a contribution to the literature by addressing agricultural adaptation in the face of increasing climate risk using a novel setting (three watersheds in India). Using a binary logistic model, this work quantifies the impact of various explanatory variables that affect households' choices of adaptation strategies in the three study

areas. The basis of the empirical model is the assumption that the households will implement climate-change adaptation strategies only if doing so increases their expected net farm benefits or reduces the perceived risk to their crop production.

For the three study sites, the results reveal that households perceive an increase in both temperature and the unpredictability of the monsoon season, which is in accordance with actual observed weather trends. Moreover, households adopt more than one adaptation strategy simultaneously, but show considerably different variations among the actual strategies implemented within the three watersheds. Moreover, the results of a binary regression model also reveal that various factors are significantly correlated with the households' choices regarding adaptations to cope with climate change. Thus, the household head's age, education and gender, as well as the farm's size and the household's size, assets, livestock ownership, poverty status and use of extension services are important characteristics that are correlated with adopting new practices. These are important and timely findings. Understanding how and which baseline characteristics correlate with adaptation allows policy makers to evaluate potential welfare gains from promoting different strategies and to use the best interventions to cope with climate change.

One of the main drawbacks of this work is the limited amount of household data available for the binary regression. Thus, in alignment with Chapter 4, it would be worthwhile to increase the number of study sites as well as the number of participants. This would allow for a deeper comparison of watershed-specific adaptation strategies and their spatial dimensions. Furthermore, to maintain a sufficient number of degrees of freedom, it was necessary to combine categories of perceptions of climate change by using a binary variable. Thus, having more observations would allow the use of a categorical (negligible to very high) variable for households, perceptions of climate change (using the different categories would require a separate dummy variable for each level). Thereby, the use of new technologies, such as smartphones, might be helpful for contacting multiple subjects in a timely and cost-efficient way. However, one would have to be careful via the implementation to avoid introducing additional biases. For example, acquiescence bias is a potential issue when it comes to personal assessments. Thus, one could ask the participants similar questions with different outcomes that would allow to see contradictions between the two answers and test for them. Moreover, it would be valuable to know how the adaptation practices used in this study area are calibrated to the actual threats of climate change. So far, the availability of reliable meteorological data made this impossible. Moreover, the adaptation strategies used within the three watersheds are initiated by the implementing agencies. Thus, this will require a detailed identification of prevailing adaptation strategies in the locality during the field data collection process.

Chapter 6 – *Project Valuation for Coastal Adaptation – A Literature Review*
This chapter provides a review of various valuation methods that can be used to evaluate coastal adaptation projects. Given that coastal areas are particularly at risk due to rising global sea-levels, and that natural hazard losses are likely to increase in the near future, adaptation strategies play a crucial role in the management of coastal regions. It is apparent that adaptation options should be given a high priority in managing the risk associated with these changing climatic conditions. Often, it is difficult for stakeholders to understand the contexts in which these various valuation methods should be applied. Thus, this work offers a guide for local government decision makers by reviewing and discussing a broad range of existing valuation methods and providing examples of practical applications. In particular, an overview of studies that have evaluated coastal adaptation projects using cost benefit and optimal timing approaches highlights methodological issues in this area of research. Thereby, recent research on real options approaches provide a way to take climate change uncertainty into account, as well as to consider the value of flexibility of investments for coastal adaptation projects. Future research should concentrate on improving existing methods by providing

more robust approaches that allow for the integration of a broad range of climate change scenarios.

Chapter 7 – *Long-Term Trends in the Australian Wave Climate*
This chapter investigates long-term trends and extreme values in the wave climate along Australia's eastern and southeastern coasts. The focus of this work is to identify historical trends in mean and extreme wave power. Extreme values in the wave power, the energy transmitted in the direction of wave propagation, play an important role for the risk to coastal regions and might help to inform adaptation strategies. The contribution of the study to the literature is twofold. First, this work uses a comprehensive data set consisting of 18 wave rider buoys ranging from 17 to 42 years of effective record years. This allows us to investigate long-term trends in wave power (and wave height) at the local scale. Second, this work introduces Laplacian embedding as a potential tool for investigating temporal and spatial variation in the wave climate between and within different locations. This allows for a comparison of the distribution of the wave power over time, providing new insights on the wave climate in Australia.

The key results of the study can be summarized as follows. The wave power along the Central Australian Coast seems to have a different behavior, from that measured for the northern and southern parts of Australia. Moreover, with bootstrapping being used to test for significant differences, various decadal changes in the median as well as the 90th and 99th percentiles have been identified. Thus, the latest decades confirm that extreme values seem to have increased for the northern and southern parts of the Australian east coast, whereas they have decreased for central parts of the eastern coast line. Moreover, a trend analysis reveals an increase in the yearly mean wave power in Brisbane, Tweed Heads, Coffs Harbour, and Port Kembla. Additionally, a significant increase in the 99th percentile, or the maximum, could be observed for seven out of the 18 locations throughout the past 40 years.

Future research might focus more on the aspects of the risk associated with changes in the wave climate, what will help with optimally allocating resources for coastal adaptation strategies. Moreover, spatial variations due to changes in the wave buoy position might have introduced a spurious trend and possibly altered the estimates. This should be investigated further and possibly validated using satellite observations. Additionally, it would be worthwhile to check for seasonal variation in the trend components to allow for better adaptation planning from a risk management perspective.

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Declaration of Authorship

I hereby declare that I completed the papers submitted and listed hereafter independently and with only those forms of support mentioned in the relevant paper or in the following supplementary list. When working with the authors listed, I contributed no less than a proportionate share of the work. In the analyses that I have conducted and to which I refer in the papers, I have followed the principles of good academic practice, as stated in the Statute of Justus Liebig University Giessen for Ensuring Good Scientific Practice.

Christoph FUNK

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