Quantitative Essays on Resource and Energy Economics

Inauguraldissertation

zur

Erlangung des Doktorgrades

der

Wirtschafts- und Sozialwissenschaftlichen Fakultät

der

Universität zu Köln

2022

vorgelegt von

Diplom-Regionalwissenschaftler Niklas Hinkel

aus

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Tag der Promotion:	12. August 2022

Acknowledgements

First of all, I would like to thank my supervisor Prof. Van Anh Vuong, Ph.D. for supervising my dissertation, for valuable inputs, and many inspiring discussions. My research benefited substantially from her guidance. Also, I am deeply grateful to Prof. Dr. Marc Oliver Bettzüge for co-refereeing my thesis. I highly appreciate his helpful comments and his continued support. Additionally, I would like to thank Prof. Dr. Johannes Münster for agreeing to chair the examination committee for the defense of my dissertation.

I am especially grateful to Prof. Dr. Felix Höffler for his constructive feedback and continuous support, as well as for the opportunity to work at his chair.

Furthermore, I am particularly thankful to my co-authors Dr. Eren Çam and Max Schönfisch. The collaboration with them was characterized by great productivity, as well as interesting discussions on energy economics and beyond.

This thesis has benefited significantly from insightful discussions with many colleagues. I would like to express my gratitude specifically to Dr. Helena Meier, Dr. Martin Paschmann, Dr. Simon Schulte, Dr. Johannes Wagner, Anne Angsten, Johannes Mössinger, Stefan Krupp, Dr. Jan Hendrik Rolfes, Dr. Martina Gocke, and Dr. Sebastian Mertesacker for their invaluable comments and suggestions.

Also, I want to thank the Institute of Energy Economics at the University of Cologne, everyone at the chair of Prof. Dr. Höffler, and the Cologne Graduate School for allowing me to conduct my research in an excellent atmosphere and for providing the necessary infrastructure via all the wonderful colleagues in the administration and IT department. Moreover, the financial support of my research by all three institutions is gratefully acknowledged.

Last but not least, I am endlessly grateful to Alexandra, my family, and friends for their patience and constant support over the years.

Niklas Hinkel — Vienna, April 2022

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List of Abbreviations

ACR avoidable cost rate

CCGT combined cycle gas turbine

CDM clean development mechanism

CEC cation exchange capacity

CIAT International Center for Tropical Agriculture

CSO Central Statistical Office of Zambia

d.d.p. delivered duty paid

EIA United States Energy Information Administration

ERB Energy Regulation Board of Zambia

FAO Food and Agriculture Organization of the United Nations

FAPRI Food & Agriculture Policy Research Institute

FISP Farmer Input Support Programme

f.o.b. free on board

FRA Food Reserve Agency of the Zambian Government

FSP Food Security Pack Programme

GHG greenhouse gas

IEA International Energy Agency

ISO independent system operator

ISP input subsidy program

MIP mixed-integer problem

N nitrogen

NPK nitrogen, phosphate, and potassium three-component fertilizer

NREL National Renewable Energy Laboratory (United States)

OCGT open-cycle gas turbine

OECD Organisation for Economic Co-operation and Development

O&M operation and maintenance

PJM Pennsylvania, New Jersey, Maryland Power Pool

R&D Research and Development

RPM Reliability Pricing Model

RSG reference soil group

VAT value added tax

1. Introduction

In many economic contexts, decision making compares alternative beneficial courses of action. When comparing competing beneficial choices, it may not suffice to assess the situation qualitatively. To guarantee the best possible outcome, a comparison may assign values to each available choice, raising the need for quantitative analysis of the options. Furthermore, a single course of action might involve opposing effects, which need to be evaluated to determine the overall effect of that course of action. Again, quantitative analysis is needed. In the vast field of energy and resource economics, many applied questions require to quantify effects of policies or benefits and costs of individual actions. These questions can relate to various energy carriers or resources, as this thesis illustrates.

Chapter 2 evaluates the benefit of a counterfactual improvement of resource use in the case of agricultural soils in Zambia. Decision makers may gain valuable insights from an analysis of the presented partial equilibrium model, which quantifies price, quantity, and welfare effects of agricultural liming. This practice improves the nutrient availability of acidic soils used for the cultivation of maize, the dominant food crop in Zambia. Chapter 3 builds on Chapter 2 and extends the focus beyond the Zambian market for maize to include also local markets for diesel, cassava, and palm oil. The chapter assesses the price, quantity, and welfare effects of a counterfactual introduction of palm oil based biodiesel on the listed markets. Special attention is given to the interaction of food and fuel production. Chapter 4 shifts the regional focus to the northeast of the United States and quantifies fixed operation and maintenance (O&M) costs of open-cycle gas turbines based on a range of generator characteristics such as operational status, capacity, vintage class, and age.

Hence, the thesis at hand has three main chapters. Although Chapter 3 builds on Chapter 2, all chapters are stand alone essays and can be read in any order. They are based on independent research articles:

Chapter 2:	Agricultural Liming in Zambia: Potential Effects on Welfare (based on Hinkel (2019))
Chapter 3:	More Biofuel = More Food? (based on Hinkel (2022))
Chapter 4:	A Stochastic Discrete Choice Dynamic Programming Model of Power Plant Operations and Retirement (based on Çam, Hinkel, and Schönfisch (2022), all authors contributed equally)

The remainder of the introduction is structured as follows: the next section exhibits a brief summary of each chapter, succeeded by a debate of the methodology and central assumptions of the chapters, as well as ideas for further research.

1.1. Outline of the Thesis

Chapter 2: Agricultural Liming in Zambia: Potential Effects on Welfare

Chapter 2 analyses the welfare effect of agricultural liming on the market for smallholder maize in Zambia. Among other factors, higher nutrient availability, most importantly that of nitrogen, phosphorus, and potassium (N, P, and K), increases maize yields. The availability of nutrients in the soil depends on the soil's acidity, measured in pH. While the optimal range of soil pH for maize is 6.0 to 7.2, low pH (acidic) soils cause reduced availability of certain nutrients, especially phosphorus, leading to lower yields. This is the case for naturally occurring nutrients and for those added as fertilizer. An established remedy for overly acidic soils is the incorporation of alkaline materials (e.g. ground limestone) into the soil, i.e., agricultural liming. Liming raises the soil pH and eventually maize yields.

In Zambia, this practice is not widely established yet, although the Zambian soils cultivated predominantly for the production of maize by smallholders are largely acidic. In the agricultural season 2010-11, over 92% of maize output was produced by over 1 mn smallholder households (CSO, 2016; Zambia Ministry of Agriculture, 2011). Survey data indicate that 70% of farmers were not aware of the need to lime acidic soils Mitchell (2005). In the representative nation-wide sample of Zambian smallholder maize farmers (based on Burke, Jayne, and Black

(2016)) used in this chapter, only 1% of the area of maize production showed pH values high enough to be considered optimal. Thus, the question arises what the benefit of widespread agricultural liming by Zambian smallholders would be, such that decision makers could weigh it against potential costs connected to the introduction of the practice (e.g. costs of an educational campaign). This chapter seeks to quantify the benefit measured via welfare gains and changes in the local price of maize.

The modeled results suggest that agricultural liming by Zambian smallholders would lower the local price of maize by 22.8% and raise related welfare by 3.4% without international trade. When exports are viable at 350 USD/t, the local price would fall by 16.1% and welfare would climb by 5.6% due to liming.

Chapter 3: More Biofuel = More Food?

This chapter illustrates the interaction between the production of biodiesel and that of food crops with the example of the Zambian markets for cassava, maize, palm oil, and (bio-)diesel. Since biofuels may be part of solutions to the challenge of reducing greenhouse gas emissions, their impact on agricultural food production will continue to matter. On the one hand, biofuels of the third and second generation do not require agricultural land, because, respectively, their feedstocks are based on algae and on by-products or plants cultivated on land unsuitable for food production. On the other hand, biofuels of the first generation need agricultural land for their feedstocks and are still widely-used. This may lead to competition for land between energy crops and food crops. At the same time, fuel is an important input for the production and transport of food crops. This chapter quantifies these two aspects of the interaction between biofuel and food crops.

The enumerated Zambian markets serve as a setting to illustrate both aspects. Zambia is a landlocked country with high fuel and transport costs that depends on costly imports of fossil fuel, but Zambia is theoretically able to produce large amounts of cheap biofuel. Hence, cheap locally produced biofuel (in this case biodiesel based on palm oil) could reduce transport costs and enable the export of food crops (maize), unlocking additional demand for the Zambian maize sector and stimulating an increase in the production of food crops. Given the necessary capacity nationwide to produce both biodiesel and food crops, the aspect of competition for agricultural land may be dominated overall by the aspect that fuel is an input to food production and transport. The assessment of production capacity for maize builds on Chapter 2 and assumes the realization of improved productivity for smallholder maize in Zambia via agricultural liming. Before considering the counterfactual production of biodiesel, this practice introduces idle production capacity (unused agricultural land) into the system.

Compared to a baseline, model outcomes suggest the counterfactual switch from fossil diesel to biodiesel to lower the diesel price by 51%. As a result, food supply increases (cassava and maize combined) by 0.4% and related prices decrease by 3%. Welfare on all modeled markets combined grows by 9.9%. If additionally, a higher world market price of maize enables barely profitable exports, overall welfare continues to increase by 9.9%, domestic food supply expands by only 0.3%, and related prices decrease by just 2%, but food supply including exports increases by 32%. Moreover, establishing a palm oil based biodiesel sector could bring the additional benefit of completely eliminating import dependency on fossil diesel and palm oil.

Chapter 4: A Stochastic Discrete Choice Dynamic Programming Model of Power Plant Operations and Retirement

Chapter 4 introduces an estimation of fixed operation and maintenance (O&M) cost parameters relevant to the decision to operate, mothball or retire an open-cycle gas turbine (OCGT). The data used for the estimation includes fuel, capacity, and electricity prices, as well as technical data and the operational status of OCGTs in the Pennsylvania, New Jersey, Maryland Power Pool (PJM) market area in the northeast of the United States. Resulting estimates for the fixed O&M costs differ by operational status and based on the technical parameters of an OCGT (capacity, vintage, and age). This differentiation offers valuable insights for regulators to better understand costs of OCGTs in the context of competition policy on electricity markets. The cost estimates also enable more realistic parametrizations in power market modeling.

For both operational and mothballed OCGTs, age of the power plant and plant vintage show statistically significant positive correlations with the OCGT's fixed O&M costs. In addition, the analysis reveals a statistically significant negative relationship between the installed capacity and the fixed O&M costs, confirming that an increase in scale leads to lower specific costs. The fixed O&M cost estimates for operational OCGTs vary from 16.3

USD/kW/year for new, large, high-efficiency units, to 50.8 USD/kW/year for older, small, low-efficiency units. Mothballing an OCGT reduces these costs by 75% to 95%, depending on plant vintage and size. The analysis indicates that decommissioning a plant has a negative cash flow, i.e., any scrap value from equipment sold on secondary markets does not cover the cost related to the decommissioning.

Applying the estimates and market data for 2008 through 2017, the chapter also shows the computing of the probabilities of operating, mothballing or retiring an OCGT. Finally, the chapter offers sensitivity analyses regarding changes in prices of capacity, electricity, and natural gas. These analyses unveil how operating decisions of OCGTs are considerably affected by the profitability potential, most strikingly by electricity prices.

1.2. Methodology and Future Research

Different quantitative modeling approaches serve to answer the research questions of the individual chapters of this thesis. While Chapter 2 and Chapter 3 apply bottom-up numerical simulation models, Chapter 4 uses an econometric estimation approach. Each of the applied models relies on specific methods and individual sets of assumptions that allow for necessary abstractions from reality. These abstractions facilitate the modeling and analysis of the economic effects of interest, while striving not to compromise the representation of the modeled situations. In order to contextualize the results of the models, it is necessary to understand which methods and assumptions they are based on. The overview in this section aims to help with this understanding, while also providing some ideas on potential future research.

The analysis of improved resource utilization on the Zambian market for smallholder maize via agricultural liming in **Chapter 2** is based on a dynamic, deterministic, welfare-maximizing, open market, spatial partial equilibrium model. Solving this bottom-up simulation model requires bounded, monotonic, non-convex mixed-integer optimizations with equilibrium constraints. The model is structured in three layers: core problem, intermediate problem, and enclosing problem.

The core problem describes the profit maximization of producers. At this level, global and local prices of maize, liming investment scenario, the initial liquidity of each producer, and time period are all exogenous model inputs. The liquidity of producers limits investments and can increase over periods via retained profits. Various liming investment scenarios describe different intensities of the counterfactual introduction of agricultural liming, based on initial soil acidity levels of producers and acidity thresholds relevant for productivity increases from the literature (Burke, Jayne, and Black, 2016). Welfare is computed from resulting input and output quantities of the producers at this level of the model.

Via a binding local demand constraint, the intermediate problem adds an equilibrium constraint to the core problem, endogenizing the local price of maize. Local demand reacts linearly to changes in local price. Solving this problem returns a subset of the solutions of the core problem, consisting of equilibria dependent on the global price of maize, the liming investment scenario, and the time period. Each step of the iterative solution approach (a bisection algorithm) for the intermediate problem solves the core problem and converges towards a market equilibrium.

The enclosing mixed-integer problem describes the decision on discrete liming investment scenarios. For each scenario, it solves the intermediate problem for all time periods and computes respective total discounted welfare. Maximizing this metric, the optimal liming investment scenario is selected for all considered global prices of maize.

Subsequently, the incentive compatibility of each liming investment scenario is tested. The test compares each producer's total discounted surplus associated with a scenario with the respective producer's total discounted surplus given this producer's liming investment deviates from the current scenario. This is repeated for all considered global prices of maize.

A central assumption of this model concerns the behavior of the modeled market as perfectly competitive. This can be justified by the large number of producers and consumers of smallholder maize in Zambia. Furthermore, the traded good is close to homogeneous and there are no obvious externalities or limitations to the mobility of production factors. By assumption, there is no stochasticity with respect to the production process and the market. This may be interpreted as expectations of highly experienced producers and consumers. In addition, the production process of maize is modeled in a simplified manner with other farm activities considered outside the scope of this analysis. The related assumption is that disregarded interactions between the cultivation of maize and other farm activities play a negligible role for the analyzed effects. Generally, adding other farm activities to the analysis would be interesting for further research and could offer insights on second degree effects to the present analysis of counterfactual agricultural liming. Besides scrutinizing complementary farm activities, the present analysis might be broadened by including markets for processed maize products or for fertilizers used in the production of maize. More efficient nutrient uptake in limed soils for maize cultivation could have interesting consequences on the markets for fertilizers that supply these nutrients.

Chapter 3 compares different counterfactual scenarios of food and biofuel production in Zambia. The scenarios are based on an open market, welfare maximizing, static, spatial partial equilibrium model for three interdependent goods: fuel, fuel feedstock, and food. These goods are represented by diesel/biodiesel, palm oil, and cassava/maize respectively. All markets are assumed to generate welfare maximizing outcomes due to perfect competition or regulation (for diesel). The arguments for perfect competition from Chapter 2 apply, including near-homogeneous goods, as well as large numbers of consumers and agricultural producers. This perfectly competitive setting is implemented as a welfare maximization over all markets. Local demand is modeled as linear.

In the model, fuel is both input and output. Thus, the model is similar to welfare maximizing partial equilibrium models with basic and refined goods, where the production processes of refined goods use basic goods as inputs. One such model with refinement of goods is the global forestry model of Kallio, Moiseyev, and Solberg (2004), based on the theory of spatial equilibria in competitive markets (Samuelson, 1952). The model in Chapter 3 extends this type of model, as one refined product (biodiesel) is also the input for all products. Therefore, the local price of fuel and its local demand are determined simultaneously. Also, fuel costs of the production and transport of fuels are modeled as "iceberg" costs (Samuelson, 1954), i.e. a quantity of fuel output shrinks by its fuel requirements for production and transport to its point of sale.

To a large extent, the market for maize in Chapter 3 is based on Chapter 2, yet the production function is fixed at levels deemed optimal with respect to fertilizer and lime inputs. Given the promising results from Chapter 2 regarding the potential virtues of agricultural liming in Zambia, the introduction of soil pH management with lime appears likely to be implemented before an even larger effort is made to introduce local capacity for an economy-wide supply of biodiesel.

Since the model maximizes welfare over all markets, an explicit profitability constrained is introduced for the domestic diesel market to prevent the model from endogenously subsidizing fuel. The assumption of profit maximizing companies is not generally remarkable, but other objectives than profit are imaginable, especially in the context of regulating the fuel sector.

This static model assumes a fully developed market for biodiesel, where counterfactual infrastructure and production are operational in the modeled period. This assumption is in place, since the research question focuses on the effect of cheap biodiesel on the modeled markets, without concern for the ramp-up period of the biodiesel sector.

An obvious extension to Chapter 3 could address social and environmental effects of the counterfactual biodiesel production. The analysis of environmental effects could include the impact of the introduction of biodiesel on direct and indirect greenhouse gas emissions and savings. Furthermore, the application of this model to other countries with high fuel costs and large agricultural potential for biofuels could be of interest.

The model structure of **Chapter 4** is closely related to the model presented in Das (1992) and can be qualified as a stochastic discrete choice dynamic programming model. This type of model assumes rational forward looking, risk-neutral actors who maximize their expected profits over multiple time periods. In this case, the actors manage OCGTs and are assumed to operate in a competitive environment, where their decisions arise only from prices and costs and not from any strategic behavior. Actors' profits consist of capacity payments, and the margin between electricity and natural gas prices less specific costs of the generation unit. The specific costs are not readily observed and must be estimated. The actors take a sequence of operating decisions (operate, mothball, or decommission the OCGT) to maximize their expected discounted payoffs based on their current information. This behavior is described by the actors' value functions, which are the recursive solutions to a Bellman equation. By matching the modeled decisions to those observed in the data, the unobserved specific costs can be estimated via the maximization of a likelihood function.

The assumption of competitiveness of the market should be guaranteed by the size and liquidity of the PJM market area, as well as by competitiveness reports for that market (Monitoring Analytics, 2020). Any strategic behavior would cause cost estimates to be biased. Besides competition, another key assumption is that prices for capacity, natural gas, and electricity move jointly in a first-order Markov process and transition probabilities between price states match the relative frequency of the price state in the data set. These assumptions reduce the computational burden of the model considerably and while a codependency between prices seems reasonable, a perfectly joint movement of prices might be prevented by factors outside the scope of this analysis. Furthermore, an extension of the data set, considering additional time periods and corresponding prices would impact the aforementioned transition probabilities and more generally possible payoffs of actors.

An extension of the work in Chapter 4 might expand the choices an OCGT operator has. For example, due to a lack of data, this chapter does not consider retrofits that improve the operating efficiency, lower costs, or lengthen the operational lifetime of an OCGT. Retrofits improve the forward-looking payoffs of the operator. Dependent on expectations about the future, such an investment may be rational, adding a fourth alternative to the existing choices of operating, mothballing, or retiring.

The overview provided in this section is meant as a primer for the methods and related assumptions used in the analyses of the following chapters, as well as for ideas on further research. The individual chapters offer more in-depth discussions and context of the applied methods, their assumptions, and the outlook on potential extensions.

2. Agricultural Liming in Zambia: Potential Effects on Welfare

Soil acidity is crucial for crop yields. Acidic soils decrease the availability of important nutrients to plants, causing lower yields. This applies to both naturally occurring nutrients and fertilizer. A well-known remedy is to provide soils with alkaline materials, like ground limestone. This raises their pH levels, increasing the availability of nutrients to the plant and eventually crop yields. So far, this practice is not widespread in Zambia, a country with largely acidic soils in agricultural areas. The agriculture of Zambia is dominated by smallholder farmers, growing predominantly maize. This chapter seeks to quantify the effects on welfare that the introduction of liming would have in the Zambian smallholder maize market. For this purpose, I develop a dynamic, deterministic, open market, spatial partial equilibrium model. Solving the model requires bounded, monotonic, non-convex mixed-integer optimizations with equilibrium constraints. Model results indicate that liming in this market would reduce prices by 22.8% and increase welfare by 3.4% without international trade. With exports at 350 USD/t, the local price would drop by 16.1% and welfare would increase by 5.6% due to liming.

2.1. Introduction

In Zambia, less than 2% of smallholder farmers (farm size <20 ha) growing maize (Zea mays L.) apply agricultural lime, even though soils are predominantly acidic or extremely acidic (nationwide sample of Burke, Jayne, and Black (2016)).[1] Survey data show that 70% of farmers were not aware of the need to lime and many never did (Mitchell, 2005). More recent anecdotal evidence also suggests that smallholders' insufficient knowledge of the soil deacidifying benefit of liming may cause this low adoption rate (Burke, Jayne,

[1] Mason, Jayne, and Mofya-Mukuka (2013) states, that in the 2010-11 agricultural season only 0.4% of Zambian smallholder households applied lime.

and Black, 2016). Jayne and Rashid (2013) analyzes sub-Saharan African agricultural policies and suggests initiatives for improved soil fertility. Among other measures, this includes addressing soil acidity and the deacidification of the Brazilian Cerrado region is given as a successful example. Jayne and Rashid (2013) sees soil testing and educational campaigns targeting farmers' knowledge gap as crucial for this measure.

Although qualitatively advisable, these campaigns face a problem: the desire of politicians to tangibly demonstrate their support to their constituents makes input subsidy programs (ISPs) more popular in the region (Jayne and Rashid, 2013).[2] Different from ISPs, a government intervention in the form of an educational campaign requires a substantial amount of time until benefits manifest (Jayne and Rashid, 2013). This deferral of benefits and uncertainty over their size may decrease the value of such an intervention in the eyes of politicians.

This chapter quantifies the benefits of a government intervention to make the virtues of agricultural liming common knowledge in Zambia. The intervention compliments existing ISPs for fertilizers. By assumption, the government covers all potential costs of the intervention. The benefits are computed as reductions in the local price (p) of maize, caused by higher productive efficiency from liming. Also, related increases in welfare (WF) on the maize market are calculated, as a measure for the induced change in well-being of both consumers and producers combined. This way, I attempt to provide valuable information as basis for government decisions on future support schemes to reduce poverty and food insecurity and to enable growth.[3]

The political importance of maize in Zambia stems from its status with both producers and consumers. Combined, over 1 mn smallholder households account for >92% of maize output in the agricultural season 2010-11 (CSO, 2016; Zambia Ministry of Agriculture, 2011). Maize supplies around 60% of caloric intake in Zambia, making it the dominant food crop (Mason and Myers, 2013). Sitko, Chamberlin, et al. (2017) states that the price of maize is considered an indicator of the effectiveness of the Zambian government. Sitko, Chamberlin, et al. (2017) illustrates this with food riots in 1986 after a spike in prices of maize meal, believed to have been caused by a discontinuation of maize subsidies. The riots

[2]This study, similar to Jayne and Rashid (2013), considers ISPs to subsidize only fertilizer and not lime.

[3]Cf. Collier and Dercon (2014) for a discussion on the role of smallholder agriculture in poverty reduction and economic growth policies.

led to a departure from austerity measures imposed by the IMF, which provoked a withdrawal of IMF funding the following year, succeeded by a crash of the Zambian economy, bringing nearly 30 years of single party rule to an end (Sitko, Chamberlin, et al., 2017).

With this in mind, I assume that the government wants to ensure the effectiveness of ISPs on the market for maize. To that end, it is important to understand the impact of soil acidity (measured in pH) on nutrient availability. Soil acidity between 5.0 and 8.0 allows the successful cultivation of maize, while the optimal range is 6.0 to 7.2 (Verheye, 2010a). The accessibility of important nutrients to plants declines with rising acidity, i.e. decreasing pH (Figure 2.1). Thus, nutrients added as fertilizers are more likely to be wasted the more acidic

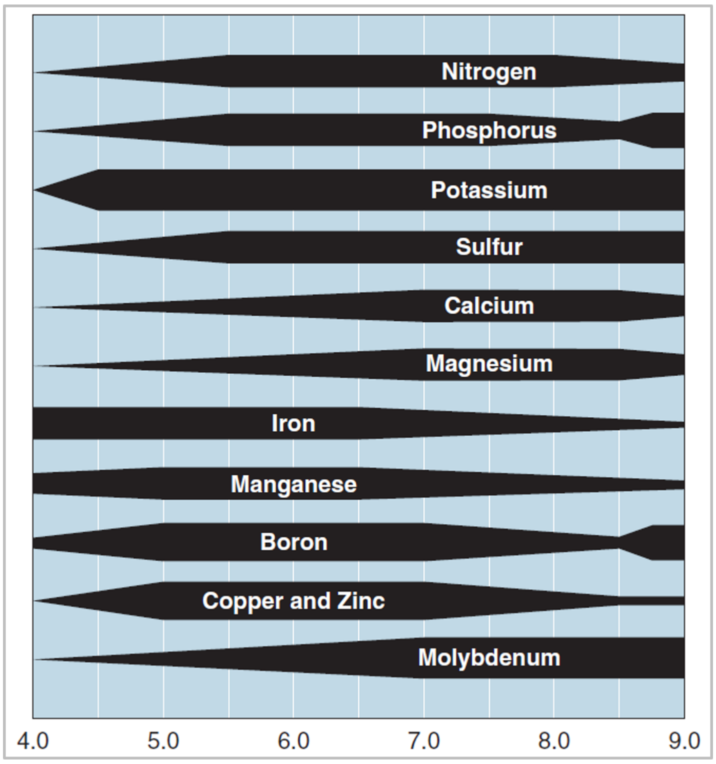

Figure 2.1.: Nutrient availability by soil pH (Fernández and Hoeft, 2017)

soils are. On extremely acidic soils (pH <4.5) up to 70% of fertilizer may be wasted, predominantly phosphate (Mosaic Company, 2017). It appears reasonable to prevent such waste, especially since no established alternatives for fertilizer from mined phosphate exist and global phosphate mining is concentrated among few producers (cf. Gilbert (2009)). At least two effects inhibit plants from accessing nutrients in acidic soils (Fageria and Baligar, 2008): first, nutrients react with aluminum or iron and become unusable to plants. Second, exchangeable and soluble aluminum and manganese increase with acidity. High concentrations of these are phytotoxic, curbing root growth.

Figure 2.2 shows that Zambian smallholders grow maize mostly on acidic soils. By the definitions above, 45% of the area of production is extremely acidic, 39% is deemed adequate for maize growing, but only 1% is in the optimal range of soil pH.

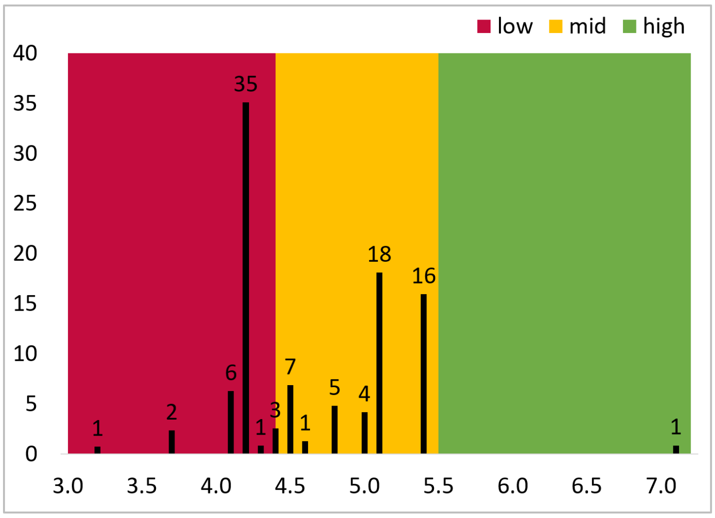

Figure 2.2.: Sample distribution by soil pH;
in percent of sample area;
data: Burke, Jayne, and Black (2016)

Burke, Jayne, and Black (2016), as well as already Burke (2012) more extensively, argue that the positive effect of liming on soil acidity is known to Zambian agronomists. The et al. (2006) examines the relationship of acidic tropical soils and maize cultivation based on experimental data, recommending liming alongside the use of acid soil-tolerant cultivars.

This chapter contributes to ongoing research into soil management for the benefit of agriculture in regions in development. For example, Nakhumwa and Hassan (2012) models dynamic decisions regarding general soil erosion for the smallholder maize market in Malawi, focusing on the supply side, disregarding consumer surplus and endogenous price effects. I extend the literature[4] with a country-wide model including market access costs and external trade. These

[4] e.g. Øygard (1986) develops a simple farm level model for liming decisions in Zambia.

extensions enable an overall economic view of a self-sufficient country with the capacity to produce for the global market.

The remainder of this chapter is organized as follows: Section 2.2 gives background information on the management of soil acidity and agricultural liming. Section 2.3 outlines an economic model for liming in the Zambian market for smallholder maize. Section 2.4 describes the data used in the model. Section 2.5 explains how the model is solved. Section 2.6 analyzes the outcomes of the model and Section 2.7 concludes and gives an outlook.

2.2. Management of Soil Acidity

Traditionally, Zambian smallholders coped with acidic soils, especially in the high rainfall northern areas of the country, via a shifting slash-and-burn cultivation, locally known as Chitemene (Mitchell, 2005; Shitumbanuma et al., 2015). In this approach, land is cleared from the natural bush vegetation, which is then dried and burnt, so the ashes can add nutrients to the soil they are worked into and raise its pH level (Mitchell, 2005; Shitumbanuma et al., 2015). The cleared area is cultivated for 4 to 5 years and then abandoned for 20 to 30 years to recover, but due to population growth and related pressure on food production, this traditional approach is no longer sustainable (Mitchell, 2005; Shitumbanuma et al., 2015). Smallholders moved on from Chitemene[5] to a mix of traditional and modern farming practices, where burning of fields before planting is still common (Mitchell, 2005; Umar et al., 2012; Conservation Farming Unit, 2011). Negative effects of the traditional burning of fields are the reduction in soil carbon stocks and emissions of this carbon into the atmosphere (CIAT and World Bank, 2017).[6]

The benefit of liming acidic soils include higher pH levels and better soil structure (Bolan et al., 2008). Both result in higher crop yields. Thus, liming is an alternative to traditional forms of acidity management and combined with fertilizer use may replace them. Apart from higher yields due to less acidic soils, a switch to liming could eliminate the practice of burning fields with its negative effects. Rengel (2003) describes potential harm from overliming, namely the chance of a deficiency in manganese and zinc at high pH levels. The reaction of lime with acidic soil also emits CO_2 (West and McBride, 2005). I

[5] In the agricultural season 2010-11, less than 1% of maize growing households prepared fields this way (CSO, 2016).

[6] Burning of grasslands makes up around 60% of greenhouse gas (GHG) emissions from agriculture in Zambia in 2012 (CIAT and World Bank, 2017).

focus on the conventional effect of agricultural liming: raising soil pH to improve the efficiency of agricultural production.

To simulate the benefit of liming it is necessary to quantify the relationship between the amount of applied lime and the increase in pH and that between pH and maize output. For the former relationship, I consider liming recommendations based on initial pH level, target pH level, and soil texture from Vossen (2016). Soil texture correlates with cation exchange capacity (CEC), which makes soils less sensitive to pH change and liming (Sishekanu et al., 2015). For the effect of lime on maize output, I use an empirically estimated yield function for smallholder maize in Zambia (Burke, Jayne, and Black, 2016), which depends on soil pH and reference soil groups (RSGs) of the Food and Agriculture Organization of the United Nations (FAO). Burke, Jayne, and Black (2016) aggregates RSGs by texture characteristics, which I map to the texture categories in Vossen (2016) (e.g. Arenosols grouped into "sandy and less developed soils" mapped to "sand and loamy sand").[7]

In this chapter, all lime is ground limestone (calcium carbonate, $CaCO_3$). Neither quicklime (CaO) nor hydrated lime ($Ca(OH)_2$) are considered given their prohibitively high production costs (West and McBride, 2005). Resources of carbonate rock, e.g. dolomite, suitable for agricultural lime production exist throughout Zambia, even in regions with acidic soils (Mitchell, 2005). This availability and the feasibility of setting up small-scale local lime production within farming districts allows nation-wide supply of lime (Mitchell, 2005). Lime is assumed to be fine ground (approx. 150 µm or 100 mesh), as deemed reasonable for local production (Mitchell, 2005). The large surface of fine lime guarantees quick reaction with soil.

This chapter considers not only elevating soil pH, but also maintaining it at the desired level. While nitrogen (N) fertilizer application may acidify soils, liming at a rate of 3.6 kg/kg of N fertilizer can neutralize the acidifying effect of the fertilizer (McLaughlin (2010), cf. Peters and Kelling (1998)).

[7] Solonetz, Fluvisols, Phaeozems, and Planosols are aggregated into "other soils". Uniformly neutral Solonetz (pH of 7.1 for all observations) needs no liming or mapping to a texture category and is considered independently. The latter three acidic RSGs are mapped to Vossen (2016) based on International Union of Soil Sciences Working Group WRB (2015) (see data appendix).

2.3. Model

The object of this analysis is the Zambian market for smallholder maize. If not otherwise qualified, all values refer to it.

The purpose of the analysis is to evaluate potential effects on WF from the adoption of agricultural liming in the Zambian market.[8] To focus on this market, a fundamental partial equilibrium model is used. Optimal input and output choices are quantified dependent on global prices ($g \in G$), liming investment scenarios ($s \in S$), and modeled period ($t \in T$).

Zambia has a history of frequent government interventions in the maize market (Sitko, Chamberlin, et al., 2017). I model tariffs, subsidies, and official recommendations on fertilizer rates as exogenous, constant government actions.

2.3.1. Perfect Competition

Many producers[9] and consumers, each with low individual capacities, trade a homogeneous good, maize, at a uniform price. Information on prices and capacities is transparent. No externalities exist. Production factors are mobile in the market. Due to these characteristics, perfect competition is assumed and profit maximization leads to a WF optimal outcome.

2.3.2. Trade

The model allows trade, while treating Zambia as a small country, i.e. price taker on the global market. Global prices ($g \in G$) are exogenous. Trade is costly because of transport and tariffs. It occurs if the absolute value of the difference between global price and a hypothetical Zambian equilibrium price in isolation (absence of trade) exceeds the costs of trade (Figure 2.3). The latter are exogenous, while the hypothetical local price in isolation is endogenous and depends on the local production functions. Liming affects these functions.

In the model, trade changes the effective local price, increases, and redistributes WF compared to isolation (Figure 2.3). WF is the integral under the active demand curve (D) and above the active supply curve (S).[10] It combines consumer

[8] I disregard distributional issues.
[9] Over 1 mn households grew maize in the agricultural season 2010-11 (CSO, 2016).
[10] Demand is modeled in Section 2.3.4. A supply curve is not explicitly formulated but rather a result of the optimization of producer surplus (Section 2.3.10).

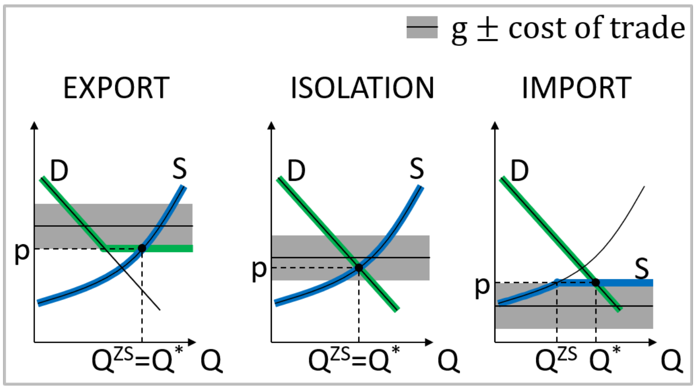

Figure 2.3.: Equilibria with costly trade;
active curves colored

surplus (CS) and producer surplus (PS). CS is the integral under D and above p, while PS is the integral under p and above S, i.e. the combined profit of all producers.

In both trade cases, compared to isolation, a larger equilibrium quantity increases WF. In the export case, the increase in PS exceeds the decrease in CS, while in the import case, CS increases more than PS decreases.

CS is generated by all local consumption regardless of origin of the consumed maize (import or local production). PS stems from all local production regardless of destination of the produced maize (export or local consumption). Other CS and PS on the world market are disregarded.

2.3.3. Dynamics

The model is dynamic and deterministic. It simulates the nature of liming with an investment phase in one year and a subsequent benefit phase of multiple years. It has an infinite time horizon divided into discrete one-year-periods (t). Markets are assumed to clear in each period.

The periods resemble the agricultural season of Zambia, starting with planting in October. Due to superior data availability (Section 2.4) the Zambian agricultural season of October 2010 through September 2011 is defined as reference for the initial model period (t_0) and used to measure the goodness of fit of the model (Section 2.6.1).[11]

[11]Among others, CSO (2016) provides valuable data for the reference season.

The model is evaluated in the first month of the reference season, October 2010. All future monetary values are discounted to this point in time with the real annual interest rate.[12] Parameters from the reference season remain constant over the modeled periods and can be interpreted as expected values. Production related costs occur in October, revenues and related costs in the following August.

An appropriate measure to evaluate WF in a multi-period-setting is the cumulative present value of WF, i.e. total WF (TWF). It sums current and all discounted future per period WF.

2.3.4. Demand

The local demand (Q^{DZ}) linearly dependent on p is given by:

$$Q_p^{DZ} = Q_{sat} + slope^{DZ} \cdot p \tag{2.1}$$

The slope of local (Zambian) demand ($slope^{DZ}$) stems from multiplying the price elasticity of demand (ε) with the ratio of the equilibrium quantity of the reference season (Q_{ref}) and the equilibrium price of the reference season (p_{ref}). The intercept is a parameter for the market saturation quantity (Q_{sat})[13].

With the local market modeled as a small country, demand from the global market (Q^{DG}) is perfectly elastic:

$$Q_{g,p}^{DG} = \begin{cases} \infty & if \quad g - c_{exporting} > p \\ 0 & if \quad g - c_{exporting} \leq p \end{cases} \tag{2.2}$$

Q^{DG} depends on p, g, and the constant cost of exporting ($c_{exporting}$).

The maximum of Q^{DG} and Q^{DZ} defines demand (Q^D), creating a kinked Q^D curve in case of exports (Figure 2.3). Since individual producers are price takers, Q^D is exogenous to their decisions.

[12] The interest rate, r, is used to form a discount factor $\frac{1}{(1+r)}$. For the parametrization of the interest rate see Section 2.4.

[13] $Q_{sat} = Q_{ref} - slope^{DZ} \cdot p_{ref}$

2.3.5. Producers

Individual, atomistic producers are distributed over a range of conditions of production, including soil texture and acidity, which influence their yield and cost functions (Sections 2.3.7 and 2.3.9 respectively). To limit computational complexity, atomistic producers with equal soil conditions are aggregated into a set of eight heterogeneous representative producers ($i \in I$) (Section 2.4.2). They maximize their expected profits by choosing their input and output quantities at a given price ($p \in P$). The producer surplus as the combined profit of all producers ($PS_{g,p,s,t}$) is the objective variable of the combined maximization problem of producers in each period (Section 2.5.1).

Producers have perfect knowledge and foresight of the market, so production is efficient.

2.3.6. In- and Outputs

Inputs are capital, labor, and land. Ratios of labor to land and of capital (excluding fertilizer) to land are fixed, thus labor and some capital are implicitly chosen while choosing how much land to employ, i.e. the share of area used ($x^{\alpha}_{i,g,p,s,t}$).

Fertilizers (two types: top dressing and basal (Section 2.4.2)) are capital inputs chosen independently from $x^{\alpha}_{i,g,p,s,t}$. Eligible smallholders receive subsidized fertilizer. Thus, producers can choose not only between both fertilizers, but, up to a limit, also between the subsidized and market versions thereof. The four elements of the vector of fertilizer rates ($\boldsymbol{x}^{f}_{i,g,p,s,t}$) stand for applied rates of both fertilizers bought each at full market prices and subsidized prices.

Producers face the additional choice of whom to sell their maize to. Produced quantities depend on the set of buyers (J), which includes on- and off-farm private domestic buyers, the Food Reserve Agency of the Zambian Government (FRA), and foreign buyers. The FRA buys maize from eligible smallholders at subsidized prices above the competitive market price and resells it at an increased competitive price later in the season. Given the FRA sells at a profit (Mason and Myers, 2013) and assuming an efficient process, this program redistributes WF from consumers to producers. Even though the FRA publishes neither prices nor quantities at planting time, the deterministic nature of the model assumes that producers form adequate believes about them. Also, prices have maintained stable over seasons. Quantities sold to the different buyers are the four elements of the vector of quantities of maize sold to different buyers ($\boldsymbol{x}^q_{i,g,p,s,t}$).

In summary, each i maximizes his profit with respect to nine decision variables, categorized into three groups: $x^{\alpha}_{i,g,p,s,t}$, $\boldsymbol{x}^f_{i,g,p,s,t}$, and $\boldsymbol{x}^q_{i,g,p,s,t}$.

All decision variables are non-negative and all but the quantity of exported maize are parametrically bounded above. Exports are bounded above only by production constraints (Equation 2.7).

$$0 \leq x^{\alpha}_{i,g,p,s,t} \leq 1 \tag{2.3}$$

$$0 \leq \boldsymbol{x}^f_{i,g,p,s,t} \leq \bar{\boldsymbol{x}}^f \tag{2.4}$$

$$0 \leq \boldsymbol{x}^q_{i,g,p,s,t} \leq \bar{\boldsymbol{x}}^q_i \tag{2.5}$$

Usage of area is assumed to be limited at its level in the reference period (Equation 2.3). Arable land is unlikely to be a limiting factor for production capacity in Zambia (cf. Export.gov (2017)). Given low mechanization, not land itself, but rather the supply of capital to cultivate it limits production. Yet, due to data availability, cultivated land is used as a proxy for the exogenous limit of this input.

Reference period subsidy levels limit the application of subsidized fertilizer and the government recommendation on total fertilizer rates sets an upper bound on the application of each fertilizer bought at full price (Equation 2.4). Government recommendations on fertilizer rates (200 kg/ha (Mason, Jayne, and Mofya-Mukuka, 2013)) cater to the need of maize plants for a balanced nutrient supply.[14]

Equation 2.5 institutes bounds for sold quantities. The total quantity sold to the FRA may not exceed its reference level, allocated to producers weighted by area (their share of planted area in the reference season). On-farm sales, which include own consumption, are limited at the area weighted difference of total

[14] cf. also Donovan et al. (2002) and Saïdou et al. (2018)

production and sales to the FRA in the reference season. Off-farm sales have to be smaller than or equal to Q_{sat}.

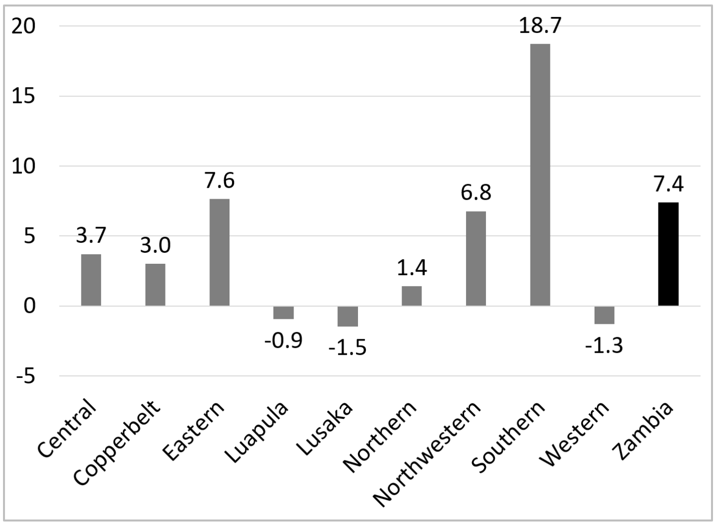

Figure 2.4.: Average difference of fertilizer rates, district data weighted with area planted to maize;
in percent of top dressing rate;
data: CSO (2016) for 2010-11

As recommended, both fertilizers have similar application rates in the reference period (Figure 2.4). The recommendations limit producers' input choices. In the model, they restrict divergence of fertilizer rates to a 15% range:

$$\sum_{\kappa=1}^{|K|} x^f_{i,g,p,s,t,\phi,\kappa} \leq \sum_{\kappa=1}^{|K|} x^f_{i,g,p,s,t,\psi,\kappa} \cdot (1 + \mathit{range}) \tag{2.6}$$

$$s.t.\ \psi, \phi \in \{\mathit{basal}, \mathit{top\ dressing}\};\ \psi \neq \phi$$
$$\kappa \in K = \{\mathit{subsidized}, \mathit{full\ price}\}$$

Equations 2.3 to 2.6 are linear and monotonic.

2.3.7. Production

A producer's production may not fall short of the sum of his sales to all buyers. This constraints production (Equation 2.7) in a market wide profit maximization (Equation 2.9). Increased fertilizer use shows diminishing returns (Burke, Jayne, and Black, 2016). Hence, the yield function (parenthesis in Equation 2.7) is concave and quadratic. It consists of the fertilizer variables, the coefficient matrix of the quadratic terms ($\boldsymbol{A}$), the producer specific coefficient vector of the linear terms ($\boldsymbol{\beta}_{i,s,t}$), and a producer specific yield shifter ($\boldsymbol{\gamma}_{i,s,t}$)[15]. Multiplying the yield function with $x^{\alpha}_{i,g,p,s,t}$ and the constant individual area of a producer (a_i) completes the quasiconcave, cubic production function (RHS of Equation 2.7), which describes the hypograph above zero of the yield function. The constraints are multiplicative concave and monotonic on the domain set by the bounds.

$$\sum_{j=1}^{|J|} x^{q}_{i,g,p,s,t,j} \leq \left(\frac{1}{2}\boldsymbol{x}^{f}_{i,g,p,s,t}{}^{T}\boldsymbol{A}\boldsymbol{x}^{f}_{i,g,p,s,t}+\boldsymbol{\beta}_{i,s,t}{}^{T}\boldsymbol{x}^{f}_{i,g,p,s,t}+\boldsymbol{\gamma}_{i,s,t}\right)\cdot x^{\alpha}_{i,g,p,s,t}\cdot a_i \quad (2.7)$$

2.3.8. Lime

Lime is an additional input. After producers apply it, lime improves their production functions for future periods. By assumption, producers are unaware of this and learning about the benefits of liming is prohibitively expensive for them.[16] Therefore, they disregard lime as an input. Considering lime in this way maintains the outcome established above (Section 2.3.1). Yet, the outcome is no longer necessarily WF optimal, if an exogenous intervention can introduce universal knowledge on liming. If investments in liming lead to net-increases in WF, the introduction of this technology is socially desirable.

In t_0, producers in the lower two pH groups (Figure 2.2) make a one-time, discrete choice whether to ascend to one of the higher two groups via liming.[17] In all following periods, they belong to their group of choice with a correspondingly higher yield curve, due to higher $\boldsymbol{\beta}_{i,s,t}$ and $\boldsymbol{\gamma}_{i,s,t}$ (Equation 2.7).[18]

The decision to lime is costly. I consider two forms of liming: initial and ongoing. Initial liming is a single application of lime to raise soil pH to the desired level. It causes sunk, positive investment ($invest_{i,s,t}$) for a_i in t_0.[19] Since

[15] $\boldsymbol{\gamma}_{i,s,t}$ groups characteristics of the yield function of Burke, Jayne, and Black (2016) that are not interacted with fertilizer rates or pH. It contains, among others, information on soil groups, weather, and tillage techniques.

[16] This is based on the survey data from Mitchell (2005) and the anecdote in Burke, Jayne, and Black (2016).

[17] Producers with neutral soils do not suffer from acidity and hence do not lime.

[18] Meyer and Volk (1952) mentions large applications of lime (>7 t/ha) to acidic soils raising pH levels above the thresholds of Burke, Jayne, and Black (2016). These applications raise pH considerably even within the first months, before reaching final pH levels (cf. also Peters and Kelling (1998) for finely ground lime).

[19] In addition to a_i, an area equivalent to a fraction of a_i is kept fallow every period. This fraction of a_i receives the initial liming in the second model period (t_1).

the application of N fertilizer acidifies soils, ongoing soil management is necessary to maintain the pH level of the soil.[20] Comparable to traditional practices, which offer a certain stability at the initial pH level, ongoing liming maintains the elevated pH levels without having to move to new fields. By assumption, producers who are convinced of the benefits of liming and invest in an initial application, will continue to manage soil acidity with lime rather than traditional practices. Thus, on initially limed soils, costly ongoing liming takes place in all following periods, slightly increasing the variable cost of applying N fertilizer.

2.3.9. Cost Functions

Equation 2.8 describes the total costs ($c_{i,g,p,s,t}$) of producers, including $invest_{i,s,t}$, the cost coefficient for used area (c_i^a), the cost coefficient vector for fertilizers ($\boldsymbol{c}_{i,s,t}^f$), and the cost coefficient vector for sold quantities ($\boldsymbol{c}_i^q$):

$$\begin{aligned} c_{i,g,p,s,t}(x_{i,g,p,s,t}^{\alpha}, \boldsymbol{x}_{i,g,p,s,t}^{f}, \boldsymbol{x}_{i,g,p,s,t}^{q}) = x_{i,g,p,s,t}^{\alpha} \cdot a_i \cdot \left({\boldsymbol{c}_{i,s,t}^{f}}^T \boldsymbol{x}_{i,g,p,s,t}^{f} + c_i^a \right) \\ + \boldsymbol{c}_i^{qT} \boldsymbol{x}_{i,g,p,s,t}^{q} + invest_{i,s,t} \end{aligned} \tag{2.8}$$

$c_{i,g,p,s,t}$ includes both planting time expenses and marketing expenses discounted to the beginning of the planting season.

Costs of lime for maintenance and its transport elevate $\boldsymbol{c}_{i,s,t}^f$ from t_1 onwards. Potential cost reductions in c_i^a from discontinuing traditional management of soil acidity are assumed to be negligible and offset by the similarly negligible cost of applying lime during field preparation.

The functions are monotonic and bilinear, since producers consider quantities of fertilizers, determined by the product of $\boldsymbol{x}_{i,g,p,s,t}^f$ and $x_{i,g,p,s,t}^{\alpha}$.

[20] I disregard acidification from crop extraction and rain leaching. The former is economically insignificant, demanding liming at approx. 2.4 kg/t of maize harvested, (own calculation based on Pierre and Banwart (1973)). Price changes for maize would be <0.1%. Rain leaching is ignored, since soil exposed to pure rain (pH = 5.67) gravitates to a pH of 5.2 in the long term (Robson, 1989). Most Zambian soils would benefit from this. Yet, rain may be acidic in industrial areas, e.g. in Copperbelt Province (pH = 4.7 in Kitwe) (Tidblad et al., 2007).

2.3.10. Objective Function

$PS_{g,p,s,t} : \mathbb{R}_{+}^{72} \rightarrow \mathbb{R}_{+}$ takes individual profits as the difference of individual revenues ($rev_{i,g,p,s,t}$) and $c_{i,g,p,s,t}$ and sums them over I. The dot products of the price vector for sold quantities ($\boldsymbol{p}^q$) and of $\boldsymbol{x}^q_{i,g,p,s,t}$ defines $rev_{i,g,p,s,t}$ as linear functions.

$$PS_{g,p,s,t} = \sum_{i=1}^{|I|} \boldsymbol{p}^{qT} \boldsymbol{x}^q_{i,g,p,s,t} - c_{i,g,p,s,t} \tag{2.9}$$

Equation 2.9 is monotonic and bilinear due to $c_{i,g,p,s,t}$.[21]

2.3.11. Local Demand Constraint

The sum of supply from all local producers to all local buyers (Q^{SZ2Z}) may not exceed Q^{DZ}.

$$\sum_{i=1}^{|I|} \sum_{j=1}^{|J|} x^q_{i,g,p,s,t,j} - Q^{DZ}_p \leq 0 \tag{2.10}$$

$$s.t. \; j \neq export$$

In case of imports, slack in this constraint equals the import quantity. The constraint is linear and monotonic.

2.3.12. Liquidity Constraints

Producers' limited budgets create liquidity constraints (Equation 2.11). Costs cannot exceed respective budgets, i.e. liquidity ($l_{i,g,p,s,t}$). The parameter for initial liquidity in t_0 ($l_{i,g,p,s,0}$) grows with retained profits in each period.

$$c_{i,g,p,s,t} - l_{i,g,p,s,t} \leq 0 \tag{2.11}$$

These constraints are monotonic and bilinear due to $c_{i,g,p,s,t}$.

[21] Fixed investment costs are not stated, since they are only relevant for the optimization in the liquidity constraint (Equation 2.11), not in the objective function.

2.3.13. Interventions for Lime

Under these circumstances, the government can increase TWF via liming in two steps: First, it can intervene by making producers aware of the benefits of liming. With such updated information, producers will maximize their profits by choosing adequate investment levels for lime. Before investments take place and after assessing if individual profit maximizing investments are TWF optimal, the government may intervene a second time to guarantee TWF optimal investments (e.g. by manipulating costs of lime).

To quantify the TWF impact of these interventions, I consider two states of the model: The first state is a baseline before the interventions, where no producer has knowledge on liming and acquiring this knowledge is prohibitively costly, so no one limes in the TWF optimum. The second state is a counterfactual, where the government has eliminated the cost of knowledge on liming with an educational and soil testing campaign, so every producer chooses an adequate investment in liming. In both states TWF is computed. The WF potential of liming is the difference between the TWF of a counterfactual with TWF optimal liming and TWF of the baseline without liming.

It is possible that the counterfactual liming investments as chosen by the producers are not TWF optimal, i.e. they are not incentive compatible with the social optimum, requiring the second government intervention. Incentive compatibility is tested by comparing the benefit of each i ($\mathrm{TPS_i}$) in the TWF optimum with the respective $\mathrm{TPS_i}$ when i's investment deviates from the TWF optimal investment. $\mathrm{TPS_i}$ is defined by the individual cumulative present value of PS, i.e. total PS (TPS). When $\mathrm{TPS_i}$ is highest in the TWF optimum for each i, then individual profit maximizing investment choices are incentive compatible with the social optimum and the TWF optimum is an equilibrium.

2.4. Data

Data used in the model is collected from various sources. This section introduces the principal sources.

All monetary values are denominated in October 2010 US dollars (USD). If necessary, original monetary data are inflated, deflated and converted accordingly.[22] Exogenous data are constant over time. The real annual interest rate is r = 23.57% p.a.[23]

2.4.1. Equilibrium

The reference market equilibrium is at Q_{ref} of 2.718 mn t (CSO, 2016) and p_{ref} of 189.42 USD/t (used for Q_{sat}, Equation 2.1). This price is a season average of monthly retail prices of all Zambian provincial capitals (Famine Early Warning System Network, 2012), weighted with the populations of the provinces (CSO, 2012).

In the reference season, the FRA purchased 1.752 mn t (Mason, Jayne, and Myers, 2015) (64%) of all smallholder maize production (CSO, 2016) (Equation 2.5) at an above market price of 263 USD/t (Mason, Jayne, and Myers (2015) converted to USD) (Equation 2.9).

By assumption, the own price elasticity of demand for maize in Zambia ($slope^{DZ}$, Equation 2.1) equals the respective elasticity in South Africa (average from elasticity of demand for food and feed) at -0.19. Maize is the dominant staple crop in both of these southern African countries (Mason and Myers, 2013; Gouse et al., 2005).

2.4.2. Production

Burke, Jayne, and Black (2016) provides a set of panel data with a range of conditions of production and estimation coefficients for a yield function of smallholder maize in Zambia. Among others, conditions of production depend on soil texture and acidity. Individual, atomistic producers are distributed over this range of conditions of production. This study includes five categories of soil texture: clay loam, sand and loamy sand, muck, sandy loam, and Solonetz. The

[22] For exchange rates see Bank of Zambia (2015), for US inflation see Organisation for Economic Co-operation and Development (OECD) (2017), and for Zambian inflation see World Bank (2016b).

[23] r is based on the nominal interest rate of 30% p.a. as experienced by Zambian smallholders (Haggblade, Kabwe, and Plerhoples, 2011) and the Zambian 2011 inflation rate of 6.43% p.a. (World Bank, 2016b). Future periods ignore inflation, i.e. all future values are in October 2010 USD. Since future values are mainly used to generate cumulative present values, inaccuracies caused by the neglect of inflation are assumed to be minimal. The neglect may cause problems if inflation rates for goods in the model vary significantly.

latter is neutral and therefore irrelevant for deacidifying liming investments.[24] Soil acidity is defined by initial pH levels and clustered into three groups: low, mid, and high pH with thresholds at 4.4 and 5.5 (Figure 2.2) (cf. Burke, Jayne, and Black (2016)). I add the soil texture dimension to the distribution over initial pH levels as depicted in Figure 2.2 and sum area shares within the three soil acidity groups for the distribution in Table 2.1. This results in eight soil types, i.e. unique combinations of textures and initial pH groups. Representative producers ($i \in I$) originate from these soil types.

Table 2.1.: Share of area by soil texture and pH;
in percent;
data: based on Burke, Jayne, and Black (2016)

	low	mid	high
clay loam	41.9	26.3	-
loamy sand	1.5	21.2	-
muck	1.7	6.1	-
sandy loam	0.6	-	-
Solonetz	-	-	0.8

I model the production of one good, maize. Even though, crop rotation and intercropping (in part with N fixing plants) is widespread in Zambia, I consider these as separate economic activities outside the scope of this model.[25] A 20% share of fallow agricultural land is assumed (Burke, Frossard, et al., 2016) (cf. initial liming in t_1, Section 2.3.8).

The data set of Burke, Jayne, and Black (2016) is adapted for this chapter by dropping all observations with missing field size or soil characteristics (soil group and RSG[26]), retaining $6,330$ of initially $7,131$ observations. To update the yield function to the reference season, I maintain the constant, coefficients, and time invariant variables of the estimated function and update its time

[24] High clay content of Solonetz (International Union of Soil Sciences Working Group WRB, 2015) also guarantees a certain robustness against acidifying N fertilizer.

[25] In Burke, Jayne, and Black (2016) only 0.8% of fields were used for N fixing crops in the preceding year and only 3.6% were intercropped with them in the current year. Also in the sample used in Namonje-Kapembwa, Black, and Jayne (2015) only 2.3% of fields are intercropped, but the authors mention intercropping was a common practice in Zambia. Other sources indicate high adoption rates of crop rotation in Zambia, cf. Manda et al. (2016) for Eastern Province (77% of their sample) and Mason, Jayne, and Mofya-Mukuka (2013) states 62% for 2010-11 and/or 2009-10 based on data from the 2012 Rural Agricultural Livelihood Survey (RALS).

[26] cf. International Union of Soil Sciences Working Group WRB (2015)

variant variables with averages from the literature for the reference season (mostly Namonje-Kapembwa, Black, and Jayne (2015) and CSO (2016)).[27]

To create a production function (Equation 2.7) from the yield function, the latter is scaled with a capacity variable representing area.

The production function considers two types of inputs: area (including capital and labor for its cultivation) and fertilizers.

Area is total area used for maize in the reference season, 1.33 mn ha (CSO, 2016). It is allocated to producers by their share of area in the sample of Burke, Jayne, and Black (2016).

The fertilizers in the model, which also represent nearly all fertilizer used by Zambian smallholders are: Compound D (NPK fertilizer applied as basal at planting time, with a 10-20-10 percentage mix of N, phosphate, and potassium) and urea (N fertilizer applied after planting as top dressing, with a 46-0-0 mix) (Burke, Frossard, et al., 2016).

An additional input is lime, which can shift the production function upwards. Liming requirements per producer show the necessary quantity of lime to rise into a higher pH group. They are based on pH change as quadratic functions of liming for each texture group. The functions are fitted through the respective discrete recommendations in Vossen (2016). The assumption of a quadratic relationship between liming rates and soil pH is based on diminishing returns of liming as stated and illustrated for present-day Zimbabwe in Grant (1970). It is further supported by a statistically significant quadratic effect of liming rates on soil pH for Brazilian oxisols (Fageria and Baligar, 2008).

2.4.3. Cost

Adding exogenous cost data (predominantly Burke, Hichaambwa, et al. (2011)) allows the formulation of a cost function (Equation 2.8) for a profit maximization problem subject to exogenous output prices.

Transport costs vary by producer, based on average distances to the nearest district town in the sample of Burke, Jayne, and Black (2016), and distance to the nearest private fertilizer sales point (Chapoto and Jayne, 2011). For outputs, they also vary based on buyers (cf. Chapoto and Jayne (2011)). Transport of lime is considered to be between farms and the nearest district town.

[27] Interaction terms are products of averages.

There is no direct cost of land, because most Zambian farmers are granted free use of land by traditional local authorities (Burke, Hichaambwa, et al., 2011). Hence, modeled costs of area are rather costs for cultivating that area, exclusive of fertilizer and lime. They include costs of labor, animals, and machines, each hired and owned, and costs of seeds and pesticides (Burke, Hichaambwa, et al., 2011).[28] They amount to 216 USD/ha, based on Burke, Hichaambwa, et al. (2011).

Fertilizer prices at sales points of 578 USD/t for basal and 555 USD/t for top dressing are averages based on Thapa and Keyser (2012) weighted by provincial fertilizer use (CSO, 2016). Some fertilizer is subsidized, predominantly via the Farmer Input Support Programme (FISP) at 209 USD/t for each: basal and top dressing (Mason, Jayne, and Mofya-Mukuka, 2013).[29] The average price of lime at sales points is 20 USD/t, based on Mitchell (2005).

Producers' budgets set an upper limit to costs (Equation 2.11). They are based on the financial share (Davies, Lluberas, and Shorrocks, 2012) of median wealth per adult (>19 years old) in Zambia (Shorrocks, Davies, and Lluberas, 2010). This per adult wealth leads to average rural household wealth when multiplied with the rural population share of adults and average rural household size (CSO, 2012). Finally, multiplying the household wealth by total maize producers (CSO, 2016) and weighting this with the share of households per producer in the sample based on Burke, Jayne, and Black (2016) yields producers' budgets.

2.4.4. Trade and Taxes

Trade is modeled between Zambia and global commodities markets (Equation 2.2). In the status quo, Zambian maize exports generally stem from large scale farmers (Export.gov, 2017). These were projected to produce 0.233 mn t of maize in the reference season (Zambia Ministry of Agriculture, 2011). Exports in the reference season reach 0.358 mn t at an average free on

[28] Costs for machines are subdivided into fuel and other cost using Conservation Farming Unit (2011) and ERB (2017).

[29] I exclude subsidies of the Food Security Pack Programme (FSP), which may include 100 kg of lime in areas with acidic soils, due to the limited scope of the program (approx. 15,400 recipients in 2010-11) (Mason, Jayne, and Mofya-Mukuka, 2013).

board (f.o.b.) value of 379.35 USD/t (Figure 2.5), while imports at 305 t are negligible (United Nations Statistics Division, 2016).[30, 31]

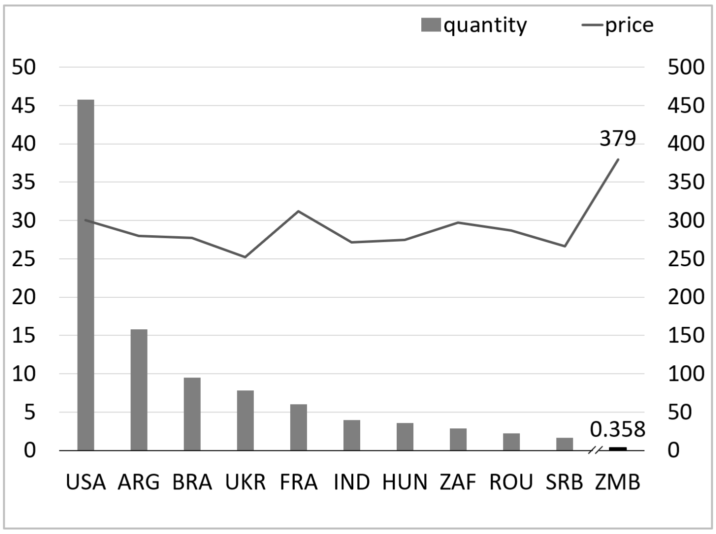

Figure 2.5.: Maize export quantities and average f.o.b. prices of top 10 exporters 2011 and Zambia;
in mn t, 2011 USD/t;
data: United Nations Statistics Division (2016)

Due to the dominance of US exports (Figure 2.5)[32], global maize prices used for the counterfactual scenarios (Section 2.6.3) are based on the range of US Gulf f.o.b. export prices (Figure 2.6). They are modeled as constant over periods. Comparing them with prices of Zambian maize f.o.b. in the port of Dar es Salaam, decides whether exports are profitable. Transport is considered to be by truck rather than by train, because of the "poor state of rail infrastructure" in Zambia (ERB, 2010). Export costs, including all transport costs and port charges, amount to 180 USD/t based on Teravaninthorn and Raballand (2009) and Tanzania Ports Authority (2012). Comparing global delivered duty paid (d.d.p.) prices in Lusaka with prices of Zambian maize, decides whether imports are profitable. Imports are assumed to enter from South Africa and import costs include all transport costs, amounting to 140 USD/t (Nkonde

[30]Food and Agriculture Oranization of the United Nations (2017) shows higher exports of 0.496 mn t at a nearly identical average value of 379.09 USD/t based on production forecasts from Zambia Ministry of Agriculture (2011).

[31]In the reference season, an export ban on maize bran was imposed (Sitko, Chamberlin, et al., 2017).

[32]The ten largest exporters combined accounted for over 90% of global maize exports by quantity in 2011, but the US is the most dominant.

et al., 2011), and import duty. Maize incurs 15% import duty, but no export duty, excise tax, or VAT (Zambia Revenue Authority, 2014).

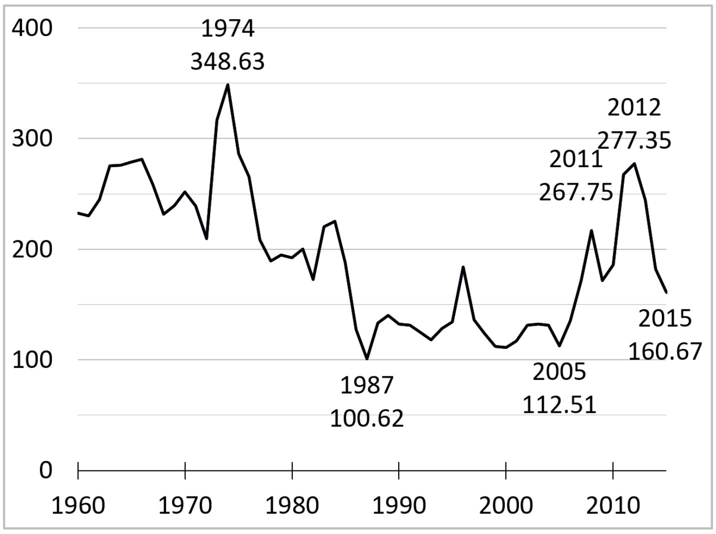

Figure 2.6.: Global price of maize over time, based on annual US Gulf price f.o.b.; in 2010 USD/t;
data: World Bank (2016a)

2.5. Solution

The model is set up in three layers of mathematical problems: core problem (Section 2.5.1), intermediate problem (Section 2.5.2), and enclosing problem (Section 2.5.3).[33]

The core problem is the profit maximization of producers. It uses exogenous inputs for G, P, S, and T, where $g \in G$, $p \in P$, $s \in S$, and $t \in T$. Outputs are used to calculate WF.

The intermediate problem adds an equilibrium constraint to the core problem, endogenizing p. This is achieved via a binding local demand constraint (Equation 2.10). Solving this problem returns a subset of the solutions of the core problem, consisting of equilibria dependent on g, s, and t. In each step of its iterative solution approach, the core problem is solved.

[33] The model is implemented in the Python programming language, version 3.6.3 (Rossum, 2017). Essential Python packages for the implementation are pandas 0.23.3 (McKinney et al., 2018), NumPy 1.14.5 (Oliphant, 2018), and Pyomo 5.5.0 (Hart et al., 2017).

The enclosing mixed-integer problem (MIP) describes the decision on discrete liming investment. For each s it solves the intermediate problem for all t and computes respective TWF. On this basis, the TWF optimal s is selected for all $g \in G$.

Subsequently (Section 2.5.4), the incentive compatibility of each s is tested by comparing each $\mathrm{TPS_i}$ associated with s with the respective $\mathrm{TPS_i}$ under liming investments of i that deviate from s. This is repeated for all $g \in G$.

At the prevailing real interest rate, model results of the first 20 periods matter for the analysis.[34]

2.5.1. Core Problem

The core problem is monotonic, since all constraints (Equations 2.3 to 2.7, 2.10 and 2.11) and the objective function (Equation 2.9) are monotonic. Because of the constraints, it is also bounded on a non-negative domain. In addition, Equations 2.3 to 2.6 and 2.10 are linear, Equation 2.7 is cubic and quasiconcave, and Equation 2.9 is bilinear. Therefore, the core problem is a non-convex, bounded, monotonic, cubicly constrained bilinear program (cf. Tuy (2000)). Also, the objective function (Equation 2.9) and the cubic production constraints (Equation 2.7) are multiplicative concave (cf. Konno and Kuno (1995)).[35]

Besides the optimal values for decision and objective variables, outputs of the core problem are CS and WF.

2.5.2. Intermediate Problem

The purpose of the intermediate problem is to find a hypothetical short term market equilibrium without trade, consisting of a price and the corresponding quantity. A binding local demand constraint (Equation 2.10) in the core problem characterizes the equilibrium. Whereas in the core problem, p is exogenous, in the intermediate problem, it is not. A bisection algorithm is applied to potential ps. In each iteration of the bisection the core problem is solved with a different p, decreasing the slack variable of the local demand constraint. To ensure isolation, g is continuously set equal to p. The resulting price gap of zero cannot exceed positive costs of trade. When the slack variable is close enough to zero, the

[34]Present values of the last model period (t_{19}) are $<2\%$ of their future values.
[35]The core problem is solved using Ipopt, version 3.12.4 (Wächter and Biegler, 2006).

constraint is considered binding and the algorithm stops. The instance of the core problem solved in the last bisection iteration returns the equilibrium.

To evaluate trade opportunities later on, the core problem can be solved with an independent g and p from the established hypothetical equilibrium in isolation.

2.5.3. Enclosing Problem

Each of the 648 viable permutations of producers' choices of pH groups is considered a liming scenario. Scenarios are ordered by area in higher pH groups, thus in $s = 0$ no one limes, while in $s = 647$ all producers lime enough to reach the high pH group (cf. Figure A.1).

The MIP is solved by applying the intermediate problem to find the market equilibria of all s for all t and calculating respective TWF. Then, the TWF maximizing s is selected for all $g \in G$.

2.5.4. Incentive Compatibility

Since in the enclosing problem (Section 2.5.3) the TWF maximizing liming scenarios are selected and are not the immediate results of the profit maximization of producers, it is necessary to check whether these results are compatible with producers' incentives. Therefore, the incentive compatibility of each investment scenario is tested: For each i, regular $\mathrm{TPS_i}$ (all producers invest according to s) is compared to the respective $\mathrm{TPS_i}$ resulting from i deviating from s in his investment.

The deviation $\mathrm{TPS_i}$ is calculated by solving the core problem (Section 2.5.1) for all periods with i as only producer. In this calculation, to model i as atomistic price taker, p is maintained fixed at its values from the regular solution and the local demand constraint (Equation 2.10) is dropped. This is repeated for all possible deviations of i and all $s \in S$, selecting the maximum $\mathrm{TPS_i}$ for each s.

If lime investments at maximal $\mathrm{TPS_i}$ deviate from s, s is unstable and the scenario resulting from the deviation is tested. Repeating these steps, the model either converges to a stable investment scenario, i.e. an incentive compatible equilibrium (that can differ from the TWF optimum), or it oscillates between scenarios, i.e. it remains in a disequilibrium.

This is repeated for all $g \in G$.

2.6. Results

After an assessment of the goodness of fit of the model (Section 2.6.1), the model is used for a comparative analysis between a baseline (Section 2.6.2) and counterfactual scenarios (Section 2.6.3). The baseline considers neither trade nor liming, whereas the counterfactuals consider both. The goal is to quantify the WF effect of the government introducing knowledge about the benefits of liming into the market and potentially in a second step of it guaranteeing WF optimal investments in liming. Table A.1 shows the absolute values of the model results. Section 2.6.4 presents sensitivity analyses on producers' budgets, fertilizer prices, transport costs of lime, and interest rates.

2.6.1. Goodness of Fit

I test the goodness of fit of the cumulative production function and of the entire model. To test the fit of the production function, I compare the sum of the outputs of all production functions without liming with the 2.718 mn t of maize produced by Zambian smallholders in the reference period (CSO, 2016). Parameters and decision variables (shares of available areas used and fertilizer rates) of the production functions are fixed at their averages for the reference period. This shows that the output of the cumulative production function at 2.651 mn t is only 2.45% below the reference value (Figure 2.7).

To assess the goodness of fit of the entire model, I solve the intermediate problem (Section 2.5.2), which contains various instances of the core problem (Section 2.5.1), without liming investments (scenario 0). Different from the testing of the production function, here, all decision variables are endogenous and prices matter. The resulting input and output quantities (Table A.1, column: baseline) are compared with those of the reference year (Figure 2.7).

The modeled market equilibrium is at a price of 203.12 USD/t and a produced quantity of 2.680 mn t. The baseline price exceeds the reference of 189.42 USD/t by 7.2%. Quantity falls short of the reference by 1.4%. No maize is exported at a global price of 268 USD/t (World Bank, 2016a). At the given costs of trade, the market will be isolated at global prices on the interval from the historical low of 100 USD/t up to 382 USD/t (Figure 2.6). In the reference season, exports exceeded projected production from large scale producers by 0.125 mn t at an average export value of 379.35 USD/t (Section 2.4.4). Most of

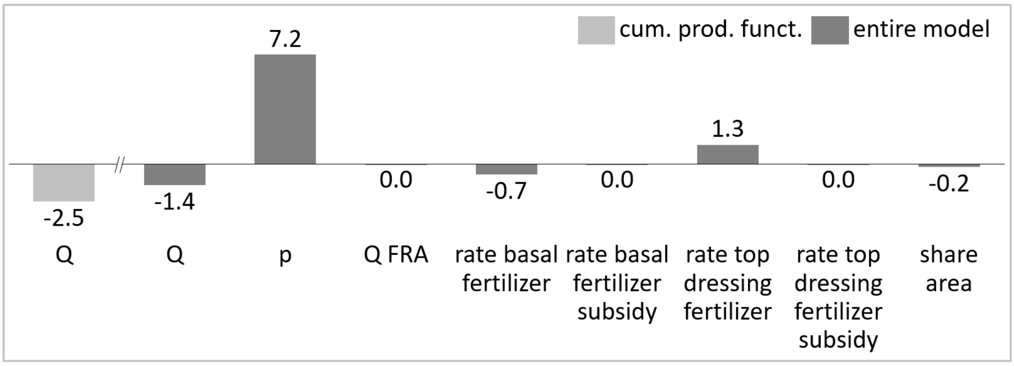

Figure 2.7.: Goodness of fit of production function and entire model via difference between model results and values of reference season; in percent of reference values

this moderate export quantity went to neighboring Zimbabwe (United Nations Statistics Division, 2016) and for the purpose of this analysis, is not considered participation in the global maize market.

At a subsidized price of 263 USD/t[36], selling maize to the FRA is profitable even at high global prices. In all model runs (Table A.1), the largest possible amount of 1.752 mn t is sold to the FRA, equaling the reference value.

Rates of subsidized fertilizers match the average rates of the reference year at 41 kg/ha. The overall rates of basal and top dressing fertilizer of 80 and 89 kg/ha respectively resemble the reference values of 80 and 87 kg/ha. Also, the preference for top dressing fertilizer is matched, reflecting the limited impact of phosphate fertilizer on acidic soils. The difference between subsidized and overall rates is bought at market prices. At 99.8%, practically all area is employed, where the reference value is 100%.

2.6.2. Baseline

In addition to the goodness of fit assessment, the baseline offers the following information: Due to the absence of liming in the baseline, producers' acidity levels remain constant over all periods and equal to those of the sample data. The sector-wide share of soils with high, medium, and low pH is 0.8%, 53.6%, and 45.6% respectively. Since additionally, the liquidity constraints are non-binding, all periods are equal.

[36] 65,000 ZMK/50kg (Mason, Jayne, and Myers, 2015)

With this input combination, producers reach an average yield for maize of 2.02 t/ha and an average PS per area of 105.25 USD/ha.

In each period, CS of 1,212.4 mn USD and PS of 139.6 mn USD add up to WF of 1,351.9 mn USD. Thus, TWF amounts to 6,984.9 mn USD. The TPS is 721.1 mn USD and cumulative present value of CS, i.e. total CS (TCS) is 6,263.7 mn USD. The low ratio of PS to WF stems from the elastic supply and relatively inelastic demand of the industry. This is plausible for a staple food like maize.

2.6.3. Counterfactuals

The counterfactual analysis shows that imports are unprofitable at any historical global price (Figure 2.6), i.e. ≥100 USD/t. It also shows that with optimized liming, exports become lucrative at around 340 USD/t, which is expensive in the historical context and above the average prices of large exporters in 2011 (Figure 2.5).

Below, I describe the counterfactual results for two trade cases: first, isolation caused by global prices assumed to be on the interval 100 to 340 USD/t and second, an export case with the global price assumed to be at the historical peak-price of 350 USD/t. The latter is of interest to show the impact of exports. Yet, it should be seen as an unlikely event, since historically, a price of 350 USD/t was an exception. Differences between outputs of the two cases single out the effect of trade at that price after liming is adopted.

In both trade cases, before liming takes effect in t_1, acidity levels are the same as in the baseline. With investment in liming, they rise and production functions improve from t_0 to t_1. In the export case it is TWF optimal to lime all soils, so from t_1 onwards, high pH soils make up 100.0% of the available area (optimal scenario: 647). In isolation (optimal scenario: 414), high pH soils make up 50.4% of the available area. Neither low pH clay loam, nor muck soils (no matter their initial acidity) are limed beyond a medium pH and account for the remaining 49.6% medium pH soils. Low pH soils exist in neither trade case. These pH changes are achieved by a total average liming rate in t_0 of 4.17 t/ha for the export case and of 1.51 t/ha in isolation.

For some producers, this investment exhausts budgets, which are replenished over time with cumulative profits. Without trade, budget constraints bind only in t_0 and t_1, thus all following periods are identical. In the export case, more is invested into liming and exports require higher levels of production inputs, so, budget constraints bind longer. Thus, this section focuses on the initial and the first and last future periods (t_0, t_1, and t_{19}).

The initial period differs as follows from the baseline:

Producers with binding budget constraints reduce inputs other than lime and thereby their outputs. In isolation, these producers' soils are medium pH clay loam soils. In the export case, additionally, producers with both low and medium pH muck soils are financially constrained. Other producers take advantage of their rivals' price increasing quantity reductions by expanding their own quantities via higher input application.

Due to these not fully compensated reduced quantities, total quantity declines compared to the baseline (isolation: -0.6% to 2.663 mn t, export case: -1.1% to 2.650 mn t). Also, due to diminishing returns of fertilizers experienced by the financially unconstrained producers, marginal costs and local prices rise (isolation: +3.1% to 209.45 USD/t, export case: +5.5% to 214.38 USD/t). Exports are not yet profitable.

Figure 2.8 illustrates relative changes in production inputs caused by liming. In t_0, average fertilizer rates decline slightly overall. Returns to land do not diminish, so the share of used area hardly changes in t_0.

In both trade cases, WF declines in t_0 due to liming investments that lower PS and higher prices that lower CS. In isolation WF is 1,300.9 (-3.8%), PS is 94.4 (-32.4%), and CS is 1,206.5 mn USD (-0.5%), whereas in the export case they are 1,211.4 (-10.4%), 9.3 (-93.3%), and 1,202.1 mn USD (-0.8%) respectively. This translates into profits per area of 71.15 USD/ha (-32.4%) in isolation and 7.01 USD/ha (-93.3%) in the export case.

In both trade cases, binding budget constraints still hamper input application in t_1, but not in t_{19}, so over the future periods the following developments take place:

In isolation, total output reaches 2.795 mn t (+4.3%) in t_1 and 2.807 mn t (+4.7%) in t_{19}. Based on improved efficiency, this causes local equilibrium prices to drop by 20.8% to 160.94 USD/t in t_1 and by 22.8% to 156.72 USD/t in t_{19}.

Exports start in t_1 and increase as budget constraints loosen. They reach 1.348 mn t in t_1 and 2.116 mn t in t_{19}. Total output climbs to 4.117 mn t (+53.6%) in t_1 and 4.885 mn t (+82.3%) in t_{19}. In the export case, the

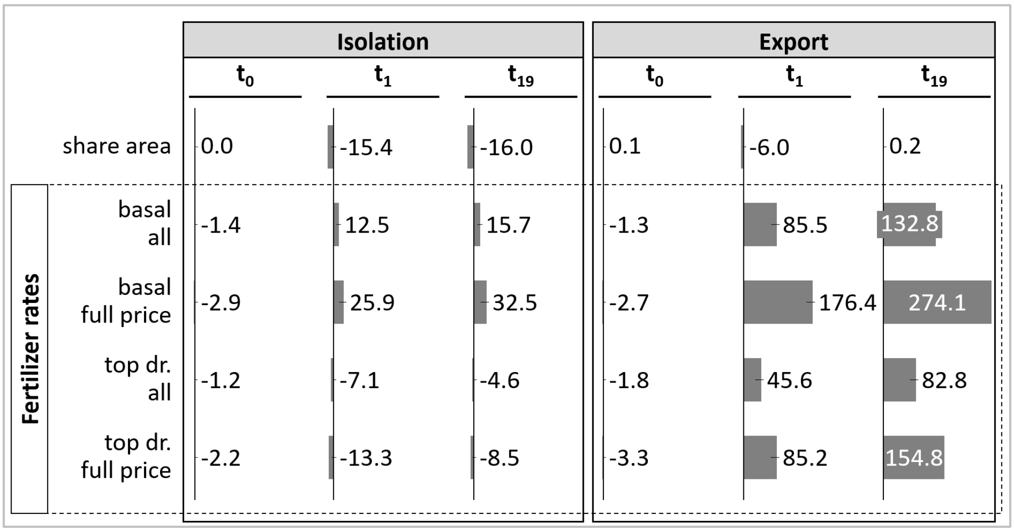

Figure 2.8.: Changes in production inputs: optimal scenarios (414 in isolation and 647 at a global price of maize of 350 USD/t); in percent of baseline

efficiency effect on prices is counteracted by the additional demand from abroad. With global prices at 350 USD/t, optimal liming still lowers prices by 16.1% to 170.50 USD/t starting with exports in t_1.

In isolation, these outputs are made possible by the following input combination (Figure 2.8): The used share of available area is 84.4% (-15.4%) in t_1 and 83.9% (-16.0%) in t_{19}. The basal fertilizer rate is 91 kg/ha (+12.5%) in t_1 and rises to 93 kg/ha (+15.7%) in t_{19}. This includes market purchases corresponding to 49 kg/ha (+25.9%) in t_1 and 52 kg/ha (+32.5%) in t_{19}. On the other hand, the top dressing rate declines to 83 kg/ha (-7.1%) in t_1 and ends at 85 kg/ha (-4.6%) in t_{19}. Therefore, top dressing rates at market prices amount to 41 kg/ha (-13.3%) and 44 kg/ha (-8.5%) respectively. In all periods, subsidized fertilizer rates reach their caps at 41 kg/ha each, which happens also in the export case. To maintain the elevated pH levels, reacidification from top dressing fertilizer is neutralized with liming at 0.73 t/ha in t_1 and at 0.29 t/ha in t_{19}.[37] Based on the used area, average yield is 2.49 t/ha (+23.3%) in t_1 and 2.52 t/ha (+24.6%) in t_{19}.

In the export case, 93.8% (-6.0%) of area is used in t_1 and at 100.0% (+0.2%) all of it in t_{19}. Basal fertilizer rates rise to 149 kg/ha (+85.5%) in t_1 and to

[37]Liming in t_1 includes initial liming of fallow fields, while all following liming exclusively maintains pH.

187 kg/ha (+132.8%) in t_{19}, showing market purchases of this fertilizer of 108 kg/ha (+176.4%) in t_1 and 146 kg/ha (+274.1%) in t_{19}. In contrast, top dressing fertilizer rates rise less steeply to 130 kg/ha (+45.6%) in t_1 and 163 kg/ha (+82.8%) in t_{19}. Thus, top dressing rates at market prices equal 88 kg/ha (+85.2%) and 121 kg/ha (+154.8%) respectively. Counteracting reacidification from top dressing fertilizer, 1.57 t/ha of lime are applied in t_1 and 0.58 t/ha in t_{19}. The sector reaches an average yield of 3.30 t/ha (+63.5%) in t_1 and 3.68 t/ha (+82.0%) in t_{19}.

In both trade cases, the change in fertilizer rates from a dominance of top dressing to one of basal fertilizer reflects that in deacidified soils phosphate is more available to plants. Furthermore, these numbers illustrate the sizable savings of resources in relation to output. These freed resources may be employed in the production of other goods or potentially in expanding production for exports as seen above. Regarding fertilizers in particular, the government could evaluate scaling back subsidies or fertilizer imports could decrease.

CS increases from liming but decreases with exports. In the final period, when adaptation to liming does not influence production anymore, CS reaches 1,258.4 mn USD (+3.8%) in isolation and 1,244.1 mn USD (+2.6%) with exports.

Like CS, PS per area and PS increase with pH, after a decline in t_0. In future periods in isolation, PS per area reaches 140.20 USD/ha (+33.2%) in t_1 and finally, 149.14 USD/ha (+41.7%) in t_{19}. This corresponds to PS of 157.3 mn USD (+12.7%) and 166.2 mn USD (+19.1%) respectively. With exports, PS per area grows to 158.87 USD/ha (+51.0%) in t_1 and then 184.25 USD/ha (+75.1%) in t_{19}, equivalent to PS of 198.0 mn USD (+41.8%) and 244.8 mn USD (+75.4%) respectively.

Not all producers increase their profits with widespread liming in the sector. In both trade cases, producers with already high pH soils experience a decline in profits due to the loss of their competitive advantage. In isolation this also holds for medium pH muck soils, which are not limed in this optimum.

Together, growing CS and PS lead to a surge in WF. In isolation, WF reaches 1,411.2 mn USD (+4.4%) in t_1 and 1,424.6 mn USD (+5.4%) in t_{19}. With exports, it amounts to 1,442.1 mn USD (+6.7%) in t_1 and 1,488.9 mn USD (+10.1%) in t_{19}.

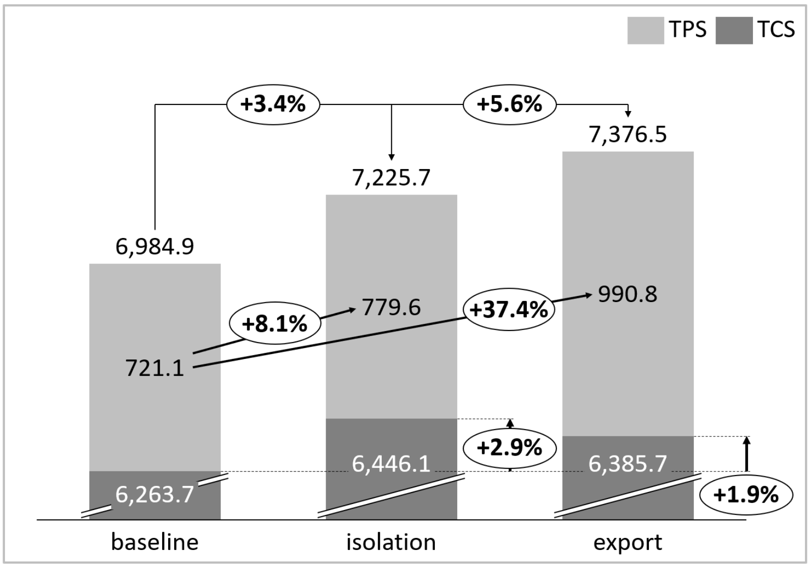

Figure 2.9.: Model results: baseline (0 in isolation) and optimal scenarios (414 in isolation and 647 at a global price of maize of 350 USD/t); in mn USD

Finally, cumulative present values of CS, PS, and WF allow a combined evaluation of investment costs and benefits spread over time (Figure 2.9). TWF is the objective variable of the enclosing problem (Section 2.5.3). Therefore, each counterfactual TWF necessarily at least equals that of the baseline. In isolation, with 7,225.7 mn USD it exceeds the baseline by 3.4% (WF effect). This increase is composed of growth in CS by 2.9% to 6,446.1 mn USD and of growth in PS by 8.1% to 779.6 mn USD. In the export case, TWF of 7,376.5 mn USD exceeds the baseline by 5.6%. Here the rise is composed of CS augmented by 1.9% to 6,385.7 mn USD and PS augmented by 37.4% to 990.8 mn USD.

Even thought, the size of the WF effect may look small at 3.4% and 5.6% (isolation and export case respectively), price reductions from liming at 22.8% and 16.1% are remarkable. Low price elasticity of demand causes large CS and influences the size of the relative WF effect. This should not dwarf the perception of the absolute TWF increase at 240.9 mn USD and 391.6 mn USD or of the economically and politically highly significant price reductions.

As described in Section 2.5.4, I test all lime investment scenarios for their incentive compatibility. Test outcomes for the TWF optima of both trade cases are shown in Figure 2.10.

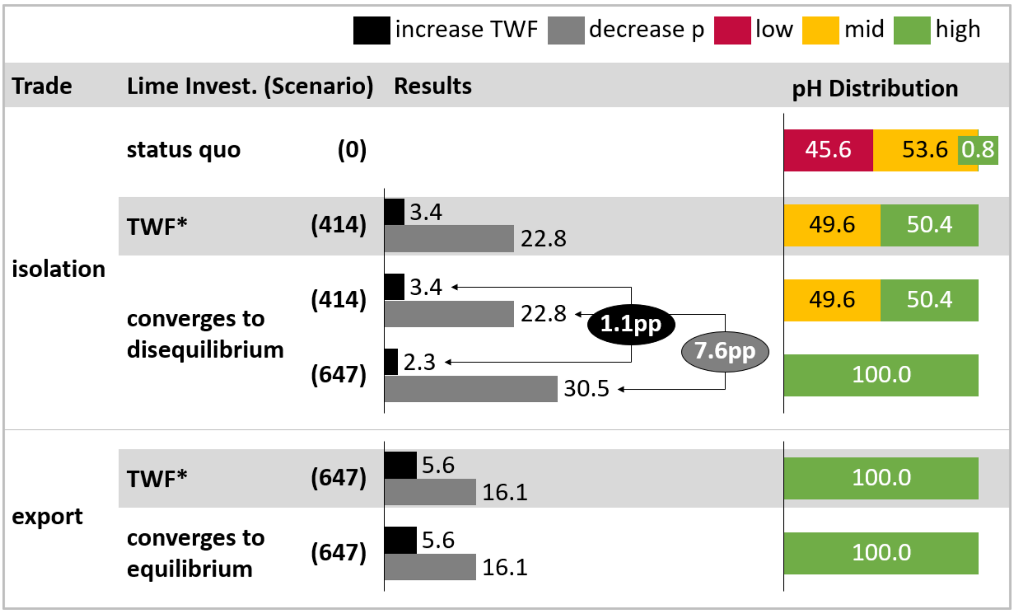

Figure 2.10.: Incentive compatibility of TWF optimal model results by trade case; in percent (of reference season or of total area for pH) and percentage points (pp)

In the export case the TWF optimal scenario (647) is an equilibrium. In isolation, the TWF optimum (414) is not stable. Here, the model oscillates between the TWF optimal investment scenario and the scenario where all soils are limed into the high pH group (647). Optimally, 49.6% of soils would stay in the medium pH group. If the government lets producers lime these soils further, the TWF increase might fall by 1.1 percentage points to 2.3% compared to the optimal increase of 3.4%. At the same time the price decrease might be even more accentuated at 30.5%, surpassing the TWF optimal decrease of 22.8% by 7.6 percentage points. Without the second intervention (Section 2.3.13) the sector converges to and remains in a disequilibrium, where either of the two solutions may manifest.

2.6.4. Sensitivities

To check the robustness of the regular results (Section 2.6.3), I run sensitivity analyses on four parameters: budget for maize production, fertilizer prices, interest rate, and transport cost of lime. I solve the model with each parameter value independently reduced or increased compared to its regular value. The analyses show differences in resulting soil pH (Figure 2.11), in increases of TWF, and in decreases of final local prices (Figure 2.12).

The budget for maize is considered at 80%, 120%, and 1000% of the regular value. In contrast to the former two values, the latter renders the budget constraint irrelevant. With a reduction to 50% of the regular budget, the model would become infeasible.

Fertilizer prices are altered to 50% and 150%, based on recent variation of the global prices of urea and phosphate rock (World Bank, 2016a).[38]

I consider interest rates at 80% and 120% of the regular value.

Transport costs of lime are altered to 90% and 300% of their regular values. In the counterfactuals, because of widespread demand, lime is produced in proximity to maize farmers and bought at the nearest district town. Resulting transport costs can be considered low compared to empirically observed transport costs (Mitchell, 2005). Hence, I lower the parameter value only slightly on the lower end, but triple it on the upper end.

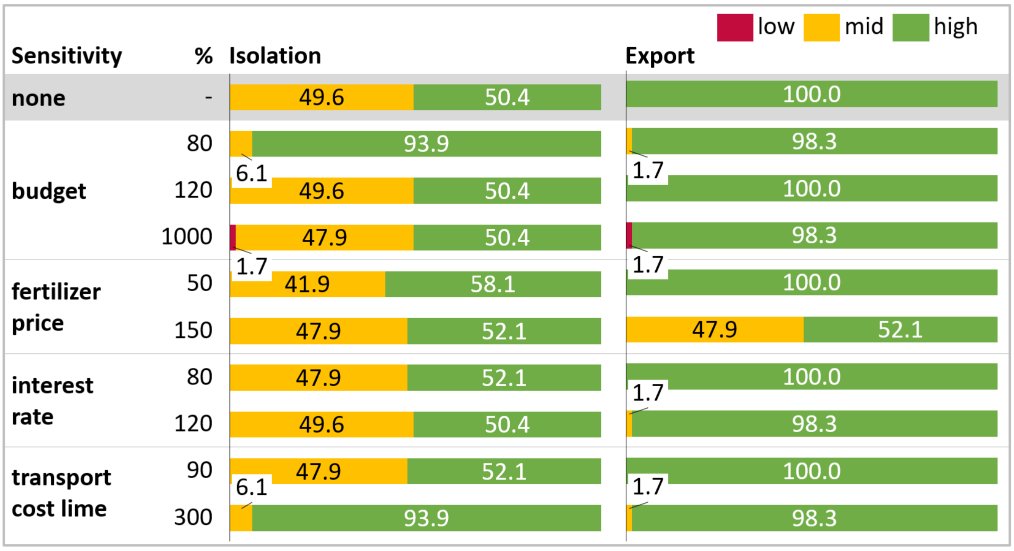

Figure 2.11.: Sensitivity of acidity: optimal scenarios in isolation and at a global price of maize of 350 USD/t;
in percent of total area

Regarding the distribution of soil acidity after TWF optimal liming (Figure 2.11), in isolation, regular results are mostly stable (49.6% in the medium and 50.4% of soils in the high pH group). Only the cases with reduced

[38] I consider prices after the spike of 2008.

budgets and with increased transport costs of lime deviate markedly. Both cases show 93.9% of soils with high pH and the remainder with medium pH (initially low pH muck).

In the export case, it stands out that only increasing fertilizer prices changes the acidity distribution significantly, when 47.9% of soil (initially low pH clay loam and medium pH muck) remain in the medium pH group and the other 52.1% have high pH. Since these high fertilizer prices render exports unprofitable, the acidity distribution equals that in isolation. With all other alterations the high pH group includes nearly all (98.3%) or all soils, as in the regular case.

Independent of trade, it is noticeable that the only accounts of unlimed low pH soil appear when, due to a sizable initial budget, no liquidity constraint exists.

With respect to increases in TWF (Figure 2.12), in isolation, three parameters (budget in t_0, interest rates, and transport costs of lime) are negatively correlated with the respective increase in TWF. On the other hand, fertilizer prices are positively correlated with the increase in TWF. The largest negative deviation from the regular value (at 3.4%) happens without budget constraints or with low fertilizer prices (both at 2.9%). The largest positive deviation stems from high fertilizer prices (at 5.1%).

In the export case, the tendencies persist for interest rates and transport costs of lime, but changes in fertilizer prices stand out. Since increased fertilizer prices make exports unprofitable, the changes in TWF and p are the same as in isolation in this case. In contrast, low fertilizer prices allow exports even without liming. The largest positive deviation from the regular increase in TWF (at 5.6%) takes place at these low fertilizer prices (at 7.4%). The largest negative deviation (at 4.3%) happens without budget constraints or with increased costs of transport of lime.

Evaluating decreases in p (Figure 2.12), the values of the isolation case are close to the regular outcome (at 22.8%) with three exceptions: low initial budgets, high fertilizer prices, and high transport costs for lime. All of these reduce supply and raise p in t_0 and then show larger reductions in p.

With exports most decreases in p are equal to the regular outcome (at 16.1%). Fertilizer prices cause the extreme exceptions: High fertilizer prices prevent exports and show the same decrease in p as the isolation case. Low fertilizer prices allow exports without liming, so global prices always determine the local price and no decrease in p exists.

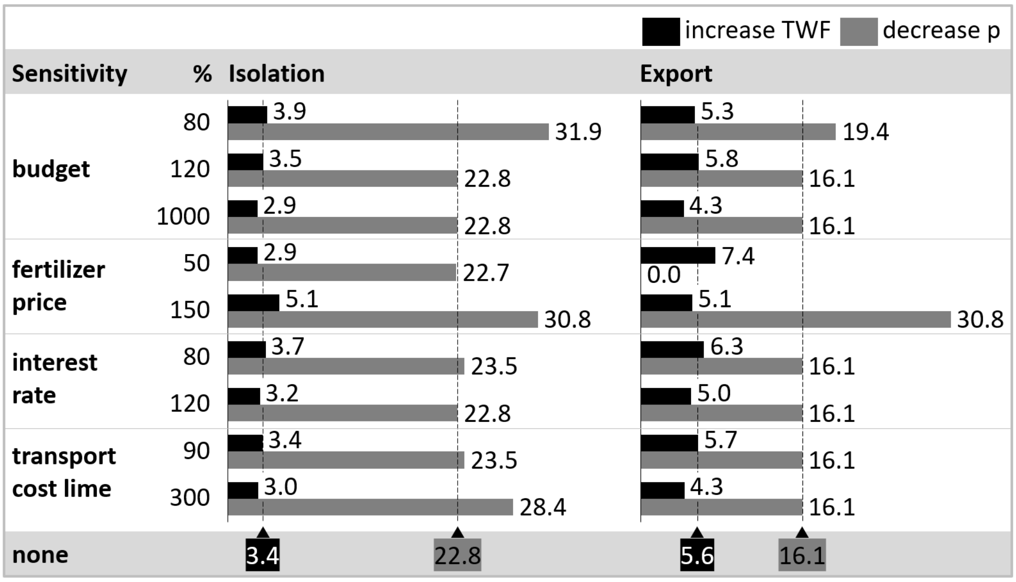

Figure 2.12.: Sensitivity of increases in TWF and decreases in price in the final period: optimal scenarios in isolation and at a global price of maize of 350 USD/t; in percent of respective baseline

In summary, results are sensitive to the tested parameters. Yet, they look robust, if trade decisions and budget constraints are not influenced too much.

2.7. Conclusion

This chapter quantifies the WF effect of the counterfactual introduction of widespread agricultural liming on the Zambian smallholder maize market. Liming could raise pH levels of predominantly acidic farmland to more adequate levels for maize cultivation, improving fertilizer efficiency and consequently the efficiency of ISPs. Agricultural liming is well established in other regions.

The main finding is that at common world market prices, the market would be isolated from global trade and compared to the status quo, liming would optimally increase TWF by 3.4% accompanied by a local price reduction of 22.8%. Yet, the Zambian government might have to prevent liming that surpasses TWF optimal rates. In the case of global prices of 350 USD/t, the sector would export and its TWF would increase by 5.6% while the local price would drop by 16.1%. The size of the price and WF effects in both cases are economically significant. Considering the status of maize in Zambia, the results also carry great political weight.

Apart from the favorable price and WF effects, liming leads to a relative reduction of top dressing with N fertilizer. The need to counteract the acidifying effect of N to maintain elevated pH levels increases the cost of this fertilizer. On the other hand, application of basal fertilizer, a mix of N, phosphate, and potassium, increases in relative and absolute terms. Higher pH levels increase the availability of these nutrients to plants, improving the profitability of the fertilizer. This increased profitability of basal fertilizer further reduces the relative use of top dressing fertilizer. Given the local abundance of limestone, its application seems recommendable to increase the profitability of fertilizers. This could increase outputs, as shown in the model, or reduce costly imports of fertilizer while maintaining output levels.

In any case, the increased efficiency offers a way to make better use of scarce resources. This is welcome, especially in face of the debate on the limited availability of phosphate.

Widespread adoption of agricultural liming may not be beneficial to everyone. Producers with less acidic soils may lose their competitive advantage and suffer declining profits. Also, producers unable to afford up front expenses for liming their acidic soils would be at a competitive disadvantage. In this case, the government might facilitate financing or shift subsidies from fertilizers to lime. The FSP is an example of this, yet on a small scale in the reference season of 2010-11 (Mason, Jayne, and Mofya-Mukuka, 2013).

The focus of the analysis on the maize market, leaves repercussions on other markets open for further research. Expanding demand for lime would raise WF on its own market. On the other hand, WF on fertilizer markets may decrease if its consumption declined. Also, down the maize value chain, liming may cause changes that are out of the scope of this analysis: potentially lower prices of maize as input may impact WF on markets of maize derivatives.

3. More Biofuel = More Food?

In face of increased efforts to mitigate climate change, biofuels may be included in reduction plans for greenhouse gas emissions. Feedstock for first generation biofuels and food crops both use arable land and may compete for it. Also, fuel is an input for the production and transport of food. The purpose of this chapter is to quantify with empirical data how these two aspects affect market outcomes and to introduce a counterfactual setting where the latter aspect dominates the former. The setting allows an expansion of biofuel production to increase food production by lowering costs of production and transport. Namely, lower costs increase market access, allowing a higher utilization of idle production capacities for food crops. For this quantification, I develop an open market, welfare maximizing, partial equilibrium model for three interdependent goods fuel, fuel feedstock, and food (these goods are represented by diesel/biodiesel, palm oil, and cassava/maize respectively). The model is calibrated to Zambia, which exhibits the necessary underlying conditions of underutilized agricultural capacity, high transport costs, and low exports of food. Compared to a baseline, model results show the counterfactual switch from fossil diesel to biodiesel to reduce the diesel price by 51%. This increases food supply (cassava and maize combined) by 0.4% and decreases related prices by 3%. Overall welfare increases by 9.9%. If additionally, a higher world market price of maize renders exports just profitable, overall welfare continues to gain 9.9%, domestic food supply rises by 0.3%, and related prices drop by 2%, but food supply including exports grows by 32%. Furthermore, the introduction of a palm oil based biodiesel sector eliminates import dependency on fossil diesel and palm oil.

3.1. Introduction

In the mid-2000s, food prices rose distinctly, while biofuels became more popular. A relationship between the two trends is disputed, but the underlying fact that feedstock for first generation biofuels and food crops use land should be considered when contemplating large expansions of biofuel production.[1] While second and third generation biofuels aim to prevent the competition with food crops for land, future plans to avoid greenhouse gas emissions may also include first generation biofuels, thus the question about competition for land matters, at least in the medium term.

A second connection between food crops and fuel is that the latter is an input for the production and transport of the former. Thus, the price of fuel influences the costs of food crops and subsequently their supply. This connection is less prominent in the discussion on biofuels.

I explore the interaction of both aspects by introducing a setting where the second aspect is crucial. In fact, an expansion of cheap biofuel production can be beneficial to food supply, if high fuel prices cause high costs of production and of market access, secluding producers of underutilized agricultural areas from markets. Biofuel production would lower fuel costs and thus, transport and market access costs. Given favorable market conditions, producers would increase food output to profitably supply it to the market.

To scrutinize how different parameters affect the two aspects and the economic viability of the setting, I develop a static, spatial, welfare maximizing partial equilibrium model of the involved sectors (fuel, fuel feedstock, and food) with domestic markets and distant world markets. Different model scenarios show under which circumstances food production profits from biofuels. The model uses fuel as input and output and is similar to welfare maximizing partial equilibrium models with basic and refined goods. In those models, the production processes of refined goods use basic goods as inputs. An example for this type of model is the global forestry model of Kallio, Moiseyev, and Solberg (2004), based on the theory of spatial equilibria in competitive markets (Samuelson, 1952).

The specific setting, where biofuel production benefits food production, requires high fuel prices causing high costs of both, production and transport of food, underutilized agricultural capacity, and as a result, a low level of food supplied to markets.[2] I choose Zambia as an application of the modeled setting, because it meets all requirements. Due to good data availability I pick the

[1] Generally, the first generation of biofuels uses edible crops as feedstock, the second generation uses non-edible biomass, and the third generation is based on algae.

[2] While the specific setting requires these conditions, the model itself can be flexibly used to analyze the modeled sectors without strict requirements on capacities, costs, or prices.

agricultural season of 2010-2011 (based on maize) as reference period to measure the goodness of fit of the model.

The production and transport of crops predominantly uses diesel as fuel. Zambian diesel prices are high in comparison with other countries (World Bank, 2016b) and all diesel is imported (ERB, 2010). Because of Zambia's geography as a vast landlocked country, distances to domestic markets and international ports are long. Thus, diesel prices matter for transport costs. The biofuel substitute for fossil diesel is biodiesel, which is currently not produced in Zambia.[3]

Underutilized agricultural capacity exists, because maize, the most important Zambian staple food, has significant potential for yield improvements. Smallholders produce over 92% of maize output (CSO, 2016; Zambia Ministry of Agriculture, 2011), but they use less than the recommended amounts of fertilizer and suffer from acidic soils (Burke, Jayne, and Black, 2016). Hence, yields can be improved via increased use of fertilizers and soil acidity management (Hinkel, 2019). The analysis considers only maize production by smallholders.

Due to its warmer climate with more rainfall, Zambia's north[4], as opposed to the rest of the country, allows the production of cheap biodiesel based on palm oil (Haggblade and Nyembe, 2008; Sinkala, Timilsina, and Ekanayake, 2013).[5,6] Palm oil is the most efficient potential feedstock for Zambian biodiesel (Sinkala, Timilsina, and Ekanayake, 2013). In the reference season, it is not produced in a significant amount in Zambia and imported on a low level for non-fuel purposes (Sinkala, Timilsina, and Ekanayake, 2013; United Nations Statistics Division, 2016). Cassava, is the second most important staple food in Zambia, and lacks far behind maize in terms of national output, but in the north, it is more important than maize (Haggblade and Nyembe, 2008). Therefore, it is included in the analysis.

This chapter assumes a fully developed market for biodiesel, where counterfactual infrastructure and production sites are in place and running in

[3] By 2017, no commercial biodiesel production exists (Samboko, Subakanya, and Dlamini, 2017). Potential non-commercial production is not considered.

[4] As modeled, northern Zambia includes Luapula and Northern Province, which in the reference season, also include most of present-day Muchinga Province.

[5] Cf. Verheye (2010b) for general information on the cultivation of oil palms.

[6] Zambia's first palm oil plantation is located in Mpika (Muchinga Province) in northern Zambia (Zambeef Products plc, 2015).

the modeled period. Thus, the effect of cheap biodiesel on the modeled sectors is not confounded by a multi-year ramp-up period for the establishment of production (e.g., initial growing of oil palms) and infrastructure. The lack of an adequate political and regulatory framework or additional constraints in the modeled value chains can change the results via additional costs, as Hartley et al. (2019) observes for a model of a counterfactual export-oriented Zambian bioethanol industry. In mid-2019, the Zambian government communicated that it developed a blending ratio and pricing mechanism for biodiesel without giving further details (Sapp, 2019).[7]

Drabik, Gorter, and Timilsina (2016) analyses the production of biodiesel in Zambia based on soybeans, but does not consider the effects on transport costs. This chapter extends Drabik, Gorter, and Timilsina (2016) by endogenizing fuel costs and by linking biodiesel production to food production and trade with the world market.

Model results indicate that local production of biodiesel reduces import dependency by eliminating pricey imports of fossil diesel and palm oil.

Compared to a baseline, using only biodiesel reduces the diesel price by 51%, which reduces transport and production costs and increases food supply (cassava and maize combined) by 0.4% while decreasing their price by 3%. Overall welfare expands by 9.9%. If additionally, export to the world market is just profitable, diesel prices fall by 49% and overall welfare still expands by 9.9%, since export profits are not big enough to markedly raise welfare. Domestic food supply increases by 0.3%, and the related price drops by 2%. Food supply including exports grows by 32%. This biodiesel based export case causes an expansion in the use of available land for food crops. Since these increases in production stem from technological progress rather than from net-expansion of agricultural area, welfare is assumed to rise with limited ecological impact.[8]

The focus of the analyses lies on overall welfare implications of different biodiesel scenarios and related changes in prices, quantities, and land use. Therefore, distributional issues or the organization of production, as well as potential implications on greenhouse gas emissions lie outside the scope of this analysis.

[7] Already in 2011, the government announced a 5% blending ratio for biodiesel to be reached by 2015 (Sinkala, Timilsina, and Ekanayake, 2013), but the ratio was never implemented (Samboko, Subakanya, and Dlamini, 2017).

[8] The model does not quantify ecological impact (e.g., effects on biodiversity or greenhouse gas emissions).

The remainder of this chapter is organized as follows. Section 3.2 describes the model. Section 3.3 outlines the data. Section 3.4 analyses and discusses the model outcomes, including a sensitivity analysis and Section 3.5 concludes.

3.2. Model

I develop a static, deterministic, computable, and spatial partial equilibrium model.[9] It consists of the linked Zambian markets for cassava, crude palm oil, maize[10], and diesel.

All markets are assumed to generate welfare (WF) maximizing outcomes due to perfect competition or regulation. A high number of consumers and price-taking producers defines the markets of the homogeneous agricultural goods, guaranteeing perfect competition. The market for diesel is a regulated monopoly, assumed to produce a homogeneous good at marginal costs. In addition, the counterfactual production of biodiesel is assumed to be fragmented, adding a competitive fringe to the market for diesel. Information on prices and capacities is transparent and no entry or exit barriers exist. By assumption, production factors are mobile and no externalities exist. This perfectly competitive setting is implemented as a WF maximization over all markets. Matching supplies with demands, equilibria on the markets consist of sold quantities and market clearing prices for the respective goods.

This static model focuses on a single annual period, representing the annual production cycle of the dominant agricultural good, maize.[11] The model is evaluated at a point in time at the beginning of the annual growing cycle. All markets clear simultaneously during the period.[12]

Markets are generally open for trade (import and export) considering costs of trade, i.e. transport costs and trade charges. Restrictions to trade (quotas and tariffs) may be implemented (cf. Section 3.2.2). Neither re-import nor re-export are considered.

[9] The model is implemented in the Python programming language (Rossum, 2017). Used packages include Pyomo (Hart et al., 2017) and Pandas (McKinney et al., 2018). The model is solved with version 3.12.4 of the Ipopt solver (Wächter and Biegler, 2006).

[10] The market for maize is extensively based on Hinkel (2019).

[11] Other modeled goods are less cyclical.

[12] For maize, storage losses alone reach 7% in the private sector and up to 32% at government storage sites (Sitko and Kuteya, 2013). Thus, generally high storage costs (losses and other costs) and therefore no significant storage of goods between periods are assumed.

3.2.1. Goods

The partial equilibrium model focuses on a selection of goods, $g \in G = \{$biodiesel (bid), cassava (cas), crude palm oil (cpo), diesel (dsl), fossil diesel (fod), maize (mze)$\}$.

In this model, diesel is a blend of biodiesel and fossil diesel, based on an exogenously regulated mixed in share of biodiesel ($\mu \in [0, 1]$, Equation 3.5). Biodiesel has a lower energy density than fossil diesel. Fuel demand is given in fossil diesel units and its energy content must be met by supply. Thus, at any given price, with growing μ, supplied quantity of blended fuel increasingly exceeds that of fossil diesel. Once energy content is internalized in such a way, consumers are assumed to consider all fuels equivalent.[13] By-products of biodiesel production are disregarded due to their low economic value.[14,15]

Both cassava and maize are starchy staple foods. The analyses assume perfect substitution and trade both goods on the same market.[16] While cassava is consumed in various forms (e.g. fresh roots), in the model, it is represented as dried chips, i.e. flour equivalent units, to guarantee comparability with maize (cf. Haggblade and Nyembe (2008)).[17] By-products of cassava (leaves and peel) are disregarded due to their low economic value as food or animal feed (Cadoni, 2010).

Crude palm oil is sold for conventional final consumption (mainly cooking). Based on the situation in neighboring Tanzania (3ADI+, 2019), it is assumed

[13] Needs for extra tank volume seem negligible for biodiesel with 91% of the energy content of fossil diesel (Drabik, Gorter, and Timilsina, 2016). A higher solidifying temperature of biodiesel is another prominent difference to fossil diesel, but negligible in tropical climates (Cukalovic et al., 2013).

[14] Cf. Farm-Energy (2019): Producing ten units of biodiesel generates approx. one unit of crude glycerol. In Zambia, glycerol is assumed to lack a viable market. In the United States, it sells at only 2.5-5 cents/lbs, so export is not an option. It may be disposed of in various ways, incl. composting, burning, or as animal feed.

[15] The production of biofuels can generate income from clean development mechanisms (CDMs) (Sinkala, Timilsina, and Ekanayake, 2013). This is not modeled, but would increase the profitability of biodiesel.

[16] Varying ratios of cassava to maize consumption and prices can be observed in different regions of Zambia, labeled "maize belt", "dual staple zone", and "cassava belt", cf. (Haggblade and Nyembe, 2008). The modeled price setting market of starchy foods considers cassava sales distant from production, such that production and transport costs of cassava closely resemble those of maize. This is the case between the dual staple zone and the maize belt (Haggblade and Nyembe, 2008).

[17] Fresh and dried cassava (weight ratio 4 : 1) differ in water content. Fresh roots are more perishable and their weight increases transport costs. Producing households in Zambia consume about 92% of cassava on-site (Haggblade and Nyembe, 2008).

that by-products (e.g. kernel cake and palm trunks) have no commercial value in Zambia, so they are not considered. For this model, palm oil[18] is chosen as the feedstock for biodiesel, due to its high yield and subsequently low cost of production (Sinkala, Timilsina, and Ekanayake, 2013). Palm oil used for fuel is assumed to enter the biodiesel production process directly at the plantation and is not sold. This way, biodiesel production influences the market of palm oil by competing for suitable land, rather than by increasing demand for palm oil.

In general, interactions between markets are modeled fundamentally via the competition for production inputs (fuel and arable land). Besides this competition for inputs and the possibility of substitution between flour equivalent starchy foods and energy equivalent fuels, markets of different goods are assumed to be unrelated.

3.2.2. Government

Besides the mentioned regulation of the fuel market, modeled government interventions on markets include subsidized inputs and purchases, the levy and refunding of value added tax (VAT), tariffs, and export quotas. Only export quotas are manipulated in the analyses to influence scenario results. All other government actions are modeled as constant and exist only to resemble the underlying markets better.

Subsidized inputs of fertilizers lower production costs of agricultural goods. Subsidized purchases by the Food Reserve Agency of the Zambian Government (FRA) exist for maize and guarantee qualified farmers a premium above the market price. FRA purchases of maize are limited at the level of the reference period. They are resold to the market at competitive prices later in the season.

VAT with non-zero rates increase costs to consumers and lower WF on the affected market.[19] There is no VAT on exports. Sellers of goods with non-zero VAT rates and exporters may reclaim input VAT.[20]

[18] This analysis exclusively considers crude palm oil opposed to refined palm oil, therefore, I drop the qualifier from here on.

[19] The present analyses do not cover government actions funded by VAT from the modeled sectors, but increasing WF elsewhere.

[20] By assumption, producers do not export goods directly, but sell to an exporter who pays market prices and reclaims all input VAT (on the market price and on the cost of transport). This market structure is in line with the pre-2010 illustration in Sitko and Kuteya (2013). Selling to exporters at market price, producers are assumed not to profit from the exempt rate on exports and can only reclaim input VAT if their sales already have non-zero VAT rates.

Tariffs are charged on different imports and exports, increasing the costs of trade. Export quotas exist only in the counterfactual analyses, where indicated.

3.2.3. Supply

Each producer ($i \in I$) chooses to produce non-negative quantities ($q_{g,i,j}$) of goods ($g \in G$) for different buyers ($j \in J$). Quantities are capped by upper bounds $\bar{q}_{g,i,j}$ based on finite capacities and demand (e.g., maximum demand from government for subsidized maize). Quotas can further limit exports.

$$0 \leq q_{g,i,j} \leq \bar{q}_{g,i,j} \tag{3.1}$$

All producers face unit costs of production ($cp_{g,i,j}$) and transport ($ct_{g,i,j}$), each divided into fuel costs and non-fuel cost parameters ($cp^{nf}_{g,i,j}$, $ct^{nf}_{g,i,j}$). Fuel costs for goods other than fuels are the constant fuel requirements for production ($rp_{g,i}$) and transport ($rt_{g,i,j}$) multiplied with the endogenous market price for diesel (p_{dsl}). Fuel requirements and non-fuel costs are constant.

Fuel costs of the production and transport of fuels are modeled as "iceberg" costs (Samuelson, 1954), i.e. a quantity of fuel destined for sale shrinks by its fuel requirements for production and transport. Fuel quantities lost as iceberg costs must be produced, but by assumption, are not transported.[21]

The total cost of supply (C) is the sum of all costs from production and transport:

$$C = \sum_g \sum_i \sum_j q_{g,i,j} \cdot \left(cp^{nf}_{g,i,j} + ct^{nf}_{g,i,j} + gov_{g,i,j} \cdot p_{dsl}(Q^{SZ}_{dsl}) \cdot (rp_{g,i} + rt_{g,i,j}) \right) \tag{3.2}$$

[21] This chapter considers the quantity of output lost in production and transport as first degree iceberg costs of production and transport respectively. Second degree iceberg costs describe the amount of output lost in the respective production and transport of first degree iceberg costs. Higher degree iceberg costs follow the same pattern. This chapter neglects higher degree (>1) iceberg costs, since their size would be relatively small and diminishing with increasing degrees. First degree iceberg costs of transport are consumed during the journey of a payload from producers to consumers, further decreasing the importance of higher degree iceberg costs of transport. Thus, first degree iceberg costs of transport cause first degree iceberg costs of production but no higher degree iceberg costs of transport, i.e. they are produced but not transported.

p_{dsl} is a function of the endogenous supply to the domestic (Zambian) diesel market (Q^{SZ}_{dsl}). Both, p_{dsl} and Q^{SZ}_{dsl}, are determined simultaneously.

For a better representation of the underlying markets, if it corresponds to the situation in Zambia, costs are adjusted for VAT and tariffs within $cp^{nf}_{g,i,j}$ and $ct^{nf}_{g,i,j}$, as well as in a non-negative parameter of government intervention ($gov_{g,i,j}$).

Producers are subdivided into Zambian agricultural producers (i.e. soils, $s \in S$), an importer, and a fuel blender.

Agricultural Producers

Agricultural producers are based on a nationwide data set of Zambian smallholder maize farmers (Burke, Jayne, and Black, 2016) grouped to representative producers defined by circumstances of production (Hinkel, 2019).

Building on Hinkel (2019), the counterfactual analyses assume that all producers lime their soils to sustainably raise pH levels to the optimal range for maize cultivation. This guarantees high efficiency in maize production and shows Zambian agricultural potential to produce additional outputs.

Agricultural producers differ based on their soil properties, their geography, and their remoteness. Soil properties, such as soil types (e.g. sandy soils) and typical tilling techniques, influence maize yields (Hinkel, 2019). Geographical location in northern Zambia, as opposed to the rest of Zambia, allows the cultivation of oil palms. Remoteness describes the average distances to sales points of agricultural inputs and outputs (Hinkel, 2019) and influences costs and fuel requirements of transport.

An additional representative northern producer group stands for farmers cultivating cassava, the dominant food crop of northern Zambia. Due to their location, they can grow oil palms. Based on their past preference for cassava over maize, by assumption, they cannot grow maize.

The ability to cultivate oil palms enables northern producers to supply crude palm oil and/or biodiesel based on palm oil.

Goods of agricultural origin (biodiesel, cassava, palm oil, and maize) compete for a common input, the exogenously limited arable area of agricultural producer s (A_s). In itself, arable land is not likely to be the capacity limit in Zambian agriculture, but it serves as a proxy for labor and capital restrictions on production (Hinkel, 2019) and generates the capacity constraints:

$$A_s \geq \sum_g \sum_j \frac{q_{g,s,j}}{yield_{g,s}} \tag{3.3}$$

$yield_{g,s}$ is defined as the constant average output of g, which producer s receives by applying a unit of arable land.

In addition to capacity constraints, sales to all markets are capped at respective saturation quantities.[22]

Importer

The importer can supply crude palm oil and fossil diesel from the world market.[23] World market prices of imported goods resemble constant production costs. Constant transport costs abroad include tariffs. Neither of these costs is divided into non-fuel and fuel costs, since there is no relation to Zambian diesel prices. Transport costs in Zambia are treated like those of domestically produced goods. Imports are limited to the saturation quantities of Zambian markets.

Fuel blender

A single fuel blender produces diesel as a blend of fossil diesel and biodiesel. Thus, it is not only a producer of diesel, but also a buyer of biodiesel and fossil diesel. Since the fuel market is strictly regulated, it is assumed that consumers can only buy fuel from the single blender, who sells at cost. Blending is bound by an input-output constraint, which states that diesel sales from the single blender to all buyers (j) must not exceed the sum of the blender's inputs (biodiesel and fossil diesel) from all its suppliers (i):

$$\sum_j q_{dsl,blender,j} \leq \sum_i q_{fod,i,blender} + q_{bid,i,blender} \tag{3.4}$$

The regulator exogenously predetermines the fuel blender's constant input ratio, μ:

[22] The saturation quantity is defined at the intersection of the market demand function with the quantity axis, i.e. where the quantity is so large that the price is zero.

[23] Other imports (biodiesel, cassava, and maize) are historically irrelevant (United Nations Statistics Division, 2016) and therefore expected to have no effect on the analyses.

$$\mu = \frac{\sum_i q_{bid,i,blender}}{\sum_i q_{fod,i,blender} + q_{bid,i,blender}} \tag{3.5}$$

Reformulating it creates the input constraint:

$$\sum_i q_{fod,i,blender} \cdot \mu = \sum_i q_{bid,i,blender} \cdot (1 - \mu) \tag{3.6}$$

All costs of blending and subsequent delivery to fuel markets are modeled as contained in the costs of the two inputs. Diesel sales to the Zambian market are capped at its saturation quantity.

3.2.4. Demand

All market demand ($Q^D_{g,j}$) stems from the different representative buyers and is divided into input demand for fuels and final consumption of all goods.[24]

Input Demand

Fuel requirements from the production and transport of non-fuel goods multiplied with the quantities of these goods (Section 3.2.3) create input demand for fuel. This demand is attributed to two representative buyers: demand from crop production ($dprd$) and demand from crop transport ($dtrn$). Input demand reduces free production capacity. It is always met, generating the constraints:

$$\begin{gathered} Q^D_{fod,j} \leq q_{dsl,i,j} \cdot \eta_{dsl} \\ s.t.\ j \in \{dprd, dtrn\},\ \ i = blender \end{gathered} \tag{3.7}$$

η_{dsl} is the constant ratio of energy content of diesel compared to fossil diesel. It adjusts with exogenous changes to μ.

[24]Final consumption is defined broadly, as perceived by the sectors in the partial equilibrium model. For the parametrization of demand see the reference equilibria in Section 3.3.1 with reference prices, quantities, and price elasticities of demand.

Final Consumption

Potential final consumers form a sub-set of J which includes an exporter who sells to the world market, on-farm consumers of cassava and maize, and private buyers geographically distant from agricultural producers. Since reference prices are based on sales to the latter, these sales are understood to form the price setting markets and other domestic markets follow them.

The FRA (Section 3.2.2) is rather an intermediary than a final consumer, yet it adds WF to the partial equilibrium model. The government agency is modeled to buy maize at a fixed premium above the market price up to a limit based on its purchased quantity in the reference season. Later in the season, FRA purchases are resold to private buyers at market rates and therefore maintain the supply to the domestic market. Whereas sales to the FRA create production and transport costs, sourcing and marketing costs of the FRA are outside of the model. Thus, the per unit net-impact of the subsidy on WF is the sum of the premium and the difference of transport costs from the producer to private markets versus to the FRA.

Exports decrease the supply to domestic markets. Compared to world markets, Zambian markets have *small country* properties, i.e. trade with Zambia does not influence world market prices and demand functions on world markets (Q_g^{Dw}) are defined as:

$$Q_g^{Dw} = \begin{cases} \infty & \textit{if} \quad p_g^w - ct_{g,j}(p_{dsl}) > p_{g,j'} \\ 0 & \textit{if} \quad p_g^w - ct_{g,j}(p_{dsl}) \leq p_{g,j'} \end{cases} \tag{3.8}$$

$$s.t. \; j = export, \;\; j' = private\ buyers$$

Q_g^{Dw} depends on domestic market prices ($p_{g,j'}$), prices on the world market (p_g^w), and costs of the exporter ($ct_{g,j}$), which depend on domestic fuel prices just like other transport costs do.

On-farm consumption of cassava and maize is possible for every agricultural producer, s.[25] This consumption counts as supplied to the domestic market.

[25] Palm oil is assumed to be produced on plantations without direct consumption (cf. 3ADI+ (2019), Zambeef Products plc (2015)).

On-farm prices can be deducted from the general market price by subtracting transport costs.

Apart form the exceptions (FRA subsidies, input demand, exports), modeled domestic (Zambian) demand quantities ($Q_{g,j}^{DZ}$) based on off-farm private buyers and on-farm consumption, are linearly dependent on market prices ($p_{g,j}$). Thus, the inverse demand functions are:

$$p_{g,j} = p_{g,j}^{ref} \cdot \left(\left(\frac{Q_{g,j}^{SZ}}{Q_{g,j}^{ref}} - 1 \right) \cdot \frac{1}{\varepsilon_g} + 1 \right) \tag{3.9}$$

$$s.t.\ j = private\ buyers + on\text{-}farm\ consumers$$

Here, the own price elasticities of demand (ε_g) determine the slopes, while the reference equilibria (equilibrium quantities of the reference season ($Q_{g,j}^{ref}$) and equilibrium prices of the reference season ($p_{g,j}^{ref}$)) position the functions. $Q_{g,j}^{SZ}$ contains admissible on-farm consumption and sales to private buyers by producers, importers, fuel blenders, and the FRA. Reference quantities are defined in the same way.

On the price-setting fuel market, demand stems from not further specified domestic fuel use excluding input demand of the modeled sectors (Section 3.2.4). Input demand reduces the supply available to meet final demand for fuel. The export of fuel is assumed to be undesirable and not allowed in the model. Quantities trade on the fuel market in energy equivalent units of fossil diesel.

3.2.5. Welfare

Total WF summed over all markets is the objective variable to be maximized by the model. It comprises all surpluses of domestic producers and consumers, while disregarding government surpluses or deficits and surpluses abroad (i.e. from the consumption of exports and from sales to the Zambian importer).

WF is defined as the difference of the integrals under each price function and total costs over all markets at the equilibrium quantities ($Q_{g,j}^{*}$) (cf. Kallio, Moiseyev, and Solberg (2004)):

$$\max_{q_{g,i,j}} WF = \sum_{g} \sum_{j} \int_{0}^{Q^*_{g,j}} p_{g,j}(Q_{g,j})\, dQ_{g,j} - C \tag{3.10}$$

$$s.t.\ Q_{g,j} = \sum_{i} q_{g,i,j}$$

A further unconstrained WF maximization would exploit market links to the extent where market equilibria deviate from competitive outcomes.[26] To prevent such model behavior, an explicit profitability constraint for the domestic diesel market is necessary (Equation 3.11).[27] Costs of producing and transporting fuel via the blender to the market (including iceberg costs) must not exceed the blender's revenue on the diesel market ($dslm$). The revenue stems from selling quantities of diesel adjusted by their energy content ($\eta_{g'}$) to meet fossil diesel energy equivalence:

$$\sum_{g} \sum_{i} (cp_{g,i,j} + ct_{g,i,j}) \cdot q_{g,i,j} \leq p_{g',j'} \cdot q_{g',i',j'} \cdot \eta_{g'} \tag{3.11}$$

$$\begin{aligned} s.t.\ & g \in \{bid, fod\},\ j = i' = blender, \\ & g' = dsl,\ j' = dslm \end{aligned}$$

3.3. Data

The model uses data from a range of sources, building on the data set of Hinkel (2019) and extending it especially with data on biodiesel, cassava, and palm oil. This section gives an overview of the type of data used and presents the main sources of data.

The time frame of the model is the Zambian 2010-11 maize season. All values are evaluated at the beginning of that season, i.e. October 2010. If necessary,

[26] Exploiting market links of the diesel market would manifest in unprofitable sales lowering the price of diesel. This would cause both, decreasing WF on the diesel market and lower fuel input costs on all other markets, leading to a net-increase in overall WF.

[27] This constraint is binding, since the optimization of the linked markets tries to exploit the fuel sector for the benefit of overall welfare. The shadow price of this constraint indicates the WF gain from a potential fuel subsidy, which is not considered here.

any monetary value is inflated, deflated, and converted into US dollars of this point in time. To be able to compare all monetary values resulting from the model, sub-seasonal prices and costs are discounted to October 2010 using real interest rates. Distributions of sales and costs over the months of the season are approximated by a uniform distribution (for fuel and palm oil), maize planting and harvesting cycles (Hinkel, 2019), and cassava sales of prior years (Haggblade and Nyembe, 2008).[28]

3.3.1. Reference Equilibria

For the reference season in Zambia, an equilibrium on the maize and cassava market is considered at a quantity of 2.718 mn t of maize (CSO, 2016) and 0.503 mn t flour equivalent cassava at a price of 189 USD/t. Cassava production in the model stands for that of northern Zambia, where competition with palm oil is possible. This region represents 73% of area planted with cassava nationally and similar shares of households selling cassava (CSO, 2016). Cassava quantities are based on sales data (CSO, 2016) and an estimated sales to production ratio (Haggblade and Nyembe, 2008). The price is a national season average of population weighted monthly provincial maize prices (Hinkel, 2019). The modeled market does not trade significant amounts of maize (Hinkel, 2019) or cassava with the world market (United Nations Statistics Division, 2016). The assumed own price elasticity of demand for cassava and maize is -0.19.[29]

In the reference season, Zambia produces and exports no palm oil, such that consumption equals imports of 0.026 mn t at an average unit value of 1,228 USD/t (United Nations Statistics Division, 2016). Adding tariffs and domestic transport, the estimated equilibrium price is 1,374 USD/t. Palm oil is assumed to be imported via the port of Dar-es-Salaam from the leading global exporter, Malaysia (World Bank, 2016a). The assumed price elasticity of palm oil is -0.38 (FAPRI, 2017).[30]

[28] Cf. Hinkel (2019), exchange rates are based on Bank of Zambia (2015), US inflation on Organisation for Economic Co-operation and Development (OECD) (2017), Zambian inflation on World Bank (2016b), nominal interest rates for Zambian smallholders on Haggblade, Kabwe, and Plerhoples (2011), and those for a counterfactual Zambian palm oil and biodiesel sector on Sinkala, Timilsina, and Ekanayake (2013).

[29] Cf. Hinkel (2019) for maize, based on FAPRI (2017). This is in the range of elasticities for maize in Dorosh, Dradri, and Haggblade (2009), which also estimates a Zambian own price elasticity for cassava of -0.2.

[30] For every available country including developing countries Malaysia, Indonesia, and India, which by assumption have a comparable elasticity as Zambia.

The reference equilibrium on the diesel market includes no biodiesel, but an estimated 639.9 mn l fossil diesel, sold for an average seasonal price of 1.58 USD/l (ERB, 2017). For the equilibrium quantity, iceberg costs of fuel distribution and estimated input fuel demand for the other modeled sectors are subtracted from 651.1 mn l of fossil diesel (ERB, 2015b)[31] imported from Tanzania via the TAZAMA pipeline (ERB, 2010). The assumed price elasticity of demand of fossil diesel is -0.13 (Dahl, 2012).

3.3.2. Production and Transport

Producers of agricultural goods, ($s \in S$, Table 3.1) are defined by their circumstances of production (choice of arable goods based on local climatic conditions, soil type, and distance to markets). Each s is representative for a group of atomistic individual producers of the same circumstances of production.[32]

Table 3.1.: Agricultural producers: share of arable area and potential production of that area;
in percent;
data: based on Hinkel (2019), Burke, Jayne, and Black (2016), CSO (2016)

soil	area share	arable goods
nor cassava	18.5	bid, cas, cpo
nor clay loam	6.3	bid, cpo, mze
nor loamy sand	0.6	bid, cpo, mze
nor muck	1.1	bid, cpo, mze
roz clay loam	49.3	mze
roz loamy sand	17.9	mze
roz muck	5.2	mze
roz sandy loam	0.5	mze
roz Solonetz	0.7	mze

Producers are uniquely identified by their location and soil type (if relevant). The label "*nor*" indicates location in the warmer, higher rainfall north of Zambia (Haggblade and Nyembe, 2008), which enables the cultivation of oil palms for palm oil or biodiesel. Producers in the rest of Zambia (*roz*) lack these climatic

[31] This includes all gas oil and low sulphur gas oil sales except exports (irrelevant and minuscule in size) and sales between oil marketing companies (OMCs) to prevent double counting.

[32] During the evaluation of the goodness of fit of the model (Section 3.4.1), some producers from Table 3.1 are further split along their initial soil acidity levels (low, medium, or high). This distinction disappears after the assumed treatment of soils in the counterfactuals.

conditions. The producer *nor cassava* represents all modeled cassava cultivation (see Section 3.3.1). Other producers can grow maize instead of cassava. These are distributed over soil types based on the data-set of maize cultivating Zambian smallholders from Burke, Jayne, and Black (2016) (cf. Hinkel (2019)). Total cultivated area in the reference season is 1.63 mn ha, divided among producers as shown in Table 3.1.

Constant yields of maize differ with soil types and can be improved exogenously via soil acidity management with agricultural lime (Burke, Jayne, and Black, 2016; Hinkel, 2019) and fertilizer rates at recommended levels (Mason and Myers, 2013). Outside a goodness of fit evaluation (Section 3.4.1), the analyses always consider these improvements, generating individual, elevated yields between 3.56 t/ha and 4.25 t/ha. Constant yields of cassava[33] at 1.78 t/ha and palm oil[34] at 3.67 t/ha are modeled as unrelated to soil types. Palm oil is processed into biodiesel at a fixed rate (Whistance and Thompson, 2014), creating an overall biodiesel yield of 3,981 l/ha.

Production cost of maize is based on Burke, Hichaambwa, et al. (2011) and Hinkel (2019), that of cassava production on Cadoni (2010), and costs of palm oil and biodiesel production stem from Sinkala, Timilsina, and Ekanayake (2013). Cost shares of included transport and other fuel costs stem from the same sources and in the case of palm oil from Basiron (2005). Dividing fuel costs by fuel prices (ERB, 2017) yields fuel requirements of production.

Transport over land is considered to be by truck rather than by train, since the poor state of train infrastructure inhibits the use of this potentially cheaper transport option (ERB, 2010). Agricultural producers' remoteness is based on distances to district towns and markets in the aforementioned data-set from Burke, Jayne, and Black (2016) and Chapoto and Jayne (2011) respectively (cf. Hinkel (2019)). It is the ratio of a producer's average distance to towns and markets over the overall average distance. Transport costs included in production costs are weighted by remoteness and split into non-fuel and fuel cost using typical fuel shares of regional transport costs in southern Africa

[33] Cassava yield is an average yield of surveyed districts weighted by the number of cassava growing households per district and excluding extreme values (Cadoni, 2010).

[34] Palm oil yield combines fresh fruit bunch yield (Sinkala, Timilsina, and Ekanayake, 2013) with an oil extraction rate (Verheye, 2010b). It includes palm kernel oil and is comparable to expected yields at the first Zambian palm oil plantation (Zambeef Products plc, 2015). Modeled oil palms are assumed to be hybrids of the high yielding tenera variety and the Kigoma dura variety, which is adapted to regional growing conditions in neighboring Tanzania (3ADI+, 2019).

(Teravaninthorn and Raballand, 2009). Dividing these fuel costs by fuel prices (ERB, 2017) yields fuel requirements of transport.

The analyses consider delivered duty paid (d.d.p.) import prices (United Nations Statistics Division, 2016; ERB, 2015a), which include production, transport, and duties. The inner-Zambian shares of transport costs in the import prices are split into non-fuel cost and fuel requirements like the costs of domestic goods.

3.3.3. Government

In the reference period in Zambia, three VAT rates exist: standard, zero rated, and exempt.[35] Standard rates apply to fuels, palm oil, and transport services, are levied at 16%, and qualify for input VAT refunds. Zero rated goods (including all exports) and exempt goods (including cassava, maize, and many farming inputs) attract no VAT. While zero rated goods qualify for input VAT refunds, exempt goods do not. All consumer costs and therefore prices include respective VAT. Input VAT on fuel inputs and transport services are refunded, where admissible.

Maize is the only modeled good benefiting from subsidized government purchases. In the reference season, these amount to 1.752 mn t, bought at a premium above the market price. The constant premium is defined as the difference between the fixed subsidized price of 263 USD/t[36] and the market price, both in the reference period.

Maize exports are not explicitly banned in the reference season (Sitko, Chamberlin, et al., 2017), but implicit hurdles exist, such as limited issuance of export licenses (Mason and Myers, 2013) and availability of export permits only in the capital, Lusaka (Nkonde et al., 2011). While no export tariffs are levied on the modeled goods, import tariffs exist for maize (15%) and for cassava and fuels (25%). Additionally, 15% excise duty is levied on fossil diesel. I model only explicit trade barriers.

[35] For information on VAT and tariffs cf. Zambia Revenue Authority (2014), Zambia Revenue Authority (2020).

[36] Cf. Mason, Jayne, and Myers (2015) and Hinkel (2019).

3.4. Results

Following an evaluation of the goodness of fit of the model (Section 3.4.1), I establish a baseline for the counterfactual analyses (Section 3.4.2). In a static comparative analysis, the solutions of various model scenarios are checked against this baseline (Section 3.4.3). Finally, a sensitivity analysis shows the effect of increasing biodiesel use in one of the counterfactual scenarios (Section 3.4.4).

Different values for a range of model inputs define the scenarios (Table 3.2). These inputs are: use of improved maize yields, biodiesel share (μ), the maize price on the world market (p^w_{mze}), possibility of domestic palm oil production, and application of an export ban on palm oil.

Table 3.2.: Scenario definition: status-quo and counterfactuals

scenario	improved yield mze	μ (percent)	p^w_{mze} (USD)	domestic cpo production	export ban cpo
STATUS QUO	no	0%	224	no	n/a
CF BASE	yes	0%	224	no	n/a
CF ISOB	yes	100%	224	yes	yes
CF EXPO cpo	yes	100%	224	yes	no
CF ISOF	yes	0%	278	yes	yes
CF EXPO mze	yes	100%	278	yes	yes

3.4.1. Goodness of Fit

Based on the assumption of perfectly competitive or regulated markets in the reference season (Section 3.2), the goodness of fit of the model is evaluated by comparing the market equilibria resulting from the WF maximization in the status quo scenario (*STATUS QUO*) with the reference market equilibria from the literature. It is important to note, that monetary values from the literature as shown undiscounted in Section 3.3.1 are discounted to the beginning of the maize season to be used in the model and these discounted values are compared with the equally discounted model results.

STATUS QUO models the situation in the reference season by considering observed agricultural productivity in the cultivation of maize[37] and by not

[37] This includes observed, lower than recommended fertilizer use and untreated soil acidity.

dedicating land to oil palms, neither for palm oil nor for biodiesel. Hence, all diesel is imported fossil diesel and all palm oil is imported, too.

The optimized equilibrium quantity on the diesel market is 640.6 mn l at a price of 1.52 USD/l. Quantities differ from the reference by -0.1%, leading to a deviation of 0.5% from the reference price (Figure 3.1).

The equilibrium quantities on the market for starchy foods are 2.642 mn t of maize and 0.537 mn t of cassava, selling for 170 USD/t. Thus, quantities deviate from the reference by -2.8% and 6.8% respectively, which balances to a deviation of -1.3% for the combined equilibrium quantity. The resulting difference in price is 6.7%. The model matches the maximum amount of subsidized maize purchases of 1.752 mn t, equaling the amount in the reference season.

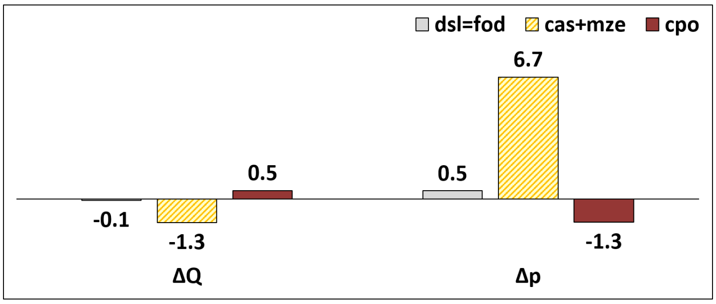

Figure 3.1.: Difference between model outputs and respective reference values; in percent of reference value

In the model, 0.026 mn t of palm oil are consumed for 1,302 USD/t, which differs from the reference by 0.5% and -1.3% respectively.

Like in the reference, there are no exports to the world market.

The amplitudes of price differences exceed those of quantity differences due to relatively inelastic demand functions, which are typical for basic goods such as fuel and staple foods.

Overall the model uses 100% of the arable land used in the reference season. Therefore, the areas dedicated to the two available crops, cassava 19% and maize 81%, equal the areas of the producers able to cultivate these crops (Figure 3.2).

3.4.2. Counterfactual Baseline

The *STATUS QUO* aims to match the situation in the reference season as close as possible and is used to assess how well the model is calibrated. Its use as benchmark against the counterfactual scenarios is limited, because the effects of too many changes would overlap. The counterfactual baseline (*CF BASE*) serves this purpose better, because different from *STATUS QUO* and like all counterfactuals, it considers effective yield improvements for maize via liming and recommended fertilizer rates. Apart from this, it is equal to *STATUS QUO* in its inputs. The exogenous one-time improvement of all individual maize yields relaxes the capacity constraints on land suitable for maize production (Equation 3.3) and lowers unit costs (Equation 3.2).

The baseline generates an equilibrium on the diesel market with 639.4 mn l of fossil diesel, marketed at 1.53 USD/l. On the market for starchy foods, the equilibrium quantity is 3.373 mn t combining 2.905 mn t of maize and 0.468 mn t of cassava, showing the shift in competitiveness of the two crops after the improvement of maize yields. The related price is 119 USD/t. Imports of palm oil continue to supply the entire market of 0.026 mn t for 1,302 USD/t.

3.4.3. Counterfactual Scenarios

Different from *CF BASE*, all following counterfactual scenarios consider the domestic production of palm oil for import substitution.

The main counterfactual scenario, *CF ISOB*, still shows isolated (*ISO*) markets without trade, even though it is 100% biodiesel-based (*B*). Its share of biodiesel is varied in a sensitivity analysis (Section 3.4.4).

CF EXPO cpo extends *CF ISOB* by allowing exports of palm oil, which are prevented in other scenarios via export quotas at 0 t.

CF ISOF differs from *CF ISOB* by using only fossil diesel (*F*) and by considering an elevated p^w_{mze}, regardless of which, isolation from trade persists (*ISO*).

CF EXPO mze varies from *CF ISOF* by considering μ at 100%, instead of at 0%. Given the high p^w_{mze}, the cheaper biodiesel tips the trade regime of maize from isolation to export.

Due to the exogenous improvement of all individual maize yields, relaxed capacity constraints are apparent in Figure 3.2, where all counterfactuals remain well below the overall land constraint of 100% reached in *STATUS QUO*. In the north, producer specific binding land constraints return for all producers in *CF ISOB*, *CF EXPO cpo*, and *CF EXPO mze*. This is

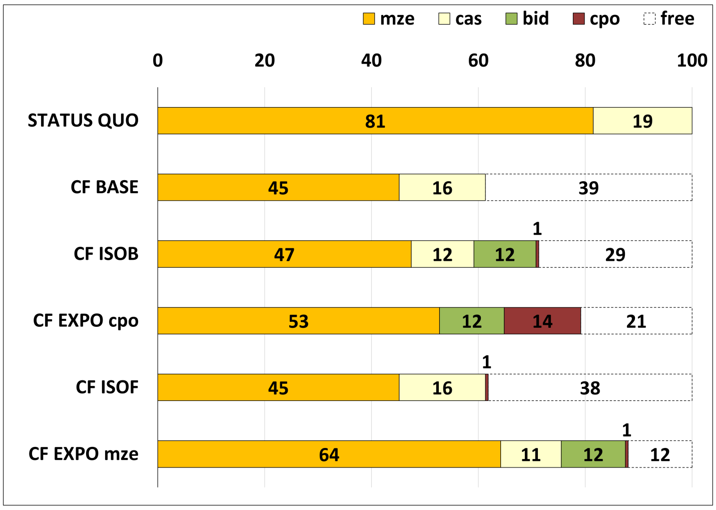

Figure 3.2.: Share of available area used by scenario and good; in percent

mostly due to the production of northern goods (biodiesel, cassava, and palm oil, but not maize), as their joint land use approaches the combined land share of northern producers, 26%. While some producers in the rest of Zambia reach their capacity limits in all counterfactuals, overall capacity for maize production is never exhausted in the counterfactuals.

In the counterfactual scenarios, land use for maize continues to dominate. Without the fuel cost reducing production of biodiesel (*CF BASE* and *CF ISOF*), it makes up 45% of available area. With biodiesel, but without exports (*CF ISOB*) it reaches 47%. If exports of palm oil are not banned, palm oil uses 14% of available land, together with biodiesel production squeezing out cassava production in the north of the country. Maize, which in the rest of Zambia does not compete with either palm oil or biodiesel, replaces the missing quantities of cassava on the market and increases its own share of land to 53%. In other scenarios with palm oil, but without its export (*CF ISOB*, *CF ISOF*, and *CF EXPO mze*), 1% of available area suffice to meet domestic palm oil demand. When a world market price of maize at 278 USD/t and low fuel costs due to biodiesel make the export of maize just profitable (*CF EXPO mze*), land use for maize climbs to 64%.

Land use for cassava without competition from biodiesel and exports reaches 16% (*CF BASE* and *CF ISOF*). Improved maize yields reduce this share from previously 19% by rendering any cassava consumption unprofitable that has to be transported to more distant buyers. The production of biodiesel on a scale to replace all fossil diesel (even with additional input demand from exports) needs 12% of available land. This decreases land use of cassava to 12% (*CF ISOB*), 0% with additional competition from palm oil exports (*CF EXPO cpo*), and 11% with maize exports (*CF EXPO mze*).

It stands out, that compared to land use for starchy food crops at 61% in *CF BASE* and *CF ISOF*, this land use increases to 76% in *CF EXPO mze*, due to the introduction of biodiesel.

Market equilibria in the scenarios differ from the baseline (Figure 3.3). Compared to *CF BASE*, the introduction of cheap, domestic palm oil production replaces inputs in every scenario and reduces its price by 59% if no palm oil is exported (*CF ISOB*, *CF ISOF*, and *CF EXPO mze*). Due to the lower price, demand and the equilibrium quantity rise by 22%. If palm oil exports are not banned (*CF EXPO cpo*), export demand allows prices only to drop by 44% and quantities remaining in the country exceed those in *CF BASE* only by 16%. Palm oil exports amount to 0.828 mn t and do not count towards the domestic equilibrium.

Blends of diesel in the scenarios either use 100% biodiesel (*CF ISOB*, *CF EXPO cpo*, and *CF EXPO mze*) or none (*CF ISOF*). The latter case matches *CF BASE* in quantity and price of the diesel equilibrium. Due to lower costs of biodiesel compared to imported fossil diesel, the biodiesel based *CF ISOB* shows a decline of the price of diesel of 51%. Quantities expand by 17%. Exhibiting additional input demand for exports, each *CF EXPO cpo* and *CF EXPO mze* see a drop in the price of diesel by 49%, and an increase in supply by 17%.[38]

While *CF ISOF* resembles the equilibrium in the starchy foods market of the baseline, the biodiesel based scenarios overall see expansions in quantity and reductions in price. Lacking export, *CF ISOB* shows the clearest effect of the introduction of biodiesel on the starchy foods markets, where quantities increase by 0.4% and price declines by 3%. The small change in overall quantity masks larger shifts between cassava and maize. Replaced by biodiesel, cassava production drops by 27% and maize production expands by 5%. As seen in the *CF BASE* equilibrium, maize production markedly outweighs that of cassava, such that the smaller relative increase suffices to reach an overall surplus. In the cases with exports (*CF EXPO cpo* and *CF EXPO mze*), the effects are

[38] Compared to *CF ISOB*, the input demand for diesel from exports decreases the equilibrium quantity only in the decimals, but causes a visible difference in price changes in Figure 3.3.

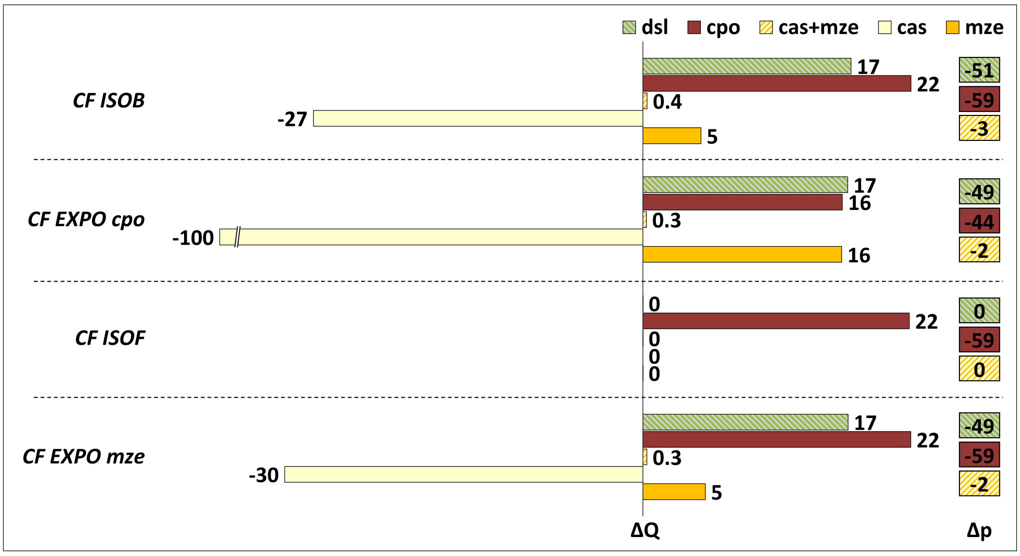

Figure 3.3.: Relative differences of equilibrium quantities and prices; in percent of *CF BASE*

similar, but smaller overall while more extreme for the separate crops. In both scenarios, overall quantity increases by 0.3% and the price decreases by 2%. In *CF EXPO cpo* palm oil exports require so much northern land, that no cassava is produced and maize compensates the shortfall with an increase of 16%. When maize is exported (*CF EXPO mze*), northern land is not as crucial, but cassava output still plummets by 30%, while the equilibrium quantity of maize increases by 5%. Additionally, 1.072 mn t of maize are exported. Including these exports, the overall supply of starchy foods increases by 32% compared to *CF BASE*. Since the FRA subsidized purchase price of maize is a net-inflow of WF to the model, the upper limit of possible sales to the FRA is reached in every counterfactual but *CF EXPO cpo*, where northern producers choose to replace maize cultivation with that of oil palms for either palm oil directly, or for biodiesel. The amount of maize sold to the FRA still reaches 1.582 mn t.

Considering WF (Figure 3.4), all counterfactuals exceed *STATUS QUO* in total WF (5.32 bn USD), since they produce maize more efficiently. When exports create additional profits, total WF is highest (*CF EXPO cpo* at 6.08 bn USD and *CF EXPO mze* at 5.93 bn USD). Since maize exports in *CF EXPO mze* are only just profitable, WF does not differ significantly from *CF ISOB* at 5.93 bn USD. Comparing *CF ISOB* with *CF EXPO cpo*, the pure WF effect of palm oil exports is revealed as an increase of 2.6%.

Introducing biodiesel to take advantage of an export opportunity at global market prices of maize at 278 USD/t generates a jump in WF of 9.4% (*CF ISOF* versus *CF EXPO mze*). Without this export opportunity the introduction of biodiesel (and palm oil) expands WF by 9.9% (*CF BASE* versus *CF ISOB*).

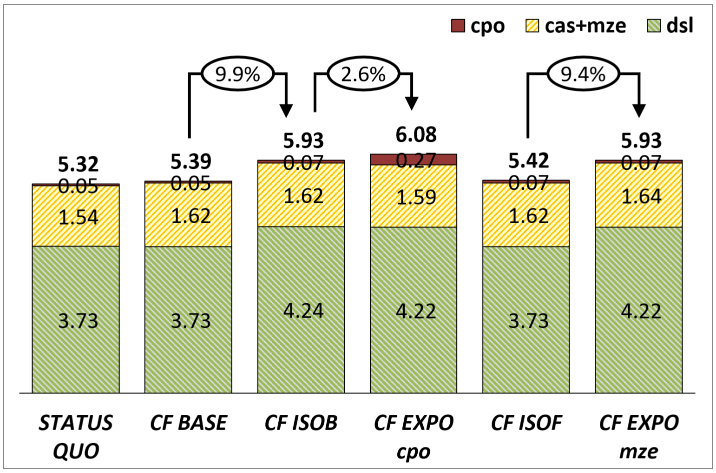

Figure 3.4.: Welfare by scenario and good; in bn USD

Without biodiesel, WF on the diesel market is 3.73 bn USD. Using only the cheaper biodiesel reduces the fuel price and thus increases WF on this market to 4.22 bn USD with supply-reducing fuel input demand for exports and to 4.24 bn USD without it.

WF on the starchy foods market increases from 1.54 bn USD to 1.62 bn USD, once soils are treated for improved maize production (*STATUS QUO* versus *CF BASE*). Due to rather small increases in overall output of starchy foods with the introduction of biodiesel (+0.4%), WF in the sector at 1.62 bn USD does not increase markedly (*CF BASE* versus *CF ISOB*). Profits from just profitable maize exports (*CF EXPO mze*) raise sector WF slightly to 1.64 bn USD. Exports of palm oil compete with starchy foods for land and reduce their WF to 1.59 bn USD, also because of lower subsidized sales of maize to the FRA.

The sole introduction of domestic palm oil production without the production of biodiesel brings an increase in WF of this comparatively small sector from 0.05 bn USD to 0.07 bn USD. At prices from the reference season, the export of palm oil raises sector WF to 0.27 bn USD.

3.4.4. Sensitivity

To evaluate how different biodiesel mandates influence land use, the diesel price, and WF, I apply *CF ISOB* with μ ranging from 0% to 100%, growing in single percentage point increments (Figure 3.5).[39]

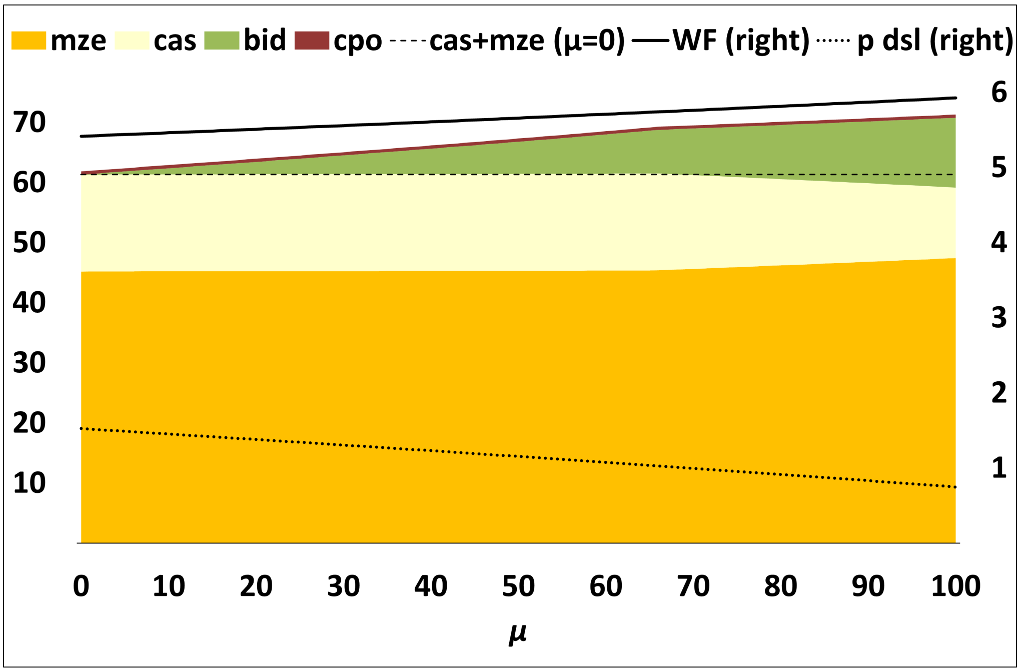

Figure 3.5.: Total welfare, diesel price, and share of available area used per good, all by μ (*CF ISOB*);
in percent (left and bottom axis),
in bn USD and USD/l (right axis)

It is apparent that WF increases with μ. A comparison of the extremes of μ at 0% and 100% shows an increase in WF of 9.4% from 5.42 to 5.93 bn USD, while a more moderate μ at 10% raises WF by 0.9%. The relationship is almost linear.

The growth of WF is plausible, since the use of biodiesel replaces costly fossil diesel imports and lowers fuel input costs, as indicated by the constantly decreasing price of diesel. The WF maximizing endogenous price of diesel reacts to decreasing costs of diesel, which the blender forms as a weighted average of the costs of biodiesel and fossil diesel. The diesel price at $\mu = 0\%$ is 1.53 USD/l and decreases close to linearly to 0.75 USD/l at $\mu = 100\%$. The moderate μ of 10% generates a diesel price of 1.45 USD/l.

[39] The figure interpolates values between increments.

Initially, expanding μ is not constrained by availability of arable land in the north of Zambia and even at higher μ, changes in land use are small between goods. Total land use increases from 61.8% to 71.3% with μ, mostly due to biodiesel. Barely noticeably, total area of starchy food crops initially grows due to lower fuel costs (combined cassava and maize area surpasses the dashed line). At μ of 65% it gains a maximum of 0.2 percentage points compared to μ at 0% and starts declining.

Beginning at μ of 69%, less land is dedicated to starchy food crops than without any use of biodiesel (combined cassava and maize area drops below the dashed line). Land use shifts from cassava to biodiesel feedstock, due to limited suitable land in the north.

At the same time, land use by maize rises more steeply with μ, because less efficient maize areas, that so far have not supplied the market, become profitable thanks to the lower fuel price and replace the cassava producer. Hence, prices of starchy foods decrease and demand grows (Section 3.4.3). Because maize is higher yielding (t/ha) than cassava, the overcompensation of declining cassava production by maize is only partial in terms of land use.[40] Combined land use continues under its initial level with μ at 0%.

Land use for palm oil is fairly constant at a low level, averaging 0.5% over the whole range of μ.

3.5. Conclusion

The preceding analyses use a welfare maximizing partial equilibrium model for food, fuel, and fuel feedstock in Zambia to scrutinize a range of scenarios regarding the interaction between food crops and biodiesel.

The general discussion on biofuel stresses the competition between fuel feedstock and food crops for arable land. The fact that fuel is also an input for the production and transport of food is less prominent. Considering both aspects, I introduce a setting where the latter effect leads to an increase in food production. If biofuel is cheaper than fossil fuel, it lowers the costs of production and transport of food, causing an expansion in food supply. Given favorable global market prices, reduced fuel costs allow exports, causing even bigger food supply and an increase in land use for food crops.

[40] Due to constant yields, output relates linearly to the area of each producer.

Necessary circumstances for this setting include underutilized agricultural capacity, high fuel prices and transport costs, and low exports of food. I model the setting for Zambia, because it exhibits all of these conditions. In this context fuel is represented by diesel and biodiesel, food by the two starchy staple foods cassava and maize, and biofuel feedstock by palm oil, which is also used for other direct consumption.

To model the underutilized agricultural capacity, I consider yield potential for maize from improved soil acidity management and increased fertilizer use. A counterfactual baseline implementing these improvements serves as a benchmark to evaluate different counterfactual biodiesel scenarios.

Compared to the baseline, model results show that replacing all imported fossil diesel with biodiesel reduces the diesel price by 51%. Therefore, reduced transport and production costs increases food supply (cassava and maize combined) by 0.4% and decreases their price by 3%. These fuel price induced changes are moderate due to the small share of fuel costs in the cost of Zambian maize and cassava produced by smallholders with limited mechanization. Overall welfare expands by 9.9%. An export case, in addition, considers an elevated world market price of maize that allows just profitable exports. Here, diesel prices fall by 49% and overall welfare expands similarly by 9.9%. Domestic food supply increases by 0.3%, and prices of starchy foods drop by 2%. Food supply including exports grows by 32%, causing an expansion in the use of available land for food crops from 61% in the baseline to 76%.

In a sensitivity analysis not considering maize exports, I vary the counterfactual share of biodiesel in fuel. The analysis shows that the price of the fuel blended from fossil and biodiesel steadily decreases with an increasing share of biodiesel, causing a similarly steady increase in welfare. It also shows how competition for land only becomes a binding constraint with blends of $\geq$65% biodiesel and only causes land use for starchy foods to fall below its level without biodiesel, when blends reach $\geq$69% biodiesel.

Beyond the analyses of welfare and price effects at hand, import substitution for basic goods like diesel and palm oil may have additional national advantages, like increased local employment and greater stability and independence of supply.

Considering fully developed, operational counterfactual sectors, the analyses show the general welfare benefit of introducing biodiesel in the modeled markets. The analyses do not include the implementation of the counterfactual sectors and therefore, do not involve an adjustment period with initial needs for financing. Potentially large shifts in employment in the affected sectors and in public finances during the adjustment period may also be of political concern. Furthermore, data with finer geographic and temporal granularity would allow the additional modeling of sub-seasonal and provincial effects.

Looking forward, the evaluation of the climate impact of the depicted scenarios may be of interest. An extension of the analyses may map greenhouse gas emission parameters to actions in the model. The resulting emission flows may be priced into the modeled equilibria, for example using CDMs.

Besides Zambia, several other landlocked African countries display the requirements for the analyzed setting, potentially allowing an increase in welfare for millions of people, if biofuels help to unlock the agricultural potential of these countries. Thus, it would be interesting to apply this analysis to other promising countries.

4. A Stochastic Discrete Choice Dynamic Programming Model of Power Plant Operations and Retirement

We present a methodology to estimate fixed cost parameters relevant to the decision to operate, mothball or retire an open-cycle gas turbine (OCGT) using a dynamic discrete choice model, based on fuel and electricity prices, as well as technical data and the operational status of OCGTs in the PJM market area. With operational and mothballed OCGTs, we find for both, age of the power plant and plant vintage statistically significant positive correlations with the fixed operation and maintenance (O&M) costs. We also show a statistically significant negative relationship between the installed capacity and the fixed O&M costs, confirming that an increase in scale results in lower specific costs. The estimated fixed O&M cost parameters for an operational OCGT vary from 16.3 USD/kW/year for new, large, high-efficiency units, to 50.8 USD/kW/year for older, small, low-efficiency units. Mothballing a plant reduces these costs by 75% to 95%, depending on plant vintage and size. Decommissioning an OCGT was found to be cash flow negative, which means that the associated cost exceeds any scrap value the equipment may have on secondary markets. Our estimated cost parameters depend on operational status, capacity, vintage, and age of a generation unit. This differentiation is valuable for a better understanding of costs in the context of competition policy. It would also allow for a more realistic parametrization of power market models. Using the estimates and market data, we also compute the probabilities of operating, mothballing or retiring an OCGT. Sensitivity analyses regarding changes in prices of capacity, electricity, and natural gas reveal that the operating decisions for OCGTs are significantly affected by the profitability potential, most notably by electricity prices.

4.1. Introduction

The objective of this chapter is to estimate fixed cost parameters relevant to the decision to operate, mothball or retire an open-cycle gas turbine (OCGT) in the Pennsylvania, New Jersey, Maryland Power Pool (PJM)[1] using a dynamic discrete choice model supplied with data on fuel and electricity prices, as well as technical data and the operational status of OCGTs in the PJM market area.

Characterized by low investment but high variable costs, OCGTs are usually operated as peaking power plants that come online only when electricity prices are high enough to cover their variable costs. Due to their position at the top end of the merit order[2] of the market, they are often the price-setting technology in peak hours. Furthermore, new OCGTs are often the price setting technology in capacity remuneration mechanisms such as PJM's Reliability Pricing Model (RPM) designed to incentivize the deployment of sufficient firm capacity to maintain security of supply at times of very high demand. The upshot of this is that OCGTs are a pivotal technology when it comes to the potential of market participants to exert market power on both electricity and capacity markets, i.e. by withholding capacity in critical hours on the electricity market, or in auctions on the capacity market. In order to assess the structure and competitiveness of both electricity and capacity markets, regulators need robust data on the cost structures of peaking power plants in particular. However, publicly available reports on the operating costs of power plants, published by public organizations such as the Energy Information Administration (EIA, 2016), the International Energy Agency (IEA, 2010; IEA, 2020), market operators (PJM, 2014; PJM, 2018a), as well as private engineering and consulting firms (e.g. NREL (2012) or Lazard (2020)), tend to focus on newly built plants and usually provide point estimates for an average unit only. The dynamic discrete choice model described in this chapter, on the other hand, can be used to generate a larger set of more differentiated cost estimates for a single technology such as an OCGT, dependent on plant characteristics such as age, capacity or vintage. Additionally, it is able to provide estimates for the operation and maintenance (O&M) costs of

[1] PJM is the independent system operator (ISO) for all or parts of Delaware, Illinois, Indiana, Kentucky, Maryland, Michigan, New Jersey, North Carolina, Ohio, Pennsylvania, Tennessee, Virginia, West Virginia and the District of Columbia. PJM operates the high-voltage transmission system, the wholesale market for electricity and an auction-based mechanism for the provision of secure capacity.

[2] The term *merit order* describes the short-run supply curve of an electricity market.

mothballed plants, as well as the cost associated with the final decommissioning of plants. Better cost estimates improve market transparency, potentially lowering market entry barriers for the general benefit of competition on the market.

Furthermore, such differentiated cost estimates for generating units of varying operational status, capacity, age, and vintage are valuable parameters for the modeling of energy systems. The fight against climate change, not least via a growing share of intermittent generation in the power supply, increases the importance of such models. They provide insights into questions on network stability, investment decisions, and greenhouse gas emissions and would benefit from more differentiated cost data, as provided in this chapter.

Dynamic discrete choice models assume that rational, forward looking, risk-neutral agents maximize expected payoffs across time. Based on the principle of *revealed preference* (Aguirregabiria and Mira, 2010), they allow for the estimation of unknown parameters in an agent's profit function using data on agent choices and choice outcomes. For the model to replicate operator behavior and produce valid cost estimates, the market under investigation needs to be competitive, i.e. market participants have to behave as price-takers whose decisions are determined by costs and prices only, rather than strategic considerations. Otherwise, the cost estimates might be biased. We assume that as a large and liquid market, PJM is sufficiently competitive for the model to generate valid cost estimates and therefore suitable to estimate the O&M costs of peaking power plants. To support this assumption, we analyze PJM's annual state of the market reports for the 2008 to 2017 period. The annual reports find that electricity prices in PJM are set mostly by marginal units at or close to their marginal cost of production. They conclude that in all years, both energy and capacity market outcomes are broadly consistent with competitive behavior among the market participants (Monitoring Analytics, 2020).

Since OCGTs are largely standardized, the cost estimates derived in this chapter should also apply to OCGTs in other electricity markets of the United States or the Organisation for Economic Co-operation and Development (OECD). Thus, they could provide useful information to researchers and regulators assessing the competitiveness of other electricity or capacity markets.

Econometric dynamic discrete choice models are applied to a wide range of microeconomic problems. Some of the seminal works are, Wolpin (1984) on fertility and child mortality, Rust (1987) on the optimal replacement of bus engines, Das (1992) on capital utilization and retirement decisions in the cement industry, and Keane and Wolpin (1997) on the educational and occupational choices of young men. Other notable works include Hartmann and Viard (2008) on switching costs in frequency reward programs, Nevo, Turner, and Williams (2016) on the consumer response to usage-based broadband pricing and Peters, Roberts, et al. (2017) on firm Research and Development (R&D) spending. Aguirregabiria and Mira (2010) provides an overview of dynamic discrete choice estimation procedures commonly used in the literature.

In an electricity industry context, dynamic discrete choice models are used to assess investment, operational, and retirement decisions associated with electricity generators. In particular, they are used to study the impact of external shocks on managerial decision-making and to estimate unknown cost parameters in a variety of contexts. Rothwell and Rust (1997), for instance, models the long-term decision problem (operate or decommission) of a nuclear power plant operator in order to determine the optimal lifetime of existing plants. The paper takes account of major unplanned outages (*problem spells*) in the model specification and assumes that such outages become more likely as a plant ages. Cook and Lin Lawell (2019) uses a dynamic structural model to analyze the impact of government policy on the investment in, decommissioning, or replacement of small-scale wind turbines in Denmark. The paper finds that government policy had a greater impact on the growth of wind power in Denmark than technological improvements, and that specific policy changes had a substantial impact on the timing of expansion, shutdown and replacement decisions made by wind turbine operators.

According to the principle of revealed preference (Aguirregabiria and Mira, 2010), the decisions of production units can be used to estimate unknown cost parameters, provided some other parameters are known. Fleten et al. (2020), for example, uses data on startup and shutdown events, natural gas and electricity prices in the northeastern United States (including PJM), covering the years 2001–2009, to estimate maintenance and state switching costs for OCGTs with the help of a dynamic discrete choice framework. Based on the derived estimates, the paper calculates the avoidable cost rate (ACR) associated with switching from an operational to a mothballed and from a mothballed to a decommissioned state and finds that the estimated ACRs are lower than the clearing prices observed in PJM's market for secure capacity.

Based on this, the conclusion is that consumers are likely overpaying for the provision of secure capacity in the PJM Interconnection.

Building on the methodological approach of Das (1992), our study expands on the work of Fleten et al. (2020). Unlike the latter, we explicitly model how fixed costs relate to characteristics of the generating unit, such as plant age and plant size. This means that our model allows us to quantify hidden cost parameters (fixed O&M costs) for different plant sizes and vintages. Furthermore, we incorporate capacity prices for the years 2008–2017 into our model, recognizing that these represent a significant source of additional revenue for OCGTs, which operate only in peak hours.

Using a dynamic model to estimate power plant costs has several advantages: costs are usually estimated based on engineering studies of plant designs, or operator questionnaires. Furthermore, they are usually provided only for operational units. Through the use of a dynamic model, we generate parameter estimates based on the actual behavior of market participants. Therefore, we can estimate costs that are not usually included in engineering studies or surveys, for instance costs of plants in a mothballed state or costs/revenues associated with the final retirement of a production unit (decommissioning costs/scrap value). In addition, using the estimated cost parameters, the fitted model itself can be used to predict the behavior of plant operators in response to changes in exogenous parameters, such as fuel or electricity prices.

For both operational and mothballed OCGTs, we find statistically significant, positive relationships between the age of the power plant and the inverse of the efficiency of the turbine (which serves as a proxy for the plant vintage) and the fixed O&M costs. We also show a statistically significant, negative relationship between the installed capacity and the fixed O&M costs, confirming that an increase in scale results in lower specific costs. Decommissioning an OCGT was found to be cash flow negative, which means that the associated cost exceeds any scrap value the equipment may have on secondary markets.

This chapter is structured as follows: the model, its assumptions and the underlying data are presented in Section 4.2. The estimated parameters, as well as a simulation based on these parameters follow in Sections 4.3. Section 4.4 contains sensitivity analyses using the fitted model. Section 4.5 concludes this chapter.

4.2. Methodology

4.2.1. Assumptions and Data

PJM operates three separate markets in its area of operations: a wholesale market for electricity, a market for secure capacity, and a market for ancillary services. The day-ahead market forms the core of PJM's wholesale market for electricity. Prices are derived by matching offers from generators with bids from consumers, with the most expensive offer cleared setting the price. The day-ahead market is augmented by a real-time market, which allows market participants to make final adjustments to their positions shortly before delivery. The PJM capacity market—called the Reliability Pricing Model (RPM)—is designed to ensure that sufficient levels of secure capacity are available to meet the projected peak demand of a given year, plus a reserve margin. The main capacity auction (base residual auction) is held three years in advance of the delivery period. 95 percent of the capacity required by PJM is purchased in the base residual auction. The remaining 5 percent are acquired in a series of incremental auctions. Capacity cleared in the auctions is committed to be available in the delivery period, which ranges from June 1st to May 31st of the following year. This means that the plant has to be operational, and can neither be mothballed nor decommissioned. Participation in the capacity market is mandatory for existing generators and optional for yet to be commissioned newly built generators. Each generator that has cleared a sell offer in one of the auctions will receive a daily payment that is equal to the MW amount cleared times the respective auction's clearing price for the delivery period (pay-as-cleared). A penalty applies in case of non-delivery (PJM, 2018b).

For the model-based analysis, we use average hourly real-time electricity prices used for the PJM interconnection (PJM, 2020b), as well as the respective year's capacity price (PJM, 2020a)[3]. Monthly natural gas prices for the states serviced by PJM are taken from (EIA, 2020b). The average annual values are presented in Table 4.1.

We use detailed power plant data provided by the Energy Information Administration (EIA) in their Annual Electric Generator Reports (EIA-860). The annual data set includes the commissioning date, operational status, location, generation capacity and fuel type of individual units. The operational

[3] Annual capacity prices are weighted averages of seasonal capacity prices. A RPM season runs from June to May.

status of the units include being operational, being in standby mode or being out of service and being retired. We consider the standby and out of service status in the data set as mothballed status.

Table 4.1.: Proportion of operated, mothballed and decommissioned units, and the development of mean capacities, electricity and natural gas prices, spark spreads, and capacity prices throughout the considered period

Year	No. of units	OP	MB	DC	Age	Capacity	P_{el}	P_{ng}	Spark spread	Capacity payment
		%	%	%	years	MW	USD/ MWh	USD/ MWh	thousand USD/MW	thousand USD/MW
2008	606	70.6	10.9	18.5	7.9	60.8	66.12	33.76	17.20	25.71
2009	520	84.6	11.3	4.0	8.7	63.6	37.00	25.39	9.45	39.35
2010	530	82.8	11.3	5.8	9.6	63.9	44.57	22.81	31.52	48.23
2011	555	79.8	10.8	9.4	10.6	63.1	42.52	22.31	32.04	53.84
2012	533	89.7	7.5	2.8	11.3	63.6	32.79	19.04	34.35	25.92
2013	543	90.4	6.1	3.5	12.1	62.9	37.15	17.87	23.93	7.72
2014	531	90.0	7.9	2.1	13.1	63.4	49.33	19.19	83.17	25.07
2015	535	84.9	5.8	9.3	14.0	63.9	34.12	16.14	75.05	47.51
2016	519	89.2	5.8	5.0	15.1	66.2	28.10	13.15	55.03	37.99
2017	531	87.4	4.9	7.7	16.1	64.3	29.48	15.02	32.18	30.89

In practice, the economic lifespan of OCGTs is around 25 years and the maximum technical lifespan is considered to be 30 years (IEA ETSAP, 2010). However, in the EIA data, a significant number of units (225 out of 740 units) had commissioning dates which indicated turbine units older than 30 years. As those commissioning dates were most likely not updated with retrofit dates, we assume those units to have received retrofits at some point, which is not specified in the data sheet. Thus, we assume major retrofits to occur every 30 years after a plant's original commissioning.

OCGTs, traditionally characterized by low fuel-to-electricity conversion efficiencies, have seen significant improvements in efficiency due to advances in technology over the past decades. As such, it can be assumed that efficiency of a turbine strongly depends on the era the turbine was commissioned in. Within this context, we assign the observed units into *vintage classes* corresponding to their commissioning years. We consider three vintage classes representative of the technology progress, and hence the efficiency of the turbines. Units built between 1972–1999 are assigned an efficiency of 0.28, units built between 2000–2014 an efficiency of 0.35, and those built from 2015 onward 0.40. The efficiency of retrofitted plants is assumed to correspond to that of new plants commissioned in the same year as the retrofit. The efficiency of a retrofitted plant corresponds to that of a plant commissioned at the time of the retrofit.[4]

Similarly, in order to reduce model complexity, we consider the capacities of observations in several classes. The observed capacities are clustered into four capacity sizes corresponding to the mean values of the quartiles of the data. The assumed vintage classes with their corresponding efficiencies and the considered mean capacities for the clusters of observations are provided in Table 4.2. For each vintage class, there are four capacity clusters, which makes a total of 12 unit types.

Table 4.2.: Vintage classes depending on the commissioning year and the capacity clusters assumed for the OCGT units

Vintage	Efficiency	Capacity (MW)
up to 1999	0.28	24, 48, 81, 150
2000 to 2014	0.35	24, 48, 81, 150
2015 onward	0.40	24, 48, 81, 150

The yearly energy payments (in USD per MW) that the considered unit types receive on the electricity market are estimated as the sum of hourly positive spark spreads throughout a year. These correspond to the integral of the price duration curve above the total variable costs of the unit. These costs comprise variable fuel costs and variable operation and maintenance costs. The variable fuel costs are assumed to be the cost of fuel (i.e. the price of natural gas) divided by the efficiency. Average variable operation and maintenance costs are assumed to be 5.5 USD/MWh (EIA, 2020a). Hence, the short run profit indicator, S, corresponds to the sum of positive spark spreads throughout a year plus the respective capacity payment.

[4] We are aware that the assumption of fixed efficiencies may not represent the real efficiencies of some units; especially those with commissioning dates bordering the dates of another vintage class. Considering more vintage classes with interpolated efficiency assumptions would result in a more realistic representation, but with exponentially increasing duration for model convergence. Hence, we found limiting the number of vintage classes to three to be a necessary simplification that allows for reasonable model convergence duration. The vintage classes are based on OCGT vintage classes used in the DIMENSION electricity market model maintained at the Institute of Energy Economics at the University of Cologne (Richter, 2011).

4.2.2. Model

The model structure is closely related to the model presented in Das (1992).[5] A power plant operator's decision problem consists of choosing a sequence of decision rules $I = i_t = f_t(x_t, \epsilon_t, \theta)$ for each time period t, which maximizes the expected discounted sum of profits of the managed power plant unit, as expressed in Equation 4.1:

$$\max_I \; E_0 \left\{ \sum_{t=0}^{T} \beta^t \, u(x_t, i_t, \epsilon_t, \theta) \right\} \tag{4.1}$$

where E_0 is the expectation based on today's information, T is the lifespan of a plant, and β is the discount rate.[6] The instantaneous profit function of a unit, $u(\cdot)$, depends on the vector of exogenous variables, x_t (installed capacity of the unit, its age, its commissioning year, and the short-run profit indicator determined by the electricity prices, fuel prices, other variable O&M costs, and capacity payments); the vector of the unobserved random components, ϵ associated with the decisions i; and the vector of parameters to be estimated, θ.

Equation 4.1 is also called the value function, $V_t(x_t, i_t, \epsilon_t, \theta)$, which corresponds to the recursive solution of the Bellman equation, where the operator picks i_t from a set of three choices, $C = \{op, mb, dc\}$. Those are whether to operate, mothball, or decommission the unit:

$$V_t(x_t, \epsilon_t, \theta) = \max_{i \in C} \{u(x_t, i_t, \epsilon_t, \theta) + \beta \, EV_t(x_t, i_t, \epsilon_t, \theta)\} \tag{4.2}$$

where the expected value EV_t is:

$$EV_t(x_t, i_t, \epsilon_t, \theta) = \int_{x_{t+1}} \int_{\epsilon_{t+1}} V_{t+1}(x_{t+1}, \epsilon_{t+1}, \theta) \, dPr(x_{t+1}, \epsilon_{t+1} \mid x_t, i_t, \epsilon_t) \tag{4.3}$$

As also shown in Rust (1988), under certain regularity conditions the optimal choice then corresponds to Equation 4.4, where the aim is to estimate the vector of parameters θ.

$$f(x_t, \epsilon_t, \theta) = \arg\max_{i \in C} \{u(x_t, i_t, \epsilon_t, \theta) + \beta \, EV_t(x_t, i_t, \epsilon_t, \theta)\} \tag{4.4}$$

[5] Our model is implemented in the Python programming language (Rossum, 2017) and solved using the L-BFGS-B algorithm (Byrd, Lu, and Nocedal, 1995; Zhu et al., 1997).

[6] In line with Das (1992), we assume a discount factor of 0.9.

In this respect, the instantaneous profit function can be written as:

$$u(\cdot) = \begin{cases} K \cdot S_t - F_{t,op} + \epsilon_{t,op} & i = op \\ -F_{t,mb} + \epsilon_{t,mb} & i = mb \\ -F_{t,dc} + \epsilon_{t,dc} & i = dc \end{cases} \tag{4.5}$$

When a unit runs, the positive term of its payoff consists of its capacity K, multiplied with the short-run profit indicator, S_t, which already contains any variable costs.

The negative term of the payoff of an operating unit equals its fixed O&M costs. They are assumed to linearly depend on the capacity K of the unit. The larger the unit capacity, the higher the fixed O&M costs. Similarly the costs are assumed to linearly depend on the age of the unit, A. The older the unit, the higher the fixed costs. Further, we assume that as plant technology improves, those costs decrease. We map plant efficiency to the vintage class of a plant. Since units with newer technology have higher efficiencies, the specific fixed O&M costs are assumed to be inversely related with the unit efficiency η. The simplifying assumption of a linear relationship is consistent with the literature (Fleten et al., 2020). The fixed O&M costs for an operating unit can then be expressed as follows:

$$F_{t,op} = \theta_{K,op}\, K + \theta_{A,op}\, A_t + \theta_{\eta,op}\, \frac{1}{\eta} \qquad \theta_{K,op}, \theta_{A,op}, \theta_{\eta,op} > 0 \tag{4.6}$$

A mothballed unit does not have variable costs and is assumed to have fixed costs only. The O&M costs of a mothballed plant are expected to be significantly reduced compared to those of an operating unit, hence the incentive to mothball a temporarily unprofitable plant. The fixed costs in this case are similarly assumed to be a function of unit capacity, age and vintage class:

$$F_{t,mb} = \theta_{K,mb}\, K + \theta_{A,mb}\, A_t + \theta_{\eta,mb}\, \frac{1}{\eta} \qquad \theta_{K,mb}, \theta_{A,mb}, \theta_{\eta,mb} > 0 \tag{4.7}$$

The fixed cost associated with decommissioning are assumed to linearly depend on unit capacity as shown in Equation 4.8. The cost term F_{dc} can be positive or negative, depending on whether the cost of decommissioning exceeds the salvage value obtained on secondary markets for combustion turbines.

$$F_{dc} = \theta_{dc} K \tag{4.8}$$

The vector of estimable parameters of the problem is then $\theta = (\theta_{K,op}, \theta_{A,op}, \theta_{\eta,op}, \theta_{K,mb}, \theta_{A,mb}, \theta_{\eta,mb}, \theta_{dc})$, where the exogenous variables are $x_t = (K, A_t, S_t, \eta)$.

The parameters of the vector θ are estimated by maximizing the likelihood function:

$$L(\theta \mid i, x) = \prod_{n=1}^{N} \prod_{t=1}^{T_n} Pr(i_{n,t} \mid x_{n,t}, \theta) \tag{4.9}$$

where $Pr(i_{n,t} \mid x_{n,t}, \theta)$ are the optimal choice probabilities, given the vector i contains every unit's choice and the vector x includes the state variables for each period. The total number of units is denoted by N, and T_n corresponds to the number of observations for unit n.

The capacity K of a unit and its efficiency η are assumed to be constant over time. The age of a unit however changes over the time periods. If the decision i_t is not to retire, then the age increases by one each year, i.e. $A_{t+1} = A_t + 1$. If the decision i_t is to retire or the maximum age of 30 years is reached then an absorbing state is reached, i.e. $A_{t+1} = A_t$. The absorbing state of the age variable assumes that after reaching the end of a turbine's lifespan, i.e. after 30 years or after decommissioning, an additional year no longer has an effect on costs.

We assume that prices of capacity, natural gas, and electricity jointly follow a first-order Markov process, denoted by $Pr(P_{capa,t+1}, P_{el,t+1}, P_{fuel,t+1} \mid P_{capa,t}, P_{el,t}, P_{fuel,t})$. Therefore, the short-run profit indicator, S, can be assumed to follow the process $Pr(x_{t+1} \mid x_t)$. Consequently, for each unit type we have the process $Pr(A_{t+1} \mid A_t, i_t) \cdot Pr(x_{t+1} \mid x_t)$, where the change in age is deterministic. By assumption, the non-deterministic transition probabilities correspond to the respective relative frequencies of x_t in the data set.

The conditional independence assumption[7] reduces the problem from $EV(x_t, i_t, \epsilon_t, \theta)$ to $EV_t(x_t, i_t, \theta)$. The value function can thus be re-expressed as:

$$V_t(x_t, \epsilon_t, \theta) = \max\{V_{t,op}(x_t) + \epsilon_{t,op}, \quad V_{t,mb}(x_t) + \epsilon_{t,mb}, \quad V_{t,dc}(x_t) + \epsilon_{t,dc}\} \tag{4.10}$$

[7]See Rust, 1987 for detailed information on this assumption.

The individual value functions for the respective decisions (i.e. operate, mothball, decommission) can then be written as follows:

$$
\begin{aligned}
V_{t,op}(x_t) &\equiv K \cdot S_t - (\theta_{K,op}\, K + \theta_{A,op}\, A_t + \theta_{\eta,op}\, \frac{1}{\eta}) + \beta\, EV_t(x_t, \theta) \\
V_{t,mb}(x_t) &\equiv -(\theta_{K,mb}\, K + \theta_{A,mb}\, A_t + \theta_{\eta,op}\, \frac{1}{\eta}) + \beta\, EV_t(x_t, \theta) \\
V_{t,dc}(x_t) &\equiv -\theta_{dc}\, K
\end{aligned}
$$

Based on the assumption that the density of ϵ for a given x follows an extreme value distribution, our choice probabilities can be expressed as:

$$
\begin{aligned}
Pr(op \,|\, x_t, \theta) &= \frac{e^{V_{t,op}(x_t)}}{M_t} \\
Pr(mb \,|\, x_t, \theta) &= \frac{e^{V_{t,mc}(x_t)}}{M_t} \\
Pr(dc \,|\, x_t, \theta) &= \frac{e^{V_{t,dc}(x_t)}}{M_t}
\end{aligned}
\tag{4.11}
$$

where $M_t = e^{V_{t,op}(x_t)} + e^{V_{t,mb}(x_t)} + e^{V_{t,dc}(x_t)}$ and $EV_t(x_t, \theta)$ stem from the unique solution of:

$$
EV_t(x_t, \theta) = \int \log(e^{V_{t+1,op}(x_{t+1})} + e^{V_{t+1,mb}(x_{t+1})} + e^{\theta_{dc}})\, Pr(x_{t+1} \mid x_t, i_t)\, dx_{t+1} \tag{4.12}
$$

4.3. Results

4.3.1. Parameter Estimates

The combination of the discrete choice dynamic programming algorithm and the maximum likelihood estimation procedure generates the following parameter estimates for $\theta_{A,op}$, $\theta_{K,op}$, $\theta_{\eta,op}$, $\theta_{A,mb}$, $\theta_{K,mb}$, $\theta_{\eta,mb}$ and θ_{dc} (see Table 4.3).

Table 4.3.: Parameter estimates, standard errors and t-ratios

	$\theta_{A,op}$	$\theta_{K,op}$	$\theta_{\eta,op}$	$\theta_{A,mb}$	$\theta_{K,mb}$	$\theta_{\eta,mb}$	θ_{dc}
Estimate	311.1***	14,213***	244,931***	99.98***	111.7	85,073***	1,004***
Standard Error	(34.90)	(2,041)	(39,917)	(0.017)	(665.9)	(29,009)	(7.795)
T-ratio	8.92	6.96	6.14	5,743	0.17	2.93	128.8

The standard errors and t-ratios are derived using parametric bootstrapping. The t-ratios (with 49 degrees of freedom) indicate that the estimates for $\theta_{A,op}$, $\theta_{K,op}$, $\theta_{\eta,op}$, $\theta_{A,mb}$, $\theta_{\eta,mb}$ and θ_{dc} are statistically significant at the 99% confidence level. The parameter estimate for $\theta_{K,mb}$ is found not to be statistically significant.

The parameter $\theta_{A,op}$ interacts with the age, the parameter $\theta_{K,op}$ with the installed capacity and the parameter $\theta_{\eta,op}$ with the efficiency of the power plant. They are part of the fixed O&M cost term of the profit function of an operational OCGT. The fixed O&M costs are expressed in USD/MW/year and scale linearly with the three parameters.

The statistically significant estimate for $\theta_{A,op}$ (311.1) shows that an OCGT's fixed O&M costs are positively correlated with the power plant's age, but the economic impact of the estimate is small.[8] This is consistent with the assumption that the wear and tear associated with long-term operation necessitates increased maintenance as the turbine ages. The mean age of the turbines in our sample increases from 8 years in 2008 to 16 years in 2017. Furthermore, plant fixed O&M costs are also assumed to scale linearly with capacity and the inverse of the efficiency of the turbine. Larger turbines are assumed to be more costly to maintain, while efficiency serves as a proxy for the plant vintage: Newer, more modern and efficient plants likely have lower maintenance costs per unit of capacity than older units. All other things being equal, a higher efficiency would therefore translate to lower fixed O&M costs per unit of capacity. The parameter estimates for $\theta_{K,op}$ (14,213) and $\theta_{\eta,op}$ (244,931) confirm these relationships.

For the operator of a mothballed plant all costs are fixed costs. The statistically significant estimate for $\theta_{A,mb}$ (99.98) shows that the fixed costs increase with the age of the plant. However, we are unable to detect a statistically significant relationship between fixed costs and the capacity of the plant ($\theta_{K,mb}$). As expected, we find that mothballing significantly reduces a plants cost footprint.

[8] Multiplying an estimate with its respective state variable shows the impact of the estimate on the economics of the plant. Cf. Tables 4.4 and 4.5.

The parameter θ_{dc} interacts with the plant capacity and describes the costs associated with the permanent shutdown of a plant. It is estimated as 1,004 USD/MW. Since the parameter estimate of θ_{dc} is positive, we are able to deduce that the process of decommissioning a plant is cash flow negative, which means the costs are higher than the potential revenue from selling old equipment such as the turbine on a secondary market.

Table 4.4 displays the model-derived fixed O&M costs for selected operational OCGTs in USD/kW/year, based on the capacity clusters and plant-vintage-based efficiencies used in this study.[9]

Table 4.4.: Fixed O&M cost estimates for an operational 10-year-old OCGT, by vintage class and capacity cluster; in USD/kW/year

Vintage	Efficiency	24 MW	48 MW	81 MW	150 MW	300 MW
up to 1972	28%	50.8	32.5	25.1	20.1	17.1
1973 to 2000	35%	43.5	28.9	22.9	18.9	16.6
2001 to 2015	40%	39.9	27.0	21.8	18.3	16.3

As shown above, the costs negatively correlated with the vintage/efficiency of a plant. The older and less efficient the turbine, the higher the associated costs. At the same time, costs scale inversely with the capacity of a plant: the larger the unit, the lower the specific fixed O&M cost per unit of capacity. Our model estimates fixed O&M costs with a range from 16.3 USD/kW/year for a relatively new and efficient, large (300 MW) gas turbine, to 50.8 USD/kW/year for a small, relatively old low efficiency 24 MW turbine.

Table 4.5.: Fixed O&M cost estimates for a mothballed 10-year-old OCGT, by vintage class and capacity cluster; in USD/kW/year

Vintage	Efficiency	24 MW	48 MW	81 MW	150 MW	300 MW
up to 1972	28%	12.8	6.4	3.9	2.1	1.1
1973 to 2000	35%	10.3	5.2	3.1	1.7	0.9
2001 to 2015	40%	9.0	4.6	2.7	1.5	0.8

[9] We also show out of sample predictions for plants with a capacity of 300 MW, as turbines of this size are commercially available. See, for example, PJM (2014) and PJM (2018a).

The estimated fixed O&M cost for different capacity cluster/plant vintage combinations of mothballed OCGTs are shown in Table 4.5. They vary from 0.8 USD/kW/year for a new, large 300 MW OCGT to 12.8 USD/kW/year for a small, old unit. As with operating units, the larger a unit, the lower the specific fixed O&M cost. Overall, fixed O&M costs in the mothballed state are estimated to be around 25% of the fixed O&M costs in the operating state for smaller, older plant. The fixed O&M costs are as little as 5% for a large new unit. This shows that the relative benefit of mothballing is greater for larger plants.

The derived parameter estimates are broadly in line with what can be found in the relevant literature. PJM's own reports on the cost of newly built capacity (PJM, 2014; PJM, 2018a) give figures ranging from 12.2 to 25.5 USD/kW/year for the fixed O&M cost of a newly built operational gas turbine-equipped peaker plant, which is in the lower half of the range of estimates given by the dynamic model. It should be noted that the PJM estimates are for new, large (+300 MW) plants, while the data set analyzed using our model contains a significant number of smaller, older, lower efficiency units, which, as shown in Table 4.4, are likely to have higher specific fixed O&M costs.

Similarly, EIA (2016) states a fixed O&M cost estimate of 10 USD/kW/year for a simple combustion turbine and 17.5 USD/kW/year for a more advanced turbine. This is slightly below our own estimates. Again, this is not surprising, since these estimates too are for new plants, while most units in our data set are of older vintages.

Estimates of the costs of a mothballed unit or of decommissioning OCGTs are harder to come by. A report by the Dutch transmission system operator TenneT (2019) states that mothballing cuts the fixed O&M expenses of large (800 MW) combined cycle gas turbine (CCGT) power stations by roughly 95%. Our estimates suggest that the relative savings are of a similar magnitude for large OCGTs.

According to Raimi (2017), the costs of decommissioning gas fired power stations in the US range from 1,000 USD/MW to 50,000 USD/MW, with a mean value of 15,000 USD/MW. The source does not differentiate between simple OCGTs and the more complex CCGTs, but it appears reasonable to assume that the lower end of the range is more likely to be representative of the costs associated with decommissioning the smaller and less capital-intensive OCGTs. This is in line with our estimate of 1,004 USD/MW.

4.3.2. Fit of the Model and Model Predictions

Using the parameter estimates described above, we are able to compare the model predictions to the data. In Figures 4.1, 4.2, and 4.3, we plot the estimated probability to operate, mothball or retire an OCGT against the actual observations for each of the observed years, providing a qualitative indication of the goodness of fit of the model.

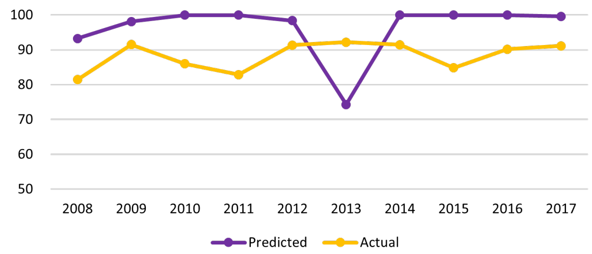

Figure 4.1.: Probability of operating: model predictions vs actual observations; in percent

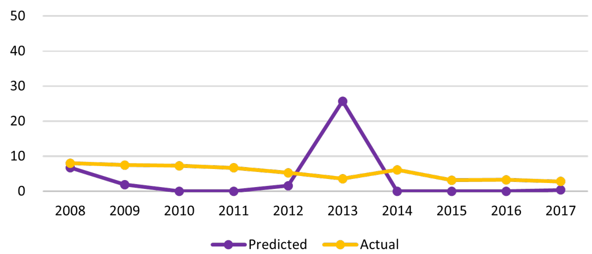

Figure 4.2.: Probability of mothballing: model predictions vs actual observations; in percent

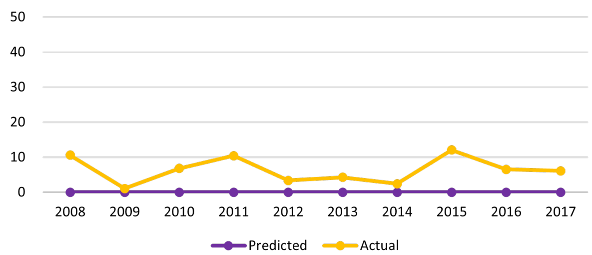

Figure 4.3.: Probability of decommissioning: model predictions vs actual observations; in percent

It is evident that the model over-predicts the probability to operate. Mothballings are predicted to occur only in 2008, 2009, 2012, and 2013. In the data, mothballings are observed in all years, although there is a declining trend in line with the long-run decline of natural gas prices and the improving relative competitiveness of gas-fired power plants. The model assumes that operators value the present more than the future, therefore the decision to mothball in a bad year would be rational. This is reflected in the behavior of the model: the spike in estimated mothballings in 2008 can be explained by the prevailing high natural gas price (33.76 USD/MWh), the second peak in 2013 with low capacity payments (7.72 USD/kW/year) in the PJM. In both years, profits are low enough to make mothballing the most economical choice in older vintage classes. A key assumption underpinning the model is that operators assign an equal probability to all future outcomes, in this case any of the ten years covered by the data set. Eight of these years are good profit years. In reality, however, operator expectation about the future may very much be shaped by recent trends and forecasts. In 2008, operators were probably still deciding based on the past experience of a high gas price world. From 2008 onward, for example, there has been a continuous decline in the gas price. 2008 is in fact the only year in the data set with a gas price above 30 USD/MWh. Operators would therefore assign a lower probability to such an outcome–a sharp increase in the gas price–than to the possibility of gas prices remaining low.

While the cost estimates are in line with the literature, the model does not predict any decommissionings, even though they can be observed in all of the years considered. The fact that in reality, retirements are more likely to occur than predicted by the model might also be explained by unobserved shocks, such as major failures in units that are potentially close to the end of their technical lifespan.

Despite the highlighted model limitations, it should be noted that in the data, mothballings account for less than 10% of the observations between 2008 and 2014 and less than 5% of the observations between 2015 and 2017. Decommissionings are similarly rare in any given year. There are peaks in 2008, 2011 and 2015 where they account for close to 10% of the total observations, but in most other years, the probabilities here are also lower than 5%. Taking the relative infrequency of both mothballings and decommissioning in the data into account, the predictive power of the model appears reasonable.

4.4. Sensitivity Analysis

The model estimates can be used to perform sensitivity analyses with respect to changes in the state variables of the model. Figures 4.4 to 4.6 display the impact—ceteris paribus—of a percentage change in capacity prices, electricity prices, and natural gas prices, respectively, on the probability of operating, mothballing or retiring a plant. These three state variables strongly influence the economics of the plant operator's decision problem. The sensitivity analyses are carried out as follows: the three state variables are analyzed separately. For all time periods, the respective state variable is altered to the indicated percentage level. Subsequently, we run the model using our estimated cost parameters. Finally, the overall percentage shares of the three operational states are calculated from the probabilities delivered by the model runs.

In summary, an increase in the capacity or electricity prices elevates the probability of choosing to operate, and an increase in natural gas prices raises the probability of choosing to mothball or retire a plant.

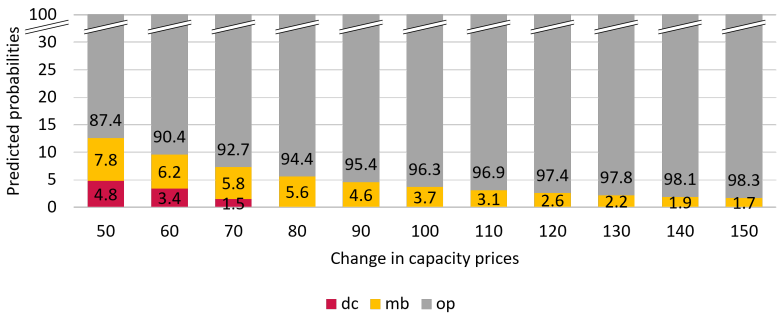

Figure 4.4.: Predicted probabilities in response to a change in capacity prices; in percent

Figure 4.4 shows that the probability to operate declines to 87.4% when the capacity prices decline to 50% of their respective values over the 2008-2017 period under investigation. At the same time, the probability of mothballing increases from 3.7% to 7.8%, while the probability of decommissioning increases to 4.8%. At the average capacity price level, decommissionings are—all else equal—never the most profitable choice and the related probability is thus 0%.

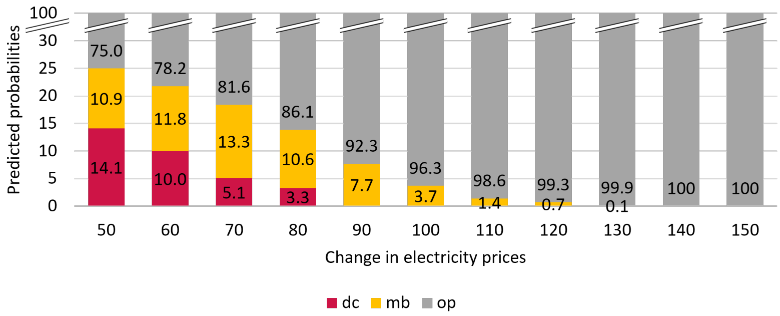

Figure 4.5.: Predicted probabilities in response to a change in electricity prices; in percent

In Figure 4.5, the electricity prices vary between 50% and 150% of the electricity price level over the periods under investigation. In the context of the sensitivity analyses, a decline in the electricity prices has the strongest effect on the probability to decommission. It increases to 14.1% when the prices of electricity are at the 50% level. The probability of mothballing peaks with a value of 13.3% at prices that are at the 70% level. At even lower prices, it declines again as decommissioning becomes a more profitable choice relative to it. This suggests that sustained periods of significantly lower electricity prices would likely lead to an increase in the number of plants exiting the market.

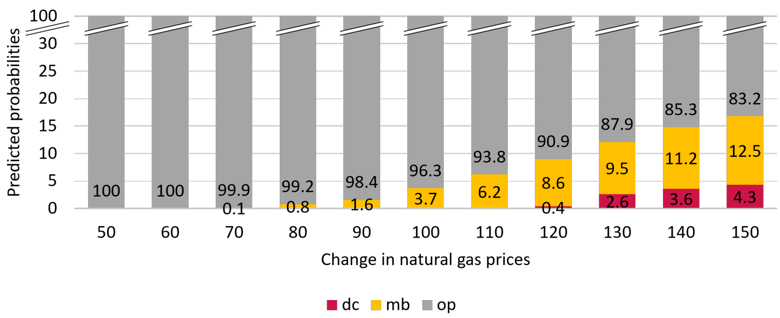

Figure 4.6.: Predicted probabilities in response to a change in natural gas prices; in percent

In Figure 4.6, natural gas prices vary between 50% and 150% of the original natural gas price level for the years 2008–2017. The probability of mothballing increases from the original 3.7% to 12.5% with a 50% rise in gas prices. The probability of retiring the plant first becomes larger than zero (0.4%) at the 120% natural gas price level. After a jump to 2.6% at the 130% price level it finally reaches 4.3% at the 150% price level.

In conclusion, the sensitivity analyses confirm that the original price levels describe a fairly profitable situation for OCGTs. For instance, only large deviations of the state variables over the entire observed period lead to projected decommissionings (at least -20% in electricity prices, +20% in natural gas prices, and -30% in capacity prices).

4.5. Conclusion

The chapter at hand presents a methodology to estimate fixed cost parameters relevant to the decision to operate, mothball, or retire an OCGT using a combination of a discrete choice dynamic programming algorithm and a maximum likelihood estimation procedure. The model uses data on capacity, fuel, and electricity prices, as well as technical data and the operational status of OCGTs in the PJM market area.

For both operational and mothballed OCGTs, we find statistically significant, positive relationships of the fixed O&M costs of the power plant with the age of the plant, as well as with the inverse of the efficiency of the plant (which serves as a proxy for the plant vintage). As expected, we also find a statistically significant, negative relationship between the installed capacity and the fixed O&M costs of operational plants, confirming that an increase in scale results in lower specific costs. The estimated fixed O&M cost parameters for an operational OCGT vary from 16.3 USD/kW/year for new, large, high efficiency units, to 50.8 USD/kW/year for older, small, low efficiency turbines. Mothballing a plant reduces these costs by 75% to 95%, depending on plant vintage and size. Decommissioning an OCGT is found to be cash flow negative, which means that the associated cost exceeds any scrap value the equipment may have on secondary markets. The estimates are broadly in line with those provided by other sources, most notably PJM's own independent reports on the cost of new peaking capacity (PJM, 2014; PJM, 2018a). Yet, our results offer the additional benefit of a differentiation by technical attributes of a power plant. This differentiation is valuable for a better understanding of costs in the context of competition policy. It also allows for more accurate energy system modeling with the goal of more realistic analyses of network stability, investment decisions, and greenhouse gas emissions.

Using the estimates, we also analyze the sensitivity of operational choices of an OCGT with regard to changes in model inputs, namely capacity prices, electricity prices, and natural gas prices. The sensitivity analyses confirm the model to behave as expected, with a decrease in the capacity or electricity prices, first the probability of mothballing, and at lower price levels, also the probability of decommissioning an OCGT increases. The reverse is true for natural gas prices. Here, a price increase results in rising probabilities for plant mothballings and retirements.

A limitation of the approach used in this chapter is that it relies on the assumption that the markets for electricity and capacity in PJM are perfectly competitive in order to derive robust parameter estimates. If players exert market power by withholding capacity (e.g. by mothballing otherwise profitable power plants), the costs estimated by the model could be exaggerated. However, the general alignment of the estimated parameters with cost estimates from other sources that employ different methodologies suggests this to be unlikely. Additionally, PJM's own state of the market reports underline that both the electricity and the capacity market have been broadly competitive throughout the period under investigation (Monitoring Analytics, 2020).

Future extensions of this work may consider additional choices a plant operator may make. Owing to a lack of data, for instance, this chapter does not consider retrofits that improve the operating efficiency, lower costs, or extend the operational lifetime of a power plant. Retrofits improve the forward-looking profit margin of a power plant. Based on expectations about future profits, it may be rational for such an investment to be undertaken, adding a fourth alternative to the choice of operating, mothballing, or retiring.

A. Appendix for Chapter 2

A.1. Absolute Values of Results

Table A.1.: Model results by liming scenario: baseline (0 in isolation) and optimal scenarios (414 and 647 s.t. global price of maize)

	unit	baseline	counterfactuals					
p global	USD/t	[100,382]	[100,340]			350		
scenario	-	0	414			647		
t	year	all	0	1	19	0	1	19
trade	-	isolation	isolation	isolation	isolation	isolation	export	export
TWF	mn USD	6,984.9	7,225.7	-	-	7,376.5	-	-
TCS	mn USD	6,263.7	6,446.1	-	-	6,385.7	-	-
TPS	mn USD	721.1	779.6	-	-	990.8	-	-
R lime	t/ha	0	1.51	0.73	0.29	4.17	1.57	0.58
Share pH hi	%	0.8	0.8	50.4	50.4	0.8	100.0	100.0
Share pH mi	%	53.6	53.6	49.6	49.6	53.6	0	0
Share pH lo	%	45.6	45.6	0	0	45.6	0	0
p EQ	USD/t	203.12	209.45	160.94	156.72	214.38	170.50	170.50
WF	mn USD	1,351.9	1,300.9	1,411.2	1,424.6	1,211.4	1,442.1	1,488.9
CS	mn USD	1,212.4	1,206.5	1,254.0	1,258.4	1,202.1	1,244.1	1,244.1
PS	mn USD	139.6	94.4	157.3	166.2	9.3	198.0	244.8
PS per Area	USD/ha	105.25	71.15	140.20	149.14	7.01	158.87	184.25
Yield	t/ha	2.02	2.01	2.49	2.52	2.00	3.30	3.68
QS	mn t	2.680	2.663	2.795	2.807	2.650	4.117	4.885
QS Z2Z	mn t	2.680	2.663	2.795	2.807	2.650	2.769	2.769
Q export	mn t	0	0	0	0	0	1.348	2.116
Q FRA	mn t	1.752	1.752	1.752	1.752	1.752	1.752	1.752
production inputs								
Utilization	%	73.9	58.7	61.6	61.9	51.3	79.8	94.7
Share area	%	99.8	99.8	84.4	83.9	99.9	93.8	100.0
R fbas	kg/ha	80	79	91	93	79	149	187
R fbas sub	kg/ha	41	41	41	41	41	41	41
R fbas fup	kg/ha	39	38	49	52	38	108	146
R ftop	kg/ha	89	88	83	85	88	130	163
R ftop sub	kg/ha	41	41	41	41	41	41	41
R ftop fup	kg/ha	48	47	41	44	46	88	121

Utilization is defined for each liming scenario (s) as the ratio between optimized output and technically maximal output, which is based on the upper bounds of fertilizers and land use.

A.2. Liming Scenarios

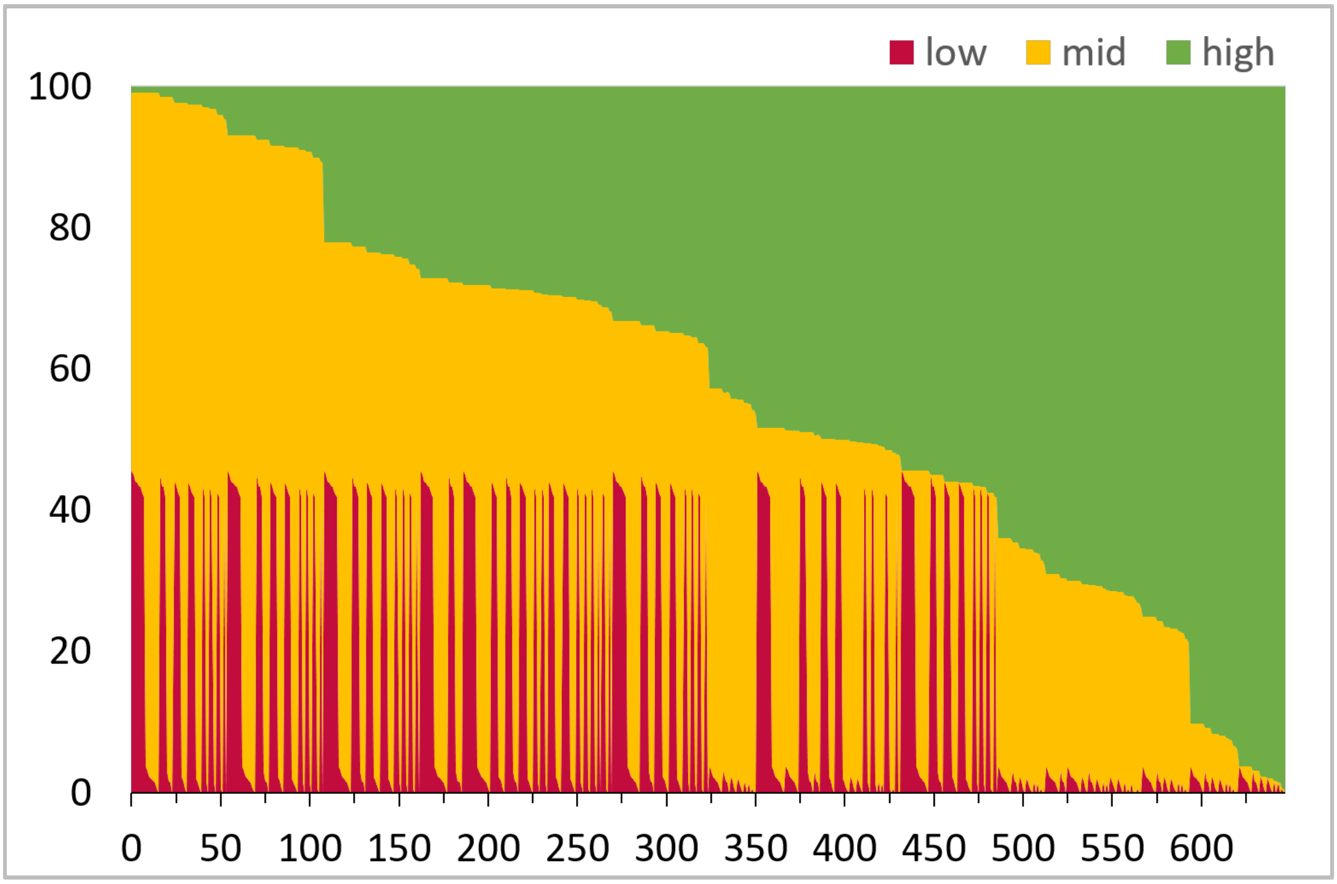

Figure A.1.: All 648 liming scenarios ordered by share of area in higher pH groups; in percent of total area

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