Empirical essays on the price formation in resource markets

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Abbreviations

ADF	Augmented Dickey Fuller
AE	United Arab Emirates
AIC	Akaike information criterion
API	Argus McCloskey price indices
ARA	Amsterdam, Rotterdam and Antwerp
BC	Battese and Coelli
bcm	billion cubic metres
BEKK	Baba, Engle, Kraft and Krone
BF	blast furnaces
BFGS	Broyden, Fletcher, Goldfarb and Shanno
BGR	Bundesanstalt für Geowissenschaften und Rohstoffe (Federal Institute for Geoscience and Natural Resources)
BHBP	BHP Billiton
BIC	Schwarz information criterion
BOF	Basic Oxygen Furnace
BREE	Bureau of Resource and Energy Economics
CIF	cost, insurance and freight
CSN	Companhia Siderúrgica Nacional
DL	division level
DPT	Diks-Panchenko-test
DRI	direct reduced iron
DWT	deadwheight tonnes
EAF	eletric arc furnace
ENTSOG	European Network Transmission System Operators for Gas
EU	European Union

EWI	Insitute of Energy Economics at the University of Cologne
EPEC	equilibrium problem with equilibrium constraints
Fe	Ferrum (chemical element)
FGE	Facts Global Energy
FL	firm level
FMG	Fortescue Metal Group
FOB	free on board
FOC	first-order condition
GAMS	General Algebraic Modeling System
GARCH	general autoregressive conditional heteroscedasticity
GDP	gross domestic product
GIIGNL	The International Group of Liquefied Natural Gas Importers
HM	heating and miscellaneous
IEA	International Energy Agency
IP	industry and power
JP	Japan
kcm	thousand cubic metres
KKT	Karush-Kuhn-Tucker
kWh	kilowatt hour
LI	Lerner index
LKAB	Luossavaara-Kiirunavaara Aktiebolag
LNG	liquefied natural gas
LP	linear program
LR	likelihood ratio
LTC	long-term contract
mcm	million cubic metres
MCP	mixed complementarity problem
MGARCH	multivariate general autoregressive conditional heteroscedasticity
MILP	mixed integer linear problem
MPEC	mathematical problem with equilibrium constraints
MSE	mean-squared error
Mt	million tonnes
NBP	National Balancing Point
OECD	Organisation for Economic Co-operation and Development

OLS	ordinary least squares
OME	Observatoire Méditerranéen de l'Energie
OTC	over-the-counter
PC	perfect competition
PCI	pulverised coal injection
PP	Philipps-Perron
PVI	parallel vertically integration
RB	Richards Bay
QA	Qatar
SEC	Securities and Exchange Commission of the United States
SNIM	Société Nationale Industrielle et Minière
SPEP	spatial price equilibrium problem
TNEP	traffic network qeuilibrium problem
TTF	Title Transfer Facility
UK	United Kingdom
USA	United States of America
USD	United States Dollar
VAR	vector autoregression
VECM	vector error correction mechanism
VI	variational inequality
SFA	stochastic frontier analysis
WSA	World Steel Association

For Christa, Veronika and Werner

Kapitel 1

Introduction

1.1 Motivation

The thesis at hand seeks to augment the understanding of price formation in resource markets. The investigation of price formation may encompass a variety of research questions such as whether and how strong, e.g., macroeconomic factors or the regulatory environment affect the price of the resource commodity under investigation. In the case of an internationally traded commodity with differences in quality, one may be interested to determine the exact nature of the long-term equilibrium relationship between prices of the same good but with different qualities. The thesis at hand, as such, is concerned with two specific aspects:

- Do players in resource markets behave strategically and, if so, how does their behaviour influence price formation?
- How do different trade products of the same commodity influence each other's price formation?

The research presented in Chapters 2 through 5 seeks to answer variations of the former research question for resource markets such as iron ore, natural gas and thermal coal. In general, characteristics consistent across all of these markets may motivate strategic behaviour of certain players – either firms or countries – in international trade.

Resource markets, including the markets for energy resources, are usually spatial markets. Since resources are distributed unevenly over the world and transport costs tend to be lower than the differences in production costs or quality, there may be great distances between supply and demand. Thus, producers may have the possibility to exercise spatial market power. Furthermore, the supply side of many resource markets is highly concentrated, with only a handful of firms or countries accounting for the majority of the market share. Part of the explanation for such a concentration is the natural endowment of the resource itself or one with higher quality and/or lower production costs. Further reasons may include, for example, state monopolies, the existence of economies of scale and experience effects. Strategic behaviour may also be fostered in some resource markets by the low elasticity of demand caused by the difficulty or costliness of substituting the resource in production processes. In this context, Chapters 2 through 5 of this thesis analyse different aspects of strategic behaviour.

Chapter 2 assesses the effects of a supply shock on the global natural gas market. By modelling gas supply as a spatial Cournot oligopoly, the paper investigates the vulnerability of different gas importing countries to price increases during a supply shock. It seeks to evaluate the countries' strategic positions during a crisis, which are mainly influenced by their access to gas infrastructure and resource endowment.

Chapter 3 deals again with supply-side oligopolies. However, the paper presented here does not account only for one market but rather for two interacting markets. The research is motivated by the need for complementary inputs in steel production, namely iron ore and coking coal. Interestingly, some of the biggest mining companies play a major role in both markets. Therefore, we question the optimal business strategy for these oligopolists: To optimise the iron ore and the coking coal divisions on a firm or a division level?

Characteristics of a specific market often allow it to justify more than one market setting. The international coking coal market is a good example. Yet some of these settings such as two-stage games are difficult to model. Chapter 4 adds to the literature by analysing a broad variety of different market settings including multi-leader-follower-games using different simulation models.

In contrast to the previous chapters, Chapter 5 is an econometric analysis that uses a novel application of stochastic frontier analysis (SFA) to determine the exercise of market power in the iron ore market on a firm level. More specifically, the effect of macroeconomic variables and firm-specific characteristics on the individual firm's ability to drive prices above marginal costs measured by firm-specific Lerner indices is estimated.

The final chapter of this thesis is concerned with the latter of the two research questions posed at the beginning of this section. More specifically, its focus lies on the analysis of price formation in the international market for thermal coal. International trade of thermal coal, and in particular trade of derivatives, is still in its infancy compared to other commodity markets. Most trade is done over-the-counter (OTC) and no stock exchange exists where standardised spot trades can be carried out. We are interested in better understanding the process of price formation in such an environment. To this end, we analyse price formation in an intertemporal framework, i.e., the causal relationship between spot and futures prices, as well as an interregional context, i.e., between prices of two of the most important global trading hubs.

1.2 Methodology

In the various chapters of the thesis at hand, a broad range of methodological approaches is applied. While Chapters 2 through 4 make use of different simulation models (all of which are based on the idea of complementary programming) the analyses presented in Chapters 5 and 6 use econometric tools to answer their respective research questions.

1.2.1 Analysing resource markets using complementary programming

Regional differences in geological conditions (e.g., resource availability), labour costs and supply or tax legislation are, amongst others, reasons why commodity markets and, in particular, resource markets are often spatial markets. In other words, it is cheaper to produce the respective product in a different place than where it is consumed. In this context, one question that immediately comes to mind, assuming various dispersed supply and demand markets, is what could be the optimal (here the cost minimal) distribution of total supply to the various demand regions. This research question is referred to as the traffic network equilibrium problem (TNEP) or the transportation problem, which was first formalised by the French scientist Gaspard Monge in the late 18th century (Monge, 1781). In the 1930's and early 1940's, Leonid Kantorovich made significant contributions to the field, which explains why the problem in its general form is also referred to as the Monge-Kantorovich-transportation problem. It was once again Kantorovich along wih Tjalling C. Koopmans and Frank L. Hitchcock who, at the beginning of the 1940's, proposed the first linear formulations and solutions to the problem (see, e.g., Hitchcock, 1941, Kantorovich, 1942). Dantzig's development of the simplex algorithm (Dantzig, 1951) was another milestone in the research on the transportation problem, since it made larger problems tractable.

It was Enke (1951) who first described the problem of a spatial market by proposing a solution method that uses a simple electric circuit to determine equilibrium prices and quantities in competitive markets. However, Paul A. Samuelson is widely associated with laying the groundwork for spatial market analysis and the use of mathematical programming. In his seminal paper (Samuelson, 1952), Samuelson proposes the spatial price equilibrium problem (SPEP), which is similar to the transportation problem.[1]

[1] In fact, Dafermos and Nagurney (1985) show that any SPEP can be solved as a TNEP.

Samuelson (1952) shows how the problem can be cast into a (welfare) maximisation problem and states that given a fixed demand and price-taking players, standard linear programming algorithms could be used to solve the problem.

However, considering the market structure in many resource markets, the assumption of a perfectly competitive supply side may turn out to be too strong. Consequently, the work by Takayama and Judge (1971), who develop a spatial monopoly model, is considered a seminal publication for energy and resource economics. Beckmann (1972, 1973) extended the Samuelson-Takayama-Judge-model to spatial oligopolies. In contrast to the classical SPEP of Samuelson (1952), all models deviating from the assumptions of perfect competition are nonlinear since an elastic demand function is assumed. In this case, players on the supply side take the elastic demand function into consideration when trying to maximise their profits, e.g., by setting quantites (Cournot model). Harker (1984) introduces the idea of using a variational inequality (VI) approach to model spatial oligopolistic markets. Since Harker (1984), progress in solution algorithms has allowed so-called mixed complementary problems (MCP), which are based on the VI approach, to become the standard approach to modelling non-competitve behaviour when decisions by all players are taken simultaneously. Mixed complementary problems are used to model the spatial markets analysed in Sections 2 and 3.

Instead of directly using the objective function of the optimisation problem, a MCP generally consists of the first-order conditions (FOC) of each player's profit maximisation problem. We consider a market with S producers and D demand regions with $x_{s,d}$ being the amount shipped from $s \in S$ to $d \in D$. The profit function of supplier s is given by

$$\Pi_s(x_{s,d}) = \sum_{d}^{D} (P_d(X_d) - t_{s,d})x_{s,d} - C_s(X_s), \tag{1.1}$$

with $X_s = \sum_d^D x_{s,d}$ being total production of supplier s, $t_{s,d}$ being the transport costs, C_s being the production cost function, X_d being total demand in market d and P_d the inverse demand function. The first partial derivate of the profit function with regard to $x_{s,d}$ yields the following first-order condition:

$$\frac{\partial \Pi_s}{\partial x_{s,d}} = P_d(X_d) + \left(\frac{\partial P_d(X_d)}{\partial x_{s,d}} + \frac{\partial P_d(X_d)}{\partial x_{-s,d}} \frac{\partial x_{-s,d}}{\partial x_{s,d}} \right) x_{s,d} = 0 \quad \forall\ s, d \tag{1.2}$$

with $x_{-s,d}$ being the supply of the remaining producers to demand region d. Assuming a linear demand function, $p_d \left(\sum_s^S x_{s,d} \right) = a - b * \sum_s^S x_{s,d}$, and constant marginal production costs, c_s, this FOC results in the following complementary slackness condition:

$$0 \leq x_{s,d} \perp -p_d + b * x_{s,d} + c_s + t_{s,d} \geq 0 \Leftrightarrow x_{s,d} * (p_d - b * x_{s,d} - c_s - t_{s,d}) = 0. \tag{1.3}$$

This complementary slackness condition states that each supplier s is willing to ship a positive amount to demand region d if the price in that region covers the production and transport costs plus the oligopoly markup, $b * x_{s,d}$. In case, costs and markup exceed the price, no trade takes place between the two markets. If the model is more complex, e.g., if it includes production constraints, the FOCs are derived using the Lagrangian of each player instead of simply using the revenue function. In addition to the FOC of the various players, the constraints restricting the decision space of the players form the MCP.

The analysis in Chapter 2 is conducted using a spatial Cournot oligopoly model of the global gas market, named COLUMBUS and formulated as a MCP. The simulation model has been developed in a joint work with Harald Hecking. In COLUMBUS, we aim to find a spatial equilibrium for gas suppliers, infrastructure operators and the demand side of the market. We include the most relevant players active in the global gas market, i.e., pipeline operators, liquefied natural gas (LNG) facilities, storage operators and gas producers as well as their trading branches, the so-called gas exporters. Since COLUMBUS also includes the decisions on future infrastructure investment and the operation of gas storage, the model is intertemporal. Nonetheless, it is a one-shot Cournot game since all players make all decisions simultaneously over the entire time horizon of the model. Concerning the analysis in Chapter 2, the model enables us to derive the fundamental price effects of a supply shock and to disentangle these price effects into factors that increase or decrease prices.

Although the MCP approach is useful to model a spatial Cournot oligopoly, some simplifying assumptions limit the representation of the gas market as it works in reality. First of all, we assume perfect information of all players: That is, every player has full knowledge about future market developments such as production costs and capacity as well as demand. In particular, each player has perfect information about the costs, the capacities and the delivery options of all the other players in the market. Additionally, players have perfect foresight, i.e., they can anticipate shocks like a supply disruption and, in particular, the disruption's duration. Modelling of the gas market's demand side is another difficulty. Modelling a Cournot oligopoly requires the specification of an elastic demand function. Obviously, the assumed specification of the demand function including its elasticity is a major driver of equilibrium prices and demand. Furthermore, data requirements for modelling the global gas market using a model such as COLUMBUS are very high: The model requires data on country-wise, sector-wise and seasonal gas demand as well as production and transport costs and capacities. Although data has been collected thoroughly, in some cases reasonable assumptions have to be made. To cope with this problem, we have included a detailed sensitivity analysis on the assumptions.

The simulation model used in the research presented in Chapter 3 is again formulated as a MCP. Together with Harald Hecking, we develop two spatial and interacting Cournot oligopoly models: one simulating the global iron ore trade, the other simulating international coking coal trade. Since both goods are complementary inputs in pig iron production (which is the main input in producing steel), we solve both models simultaneously such that the interaction between the two commodities is accounted for. In order to solve the two Cournot oligopolies simultaneously, we need to make assumptions. First, since both products are complementary, the market output of iron ore x_i has to equal that of coking coal x_c in each demand market (market clearing). Second, the price of the final product (pig iron) p_{pi} equals the price of iron ore p_i plus that of coking coal p_c, thereby neglecting the other costs of pig iron production. These conditions are common knowledge to all Cournot players in both markets and are, thus, included in the players' optimisation rationales. The integrated simulation model enables us to investigate whether mining companies that are integrated in the production of both coking coal and iron ore have an incentive to optimise the output of both goods on the firm instead of on the division level.

Besides the drawbacks that generally apply to MCP simulation models (as discussed above), our integrated model of complementary inputs requires two strong assumptions: First, players active in one input market regard the price of the other complement as given and, second, markets clear at all times. These assumptions have the following effect: Iron ore producers, for example, optimise their output with respect to the pig iron demand function given a certain metallurgical coal price. The two prices induce a certain market output for each of the goods. However, if the output of both goods is not equal, the two markets are not in equilibrium. The iron ore and coking coal producers therefore have to include this equilibrium condition in their optimal output decision. The strict equality of iron ore and coking coal output is a strong assumption that does not need to hold in reality as, for example, stocking of coal and iron ore is an opportunity to balance markets. Sonnenschein (1968) introduced the contrary extreme to the assumption just discussed: If the output of one good exceeds the output of the other good, then the price of the first good drops to marginal costs; which is by no means more realistic. Thus, developing a better modelling approach for two or more oligopolies of complementary goods is still open for future research.

In Section 4, a joint work with Stefan Lorenczik is presented, in which in addition to a MCP more complex simulation models are used. These models allow to simulate two-stage (Stackelberg) games with one – mathematical problem with equilibrium constraints (MPEC) – or more leaders – equilibrium problem with equilibrium constraints (EPEC). Both MPEC and EPEC include a MCP that is used to model the followers and, in addition, one or more maximisation problems similar to the one in Equation 1.1 yet taking into account the equilibrium conditions of the followers.

In the MPEC model, we seek to represent a Stackelberg market structure with one leader (l) taking into account the equilibrium decisions of the followers ($-s$):

$$\max_{x_{l,d}} \sum_{d}^{D} (P_d(X_d) - t_{l,d}) \cdot x_{l,d} - C_l(X_l) \tag{1.4}$$

subject to

$$0 \leq -P_d + b \cdot x_{s,d} + c_s + t_{s,d} \perp x_{s,d} \ \forall \ s \neq l, d. \tag{1.5}$$

Thus, the leader decides on her supply, taking the equilibrium outcome of the second stage (which influences the market price) into account. The followers ($-s$) take the other followers' as well as the leader's supply as given. The objective function is non-convex and thus solving the MPEC problem in the form previously described usually does not guarantee a globally optimal solution. Thus, we rewrite the model as a mixed integer linear problem (MILP) that can be solved to optimality with prevalent solvers.

There exist several approaches for linearising the nonlinearities. Due to its simple implementation, we follow the approach presented by Amat (1981) for the complementary constraints (for an alternative formulation see Siddiqui and Gabriel, 2013). The nonlinear constraint

$$0 \leq -P_d + b_d \cdot x_{s,d} + t_{s,d} + c_s \perp x_{s,d} \geq 0 \tag{1.6}$$

is replaced by the following linear constraints

$$0 \leq -P_d + b_d + t_{s,d} + c_s \cdot x_{s,d} \leq M \cdot u_{s,d} \tag{1.7}$$

$$0 \leq x_{s,d} \leq M(1 - u_{s,d}) \tag{1.8}$$

with M being a large enough constant and $u_{s,d}$ being a binary variable. For the remaining nonlinear term in the objective function ($P_d \cdot x_{l,d}$), we follow the approach presented by Perreira (2005) using a binary expansion for the supply variable $x_{l,d}$. The continuous variable is replaced by discrete variables

$$x_{l,d} = \Delta_x \sum_k 2^k b^x_{k,l,d}, \tag{1.9}$$

where Δ_x represents the step size, i.e., the precision of the linear approximation, and k the number of steps. Variables $b^x_{k,l,d}$ are binary. The term $P_d \cdot x_{l,d}$ in the objective function is replaced by $P_d \cdot \Delta_x \sum_k 2^k z^x_{k,l,d}$. In addition, the following constraints have to be included in the model:

$$0 \leq z^x_{k,l,d} \leq M^x b^x_{k,l,d} \tag{1.10}$$

$$0 \leq P_d - z^x_{k,l,d} \leq M^x \left(1 - b^x_{k,l,d}\right) \ . \tag{1.11}$$

MPEC models reformulated in such a way constitute a MILP that can be reliably solved to a globally optimal solution. An EPEC consists of as many MPEC problems as there are Stackelberg leaders, with each of the optimisation problems maximising the output of one of the Stackelberg leaders given the output of the other Stackelberg leaders. The various MPECs are solved repetitively until the change in the resulting outcomes undershoots a certain threshold.

The results presented in Chapter 4 make clear that, despite using various statistical tests or indices, it may be difficult to decide on the one setting that provides the best fit. In our research we therefore not only compare trade data to the real market outcomes but also add further analyses such as comparing production volumes. Unfortunately, such additional analyses are often limited by data availability. Consequently, using a larger variety of different simulation models is a first step in improving the analysis of markets but may not be sufficient to conclusively determine the correct market setting.

1.2.2 Using stochastic frontier analyses to determine the exericse of market power

As pointed out in Subsection 1.1, many resource commodity markets display characteristics suggesting that companies or countries may theoretically be able to exercise market power. Consequently, there has been substantial academic research devoted to the attempt to check whether market players actually do exercise market power. In doing so, one of two different methodological approaches – econometrics or simulation models – is applied. While Chapters 2 through 4 make use of the latter approach, Chapter 5 applies an econometric procedure. In this joint work with Robert Germeshausen and Heike Wetzel, we estimate an empirical model based on an approach introduced by Kumbhakar et al. (2012) that uses stochastic frontier analysis techniques, normaly used for benchmarking, in an innovative way.

The basic idea of a SFA is that the deviation of an individual decision-making unit from the estimated best-practice frontier (in the majority of cases a production or cost frontier) may be divided into two distinctive parts: a classical stochastic noise component and a skewed residual capturing individual inefficiency. Kumbhakar et al. (2012), however, do not estimate a production or cost frontier but rather a frontier of the ratio of revenue to total cost.

In order to derive their model, Kumbhakar et al. (2012) start from the observation that in the case of market power, the firm's individual output price (P) is larger than its individual marginal cost (MC): $P > MC$. Augmenting this inequality with the ratio of output to total cost (Y/C) and rearranging gives $PY/C > E_{CY}$, with E_{CY} being the cost elasticity. Adding an equality residual – which, similar to the classical SFA, is composed of a stochastic and symmetric noise component v and a skewed residual u – to this inequality leads to

$$\frac{PY}{C} = E_{CY} + v + u. \tag{1.12}$$

The skewed part of the residual in their specification can thus be assumed to represent a firm-specific markup term, which again can easily be transformed into a firm-specific estimate of the familiar Lerner index, i.e., the relative markup of price over marginal cost, a frequently used measure of market power. Combining this approach with the SFA model proposed by Battese and Coelli (1995), we analyse the relationship between firm characteristics, macroeconomic conditions and the individual ability of firms to generate markups in the global iron ore market.

The specification thus far relies on the usage of input price data to estimate the cost elasticity E_{CY}. Kumbhakar et al. (2012), however, show by using the envelope theorem and an input distance function (Shephard, 1970) $D(X, Y)$, which only relies on a vector of inputs X and outputs Y, that

$$E_{CY} = \frac{\partial \ln C(w, Y)}{\partial \ln Y} = -\frac{\partial \ln D(X, Y)}{\partial \ln Y} \tag{1.13}$$

holds true. Using a translog specification for the input distance function together with some basic requirements derived from economic theory such as linear homogeneity and concavity, one can estimate Equation 1.12 without relying on input price data.

The applied estimation procedure has thus several advantages over the traditional econometric estimation methods often used to assess the exercise of market power. Two advantages, in particular, of the method proposed are (i) its data requirements are easier to fulfill and (ii) it requires less strict assumptions in obtaining valid estimates. Both advantages make the applied methodology a potentially valuable tool for political and legal institutions interested in (empirically) assessing the abuse of market power by firms. Yet, one needs to be cautious when interpreting the resulting levels of the Lerner indices. Whereas a low level of an estimated Lerner index can be interpreted as the absence of market power (Elzinga and Mills, 2011), finding a high Lerner index does not necessarily translate into evidence for the exercise of market power. Economies of scale as well as the need to recover fixed cost or scarcity prices due to demand peaks may also be captured in the estimates. Therefore, if possible, the estimation of the Lerner index should be augmented by additional analyses that put the estimated values in perspective, e.g., by relating the estimated Lerner indices to the level and the development of fixed costs.

1.2.3 Assessing price formation using time series econometrics

In contrast to the other research that is included in the thesis at hand, the topic presented in Chapter 6 is not concerned with market inefficiency caused by strategic behaviour of market participants but rather with the process of price formation. We address two different questions both in the interregional as well as in the intertemporal context, which are both answered using tools from time series econometrics.

We first assess whether a long-run equilibrium relationship exists between the nonstationary time series by applying cointegration analyses developed by Robert Engle and Clive Granger (Engle and Granger, 1987). In the intertemporal context, for example, the finding of such a long-run equilibrium means that futures prices are a valid hedge for spot prices and, hence, can be used to hedge short-term price risks. In the interregional context, such a finding allows for the conclusion that the respective markets are integrated.

Next, in order to investigate the exact nature of price discovery in the intertemporal and interregional context, we check for both linear and nonlinear Granger causality. Granger causality (Granger, 1969) has proven to be a useful tool when investigating dependence relationships between two or more time series. The basic idea of Granger causality is that a cause may never follow the effect (Lütkepohl, 2007). Put more formally, consider two scalar-valued, stationary and ergodic time series $\{X_t\}$ and $\{Y_t\}$ and suppose that Ω_t contains all relevant information up to and including period t. Let $Y_t(h|\Omega_t)$ be the optimal, i.e., in this case the minimum mean-squared error (MSE) h-step predictor of the process Y_t in t based on the information in Ω_t. The process $\{X_t\}$ is said to *Granger-cause* $\{Y_t\}$ if

$$\sum\nolimits_Y(h|\Omega_t) < \sum\nolimits_Y(h|\Omega_t \backslash \{X_s|s \leq t\}) \qquad \text{for at least one } h = 1, 2, ... \tag{1.14}$$

with $\sum_Y(h|\Omega_t)$ denoting the forecast MSE and $\Omega_t \backslash \{X_s|s \leq t\}$ being the set that contains all relevant information except for the information in the past and present of the $\{X_t\}$ process (Lütkepohl, 2007).

Price discovery is investigated by analysing the lead-lag relationship between the respective prices series (Tse, 1999). In order to assess the lead-lag relationship in the intertemporal and interregional context, we check for linear Granger causality (Granger, 1969). If the time series are cointegrated, causality testing should be conducted in a vector error correction mechanism (VECM) environment (Chen and Wuh Lin, 2004). There is a VECM to each set of cointegrated time series that describes the process of returning to the long-run equilibrium relationship, in particular, which of the time series is driving the relationship back to its equilibrium and how fast a deviation from the equilibrium will be corrected. As all pairs of time series investigated in this paper are cointegrated, the causality tests are applied to the residuals of the VECM.

The interaction between time series may not only be restricted to the first moment. In order to build forecasting models it is thus important to account for any nonlinear relationships as well. To check for nonlinear causality, the nonparametric test for general Granger causality developed by Diks and Panchenko (2006), which they also refer to as a test for nonlinear Granger causality, is used. In deriving their test statistic, Diks and Panchenko (2006) use of a more general definition of Granger causality that reduces the need to make any modelling assumptions (e.g., assuming a linear autoregressive model) when stating that $\{X_t\}$ is not a Granger cause of $\{Y_t\}$ if,

$$Y_t(h|\{X_s, Y_s|s \leq t\} \sim Y_t(h|\{Y_s|s \leq t\}, \tag{1.15}$$

with $\sim$ denoting equivalence in distribution. Hence, Diks and Panchenko (2006) test the null hypothesis of no nonlinear Granger causality between two time series by comparing their conditional distributions. We apply their test to the VECM residuals as well, after having filtered out any existing volatility effects using multivariate general autoregressive conditional heteroscedasticity (GARCH) models, in order to check for causality in higher moments than the second.

The estimated multivariate GARCH models also allows us to investigate volatility spillovers and market dominance. Furthermore, the combination of the Diks-Panchenko-test and the multivariate GARCH models has another important advantage. In case the nonlinear causality vanishes after eliminating the multivariate GARCH effects, the results of the nonlinear Granger causality test using the unfiltered residuals should coincide with the cross-volatility spillovers estimated by the multivariate GARCH model. Thereby, a parametric and a non-parametric approach are used to evaluate the same aspect and, thus, validate each other.

1.3 Outline of the thesis

The organisational structure of the thesis is presented in the following. Chapter 2, *Supply disruptions and regional price effects in a spatial oligopoly - an application to the global gas market*, examines the effects of a supply shock on the global gas market on the output decisions of the oligopolistic gas producers as well as its implications for the security of gas supply of importing countries. This essay is a joint work with Christian Growitsch and Harald Hecking and was published in *Review of International Economics* from Wiley Blackwell (Growitsch et al., 2014).[2]

Supply shocks in the global gas market may affect countries differently, as the market is regionally interlinked but not perfectly integrated. Additionally, high supply-side concentration may expose countries to market power in different ways. To evaluate the strategic position of importing countries with regard to gas supply, we disentangle the import price into different components and characterise each component as price increasing or price decreasing. Due to the complexity of the interrelations in the global gas market, we use an equilibrium model programmed as a MCP and simulate the blockage of LNG flows through the Strait of Hormuz. This enables us to account for the oligopolistic nature and the asymmetry of global gas supply. We find that Japan faces the most severe price increases, as the Japanese gas demand completely relies on LNG supply. In contrast, European countries such as the UK benefit from good interconnection to the continental pipeline system and domestic price-taking production, both of which help to mitigate an increase in physical costs of supply as well as in the exercise of market power.

Chapter 3, *The global markets for coking coal and iron ore - complementary goods, integrated mining companies and strategic behaviour*, assesses the strategic behaviour of mining companies integrated into the production of iron ore and coking coal, with both goods being complementary inputs in pig iron production. This paper was written in co-authorship with Harald Hecking and was published in *Energy Economics* (Hecking and Panke, 2015).[3]

The global market for coking coal is linked to the global market for iron ore since both goods are complementary inputs in pig iron production. Moreover, international trade of both commodities is highly concentrated, with a few large companies active in both input markets. Given this setting, the paper investigates the strategy of quantity-setting (Cournot) mining companies that own both a coking coal and an iron ore division. Do

[2]The article is copyrighted by John Wiley & Sons Ltd. and reprinted by permission. A previous version of the paper was published in the EWI working paper series (Growitsch et al., 2013).

[3]This article is copyrighted by Elsevier Ltd. and reprinted by permission. A previous version of the paper was published in the EWI working paper series (Hecking and Panke, 2014).

these firms optimise the divisions' output on a firm level or for each division separately (division-by-division)? First, using a theoretical model of two Cournot duopolies of complementary goods, we find that there exists a critical capacity constraint below/above which firm-level optimisation results in identical/superior profits compared to division-level optimisation. Second, by applying a spatial multi-input equilibrium simulation model of the coking coal and iron ore markets, we find that due to the limited capacity firms gain no (substantial) additional benefit from optimising output on a firm level.

Chapter 4, *Assessing market structures in resource markets - an empirical analysis of the market for metallurgical coal using various equilibrium models*, simulates different market structures of the metallurgical coal market using different equilibrium models and compares them with regard to their ability to reproduce annual market outcomes for three years. The essay is a joint work with Stefan Lorenczik and was published in the EWI working paper series (Lorenczik and Panke, 2015).

We investigate the prevalent market setting in the international market for metallurgical coal between 2008 and 2010. The concentration on the supply side, the low demand elasticity and the way benchmark prices were negotiated during the time period under consideration provide arguments for a wide variety of market structures, which is why we apply different equilibrium models to test for these market structures. Thereby, we add to the literature by expanding the application of an EPEC, which is used to model multi-leader-follower games, to a spatial market (a setup with multiple, geographically disperse demand and supply nodes). Using three different statistical measures, we find that a setting in which the four largest metallurgical coal exporting firms compete against each other as Stackelberg leaders, while the other firms act as Cournot followers fits well with actual market outcomes. In addition, we find that market settings where multiple players form a cartel lack internal stability and are thus, even given a reasonable fit of market outcomes, less plausible.

Chapter 5, *Firm characteristics and the ability to exercise market power - empirical evidence from the iron ore market*, is concerned with market power on a firm level in the iron ore market. More specifically, the effect of firm characteristics on their ability to exercise market power is analysed. The paper is joint work with Robert Germeshausen and Heike Wetzel. A previous version was published in the EWI working paper series (Germeshausen et al., 2014).

This work empirically analyses the existence of market power in the global iron ore market during the period from 1993 to 2012 using an innovative stochastic frontier analysis approach introduced by Kumbhakar et al. (2012) with firm-level data. In contrast to traditional econometric procedures, this allows for the estimation of firm- and time-specific

Lerner indices. Combining the approach with the SFA model proposed by Battese and Coelli (1995), we are able to investigate the relationship between individual firm characteristics, macroeconomic conditions and the individual ability of firms to generate markups in the global iron ore market. We find that the firms' Lerner indices on average amount to 20%. Moreover, location of the main production site and experience, measured in years of production, are identified to be the most important determinants of the magnitude of firm-specific markups.

Chapter 6, *Intertemporal and interregional price formation in thermal coal markets*, examines two aspects of price formation – the long-run equilibrium relationship and price discovery – in the thermal coal market using spot and futures prices of two of the most important trade products. The paper was written by the author of this thesis and published in the EWI working paper series (Panke, 2016).

We seek to shed light on the price formation in the international thermal coal market, a market with a relatively young history of standardised trading and low liquidity. In particular, using spot and futures prices of two of the most important thermal coal products we use cointegration analysis to assess whether futures prices are a good hedge for spot price risks, separately for the Northwest European and the South African trading hub, as well as wether the two markets are integrated both on a spot and a futures prices level. Furthermore we analyse intertemporal and interregional price discovery by applying linear and nonlinear causality tests. Multivariate GARCH (MGARCH) models are used to check whether causality in higher moments is limited to volatility spillovers and to cross-check the results of the test for nonlinear Granger causality developed by Diks and Panchenko (2006). Concerning intertemporal price discovery, we find that futures prices are a valid hedge for spot prices and that futures prices lead spot prices when testing for linear Granger causality. In analysing nonlinear causality, we find evidence that price discovery in higher moments is restricted to the second moment and takes place in both markets, a result which is confirmed by the estimated MGARCH models. Focussing on the interregional relationship, our results suggest that, despite the law of one price seemingly being violated, there is a long-run relationship between the European and the South African market both in spot and futures prices. Results on price discovery, however, are mixed. While price discovery for spot prices takes places simultaneously in both markets, the European market leads South Africa in futures prices. In higher moments, we again find evidence of bi-directional nonlinear causality.

Kapitel 2

Supply disruptions and regional price effects in a spatial oligopoly – an application to the global gas market

2.1 Introduction

International resource markets link more and more of the world's economies. As interdependence increases, regional supply shocks, such as disruptions of trade flows caused by, e.g., geopolitical conflicts, may be of global relevance. The global oil market, for example, has seen several of such supply shocks in history, among the most prominent conflicts being the First Gulf War in 1991 as well as the Iraq War in 2003. As a result of the high level of integration within the global oil market, these regional conflicts caused global price shocks that affected countries all over the world.

A notable example of a resource market that is not highly integrated on a global scale is the natural gas market. Imperfect global integration is indicated by high regional price differences, e.g., between Asia and the United States. Various aspects may explain these regional price differences: First, transport of liquefied natural gas (LNG)[4], including liquefaction and regasification, is more complex and costly compared with that of crude oil. Second, the supply side of the global gas market is characterised by high market concentration, as large state-owned companies such as Gazprom (Russia), Sonatrach (Algeria), Statoil (Norway) or Qatargas (Qatar) control significant export volumes. Third,

[4]LNG is natural gas that is liquefied by cooling it down to about $-162°$C. Thereby its volume is reduced by approximately 600 times.

differences in flexibility of demand and, fourth, the degree of import diversification are further important aspects that have to be taken into account when investigating changes in prices due to supply shocks. Japan, for example, relies solely on LNG imports to meet its gas demand. Furthermore, following the catastrophic incident in Fukushima the country's natural gas demand has become more and more price inelastic owing to the reduction in nuclear power generation and the subsequent higher utilisation of the remaining coal- and gas-fired power plants.

Since gas is sometimes transported thousands of kilometres, often crossing different countries or crucial waterways, trade flows are highly vulnerable to disruption. One example of such a supply shock was the Russian-Ukrainian gas crisis in 2008/2009. While European gas prices significantly increased during the crisis, US gas prices, for example, were hardly affected, thereby illustrating the low integration of the global gas market. Another prominent example of a neuralgic transport route is the Strait of Hormuz, a passage that is 21 nautical miles wide and connects the Persian Gulf with the Indian Ocean. The Strait of Hormuz is already today of eminent importance, as LNG exports from the Persian Gulf, i.e., from Qatar (77.4 billion cubic meters (bcm)) and the United Arab Emirates (7.8 bcm), accounted for 29% of worldwide LNG trades in 2010 (IEA, 2011a). Furthermore, there is no opportunity to bypass this crucial waterway by means of pipeline transport and its importance is likely to increase considerably in the upcoming years as gas demand in Asia is expected to strongly increase. In fact, the IEA projects a doubling of gas demand based on 2011 values in China and India by 2017. The world's two largest LNG importers are Korea and Japan both satisfying more than 95% of national gas demand with LNG – and will presumably continue to increase their gas consumption as well. Although demand is not predicted to rise in Europe, decreasing indigenous production will foster imports into the European market as well (ENTSOG, 2011).

In economic terms, given the regional differences in supply structure, demand flexibility and the supply-side concentration, a potential blockage of the Strait of Hormuz could therefore be interpreted as a supply shock in a spatial oligopoly with a competitive fringe and asymmetric players. Owing to the nature of this economic problem, the price effect of the supply shock in a gas importing country may differ depending on the (i) location of the disruption and (ii) the demand-supply situation in the country under consideration.

With respect to the supply shock caused by the blockage of the Strait of Hormuz, our paper aims at identifying and quantifying the major factors influencing the magnitude of price effects in globally disperse demand regions. We therefore develop a model to disentangle the import price into different components and characterise each component as price increasing or price decreasing (hereinafter referred to as price-increasing components or price-decreasing components, respectively), such as production and transport costs, scarcity rents of production and infrastructure, oligopoly markups, supply of the competitive fringe and long-term contracts (LTCs).

Our methodology to analyse regional price effects in a spatial oligopoly is structured in three steps. First, we illustrate the price formation in a simple asymmetric Cournot oligopoly. Second, since the interrelations of the global gas market are more complex owing to, e.g., seasonal demand patterns, capacity constraints and spatial supply cost differences, we use a global gas market simulation model (Hecking and Panke, 2012). The spatial partial equilibrium model accounts for 87 countries, comprising the major national producers and importers, as well as the relevant gas infrastructure such as pipelines, LNG terminals and storages. In order to accurately simulate the global gas market, i.e., incorporate demand reactions and the possibilities of strategic behaviour, the model is programmed as a mixed complementarity problem (MCP). The flexibility and the high level of detail of the model allow us to simulate the interrelations of the global gas market within a consistent framework and to identify regional price and welfare effects. The third and central step of our approach to identify and quantify region-specific price drivers is to combine the price formation from the simple Cournot model with the gas market simulation model. By using the dual variables from the simulation, we are able to quantify to what extent marginal transport and production costs, scarcity rents of transport and production capacity as well as the exploitable oligopoly markup cause prices to increase. We are also able to identify factors that may result in decreasing prices such as trade relations to price-taking fringe suppliers and secured deliveries by long-term supply contracts.

Although a disruption of the Strait of Hormuz is fictitious, its consequences are interesting from an economic as well as a geopolitical point of view, especially since Qatar's LNG exports supply countries all over the world. We simulate a blockage lasting 6 months and focus on the USA, the UK and Japan, each serving as a prominent example of a distinct supply structure. We observe the strongest price reactions in Asia, with prices in Japan rising from an already high level (US$505 per 1000 cubic metres (kcm)) by US$171/kcm during the 6-month disruption. While US gas prices hardly change at all, European gas prices are significantly affected during the disruption, albeit to a lesser extent than in Japan, as, e.g., gas prices in UK increase by up to US$79/kcm.

We identify and quantify three factors to explain the difference in price changes between the UK and Japan. First, Japan is fully dependent on imports from the disturbed LNG market, whereas the UK has alternative supply opportunities from the European pipeline grid. Second, Japan's lower endowment with price-taking indigenous production and storage capacity explains its higher exposure to changes in supply costs as well as increased exertion of market power. Third, as Qatar is an important source of Japan's contracted LNG import volumes, the price decreasing effects of Japan's long-term contracts are reduced in comparison with the reference scenario. Consequently, Japan's gas price increase is US$92/kcm higher than any increase seen in the UK.

Thus, the spatial impact of the supply disruption becomes obvious with respect to different gas importing countries. However, the location of the supply shock matters as well. In another fictitious supply disruption scenario we assume a 6-month blockage of Ukrainian gas transits to Europe and contrast the results in this scenario with the scenario of the blockage of the Strait of Hormuz. We find that gas prices, for example, in Italy are affected most by the Ukraine blockage whereas Japanese gas prices, contrary to the disruption of the Strait of Hormuz, are hardly affected. Consequently, our analyses underline that in a spatial oligopoly shocks will have a different impact depending on (i) where they occur and (ii) the importing country under consideration.

Our research is related to literature on quantitative analyses of security of gas supply with particular attention to numerical simulations of spatial Cournot oligopolies in resource markets. Building on the seminal paper by Takayama and Judge (1964), as well as on Harker (1986) and Yang et al. (2002), a variety of research has been made on spatial Cournot oligopolies and MCP models in resource markets (see, e.g., Haftendorn and Holz (2010), Paulus and Trüby (2011) or Trüby (2013)). Applications of MCP models to natural gas markets are, e.g., Boots et al. (2004), Gabriel et al. (2005b), Holz et al. (2008) and Egging et al. (2010). Yet to our knowledge, none of the existing papers applying MCP models to natural gas markets tries to identify which factors influence price changes during a supply shock and to what extent prices may be affected.

Quantitative research on security of supply is rather scarce and solely concentrates on Europe. Three of the few examples are Lise and Hobbs (2008), Lise et al. (2008) and Dieckhöner (2012), who measure the impacts of new pipeline corridors to Europe and of new LNG ports on security of supply. Papers on simulation-based analyses of the effects of (geo-) political conflicts on the natural gas market are also rare and concentrate on Europe only.Egging et al. (2008) and Bettzüge and Lochner (2009) analyse the impact of disruptions on Ukrainian gas flows and short-run marginal supply costs. Lochner and Dieckhöner (2011) analyse the effects of a civil unrest in North Africa on European security of natural gas supply.

We contribute to the existing literature on security of supply and spatial oligopolies in energy markets in three ways. First, we develop a framework for analysing regional price reactions after a trade disruption in a spatial oligopoly by separating price components into increasing and decreasing factors. Second, we assess the strategic position of gas importing countries during a trade disruption by applying our methodology. Third, as opposed to most studies on security of gas supply, our model covers the global natural gas market, thus allowing us to analyse the consequences of a regional (geo-) political conflict across the world.

The remainder of this paper is structured as follows. The methodology is described in Section 2.2, in which we derive the spatial oligopoly simulation model and develop an approach to distinguish price components using the model results. Section 2.3 describes the data, main parameter assumptions and the scenario setting. The results are presented in Section 2.4, with particular focus on analysing the price difference between Japan and the UK, identifying the major price drivers and providing an in-depth analysis of both countries' supply situations. Section 2.5 concludes.

2.2 Methodology

We argue that international gas trade is best represented by a Cournot oligopoly with a competitive fringe, on the one hand, large state-owned companies such as Gazprom, Sonatrach, Qatargas or Statoil account for a significant share of global export volumes. On the other, a large number of companies with little annual production operate on the supply side, most of them providing no significant export volumes – thus representing a competitive fringe.[5]

In order to separate the natural gas import price into price-increasing and price-decreasing components, we first provide a theoretical foundation of how prices are determined in a Cournot oligopoly with a competitive fringe. The natural gas market is more complex than a simple Cournot oligopoly. Since international gas trade is characterised by spatially distributed demand and supply plus a complex network of pipelines and LNG infrastructure, it is necessary to develop a numerical spatial oligopoly model to simulate the market. Next, we apply the price formula from the simple Cournot oligopoly model to the numerical oligopoly model in order to identify factors that increase and decrease import prices.

[5]We provide model results for the international gas market in 2010 assuming perfect competition in Appendix A.3. We find that the model results do not match actual market results. Consequently, we choose to model the global gas market as a Cournot oligopoly with a competitive fringe. We model the eight most important LNG exporting countries and the three most important pipeline exporters as Cournot players. The countries able to exercise market power are Australia, Algeria, Egypt, Indonesia, Malaysia, Nigeria, the Netherlands, Norway, Qatar, Russia and Trinidad and Tobago. All countries have almost all of their exports coordinated by one firm or consortium. Appendix A.3 also contains the model results for our Cournot setting. By comparing these with actual market results, a better match is found than under the perfect competition setting.

2.2.1 Oligopoly pricing

We start out by quickly recalling how the price in a Cournot oligopoly with a competitive fringe is determined (see also Tirole (1988)), which provides us with a theoretical foundation for our analysis. We begin by deriving the optimal supply Q^* in a Cournot oligopoly with N asymetric players, i.e., players having differing marginal cost functions. In a second step, we derive the resulting price formula in such a market and elaborate on how a competitive fringe changes the way prices are determined in an oligopoly.

Initially, we assume that N players maximise their profits by setting their optimal supply to a single end user market (q_i). Each player $i \in N$ has individual marginal costs of supply, msc_i, that are assumed to be constant and positive. Furthermore, we assume a linear inverse demand function, where the price $P(Q)$ decreases with the total quantity $Q = \sum_{i=1}^{N} q_i$ supplied to the market, i.e.,

$$P(Q) = A - BQ \quad \text{with } A, B > 0. \tag{2.1}$$

For a player i, the first-order condition for sales is as follows:

$$\frac{\partial \pi_i}{\partial q_i} = P(Q) - Bq_i - msc_i = 0 \quad \forall\ i \tag{2.2}$$

with π_i representing the profit of player i. Substituting the wholesale price $P(Q)$ by the linear inverse demand function yields:

$$\frac{\partial \pi_i}{\partial q_i} = A - B\sum_{i=1}^{N} q_i - Bq_i - msc_i = 0 \quad \forall\ i. \tag{2.3}$$

Consequently, the profit-maximising total supply to the wholesale market, Q^*, is determined by the following equation:

$$\sum_{i=1}^{N} \frac{\partial \pi_i}{\partial q_i} = N(A - BQ^*) - BQ^* - \sum_{i=1}^{N} msc_i = 0 \tag{2.4}$$

$$\Leftrightarrow Q^* = \frac{NA - \sum_{i=1}^{N} msc_i}{B(N+1)}. \tag{2.5}$$

Inserting Equation 2.4 into the linear inverse demand function yields:

$$P^*(Q^*) = A - BQ^* \tag{2.6}$$

$$= \frac{1}{N+1}A + \frac{1}{N+1}\sum_{i=1}^{N} msc_i \tag{2.7}$$

$$= \frac{BQ^*}{N} + \frac{\sum_{i=1}^{N} msc_i}{N}. \tag{2.8}$$

Consequently, in a Cournot oligopoly with asymetric players, the equilibrium price equals the average marginal supply costs plus an average markup that depends on the slope of the demand function and total supply to the market.

The existence of a zero-cost competitive fringe with a binding capacity constraint (q_{cf}^{max}) simply leads to a reduction of the markup by $\frac{Bq_{cf}^{max}}{N}$, as the competitive fringe produces at its maximum capacity and the oligopolistic players maximise profit over the residual demand function.[6]

2.2.2 A spatial equilibrium model of the global gas market

Although we derive the formula for a simplified market, the method to determine the price is essentially the same as in a setup with multiple interconnected markets and time periods (due to, e.g., the possibility of storing a commodity). The main difference between the simplified and complex formula is that scarcity rents of production and infrastructure capacity are affected by the interrelation of all markets and time periods. Because of the size of the problem at hand (high number of players, markets and time periods), deriving an equilibrium solution is challenging. Therefore, we develop a numerical spatial oligopoly model to simulate international gas trade.

The spatial equilibrium model is formulated as a mixed complementarity problem. This method allows us to make use of elastic demand functions as well as simulate strategic behaviour in international gas trade. As we argue that the natural gas market is best represented by a Cournot oligopoly with a competitive fringe, both aspects (elastic demand and strategic behaviour) are essential to accurately model the natural gas market.[7] Figure 2.1 illustrates the logical structure of our model.

Exporters are vertically integrated with one or more production nodes and trade gas with the buyers located at the demand nodes. We use a linear function to represent total demand at each of the demand nodes.[8] Exporters compete with each other in satisfying the demand, thereby acting as Cournot players or in a competitive manner. Therefore, at each demand node, all exporters form an oligopoly with a competitive fringe. The

[6]In the natural gas market, short-run marginal costs of price-taking fringe players are substantially lower than actual market prices. In addition, capacity of the competitive fringe is low compared with overall market size. This justifies why we focus on a zero-cost competitive fringe with a binding capacity constraint. Our application therefore follows the approach chosen in Borenstein and Bushnell (1999).

[7]Haftendorn (2012) stresses the point that when modelling a Cournot oligopoly with a competitive fringe with non-binding capacity constraints using conjectural variation models, the resulting market equilibrium may yield the oligopoly players lower profits compared with a setting in which they set prices equal to marginal supply costs, i.e., act as price takers. However, this objection is of no concern to our analyses since the competitive fringe in the reference scenario, and hence also in the scenario with a blockage of the Strait of Hormuz, faces binding capacity constraints.

[8]For more details on how the demand functions are determined, please refer to Section 2.3.1.

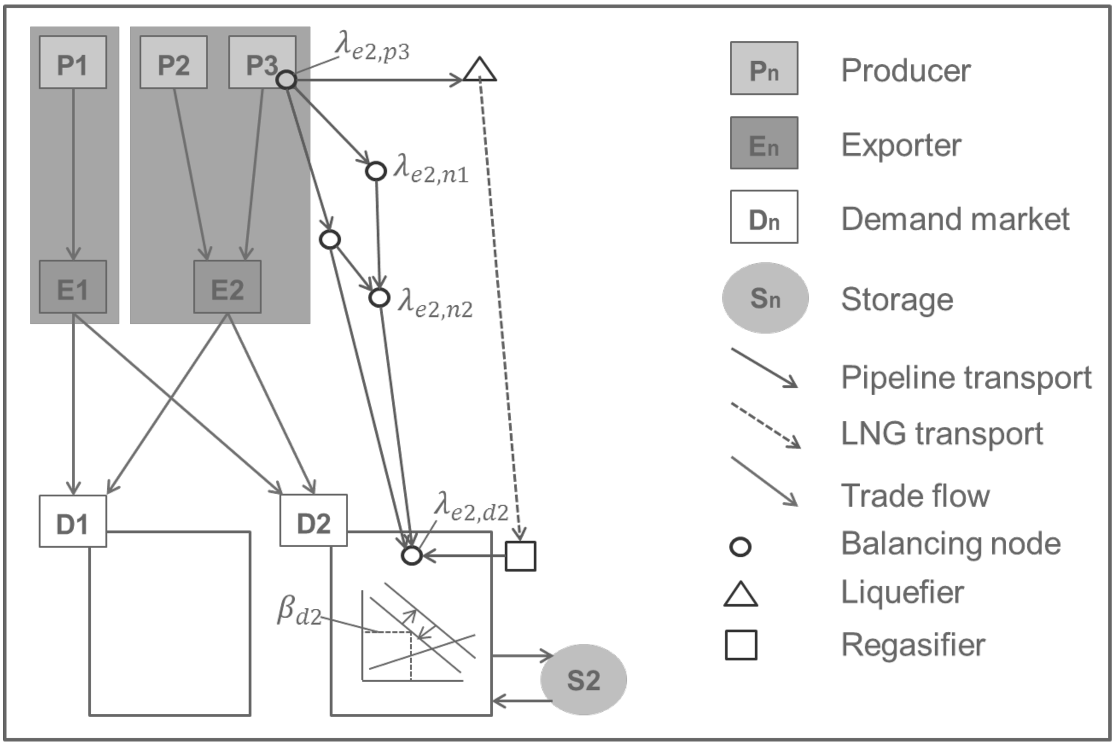

Abbildung 2.1: Logical structure of the gas market model

oligopoly is spatial and asymmetric, as each exporter's marginal supply costs ($\lambda_{e,d,t}$), i.e., the costs associated with the physical realisation of the trades, vary depending on the location of production and demand nodes. Each exporter's marginal supply costs consist of marginal production and transport costs, including the scarcity rent for production and transport capacity. As different exporters compete for transport capacity, e.g., two exporters may want to use the same pipeline to deliver gas to a demand node, trades of one exporter influence the costs of another exporter's physical transports.

We start out by developing the optimisation problems of the different players in our model and derive the corresponding first-order optimality conditions. The first-order conditions combined with the market clearing conditions constitute our partial equilibrium model for the global gas market. The vector of variables in parentheses on the right-hand side of each constraint are the Lagrange multipliers used in developing the first-order (Karush-Kuhn-Tucker (KKT)) conditions. The complementary slackness condition is indicated by the perpendicular sign, $\perp$, with $0 \leq x \perp y \geq 0 \Leftrightarrow x^t y = 0$ for vectors x and y.

2.2.2.1 The exporter's problem

The exporter $e \in E$ is defined as a trading unit of a vertically integrated firm owning one or more production regions $p \in P_e$. The exporters earn revenues by selling gas ($tr_{e,d,t}$)

on the wholesale markets of the importing regions $d \in D$. Each exporter e maximises its profits, i.e., revenues from sales minus costs of supply over all modelled time periods $t \in T$ and all importing regions d. Exporters may behave as price-takers in the market, but can alternatively be modelled as if able to exercise market power.

The profit function $\Pi_{eI}(tr_{e,d,t})$ is defined as[9]

$$\max_{tr_{e,d,t}} \Pi_{eI}(tr_{e,d,t}) = \sum_{t \in T} \sum_{d \in D} (\beta_{d,t} - \lambda_{e,d,t}) * tr_{e,d,t} \tag{2.9}$$

where $\beta_{d,t}$ is the market clearing price in importing region d, $tr_{e,d,t}$ is the quantity that trader e sold to region d at time t and $\lambda_{e,d,t}$ corresponds to the exporter's costs of physical gas delivered to demand node d. LTCs play a significant role in natural gas markets. Therefore, some of the trade flows between the exporters and importing regions have a lower bound, i.e., a minimal delivery obligation $mdo_{e,d,t}$.[10] Thus, LTCs are taken into account by incorporating the following constraint:

$$\sum_{t \in T} tr_{e,d,t} - mdo_{e,d,t} \geq 0 \; \forall \; e, d, t \quad (\chi_{e,d,t}). \tag{2.10}$$

The Lagrange of the exporter's optimisation problem is defined by Inequality 2.10 and Equation 2.9. Taking its first partial derivative with respect to the decision variable $tr_{e,d,t}$ gives us the first-order condition (FOC) for trade between exporter e and demand node d:

$$\frac{\partial L_{eI}}{\partial tr_{e,d,t}} = -\beta_{d,t} + cv_e * slope_{d,t} * tr_{e,d,t} - \chi_{e,d,t} + \lambda_{e,d,t} \geq 0 \perp tr_{e,d,t} \geq 0 \; \forall \; e, d, t. \tag{2.11}$$

The parameter $slope_{d,t}$ is the slope of the linear demand function in node d. The term cv_e is the conjectural variation of exporter e and is a binary parameter indicating whether ($cv_e = 1$) or not ($cv_e = 0$) the trader is able to exercise market power.

In addition to the LTC constraint, each exporter also faces an individual market clearing condition that has to be fulfilled for every model node in which an exporter is active

$$pr_{e,p,t} - tr_{e,d,t} + \sum_{n1 \in A_{\cdot,n}} fl_{e,n1,n,t} - \sum_{n1 \in A_{n,\cdot}} fl_{e,n,n1,t} = 0 \perp \lambda_{e,n,t} \text{ free } \; \forall \; e, n, t \tag{2.12}$$

with $A_{\cdot,n}$ a set including all transport routes leading to node n. Variables $pr_{e,p,t}$ and $fl_{e,n,n1,t}$ denote produced gas volumes in production region $p(n) \in P_e$ and physical transport volumes between node n and $n1$, respectively. Therefore, the corresponding

[9]In order to keep the formulae as simple as possible, no discount factor is included.

[10]To limit complexity, we exclude the possibility of reshipping contracted LNG to other countries, as observed in 2011 and 2012 in the USA. Volumes however are rather small.

dual variable $\lambda_{e,n,t}$ equals the exporter's costs of physical supply to node n. If we consider a demand node $d(n) \in D_e$, market clearing condition 2.12 simplifies to[11]

$$\sum_{n1 \in A_{\cdot,d}} fl_{e,n1,d,t} - tr_{e,d,t} = 0 \perp \lambda_{e,d,t} \text{ free } \forall\ e, d, t. \tag{2.13}$$

Hence, Equation 2.12 ensures that the gas volumes, which exporter e sold on the wholesale market of demand node d, are actually physically transported to the node. If we consider a production node p, market clearing condition 2.12 collapses to:

$$pr_{e,p,t} - \sum_{n1 \in A_{p,\cdot}} fl_{e,p,n1,t} = 0 \perp \lambda_{e,p,t} \text{ free } \forall\ e, p, t. \tag{2.14}$$

Thus, the gas volumes produced have to match the physical flows out of node p. Production costs are represented by a production function, as used in Golombek et al. (1995, 1998). The corresponding marginal production cost function $mprc_{e,p,t}(pr_{e,p,t})$ takes the form: $mprc_{p,t}(pr_{e,p,t}) = a + b * pr_{e,p,t} - c * ln(1 - \frac{pr_{e,p,t}}{cap_{e,p,t}})$. Since trader e and its associated production regions P_e are considered to be part of a vertically integrated firm, profit maximisation dictates that either the production entity or the trading entity sell their product at marginal costs, while the other entity exercises market power. In our setting, the trading units are modelled as oligopoly players while production is priced at marginal costs. Hence, the corresponding dual variable $\lambda_{e,p,t}$ to Equation 2.14 represents marginal production costs. Production in production region p is subject to a production constraint:

$$cap_{e,p,t} - pr_{e,p,t} \geq 0\ \forall\ e, p, t \quad (\mu_{e,p,t}). \tag{2.15}$$

Equations 2.13 and 2.14 also ensure that $\sum_{p \in P_e} pr_{e,p,t} = \sum_{d \in D_e} tr_{e,d,t}$, i.e., total production equals total trade volume for every exporter e in each time period t. As trade flows are linked to physical flows, each exporter also faces the problem of how to minimise transport costs by choosing the cost-minimal transport flows $fl_{e,n,n1,t}$. In our model, this is implicitly accounted for by a separate optimisation problem of the following form:

$$\max_{fl_{e,n,n1,t}} \Pi_{eII}(fl_{e,n,n1,t}) = \sum_{t \in T} (\lambda_{e,n1,t} - \lambda_{e,n,t} - trc_{n,n1,t} - opc_{n,t}) * fl_{e,n,n1,t} \tag{2.16}$$

where $opc_{n,t}$ is defined as the operating costs at node n in month t and $trc_{n,n1,t}$ as the cost associated with transporting gas from node n to node $n1$. Therefore, if n is a liquefaction node $l(n)$, $opc_{n,t}$ would reflect the costs of liquefying a unit of natural gas. If n is a liquefaction node then $n1$ has to be a regasification node, thus $trc_{n,n1,t}$ would be

[11] Equation 2.13 holds true if the demand node has no further connections, i.e., is a no-transit country. In case of a country such as Poland, physical flows of the Russian exporter to Poland have to equal the volumes sold to Poland plus all transit volumes.

the short-run marginal LNG transport costs from node n to node $n1$. The optimisation problem is subject to some physical transport constraints such as the pipeline capacity:

$$cap_{n,n1,t} - \sum_{e \in E} fl_{e,n,n1,t} \geq 0 \;\forall\; n, n1, t \quad (\phi_{n,n1,t}). \tag{2.17}$$

Thus, the sum over all transport flows (decided on by the traders) through the pipeline between nodes n and $n1$ has to be lower than the respective pipeline capacity $cap_{n,n1,t}$. The dual variable $\phi_{n,n1,t}$ represents the value of an additional unit of pipeline capacity. Along the lines of Inequality 2.17, we also account for capacity constraints on liquefied ($\zeta_{l,t}$ being the corresponding dual variable) and regasified volumes ($\gamma_{r,t}$), as well as LNG transport levels (ι_t).[12]

This optimisation problem may also be interpreted as a cost minimisation problem assuming a benevolent planner, since in equilibrium there will be gas flows between two nodes n and $n1$ until the absolute difference of the dual variables associated with the physical market clearing constraint (Equation 2.12) of the two nodes ($\lambda_{e,n1,t} - \lambda_{e,n,t}$) equals the costs of transporting gas from node n to node $n1$. Hence, $\lambda_{e,n,t}$ can be interpreted as the exporter's marginal costs of supplying natural gas (including production costs $\lambda_{e,p,t}$) to node n, as shown in Equation 2.9.

2.2.2.2 The storage operator's problem

Each storage facility is operated by one storage operator $s \in S$. The storage facilities are assumed to be located in the importing regions. The storage operator maximises its revenues by buying gas during months with low prices and reselling gas during months with high prices. In our model, we assume storage operators to be price takers[13] and, due to the nature of our modelling approach, to have perfect foresight.[14] Each storage operator faces a dynamic optimisation problem of the following form:

$$\max_{si_{s,t}, sd_{s,t}} \Pi_s(si_{s,t}, sd_{s,t}) = \sum_{t \in T} \beta_{d,t}\,(sd_{s,t} - si_{s,t}). \tag{2.18}$$

[12]The interested reader is referred to Appendix A.1 for a detailed description of the omitted capacity constraints.

[13]This assumption must be made in order to reduce model complexity and ensure solvability. Yet, the direction of the identified effects remains unchanged if storage operators are modelled as Cournot players.

[14]When analysing a supply disruption, this assumption may overestimate the price decreasing effect of storage. For a description of how we handled this issue, see Section 2.3.3.

Using injection $si_{s,t}$ as well as depletion $sd_{s,t}$ in month t, we can define the motion of gas stock ($st_{s,t}$), i.e., the change in stored gas volumes, as:

$$\Delta st_{s,t} = st_{s,t+1} - st_{s,t} = si_{s,t} - sd_{s,t} \ \forall \ s,t \quad (\sigma_{s,t}). \tag{2.19}$$

Additionally, the maximisation problem of the storage operator is subject to some capacity constraints:

$$cap_{s,t} - st_{s,t} \geq 0 \ \forall \ s,t \quad (\epsilon_{s,t}) \tag{2.20}$$

$$cf_s * cap_{s,t} - si_{s,t} \geq 0 \ \forall \ s,t \quad (\rho_{s,t}) \tag{2.21}$$

$$cf_s * cap_{s,t} - sd_{s,t} \geq 0 \ \forall \ s,t \quad (\theta_{s,t}). \tag{2.22}$$

Hence, we assume that storage capacity can be linearly transferred (by use of the parameter cf_s) to the restriction on maximum injection ($si_{s,t}$) and depletion ($sd_{s,t}$).

2.2.2.3 Price determination

The equilibrium problem comprises the first-order conditions derived from the different optimisation problems as well as the market clearing conditions previously discussed. In addition, we have to include one last market clearing condition:

$$\sum_{e \in E} tr_{e,d,t} + sd_{s,t} - si_{s,t} = \frac{int_{d,t} - \beta_{d,t}}{slope_{d,t}} \perp \beta_{d,t} \text{ free } \ \forall \ d,t. \tag{2.23}$$

The last market clearing condition (Equation 2.23) states that the final demand for natural gas, represented by a linear demand function (where $int_{d,t}$ and $slope_{d,t}$ represent its intercept and slope, respectively), and the gas volumes injected ($si_{s,t}$) into the storage facility at node $s(d)$ are met by the sum over all gas volumes sold on the wholesale market by traders e and gas volumes depleted ($sd_{s,t}$) from storage facility s. Thus, the dual variable associated with Equation 2.23 ($\beta_{d,t}$) represents the wholesale price in demand node d in month t.

Our model of the global gas market is defined by the stated market clearing conditions and capacity constraints, as well as the FOCs of the respective maximisation problems.[15] The model is programmed in GAMS as a MCP and solved using the PATH solver (Dirkse and Ferris, 1995a, Ferris and Munson, 2000).

[15] See Inequality 2.11 and Appendix A.1 for the remaining FOCs of our model.

2.2.3 Disentangling prices in a spatial equilibrium model

Figure 2.2 illustrates our methodology to disentangle import prices into price-increasing and price-decreasing components that we subsequently use to evaluate a certain import country's strategic position in the global gas market. In Section 2.2.1, we discuss a simple oligopoly model with a single market, asymmetric players and a competitive fringe. Here, natural gas prices equal the sum of an average oligopoly markup and average marginal supply costs of the Cournot players. In contrast, the model presented in Section 2.2.2 allows us to incorporate more complex market settings, such as additional import regions, long-term supply contracts as well as production and transport capacity constraints. As a result of the added complexity, price influencing factors are more diverse.

As seen in the exporter's FOC for optimal trade to demand node d (see Inequality 2.11), the exporter is willing to trade with demand node d as long as the price β_d covers his supply costs $\lambda_{e,d}$ and his individual oligopoly markup $cv_e * slope_d * tr_{e,d}$. If an exporter is obliged to deliver LTC volumes to a certain import node, he may even be willing to accept a β_d that is smaller than the sum of supply costs and oligopoly markups. This economic disadvantage for the exporter is denoted by $\chi_{e,d}$ in the model.

According to the oligopoly pricing formula deduced in Section 2.2.1, we are now able to identify to which extend marginal supply costs and oligopoly markups explain the different market prices β_d. The influence of marginal supply costs equals the average of all Cournot player's $\lambda_{e,d}$. Each $\lambda_{e,d}$ can be further subdivided into production costs, transport costs and scarcity rents for transport and production infrastructure. Therefore, by taking the average of all aforementioned supply cost components, we can identify to what extent these components explain prices.

The price influence of the exporters' oligopoly markups is defined as the average of each Cournot player's markup. For our analysis, we also need to identify the price-reducing effects of competitive fringe players. We therefore introduce the so-called "maximal oligopoly markup", which is the hypothetical markup that Cournot oligopolists could realise at a demand node if there were no gas volumes from a competitive fringe available. Thus, as stated in Section 2.2.1, the fringe producers reduce the maximal oligopoly markup by $slope_d * tr_d^{CF}$ and the fringe storages by $slope_d * sd_d$. Besides fringe suppliers, LTCs may also have a price-decreasing effect that can be identified by taking the average LTC opportunity costs of all Cournot players, $\chi_{e,d}$.

Now, as we are able to disentangle the import price simulated by the equilibrium model into price-increasing and price-decreasing components, we use this approach in Section 2.4 to evaluate the market position of different countries during a supply crisis. There we will distinguish between "cash-based supply costsänd exporters' "profits". We define

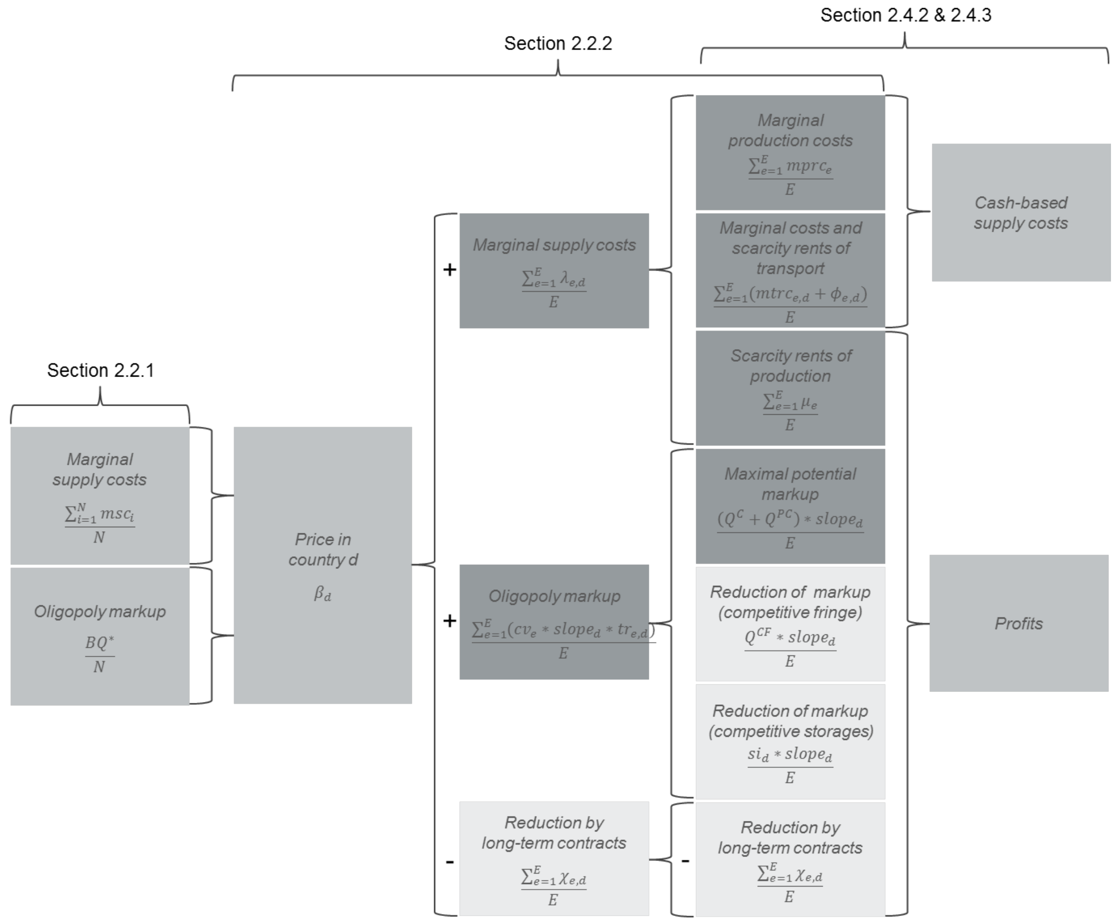

Abbildung 2.2: Disentangling prices in a spatial equilibrium model

“cash-based supply costsäs monetary costs for using transport infrastructure (marginal costs and scarcity rent) and gas production. The scarcity rent of production and the oligopoly markup may both be interpreted as monetary profit for the exporter.

2.3 Data, assumptions and scenario setting

In this section, the data used in our global gas market model as well as the scenario settings of our analysis are described. This section’s description focuses on the demand side and the role of long-term contracts in the global gas market. In addition to the information provided in this section, we list details on data used for production capacities, costs, infrastructure capacities and transport costs in Appendix A.2.1.

2.3.1 Demand

To study the economics of a disruption of the Strait of Hormuz and the effects on regional import prices with a high level of detail, we put a special focus on the demand data. In particular, monthly demand functions must be derived.

The total gas demand of a country and its sensitivity to prices are heavily affected by the sectors in which the gas is consumed. Gas consumption in the heating sector mainly depends on temperature and therefore has a seasonal pattern. On the other hand, gas consumption in industry has no seasonal and temperature-dependent demand pattern, making demand rather constant. Concerning price sensitivity, it is fair to assume that gas demand in the heating sector is rather insensitive to prices, since the gas price does not strongly change the heating behaviour and since the heating technology is fixed in the short term. On the contrary, in power generation, the gas-to-coal spread has a higher impact on gas demand, implying high price sensitivity. Moreover, price sensitivities may also vary by country: It is reasonable to assume that, e.g., Japan (because of its tight generation capacity situation) is less price sensitive in power generation than Germany.

To derive a country's gas demand function, we have to account not only for the aforementioned aspects, but for the different sectoral shares of total demand as well. In addition, owing to different seasonal demand patterns of each sector, the sectoral share of total demand may vary by month. If, for example, heating demand takes a large share of some country's total gas demand in January, then the corresponding demand function would be rather price insensitive. On the contrary, if, in July, gas is mainly used in power-generation, the demand function would be rather price sensitive.

Our aim is to consistently derive country-specific monthly linear demand functions accounting for sectoral shares, seasonalities and price sensitivities. In the following, we outline our approach to determine these functions and the accompanying data sources.

First, we use country-specific annual demand data for the years 2010 and 2012. Demand data per country for those years is taken from IEA (2011), IEA (2011a) and (ENTSOG, 2011). IEA (2011a) provides consumption data on a country by country basis for the year 2010. For natural gas demand in 2012, we rely on forecasts from IEA (2011) and ENTSOG (2011).

In a second step, annual demand is split into monthly demand, using historical monthly consumption data provided by, e.g., IEA (2011a) and FGE (2010). Concerning the linear demand functions, sufficient data is only available for 27 nodes representing China, India and most of the OECD countries. For the other countries, we assume monthly demand to be inelastic and exhibit no seasonality.

Next, we distinguish two groups of sectors: We assume “industry and power (IP)tt-o have a higher price sensitivity than “heating and miscellaneous (HM)”. IEA (2011a) provides sectoral shares of gas demand in industry, heat and power generation on an annual basis. For the heating sector, we derive monthly demand data from heating degree days provided by, e.g., Eurostat (European countries) or National Resources Canada (Canada)[16]. We further assume miscellaneous gas demand to exhibit no seasonal fluctuation. We derive the monthly demand for “industry and power generationäs a residual of total demand minus heating demand and minus miscellaneous demand. The monthly demand for both groups, IP and HM, serves as a reference demand with which linear demand curves for each group may be derived.

Monthly reference prices are provided by IEA (2011a) for the majority of countries. We add monthly price information from the spot indices Henry Hub, Title Transfer Facility (TTF) and National Balancing Point (NBP). For all European countries where no data is publicly available, we use the European average gas price provided by IEA (2011a).

Having set up reference price-volume combinations, we still have to determine the monthly price sensitivities in the relevant countries for both demand groups IP and HM to derive specific linear demand functions. We thereby stick to an approach that is commonly used in the modelling literature (e.g., Holz et al. (2008), Egging et al. (2010) or Trüby (2013)) by assuming point elasticities in the reference point. While we assume the demand elasticity of the HM group to be approximately -0.1 in all countries with a price sensitive demand function, we differentiate within the IP group. Because of the high degree of oil-price indexation as well as the tight capacity supply in Japan, we assume natural gas demand of the Asian countries to be less price sensitive than the other countries (-0.1 vs. -0.4).[17] These elasticity assumptions are in line with, e.g., Neumann et al. (2009) and Bauer et al. (2011) who assume a price elasticity of -0.3, or Egging et al. (2010) who assume price elasticities between -0.25 and -0.75.

Having derived monthly country-specific demand curves for IP and HM with different price sensitivities, we aggregate both demand functions horizontally. The resulting demand functions account for different seasonal demand patterns, different sectoral shares of total demand and different price sensitivities, therefore varying by month and country.[18]

[16] http://www.nrcan.gc.ca/energy/sources/natural-gas/monthly-market-update/1173

[17] These elasticity values provide the best fit with actual market outcomes in 2010. Please refer to Appendix A.4 for information on how prices in select countries change when the assumed elasticity is varied.

[18] Horizontal aggregation of two linear demand functions leads to a kinked demand function. Our modelling approach is only able to handle differentiable functions. After having checked all equilibrium price/quantity combinations, we can exclude the market outcomes in the steeper part of the kinked demand function. Therefore, we only use the less steep part in our analysis.

Overall, the model covers a gas demand of 3267 bcm for 2010 and 3426 bcm in 2012. This equals 99% of both global gas consumption in 2010 reported by the IEA (2011a) and global gas demand in 2012 as forecasted in IEA's Medium-Term Oil and Gas Markets report (IEA, 2011). We model 49% of total global demand to be price sensitive and 51% to be inelastic. In Asia/Oceania, 379 of 645 bcm of total demand is elastic (59%), whereas in Europe and North America, more than 90% of total demand is modelled as elastic demand functions. The comparably low share of Asian elastic demand is acceptable for our study because most of the Asian countries with inelastic demand are gas producers and are therefore import independent (e.g., Malaysia, Indonesia or Australia).

2.3.2 Long-term contracts in the global gas market

Long-term contracts still play a significant role in the natural gas market, in particular in Europe and Asia. Therefore, our model also accounts for LTCs. For Europe, data on LTCs is based on information provided by Gas Matters[19]. LTCs are also important for LNG deliveries: In 2010, about 60 bcm were traded on a spot and short-term basis[20] (GIIGNL, 2010). Of the total LNG trades that occured in 2010 (300 bcm), 80% were carried out as a result of long-term contracts.

As precise information on actual LTCs is not widely available, we model long-term contracts as a minimal delivery per annum from an exporting to an importing country, e.g., 6.4 bcm have to be shipped from Qatar to Italy over the course of the year. In other words, because the annual natural gas imports can be flexibly optimised during a year, we can neglect monthly minimal deliveries. Since our study focuses on security of supply effects during a disruption, we focus on the minimal deliveries instead of take-or-pay volumes, which serve as a means to guarantee "security of demandfor certain exporters.

Long-term contracts are often oil price indexed. This holds true in particular for the Asian LNG importers (Japan Crude Cocktail). However, our model derives prices endogenously, thus allowing the LTC reference prices to be determined via implicit modelling.[21] Our analysis focuses on a short time frame, i.e., one year.

[19]http://www.gasstrategies.com/home

[20]GIIGNL defines short-term contracts as contracts with a duration of less than 4 years. Since our analysis focuses on the effects of an LNG disruption, it is necessary to include LNG long-term contracts in the model. Neglecting that fact would presumably overestimate the flexibility of LNG trade and therefore underestimate the severity of a disruption of the Strait of Hormuz. Since we lack more detailed data and do not have information about potential flexibilities (neither in long- nor in short-term contracts), we stick to an amount of 240 bcm contracted in the long-term. We further assume this to be the contracted volume for 2012 as well.

[21]It is unclear how prices in an oil-price indexed LTC would react to a blockage of the Strait of Hormuz, as this depends on the specific contract structure as well as the change in the oil price. Therefore, the approach used in this paper is, in our view, only tractable in a partial equilibrium analysis such as the one presented.

2.3.3 Scenario setting

In our study, we simulate two scenarios. In the reference scenario, gas flows between November 2012 and October 2013 are computed assuming no disruption of the Strait of Hormuz. In the other scenario, we simulate a 6-month blockage of the Strait of Hormuz beginning in November. As our model is non-stochastic, we fix storage levels in November based on the results from the reference scenarios. Otherwise, market players would anticipate the blockage and fill the storages in advance (perfect foresight assumption). We, however, implicitly assume that storage operators have information about the length of the disruption. Concerning LNG long-term contracts, we proportionately diminish the annual minimum take/delivery quantity to match the length of the disruption (i.e., a 12 bcm contract is reduced to 6 bcm). This is in line with a reference LNG contract provided by GIIGNL (2011), according to which a blockage is a *force majeure* and relieves the contracting parties from the take/delivery obligation.

2.4 Results

2.4.1 Prices

To analyse the fundamental price effects of a disruption of the Strait of Hormuz, Figure 2.3 gives the monthly gas prices for Japan, the UK and the USA in both scenarios (no disruption and 6-month disruption).[22]

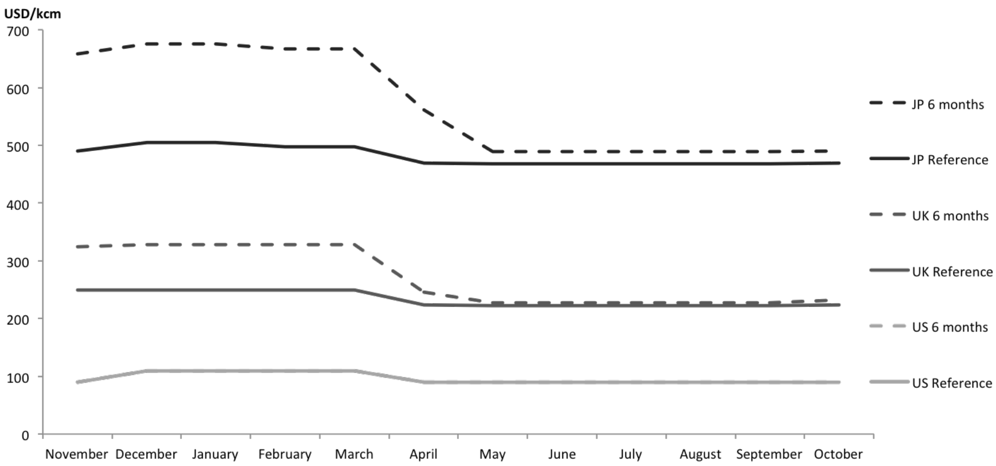

Abbildung 2.3: Price effects of a disruption of the Strait of Hormuz in three selected countries

[22]We use the market clearing price of the US southern demand node as a proxy for the monthly price of the USA.

First, we observe rather identical price curves for the USA. In our simulations, the USA neither import nor export significant amounts of LNG in 2012. Therefore, US gas prices are not affected by the blockage of the Strait of Hormuz.

Second, it can be seen that UK's natural gas price is connected to and affected by incidents on the global LNG market.[23] Whereas in the reference run the gas price varies between US$220/kcm in summer and US$250/kcm in winter, we observe an increase in the gas price when simulating a 6-months-long blockage. Once the disruption starts, the UK gas price immediately increases by up to 31% in the winter months (US$328/kcm in January).

Third, we notice that Japan, which relies solely on LNG imports, is most affected by the disruption of Qatar's and United Arab Emirates' LNG exports. The monthly gas price in Japan varies between US$467/kcm and US$505/kcm in the reference case. A 6-month long blockage of the Strait of Hormuz increases the gas price in Japan by nearly 34% (to more than US$677/kcm in January).

Thus, for both countries (Japan and the UK), we observe increasing prices during the disruption. However, it remains unclear whether an exporter's profits increase or whether higher supply costs cause the increase in prices. As an example, Figures 2.4 and 2.5 provide closer insight into the formation of January prices in both scenarios for Japan and the UK, respectively. Both figures contain the respective country's January demand function and the cash-based supply cost curves for both scenarios.[24]

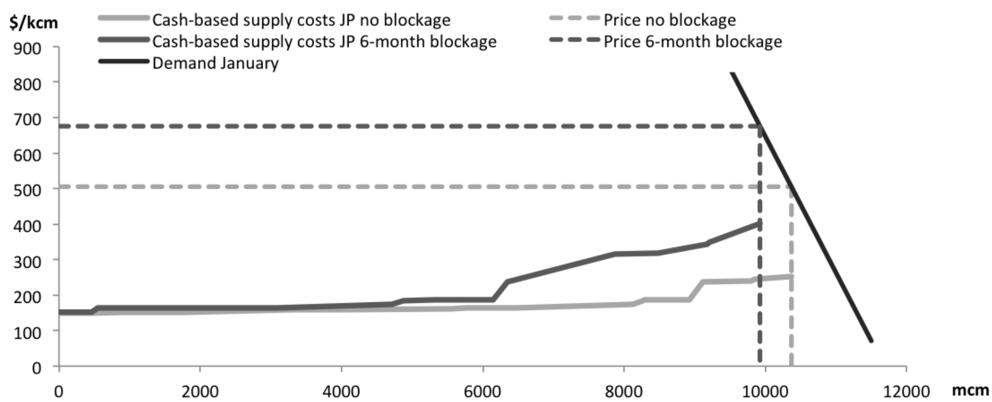

Abbildung 2.4: Changes in Japan's supply cost curve as a result of a disruption of the Strait of Hormuz

Concerning Japanese supplies, we observe a remarkable increase in supply costs, whereas in the UK, supply costs in both scenarios are nearly identical except for the rightmost part of the curve. Increasing prices, however, seem to be also driven by higher profits

[23]Around 14 bcm of the total LNG imports in 2010 (18.7 bcm) stem from long-term LNG contracts (GIIGNL, 2010).

[24]According to the terminology used in Section 2.2.3, cash-based supply costs include marginal costs of production and transport plus a scarcity rent for transport infrastructure.

for the suppliers in both countries. Yet, neither figure provides an indication as to what factors drive prices most.

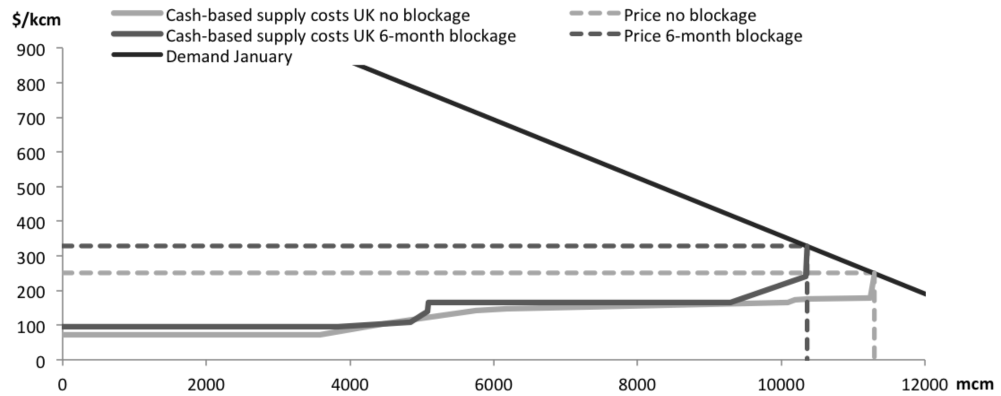

Abbildung 2.5: Changes in UK's supply cost curve as a result of a disruption of the Strait of Hormuz

Therefore, the observed price effects raise two questions: (1) Why does the import price level differ among different countries, even in the reference scenario? (2) What drivers explain the different price reactions after a supply shock? To answer these questions, we apply the approach introduced in Section 2.2.3. Using the dual variables from our simulation model, we are able to quantify price components that help us evaluate the strategic market positions of different countries. To give an application of our methodology, we next focus on the January prices of Japan and the UK in the reference scenario and during the supply shock.[25]

2.4.2 Price structure in the reference scenario

To explain the price differences between Japan and the UK, we first take a look at Figure 2.6. The figure illustrates the different components of Japanese and British import prices in January in the reference scenario (no disruption).

As stated in Section 2.2.3, we distinguish between "cash-based supply costsänd "profits". We define "cash-based supply costsäs those costs that the exporter actually has to bear in order to deliver gas to an importing country (i.e., marginal costs of production and transport as well as congestion rents for transport infrastructure). The scarcity rent for production capacity is monetary profit for the exporter. Therefore, it is part of what we refer to as "profits". Another component of the profits is the average markup, which oligopolistic players can realise in a certain import market. The term "maximal potential oligopoly markuplabels the markup that exporters could realise if the complete demand

[25]Concerning the USA, the abundant domestic production makes the country independent from imports. This does not only explain the low prices, but also the insensitivity of prices during the global supply shock (disruption of the Strait of Hormuz).

of a country was satisfied by Cournot players. However, gas purchases from price-taking players or depletion from storages lowers the “maximal potential markup”. In other words, the presence of a competitive fringe reduces the oligopoly rents. Last, LTCs have a decreasing effect on import prices and, in particular, the exporters' margin. Since LTCs are modelled as minimal deliveries from an exporter to an import country, the LTC is a binding constraint for the exporter. This can be interpreted as an economic disadvantage that the exporter has to bear or, conversely, a price advantage for the importer.

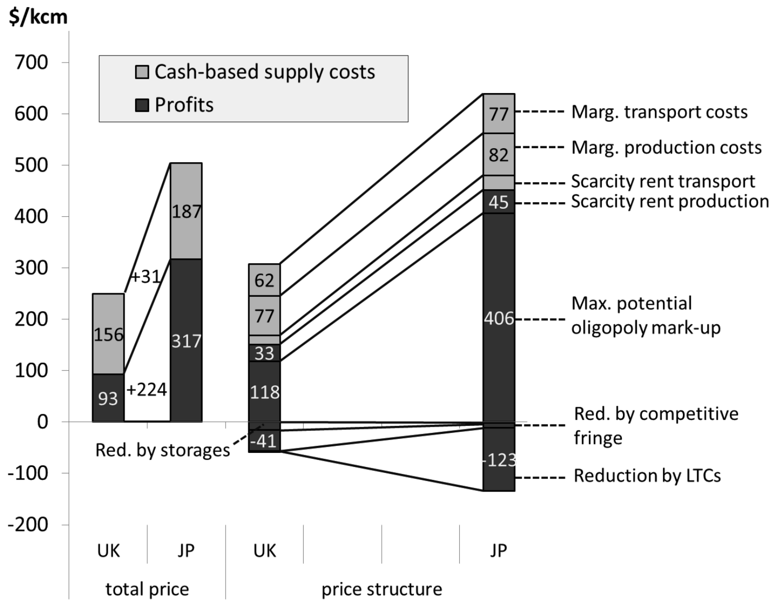

Abbildung 2.6: UK's and Japan's price structure in the reference scenario

As Figure 2.6 reveals, the total January price difference between Japan and the UK is US$255/kcm, yielding US$31/kcm to be explained by higher supply costs. The “profitsäccount for the major price difference (US$224/kcm). Whereas the scarcity rent for production capacity has a similar impact on prices in both countries, the “maximal potential oligopoly markupëxplains most of the differences between the “profits”. Compared with the UK, we assume the gas demand of Japan to be more inelastic. Thus, the high Japanese dependency on natural gas lets Cournot players realise higher markups in Japan than in the UK.

Yet, both countries are able to limit the oligopolistic markups: The UK has significant domestic production (which we assume to be provided by price-taking producers) and storage reserves that in total lead to a price reduction of US$56/kcm (-US$41/kcm and -US$15/kcm, respectively). Japan, in contrast, only has small capacities of domestic natural gas production and seasonal underground gas storages, which only reduce the gas price in total by US$12/kcm. Japan's key advantage in limiting oligopoly markups is its access to long-term contracted LNG volumes. In our setting, the contracts lead to an import price reduction of US$123/kcm. In other words, without the secured deliveries by long-term contracts, Japan would be much more likely to be exploited by its suppliers.

2.4.3 Structure of price reactions during a supply disruption

After having provided insight into the price structure of both Japan and the UK in the reference scenario, we focus next on the price increase during a blockage of the Strait of Hormuz. Figure 2.7 illustrates the January price level in both countries without a disruption (topmost bar) and with a 6-month disruption (lowest bar). Additionally, the middle bars of the figure display the cost components leading to an increase and decrease of the gas price during the disruption.

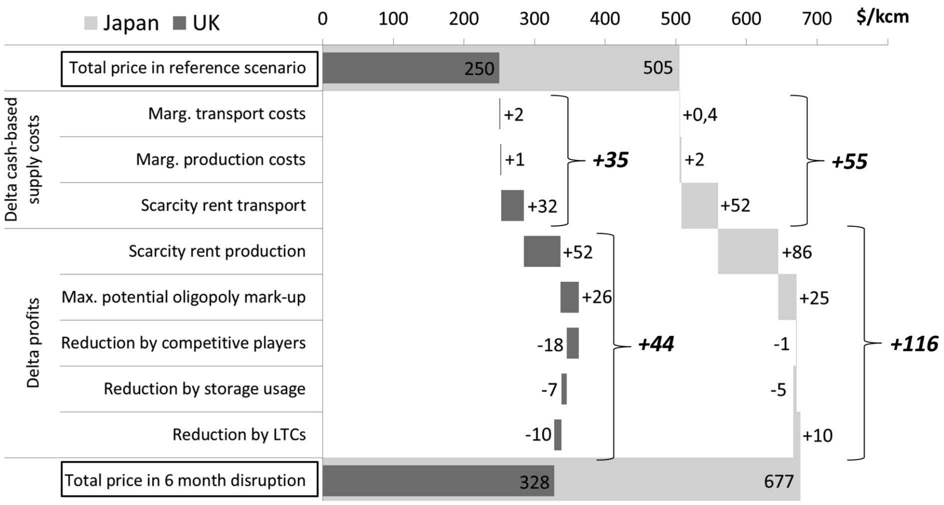

Abbildung 2.7: Structure of the import price increase in Japan and the UK during a 6-month disruption of the Strait of Hormuz

Marginal transport and production costs: We observe a slight increase in those two cost components because gas must be imported from more distant sources and gas production is intensified during the blockage. However, since both production and transport capacities already have high utilisation rates (compared with the global average) in the reference scenario, marginal production and transport costs only explain a fraction of the total price increase in Japan and the UK.

Scarcity rent of transport: A blockage of the Strait of Hormuz results in an outage of approximately 30% of global LNG trade volumes. LNG importers therefore need to find alternative sources of supply, which makes the available LNG liquefaction capacity (which we account to transport infrastructure) scarce. Costs resulting from transport scarcity explain US$52/kcm of the total price increase in Japan, but only US$32/kcm in the UK. The difference can be explained by taking a closer look at both countries' market positions: Japan depends solely on LNG imports, is price insensitive and competes for supply with other countries in the same situation (such as South Korea). The UK, however, is more sensitive to prices and, being connected to the European pipeline grid, is linked to producing countries such as Norway, the Netherlands and even Russia. Thus, the UK is less willing to buy gas from LNG terminals where capacity is scarce and prices are consequently high. Most of the increase in transport scarcity rent in the UK results from bottlenecks in the European pipeline grid, mainly caused by deliveries from Russia. Japan, in contrast, has to rely on the LNG volumes still available to the global gas market during the blockage of the Strait of Hormuz. As Japan competes for LNG supplies (and therefore also for LNG transport capacities) with other LNG-dependent importers, the opportunity costs of the transport value chain to deliver LNG to Japan increase during the blockage.

Scarcity rent of production: Production capacity costs explain the major part of the total price increase in Japan (US$86/kcm) and in the UK (US$52/kcm). The price increases induced by the scarcity rents of production are therefore higher than those induced by the transport scarcity rents. This indicates that given a blockage of the Strait of Hormuz, production capacity on a global scale is more scarce than transport capacity. Japanese import prices are, however, more affected by the scarcity of production capacity than are the British ones. The reason for the difference is similar to that of the transport scarcity rents. Whereas the UK has alternative sources of supply connected by pipelines, Japan competes with other LNG importers for the production volumes of LNG exporting countries. The opportunity costs of producing gas to sell to Japan at a later point in time therefore increase when the supply side becomes tighter as a result of a blockage of the Strait of Hormuz.

Maximal potential oligopoly markup: On the one hand, countries reduce demand during a disruption of the Strait of Hormuz, which decreases the potential markup *ceteris paribus*. On the other, as Qatar (QA) and the United Arab Emirates (AE) are not able to export gas, the number of oligopoly players decreases, which in turn increases the potential markup. In our setting, we observe that in both Japan and the UK, the impact on the price increase is approximately US$25/kcm.

Reduction by price-taking players: During the disruption, the UK increases domestic and polypolistic production, which reduces the import price increase by US$18/kcm. Japan, in contrast, covers only a small fraction of total gas supply with domestic production. Therefore, its ability to lessen the import price increase during a blockage of the Strait of Hormuz is limited.

Reduction by storage usage: The UK augments its storage depletion by 160 mcm during the disruption, leading to a decrease in the import price by US$7/kcm. Even though the storage usage in Japan is only increased by 100 mcm, we observe a reduction of US$5/kcm. This indicates that in improving a country's market position, storages increase in importance as countries grow more insensitive to prices.

Reduction by LTCs: The UK holds several LTCs, meaning it has secured deliveries from certain exporters. These LTCs lead to a reduction of the price increase by US$10/kcm during the disruption. Long-term contracts and the corresponding contractual obligations for certain LNG exporters (Algeria, Nigeria and Trinidad) to deliver gas to the UK result in opportunity costs for the exporters. These costs can be interpreted as a realisation of their price risk. Concerning Japan, LTCs explain a surprising US$10/kcm of the price increase during a blockage of the Strait of Hormuz. While LTCs lead to a price decrease of US$123/kcm in the reference scenario, LTCs only decrease the import price by US$113/kcm in the scenario with a 6-month disruption. This interesting observation can be explained by the fact that Qatar is one of the more important sources of contracted LNG volumes that, in the event of a blockage of the Strait of Hormuz, have to be substituted by non-contracted LNG volumes. Consequently, the price decreasing effect of Japanese LTCs is reduced in the case of a 6-month disruption.

So far, we have identified three factors that explain why a blockage of the Strait of Hormuz would affect the Japanese import price twice as much as the British one. First, Japan's import dependency on LNG forces Japan to compete for supplies in the disturbed LNG market. Therefore, scarcity rents for both transport and production are affected stronger than in the UK, where the connection to the European pipeline grid provides a viable alternative to LNG gas during the disruption. Second, during the crisis, the UK profits from price-taking domestic production and storage gas reserves that limit the markup rents for oligopolistic players. Japan, in contrast, has only small capacities of domestic production and underground storage and is therefore more exposed to Cournot behaviour. Third, LTCs help the UK to decrease prices by securing gas deliveries that would normally be sold to the UK at higher price levels. Japan also has significant volumes of LTCs helping to overcome the crisis; however, since part of Japan's LNG long-term contracts are supplied by Qatar (and hence not available in case of a blockage of the Strait of Hormuz), the decreasing price effect in Japan is reduced in comparison with the reference scenario.

2.4.4 The spatial impact of supply disruptions

As we have seen so far, the supply shock of a Strait of Hormuz blockage has a different impact on importing countries depending of their spatial location, i.e., the connection to exporters, e.g., via pipelines. In a spatial oligopoly model, the question is whether the location of the shock affects the importing countries differently. Therefore, we derive another scenario of a 6-months-lasting blockage of gas flows: In this setting, we assume that gas transits from Russia to Europe are blocked in the Ukraine – a situation that has already occurred in 2009, although for a shorter time period. In the Ukraine scenario, the Strait of Hormuz is not blocked.

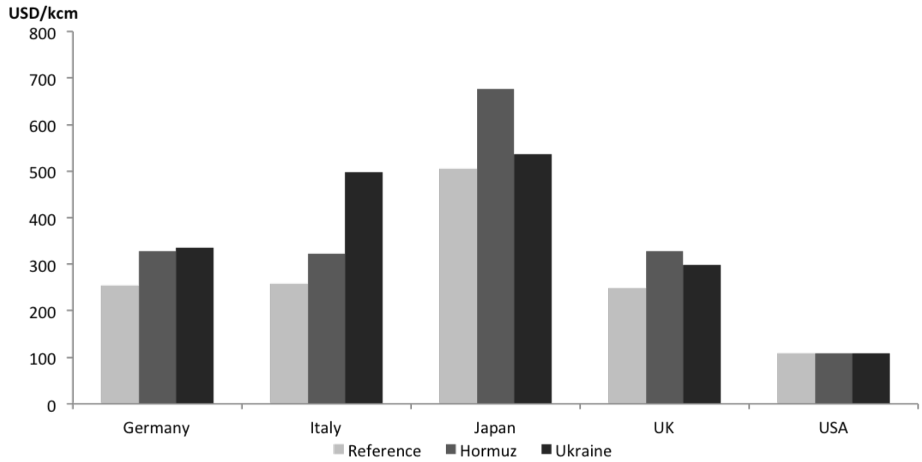

Abbildung 2.8: Select import prices during a 6-month disruption of the Strait of Hormuz's and Ukrainian gas transits, respectively

Figure 2.8 compares the price impacts of the Hormuz disruption and the Ukraine disruption: the US gas price is again not affected in the Ukraine scenario. In Germany and the UK, the price effect of both disruptions is in a similar range. The locational influence of the supply shock becomes obvious when comparing the prices of Italy and Japan for both scenarios. In Italy, we observe a strong price increase during the Ukraine disruption (+US$239/kcm), which is more than three times as high as in the Hormuz scenario. In Japan, the Hormuz disruption (+US$171/kcm) affects prices by far more than the Ukraine disruption (+US$32/kcm). The reason for this result is similar to the finding from the previous section. Italy has to compensate missing pipeline-based imports from Russia. In order to do so, Italy has to attract LNG volumes by higher prices and the other main supplier Algeria increases its oligopolistic markup in the absence of Russian gas. Japan does not receive any gas that is transited through the Ukraine. Therefore no missing volumes have to be compensated. However, since Europe attracts more LNG in the Ukraine scenario than in the reference scenario, LNG prices rise globally and thus in Japan as well.

2.5 Conclusions

The political situation in the Persian Gulf is exacerbating. Since the beginning of 2012, Iran has threatened to block the Strait of Hormuz, the world's most important liquefied natural gas choke point. Because regional security of supply depends on the individual supply structure, a potential blockage would affect gas supplies differently depending on the region of the world.

In our paper, we raise the question in which regions gas import prices would be most affected by a blockage and why so. For this purpose, we interpret the case of a blockage of the Strait of Hormuz as a supply shock in a spatial oligopoly. We analyse the compensation of missing Qatari gas supplies and compare regional price effects. Moreover, we develop a framework to disentangle regional prices into components and characterise them as price-increasing or price-decreasing components. Identifying the main price drivers allows us to quantify the supply situation in different regions.

We find that the gas price increases most in Japan. We also observe that gas price increases in the UK are significantly lower than those in Japan. US gas prices are hardly affected, as the country is rather independent from global gas trade.

We identify three reasons why a blockage of the Strait of Hormuz affects the import price in Japan much more than that in Britain. First, Japanese gas supplies fully depend on the disturbed liquefied natural gas market. The UK, on the other hand, has access to the European pipeline grid, which is supplied by important producers such as Russia and Norway. Thus, the UK faces an alternative market that – as opposed to the liquefied natural gas market – is only accessible by European (and not global) competitors. In turn, Japan has to compete globally for liquefied natural gas supplies. This translates into higher scarcity rents that Japan has to pay in order to receive liquefied natural gas volumes.

Second, the UK is less exposed to market power than Japan. Unlike in Japan, UK profits from price-taking domestic production and underground long-term storages (which act as a competitive fringe), thus decreasing markup rents of oligopolistic players.

Third, long-term contracts limit the price increase in the UK, since they secure gas volumes that otherwise would have been sold to the UK at higher prices. In contrast, the price-decreasing effect of long-term contracts diminishes in Japan: The blockage of the Strait of Hormuz suspends long-term contracts between Qatar and Japan. Therefore, Japan loses its price advantage from the Qatari long-term contracts' volumes. In other words, during the disruption, the missing volumes have to be replaced at comparably higher prices.

However, a supply disruption does not only affect diverse demand regions differently. Also the location of the disruption matters in a spatial market. To illustrate this effect, we simulate a fictitious 6-month blockage of Ukrainian gas transits to Europe. We find that Italian gas prices are by far more affected in the Ukraine scenario than in the

Hormuz scenario whereas for Japan the Hormuz disruption has the most severe price consequences.

This study investigates the regionally dispersed price effects following a supply shock in the natural gas market. However, mainly due to computational issues, some simplifying assumptions had to be made in our analysis. First, we assume perfect foresight, which may be a strong simplification, particularly for storage operators. Second, we model storage operators as price takers, despite the fact that a supply shock may allow them to maximise profits by initially refraining from storage depletion and thereby further increasing gas market prices. Third, we use a partial equilibrium model of the global gas market, thus failing to consider, e.g., the interdependencies between the oil and gas market. The interaction of substitutive fuels, such as oil and gas, could affect regional prices differently during a supply shock. In particular, the analysis of global inter-fuel competition using a model that accounts for strategic behaviour in the respective markets is an interesting possibility for further research.

Kapitel 3

The global markets for iron ore and coking coal - complementary goods, integrated mining companies and strategic behaviour

3.1 Introduction

The research presented in the paper at hand is inspired by an important energy source that exhibits the characteristics of a complementary input factor: coking coal. Coking coal is a complementary input to iron ore for steel production. Both goods are indispensable when making crude steel using the so-called "oxygen route", i.e., first producing the pig iron in a basic oxygen furnace and, second, using the pig iron in a blast furnace to create the final product, crude steel. From an energy economics perspective, this industry example is of particular interest because (i) the goods are complements, (ii) each of the inputs is of little use in alternative applications (e.g., power plants typically use coals of different quality), (iii) international trading of both commodities is highly concentrated and (iv) only a few (large) firms are active in both input markets (parallel vertical integration), i.e., produce both coking coal and iron ore, with none of these firms being forward-integrated into the production of steel. Given this market setting, the paper presented investigates the strategy of Cournot-behaving mining companies that own both a coking coal and an iron ore division. Do these firms optimise the divisions' output on a firm level or for each division separately (division by division)?

In order to answer this question, our analysis comprises two steps: First, we derive a stylised theoretical model to investigate the profitability of firm-level optimisation in a setting with two homogeneous Cournot duopolies of complementary goods. In total, three firms are active in both duopolies: Two firms each serve solely one of the markets and one firm serves both markets. The latter firm can either optimise both divisions' output separately or on a firm level. Comparing total profits of the integrated firm allows us to answer our research question from a theoretical point of view. We consider two cases: one with unlimited capacities and one incorporating a binding capacity constraint on one of the divisions' output.

The actual markets for coking coal and iron ore are, however, more complex as (i) both markets have more than two suppliers, (ii) there are multiple firms that are parallel vertically integrated, (iii) production costs are heterogeneous, (iv) both markets are spatial with multiple demand and supply regions and (v) several producers face a binding capacity constraint. We therefore, in a second step, develop and employ a numerical, multi-input, spatial oligopoly simulation model of the coking coal and iron ore market, calibrated with data from a unique data set for the years 2008 to 2010. We run the model for a range of assumed demand elasticities for the complementary product (pig iron) to assess the profits of the integrated companies in both cases, i.e., the optimisation on a firm level or on a division level. Furthermore, we compare the simulation results of three specific market settings to the actual market outcomes: In addition to one perfect competition scenario, we assess one scenario assuming division-by-division optimisation of all integrated firms and another one assuming firm-level optimisation of the integrated companies' business units. We then assess which of these three scenarios best explains the actual market outcomes with regard to trade flows, production volumes and prices of the two commodities. Concerning trade flows, we use three statistical measures to evaluate which setting provides the best fit.

The theoretical model confirms that firm-level optimisation is more beneficial compared to division-by-division optimisation. However, if one of the divisions' production capacity is limited, we show that there exists a critical capacity constraint (i) below which optimisation on a firm level and on a division level yield indifferent results, (ii) above which firm-level optimisation is always beneficial and (iii) that becomes smaller with a lower demand elasticity.

Applying the simulation model for the coking coal and iron ore market yields three main findings: First, the lower the pig iron demand elasticity is, the more profitable the firm-level optimisation is compared to the division-level optimisation for an integrated mining company. However, for demand elasticities lower than -0.5 to -0.6, the benefits of firm-level optimisation tend to zero. Second, comparing simulation results and actual market outcomes for the years 2008 to 2010 with respect to trade flows, prices and production volumes, the scenario assuming perfect competition, other than the two scenarios that assume players to behave in a Cournot-manner, does not match actual market outcomes. Third, the scenario assuming division-level optimisation provides a more consistent fit with actual market outcomes than the firm-level optimisation scenario, although one scenario does not unambiguously dominate the other. Thus, no indication is found that mining companies integrated into coking coal and iron ore production have applied firm-level optimisation during the years 2008 to 2010.

At least two explanations for this finding are possible: First, because of capacity constraints, firm-level optimisation only generates additional profits compared to division-level optimisation if demand for the final product (pig iron) is rather inelastic. Second, additional management costs (increased organisational and transactional costs) that go along with firm-level optimisation may outweigh additional profits. Hence, division-level optimisation may leave sources of profits untapped but can be the profit-optimising strategy of a mining company integrated in both coking coal and iron ore production.

Our research is motivated by two strands of literature. The starting point is the seminal publication by Cournot (1838) concerning the theory of complementary oligopolies. More recent papers on the topic of strategic behaviour and complementary goods were inspired by Singh and Vives (1984), who develop a duopoly framework that allows for the analysis of quantity- and price-setting oligopolies assuming goods to be substitutes, independent or complements. Building on Singh and Vives' findings, a whole body of literature emerged, devoting its attention to analysing the problem of complementary monopolies under different setups. However, the setting in which we are interested is different from the ones assumed in most of the papers belonging to this strand of literature: In our setting, the supply of each complement is characterised by an oligopoly, i.e., there are few substitutes for each complement, whereas most of the papers belonging to the body of literature referred to above assume each complementary good to be produced by a monopolist. Salinger (1989) is the only one to use a similar setting as the one presented in this paper.

Second, research on market power coordination and interdependent demand is an important stream of empirical literature for this paper. Hagem et al. (2006), for example, analyse the interdependency of natural gas demand and demand for emission permits and how a dominant player in these markets can benefit from coordinating its market power. Similarly, Pineau et al. (2011) investigate the market power of power generators concerning the interdependent demand of peak-load and base-load electricity. Furthermore, two analyses on strategic behaviour on the coking coal market have inspired our research: Graham et al. (1999) and Trüby (2013). Graham et al. (1999) simulate the coking coal trade for the year 1996 for several supply- and demand-side market power cases. Trüby (2013) analyses different market structures such as Cournot or Stackelberg behaviour of mining companies to find evidence of non-competitive behaviour. Further empirical papers dealing with the analysis of coking coal and iron ore trading have been published (e.g., Toweh and Newcomb (1991), Labson (1997) or Fiuza and Tito (2010)). However, to the best of our knowledge, there has yet to be a publication that handles the strategic interaction between both markets or that applies the theory of complementary inputs to a real-world setting.

Consequently, this paper contributes to the literature in three ways: First, we add a new dimension to the existing literature on the strategic behaviour of coking coal producers by taking into account the iron ore market and the complementarity of both goods in pig iron production. Second, we extend the literature on resource market simulations by developing a spatial multi-input equilibrium model that accounts for coking coal and iron ore as complementary inputs and enables the simulation of market power on a firm level. Third, we assess the strategic behaviour of firms that produce both coking coal and iron ore, thereby specifically accounting for capacity constraints.

The remainder of this paper is structured as follows: Section 3.2 introduces our theoretical framework and establishes our theoretical findings. The third section presents the motivation for our industry example, explains the structure of the simulation model used to model the coking coal and iron ore market and describes the numerical data used in this study. Section 3.4 analyses the results obtained from the model simulations. More specifically, Subsection 3.4.1 analyses, from the perspective of individual firms, the impact of firm- versus division-level optimisation on the firms' profits. Subsection 3.4.2 assesses which of the three scenarios best explains the actual outcomes of the coking coal and iron ore market. Subsection 3.4.3 briefly discusses the strategic implications of these findings. Finally, Section 3.5 concludes.

3.2 Quantity-setting complementary oligopolies

In the setting we are interested in, supply of each complement, coking coal and iron ore, is characterised by a quantity-setting (Cournot) oligopoly. Each of the two complementary goods is considered as homogeneous. Furthermore, the setting is characterised by the existence of a number of parallel vertically integrated firms, i.e., mining companies which produce both coking coal and iron ore.[26] Consequently, we model two simultaneous

[26]In reality, there are steel companies which are backward-integrated, i.e., produce iron ore or coking coal. However, addressing this market structure would be beyond the scope of our research. In addition, these firms make up for only a small share of globally traded volumes of iron and coking coal. We explain how we dealt with this issue in Footnote 35 in Section 3.3.3.2.

Cournot equilibria, both of which influence the composite good's demand and thus the price of the two complementary goods. The approach chosen in this paper resembles the one in Salinger (1989), who uses a similar setting of complementary oligopolies to investigate how different definitions of the terms "upstreamänd "downstreamchange the impact of a vertical merger on competition. Following Salinger (1989), we assume players active in one input market to take the price of the other complement as given, we thus assume $\frac{\partial p_1}{\partial x_2} = \frac{\partial p_2}{\partial x_1} = 0$.

This assumption implies that we abstract from the "tragedy of the anticommonspp-roblem. The problem was first described by Sonnenschein (1968), who pointed out the duality between a Bertrand duopoly with substitutes and a Cournot complementary monopoly. Sonnenschein (1968) showed for a setup in which each complementary good is produced by one monopolist and each monopolist maximises its profit by choosing the optimal quantity of its good, an incentive arises to undercut total output of the other complement. In his setting, an oversupply of one of the complements would cause its price to drop to zero (or to marginal costs if they are assumed to be greater than zero), leaving all the profits to the other complement's supplier. In the end, this would lead to a race-to-the-bottom in quantities. The unique Nash-equilibrium where such a deviation is not profitable is one where no firm produces at all. This finding remains valid even if each complement is produced by a number of oligopoly firms instead of a monopolist. The incentive to cut the own production by a marginal unit and, thus, create excess supply of the complementary good continues to exist, if this drives the complement's price down to zero, which in turn leads to an increase in the own good's price (Dari-Mattiacci and Parisi, 2006). Hence, the "tragedy of the anticommonsproblem relies heavily on the strong effect of excess supply. An effect which already Sonnenschein himself referred to as "somewhat obscure".[27] [28]

In the following, we will use a stylised theoretical model to investigate the profitability of firm-level optimisation in a setting with two homogeneous Cournot duopolies of complementary goods. In Subsection 3.2.1, unlimited production capacity is assumed.

[27]This remark can be found in Footnote 4 of Sonnenschein (1968).

[28]Another interesting aspect of complementary goods and Cournot competition was first brought forward by Singh and Vives (1984). They develop a duopoly framework that allows to analyse quantity- and price-setting oligopolies (Bertrand, 1883) assuming goods to be substitutes, independent or complements. The two authors proof that in the case of a complementary monopoly companies prefer to offer price instead of quantity contracts, as this maximises their profits. Amongst other things, Häckner (2000) shows that this finding also holds true under more general assumptions including a setting with more firms (each producing one complementary good). In the paper at hand, both input markets are characterised by oligopolies with firms having production constraints. Therefore, if firms were assumed to engage in Bertrand competition and production capacity would be unconstrained prices of each complement would equal marginal costs and, thus profits would amount to zero. In the case of capacity constraints it has been shown that first-order conditions for profit maximisation may have a kink, such that equilibria may not be well defined. Therefore, companies would prefer quantity contracts over price contracts in our setting.

In Subsection 3.2.2, we first investigate if the introduction of a binding capacity constraint on one of the complementary goods of the parallel vertically integrated firm may change the favourability of firm-level optimisation. Second, we propose and proof three propositions characterising the profitability of firm-level optimisation and the effect of capacity constraints.

3.2.1 A model of two complementary duopolies with unlimited capacities

We start out by considering a simple market of three firms producing two complementary goods. Firm 1 holds two divisions, one (c_1) produces complement C (coking coal) and the other (i_1) produces complement I (iron ore). The other two firms are specialised and, thus, own one division. Firm 2 solely produces coking coal (c_2) and the third firm solely produces iron ore (i_2). Thus, there are $N = M = 2$ producers of each of the two complements, coking coal and iron ore. For simplification of the analysis, production costs are assumed to be zero, although this does not qualitatively alter the results. Complements I and C may be combined in fixed proportions (here: one unit each) to produce the composite good pi (pig iron), i.e., it holds true that $x_{pi} = x_i = x_c$ with $x_c = \sum_n^N x_c^n$ and $x_i = \sum_m^M x_i^m$. Consequently, the supply of each good depends on the supply of the other complement, $x_c\left[x_i\right]$ and $x_i\left[x_c\right]$.

In addition, we assume full compatibility among the complements and perfect competition in the market for the composite good, such that NxM composite goods exist, all of which are available at price $p_{pi} = p_i + p_c$. Thus each complement's price, $p_i\left[\sum_m^M x_i^m, p_c\right]$ and $p_c\left[\sum_n^N x_c^n, p_i\right]$, depends on the supply of the complement ($\sum_m^M x_i^m$ or $\sum_n^N x_c^n$) as well as the price of the other complement. However, the price of the other complement is perceived as a cost component due to the assumption $\frac{\partial p_1}{\partial x_2} = \frac{\partial p_2}{\partial x_1} = 0$. We also rule out that there is product differentiation in the composite good market, thus all NxM composite goods are perfect substitutes as well. Initially, we do not assume the composite good's inverse demand function to be of a specific functional form.

Assuming that firm 1 chooses to optimise the output of divisions c_1 and i_1 *not* on a firm level but division by division, the profit functions of the two divisions and the remaining two firms are given by

$$\Pi_{i_m} = p_i\left[x_i, p_c\right] x_i^m\left[x_c\right] \tag{3.1}$$

$$\Pi_{c_n} = p_c\left[x_c, p_i\right] x_c^n\left[x_i\right]. \tag{3.2}$$

Taking, for example, the first partial derivate of the profit function of division i_1 yields the following first-order condition:

$$\frac{\partial \Pi_{i_1}}{\partial x_i^1} = p_i + \left(\frac{\partial p_i}{\partial x_i^1} + \frac{\partial p_i}{\partial x_i^{-m}} \frac{\partial x_i^{-m}}{\partial x_i^1} + \frac{\partial p_i}{\partial p_c} \frac{\partial p_c}{\partial x_i^1} \right) x_i^1 = 0 \tag{3.3}$$

with x_i^{-m} being the iron ore production of the competitor. Due to the assumption that the firms engage in Cournot competition, it holds true that $\frac{\partial x_i^{-m}}{\partial x_i^1} = 0$. As discussed previously, in our model we assume that $\frac{\partial p_1}{\partial x_2} = \frac{\partial p_2}{\partial x_1} = 0$, hence Equation 3.3 simplifies to

$$\frac{\partial \Pi_{i_1}}{\partial x_i^1} = p_i + \frac{\partial p_i}{\partial x_i^1} x_i^1 = 0. \tag{3.4}$$

In order to derive the market results, we assume the demand function to be linear in form, i.e., $p_{pi} = a - bx_{pi}$.[29] The first partial derivative of the profit function of division i_1 yields the following first-order condition, which due to the assumed symmetry looks analogue for the other firms and divisions:

$$\frac{\partial \Pi_{i_1}}{\partial x_i^1} = p_i - bx_i^1 = 0. \tag{3.5}$$

Solving the resulting system of equations allows us to derive equilibrium output and prices under division-by-division optimisation:

$$x_{pi}^* = x_i^* = x_c^* = \frac{a}{2b}, \quad p_c^* = p_i^* = \frac{a}{4} \quad \text{and} \quad p_{pi}^* = \frac{a}{2}. \tag{3.6}$$

Next we now consider a setup in which firm 1 optimises the output of its divisions c_1 and i_1 simultaneously, i.e., on a firm level. In the literature, firm-level optimisation is often referred to as parallel vertically integration (PVI). To distinguish the results of firm-level optimisation from division-level optimisation, we use the notation "PVIïn the following. In its general form, i.e., without a specific functional form of the (inverse) demand function, the profit function is given by

$$\Pi_{PVI} = p_i [x_i, p_c] \, x_i^{PVI} [x_c] + p_c [x_c, p_i] \, x_c^{PVI} [x_i] \, . \tag{3.7}$$

[29]Choosing a linear functional form is a simplification of the real, unobservable demand function. It implies that the absolute price reaction to a 1%-change in pig iron output is constant. The price elasticity, however, is not constant and depends on the price/output combination. The choice of a linear demand function simplifies the proof and enables to derive a simple representation of the market equilibria. Choosing different functional forms would lead to a complex system of equations, in particular since the pig iron price (function) is the sum of the coking coal and iron ore price. A more general proof, i.e., one that is irrespective of the functional form, would be interesting research extending this work.

Taking the first partial derivate of Equation 3.7 with respect to x_i^{PVI} and x_c^{PVI} yields:

$$\frac{\partial \Pi_{PVI}}{\partial x_i^{PVI}} = p_i + \frac{\partial p_i}{\partial x_i^{PVI}} x_i^{PVI} + \frac{\partial x_c^{PVI}}{\partial x_i^{PVI}} p_c = 0 \tag{3.8}$$

$$\frac{\partial \Pi_{PVI}}{\partial x_c^{PVI}} = p_c + \frac{\partial p_c}{\partial x_c^{PVI}} x_c^{PVI} + \frac{\partial x_i^{PVI}}{\partial x_c^{PVI}} p_i = 0. \tag{3.9}$$

We already know that $\frac{\partial p_i}{\partial x_c} = \frac{\partial p_c}{\partial x_i} = 0$ and $\frac{\partial x_i^{-m}}{x_i^m} = \frac{\partial x_c^{-n}}{x_c^n} = 0$, which is why the partial derivatives that include these expressions were omitted in Equations 3.8 and 3.9. Keeping in mind that in this example a factor intensity (*fin*) of 1 is assumed, it must hold true that $\frac{\partial x_c}{\partial x_i^{PVI}} = \frac{\partial x_i}{\partial x_c^{PVI}} = 1$. Because of production costs being zero and prices of both composite goods being positive, in case of a parallel vertically integrated firm it holds true that $\frac{\partial x_c}{\partial x_i^{PVI}} = \frac{\partial x_c^{PVI}}{\partial x_i^{PVI}} = fin = 1$ and $\frac{\partial x_i}{\partial x_c^{PVI}} = \frac{\partial x_i^{PVI}}{\partial x_c^{PVI}} = \frac{1}{fin} = 1$.[30] Thus, a firm-level optimising firm knowing that an increase in one of the complement's output needs an equally large increase of the other complement in order to increase the output of the composite good, would always find it beneficial to increase output of both goods at the same time.This does not necessarily mean that the producer of the composite good (pig iron) has to buy a bundle from the same PVI firm. It only means that a PVI company sells the same amount of both complementary goods to the end-user market. Assuming a linear inverse demand function of the composite good and using Equations 3.8 and 3.9, respectively, the resulting first-order conditions are:

$$\frac{\partial \Pi_{PVI}}{\partial x_i^{PVI}} = a - 2bx_i^{PVI} - bx_i^2 + p_c = p_i + p_c - bx_i^{PVI} = 0 \tag{3.10}$$

$$\frac{\partial \Pi_{PVI}}{\partial x_c^{PVI}} = a - 2bx_c^{PVI} - bx_c^2 + p_i = p_i + p_c - bx_c^{PVI} = 0. \tag{3.11}$$

Taking a closer look at the Equations 3.10 and 3.11, we see that due to the complementarity of the goods, in order to maximise its overall profits, the mining company which optimises output on a firm level has to take into account not only the production of its direct competitors, but also the price of the complementary good. Solving again the resulting system equations allows us to derive equilibrium output and prices under

[30] A different way of approaching this optimisation problem is to assume that each firm would only be able to sell the composite good as a bundle x_{pi} (refer to Equation 3.13 for a similar yet slightly different argumentation). While the integrated firm can choose between make, x_i^{PVI} and x_c^{PVI}, (by incurring marginal production costs, mpc_i^{PVI} and mpc_c^{PVI}) or buy, x_i^{-m} and x_c^{-n}, (paying the current markt price of the respective commodity), the independent firms only have the latter option. The integrated firm's profit function (assuming a linear cost function) would look like this: $\Pi_{PVI} = (p_i + p_c) * x_{pi}^{PVI} - mpc_i^{PVI} * x_i^{PVI} - p_i * x_i^{-m} - mpc_i^{PVI} * x_c^{PVI} - p_c * x_c^{-n}$. Now if the firm were to increase the output of one of the complementary goods, say $\partial x_c^{PVI} = 1$, then $\partial x_i^{PVI} + \partial x_i^{-m} = 1$ must hold as well. As long as the costs of delivering the own good to the respective market place are below the prevalent market price, i.e., $\frac{\Pi_{PVI}}{\partial x_i^{PVI}} = mpc_i^{PVI} < \frac{\Pi_{PVI}}{\partial x_i^{-m}} = p_i$, the integrated firm will opt to produce the good itself.

firm-level optimisation:

$$x_{pi}^* = x_i^* = x_c^* = \frac{2a}{5b}, \quad p_c^* = p_i^* = \frac{a}{5} \quad \text{and} \quad p_{pi}^* = \frac{2a}{5}. \tag{3.12}$$

By comparing the equilibrium solutions, i.e., with (Equations 3.12) and without (Equations 3.6) firm-level optimisation, we find that firm-level optimisation results in higher supply of the composite good and, therefore, of the two complementary inputs, which in turn leads to lower prices. Hence, firm-level optimisation increases consumer welfare.

TABELLE 3.1: Market outcomes based on the strategy choice of the integrated firm

	Division level	**Firm level**
Price of composite good	$\frac{a}{2}$	$\frac{2a}{5}$
Price of complements	$\frac{a}{4}$	$\frac{a}{5}$
Quantity ($x_{pi} = x_i = x_c$)	$\frac{a}{2b}$	$\frac{3a}{5b}$
Each firm's output	$x_i^m = x_c^n = \frac{a}{4b}$	$x_i^{PVI} = x_c^{PVI} = \frac{2a}{5b}$ $x_i^2 = x_c^2 = \frac{a}{5b}$
Each firm's profit	$i^m = c^n = \frac{a^2}{16b}$	$PVI = \frac{4a^2}{25b} \quad i_2 = c_2 = \frac{a^2}{25b}$

While consumers benefit from firm-level optimisation, the specialised, i.e., not parallel vertically integrated firms lose market share and make less profit. This is due to the fact that firm-level optimisation effectively internalises a negative externality. The externality is negative due to the the fact that $\frac{\partial p_1}{\partial x_2} = \frac{\partial p_2}{\partial x_1} = 0$ (see also Salinger (1989)). If a company, which is specialised in producing one of the complements, chooses to reduce its output, the production of the composite good is reduced as well, thereby raising the composite good's price. This increases the price of the company's complement, while the other complement's price is not changed (because of $\frac{\partial p_1}{\partial x_2} = \frac{\partial p_2}{\partial x_1} = 0$). However, due to the reduction of the composite good's output, the output of the other complement, too, is reduced. Consequently, reducing the output of one of the complements causes a negative externality on the firms producing the other complement. Hence, the PVI company, internalising this negative externality, is willing to supply a larger amount of both inputs, which then leads to a reduction of the output of the remaining independent companies (see Table 3.1). Another interesting aspect is that, in contrast to Cournot oligopoly with substitutes and no capacity constraints, there is no merger paradox. That is, profits of the firm-level optimising company (which may be interpreted as a merger situation) are always larger than the combined profits of the two divisions under division-level optimisation (equivalent to a non-merger situation), again due to the internalisation of the negative externality.

Summing up, we recalled that a parallel vertically integrated company maximises its profits by optimising output of both goods on a firm level. Assuming unlimited production capacity, we showed that firm-level optimisation of divisions producing different complements is always profitable, i.e., it increases overall profit of the holding.

3.2.2 Profitability of firm-level optimisation under constrained capacity

As shown in Subsection 3.2.1, the profitability of firm-level optimisation of a parallel vertically integrated company arises from increasing the output of both complements compared to the case of division-level optimisation. Therefore, the question arises whether a constraint restricting the potential output of one of the two complements may alter the result that firm-level optimisation is beneficial.

In order to do so, we need to recall from Subsection 3.2.1 that, first, an unconstrained integrated firm behaves in a manner similar to a Stackelberg leader, i.e., by internalising the negative externality of the two complements, the firm increases its output compared to the case of division-level optimisation (see Table 3.1). Second, the integrated firm maximises its profit by supplying the same amount of both complements (in case of a factor intensity of both goods of 1), i.e., it provides both complements as a bundle. However, in case of a binding capacity constraint on one of the complements, the firm could also choose to supply different quantities of its two goods. Consequently, one can rewrite the profit function of the parallel vertical integrated firm from the previous subsection (Equation 3.7) as:

$$\Pi_{PVI} = (p_i + p_c)x_b + p_i x_i^{-b} + p_c x_c^{-b}, \tag{3.13}$$

with x_b referring to the amount of bundled sales supplied to the market, thus it represents at the same time sales of iron ore as well as coking coal, while x_i^{-b} and x_c^{-b} need not be sold at a similar ratio. Thus the firm's total coking coal and iron ore output amounts to $x_c^{PVI} = x_b + x_c^{-b}$ and $x_i^{PVI} = x_b + x_i^{-b}$, respectively. In the following, using Equation 3.13 and a linear demand function, we would like to investigate the profitability of firm-level optimisation in the event of a binding capacity constraint in more detail. Therefore, we propose three propositions that we will proof subsequently:

Proposition 1 *Given a specific linear demand function, there exists a critical capacity limit, $\overline{x}_b$, that makes the integrated firm indifferent between firm-level and division-level optimisation, i.e., profits are identical for both strategies. For capacity limits lower than $\overline{x}_b$ profits of both strategies remain identical as well.*

Proposition 2 *Given a specific linear demand function, for every capacity limit $\hat{x}_b$ that fulfills $\hat{x}_b > \overline{x}_b$, firm-level optimisation is profitable despite a binding capacity constraint.*

Proposition 3 *The less elastic the linear inverse demand function of the composite good, the lower becomes the critical capacity constraint, $\overline{x}_b$.*

Concentrating first on Proposition 1, we need to show that for a given linear inverse-demand function of the composite good, there is a capacity limit to one of the complements $\overline{x}_b$ that causes the difference between the division-level profits, $\pi_c^1 + \pi_i^1$, and the firm-level profits, π^{PVI}, to be zero.[31] To this end, we start by deriving the equilibrium profit of firm-level optimisation using the first-order conditions of the integrated firm:

$$\frac{\partial \Pi_{PVI}}{\partial x_i^{-b}} = -bx_i^{-b} - bx_b + p_i = 0 \tag{3.14}$$

$$\frac{\partial \Pi_{PVI}}{\partial x_c^{-b}} = -bx_c^{-b} - bx_b + p_c = 0 \tag{3.15}$$

$$\frac{\partial \Pi_{PVI}}{\partial x_b} = -bx_b - bx_c^{-b} - bx_i^{-b} + p_c + p_i = 0 \tag{3.16}$$

Assuming a binding capacity constraint on the iron ore output of the integrated firm ($\overline{x}_b$), the first and third first-order conditions (Equations 3.14 and 3.16) will not be needed as the firm's optimal iron ore output is $\overline{x}_b$ (hence, $x_i^{-b} = 0$), otherwise the capacity constraint would not be binding.

Knowing that the first-order conditions of the non-integrated firms remain unchanged (see Equation 3.10) and using $p_{pi} = p_i + p_c$ as well as Equation 3.15 yields

$$p_i = \frac{2a - 3b\overline{x}_b}{5}, \quad p_c = \frac{a + b\overline{x}_b}{5}, \quad x_c^{PVI} = -\frac{4}{5}\overline{x}_b + \frac{a}{5b}. \tag{3.17}$$

Therefore, the integrated firm's profit function in case of a binding capacity constraint is

$$\pi^{PVI} = \frac{a^2 + 12ab\overline{x}_b - 14b^2\overline{x}_b^2}{25b}. \tag{3.18}$$

We know from Subsection 3.2.1 that the profit of the integrated firm applying division-level optimisation amounts to $2 * \frac{a^2}{16b} = \frac{a^2}{8b}$ with each division supplying $\frac{a}{4b}$ (see Table 3.1). In order to proof Proposition 1, we thus need to show that when the capacity

[31] We use x_b since if the capacity constraint on one of the complements is binding, the firm will choose to produce at least the same quantity of the other complement, hence it will supply $\overline{x}_b$ bundles.

constraint is $\overline{x}_b = \frac{a}{4b}$ profits under firm-level optimisation equal the profits of division-level optimisation:

$$\pi^{PVI} = \frac{a^2 + 12ab\frac{a}{4b} - 14b^2\left(\frac{a}{4b}\right)^2}{25b} = \frac{4a^2 - \frac{7a^2}{8}}{25b} = \frac{\frac{25a^2}{8}}{25b} = \frac{a^2}{8b}, \tag{3.19}$$

which is the case. Now, if we consider division-level optimisation with one division being constrained in its output, e.g., the iron ore division($\overline{x}_i^2$), the function of profits (depending on the capacity constraint) is identical to that of firm-level optimisation (see Appendix B.2). In other words, if the capacity limit equals or is lower than the optimal quantity of the division-level strategy, profits of the parallel vertically integrated firm remain unchanged by optimising on a firm level, which is what we wanted to proof.

Regarding Proposition 2, we need to show that for capacity constraints that are higher than $\overline{x}_b = \frac{a}{4b}$ profits of firm-level optimisation are higher than that of division-level optimisation. We already know that the optimal output of the unconstrained integrated firm under firm-level optimisation is $\frac{2a}{5b}$. Taking a look at equilibrium output of x_c^{-b} stated in Equation 3.17, we see that x_c^{-b} is zero for $\hat{x}_b > \frac{a}{4b}$, because output in this model is restricted to be non-negative. Therefore, total output when optimising on a firm level is equal to $\hat{x}_b$ for $\hat{x}_b > \overline{x}_b = \frac{a}{4b}$. In this case, equilibrium prices and the integrated firm's profits are given by

$$p_i = p_c = \frac{a - b\hat{x}_b}{3}, \quad \pi^{PVI} = \frac{2a\hat{x}_b - 2b\hat{x}_b^2}{3} \quad \text{for } \hat{x}_b > \overline{x}_b. \tag{3.20}$$

Hence, for $\hat{x}_b > \overline{x}_b$ it holds true that the profits of firm-level optimisation change by

$$\frac{\partial \pi^{PVI}}{\partial \hat{x}_b} = \frac{2a - 4b\hat{x}_b}{9} \quad \text{for } \hat{x}_b > \overline{x}_b, \tag{3.21}$$

with $\frac{\partial \pi^{PVI}}{\partial \hat{x}_b} > 0$ for $\frac{a}{4b} < \hat{x}_b < \frac{2a}{5b}$, which proofs Proposition 2. Figure 3.1 illustrates the integrated firm's profits of division-level and firm-level optimisation depending on the iron ore capacity.

Focussing now on Proposition 3, we would like to show that the steeper the inverse demand function is the lower the optimal quantities supplied in case of division-level optimisation $\frac{a}{4b}$ (see Table 3.1) and thus the lower the critical capacity constraint becomes. Therefore, we need to establish the relationship between the ratio of a, the maximum willingness-to-pay, and b, the slope of the inverse demand function, and the assumed (absolute) point elasticity ϵ. Since it can be easily shown that a and b in the linear

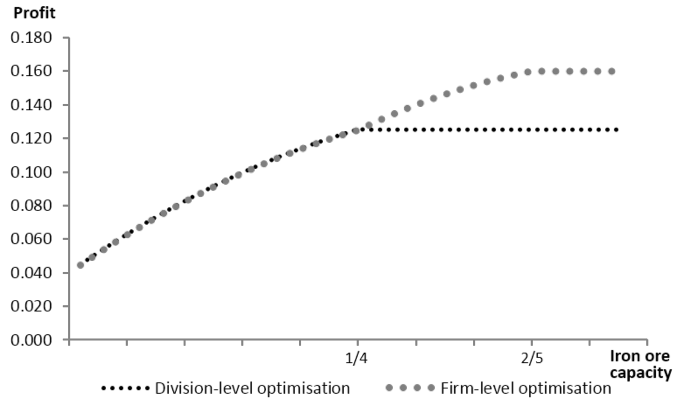

ABBILDUNG 3.1: Profits of the integrated firm optimising on a firm versus a division level depending on the iron ore capacity

demand case can be written as:

$$a = p_{ref} + b * x_{ref} \tag{3.22}$$

$$b = \frac{p_{ref}}{x_{ref}} * \frac{1}{\epsilon} \text{ with } \epsilon > 0, \tag{3.23}$$

with p_{ref} and x_{ref} being a reference price and demand, respectively, it holds true that

$$\frac{a}{b} = (1 + \epsilon) * x_{ref}. \tag{3.24}$$

Consequently, the lower the elasticity in the reference point, ϵ, i.e., the steeper the linear inverse demand function, the lower the optimal quantities when firms optimise their quantities separately. Thus, the less elastic the linear inverse demand function of the composite good, the lower the critical capacity constraint, $\overline{x}_b$ becomes (Proposition 1). The intuition behind this finding is that the steeper the demand function, i.e., the lower the point elasticity, the lower the equilibrium output. The lower the equilibrium output is the less restrictive is the capacity constraint. Furthermore, the less restrictive the capacity constraint of the integrated firm, the higher is the effect of firm-level optimisation (avoiding marginalisation of both divisions).

3.3 A spatial equilibrium model of the global coking coal and iron ore market

3.3.1 Steelmaking and the markets for coking coal and iron ore

In general, there are two main routes to produce crude steel, which is an alloy of iron and carbon. One option, also referred to as the “oxygen route”, is an integrated steel-making process involving blast furnace (BF) production of pig iron followed by a basic oxygen furnace (BOF). Alternatively, an electric arc furnace (EAF) process may be applied (the so called "electric route"), which mainly uses recycled steel (steel scrap) for steelmaking, and may also use direct reduced iron (DRI) to substitute steel scrap. Roughly 30% of global steel supply is produced using EAFs, with the remainder relying on integrated steel-making.

The main difference between the two production methods is that the basic oxygen steel-making process is self-sufficient in energy, i.e., the energy is generated during the process by the reaction of oxygen and carbon, with coke being the main source of carbon. This is not the case with EAF steelmaking, as an EAF mainly relies on the use of electricity for melting the steel scrap and DRI. Therefore, no coke is used in electric arc furnaces. Against the background that coke is essentially coking coal without impurities, it is obvious that almost the entire global coking coal supply is used in coke ovens and, therefore, in the basic oxygen steelmaking process. Furthermore, due to its chemical properties and the existence of cheaper alternative coal types (mainly thermal coal and lignite), coking coal is not used in electricity generation. Albeit to a lesser extent, this also holds true for iron ore, with the reason being that the major part of total steel scrap supply is used in EAFs, thereby reducing the need for direct reduced iron. In 2012, pig iron production amounted to 1112 Mt, while direct reduced iron production was 71 Mt, i.e., DRI accounted for 6% of global iron production (WSA, 2013). Consequently, coking coal and iron ore are complementary goods needed to produce pig iron, with both inputs being (almost exclusively) used in this single application.

Furthermore, both markets, the one for iron ore as well the one for coking coal share two interesting characteristics: First, international trade of both commodities is highly concentrated, as the biggest four exporting companies in the coking coal and iron ore market were responsible for 45% and 67% of total trade volume in 2010, respectively. Second, three global mining companies, namely BHP Billiton, Rio Tinto and Anglo American, are among the top four exporting companies in both markets. Hence, not only are they parallel vertically integrated companies, i.e., they produce both complementary inputs, but, in addition, they may have considerable market power. Given the setting of complementary inputs and market concentration, integrated companies active in both markets may have incentives to maximise their profits on a firm level by jointly choosing their coking coal and iron ore production volumes on a firm level and not separately, i.e., division by division.

3.3.2 Model logic and formulation

The partial equilibrium model presented in this section is programmed as a mixed complementary problem (MCP). The model aims at maximising annual profits of the global mining companies producing coking coal and iron ore subject to production constraints and given the various costs along the supply chain, such as seaborne and inland transport costs. Section 3.2, albeit in a simplified setting (i.e., non-spatial market, with only one consuming region and homogeneous players) already discusses a firm's profit function under independent optimisation of the business units and under firm-level optimisation. Here, the discussion of the model focuses only on the first-order and the market clearing conditions, thus we do not explicitly write down the respective profit functions. Similar to the model presented in the previous section, we assume that the composite good's price ($\lambda_{d,y}$) in demand region d linearly depends on the composite good's (pig iron) demand (which is equal to pig iron production $pi_{d,y}$): $\lambda_{d,y} = int_{d,y} - slo_{d,y} * pi_{d,y}$.[32] [33]

The model distinguishes the physical transports of input factor f by mining company n in year y produced in mine m to a demand market d ($tr_{n,f,m,d,y}$) and the sales of a company to a market ($sa_{n,f,d,y}$). If the firm optimises output on a firm level, it can also sell both composites as a bundle ($sa^b_{n,d,y}$).

Transports $tr_{n,f,m,d,y}$ are constrained by the annual production capacity $cap_{n,f,m,y}$ of mine m. Hence, the amount of transported volumes is subject to the following constraint

$$cap_{n,f,m,y} - \sum_{d \in D} tr_{n,f,m,d,y} \geq 0 \quad \forall n, f, m, y \qquad (\mu_{n,f,m,y}), \tag{3.25}$$

thereby $\mu_{n,f,m,y}$ represents the value of an additional unit of production capacity at mine m in year y, which may also be interpreted as a scarcity rent of production capacity.

For each input, the sum of transported volumes to a demand market has to equal the sales of each company. If firm-level optimisation is enabled the parameter sim_n is equal to 1.

$$\sum_{m \in M(n)} tr_{n,f,m,d,y} = sa_{n,f,d,y} + sa^b_{n,d,y} * sim_n \quad \forall n, f, d, y \qquad (v_{n,f,d,y}), \tag{3.26}$$

thereby $v_{n,f,d,y}$ can be interpreted as the value of the transported goods, i.e., the sum of production costs, scarcity rent and transport costs.

[32] Although all sets, parameters and variables used throughout this subsection are explained in the text, the reader is referred to Table B.1 in Appendix B.1 for an overview of the nomenclature.

[33] To keep the formulae as simple as possible, all parameters used in the model description have been adjusted for the factor intensity.

A mining company is only willing to produce and transport a good to a market if the sum of production costs, scarcity rent and transport costs is covered by the resulting value in the market.

$$\begin{aligned}\frac{\partial \text{L}_{\Pi_n}}{\partial tr_{n,f,m,d,y}} = & - v_{n,f,d,y} + pco_{f,m,y} + tco_{f,m,y} \\ & + \mu_{n,f,m,y} \geq 0 \quad \perp \quad tr_{n,f,m,d,y} \geq 0 \qquad \forall n,f,m,d,y.\end{aligned} \tag{3.27}$$

Each mining company n maximises its profit by selling volumes to demand region d as long as the price of the input factor ($\rho_{f,d,y}$) exceeds the value of the good $v_{n,f,d,y}$. In case the company is assigned market power (which is indicated by setting the binary parameter $cva_{n,y}$ equal to one), $\rho_{f,d,y}$ must not only exceed physical delivery costs but also the company's markup, which depends on the slope of the composite good's demand function ($slo_{d,y}$) and sales volume of the company ($sa_{n,f,d,y}$ and $sa^b_{n,d,y} * sim_n$ in case of firm-level optimisation).

$$\begin{aligned}\frac{\partial \text{L}_{\Pi_n}}{\partial sa_{n,f,d,y}} = & - \rho_{f,d,y} - cva_{n,y} * slo_{d,y} * (sa_{n,f,d,y} + sa^b_{n,d,y} * sim_n) \\ & + v_{n,f,d,y} \geq 0 \quad \perp \quad sa_{n,f,d,y} \geq 0 \qquad \forall n,f,d,y.\end{aligned} \tag{3.28}$$

If an integrated mining company decides to optimise its divisions on a firm level it has to decide additionally about the amount of bundles of complementary input factors that it sells to each market. The price of both input factors, i.e., of the bundle, has to equal the oligopolistic markup (see Equation 3.16) plus the physical value of both inputs.

$$\begin{aligned}\frac{\partial \text{L}_{\Pi_n}}{\partial sa^b_{n,d,y}} = & - \sum_f (\rho_{f,d,y}) - cva_{n,y} * slo_{d,y} * \left(\sum_f (sa_{n,f,d,y}) + sa^b_{n,d,y} * sim_n \right) \\ & + \sum_f v_{n,f,d,y} \geq 0 \quad \perp \quad sa^b_{n,d,y} \geq 0 \qquad \forall n,d,y.\end{aligned} \tag{3.29}$$

Finally, in order to model an oligopoly in complementary goods the model encompasses three market clearing conditions:

$$\lambda_{d,y} = int_{d,y} - slo_{d,y} * pi_{d,y} \quad \perp \quad \lambda_{d,y} \quad \text{free} \qquad \forall d,y \tag{3.30}$$

$$pi_{d,y} = \sum_{n \in N} (sa_{n,f,d,y} + sa^b_{n,d,y} * sim_c) \quad \perp \quad \rho_{f,d,y} \quad \text{free} \qquad \forall f,d,y \tag{3.31}$$

$$- \lambda_{d,y} + \sum_{f \in F} \rho_{f,d,y} \geq 0 \quad \perp \quad pi_{d,y} \geq 0 \quad \forall d,y. \tag{3.32}$$

These market clearing conditions represent three aspects: First, Equation 3.30 determines the price of pig iron ($\lambda_{d,y}$) using the inverse linear demand function. Second, Equation 3.31 states that each input's total sales (including bundles of input factors) to demand region d needs to equal total pig iron demand ($pi_{d,y}$). This equation is used to model coking coal and iron ore as complementary goods, with the composite good being produced using a fixed-proportion production technology. Finally, Inequality 3.32 needs to be incorporated to establish the relationship between input factor prices ($\rho_{f,d,y}$) and pig iron price ($\lambda_{d,y}$). For simplification, we assume that the pig iron price is fully explained by the prices of coking coal and iron ore, i.e., does not include any further marginal costs for the production process. This does not affect the results qualitatively though as the final product's price is of no further importance for our analysis.

3.3.3 Data and scenario setting

This subsection describes the data of the coking coal and iron ore market that we use in the numerical simulation. The dataset comprises demand, production and transport data of the years 2008 to 2010.[34]

3.3.3.1 Demand data

Iron ore consumption data in international statistics (e.g., World Steel Association (WSA)) is usually specified in metric tons, thereby abstracting from the iron content in the ore (Fe-content). This however complicates our analysis: As we are interested in iron ore consumption as an input in pig iron production, we need information on the amount of pure iron contained in the consumed ore. For example, a country has an annual consumption of 1 million tonnes (Mt) of iron ore. It is supplied by one producer delivering 0.7 Mt of 40% Fe and another delivering 0.3 Mt of 60% Fe. Thus, the country consumes 0.46 Mt of pure iron. A second country also consumes 1 Mt of iron ore, but the material has an iron content of 65% Fe. Hence the country consumes 0.65 Mt of pure iron. Even though both countries consume 1 t of iron ore, the pure iron consumption as an input for pig iron production is nearly 50% higher in the second country.

To cope with this problem, we use annual pig iron production data provided by WSA as a proxy for the actual iron ore consumption, thereby assuming that 1 Mt of pure iron is consumed to produce 1 Mt of pig iron.

Concerning coking coal, we do not face this problem as we account for coking coal consumption specified in energy units (IEA, 2012). However, it is necessary to define the

[34]Furthermore, our dataset includes historic trade data of coking coal and iron ore, albeit only on a country level, which are provided in B.4.

factor intensity of coking coal in pig iron production. Comparing coking coal consumption and pig iron production we assume a factor intensity of 70% which means that 0.7 Mt of coking coal are needed to produce 1 Mt of pig iron.

We assume that in the simulation model both coking coal and iron ore are exclusively used for pig iron production. In reality, 6% of global annual iron ore production serves as input for so-called direct reduced iron (DRI). Concerning coking coal, IEA statistics suggest that some minor quantities (4% globally) of coking coal are used for power generation as well. We correct our data for this in the following to limit complexity of our analysis. For the same reason, we abstract from stocking of iron ore or coking coal, which can be observed in both markets.

As stated in Section 3.3, linear inverse-demand functions for pig iron are required in order to simulate different market settings. To derive those country specific demand functions, we stick to an approach that has been widely used in literature on market models programmed as a mixed complementary problem (MCP): Using a reference price, a reference volume and an elasticity yields slope and intercept of the demand function. We use the annual pig iron production as reference volume. The reference price, however, is more difficult to obtain since we are not interested in the real pig iron price (containing price elements such as labour costs) but only the part of the price that can be explained by those input factors being in the scope of our analysis, i.e., the prices of coking coal and iron ore. The reference price is therefore calculated as follows

$$p_{pi} = p_i + p_c. \tag{3.33}$$

The annual average prices of coking coal and iron ore are derived based on information from BGR (2011) and BREE (2011).

3.3.3.2 Production data

We include detailed iron ore production data containing mine-by-mine production costs and region-specific iron contents (World Mine Cost Data Exchange, 2013). Concerning coking coal, we integrate the dataset of Trüby (2013) comprising mine-by-mine production costs as well. The production costs have to be interpreted as free on board (FOB) costs, i.e., inland transport costs are already taken into account. Additionally, we analyse historic coking coal and iron ore production data of the most important export companies such as Vale, Rio Tinto, BHP Billiton (BHPB), Anglo American/Kumba, XStrata or FMG using their annually published production reports. Using those data sources in addition to annual country specific production and export volumes (iron ore: WSA

(2010, 2011, 2012), coking coal: IEA (2012)), we obtain a detailed and nearly complete dataset of both factor market's supply side.[35]

However, for two major producing countries it is difficult to access detailed mine sharp production data in both markets: China and India. For China, World Steel Dynamics (2011) provides us with cost and capacity information on iron ore production differentiating between several cost levels. Concerning Chinese coking coal production and both inputs in India, we use the annual iron ore production from WSA respectively the annual coking coal production from IEA (2012), however, not differentiating between different mines. This simplification does not severely affect our analysis as both in China and in India there is no dominant iron ore or coking coal producer that has a significant influence on global trade. Therefore, we assume an atomistic supply side in those two countries, i.e., coking coal and iron ore producers from both countries are modelled as competitive players.

Firms modelled as Cournot players are Vale, Rio Tinto, BHPB, FMG, Anglo American (Kumba), CSN, LKAB and SNIM in the iron ore market and Rio Tinto, BHPB, Anglo American and XStrata in the coking coal market. In line with Trüby (2013), we model US coking coal exporters as one Cournot player (US_CC), since the main export ports and the inland transport rails are controlled by one player and market power is assumed to be exerted via the infrastructure. Other smaller and mostly domestic producers are assumed to market their production volumes as competitive players.

Figure 3.2 shows the global FOB supply cost curves of major coking coal and iron ore exporters in 2008. Note that this figure does not exactly reflect the seaborne traded iron ore volumes since exporters also partly supply their domestic markets as well. We observe that the production costs of the three biggest iron ore exporters, Vale, Rio Tinto and BHP Billiton, are for most part in the lower half of the global FOB cost curve.

[35]This dataset also includes mines that belong to steel producing companies such as Tata Steel. We assume that the production of these mines is used by the steel company itself, i.e., if a mine is located in North America and the steel company has steel production centers in the country as well, the total production of the mine is supplied to the domestic market. Otherwise the production is assumed to be transported to the country where the firm's main production site is located.

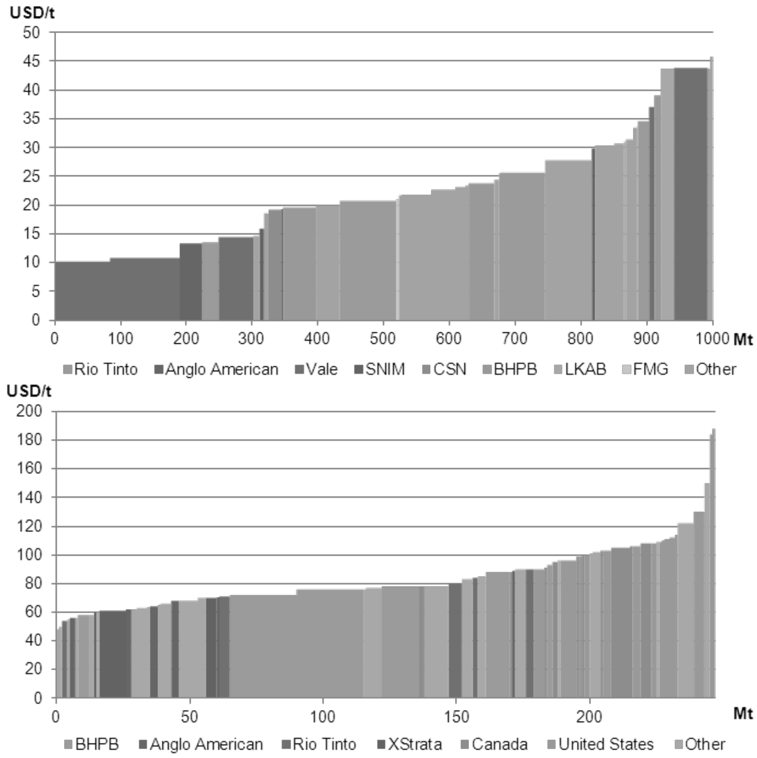

Abbildung 3.2: Coking coal and iron ore FOB cost curves of major exporters in 2008

3.3.3.3 Transport data

The dataset used in this analysis comprises distances between major export and import ports using a port distance calculator. Additionally, the dataset contains freight rates of bulk carrier transports on numerous shipping routes for the time period 2008 to 2010. Using freight rates and transport distances, we calculate a proxy for the seaborne transport costs. For most of the inland transport routes, costs are already accounted for since the cost data are free on board, i.e., the costs comprise production, inland transport and port handling costs. The only exceptions are inland transports from Russia to Europe and China, where rail freight rates are used.

To limit model complexity, we do not explicitly account for capacity limitations of neither port nor rail infrastructure nor ship capacities. We implicitly assume that scarce bulk carrier capacities are already represented by the freight rates. Capacity limitations of export port or rail infrastructure both are subsumed under the production capacity of a production region. For example, if a production region has a capacity of 100 and the respective port only has a capacity of 80, the production capacity we use in our model is 80.

3.4 Results of the applied analysis

3.4.1 The profitability of parallel vertical integration in the coking coal and iron ore market

We apply our computational model to investigate whether or not firms benefit from behaving parallel vertically integrated, i.e., optimising output of the complementary goods on a firm level. Therefore, in a first step, we simulate the coking coal and iron ore market for the years 2008 to 2010 to derive the profitability of the integrated companies Anglo American, Rio Tinto and BHP Billiton. Since the strategy choice of the competitors may influence the profitability of the own strategy, we model a simple static simultaneous game with two stages. In the first stage, each integrated company chooses between two strategies: "optimising on a firm level (FL)" and "optimising on a division level (DL)". In the second stage, all companies in the coking coal and iron ore market (also companies active in only one of the markets) set the production quantities, thereby knowing each of the integrated companies' strategy choices, FL or DL. Thus, in total we simulate 8 model runs and use each company's total profit margin as payoff function.[36]

The question arises if the proposed two-stage game is a realistic representation of the market. Is an integrated company able to credibly commit optimising both divisions separately and can this be observed by the other players? The commitment to division-level optimisation could be realised by incentive contracts for the division managers, e.g., by remuneration depending on profitability of the division. Although these contracts are unlikely to be seen by the other players, division-level optimisation could be observable by founding a subsidiary company for, e.g., the iron ore business. Ideally, the holding would sell minor shares of the subsidiary in order to further incentivise that each division is optimising itself separately. Although in reality, coking coal and iron ore businesses of integrated companies are rather subdivisions[37] than subsidiaries, the strategy DL could per se be committed to in a credible and observable way.

Figure 3.3 illustrates the profitability of choosing FL over DL for each of the three integrated companies given the other companies' strategy choices and the assumed demand elasticity. The profitability is derived as the difference in profit margins between option

[36]Since we have no data about fixed costs of iron and coking coal mining, we focus on the profit margin, i.e., price minus marginal costs times quantity sold. This is sufficient for our analysis since we only compare differences of profit margins whereas fixed costs only change the level of the total profits.

[37]Interestingly, for both Rio Tinto and BHP Billiton, the head offices of the iron ore divisions are situated in Perth, the coal divisions in Brisbane and the holdings in Melbourne, which could suggest a DL approach. However, in the case of BHP Billiton, its organisational structure includes a central Marketing subdivision, which "sells and moves to market BHP Billiton's products"(http://www.bhpbilliton.com/home/businesses/Marketing/Pages/default.aspx). This could suggest that the company indeed applies the strategy FL although there is no further information available on how the Marketing unit itself is organised internally.

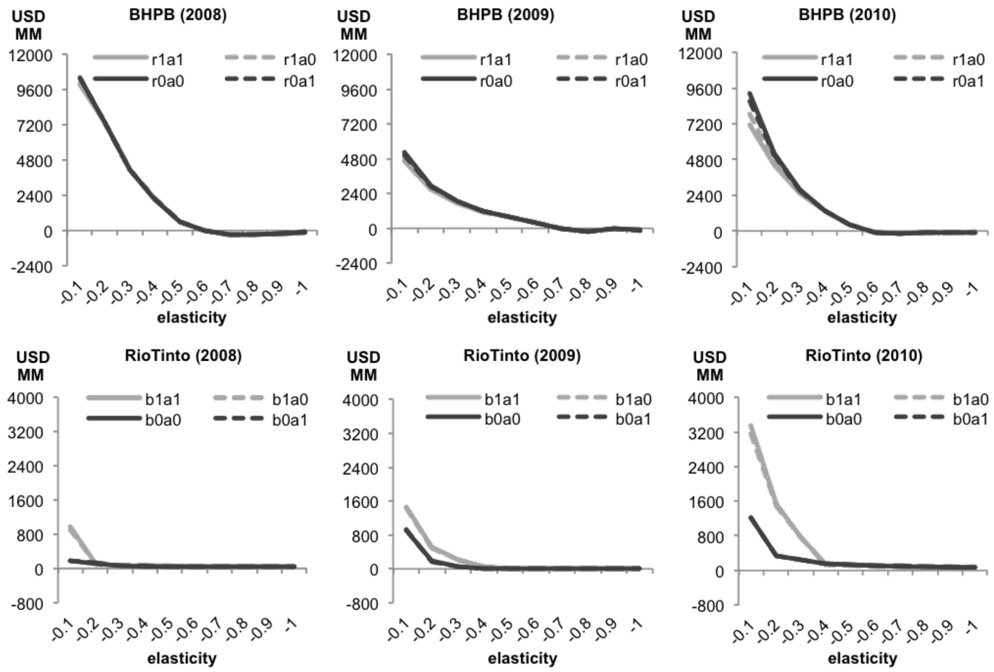

ABBILDUNG 3.3: Additional profits from firm-level (1 = FL) vs. division-level (0 = DL) optimisation depending on the other integrated companies' strategy (b = BHP Billiton, r = Rio Tinto, a = Anglo American).

FL and option DL. These results seem to confirm Proposition 3 from 3.4.1: The more inelastic the demand is, the higher is the additional benefit of choosing FL over DL. With an increasing demand elasticity the additional benefit of FL converges to zero.[38]

As already stated in Subsection 3.2.2, capacity constraints of at least one of the complementary goods can be one explanation for the decreasing profitability of strategy FL. For BHP Billiton, for example, the iron ore capacity is binding in all three years as soon as the demand elasticity (in absolute terms) is higher than 0.5. Rio Tinto's coking coal capacity is binding in all of the scenarios and the iron ore capacity becomes binding for elasticities of 0.3 and 0.4 and higher. This might be an explanation why the additional benefit of strategy FL is generally higher for BHP Billiton than for Rio Tinto.

3.4.2 A comparison of three market settings

So far, the model results revealed that FL is a beneficial strategy for integrated companies if the demand is rather inelastic or, in other words, if the production capacity of both complementary goods is not scarce. However, the outcomes of FL and DL are equal when higher demand elasticities are assumed. In the following, searching for evidence whether or not integrated players optimise their coking coal and iron ore divisions on

[38]For BHP Billiton, we observe slightly negative values for the years 2008 and 2009. This phenomenon can be explained by numerical issues during the solution process of the model.

a firm level, we investigate which of the strategy choices and which demand elasticities best represent historical market outcomes. To this end, we compare model results and historical market outcomes, i.e., prices, trade flows and production volumes.

TABELLE 3.2: P-values of the F-tests ($\beta_0 = 0$ and $\beta_1 = 1$) for a wide range of elasticities

Coking	Perfect competition			Division level			Firm level		
coal	2008	2009	2010	2008	2009	2010	2008	2009	2010
e = -0.1	0.01**	0.00***	0.00***	0.08*	0.04**	0.03**	0.64	0.14	0.49
e = -0.2	0.01***	0.00***	0.00***	0.22	0.06*	0.04**	0.39	0.08*	0.44
e = -0.3	0.01***	0.00***	0.00***	0.46	0.12	0.14	0.37	0.11	0.33
e = -0.4	0.01***	0.00***	0.00***	0.64	0.26	0.50	0.36	0.14	0.36
e = -0.5	0.01***	0.00***	0.00***	0.71	0.54	0.93	0.32	0.14	0.31
e = -0.6	0.01***	0.00***	0.00***	0.63	0.92	0.59	0.27	0.13	0.20
e = -0.7	0.01***	0.00***	0.00***	0.41	0.92	0.20	0.19	0.11	0.10*
e = -0.8	0.01***	0.00***	0.00***	0.26	0.56	0.08*	0.11	0.09*	0.08*
e = -0.9	0.00***	0.00***	0.00***	0.13	0.38	0.07*	0.08*	0.05*	0.07*
e = -1.0	0.00***	0.00***	0.00***	0.10*	0.12	0.07*	0.06*	0.04**	0.06*
Iron	Perfect competition			Division level			Firm level		
ore	2008	2009	2010	2008	2009	2010	2008	2009	2010
e = -0.1	0.00***	0.00***	0.00***	0.85	0.15	0.32	0.87	0.41	0.55
e = -0.2	0.00***	0.00***	0.00***	0.88	0.62	0.72	0.91	0.89	0.95
e = -0.3	0.00***	0.00***	0.00***	0.66	0.87	0.95	0.74	0.79	0.73
e = -0.4	0.00***	0.00***	0.00***	0.37	0.62	0.79	0.59	0.25	0.41
e = -0.5	0.00***	0.00***	0.00***	0.18	0.13	0.44	0.42	0.03**	0.19
e = -0.6	0.00***	0.00***	0.00***	0.09*	0.01**	0.19	0.27	0.00***	0.09*
e = -0.7	0.00***	0.00***	0.00***	0.04**	0.00***	0.09*	0.17	0.00***	0.05*
e = -0.8	0.00***	0.00***	0.00***	0.02**	0.00***	0.05**	0.08*	0.00***	0.03**
e = -0.9	0.00***	0.00***	0.00***	0.01***	0.00***	0.05**	0.06*	0.00***	0.03**
e = -1.0	0.00***	0.00***	0.00***	0.01***	0.00***	0.01**	0.06*	0.00***	0.01**

Significance levels: 0.01 '***' 0.05 '**' 0.1 '*'

In total, we focus on three market settings in this section: First, we investigate whether non-competitive behaviour is observed in both the iron ore and the coking coal market. Hence, we run a scenario in which all players in the market behave in a perfectly competitive manner ("Perfect competition"), i.e., act as price takers. Second, we run another two model simulations each assuming Cournot behaviour in both markets. One in which Anglo American, BHP Billiton and Rio Tinto each optimise output on a firm level ("Firm level") and another one in which each of those firms' coking coal and iron ore business units optimise their profits separately ("Division level"). By comparing model outcomes to actual price, production and trade data for the time period from 2008 to 2010, we aim at identifying the setting which has the better fit with the realised values. To compare trade flows, we use three statistical tests that are discussed in detail in Appendix B.3.[39]

[39]The interested reader is referred to Appendix B.4 for a series of tables displaying trade flows for both commodities at a demand elasticities of -0.5 as well as actual trade flows in the respective years. Trade flows for both commodities at all demand elasticities in the respective years are available from the authors upon request.

Starting with the analysis of the “Perfect competitionßetting, we find that the test statistics of the F-test allow us to reject the null hypothesis ($\beta_0 = 0$ and $\beta_1 = 1$) on a 99.9% level for both goods in all years and elasticities (Table 3.2). Interestingly, whereas this result is confirmed by higher Theil’s inequality coefficients and lower Spearman rank correlation coefficients in the case of iron ore in all years, this is not the case with coking coal trade flows in 2008 (Figure 3.4).

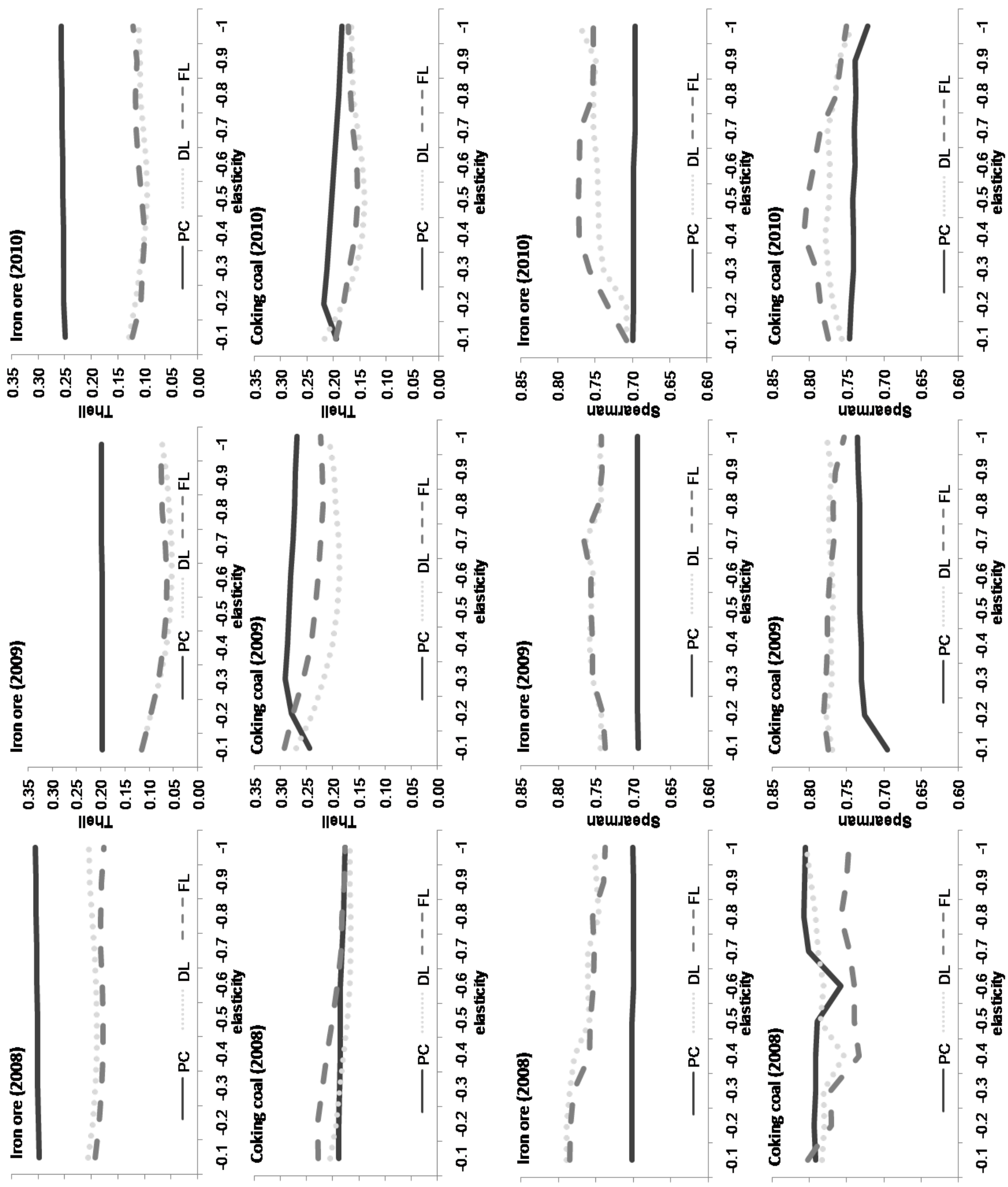

Abbildung 3.4: Theil’s inequality coefficient and the Spearman rank correlation coefficient contingent on the demand elasticity[40]

However, considering prices and production in the perfect competition setting (PC) in addition to the trade flows, we conclude that the two market settings, in which players behave in a non-competitive manner, outperform the perfect competition setting. The model, when run with all players acting as price takers, cannot reproduce iron ore prices for most part of the elasticities that were investigated (Figure 3.5). In addition, total production of both commodities is too high in this market setting and, more importantly, the model cannot capture production behaviour of the largest company in each market (Figure 3.6), i.e., Vale in the case of iron ore and BHP Billiton in the case of coking coal: For almost each assumed demand elasticity, these producers produce up to full capacity.

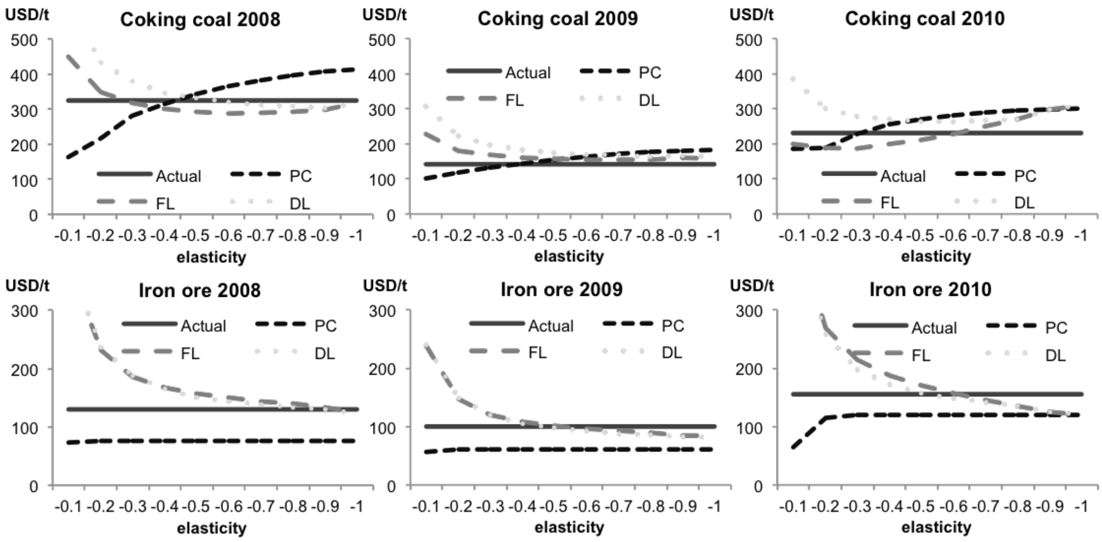

Abbildung 3.5: Coking coal and iron ore prices contingent on the demand elasticity

Concerning the comparison of the FL and the DL setting, the picture is more ambiguous. Starting out by looking at the results of the hypothesis tests for iron ore trade flows, one may be drawn to the conclusion that both of the two Cournot settings are able to reproduce actual trade flows, as for a large part of the range of elasticities we investigated the hypothesis tests cannot reject the null hypothesis. Contrasting the findings of the linear hypothesis test with Theil's inequality coefficient and Spearman's *rho*, we see from Figure 3.4 that both non-competitive settings perform similarly well in the case of iron ore. For coking coal, the DL setting performs better than the FL setting as Theil's inequality coefficient is lower and Spearman's *rho* is higher than in the DL setting.

Concerning prices, we observe that the FL setting generates lower coking coal prices and higher iron ore prices than the DL setting, although the simulated iron ore prices are very similar, with the difference never exceeding 8%. Iron ore prices match the actual market outcome for the years 2009 and 2010 for an assumed demand elasticity of -0.5 to -0.6. In this range of elasticities for the year 2008, the simulation results overestimate

[40]Due to an error (wrong graphs for the coking coal market's coefficients in 2009 and 2010) Figure 3.4 has been changed compared to Hecking and Panke (2015).

the actual iron ore prices by US$20/t (DL) and US$27/t (FL). Concerning coking coal the DL setting fits the actual coking coal price of 2008 for an assumed demand elasticity of -0.5 to -0.6 whereas the FL setting underestimates the price by US$35/t. In contrast, for 2009, the FL setting is closer to the actual coking coal price than DL in the whole range of simulated elasticities. For a demand elasticity of -0.5 to -0.6 the differences to the actual values are US$15/t and US$30/t, respectively. For the year 2010 and a demand elasticity of -0.6, the FL setting seems more appropriate to represent the coking coal price.

Finally, we take another look at the companys' production output depicted in Figure 3.6. Whereas the iron ore production is similar in both scenarios (see the example of Vale in Figure 3.6), the coking coal production volumes differ significantly in the case of BHP Billiton and the US coking coal player. The FL case overestimates the actual production volumes of BHPB in the whole range of elasticities in all years. In the DL case, the BHPB production volume is matched at elasticities of -0.5 to -0.7 between 2008 and 2010. The US coking coal production in the FL case is always lower than in the DL case. For lower elasticities, the DL case is closer to the actual production whereas the production volumes converge for higher elasticities in the years 2008 and 2010.

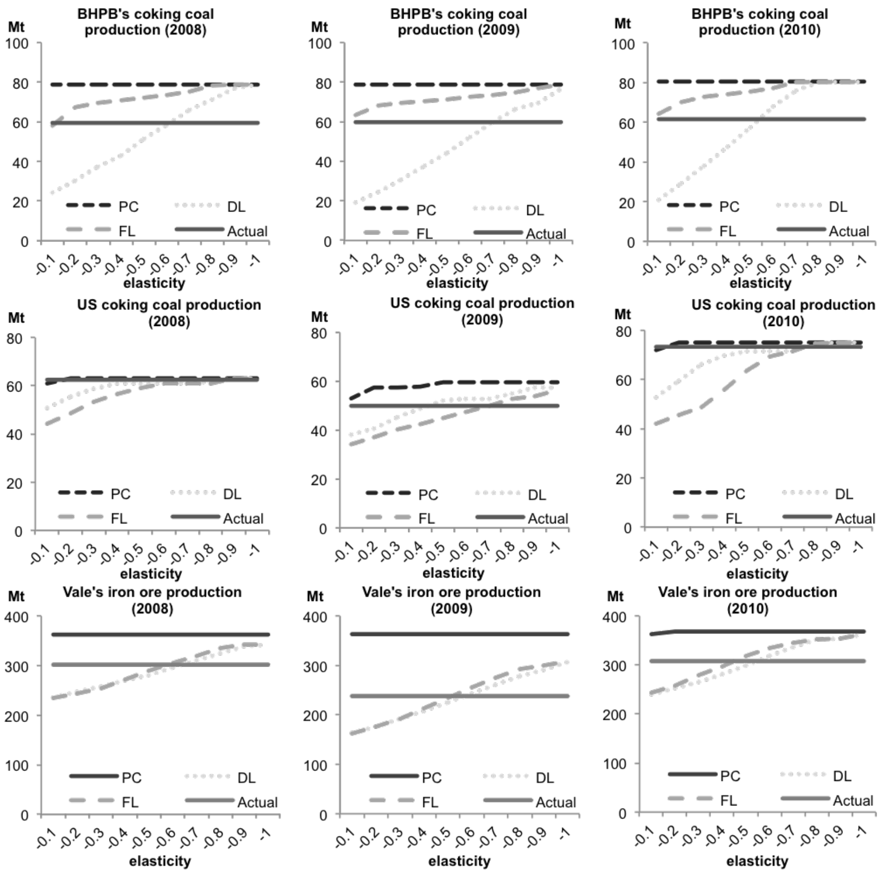

ABBILDUNG 3.6: Production of Vale, BHP Billiton and US coking coal producers depending on the demand elasticity and the market setting

Summing up, we found no evidence supporting the idea that players in the two commodity markets behave in a perfectly competitive manner. In contrast, the two non-competitive market settings resulted in market outcomes that match actual outcomes better than in the perfect competition case. Yet one needs to be cautious when interpreting the results of our simulations as clear evidence for Cournot behaviour of the mining companies. It cannot be ruled out that other market settings may explain the market outcomes equally well or even better such as a setting in which one or more firms move first with the others being price takers (see, e.g., Lorenczik and Panke, 2015, Trüby, 2013) or a setting in which the supply as well as the demand side have market power and engage in Nash bargaining. However, investigating these questions is beyond the scope of this paper, in particular, since building a simulation model for these two settings using a dataset as detailed as ours is beyond the current capacities of most solvers. Regarding the comparison of the case of DL and FL optimisation of the business units' profits, we did not find overwhelming evidence to dismiss one of the two settings. But, the results of the statistical tests and the comparison of production and price data draw a more consistent picture in the DL than in the FL setting, with the model performing best for elasticities of -0.5 and -0.6.

3.4.3 Strategic implications

The comparison of actual market outcomes and model results provides an indication that the DL setting best represents the market outcome. However, since the analysis did not allow to unambiguously opt for one setting this subsection aims at delivering an economic argument why the three merged companies might indeed have chosen strategy DL over FL in reality.

If a firm decides to optimise both the coking coal and the iron ore division on a firm level (i.e., choosing strategy FL), a sophisticated organisational structure is required such that the economic agents within the firm are incentivised to act in a way which in fact leads to a global optimum. Both divisions have specialised knowledge regarding their specific markets, they possess a high technical know-how, they know their production costs and capacities and have an idea about their own market position compared to their competitors. However, to make both divisions act according to strategy FL, it is required that both divisions coordinate themselves to sell the optimal combination of coking coal and iron ore to a demand market. And even more challenging, the division managements have to be incentivised to act as such. Höffler and Sliwka (2012) discuss that symmetric incentives based on the units' performance provide incentives for haggling within the organisation whereas symmetric incentives based on the overall profit would lead to free-rider behaviour because of reduced individual responsibility for the overall performance. The authors state that these inefficiencies become stronger with increasing interdependencies between units. They find that asymmetric incentive structures, which make one unit dominant in the organisation, could reduce these inefficiencies: The dominant unit should have unit based incentives whereas the other unit should have incentives based on the overall profit.

Although asymmetric incentive structures reduce organisational inefficiencies, simultaneous optimisation of the divisions nevertheless incurs additional transactional and organisational costs. Coming back to the finding from Section 3.4.1 an integrated company will only choose FL over DL, if the additional profit from FL is sufficiently high to overcompensate the additional transactional and organisational costs incurred by strategy FL. As seen before, this is only the case if the production capacity of both goods is sufficiently high to benefit from FL by increasing the output. The lower the demand elasticity becomes, the less restrictive the capacity constraint. In the real world application, we have seen that BHP Billiton is the leading company in the coking coal market but faces a binding capacity constraint in the iron ore market the higher the assumed demand elasticity is. Therefore, the extra benefit of FL versus DL tends to zero for higher elasticities whereas it can become significant for lower demand elasticities. The simulation model, however, reproduced market results more consistently when simulating elasticities of -0.5 to -0.6 where the benefit of firm-level optimisation was converging to zero.

3.5 Conclusions

In this paper, we examine the strategic behaviour of quantity-setting mining companies that are relevant players in both the coking coal and the iron ore market. This setting is of particular interest in the analysis of energy and resource markets since (i) both goods are complementary inputs for steel production, (ii) both goods have little alternative use, (iii) both goods exhibit high supply-side concentration and (iv) some of the biggest producers are active on both markets. Given these characteristics, this paper investigates whether the integrated mining companies optimise their output on a firm level or on a division level.

We first assess the profitability of firm-level optimisation in a theoretical model of two homogeneous Cournot duopolies of complementary goods that interact with each other. We consider two cases: one with unlimited capacities and one with a binding capacity constraint on one of the divisions' output. Firm-level optimisation is always profitable if capacities are unlimited. However, we prove three propositions for the case in which one of the divisions faces a binding capacity constraint. There exists a critical capacity constraint (i) below which the parallel vertically integrated firm is indifferent between firm-level and division-level optimisation, (ii) above which firm-level optimisation is always beneficial and (iii) that becomes smaller with a lower demand elasticity.

Next, we investigate whether these findings also hold in a real-world application. The markets for coking coal and iron ore are more complex than the theoretical model as (i) there are more than two suppliers in each market, (ii) there are more than one firm that are parallel vertically integrated, (iii) production costs are heterogeneous, (iv) both markets are spatial markets and (v) most of the producers face a binding capacity constraint. Therefore, we developed a numerical spatial multi-input equilibrium model of both markets based on a unique data set. Assessing the profitability of the integrated companies, the results from the theoretical model were confirmed in the simulation. The coking coal market leader BHP Billiton generates additional profits from firm-level optimisation under low elasticities because, in this case, the iron ore capacity is not binding. With increasing demand elasticity, the benefits of simultaneous optimisation tend to zero. Lastly, we compare the model results of one simulation assuming division-level optimisation and one assuming firm-level optimisation to the actual price, trade flow and production data for the years 2008 to 2010. Although no scenario is dominant, the scenario assuming division-level optimisation fits the actual market outcomes slightly better. Hence, the simulation does not reveal any evidence of firm-level optimisation over the respective years.

Apart from the arguments made within this analysis, there may be other economic reasons for division-level optimisation that were not the main focus of this paper and could be interesting for further research. For example, the firm-level optimisation of two business units could create inefficiently high organisational costs. Therefore, it may be challenging to create incentives for both divisions to not optimise profits division by division but rather on a firm level. Since this analysis focuses on a comparison of historic and model-based market outcomes, it may be insightful to further assess the strategic investment of companies in a prospective analysis. The decision whether to grow in one or the other complementary factor market, thereby altering the own strategic position or the one of the competitor, may be another interesting sequel to this paper.

Kapitel 4

Assessing market structures in resource markets - an empirical analysis of the market for metallurgical coal using various equilibrium models

4.1 Introduction

Many resource markets suffer from high concentration on the supply side and low demand elasticity. Market results are therefore frequently assumed to be an outcome of strategic interaction between producers. The use of mathematical models to analyse market outcomes to gain insights into underlying market structures has a long tradition in the economic literature. Common models are one-stage games representing competitive markets or Cournot competition. More advanced two-stage models of the Stackelberg kind take into account a single leader followed by one or more players. We add to the literature by expanding the application of mathematical models and applying an equilibrium problem with equilibrium constraints (EPEC) to a spatial market, i.e., a setup with multiple, geographically disperse demand and supply nodes. This model class is used to simulate multi-leader-follower games. This enables us to investigate more complex market structures that have been neglected in previous studies on resource markets. Omitting these market structures may result in false conclusions about the prevalent state of competition.

The paper at hand investigates which market structure was prevalent in the international market for metallurgical coal during the time period 2008 to 2010.[41] The international metallurgical coal market is particularly suited for this kind of analysis since, first, the supply side is dominated by four large mining firms (hereafter referred to as the Big-Four), namely BHP Billiton (BHPB), Rio Tinto, Anglo American and Xstrata. Second, metallurgical coal is an essential input factor in producing pig iron and difficult to substitute, causing demand to be rather price inelastic. Third, in the period under scrutiny in this paper, yearly benchmark prices were negotiated between representatives of the Big-Four and representatives of the large Asian steel makers (Bowden, 2012). Fourth, one of the firms of the Big-Four, BHP Billiton, is by far the largest firm in the international market for metallurgical coal. Nonetheless, the other firms played a central role in the negotiations as well. Consequently, a wide variety of market structures may be a plausible approximation of the actual market setting.

Our research adds to that of Graham et al. (1999) and Trüby (2013) who were the first to analyse the market for metallurgical coal. The former investigates various market settings for the year 1996, in which firms or consumers simultaneously choose quantities. In contrast, the latter focusses on the time period from 2008 to 2010. Regarding the market structures, the author arrives at the conclusion that assuming the Big-Four jointly act as a Stackelberg leader provides the best fit to the actual market outcome. However, Trüby (2013) finds that it cannot be ruled out that firms in the market simply engaged in an oligopolistic Cournot competition. We add to the literature by extending the scope of possible market structures. More specifically, we simulate one scenario in which the Big-Four compete against each other at a first stage, i.e., choose output to maximise individual profits, while the remaining firms form a Cournot fringe and act as followers. This constitutes a multi-leader-follower game. In another scenario, BHP Billiton takes on the role as the sole Stackelberg leader, with the rest of the Big-Four choosing quantities simultaneously with the remaining players as followers. Thereby, we broaden the range of market structures analysed in the field of spatial resource markets as multi-leader games have thus far been omitted from existing studies. As investigating collusive behaviour in markets using simulation models crucially depends on an appropriate and comprehensive market representation, multi-leader games may help to expose previously overlooked market structures. Since it is a priori not clear which is the correct demand elasticity, we run the market simulations for a wide range of values. To assess whether one of the market structures is superior to the others, we compare simulated prices, trade flows and production volumes of the Big-Four to realised

[41] The terms metallurgical and coking coal are often used interchangeably in the related literature as well as throughout this paper. Yet, this is not entirely correct since metallurgical coal includes coals (as it is the case in our dataset) that technically are thermal coals but can be used for metallurgical purposes as well, such as pulverised coal injection (PCI).

market outcomes. In order to compare trade flows, different statistical measures/tests are applied as suggested by, e.g., Bushnell et al. (2008), Paulus et al. (2011), and Hecking and Panke (2014).

This paper contributes to the literature on applied industrial organisation and, more specifically, the analysis of the international market for metallurgical coal. We expand previous studies by applying an EPEC, a mathematical program used to model multi-leader-follower settings, to a spatial market, i.e., a market with multiple, geographically disperse supply and demand nodes. In doing so, we find that the two additional market settings proposed in this paper provide a good fit with realised market outcomes for the time period 2008 to 2010. In addition, by analysing production volumes and profits of the Big-Four, we enhance the market structure analysis by providing an additional plausibility check. We are able to show that even if simulated prices and trade flows fit well with market outcomes, a scenario in which the Big-Four form a Cartel that acts as a Stackelberg leader is less likely since production volumes deviate from actual production. More importantly, additional revenues of the Big-Four from forming and coordinating a cartel are rather small compared to a scenario in which all four compete against each other at a first stage. Accounting for the transaction costs caused by the coordination of the cartel would further decrease possible benefits. Concerning the demand elasticity, we detect that simulated prices for elasticities from -0.3 to -0.5 seem to be within a reasonable range for most of the market structures.

Summing up our findings, one of the main advantages of simulation models is that they allow us to assess different market structures. Yet, as shown in our paper, it may be difficult to decide on one setting that provides the best fit. Consequently, such analyses need to be accompanied by additional analyses similar to our comparison of production volumes of the Big-Four. To be able to further narrow down the number of potential market structures, additional data such as firm-by-firm export volumes, which were not available for all relevant firms in our example, would be helpful.

The remainder of this paper is structured as follows. Section 4.2 offers an overview of the relevant literature, while the methodology is described in Section 4.3. The fourth section briefly describes the numerical data used in this study. Section 4.5 is devoted to the analyses of the empirical results. Section 4.6 concludes.

4.2 Literature review

Commodity markets have often been subject to concerns about high concentration on the supply side, with several prominent examples being the markets for energy resources such as oil, natural gas or metallurgical coal. Consequently, there has been substantial academic research in an attempt to assess whether companies or countries exercised market power. In order to do so, one of two different methodological approaches – econometric methods or simulation models – is applied. While both approaches have their respective advantages and disadvantages[42], one of the most persuasive arguments in favour of using simulation models to assess the exercise of market power is that they are highly flexible with respect to the specific market structure. This, in principle, not only enables researchers to answer the question whether or not market power in a specific market has been exercised, but also provides hints as to which kind of market structure is prevalent, e.g., whether firms form a cartel or show no signs of explicit cooperation.

The use of mathematical programming models to analyse spatial markets has a long tradition in economics. Enke (1951) first described the problem of spatial markets, proposing a solution method using a simple electric circuit to determine equilibrium prices and quantities in competitive markets. Samuelson (1952) showed how the problem can be cast into a (welfare) maximisation problem and thereafter be solved using linear programming. Together with Takayama and Judge (1964, 1971) who extend the spatial market representation (e.g., by including monopolistic competition), Samuelson's work is generally considered to have laid the groundwork for spatial market analysis using mathematical programming.

Advances in the representation of markets were made during the 1980s by modelling imperfect competition (e.g., by Harker, 1984, 1986, Nelson and McCarl, 1984). This has frequently been done since then, e.g., for steam coal markets (Haftendorn and Holz, 2010, Kolstad and Abbey, 1984, Trüby and Paulus, 2012), natural gas markets (Boots et al., 2004, Egging et al., 2010, Gabriel et al., 2005a, Growitsch et al., 2014, Holz et al., 2008, Zhuang and Gabriel, 2008), wheat markets (Kolstad and Burris, 1986), oil markets (Huppmann and Holz, 2012) or for the coking coal and iron ore markets (Hecking and Panke, 2014).

We focus our analysis on the metallurgical coal market. A recent analysis of short-term market outcomes by Trüby (2013) indicates that the market from 2008 to 2010 may have been characterised by firms exercising market power. This rejects the previous finding by Graham et al. (1999), although this study focusses on 1996.

Most of the aforementioned studies use models that assume players make decisions simultaneously. This model type can be extended to represent bi-level games, the classical example being Stackelberg games (Stackelberg, 1952). There are several applications for this type of problem, which can be modelled as a mathematical problem with equilibrium

[42]For a brief overview of the various econometric approaches used in the literature and their respective advantages and drawbacks, see Germeshausen et al. (2014).

constraints (MPEC). MPECs are constrained optimisation problems, with constraints including equilibrium constraints (see Luo et al., 1996, for an overview of MPECs). MPECs have for instance been used to model power markets, e.g, by Gabriel and Leuthold (2010), Wogrin et al. (2011) and natural gas markets, e.g., by Siddiqui and Gabriel (2013). Bi-level games are, due to nonlinearities, computationally more challenging to solve in comparison to one-level games.

The single-leader Stackelberg game can be extended to a multi-leader-follower game in which several players make decisions prior to one or more subsequent players. Any solution to this game must maximise leaders' profits while simultaneously taking into account the equilibrium outcome of the second stage. This results in an equilibrium problem with equilibrium constraints (EPEC). Due to the concatenation of several MPEC problems to one EPEC and the resulting high nonlinearity, EPECs are even more difficult to solve than MPECs. Previous EPEC models have mostly been used to analyse electricity markets, e.g., by Barroso et al. (2006), Sauma and Oren (2007), Shanbhag et al. (2011), Yao et al. (2008) and Wogrin et al. (2013). In addition, Lorenczik et al. (2014) analyse investment decisions in the metallurgical coal market using an EPEC.

4.3 Methodology

4.3.1 Market structures

Due to its market structure (with few large producers and relatively low demand elasticity), the metallurgical coal market is often presumed to lack competition. This suspicion is confirmed by a recent study showing that market outcomes can be reproduced by assuming strategic rather than competitive behaviour. Trüby (2013) finds that over the years 2008 to 2010, assuming perfect competition, neither trade flows nor prices match well with actual market results. In contrast, the non-competitive market structures considered in the paper perform reasonably well with the exception of the Cournot Cartel case.[43] The paper's conclusion regarding the market structures is that assuming the Big-Four jointly act as a Stackelberg leader provides the best fit to the actual market outcome. However, it cannot be ruled out that firms in the market simply engaged in an oligopolistic Cournot competition. Therefore, two of the scenarios analysed in Trüby (2013), namely the case of Cournot competition (hereafter, referred to as MCP, short for mixed complementary problem, which is the programming approach used to simulate

[43]In the Cournot Cartel case, the Big-Four are assumed to engage in a cartel and, thus, jointly optimise their total supply. Trüby (2013) finds that under this market setting, prices could only be reproduced when assuming very high elasticities. Concerning trade flows, the linear hypothesis tests suggest that simulated trade flows do not resemble actual market outcomes in 2009 for all elasticities, while in the other years the H_0-hypothesis could be rejected for elasticities up to -0.2 (2008) and -0.3 (2010).

the market setting) and a setting in which the Big-Four form a cartel that acts as the Stackelberg leader (MPEC Cartel) are taken into consideration in this paper as well to ease the comparison of results.

We expand the range of investigated market structures by analysing a multi-leader-follower game as well as one additional market setting involving one Stackelberg leader. In the multi-leader-follower game, the Big-Four compete against each other at the first stage and take into account the reaction of the other firms engaging in Cournot competition at the second stage (EPEC Big 4). We reason that this setting is relevant since, first, benefits in terms of additional revenues from forming a cartel are rather small when compared to the EPEC Big 4 scenario, even without accounting for the transaction costs that go along with coordinating a cartel. Thus, while still acting as leaders, it is reasonable to assume that the Big-Four compete against each other. Second, the simulated production volumes by the Big-Four fit historical production data better in the two additional settings proposed in this paper than in the MPEC Cartel case. Thus, they are worth a closer investigation. Both reasons will be discussed in depth in Section 4.5.3.

Finally, we simulate an additional single Stackelberg leader setting in which BHP Billiton sets quantities in a first stage with the remaining firms being followers (MPEC BHBP). The main reason that modelling such a market structure is intuitive is the fact that BHBP is by far the world's most important coking coal miner. Figure 4.1 provides an overview of the market structures investigated in this paper.

	first stage		second stage
EPEC Big 4	BHP, Rio, Anglo, Xstrata	→	others +
MPEC Cartel	Big 4*	→	others +
MPEC BHPB	BHP	→	Rio, Anglo, Xstrata, others +
MCP	BHP, Rio, Anglo, Xstrata, others +		

* corresponding exporters form a cartel; + players not belonging to the "Big4", but individually maximize profits

Abbildung 4.1: Overview of modelled market structures

To simulate the different aforementioned coking coal market settings, three different types of simulation models are used. The first calculates the expected market outcome in a Cournot oligopoly in which all players decide simultaneously about produced and shipped quantities. The two other models constitute bi-level games in which players act in consecutive order. In the Stackelberg game, one player (or a group of players forming a cartel) acts first followed by the remaining players. The last model type represents a market with multiple (Stackelberg) leaders and one or more followers. From a modelling perspective, the first model constitutes a MCP. The second and third models are implemented as a MPEC and an EPEC, respectively.

4.3.2 Model descriptions

Although we focus our analysis on the coking coal market, the model is suitable for a multitude of similar commodity markets such as the iron ore, copper ore, oil or gas market, which are characterised by a high concentration on the supply side and therefore may not be competitive. Thus, we use general terms for the model description as well as generic notation to emphasise the applicability of our approach to markets other than the coking coal market. Table 4.1 summarises the most relevant nomenclature used throughout this section, i.e., displays the abbreviations used for the various model sets, parameters and variables and provides a short description. Additional symbols are explained throughout the text where necessary.

TABELLE 4.1: Model sets, parameters and variables

Abbreviation	Description
Model sets	
$i \in I$	Players
$j \in J$	Markets
$m \in M$	Production facilities
Model parameters	
a_j	Reservation price [per unit]
b_j	Linear slope of demand function
c_m	Variable production costs [per unit]
cap_m	Production capacity [units per year]
$tc_{i,j}$	Transportation costs [per unit]
Model variables	
P_j	Market price [per unit]
$s_{i,j}$	Supply [units]
x_m	Production [units]

4.3.2.1 The MCP model

The first model assumes a market in which all producers decide simultaneously about the use of production facilities and the delivery of goods. Each player $i \in I$ maximises profits according to:

$$\max_{x_m, s_{i,j}: m \in M_i} \sum_j P_j \cdot s_{i,j} - \sum_{j \in J} tc_{i,j} \cdot s_{i,j} - \sum_{m \in M_i} c_m \cdot x_m \tag{4.1}$$

subject to

$$cap_m - x_m \geq 0,\ \forall m \in M_i\ (\lambda_m) \tag{4.2}$$

$$\sum_{m \in M_i} x_m - \sum_j s_{i,j}\ \geq 0\ (\mu_i) \tag{4.3}$$

$$P_j = a_j - b_j \cdot (s_{i,j} + S_{-i,j}),\ \forall j \tag{4.4}$$

$$s_{i,j} \geq 0,\ \forall j \tag{4.5}$$

$$x_m \geq 0,\ \forall m \in M_i\ . \tag{4.6}$$

Total supplied quantities $S_{-i,j}$ ($= \sum_{-i \neq i} s_{-i,j}$) to market j by other producers ($-i$) are taken as given. Hence, each producer maximises revenues minus costs (production plus transportation) taking into account capacity restrictions (with λ_m being the dual variable for the capacity limit) and the restriction that total production has to be at least as high as total supply (with μ_i as the respective dual variable). As all production facilities of each player are located in the same area, transportations costs between production and specific demand nodes are assumed to be identical. Since different years are not interlinked, they can be optimised separately. Maximising each players' profits is equivalent to finding a solution that satisfies the following Karush-Kuhn-Tucker (KKT) conditions simultaneously for all players:

$$0 \leq tc_{i,j} - P_j + b_j \cdot s_{i,j} + \mu_i \perp s_{i,j} \geq 0,\ \forall\ i, j \tag{4.7}$$

$$0 \leq c_m + \lambda_m - \mu_i \perp x_m \geq 0,\ \forall\ m \in M_i \tag{4.8}$$

$$0 \leq cap_m - x_m \perp \lambda_m \geq 0,\ \forall\ m \tag{4.9}$$

$$0 \leq \sum_{m \in M_i} x_m - \sum_j s_{i,j} \perp \mu_i \geq 0,\ \forall\ i \tag{4.10}$$

$$P_j = a_j - b_j \cdot (s_{i,j} + S_{-i,j}),\ \forall\ j \tag{4.11}$$

$$s_{i,j} \geq 0,\ \forall\ i, j \tag{4.12}$$

$$x_m \geq 0,\ \forall\ m\ , \tag{4.13}$$

with the perp operator ($\perp$) meaning that the product of the expressions to the left and to the right has to equal zero. The first inequality reflects the first order condition for the optimal supply of player i to region j: Marginal revenues of additional supply (i.e., market price P minus transportation costs tc and the marginal costs of supply μ) have to equal supply times the slope of the linear demand function b, i.e., the reduction of revenue due to the negative price effect of additional supply. The second inequality, which represents the first order condition for production, reflects the marginal costs of supply μ

as the sum of variable production costs c and the scarcity value of capacity λ. The third and fourth conditions represent the complementarity conditions forcing production to be within the capacity limit (with λ being the scarcity value of capacity) and production to meet supply (with marginal production costs μ). The equality condition constitutes the linear demand function followed by non-negativity constraints for supply and production.

Due to the quasi-concave objective function and the convexity of restrictions, the solution is unique and the KKT conditions are necessary and sufficient.

4.3.2.2 The MPEC model

In the MPEC model, we seek to represent a Stackelberg market structure with one leader (l) taking into account the equilibrium decisions of the follower(s). The model equations are as follows:

$$\max_{x_m, s_{l,j}, \lambda_m, \mu_i} \sum_j P_j \cdot s_{l,j} - \sum_{j \in J} tc_{l,j} \cdot s_{l,j} - \sum_{m \in M_l} c_m \cdot x_m \tag{4.14}$$

subject to

$$0 \leq tc_{i,j} - P_j + b_j \cdot s_{i,j} + \mu_i \perp s_{i,j} \geq 0, \ \forall \ i \neq l, j \tag{4.15}$$

$$0 \leq c_m + \lambda_m - \mu_i \perp x_m \geq 0, \ \forall \ m \in M_{i \neq l} \tag{4.16}$$

$$0 \leq cap_m - x_m \perp \lambda_m \geq 0, \ \forall \ m \in M_{i \neq l} \tag{4.17}$$

$$0 \leq \sum_{m \in M_i} x_m - \sum_j s_{i,j} \perp \mu_i \geq 0, \ \forall \ i \neq l \tag{4.18}$$

$$P_j = a_j - b_j \cdot (S_{-i,j} + s_{l,j}), \ \forall \ j \tag{4.19}$$

$$s_{i,j} \geq 0, \ \forall \ i, j \tag{4.20}$$

$$x_m \geq 0, \ \forall \ m \ . \tag{4.21}$$

Thus, the leader decides on supply taking the equilibrium outcome of the second stage (which influences the market price) into account. The followers $(-i)$ take the other followers' as well as the leader's supply as given. The objective function is non-convex and thus solving the MPEC problem in the form previously described does usually not guarantee a globally optimal solution. Thus, we transform the model into a mixed integer linear problem (MILP) that can be solved to optimality with prevalent solvers.

There exist several approaches for linearising nonlinearities. Due to its simple implementation, we follow the approach presented by Amat (1981) for the complementary constraints (for an alternative formulation see Siddiqui and Gabriel, 2013).

For instance, the nonlinear constraint

$$0 \leq c_m - P_j + b_j \cdot s_{i,j} + \lambda_m \perp s_{i,j} \geq 0 \tag{4.22}$$

is replaced by the following linear constraints

$$0 \leq c_m - P_j + b_j \cdot s_{i,j} + \lambda_m \leq M \cdot u_{i,j} \tag{4.23}$$

$$0 \leq s_{i,j} \leq M(1 - u_{i,j}) \tag{4.24}$$

with M being a large enough constant (for hints on how to determine M, see Gabriel and Leuthold (2010)) and $u_{i,j}$ a binary variable.

For the remaining nonlinear term in the objective function ($P_j \cdot s_{i,j}$), we follow the approach presented by Perreira (2005) using a binary expansion for the supply variable $s_{i,j}$. The continuous variable is replaced by discrete variables

$$s_{i,j} = \Delta_s \sum_k 2^k b^s_{k,i,j} \tag{4.25}$$

where Δ_s represents the step size, i.e., the precision of the linear approximation, and k the number of steps. Variables $b^s_{k,i,j}$ are binary. The term $P_j \cdot s_{i,j}$ in the objective function is replaced by $P_j \cdot \Delta_s \sum_k 2^k z^s_{k,i,j}$. In addition, the following constraints have to be included in the model

$$0 \leq z^s_{k,i,j} \leq M^s b^s_{k,i,j} \tag{4.26}$$

$$0 \leq P_j - z^s_{k,i,j} \leq M^s \left(1 - b^s_{k,i,j}\right) \ . \tag{4.27}$$

The thereby formulated model constitutes a MILP that can be reliably solved to a globally optimal solution.

4.3.2.3 The EPEC model

The EPEC model extends the Stackelberg game by enabling the representation of several leaders taking actions simultaneously under consideration of the reaction of one or more followers. The solution of an EPEC constitutes the simultaneous solution of several MPECs. Whereas MPECs are already difficult to solve due to their nonlinear nature, it is even more difficult to solve EPECs. KKT conditions generally cannot be formulated for EPECs as regularity conditions are violated. Our model is solved using a diagonalisation approach. In doing so, we reduce the solution of the EPEC to the solution of a series of MPECs. The iterative solution steps are as follows:

1. Define starting values for the supply decisions $s^0_{l,j}$ of all leaders $l \in L$, a convergence criterion ϵ, a maximum number of iterations N and a learning rate R
2. $n = 1$
3. For all leaders,
   (a) Fix the supply decisions for all but the current leader
   (b) Solve current leader's MPEC problem to obtain optimal supplies $s^n_{l,j},\ \forall j$
   (c) Set $s^n_{l,j}$ equal to $(1 - R) \cdot s^{n-1}_{l,j} + R \cdot s^n_{l,j},\ \forall j$
4. If $|s^n_{l,j} - s^{n-1}_{l,j}| < \epsilon$ for all producers: equilibrium found, quit
5. If $n = N$: failed to converge, quit
6. $n = n + 1$: return to step 3.

EPECs may or may not have one or multiple (pure strategy) equilibrium solutions, and only one solution can be found per model run. In addition, if the iterations do not converge to an equilibrium, this does not necessarily mean that no solution exists. This problem can partially be solved using multiple initial values for the iteration process, but it cannot be guaranteed that additional equilibria have not been missed. Despite these drawbacks, diagonalisation has been used widely and successfully in the corresponding literature (see Gabriel et al. (2012) and the literature cited therein).

For each EPEC setting, we run our model five times with varying start values and iteration orders to check for multiple equilibria. Each run converged to similar results with deviations of prices from the mean values of maximum 5%, single trade flows below 1.2 Mt and total production per mine below 0.6 Mt. Profits of the Big-Four and the cartel groups differed to a maximum of 1%. Whether theses deviations are due to a multiplicity of (similar) equilibra or to the (lack of) precision of the applied algorithm is not quite clear. In consideration of the almost equal results, we refrain from further analyses of the deviations.

4.4 Data

Modelling international commodity markets may be computationally challenging due to their spatial nature, i.e., multiple supply and demand nodes. In most empirical examples, each supply node is able to transport the commodity to each demand node giving rise to a large set of potential trade routes. The possible routes rapidly increase with additional demand or supply nodes. Whether a certain set of trade routes turns out to be computationally challenging depends on which market structure one would like to analyse. While solvers for mixed complementary problems such as PATH (see Dirkse and Ferris, 1995b) can handle quite large systems of equations and variables, the same setup may be intractable when formulated as a mathematical problem with equilibrium constraints or other more complex problems such as an equilibrium problems with equilibrium constraints due to their high nonlinearity.

Since we are particularly interested in how well a multi-leader-follower game is able to model the coking coal market, we had to reduce the number of mines per player to one to keep the model feasible.[44] To ensure comparability, the same datasetup was used for all market structures analysed in this paper irrespective of whether the respective solvers may have been able to handle larger sets of equations and variables (see Appendix C.1 for production and shipping costs as well as capacities).

TABELLE 4.2: Overview of firms and countries used in the model

Supply nodes	**Demand nodes**	**Countries/regions belonging to demand node**
BHP Billiton	JP_KR	Japan and Korea
Rio Tinto	CN_TW	China and Taiwan
Anglo American	IN	India
Xstrata Australia	LAM	Latin America (mainly Brazil and Chile)
Canada	EUR_MED	Europe and Mediterranean
China	Other	Africa and Middle East
Indonesia		
New Zealand		
Russia		
South Africa		
United States		

In total, the model used to conduct our empirical analysis consists of twelve supply nodes and six demand nodes. The supply side consists of individual firms as well as countries. In addition to each of the four firms belonging to the Big-Four, i.e., BHP Billiton, Rio Tinto, Anglo American and Xstrata, eight country supply nodes are included in the model of the international coking coal market (Table 4.2 shows which countries on the supply and demand side are represented in the model). When aggregating the data, production capacities of each mine belonging to the same firm or country are simply added up. Concerning production costs, we use the quantity-weighted average of the individual mines of a firm or country.

[44]We would like to thank Johannes Trüby for allowing us to use his extensive mine-by-mine dataset on the international market for metallurgical coal.

The demand side is represented by six nodes, most of which represent a demand cluster, with India being the only exception. The demand clusters were chosen based on geographical proximity and importance for international trade of metallurgical coal. Geographical proximity is important because shipment costs, which represent a large share in total import costs, largely depend on the shipping distance. Due to their minor importance in terms of the share of total import volumes, we included Africa and the Middle East in one demand node despite the large area this demand node covers. Inverse demand functions are assumed to be linear (see Table C.1 in Appendix C.1 for the used market data). Since it is a priori not clear which is the correct elasticity, we run the market analyses for a range of values. More specifically, we consider elasticities from -0.1 to -0.6. This is in line with Bard and Loncar (1991), who estimated the elasticity of coking coal demand to lie in the range from -0.15 to -0.5, with Western European (Asian) demand elasticity lying in the lower (upper) part of this range. Graham et al. (1999) finds that for 1996, a demand elasticity of -0.3 characterises best the actual market outcomes, whereas Trüby (2013) concludes that for the years 2008 to 2010, demand elasticity falls in the range from -0.3 to -0.5.

4.5 Results

In this section, the model results are presented and discussed. We start out by comparing the prices under the different market settings to the actual market prices. This allows us to narrow down the range of elasticities we need to focus on. In a second step, we use three statistical measures, namely a linear regression test as suggested by Bushnell et al. (2008), Spearman's rang correlation coefficient, and Theil's inequality coefficient, to assess whether trade flows simulated under different market structures match actual trade flows. Finally, revenues and production volumes of the Big-Four are analysed.

4.5.1 Prices

Figure 4.2 displays the actual free-on-board (FOB) benchmark in 2008 (straight black line) as well as the simulated FOB prices for a range of elasticities (-0.1 to -0.6) and for the four market structure settings analysed in this paper. Four observations can be made: First, for very low elasticities, i.e., between -0.1 and -0.2, none of the market settings is able to reproduce actual market prices. Although only the results for 2008 are displayed in Figure 4.2, taking a look at the other years (see Figure C.1 in Appendix C.2) confirms this conclusion.

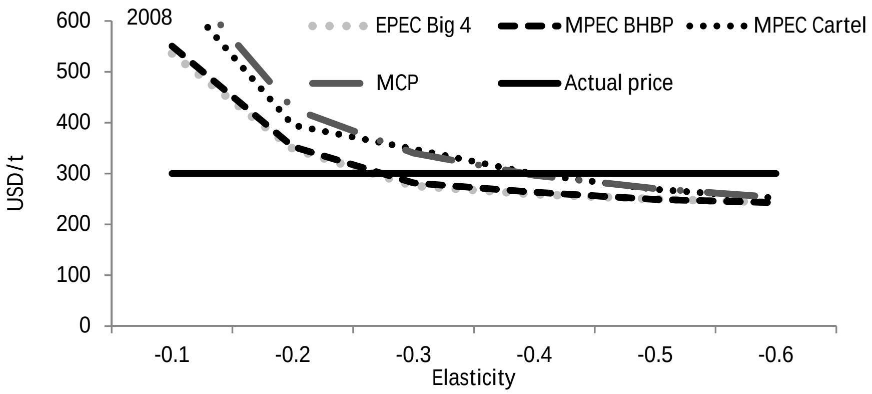

ABBILDUNG 4.2: FOB prices for a range of (abs.) elasticities - model results vs. actual benchmark price

Second, prices in the multi-leader-follower setting, EPEC Big 4, as well as in the setting in which BHP Billiton acts as a Stackelberg leader, MPEC BHPB, are more or less equivalent. This result is caused by the interaction of three effects (our argumentation follows Daughety (1990)): First, each following firm that becomes a Stackelberg leader has the incentive to increase its output since, now, it takes into account the optimal reaction of the remaining followers to a change in the output of the Stackelberg leaders. Second, increasing the number of leaders causes the output of each (incumbent) leader to drop. This may be interpreted as the result of the intensifying Cournot competition between the leaders. Third, the total output of the followers decreases with each firm becoming a Stackelberg leader. In our simulations, these effects seem to counterbalance each other, which is why the two market settings, EPEC Big 4 and MPEC BHPB, result in similar market outputs and prices.

Third, another interesting aspect is that (for low demand elasticities) prices for the case in which the Big-Four form a cartel that acts as a Stackelberg leader (labelled MPEC Cartel) are below the prices in the Cournot oligopoly (MCP).[45] In other words, the output-increasing effect of becoming a leader is stronger than the output-decreasing effect of collusion (forming the cartel). Building on Shaffer (1995), the intuition behind this finding can be explained as follows: For the case of N identical firms, zero marginal costs and a linear demand, the output of a cartel with k-members that acts as a Stackelberg leader is higher than in a Cournot oligopoly for k lower than $\frac{N+1}{2}$, but is decreasing in k. In other words, the bigger the cartel becomes, the more dominant the output-reducing collusion effect.[46] This is also in line with the results for the case in which BHPB acts as single leader (MPEC BHPB).

[45]For higher demand elasticities (i.e., larger than -0.3), prices of both cases are identical (given the tolerance of the applied linearisation method).

[46]In the case of $k = N$, i.e., the cartel consists of all firms N in the market, the price in the market would equal the monopoly price.

Finally, the higher the elasticity, the more the simulated prices converge. This can be explained by two effects: First, with increasing elasticity, total production increases as well (along with decreasing prices). As such, the capacity utilisation over all players increases from a minimum of 79 % (MCP, eta -0.1) to around 97 % (all scenarios with eta -0.6) for 2008. This narrows the ability to differentiate strategic behaviour as more players produce at their capacity limit. Second, increased price elasticity of demand itself narrows the potential for strategic choice of production as prices react more severely to changes in output.

Consequently, we conclude that the range of elasticities may be narrowed down to the range of -0.3 to -0.5, which is in line with previous analyses (see Section 4.4).

4.5.2 Trade flows

In a first step, we investigate whether simulated trade flows under the different market structures match the actual market outcomes by regressing the former on the latter. If the two were a perfect match, then the estimated linear equation would have a slope of one and an intercept of zero. Table 4.3 shows the p-values of the F-test that checks whether the coefficient of the slope and the intercept jointly equal one and zero, respectively, for six different elasticities and the four market structures.[47]

Taking a closer look at Table 4.3, we can conclude that all four market settings provide a reasonable fit with actual trade flows in the relevant range of elasticities (-0.3 to -0.5). This finding generally holds true for lower elasticities as well, with one exception. In the case of the MCP scenario, trade flows in 2008 and 2010 for an elasticity of -0.1 and in 2009 for an elasticity of -0.1 and -0.2 do not seem to provide a reasonable fit since the H_0-hypothesis is rejected. It should, however, be noted that 2009 was special in the sense that it was characterised by a significant drop in utilisation rates of the mines since steel demand and, thus, demand for coking coal plummeted compared to the previous year because of the financial crisis.

[47]See Appendix B.3 for more details on the methodology used in this subsection.

TABELLE 4.3: P-values of the F-tests ($\beta_0 = 0$ and $\beta_1 = 1$) for a range of elasticities

Elasticity	EPEC Big 4			MPEC BHPB		
	2008	2009	2010	2008	2009	2010
e = -0.1	0.86	0.86	0.64	0.86	0.85	0.68
e = -0.2	1.00	0.80	0.90	1.00	0.81	0.92
e = -0.3	0.92	0.57	0.98	0.92	0.57	0.99
e = -0.4	0.85	0.44	0.95	0.84	0.46	0.97
e = -0.5	0.74	0.48	0.91	0.73	0.50	0.92
e = -0.6	0.59	0.52	0.84	0.59	0.52	0.85
Elasticity	MPEC Cartel			MCP		
	2008	2009	2010	2008	2009	2010
e = -0.1	0.79	0.76	0.70	0.08*	0.02**	0.06*
e = -0.2	1.00	0.66	0.12	0.22	0.09*	0.16
e = -0.3	0.43	0.45	0.37	0.43	0.25	0.34
e = -0.4	0.75	0.85	0.73	0.67	0.52	0.59
e = -0.5	0.78	0.49	0.92	0.77	0.73	0.81
e = -0.6	0.57	0.40	0.85	0.61	0.90	0.84

Significance levels: 1% '***' 5% '**' 10% '*'

In order to cross-check the results from the linear hypothesis test, two additional indicators are taken into consideration. Figure 4.3 depicts Spearman's rank correlation and Theil's inequality coefficient for the different market settings and the whole range of elasticities in 2008.[48] Both coefficients confirm the analysis of the linear hypothesis test since neither of the two indicators allows us to discard one of the market settings when looking at the relevant range of elasticities.

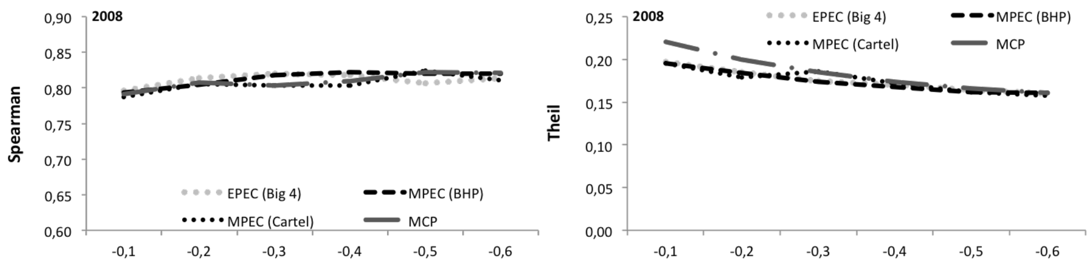

ABBILDUNG 4.3: Spearman's rank correlation coefficients and Theil's inequality coefficients for a range of (abs.) elasticities

4.5.3 Production and revenues of the Big-Four

So far the conducted analyses have not provided significant evidence that one of the market structures investigated in this paper performs better or worse than another. Therefore, we take a closer look at two further components: revenues and production volumes of the Big-Four.

[48]Conclusions remain unchanged when focussing on the other two years, as can be seen in Figure C.2 in Appendix C.2.

When analysing the differences in profits of the Big-Four between the various market structures simulated in this paper, we can observe that, as expected, the Big-Four make the largest profits in the MPEC Cartel setting. However, relative differences between the different market structures are negligible ($< 1\%$), which becomes obvious when comparing the bars in Figure 4.4.[49]

The conclusion that can be drawn from this comparison is that the gains of forming and coordinating a cartel are small even when neglecting transaction costs that go along with maintaining the cartel.

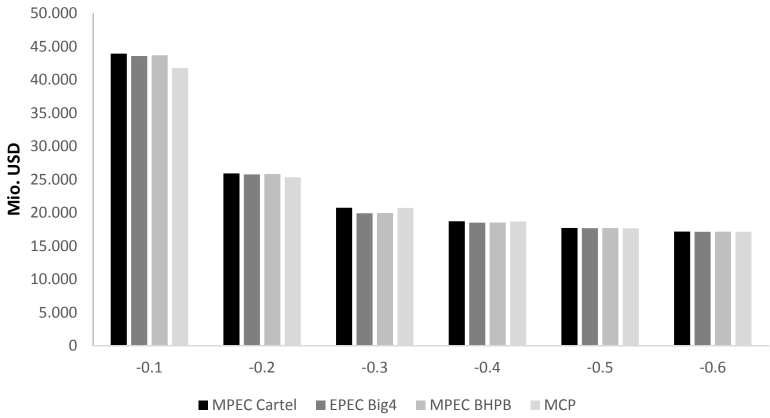

Abbildung 4.4: 2008's profits of the Big-Four in the three two-stage-games for the whole range of elasticities

Turning now to production, we compare the absolute difference in simulated versus actual production volumes of the Big-Four cumulated over the time period investigated in this paper (2008 to 2010). This indicator was chosen because it captures differences in the total production volumes of the Big-Four as well as deviations in each firm's production volumes. In addition, we compare the sum of squared differences between actual and modelled production to assess the structure of deviations. The resulting differences are depicted in Figure 4.5 for a demand elasticity of -0.4, which is the mean value of the range of elasticities found to be relevant (see Subsection 4.5.1). As can be seen in the left diagram, cumulated absolute differences to historical data lie in the range of 8% to 17%, with the MPEC Cartel setting performing worst. On the other hand, the market structures in which BHP Billiton is the sole Stackelberg leader and the case of four non-colluding leaders perform best. Taking a closer look at the individual differences of the two settings with the largest differences, it becomes obvious that the MCP setting performs reasonably well in 2008 and 2010 but fails to reproduce the decline in production of the Big-Four in 2009. This is also the reason for the poor performance regarding squared deviations. In contrast, the MPEC Cartel setting constantly overestimates the production of BHP Billiton and underestimates the one of Rio Tinto, with the reason

[49]The results for 2009 and 2010 are similar.

being that this minimises the overall production costs of the cartel. In the two cases that perform best (MPEC BHPB and EPEG Big 4), we observe no significant patterns.

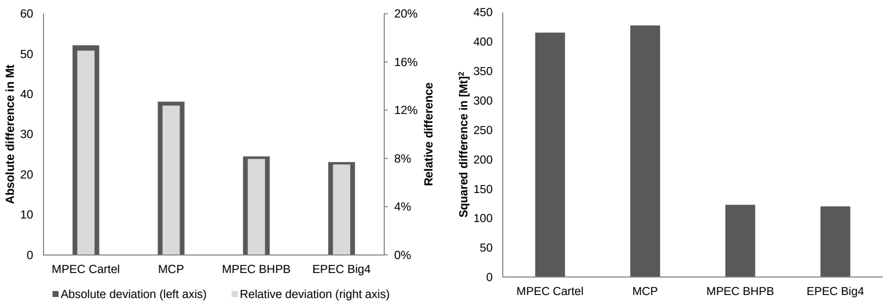

Abbildung 4.5: Cumulated absolute and squared difference in production volumes of the Big-Four to actual market outcomes at an elasticity of -0.4

In summary, three conclusions may be drawn from our analyses: i) We are able to support previous findings that the setting in which a cartel of the Big-Four acts as the Stackelberg leader, MPEC Cartel, as well as the Cournot oligopoly setting sufficiently reproduce actual trade flows and prices. ii) However, we also show that additional revenues from forming a cartel are rather small and individual production volumes of the Big-Four in the cartel setting do not match well with actual production numbers. Thus, we argue that a market structure with a cartel of the Big-Four that moves first is less likely than the other scenarios. iii) We find that the two settings with one or more leading firms reproduce actual trade flows and prices as good as the cartel and the Cournot settings. In addition, these two settings perform better than the former two settings with respect to the production volumes of the Big-Four. In particular, the methodology introduced in this paper to represent multi-leader-follower games scored among the best results in all tests used in our analysis.

4.6 Conclusions

Previous analyses of the prevailing market structure in spatial resource markets mainly focussed on the comparison of actual market outcomes to market results under perfect competition, Cournot competition and with a single (Stackelberg) leader. We add to these analyses by developing a model able to represent multi-leader market structures. We apply our model to the metallurgical coal market, which is especially suited as its market structure suggests a multitude of possible markets structures that have partly been neglected in previous analyses. Thereby, we are able to demonstrate the practicability and usefulness of our approach.

Trüby (2013) shows that market results of the metallurgical coal market indicate non-competitive behaviour. Actual prices and trade flows could rather be explained by Cournot competition or a game in which the Big-Four form a cartel that acts as a single Stackelberg leader. Our results confirm that a Cournot oligopoly as well as a cartel consisting of the Big-Four fit well with observed prices and trade flows of the metallurgical coal market from 2008 to 2010. Based on our results, however, the same is true for two additional settings: First, a market with BHPB acting as a Stackelberg leader and the remaining players competing afterwards in a Cournot fashion (MPEC BHBP). Second, a multi-leader market structure where the Big-Four independently act first followed by the remaining players (EPEC Big 4). By additionally analysing profits and comparing the actual production data with models results, we conclude that the two latter scenarios are even more likely than the previously suggested market structures.

To improve the accuracy of current market structure analyses and to further narrow down the set of potential market structures, it could be useful to have more detailed firm and market data, also for smaller market participants. In order to be able to solve the computationally challenging nonlinear bi-level games, we had to aggregate our dataset. Improving available solution methods for these problems to obtain mine-by-mine results may help to discriminate between the goodness of fit of different model results with actual market data. However, this would require detailed data availability. Unfortunately, neither mine-by-mine market results nor detailed profitability data on a firm level were available.

Our results demonstrate the multiplicity of possible market structures able to explain actual market outcomes concerning trade flows and market prices. By analysing the production data, we were able to identify the two most promising candidates for the underlying market structure. From this finding, two conclusions can be drawn: First, omitting potential scenarios can lead to false conclusions of the prevailing market structure. This is relevant especially when it comes to judging if market outcomes reveal collusive behaviour. Second, a market structure analysis solely based on market outcomes with respect to price and trade flows may not be sufficient to determine the actual market structure but should rather be completed using additional analyses.

Kapitel 5

Firm characteristics and the ability to exercise market power - empirical evidence from the iron ore market

5.1 Introduction

Steel, sometimes referred to as the backbone of industrialisation is an important input in several key economic sectors such as manufacturing and construction. As a result, economic growth in developing countries often goes along with a strong growth of the country's demand for steel. Even in wealthy economies with a lower need for, e.g., infrastructural development, steel constitutes a major economic factor. Hence, steel prices deviating from prices under perfect competition – either due to exercise of market power in the steel market itself or in one of the key input markets such as coking coal and iron ore – may lead to a deadweight loss causing significant losses in a country's economic welfare.

In this regard, the sharp increase in iron ore prices in recent years – on average 26% p.a. from 2003 to 2012 – raises the question as to whether this increase is at least partly due to iron ore producers exercising market power (see, e.g., Hilpert and Wassenberg, 2010). While the increase in prices may also be explained by increasing marginal production costs and demand growth during this period, the high concentration level on the supply side hints at non-competitive behaviour. In 2010, the three largest producers, VALE, BHP Billiton and Rio Tinto (also called 'Big3'), made up a share of more than 30% of worldwide production, and more than 58% of the worldwide seaborne trade (UNCTAD, 2011). Furthermore, the iron ore market is characterised by a low degree of demand-side substitutability (Hurst, 2012) and high barriers to entry (Asafu-Adjaye and Mahadevan, 2003). Finally, buyers and sellers of iron ore are geographically dispersed with trade costs due to the low value-to-weight-ratio separating markets. Global iron ore trade may be roughly divided into two areas: the Atlantic-based and the Pacific-based markets linked by suppliers delivering iron ore to both market areas. Therefore, transportation costs have to be considered as an additional factor that may reduce the availability of cheap supply and could strengthen the exercise of market power.

Despite the warranted interest in scrutinising firm behaviour in the iron ore market, empirical research on the exercise of market power is rather scarce. Most articles concerning the iron ore market deal with market power only indirectly via merger analysis (see, among others, Lundmark and Wårell, 2008). To the best of our knowledge, only one article exists that deals empirically with market power in the iron ore market: Smart (2011) finds that producers most likely exhibit Cournot behaviour. Overall, including the literature on mergers, the existing literature is supportive of the notion that there is a potential for non-competitive behaviour of iron ore producers. However, so far there is no empirical analysis that estimates markups on short-run marginal costs or assesses their main determinants on the firm level, a research gap that this paper intends to close.

We define an empirical model that is based on an innovative estimation approach introduced by Kumbhakar et al. (2012). They make use of a new application of stochastic frontier analysis (SFA) techniques that have been widely applied in quantitative benchmarking studies. Basically, SFA relies on the assumption that the deviation of an individual decision-making unit from the estimated best-practice frontier (in the majority of cases a production or cost frontier) can be divided into two distinctive parts: a classical stochastic noise component and an additional skewed residual that captures individual inefficiency. Kumbhakar et al. (2012), however, do not estimate a production or cost frontier but rather a frontier of the ratio of revenue to total cost. The additional skewed residual is assumed to represent a firm-specific markup term. This term can easily be transformed into a firm-specific estimate of the familiar Lerner index, which represents the relative markup of price over marginal cost and is a frequently used measure of market power.[50]

This estimation procedure differs significantly from traditional estimation procedures for analysing market power (see, e.g., Bresnahan, 1989) and bears several advantages. First,

[50] Other measures include the concept of conjectural variations, the Hall-Roeger approach or the H-statistic (for recent applications of these approaches see, e.g., Gunning and Sickles (2013), Christopoulou and Vermeulen (2012) and Huang and Liu (2014), respectively).

Kumbhakar et al.'s approach yields expressions for both time- and firm-specific markups and, hence, provides more detailed information. This is a clear advantage over most other approaches that yield either time-constant or firm/industry-constant estimates (e.g., Rezitis and Kalantzi (2016) as an example for the Hall-Roeger approach). We extend the original approach by including additional firm-specific and macroeconomic variables to explain the markup term. This allows us to analyse the impact of firm-specific characteristics and general changes in the business environment on the estimated markups. This is achieved by using the SFA model of Battese and Coelli (1995). Second, the procedure is not as restrictive as others. An error term that captures noise in the data, such as supply or demand shocks, e.g., as a result of strikes or bad weather conditions, is included. Furthermore, it relaxes some assumptions that are normally necessary to obtain valid estimates, such as constant returns to scale or certain demand conditions. Third, data availability is a crucial factor in empirical analyses. For the estimation procedure applied in this paper, supply data is sufficient and price data is not needed for all inputs and outputs. Instead, total revenue can be used and an input distance function approach can be chosen that relies on (typically) publicly available data on input and output quantities (Coccorese, 2014, Kumbhakar et al., 2012).

Overall, we find that the conjecture of firms exercising market power in the iron ore market is supported by the empirical analysis. Estimated markups are significantly different from zero, with the firms' average Lerner index amounting to 0.20. However, heterogeneity of firms seems to be significant as the producer's individual ability to charge markups varies considerably. In particular, the analysis points out that experience measured by years of production, and geographical location are the most important factors influencing the level of firm-specific markups. Yet, due to a potential reverse-causality problem one needs to be cautious with this interpretation. An alternative explanation of our finding may be that more profitable firms, i.e., firms with higher markups, stay in the market for a longer time. However, given that firms, which have a long history in iron ore mining, are more likely to have a more experienced workforce and knowing that labour productivity is an important determinant of marginal production costs, we tend to argue that the increase in the markups with every additional year of production is an indication of experience effects. Finally, we find weak evidence that annual growth of global gross domestic product (GDP) helps to explain the markup levels, albeit the influence is found to be rather small. Given the impact of firm-specific factors on markups and the only limited effect of macroeconomic conditions proxied by GDP growth, we conclude that the recent surge in iron ore prices can - at least partially - be attributed to an increase in the iron ore producers' exercise of market power.

The remainder of the paper is structured as follows: The methodology applied is explained in Section 5.2, and the data and empirical specifications are outlined in Section 5.3.

The results are presented in Section 5.4, followed by a discussion in Section 5.5.

5.2 Methodology

The 'SFA estimator of market power' introduced by Kumbhakar et al. (2012) offers a new application of classical SFA techniques to the field of market power estimation. The starting point of Kumbhakar et al.'s approach is rather simple: In the case of market power, the firm's individual output price (P) is larger than its individual marginal cost (MC): $P > MC$. Augmenting this inequality with the ratio of output to total cost (Y/C) and rearranging gives:

$$\begin{aligned} &\frac{PY}{C} > MC\frac{Y}{C} = \frac{\partial C}{\partial Y}\frac{Y}{C} = \frac{\partial\, ln\, C}{\partial\, ln\, Y} = E_{CY} \\ &\frac{PY}{C} > E_{CY} \end{aligned} \tag{5.1}$$

Hence, the intuition of the approach is to compare the revenue-cost share (PY/C) with the cost elasticity (E_{CY}). The residual of these two expressions (captured by $u \geq 0$) is related to the markup:

$$\begin{aligned} &\frac{PY}{C} = \frac{\partial\, ln\, C}{\partial\, ln\, Y} + u \\ &\frac{PY}{C} = E_{CY} + u. \end{aligned} \tag{5.2}$$

Revenue and cost data are usually observable from firm accounting data and, therefore, the revenue-cost share can be directly computed. Thus, in order to estimate Equation 5.2, an expression for the cost elasticity is needed, which can be obtained by differentiating the cost function in natural logarithm with respect to output in natural logarithm. However, this cost function approach relies on input price data, which is often not available.

As shown by duality theory, in this case a dual input distance function approach can be used instead (Shephard, 1970, p. 159). An input distance function describes a production technology by looking at a minimal proportional contraction of the input vector, given an output vector" (Coelli et al., 2005, p. 47). That is, in contrast to a traditional cost function approach, the input distance function approach does not rely on a cost-minimisation assumption based on observed market input prices. Rather, the input distance approach assumes a shadow cost-minimising behaviour, where the decision-making units minimise their costs relative to the unobserved input shadow prices.

The Lagrangian for this minimisation problem can be written as:

$$L(X, Y) = wX + \lambda(1 - D(X, Y)), \tag{5.3}$$

where w and X represent a vector of input shadow prices and inputs, respectively; λ denotes the Lagrangian multiplier; Y is the output and $D(X, Y)$ represents the input distance function.

Using the first-order conditions for the problem, it can be shown that $\lambda = C(w, Y)$ at the optimum (Färe and Primont, 1995, p. 52). In addition, cost minimisation and applying the envelope theorem yields the following expression for the log derivatives of the input distance function:

$$E_{CY} = \frac{\partial\, ln\, C(w, Y)}{\partial\, ln\, Y} = -\frac{\partial\, ln\, D(X, Y)}{\partial\, ln\, Y}. \tag{5.4}$$

Hence, the negative elasticity of the input distance function with respect to the output Y is equal to the cost elasticity of that output.

In order to obtain an explicit formulation for the cost elasticity, the functional form of the input distance function has to be determined. We follow Kumbhakar et al. (2012) and use a translog specification that allows the cost elasticity to vary across time and firms. The translog input distance function for one output Y and $J(j = 1, ..., J)$ inputs can be written as:

$$\begin{aligned} ln\, D(X, Y, T) = & \alpha_0 + \alpha_y\, ln\, Y + \frac{1}{2}\alpha_{yy}\,(ln\, Y)^2 + \sum_{j=1}^{J}\alpha_j\, ln\, X_j \\ & + \frac{1}{2}\sum_{j=1}^{J}\sum_{k=1}^{K}\alpha_{jk}\, ln\, X_j\, ln\, X_k + \sum_{j=1}^{J}\alpha_{jy}\, ln\, X_j\, ln\, Y \\ & + \alpha_t\, T + \frac{1}{2}\alpha_{tt}\, T^2 + \alpha_{yt}\, ln\, Y\, T + \sum_{j=1}^{J}\alpha_{jt}\, ln\, X_j\, T, \end{aligned} \tag{5.5}$$

where $T(t = 1, ..., T)$ is a time trend and the αs are unknown parameters to be estimated.

Economic theory requires the input distance function to be non-decreasing, concave and linearly homogeneous in inputs as well as non-increasing and quasi-concave in outputs (Coelli et al., 2005, p. 49). Linear homogeneity in inputs is given if

$$\sum_{j=1}^{J}\alpha_j = 1, \sum_{j=1}^{J}\alpha_{jk} = 0, \sum_{j=1}^{J}\alpha_{jy} = 0, \text{ and } \sum_{j=1}^{J}\alpha_{jt} = 0. \tag{5.6}$$

Imposing the restrictions in Equation 5.6 by normalising the translog input distance function in Equation 5.5 by one of the inputs (Lovell et al., 1994) and adding a symmetric error term v, the model to be estimated becomes:

$$\frac{PY}{C} = -\frac{\partial\, ln\, D(X, Y)}{\partial\, ln\, Y_m} + u + v = -\left[\alpha_y + \alpha_{yy}\, ln\, Y + \sum_{j=1}^{J-1}\alpha_{jy}\, ln\, \widetilde{X}_j + \alpha_{yt}\, T\right] + u + v, \tag{5.7}$$

where $\widetilde{X}_j$ is the quantity of j-th input factor normalised by the quantity of an arbitrary input factor (X_1).[51]

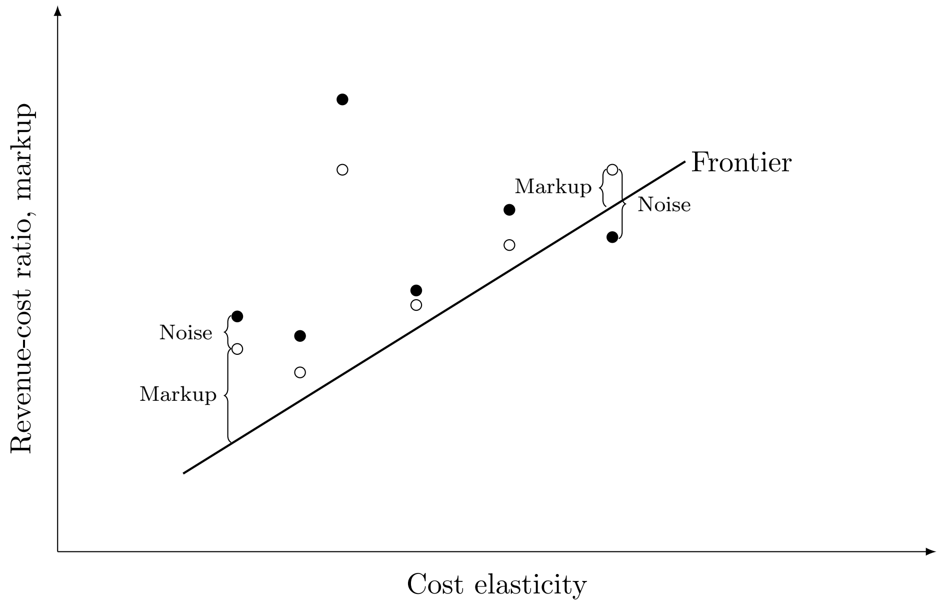

ABBILDUNG 5.1: Markups and cost elasticity

This specification is statistically equivalent to a stochastic cost frontier model with two error components, u and v. However, as shown in Equation 5.2, u does not represent cost inefficiency but is instead related to a markup component. Kumbhakar et al. (2012) denominate this approach as a non-standard application of stochastic frontier models". An illustrative description of the approach is provided in Figure 1. The vertical axis shows the revenue-cost ratio (PY/C), while the horizontal axis shows the cost elasticity (E_{CY}). Furthermore, the solid line represents the estimated frontier and the dots indicate some observed revenue-cost ratios. As shown, the deviation of the observed revenue-cost ratios from the minimum revenue-cost ratios on the estimated frontier can be separated into a noise component v and a markup component u.

Furthermore, as shown by Kumbhakar et al. (2012), an expression for the familiar Lerner index (Lerner, 1934), which represents the relative markup of price over marginal cost, $((P-MC)/P)$, can be computed from the estimated results as follows: First, the fraction by which P exceeds MC can be written as:

$$\frac{P-MC}{MC} = \frac{P-\frac{\partial C}{\partial Y}}{\frac{\partial C}{\partial Y}} = \frac{\frac{PY}{C}-\frac{\partial ln(C)}{\partial ln(Y)}}{\frac{\partial ln(C)}{\partial ln(Y)}} = \frac{u}{E_{CY}}. \tag{5.8}$$

Then, multiplying this expression by MC/P and reformulating gives the traditional Lerner index for measuring market power:

[51]The monotonicity and concavity restrictions are tested ex post after the estimation.

$$
\begin{aligned}
\frac{P - MC}{MC}\frac{MC}{P} &= \frac{u}{E_{CY}}\frac{MC}{P} \\
\frac{P - MC}{P} &= \frac{u}{E_{CY}}\frac{MC}{P} = \frac{\frac{u}{E_{CY}}}{\frac{P}{MC} - \frac{MC}{MC} + 1} \\
LI &= \frac{\frac{u}{E_{CY}}}{1 + \frac{u}{E_{CY}}}.
\end{aligned}
\tag{5.9}
$$

The range of the Lerner index is between zero and one, with one indicating the maximum possible market power and zero indicating marginal cost pricing. These values will be presented and analysed in detail in Section 5.4.1.

5.3 Data and empirical model specifications

Here we provide an overview of the data and the variables used in the analysis as well as outline and discuss the empirical model.

5.3.1 Data

The sample includes ten companies from six countries and covers the period between 1993 and 2012 with 96 observations in total (see Table 5.1). These companies represent more than 70% of the global trade and 33% of the worldwide production of iron ore in 2010.[52] The data is obtained either from the "Form 20-F" of the Securities and Exchange Commission of the United States (SEC) or from the companies' annual reports.[53]

Although the firms operate in different geographical locations all over the world, five out of the ten firms have their headquarters and main production based in Australia. Unfortunately, no producers from India and China can be included. For firms in these countries, either no data is available (especially in China) or their definitions of accounting items deviate from other companies in the sample preventing a meaningful comparison (as for Indian companies).[54]

Summary statistics for the variables used to estimate the revenue-cost frontier model described in Section 5.2 are depicted in Table 5.2. All monetary variables have been converted to US Dollar (USD) by purchasing power parity conversion rates from the

[52] For the case of companies operating in multiple countries, the country with the most production activity is chosen.

[53] "SEC Form 20-F" is a necessary form to file with the SEC if the company is listed on the stock market in the United States.

[54] For example, for Sesa Sterlite, only data on capital expenditure and total segment assets was available.

TABELLE 5.1: Overview: Companies

Company	Period	Obs.	Company	Period	Obs.
Atlas Iron	2009 - 2011	3	Fortescue Metals Group	2008 - 2011	5
BHP Billiton	2005 - 2011	7	LKAB	2000 - 2012	13
Cliffs Natural Resources	1993 - 2012	20	Mount Gibson	2006 - 2011	6
Ferrexpo	2006 - 2012	5	Rio Tinto	1997 - 2012	16
Kumba Iron Ore	2006 - 2012	7	Vale	1998 - 2012	15
Total	1993 - 2012	96			

Worldbank (2013) and inflated by the consumer price index from the OECD (2013) for each respective country to 2012 values.[55][56]

TABELLE 5.2: Summary statistics: Frontier variables

Variable	Mean	Median	Std. Dev.	Min	Max
Revenue [million USD]	6,345.44	2,368.06	9,038.27	40.59	47,536.23
Total Cost [million USD]	2,959.36	1,499.05	3,666.02	45.04	18,095.00
Revenue Cost Share	1.82	1.79	0.58	0.90	3.62
Capital [million USD]	5,342.92	1,876.21	8,272.00	9.35	37,846.00
Labor [number of employees]	7,092.67	4,470.5	8,632.35	85.00	52,374.00
Reserves [million FE units]	1,348.96	510.89	2,076.8	22.87	9,524.12
Production [million FE units]	43.12	19.81	49.68	0.55	186.59

Iron ore can be divided into three different product groups: lumps, fines and pellets. Unfortunately, detailed data on the product groups is often not available. However, although their usage is different, all three products are utilised in the production of steel. Therefore, the products are closely interconnected, at least in the long run. For this reason, the existence of different product groups is neglected in the following, and product differences among iron ore are reflected by differences in their iron content. Product and reserves are converted to FE units by different FE grades. For the production, the FE grade is the production-weighted average of the FE grades of the active mines of the respective firm. In the case of pellet production, the FE grades of the pellets are used. In calculating the FE grade of the reserves, all mines of the respective firm are considered.

[55] For the Ukraine, figures from UKRstat (2013) had to be used instead as data was not available from the OECD.

[56] For 4 of the 10 companies, the fiscal year ends in June instead of December. Hence, without adjustment, different time periods would be compared. To adjust for these cases, two consecutive years are averaged, e.g., the average of the results for July 2004 to June 2005 and for July 2005 and June 2006 would form the value for the year 2005. A consequence of this adjustment is that the second half of 2004 and the first half of 2006 are included in the value for 2005. Furthermore, it reduces the number of observations from 100 to 96.

5.3.2 Specification of the empirical model

The Lerner index should only be used if the underlying assumption of static profit maximisation is valid. In a dynamic context, marginal cost has to be adjusted to "full marginal cost", which includes a user cost describing "the sum of discounted future costs or benefits that result from current production decisions" (Pindyck, 1985). Otherwise, a high value for the Lerner index could result even if the firm behaves competitively. In a nonrenewable resource industry, the user cost will be positive if either the resource is completely exhausted or production costs are increasing with cumulative production. The former refers to a scarcity rent in style of Hotelling (1931), while the latter points to a so-called 'Ricardian stock rent' in line with Levhari and Liviatan (1977). As 4.6% of the earth's crust consists of iron ore (European Commission, 2001), the physical availability should not pose a problem in our estimations. The average of the reserves-to-production ratio of firms in the sample is, with more than 32 years, relatively high. Therefore, the existence of a scarcity rent is not very likely and is therefore not included in the analysis. The 'Ricardian stock rent', however, may be of more relevance. Pindyck (1978) mentions that while the exact transmission channel is not clear, it is reasonable to assume for mineral resources that the amount of reserves influences the level of production cost. One explanation may be that lower cost deposits are extracted first and, therefore, higher production costs must be met in the future. Following this argument, we include the iron ore reserves of each company in our empirical model specification. Given the methodology outlined in Section 5.2 as well as the variable description in Section 5.3.1 and this paragraph, the following equation is estimated:

$$\begin{aligned}\frac{PY_{it}}{C_{it}} = - \Bigg[& \alpha_y + \alpha_{yt}\, t + \alpha_{yy}\, ln\,(production_{it}) + \alpha_{1y}\, ln \left(\frac{capital_{it}}{labour_{it}}\right) \\ & + \alpha_{2y}\, ln \left(\frac{reserves_{it}}{labour_{it}}\right)\Bigg] + u_{it} + v_{it}.\end{aligned} \tag{5.10}$$

Several stochastic frontier models for panel data can be used to estimate Equation 5.10. We modify the original approach of Kumbhakar et al. (2012) by including variables assumed to directly influence the markup component. This is done by using the SFA model of Battese and Coelli (1995). Within this model, the markup term u_{it} in Equation 5.10 can be defined as:

$$u_{it} = z'_{it}\beta + W_{it}, \tag{5.11}$$

where z'_{it} is a vector of explanatory variables and W_{it} is a random component. The model can be estimated in a single stage by maximum likelihood techniques in which the stochastic term is assumed to follow a normal distribution $v_{it} \sim iidN(0, \sigma_v^2)$ and the markup term is assumed to follow a truncated normal distribution $u_{it} \sim N^+(z'_{it}\beta, \sigma_u^2)$.

Since only the composed error term $\epsilon_{it} = u_{it} + v_{it}$ is observed, the firm's markup is predicted by the conditional mean $\widehat{u}_{it} = E[u_{it}|\epsilon_{it}]$ (Jondrow et al., 1982).

Two specifications of the model are estimated. The first specification is the traditional Battese and Coelli (1995) model as presented above. The model has been used in a number of SFA applications with panel data. However, it is not a real panel data model but rather a pooled model that considers all observations as independent. Hence, the model may suffer from an unobserved heterogeneity bias that, in particular, may lead to an overestimation of markups. For this reason, we additionally estimate a second specification in which the traditional Battese and Coelli (1995) model is augmented by individual firm dummy variables as in Filippini and Wetzel (2014). These variables capture any time-invariant firm-specific unobserved heterogeneity and hence avoid the unobserved heterogeneity problem. However, a drawback of this specification is that any persistent firm-specific markups will also be attributed to the unobserved heterogeneity. Therefore, firm-specific markups may be underestimated.

In the following, we discuss the firm-specific and macroeconomic factors that are assumed to influence a firm's ability to exert markups. Altogether, six factors are explicitly included in the vector of explanatory variables z_{it} in Equation 5.11: amount of reserves, FE grade of reserves, years of production, location, market share, a change in the pricing system and the year-on-year growth rate of the world GDP. Thereby, the first four of these factors, *ceteris paribus*, reduce short-run marginal costs, which typically leads to increasing markups. Hence, these factors may explain potential variations in markups across firms.

As stated by Tilton (2001), labour is an important factor in the mining industry. One-third to one-half of variable costs are related to labour. Furthermore, Tilton (2001) finds that labour productivity positively depends on the amount of reserves. He assumes that this relationship holds because the incentive to invest in new technology or in the latest equipment may be larger for a mine with a long expected lifetime. Hence, a mine with a large amount of reserves may be extracted more efficiently. Following this argument, we, first, expect a positive influence of the amount of reserves on the markups.

Moreover, a firm that owns reserves with high FE grades will be able to produce the same quality of iron ore at lower cost compared to a competitor with reserves of lower quality: Either the firm is able to extract a smaller amount of iron ore than the competitor to produce the same amount of iron ore in FE units, or the competitor may need to further process the crude iron ore (e.g., by pelletising) to achieve the same quality of the firm's final product. Hellmer (1996) provides empirical evidence for this relationship as he finds a negative relationship between the FE grade and average cost for iron ore producers. Hence, second, a positive impact of the FE grade of reserves on the markups is expected.

Third, experience may serve as an advantage for firms operating in the iron ore market for a long time. This is particularly interesting for the period under observation as some firms have just recently entered the iron ore market. More experienced firms could have an advantage due to long lasting sales relationships and, therefore, more efficient sales divisions. Another aspect is the possible existence of individual learning effects: Learning by doing could lead to higher labour productivity. Furthermore, firms that are engaged in the iron ore production for a long time may have been able to secure better mining deposits than competitors that entered the market later.

Fourth, producers and customers are regionally dispersed. Therefore, advantages of one firm over another could result from a favourable geographical location of the main production area with respect to the main demand centers. Hobbs (1986) states that significant transportation costs and economies of scale can lead to spatial price discrimination or, in other words, to geographic market power. In all likelihood, this applies to the iron ore industry. As transportation costs depend to a large extent on the distance shipped, Australian producers should benefit from lower transportation costs to the main demand centers located in the close-by Asia-Pacific region (Galdon-Sanchez and Schmitz Jr, 2002). Hence, Australian producers may capture the freight cost differential to more distant suppliers and thus, generate higher markups (Smart, 2011). In order to capture this location factor, we include country dummies in our analysis.

Fifth, there is only a small number of active firms in the iron ore market (Sukagawa, 2010). In the economic literature, a positive correlation between industry concentration and profitability has been observed (Bain, 1951). However, there has been a debate over the causal direction. On the one hand, the structure-conduct-performance-paradigm states that high concentration facilitates collusion and, therefore, leads to the exercise of market power which is 'proxied' by high profitability of firms in a concentrated industry (Bain, 1951). On the other hand, this explanation may suffer from a reverse causality problem as the positive correlation could result from firms with higher efficiency levels growing faster and, consequently, expanding their market shares (Demsetz, 1973, Peltzman, 1977). Thus, while there is no consensus on the causal relationship, the firm's individual market share is a potential factor to explain different markups across firms. For our analysis, we define a firm's individual market share as the ratio of its own production to global production. A positive influence of the market share on markups is expected.

Furthermore, the change in the pricing system that occurred in 2010 is empirically analysed. The prices given in the long-term contracts consist of a (regional) benchmark price as a basis and a discount or premium contingent on quality, product group and transport distance (Hellmer and Ekstrand, 2013). In the past, the benchmark price was determined annually by so-called 'champion negotiations' (Sukagawa, 2010, p.56), in which the largest producers and largest buyers engaged in 'a form of an oligopoly-oligopsony negotiation' (Wilson, 2012). This pricing procedure, however, changed in the beginning of 2010 when the top three producers enforced a transition from annual price negotiations to a quarterly revised index price system based on spot market prices (Wilson, 2012). Warell (2014) found no significant impact of this change on iron ore prices. Nonetheless, we include a dummy variable equal to one for the years with the new pricing system and zero otherwise to control for possible effects of the changing price mechanism.

Finally, the year-on-year change in the world's real GDP (IMF, 2014) is included in order to analyse the impact of general economic conditions during the sample period. A positive growth of the world's real GDP should be accompanied by a surging demand for iron ore. In this case, a tighter market could make it easier for producers to generate higher markups.

Summary statistics for the markup variables are presented in Table 5.3. As for the frontier variables, the descriptive statistics show significant variance regarding all variables. Reserves and years of production, in particular, differ significantly among producers.

Tabelle 5.3: Summary statistics: Markup variables

Variable	Mean	Median	Std. Dev.	Min	Max
Reserves [million tons]	2,486.43	1,223.46	3,620.46	39.57	17,538.22
Years of production	81.23	69.50	51.25	1.00	162.00
FE grade of reserves	0.49	0.56	0.14	0.26	0.70
Market share	0.05	0.02	0.05	0.00	0.17
GDP change	3.62	3.94	1.69	-0.38	5.35

5.4 Results

This section comprises the results from the empirical analysis and is divided into two parts. The first subsection presents the results of the frontier estimation and the firm- and time-specific estimates for the Lerner index. In the second subsection, the influence of the outlined firm-specific and environmental factors on markups are illustrated.

5.4.1 Lerner indices of iron ore producers

As outlined in Section 5.2 and Section 5.3.2, the firm- and time-specific Lerner indices can be derived from the estimation results of the stochastic frontier model defined in

Equation 5.10. Two specifications of the model are estimated: one encompassing individual firm fixed effects (BC95 FE) and one without (BC95). The estimated model is a semi-log or level-log model in which all independent variables are normalised by their sample median. Furthermore, Equation 5.10 without the error terms is an expression for cost elasticity with respect to output, i.e., the relative change in cost given a relative change in output. This means that the estimated coefficients represent the absolute change in cost elasticity for a one-percent change in the respective variables evaluated at the sample median.

TABELLE 5.4: Estimation results[a,b,c,d]

Variable	Parameter	OLS	OLS ID	BC95	BC95 FE
Ln(production)	α_{yy}	0.151***	0.201	0.451***	0.460***
		(0.044)	(0.160)	(0.104)	(0.068)
Ln(capital/labour)	α_{y1}	0.114*	−0.218**	−0.198**	−0.247***
		(0.065)	(0.108)	(0.081)	(0.050)
Ln(reserves/labour)	α_{y2}	−0.083	−0.211***	−0.110**	−0.092***
		(0.068)	(0.073)	(0.049)	(0.029)
Time	α_{yt}	0.056***	0.061***	0.007	−0.035***
		(0.010)	(0.018)	(0.006)	(0.012)
Constant	α_y	1.885***	1.596**	0.877***	−0.011
		(0.048)	(0.621)	(0.123)	(0.012)
Fixed effects		No	Yes	No	Yes
Log-likelihood		−52.756	−8.878	0.763	28.782
σ_u				0.304***	0.299***
σ_v				0.076***	0.083***
λ				3.979***	3.621***
No. of observations		96	96	96	96

[a] Standard errors are in parentheses.
[b] *, **, *** indicate significance at the 10, 5 and 1% level, respectively.
[c] Estimates for the fixed effects coefficients are available from the authors upon request.
[d] All estimations have been performed in R using the “frontierpackage by Coelli et al. (2013).

In addition to our stochastic frontier model, we also estimate a conventional ordinary least squares (OLS) model for the two specifications. Using likelihood ratio (LR) tests, we evaluate whether a markup component exists at all. The LR tests have the null hypothesis: $\lambda = 0$ with $\lambda = \sigma_u/\sigma_v$ (Coelli et al., 2005). For both specifications, the null hypotheses that the OLS model is sufficient can be rejected at any conventional level of significance. Hence, the stochastic frontier model is preferred.

All coefficients in the stochastic frontier models except the ones for the linear time trend in the BC95 specification and the constant in the BC95 FE specification are statistically significant at least at the five percent level. However, the magnitude of the coefficients varies significantly between the two specifications. This indicates the existence of an unobserved heterogeneity bias in the BC95 specification without fixed effects. In fact, applying an additional LR test to choose between the BC95 and the BC95 FE specification indicates that as a group the firm dummy variables are statistically significantly different from zero. Hence, the BC95 FE is found to be the appropriate specification and is discussed more thoroughly in the following. Nevertheless, the specification without fixed effects is presented for comparison reasons.

Unfortunately, a limited number of the cost elasticity estimates yield negative values. This result is not consistent with economic theory since a well behaved cost function is required to be non-decreasing in outputs. Negative cost elasticity estimates are observed for five observations in the BC95 and seven observations in the BC95 FE specification. Four of the observations within the BC95 specification belong to Mount Gibson and one to Atlas Iron. The seven observations in the BC95 FE specification belong to BHP Billiton. Given this anomaly, the respective observations are excluded from the following analysis of the Lerner indices.[57]

The summary statistics of the Lerner index estimates are presented in Table 5.5. The estimates are derived from the estimation results of the two stochastic frontier specifications as outlined in Equation 5.9. The two specifications provide a range of possible values. The estimates from the BC95 specification are most likely upward-biased and hence may be considered as an upper bound. In contrast, the more reliable BC95 FE specification provides relatively conservative estimates. Any time-persistent markup components are captured by the fixed effects and hence are excluded from the Lerner index estimates.

Tabelle 5.5: Summary statistics of the estimated Lerner indices

Model	Mean	Median	Std. Dev.	Min	Max
BC95	0.38	0.43	0.25	0.02	0.99
BC95 FE	0.20	0.12	0.21	0.01	0.75

The BC95 specification shows a high mean value for the Lerner index estimates of 0.38. In the specification with fixed effects, the estimates are considerably lower with a mean of 0.20 and a median of 0.12. This means that half of the observations in the sample do not achieve a Lerner index of more than 0.12. It also hints at some firms having very large Lerner indices, which is consistent with the high maximum value of 0.75 compared to the mean or median.[58]

[57] In case of BHP Billiton the estimated negative cost elasticities are in all likelihood due to the fact that we had to approximate the capital variable. Data on capital was only available on the total company level but not on the iron ore business segment level. Therefore, we used two alternative approximation approaches based on asset and revenue shares to proxy the capital variable. The estimation results for the two approaches do not differ significantly. Furthermore, all models were also estimated without the respective observations. The estimated coefficients are very similar to the coefficients presented in Table 5.4 and all cost elasticity estimates show positive values as required by economic theory. Therefore, in order to have more degrees of freedom, we opted to leave all observations in the frontier estimation and exclude the ones with negative cost elasticity estimates from the second-stage Lerner indices analysis. All estimation results are available from the authors upon request.

[58] Given the differing magnitude between the two model specifications, the overall correlation of Lerner indices across specifications should be examined. The calculated Pearson correlation coefficient of 0.38 illustrates only a moderate correlation of Lerner indices across both specifications. This further stresses the importance of considering unobserved heterogeneity in the analysis.

The second important finding that can be concluded from Table 5.5 is the wide range between the minimum and maximum values of the time- and firm-specific Lerner indices. This suggests that the firms' individual abilities to generate markups differs considerably, also across time. A graphical representation of the development of Lerner indices over time and the differences across firms is given in Figure 5.2.

The figures shed light on the degree of competition in the iron ore market. Whereas a mean value of 0.38 is a rather high value, it is difficult to conclude whether a mean value of 0.20 indicates serious competition issues in the iron ore market or not. To facilitate interpretation, we compare our figures with those obtained by Kumbhakar et al. (2012), Coccorese (2014) and Bairagi and Azzam (2014) who use the same methodological approach. Although these two do not deal with the iron ore market, a comparison may help to conclude whether our estimates are low or high, relatively speaking. In the analysis by Kumbhakar et al. (2012), the mean values of the Lerner index vary among specifications between 0.07 and 0.10 and can therefore be considered as relatively low. Nevertheless, Kumbhakar et al. (2012) state that the Norwegian sawmilling firms, which were under investigation in their analysis, exercised some market power. Coccorese (2014) estimates Lerner indices of banks in various countries with an overall mean of 0.15 and a maximum mean in one country of 0.54. Bairagi and Azzam (2014) find a rather low Lerner index of 0.03 for the Grameen Bank. The results presented here are therefore more in the range of Coccorese (2014) and, hence, seem to be relatively high. Regarding the mean value, a potential caveat is that no firms from China and India are present in the sample. We would expect that especially Chinese firms operating in rather high cost mines would have smaller values of the Lerner index. This would lead to lower mean values compared to our sample of iron ore firms.

Interestingly, the second-highest Lerner index in the fixed effects specification belongs to the Swedish producer LKAB, which is considered to incur rather high production costs.[59] This provides some indication that the different values of estimated Lerner indices might not solely reflect cost differences among firms. It is in line with Hellmer and Ekstrand (2013) who state that producers in the USA and Sweden may have been able to generate economic rents during the recent rapid iron ore demand expansion as those companies were not able to raise production but nevertheless benefited from higher prices. The average annual growth rate of production over the period 2000 to 2012 is 1.8 percent for LKAB, whereas it is, e.g., 7.6 percent for VALE.[60] Therefore, the hypothesis may be supported in the case of LKAB.[61]

[59]LKAB is the only company (with large scale operations) that is engaged in underground mining, which is associated with higher costs than production in open pit operations (Hellmer, 1996).

[60]Note that these figures are calculated in FE units in order to allow for comparison.

[61]The main producer in the USA, Cliffs Natural Resources, however, does not seem to follow this hypothesis. Its average annual growth rate of production over the period 2000 to 2012 amounts to 10.3

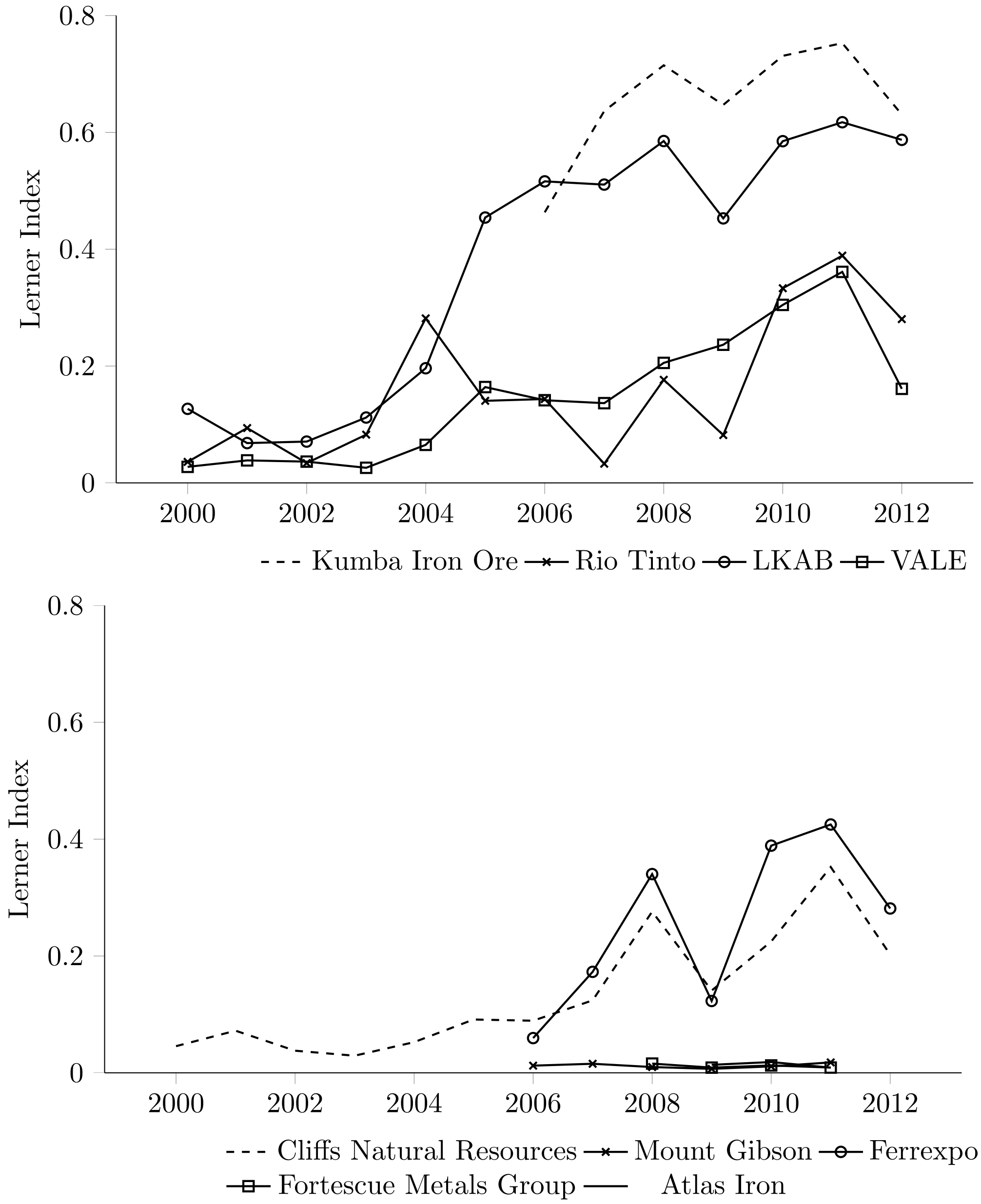

Abbildung 5.2: Firm-specific Lerner index estimates from the BC95 FE specification

Furthermore, LKAB's high values may be explained by their high quality pellets, favourable geological conditions and their strong focus on Europe as a sales market.[62] In supplying this market, LKAB does not incur high transportation costs, in contrast to, e.g., VALE whose production is located mainly in Brazil. Given the demand increase in China starting in the early 2000's and the price correlation between the European and Asia-Pacific markets, LKAB probably benefited from the price increase in the European

percent and is therefore even larger than the rate for VALE. The time-varying Lerner indices, however, remain rather flat.

[62]Hence, LKAB's cost disadvantage may be outweighed by lower pelletising costs due to a high magnetite fraction in the deposit (Hellmer, 1996).

market. This development is in line with the increase in its Lerner index from 2003 onwards.

5.4.2 Influence of firm-specific and environmental characteristics

The firm-specific and environmental characteristics assumed to influence a firm's ability to exert markups have been discussed in Section 5.3.2. Given these characteristics, Equation 5.11 in Section 5.3.2 can be explicitly written as:

$$\begin{aligned} u_{it} = &\beta_0 + \beta_1\, ln(\text{FE grade of reserves}_{it}) + \beta_2\, ln(\text{reserves in ton}_{it}) \\ &+ \beta_3 \,\text{years of production}_{it} + \beta_4 \,\text{market share}_{it} + \beta_5 \,\text{price system change}_t \\ &+ \beta_6 \,\text{GDP change}_t + \sum_{j=6}^{10} \beta_j \,\text{country}_j + W_{it}. \end{aligned} \tag{5.12}$$

The estimated coefficients are presented in Table 5.6. Among the first six evaluated firm-specific and macroeconomic factors, a statistically significant impact on the markup component is only observed for years of production and GDP change. Years of production is the proxy variable for experience. As expected, the respective coefficient in both specifications is positive and statistically significant at the 1% level. This is in line with the hypothesis formulated in Section 5.3.2 and hints at the existence of possible learning effects in production or in the marketing and sales division for iron ore producers.

The sixth factor, location, is evaluated by five country dummy variables: USA (Cliffs Natural Resources), Ukraine (Ferrexpo), South Africa (Kumba Iron Ore), Sweden (LKAB) and Brazil (VALE).[63] The reference group is Australia (Rio Tinto, Mount Gibson, Fortescue Metals Group, Atlas Iron). With all other things being equal, it is expected that companies operating mainly in Australia are able to enjoy a higher markup because of lower transportation costs, resulting from its geographical proximity to the main demand areas. As expected, all coefficients are negative and, with the exception of the one for Ukraine, also statistically significant at least at the 5% level in the fixed effects specification.

The results given in Table 5.6 hint at the direction and significance of markup influencing factors. However, the magnitude of the coefficients is difficult to interpret. Therefore, marginal effects of the factors influencing the Lerner index are calculated. In order to analyse to what extent a small change in factor z_l leads to an absolute change in the

[63]Note that this specification is not equivalent to individual fixed effects in the markup term, although each country is represented by one firm only. In contrast to individual fixed effects the reference group consists of a set of firms sharing the same characteristic (i.e., production in Australia) instead of one individual firm as in the fixed effects specification.

TABELLE 5.6: Markup component - influencing variables[a,b]

Variable	Parameter	BC95		BC95 FE	
Ln(FE grade of reserves)	β_1	1.001	(1.316)	-1.010	(1.718)
Ln(reserves in ton)	β_2	-0.143^{*}	(0.078)	0.061	(0.231)
Years of production	β_3	0.006^{***}	(0.002)	0.143^{***}	(0.054)
Market share	β_4	-0.046^{**}	(0.069)	-0.127	(0.179)
Price system change	β_5	0.455^{***}	(0.104)	-0.050	(0.240)
Change GDP	β_6	0.000	(0.023)	0.066^{*}	(0.040)
Constant	β_0	1.307^{***}	(0.320)	5.109^{***}	(1.639)
Country dummies (Reference: Australia)					
USA	β_7	-1.731^{*}	(0.970)	-18.346^{***}	(6.521)
Ukraine	β_8	0.492	(0.827)	-2.130^{*}	(1.282)
South Africa	β_9	-0.222	(0.218)	-4.385^{***}	(1.619)
Sweden	β_{10}	-0.810^{**}	(0.328)	-11.271^{***}	(4.139)
Brazil	β_{11}	-0.755^{**}	(0.329)	-3.538^{**}	(1.510)

[a]Standard errors in parentheses.
[b]*, **, *** indicate significance at the 10, 5 and 1% level, respectively.

Lerner index (LI), the partial derivative of the Lerner index defined in Equation 5.9 with respect to z_l has to be derived:[64]

$$\begin{aligned}\frac{\partial LI}{\partial z_l} &= \frac{1}{E_{CY}}\frac{\partial u}{\partial z_l}\left(1+\frac{u}{E_{CY}}\right)^{-1} - \frac{u}{E_{CY}}\left(1+\frac{u}{E_{CY}}\right)^{-2}\frac{1}{E_{CY}}\frac{\partial u}{\partial z_l} \\ &= \frac{1}{E_{CY}}\frac{\partial u}{\partial z_l}\left(1+\frac{u}{E_{CY}}\right)^{-1}\left[1-\frac{u}{E_{CY}}\left(1+\frac{u}{E_{CY}}\right)^{-1}\right] \\ &= \frac{\frac{1}{E_{CY}}\frac{\partial u}{\partial z_l}}{1+\frac{u}{E_{CY}}}(1-LI)\end{aligned} \tag{5.13}$$

Since u and E_{CY} are positive and LI is between zero and one, the sign of the marginal effect depends only on the sign of $\partial u/\partial z_l$, i.e., the partial derivative of u with respect to the l-th z variable. While the variables in this expression only have to be replaced by their empirical counterparts ($\widehat{u}$, $\widehat{E_{CY}}$ and $\widehat{LI}$), an expression for $\partial u/\partial z_l$ is needed. Two suggestions are made in the literature: Wang (2002) derives an expression based on the unconditional expectation $E(u)$, whereas, more recently, Kumbhakar and Sun (2013) develop an expression based on the conditional expectation $E(u|\epsilon)$. The latter argue that their formulation is methodologically more coherent since the conditional expectation is already used to predict the markup component u (refer to Section 5.3.2). Following this argument, Table 5.7 displays the average marginal effects computed via the approach by Kumbhakar and Sun (2013).[65]

[64]Time and firm indices are dropped for notational convenience.
[65]As the marginal effects in the model without fixed effects (BC95) are negligible, we do not discuss them in the following. The results are available from the authors upon request.

Tabelle 5.7: Average marginal effects[a]

Variable	BC95 FE	Variable	BC95 FE
Ln(FE grade of reserves)	-0.019	USA***	-0.351
Ln(reserves in ton)	0.001	Ukraine*	-0.041
Years of production***	0.003	South Africa***	-0.084
Market share	-0.003	Sweden***	-0.215
Price system change	-0.001	Brazil***	-0.068
GDP Change*	0.001		

[a] *, **, *** indicate significance at the 10, 5 and 1% level, respectively.

Concerning years of production, the average marginal effect indicates that on average one additional year of production increases the median firm's Lerner index by 0.003, holding all other variables fixed. Against the background that the mean value of years of production in the sample is 78, one may conclude that the years of production is the single most important determinant for the ability of iron ore producers to exercise market power. Yet, caution must prevail by interpreting the years of production as a proxy for experience. An alternative explanation of our finding may be that more profitable firms, i.e., firms with higher markups, stay in the market for a longer time. However, we do not observe firms leaving the market in our sample and therefore cannot relate the markup level to market exit. Given that labour productivity is an important determinant of marginal production costs, firms that have a long history in iron ore mining should profit from their experienced miners. Hence, we tend to argue that the increase in the Lerner index for every additional production year is also an indication of experience effects. Nevertheless, we are not able to unambiguously disentangle the two interpretations.

Turning now to the country dummies, one has to keep in mind that Australia is used as the reference point. Hence, the calculated effects represent one-off shifts in the Lerner index compared to Australia rather than the marginal effects. The largest significant negative shift is observed for the USA (-0.351) and the smallest for Ukraine (-0.041). The second largest is exhibited by Sweden (-0.215). Given that Cliffs Natural Resources (USA), VALE (Brazil) and LKAB (Sweden) all have comparably long shipping distances to the main demand areas in the Asia-Pacific region, the differences in the values are considerably large. In particular, at first view, the relatively low negative value for VALE (Brazil) is surprising. As Kumba Iron Ore (South Africa) has the shortest distance to the Asia-Pacific region after Australia, one would expect the country dummy for South Africa to indicate the lowest negative shift. Instead, the negative shift of Kumba Iron Ore (South Africa) is 0.016 higher than that of VALE (Brazil). This result suggests that distance is only one determinant of transportation costs.

According to Heij and Knapp (2014), vessels for iron ore are mainly of 'capesize' (60-100 thousand deadweight tonnes (DWT)) and 'panamax size' ($\geq$ 100 thousand DWT)[66]. However, there are significant differences among producers. In particular, VALE owns its own fleet of ships and is known to have one of the largest ship sizes named after the company ('valemax size' with a size of 380-400 thousand DWT). Since VALE uses larger ships than its Australian counterparts, the difference in (shipping) transportation costs between VALE and Australian companies has traditionally been smaller than the difference in distances would suggest (Sukagawa, 2010). Furthermore, in relation to Kumba Iron Ore (South Africa), our results suggest that VALE's transportation cost advantage due to the usage of its own and larger ships even outweighs the disadvantage of the larger shipping distance to the Asia-Pacific demand centers. The country dummies could in principle reflect other country specific heterogeneity but we believe that most differences among countries will result from transport costs. Altogether, our results hint at other factors such as size and control of the fleet being important factors for the firm-specific transportation cost level in addition to distance and, hence, for the individual ability of firms to generate markups.

Finally, the third factor found to have a significant influence on the firms' Lerner index is annual growth in the world's real GDP, with, ceteris paribus, an additional percentage point of GDP growth resulting in an increase of the median firm's Lerner index by 0.001. An explanation for this results may be that high economic growth drives iron ore demand, which reduces the price elasticity of demand and, consequently, strengthens the position of the suppliers in the market. However, given that the median annual GDP growth rate in the period from 1993 to 2012 amounted to 3.9%, the importance of GDP growth in determining the level of the Lerner indices is found to be rather small.

5.5 Discussion

The objective of this study was to analyse the potentially non-competitive behaviour of iron ore producers during the past decade. For this purpose, Lerner indices for ten iron ore producing companies during the period 1993-2012 were estimated using an innovative SFA approach introduced by Kumbhakar et al. (2012). The approach was further extended by using a model framework that allows to analyse the (potential) influence of firm-specific and macroeconomic characteristics on firm-specific markups.

The conjecture that iron ore producers exercise market power is supported by the empirical results. The estimated Lerner indices are significantly different from zero and indicate that the markups on average amount to 20% of the price. However, producer's individual ability to charge a markup varies considerably, also across time. On the firm

[66]This definition is used by Heij and Knapp (2014) and stems from the ship broker Braemar Seascope.

level, we find evidence that experience and geographical location of the main production area are the most important factors that influence firm-specific markups. Distance to the main demand areas, however, seems not to be the only factor that determines whether a firm benefits from its production region. For example, although Brazil is further away from the main demand centers in the Asia-Pacific region than South Africa, producing in Brazil has a weaker decreasing influence on markups than producing in South Africa, both compared to Australia. This may be due to different shipping costs among producers, with some, in particular VALE in Brazil, even controlling their own fleets with extremely large bulk carriers.

Although Lerner index estimations are frequently used in the economic literature to measure the degree of (non-)competitive behaviour, the level of the estimates must be treated with caution: Whereas a low level of an estimated Lerner index can be interpreted as the absence of market power (Elzinga and Mills, 2011), finding a high Lerner index does not necessarily translate into evidence for the exercise of market power. Economies of scale, the need to recover fixed cost or scarcity prices due to demand peaks may also be captured in the estimates. Consequently, although we do find empirical evidence for increasing markups over time, in particular beginning with the early years of the century's first decade, i.e., from 2004 onwards, this indicates only an increase in market power under the assumption that capital costs of investment projects did not increase significantly.

Summing up, our research shows that the innovative approach for measuring market power introduced by Kumbhakar et al. (2012) and utilised in this study can provide valuable insights into the competitive environment of markets that are prone to the exercise of market power. In particular, the possibility of analysing factors that most likely influence firm-specific markups is promising for applications to other markets, e.g., the electricity, pharmaceuticals or telecommunications market. In doing so, one may be interested in comparing the importance of the similar characteristics across different markets. Furthermore, because of the relatively low data requirements, the utilised approach may pose a valuable tool for political and legal institutions interested in (empirically) assessing the abuse of market power by firms. Yet, as pointed out in the previous paragraph the estimation of the Lerner index needs to be accompanied by further analyses putting the estimated values in perspective, e.g., by relating it to the level and the development of fixed costs.

Kapitel 6

Intertemporal and interregional price formation in thermal coal markets

6.1 Introduction

Coal[67] is the second most important primary energy in the world. In 2012, global coal consumption amounted to 3 773 Million tonnes of oil equivalent (Mtoe) or around 30% of total primary energy consumption (BP P.L.C., 2013). With around 80%, thermal coal accounts for the bulk share of global coal demand and has been the driver of the pronounced increase in global coal demand in the first decade of this century, with an average annual growth rate of +4.5% (compared to, e.g., a mere +1.2% for oil (IEA, 2013a)). Despite the longstanding and still growing importance of coal as a source of energy, international trade of and financial markets for thermal coal are still in their infancy when compared with other energy sources, particularly oil.

A distinct feature of the international coal market is that most trade, which is physically settled, is done on a bilateral level via over-the-counter (OTC) trades and no stock exchanges that allow the trade of standardised spot products exist. As a consequence, information on spot prices for thermal coal are published in form of indices, the so-called Argus McCloskey price indices (API), with the index of the Northwestern European import price (API 2) and the South African export price (API 4) being the most

[67]Although there are many different classifications of coal, coal can broadly be subdivided into two categories, brown and hard coal. Brown coal is younger than hard coal and, thus, has a lower calorific value than hard coal as it contains more water. With respect to hard coal, one can further distinguish between thermal coal and metallurgical coal. While the former is used to generate electricity and is the type of coal this paper deals with, metallurgical coal is used in steelmaking.

prominent ones. Coal derivatives that are financially settled against the various APIs started to emerge only in the late 1990's (Schernikau, 2010). Spurred, among others, by the pronounced gain in price levels, trade volumes of financial derivatives have increased significantly in the first decade of the 21st century. Yet, liquidity at the various exchanges remains low, particularly when compared with the liquidity of oil products such as Brent. The annual churn rate, defined as the ratio of trade volume to physical delivery and often used as a measure of liquidity, of all API 2 and API 4 derivatives, by far the most traded ones, amounted to around 10 and 5, respectively, in the first three years of this decade (IEA, 2013b).

We are interested in better understanding the process of price formation in such an environment. Using daily spot and front-month futures prices for two of the most important trading hubs in the international thermal coal market (Northwest Europe and South Africa), we analyse price formation in an intertemporal – the causal relationship between spot and futures prices at each hub – and an interregional context – the causal relationship between the two regional disperse markets, separately for spot and futures prices. More specifically, we address two questions both in the interregional and the intertemporal context, which are both answered using tools from time series econometrics.

In order to assess whether a long-run equilibrium relationship exists between the respective time series, we apply the concept of cointegration after having tested the time series for stationarity. In the intertemporal context, the finding of such a long-run equilibrium means that futures prices are a valid hedge for spot prices and, hence, can be used to hedge short-term price risks. In the interregional context, one can either examine the relationship of different exchanges trading the same product or the interaction of geographically disperse markets (market integration). In the paper at hand, we are interested in the latter aspect when posing the question as to whether the prices of two of the most important trading points in the Atlantic thermal coal market, Northwest Europe and South Africa, are integrated. Knowing that export prices plus transport costs have been higher than import prices in the past for this trading route, the law of one price seems to be violated, which calls the long-run relationship between these two important markets into question. Hence, the finding of cointegration would allow for the conclusion that the respective markets are integrated despite the law of one price being violated.

Second, we check whether price discovery, i.e., the processing of new information, predominantly takes place in one market. Thereby, we analyse both linear price discovery, i.e., do price changes in one market help to explain the price changes in the other market, and nonlinear price discovery, i.e., the causal relationship of the two price series' second or higher moments. While in the interregional context, we expect the market with higher liquidity and physical trade volume, i.e., the Northwest European market, to take the dominant position, several argument exist supporting the idea that price discovery takes place in the futures market rather than in the spot market.[68] Three reasons, in particular, exist in support of this notion (Silvapulle and Moosa, 1999): i) Transaction costs are lower in the futures market, e.g., it is easier to short sell contracts, which should attract market participants with private information. ii) Speculators tend to be active only in the futures markets, since they have no interest in the physical possession of the good. iii) If a market participant is interested in hedging a storable good but faces a binding storage constraint, he will become active in the futures market. If one or more of these arguments hold true and, thus, price discovery takes place in the futures market, the existence of these markets not only helps to hedge price risks but also helps to achieve an efficient allocation of resources.

Price discovery is investigated by analysing the lead-lag relationship between the respective price series (Tse, 1999). In order to assess the lead-lag relationship in the intertemporal and interregional context, we check for linear Granger causality (Granger, 1969). If the time series are cointegrated, causality testing should be conducted in a vector error correction mechanism (VECM) environment (Chen and Wuh Lin, 2004). As all pairs of time series investigated in this paper are cointegrated, the linear causality tests are applied to the residuals of the VECM.

Information flow between two markets, however, is not limited to changes in price levels but may also take place in higher moments, e.g., through volatility spillovers (Chan et al., 1991). Reasons for nonlinearities in the causal relationship between two time series are nonlinearities in transaction costs (Bekiros and Diks, 2008, Chen and Wuh Lin, 2004), differences in market participants including their heterogenous expectations (Arouri et al., 2013) and cross-market hedging activities (Engle et al., 1990). Similar to linear causality testing, a market may be characterised as being dominant if, for example, its lagged volatilty helps explain the other market's volatility, i.e., if cross-volatility spillovers can be detected (see Chan et al. (1991) and the literature cited therein). Furthermore, knowing whether the relationship between two price series is nonlinear may help creating more sophisticated price forecasting concepts that can be used for trading purposes, in particular, if the exact nature of the nonlinear relationship is known.

In order to examine nonlinearities in the causal relationship of the various pairs of time series, the nonparametric test for nonlinear Granger causality developed by Diks and Panchenko (2006), hereafter referred to as DPT, is used. In addition to the linear causality tests, we also apply the DPT to the VECM residuals after having filtered out any existing volatility effects using multivariate general autoregressive conditional

[68] If markets were perfectly efficient, as advocated by Fama (1970) in form of the market efficiency hypothesis, intertemporal price discovery would take place simultaneously in both markets and, thus, no lead-lag-relationship between spot and futures markets should be detectable.

heteroscedasticity (MGARCH) models. This allows us to check for causality in higher moments than the second.[69] Furthermore, we investigate cross-volatility spillovers in detail by using the estimated MGARCH models.[70] In case the nonlinear causality is restricted to the second moment, both the MGARCH model and the DPT measure the same aspect but have different power, since the former is a parametric approach while the latter is a nonparametric approach (Francis et al., 2010). Therefore, the estimated MGARCH models are used to cross-check the results of the DPT.

In carrying out the analyses outlined above, we contribute to the literature in two ways. First, we add to the existing time series analyses of thermal coal markets, which, so far, focus only on the investigation of market integration (see, e.g., Papież and Śmiech (2013), Warell (2006), Zaklan et al. (2012)), by using data with a higher granularity and assessing interregional price formation between Europe and South Africa not only in the spot but also in the futures market. Second, we extend the scope of existing thermal coal market analyses by investigating interemporal price formation, which has been an active strand of research for other energy commodities such as oil and natural gas since Bopp and Sitzer (1987), with two of the most recent examples being Shrestha (2014) and Nick (2016).

Starting with the analysis of intertemporal price formation, the empirical results suggest a long-run relationship between the spot price and the front-month futures contract. Thus, futures price represent a valid instrument for hedging the price risk that a participant may be facing in the spot market. The linear Granger causality tests reveal a significant lead-lag relationship, with the futures price leading the spot market. This finding suggests that the market efficiency hypothesis does not hold in the thermal coal market, which is line with findings for other commodity markets such as the US (Dergiades et al., 2012) and the European gas market (Nick, 2016). Applying the DPT, we find no significant lead-lag-relationship, i.e., price discovery in higher moments generally takes place in both markets and is restricted to the second moment. Hence, despite the low liquidity of the futures markets no evidence of causality in higher moments can be detected. Using the estimated multivariate GARCH models, we find evidence of bi-directional cross-volatility spillovers between the spot and futures prices, thereby confirming the result of the DPT that there is a flow of information between the second moment of the European and South African spot and futures prices, with none of the markets being dominant.

[69]We use the so-called BEKK-GARCH model, which is named after the authors, Baba, Engle, Kraft and Kroner, who developed the approach (Baba et al., 1990).

[70]Because of the large number of parameters that would otherwise have to be estimated, a two-step procedure similar to the one used when performing the causality tests and already implemented by Bekaert and Harvey (1997), Tse (1999), Ng (2000) and Bekaert and Harvey (1997) has been applied in this study. In the first step, a VECM is estimated to obtain the residuals. In the second step, first stage residuals are used to estimate the volatility spillovers between spot and futures prices.

Turning to interregional price formation, we find evidence of a long-run relationship between Europe and South Africa both in spot and futures prices, despite the law of one price seemingly being violated. This finding supports previous analyses such as Zaklan et al. (2012). Results on price discovery show a mixed picture. While price discovery for spot prices takes places simultaneously in both markets, the European market leads South Africa in futures prices. In higher moments, the DPT indicates a one-directional nonlinear causality in spot prices, with Europe leading South Africa. However, taking into account the results of the more powerful MGARCH models, we conclude that for both pairs – spot and futures prices – there seems to be bi-directional nonlinear causality. After filtering out the multivariate GARCH effects, nonlinear causality disappears in the spot price time series. In futures prices, we find evidence of causality in the third and higher moments going from South Africa to Europe. This finding, however, may be explained by the fact that despite trying multiple MGARCH models other than the BEKK-model none of the models is able to capture all multivariate GARCH effects. Therefore, the nonlinear causality in higher moments may still be caused by the remaining GARCH effects.

The remainder of this paper is structured as follows. While Section 6.2 puts the presented research into context by reviewing past publications connected to the paper at hand, the used methodology is described in Section 6.3. Section 6.4 briefly describes the dataset used in this study, presents descriptive statistics and checks the various time series for their order of integration using different unit root tests. Section 6.5 is devoted to the presentation and discussion of the results. Thereby, Subsection 6.5.1, which focusses on the analysis of intertemporal price formation is dividided into three parts: In 6.5.1.1, we discuss the results of the tests for cointegration, 6.5.1.2 focuses on the results of the linear and nonlinear causality tests, whereas 6.5.1.3 deals with the volatility spillovers between spot and futures prices. While being organised in the same way as Subsection 6.5.1, Subsection 6.5.2 is concerned with the analysis of interregional price formation. Section 6.6 concludes.

6.2 Related literature

Empirical research on thermal coal markets may be distinguished into two main categories that differ in terms of applied methodology and aim of the analysis. First, a number of researchers starting with Kolstad and Abbey (1984) and, more recently, e.g., Haftendorn and Holz (2010), Paulus et al. (2011), Trüby and Paulus (2012) have devoted their efforts to finding evidence for the exercise of market power as well as trying to assess which market structure best characterises the actual market setting in the thermal coal market. To this end, partial equilibrium models that allow to simulate different market settings were developed and applied. Second, a variety of papers use methods of econometric time series analysis to scrutinise as to whether international trade of thermal coal, in particular, between the Atlantic (mainly Europe, South Africa as well as North and South America) and the Pacific market, may be characterised as being well integrated. These will be briefly discussed in the following.

Warell (2006) tests whether the international markets for metallurgical and thermal coal can be characterised as integrated global markets using quarterly European and Japanese import prices for both types of coal and the time period 1980 to 2000 as proxys for the Atlantic and the Pacific market. Focussing on thermal coal, the results suggest that the thermal coal market is integrated. Yet, when splitting up the dataset into two subsets (Q1 1980 to Q4 1989 and Q1 1990 to Q3 2000) no cointegration relationship was found. As mentioned by the authors, this finding may, however, also be due to the relatively few observations in each of the subsets. Li et al. (2010) investigates whether the international thermal coal market is one unified market and, more specifically, if the level of market integration changed over time by applying cointegration tests as well as a Kalman filter to various monthly export prices. The results suggest that during the time period between January 1995 and July 2007 the thermal coal market was generally integrated, with the Kalman filter showing a consistently high albeit varying degree of integration over time. Using a rich dataset of weekly thermal coal export and import prices as well as transport costs for the period from December 2001 until August 2009, Zaklan et al. (2012) concludes that the international market for thermal coal is integrated. However, they also find evidence that the integration is not complete yet, since differences in the speed of re-adjustment to the long-run equilibrium between the various transportation routes could be observed. Concerning the trade route from South Africa (Richards Bay, RB) to Europe (Amsterdam-Rotterdam-Antwerp, ARA), Zaklan et al. (2012) finds that the two markets are integrated. Additionally, it is the route that returns to its long-run equilibrium the quickest, which is plausible given the long history and commercialisation of the route. Papież and Śmiech (2013) test for Granger causality both in the mean and the variance using weekly prices from January 2001 to December 2011 by applying a two-step procedure suggested by Cheung and Ng (1996). In contrast to the previous two papers, they find that dependencies between the various import and export countries are the strongest within their respective markets, thus, indicating the existence of two separate markets, the Atlantic and the Pacific market that is. Interestingly, while finding a strong correlation between the simple and squared standardised ARA and RB residuals, they do not find Granger causality, neither in the mean nor in the variance between these two trading hubs.

Summing up, existing empirical research on thermal coal has neither payed attention to intertemporal price discovery nor has it extended the analysis of regional integration to futures prices or used data with a higher frequency than weeks, gaps this paper intends to close as outlined above. Thereby, the paper adds to the vast literature on price formation in energy markets that dates back to Bopp and Sitzer (1987). In order to not overdo the literature review, two recent and representative examples of articles that deal with intertemporal price discovery in the field of energy commodities shall be briefly discussed: Nick (2016), amongst other things, uses linear and nonlinear causality tests to analyse the process of price formation at three European gas hubs with differing levels of liquidity. The linear causality tests suggest that price discovery takes place in the futures market, whereas the nonlinear causality tests indicate a bilateral relationship, which is in almost all cases limited to the second moment. However, the exact nature of the causality in higher moments and volatility spillovers is not investigated. Shrestha (2014) empirically analyses the intertemporal price discovery process for crude oil, heating oil and natural gas not using Granger causality tests but two information share measures that are based on the methods proposed by Gonzalo and Granger (1995) and Lien and Shrestha (2014). The author finds that while almost all the price discovery takes place in the futures markets for heating oil and natural gas, price discovery for crude oil takes place simultaneously in the spot and the futures market.

6.3 Methodology

6.3.1 Causality testing

Granger causality (Granger, 1969) has proven to be a useful concept when investigating dependence relationships between two or more time series. As pointed out by Lütkepohl (2007), the basic idea of Granger causality is that a cause may never follow the effect. Hence, if variable x causes variable y, then including the information of past and current values of x should lead to an improvement in the forecast of y compared to a forecast that excludes all values of x.

Put more formally, consider two scalar-valued, stationary and ergodic time series $\{X_t\}$ and $\{Y_t\}$ and suppose that Ω_t contains all relevant information up to and including period t. Let $Y_t(h|\Omega_t)$ be the optimal, i.e., in this case the minimum mean-squared error (MSE) h-step predictor of the process Y_t in t based on the information in Ω_t. The process $\{X_t\}$ is said to *Granger-cause* $\{Y_t\}$ if

$$\sum\nolimits_Y(h|\Omega_t) < \sum\nolimits_Y(h|\Omega_t \backslash \{X_s|s \leq t\}) \qquad \text{for at least one } h = 1, 2, ... \tag{6.1}$$

with $\sum_Y(h|\Omega_t)$ denoting the forecast MSE and $\Omega_t\backslash\{X_s|s \leq t\}$ being the set that contains all relevant information except for the past and present information of the $\{X_t\}$ process (Lütkepohl, 2007). In practice, the information set Ω_t is often substituted by $\{X_s, Y_s|s \leq t\}$, i.e., only the past and present information of the investigated time series are taken into consideration. Furthermore, when testing for Granger causality most studies actually test for linear Granger causality, such that the linear minimum MSE h-step predictor is used.

Apart from linear causality, it may also be of interest to investigate nonlinearities in the causal relationship between two time series. Focussing on the relationship between spot and futures prices, the existence of nonlinearities is, for example, reasoned with nonlinearities in transaction costs or the presence of noise traders (Bekiros and Diks, 2008, Silvapulle and Moosa, 1999). In the market for thermal coal, which still lacks transparency, the argument that asymmetric information and heterogenous expectations of market participants can cause nonlinearities in the causal relationship between spot and futures prices – brought forward by Arouri et al. (2013) – may be a plausible explanation for the existence of nonlinearities in the causal relationships between spot and futures prices as well. Therefore, in this paper, the nonparametric test for general Granger causality developed by Diks and Panchenko (2006), which they also refer to as a test for nonlinear Granger causality, is applied. In deriving their test statistic, Diks and Panchenko (2006) use a more general definition of Granger causality such that they do not need to make any modelling assumptions as, for example, the use of a linear autoregressive model, when stating that $\{X_t\}$ is not a Granger cause of $\{Y_t\}$ if

$$Y_t(h|\{X_s, Y_s|s \leq t\} \sim Y_t(h|\{Y_s|s \leq t\}, \tag{6.2}$$

with $\sim$ denoting equivalence in distribution. Hence, Diks and Panchenko (2006) test the null hypothesis of no nonlinear Granger causality between two time series by comparing their conditional distributions, thereby following the widely-applied nonparametric nonlinear causality test proposed by Hiemstra and Jones (Hiemstra and Jones, 1994). Dropping the time index and defining $Z = Y_t$ with $t = s + 1$, it must hold under the null that X and Z are independent conditionally on the past realisations of Y. Caused by potential variations in the conditional distributions under the null hypothesis, the Hiemstra-Jones-test tends to over-reject if the null hypothesis of no causality is true (Diks and Panchenko, 2005). The Diks-Panchenko-test (DPT) corrects this bias by accounting for these potential variations.[71]

[71] Please refer to Appendix D.1 for more details on the methodology and the parametrisation of the test used in this paper.

6.3.2 Detecting volatility spillovers

Causality and volatility spillovers are closely linked phenomena, since both describe the process of information flow and relate to the informational efficiency of markets. In order to clarify the interplay of causality and volatility spillovers, it is helpful to distinguish two sorts of volatility spillovers, namely own- and cross-volatility spillovers, which both describe the diffusion of information in two different ways (Sehgal et al., 2013). Volatility spillovers, also named volatility clustering, are a well documented phenomenon that describes the observation of large (small) changes in prices being followed by large (small) changes in prices of either sign.[72] The arrival of new information and slow-moving information processing due to, e.g. trades with heterogenous information (Engle et al., 1990), are two reasons for volatility spillovers.

If the new information only affects the fundamentals in one market, it may cause conditional volatility to increase but only in the market influenced by the shock. This is commonly referred to as volatility persistence or own-volatility spillovers. If the news in one market, however, increases conditional volatility in another market, the literature refers to this phenomenon as cross-volatility spillovers. Hence, cross-volatility spillovers measure the effect lagged volatility in one market has on the current volatility in another market (Lin et al., 1994).[73] Consequently, the finding of cross-volatility spillovers should generally coincide with the finding of nonlinear causality.[74] In contrast to the nonparametric DPT, estimating cross-volatility spillovers via multivariate GARCH models is a parametric approach. Therefore, the two approaches used to assess nonlinear interplay between different time series complement each other perfectly because of their differences in power.

In order to asses own- and cross-volatility spillovers, we apply the so-called BEKK model, which is briefly discussed in the following. Assume a vector stochastic process $\{Z_t\}$ with dimension N x 1, let Θ denote a finite vector of parameters and write:

$$Z_t = \mu_t(\Theta) + \epsilon_t, \tag{6.3}$$

[72]Already Fama (1970) noted this phenomenon but stated with regard to its meaning for the market efficiency hyptothesis that its existence “being a denial of the randon walk model but not of the market efficiency hypothesis”.

[73]Cross-volatility spillovers are of practical importance when one is interested in determining the relative importance of different trading plattforms by assessing whether one is a dominant or rather a satellite trading platform (for an overview of empirical studies concerned with this topic see, e.g., Sehgal et al. (2013) and the literature cited therein).

[74]Chan et al. (1991) were the first to extend the analysis of intertemporal price discovery by investigating own- and cross-volatility spillovers, i.e., how the volatility of price changes interacts across the spot and futures markets, in addition to linear causality.

where $\mu_t(\Theta)$ is the conditional mean vector and

$$\epsilon_t = H^{1/2}(\Theta)w_t. \tag{6.4}$$

It is assumed that the random vector w_t is of the form N x 1 and that its first moment is $E(w_t) = 0$ and its second moment is $Var(w_t) = I_N$, where I_N is the identity matrix of order N. $H^{1/2}(\Theta)$ is a positive definite N x N matrix such that H_t is the conditional variance matrix for Z_t.[75] Different methods for specifying H_t exist in the literature. The BEKK model is part of a class of multivariate GARCH models that are derived by directly generalising the univariate GARCH model developed by Bollerslev (1986). The two most challenging tasks when generalising the univariate GARCH model are to cope with the high number of parameters that need to be estimated and to ensure that the conditional variance matrix H_t is positive definite. Engle and Kroner (1995) propose a parametrisation that diretly imposes positivity by defining

$$H_t = C'C + A'\epsilon_{t-1}\epsilon'_{t-1}A + B'H_{t-1}B, \tag{6.5}$$

where C, A and B are all NxN matrices but, in addition, C is upper-triangular. In the bivariate case, using a BEKK(1,1) the individual elements of the matrices A, B and C in Equaton 6.5 are:

$$A = \begin{bmatrix} a_{1,1} & a_{1,2} \\ a_{2,1} & a_{2,2} \end{bmatrix} \quad B = \begin{bmatrix} b_{1,1} & b_{1,2} \\ b_{2,1} & b_{2,2} \end{bmatrix} \quad C = \begin{bmatrix} c_{1,1} & c_{1,2} \\ & c_{2,2} \end{bmatrix}. \tag{6.6}$$

The off-diagonal elements of matrix A, i.e., $a_{1,2}$ and $a_{2,1}$ represent the short-term cross-volatility spillovers (ARCH effects), whereas the off-diagonal elements of matrix B, i.e., $b_{1,2}$ and $b_{2,1}$ represent the long-term cross-volatility spillovers (GARCH effects). The number of parameters to be estimated in a BEKK model, N, becomes large very fast as $N = N(5N + 1)/2$, which is why this type of multivariate GARCH model usually is used only when the number of time series does not exceed three.

6.4 Data sample, descriptive statistics and unit root tests

The dataset[76] used in this analysis consists of daily spot and front-month futures prices for two important trading hubs in the international thermal coal market, namely the

[75] See Bauwens et al. (2006) for a thorough overview of the different multivariate GARCH models as well as the interplay of H and $H^{1/2}$. Θ is left out in the following for convenience purposes.

[76] Daily spot prices were obtained from McCloskey, whereas futures prices were obtained from the Intercontinental Exchange.

import price at Amsterdam, Rotterdam and Antwerp (ARA)[77] and the export price at Richards Bay (RB) Coal Terminal[78] in South Africa for the time period April 2010 to February 2014. All in all, the data set includes 978 observations.

Tabelle 6.1: Descriptive statistics of ARA and RB spot and futures price returns

	Number of observations	Mean	Variance	Skewness	Kurtosis
Δ ARA Spot	977	$0.01e^{-5}$	$1.32e^{-4}$	0.33	5.14
Δ ARA M+1	977	$0.09e^{-4}$	$1.11e^{-4}$	0.47	5.04
Δ RB Spot	977	$1.17e^{-4}$	$1.12e^{-4}$	0.11	6.73
Δ RB M+1	977	$1.38e^{-4}$	$0.98e^{-4}$	0.11	5.37

Table 6.1 displays the descriptive statistics of the four first-differenced (marked by the Δ in front of the name of the time series) logarithmic time series, i.e., the descriptive statistics of the ARA and RB spot and futures price returns. Four aspects should be highlighted: First, the mean of all time series of price returns is close to zero.[79] Consequently, in case of the four time series presented in Table 6.1, there is neither a positive nor a negative expectation for the price returns. Second, the variance of the spot prices series is always larger than the variance of the futures time series, which is in line with the Samuelson hypothesis (Samuelson, 1965).[80] Third, all time series are right-skewed. Fourth, all time series exhibit excess kurtosis, i.e., have a higher probability of extreme values than if the time series were drawn from a normal distribution.

As a first step of our analysis of price formation, all time series are investigated as to whether they are stationary and if they are not stationary their order of integration is determined. In doing so, we use two different unit root tests, namely the Augmented Dickey Fuller (ADF) and the nonparametric Philipps-Perron (PP) test. Both test the H_0 of a unit root, i.e., nonstationarity of the time series. Table 6.2 displays the test statistics as well as the p-values for the ARA and RB spot and front-month time series in (log) levels and first differences (again marked by the Δ in front of the name of the time series). While the H_0 cannot be rejected for the time series in levels, the results for the first-differenced time series, i.e., the price returns, are the opposite. Hence, both tests indicate that the time series are intergrated of order one and are thus difference stationary.

[77]The ARA import price is a so-called CIF price, i.e., it includes cost, insurance and freight and, thus, represents the actual costs of an importer at one of the ARA ports.

[78]The Richards Bay export price is a so-called free-on-board (FOB) price, i.e., it includes the costs of bringing one tonne of thermal coal on board of a bulk carrier. Therefore, a FOB-price consists of the costs of production, inland transport as well as port handling costs and fees.

[79]When regressing the respective time series against a constant the coefficient of the constant was not statistically different from zero for any of the time series.

[80]The Samuelson hypothesis states that the shorter the time to maturity the larger the volatility of price returns.

TABELLE 6.2: Results of ADF and PP unit root tests

	t-statistic ADF		p-value	t-statistic PP		p-value
ARA Spot	−1.17		0.69	−1.23		0.66
ARA M+1	−1.16		0.70	−1.12		0.71
RB Spot	−0.93		0.78	−0.86		0.80
RB M+1	−0.91		0.78	−0.83		0.81
Δ ARA Spot	−26.86	***	0.00	−26.76	***	0.00
Δ ARA M+1	−22.90	***	0.00	−23.29	***	0.00
Δ RB Spot	−26.79	***	0.00	−26.84	***	0.00
Δ RB M+1	−23.43	***	0.00	−22.99	***	0.00

Notes: Denotes significance at the 99%-level (95%-level or 90%-level). The ADF and PP tests for the level price series were conducted with only a drift being included in the estimation equation since no trend was observed in the level-data. Neither a drift nor a trend were included when performing the tests for the return price series. The lag length included in the ADF test equation was selected based on the Schwarz Information Criteria (BIC). The bandwidth for the PP test was determined according to the Newey-West procedure using a Bartlett kernel. The p-values of the ADF and PP tests are one-sided MacKinnon (1996) p-values.

6.5 Empirical results

6.5.1 Intertemporal price formation

This section is devoted to the presentation of the results of the linear and nonlinear causality tests as well as the estimation of volatility spillovers between spot and front-month futures prices for two of the most important price benchmarks in the international thermal coal market. Thereby, we start out by testing for cointegration (Subsection 6.5.1.1). In a next step (Subsection 6.5.1.2), we, first, perform linear and, second, nonlinear causality tests with the latter being conducted with and without controlling for multivariate conditional heteroscedasticity. Finally, in Subsection 6.5.1.3, we investigate volatility spillovers between the spot and futures time series.

6.5.1.1 Cointegration

In 1987, Robert Engle and Clive Granger proposed the idea of cointegration (Engle and Granger, 1987). If two variables are integrated of order d, $I(d)$, and there exists a cointegration relationship between them, a linear combination of the two is integrated of order $d-1$. Thus, in case of two I(1)-variables, the linear combination is stationary. In this paper, the Johansen test (Johansen, 1988) is applied to check whether the spot and the front-month futures prices in Europe and South Africa (intertemporal) as well as the European and South African spot and the European and South African front-month futures prices (interregional) are cointegrated. Following Enders (2009), the Johansen test can be thought of as a multivariate generalisation of the Dickey-Fuller test. The number of cointegration relationships between a vector of n variables $\{Z_t\}$ may be identified by determining the rank of matrix π in:

$$\Delta Z_t = \pi Z_{t-1} + \sum_{i=1}^{p-1} \pi_i \Delta Z_{t-i} + e_t \tag{6.7}$$

with $\pi = -\left(I - \sum_{i=1}^{p} A_i\right)$. In case the rank of π is equal to zero, the matrix is null and Equation 6.7 is a simple vector autoregression (VAR) in first-differences. However, if rank(π) = 1 a single cointegrating vector exists and the expression ΔZ_{t-i} is the error-correction term.

The number of characteristic roots that are significantly different from zero can be tested using two different test statistics. Table 6.3 displays both the trace statistic and the maximum eigenvalue statistic of the Johansen cointegration test as well as their respective p-values. While the null hypothesis of no cointegration ($r = 0$) can be rejected on a 1%-level for both pairs of time series under consideration, this is not the case for the null of one cointegration relationship. Hence, both test statistics allow for the same conclusions that the two time series are cointegrated.

TABELLE 6.3: Results of the cointegration test - intertemporal price formation

	H_0-hypothesis	Trace statistic	p-value	Max. Eigenvalue statistic	p-value
ARA Spot & M+1	$r = 0$	25.92***	0.00	24.70***	0.00
	$r \leq 1$	1.22	0.27	1.22	0.27
RB Spot & M+1	$r = 0$	23.69***	0.00	23.46***	0.00
	$r \leq 1$	0.23	0.69	0.23	0.69

Note: *** (** or *) Denotes significance at the 99%-level (95%-level or 90%-level). The Johansen test was conducted using a specification without a linear trend, but we allowed for a constant. The lag length was chosen based on a majority decision using five different criteria, namely sequential likelihood ratio test, final prediction error, Akaike information - (AIC), Schwarz information - (BIC) and Hannan-Quinn information criterion. MacKinnon-Haug-Michelis p-values (MacKinnon et al., 1999) were used.

6.5.1.2 Causal relationship

In this subsection, the results of the applied causality tests are presented and discussed. Concentrating first on linear causality for the spot and the front-month futures, which is tested by applying the concept of linear Granger causality (see Subsection 6.3.1) within a VECM environment, we find that while the null hypothesis that the spot time series do not Granger-cause the futures time series cannot be rejected on typical significance levels, the null can be rejected on a 1%-level for the front-month futures. This finding suggests that futures price returns lead spot price returns and thus (intertemporal) price discovery in the thermal coal market first takes place in the futures market.

TABELLE 6.4: Results of the tests for linear and nonlinear causality - intertemporal price formation

Direction of causality	**Linear causality** χ^2-statistic (VECM residuals)	**Nonlinear causality** t-statistic (VECM residuals)	t-statistic (GARCH-filtered VECM residuals)
ARA Spot → ARA M+1	4.54	1.08	1.21
ARA Spot ← ARA M+1	214.91 ***	3.88***	0.06
RB Spot → RB M+1	4.37	2.09**	1.01
RB Spot ← RB M+1	214.89 ***	1.99**	−0.60

Notes: *** (** or *) Denotes significance at the 99%-level (95%-level or 90%-level). Linear Granger causality was investigated within the vector error correction model (VECM), thus explicitly accounting for the cointegration relationship of the variables. For the respective specification of the BEKK-model used to filter the residuals for multivariate GARCH effects refer to Subsection 6.5.1.3.

Among others Arouri et al. (2013) argue that asymmetric information and heterogenous expectations of market participants may be a plausible explanation for the existence of nonlinear causal relationships between spot and futures prices. Since the financial markets for thermal coal still lack transparency and high liquidity, this argument may apply to the thermal coal market and, thus, could explain the finding of nonlinear causality even after having filtered the time series for multivariate conditional heteroscedasticity. When applying the nonlinear causality test developed by Diks and Panchenko (2006) to the unfiltered VECM residuals, we find evidence of bi-directional nonlinear Granger causality for the RB time series. Concerning the ARA time series only nonlinear Granger causality going from the futures prices to the spot prices is found, with the test statistic for nonlinear causality in the other direction (form spot to futures prices) being very close to significance on a 10%-level. In this case, the result of the test is quite sensitive to the choice of the bandwith (see Appendix D.1), with a slight increase (of around 2%) of the bandwidth rendering the test statistic of the spot price significant.[81] In order to check whether this nonlinear Granger causality is limited to the second moment, we again apply the test of Diks and Panchenko (2006), however, this time after having filtered the time series for multivariate conditional heteroscedascticity. For all pairs of time series, no signs of nonlinear Granger causality were left after having filtered the time series for multivariate GARCH effects. Hence, nonlinear causality is limited to the second moment.

6.5.1.3 Volatility spillovers

The results of the analysis of volatility spillovers for the two pairs of spot and front-month futures are discussed in the following, with the estimated BEKK models being displayed

[81] Diks and Panchenko (2006) only provide indications or ranges for the values that should be used for the parameters C and β, which are needed to calculate the bandwidth of the DPT. The remaining results were found to be robust to changes in the bandwidth.

in Tables 6.5 and 6.6.[82] Different specifications of the BEKK-model are used in this subsection depending on which model was sufficient to capture all GARCH effects. Hence, if the multivariate ARCH-LM test (Engle, 1982) showed signs of remaining GARCH effects when using the BEKK(1,1) model, it was investigated whether a different model specification would improve upon this result.

TABELLE 6.5: Estimated multivariate GARCH model for ARA and ARA M+1

Variables	Coefficient	t-statistic
$a_{1,1}$	0.479	7.59***
$a_{1,2}$	0.170	2.29**
$a_{2,1}$	−0.281	−4.37 ***
$a_{2,2}$	0.137	2.73***
$b_{1,1}$	0.826	13.74***
$b_{1,2}$	−0.126	−1.76 *
$b_{2,1}$	0.151	2.40**
$b_{2,2}$	1.009	29.78***
Log likelihood	6720.86	

Notes: *** (** or *) Denotes significance at the 99%-level (95%-level or 90%-level). The multivariate GARCH models were estimated by quasi-maximum likelihood estimation using the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm. Standard errors robust to misspecification and heteroscedasticity were used (see Sadorsky, 2012).

Starting with the estimates for the ARA time series, four observations can be made: First, there is evidence of bi-directional cross-volatility spillovers both in the short ($a_{1,2}$ and $a_{2,1}$) and in the long term ($b_{1,2}$ and $b_{2,1}$). This is interesting as it confirms the finding of bi-directional nonlinear causality for the ARA spot and front-month futures, which was discussed in the previous subsection. Second, volatility persistence ($b_{1,1}$ and $b_{2,2}$) seems to be strong in both time series, with the absolute level of volatility persistence being higher in case of the futures price time series. Third, cross-volatility spillover seem to be stronger from futures to spot prices, both in short- and the long-term, which is consistent with the findings of the test for nonlinear causality. Fourth, own-volatility spillovers (volatility persistence) generally seem to be more pronounced than cross-volatility spillovers.

Next, we turn to the results of the estimation of the BEKK model for the RB spot and front-month futures time series displayed in Table 6.6. Since the BEKK(1,1)-model did not capture all GARCH effects (the multivariate ARCH-LM test showed that the H_0-hypothesis of no GARCH effects can be rejected on a 1%-significance level), we apply a BEKK(2,2) as this was the most parsimonious model able to capture all GARCH effects

[82]Only the estimates for the matrices A and B are show in the tables in this subsection, since the estimates of matrix C and of the mean model were, if statistically significant, generally were very small, i.e., 0.001 or smaller. However, the estimates are available from the author upon request.

TABELLE 6.6: Estimated multivariate GARCH model for RB and RB M+1

Variables	Coefficient	t-statistic
$a(1)_{1.1}$	0.469	2.57**
$a(1)_{1.2}$	−0.052	−0.32
$a(1)_{2.1}$	−0.479	−4.38 ***
$a(1)_{2.2}$	−0.133	−1.57
$a(2)_{1.1}$	0.105	1.00
$a(2)_{1.2}$	0.225	4.76***
$a(2)_{2.1}$	0.223	1.15
$a(2)_{2.2}$	0.138	1.23
$b(1)_{1.1}$	0.353	1.66*
$b(1)_{1.2}$	0.112	0.66
$b(1)_{2.1}$	0.119	0.46
$b(1)_{2.2}$	0.477	1.92*
$b(2)_{1.1}$	0.752	3.29***
$b(2)_{1.2}$	0.057	0.28
$b(2)_{2.1}$	0.025	0.08
$b(2)_{2.2}$	0.626	2.53**
Log likelihood	6894.62	

Notes: *** (** or *) Denotes significance at the 99%-level (95%-level or 90%-level). The multivariate GARCH models were estimated by quasi-maximum likelihood estimation using the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm. Standard errors robust to misspecification and heteroscedasticity were used (see Sadorsky, 2012).

as shown in Table 6.7. In comparison to the estimates for the ARA time series, one difference is notable. We do not find evidence of cross-volatility spillovers in the long term. Regarding the cross-volatility spillovers in the short term, current innovations seem to have a positive influence on the volatility in futures prices, whereas the opposite is true for innovations in futures prices, which have a negative influence on spot price volaility. The remaing three observations stated with respect to the results displayed in Table 6.5 hold true for the RB time series as well.

Finally, we present the results of diagnostic tests that check as to to whether any serial correlation and remaining GARCH effects in the standardised residuals can be found. We use the multivariate Ljung-Box Q-statistic to test the former aspect, whereas we apply the multivariate ARCH-LM test to assess the latter aspect. Neither evidence for serial correlation nor for remaining GARCH effects can be found on a 10%-significance level, as can be seen from Table 6.7.

TABELLE 6.7: Results of the diagnostic tests for the standardised residuals - intertemporal price formation

	Multivariate Ljung-Box	Multivariate ARCH-LM
ARA Spot & M+1	38.07	25.87
	0.56	0.10
RB Spot & M+1	27.70	44.79
	0.93	0.15

Notes: For each pair of time series the values in the first row are the respective test-statistics, whereas the second row displays the corresponding p-values. The chosen lag length m for the Ljung-Box Q-statistic is 10 since Tsay (2010) recommends to set $m = ln(N)$ or higher with N being the number of observations (here: $ln(974) \approx 7$). Concerning the Multivariate ARCH-LM test, it is recommended to set $m = P + Q$ in case of a GARCH-model, which is why in case of the ARA Spot & ARA M+1 time series $m = 2$ and in case of the RB Spot & RB M+1 time series $m = 4$.

6.5.2 Interregional price formation

This subsection is devoted to the discussion of our analysis of interregional price formation in the Atlantic thermal coal market. In particular, we assess price discovery between the South African export hub, Richards Bay Coal Terminal, and the Western European import hub, Amsterdam-Rotterdam-Antwerp. This trading route is of interest for two reasons: First, it is one of the most commercialised trading routes in the global thermal coal market. Second and more importantly, the relationship between those two coal trading points is a peculiar one, i.e., the two prices do not seem to follow the law of one price. Generally, the law of one price states that the price difference between two regions that trade with each other should equal transport costs. However, when taking a look at Figure 6.1[83] this is not the case for South Africa and Northwestern Europe as the price spread of the import price ARA minus transport costs[84] minus the export price RB has been negative for quite some time now, despite trade flows between these two hubs taking place. An observation that has been labelled the ARA-RB-paradoxon (Schernikau, 2010).

Despite various market integration analyses for the global thermal coal market and, more specifically, the Atlantic market (Papież and Śmiech, 2013, Zaklan et al., 2012), the following analyses enriches the existing literature as data with a higher granularity (daily data instead of weekly or even monthly price data) is used. Furthermore, thus far, interregional price discovery analyses focussed on spot prices, but due to different players being active in the respective marktes it may be interesting to see whether the pattern of price discovery is the same in spot and futures markets.

[83] Although the data displayed in Figure 6.1 is limited to 2011, the negative price spread between South Africa and Northwestern Europe has been existing prior to 2011 and continues to exist.

[84] Freight rates of Capesize vessels provided by McCloskey were used.

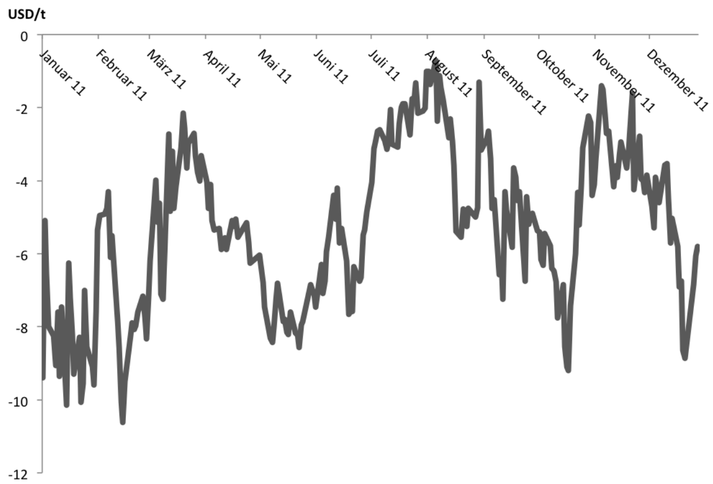

Abbildung 6.1: Development of the daily price spread between ARA and RB after accouting for transport costs in 2011

6.5.2.1 Cointegration

In order to check the process of price discovery between ARA and RB, we, first, need to check whether a long-run relationship between these two markets exists. Unfortunately, no complete set of daily transport data is available for the period under investigation.[85] Therefore, the cointegration relationship is tested without consideration of transport costs.

Tabelle 6.8: Results of the cointegration test - interregional price formation

	H_0-hypothesis	Trace statistic	p-value	Max. Eigenvalue statistic	p-value
ARA Spot & RB Spot	$r = 0$	19.33**	0.01	17.74**	0.01
	$r \leq 1$	1.58	0.21	1.58	0.21
ARA M+1 & RB M+1	$r = 0$	22.69***	0.00	21.35***	0.00
	$r \leq 1$	1.34	0.25	1.34	0.25

Note: *** (** or *) Denotes significance at the 99%-level (95%-level or 90%-level). The Johansen test was conducted using a specification without a linear trend, but we allowed for a constant. The lag length was chosen based on a majority decision using five different criteria, namely sequential likelihood ratio test, final prediction error, Akaike information - (AIC), Schwarz information - (BIC) and Hannan-Quinn information criterion. MacKinnon-Haug-Michelis p-values (MacKinnon et al., 1999) were used.

As shown in Table 6.8, the results of the Johansen test indicate that a cointegration relationship exists both for spot and front-month futures prices, which confirms the findings in Zaklan et al. (2012) albeit using data from a more recent time period and with higher granularity. However, while Zaklan et al. (2012) finds that freight rates play an important role in the long-run equilibrium relationship between these two markets

[85]In order to complete the missing data points, average values of the last and next available were used in Figure 6.1.

and, in particular, in adjusting the system back to its equilibrium, we find a stable long-run relationship without accounting for transport costs. Although we would generally not argue against transport costs playing an important role in the trade relationship between import and export thermal coal markets, we think that their role in adjusting the system back to the long-run equilibrium is not straight forward. This is due to the fact that, from our point of view, freight rates are mainly determined by the interplay of total bulk trade[86], bulk vessel capacity as well as oil prices. Hence, changes in price relationships on individual trading routes may increase or decrease trade on a specific route but do not necessarily have to influence route-specific transport costs.

6.5.2.2 Causal relationship

The test results on interregional price discovery show a mixed picture. While linear price discovery in spot prices takes places simultaneously in both markets, i.e., none of the two markets seems to lead the other, it is the European import market that leads South Africa in futures prices. Interestingly, concerning the causal relationship in higher moments, the opposite holds true, with nonlinear causality in futures prices being bi-directional, whereas Europe leads South Africa in spot prices. Altogether, it seems that in our analysis the thermal coal demand side – represented by the European import price – seems to have a stronger influence on price discovery than the supply side.

Tabelle 6.9: Results of the tests for linear and nonlinear causality - interregional price formation

Direction of causality	**Linear causality** χ^2-statistic (VECM residuals)	**nonlinear causality** t-statistic (VECM residuals)	t-statistic (GARCH-filtered VECM residuals)
ARA Spot → RB Spot	26.69***	1.79**	−0.82
ARA Spot ← RB Spot	12.69***	−0.09	−0.47
ARA M+1 → RB M+1	7.49**	2.30**	0.08
ARA M+1 ← RB M+1	4.03	2.36***	2.27**

Notes: *** (** or *) Denotes significance at the 99%-level (95%-level or 90%-level). Linear Granger causality was investigated within the vector error correction model (VECM), thus explicitly accounting for the cointegration relationship of the variables. For the respective specification of the BEKK-model used to filter the residuals for multivariate GARCH effects refer to Subsection 6.5.2.3.

The result of bi-directional causality in spot prices may seem somewhat surprising at first, since Europe is the main importing market in the Atlantic. In contrast, South Africa is merely one of three big suppliers in the Atlantic market, with the United States and Columbia being the other two. Therefore, one may have expected that it would be the European market leading the South African market, i.e., one would have expected causality to go only in one direction. However, South Africa also plays the role

[86]Although thermal coal is an important commodity for total bulk trade, other commodities, in particular iron ore, play an at least as important role.

of a swing supplies between the Atlantic and the Pacific market. The Pacific market, China in particular, has become more and more important for international trade since the beginning of the century. Thus, it may be the case that South African export price developments transmit changes in the demand-supply-balance in the Pacific market, e.g., a price increase because of a supply shortage in the Pacific, with the European import price reacting to these changes.

After filtering for multivariate GARCH effects, nonlinear causality disppears in the spot price time series. Consequently, causality in higher moments is, similar to the results of the intertemporal analysis, limited to the second moment. Yet, for the futures prices, we find evidence of causality in the third and higher moments going from South Africa to Europe, even after having filtered the VECM residuals using a multivariate GARCH model. This finding may be explained by the fact that despite trying multiple MGARCH models[87] other than the BEKK-model none of the models is able to capture all multivariate GARCH effects (see Table 6.12). Hence, it is most likely that the nonlinear causality in higher moments is caused by the remaining GARCH effects. Thus, this result should not be interpreted as evidence for nonlinear causality in higher moments than the second.

6.5.2.3 Volatility spillovers

In contrast to the analysis of nonlinear causality in the intertemporal context, the results of the estimated multivariate GARCH models do not confirm the findings of the DPT in all cases. More specifically, while the DPT indicates one-directional nonlinear causality in case of the spot time series, the estimated BEKK-model shows clear signs of bi-directional cross-volatility spillovers, both in the short and the long run (see Table 6.10). The parametric test, i.e., the MGARCH model, is generally more powerful than the nonparametric test for nonlinear Granger causality used in the previous section.[88] We, thus, infer from the estimations that there seems to be nonlinear causality running in both directions. A closer look at the estimated coefficients of the cross-volatility spillovers allows for no clear-cut conclusion regarding which of the two coal hubs seems to have the stronger (in absolute terms) effect on the other's volatility. Similar to the interemporal anaylsis, volatility persistence – both in the short and the long run coefficients – is stronger than the interplay between the two time series.

[87] In addition to the BEKK-model, we tried using the multivariate versions of the constant and dynamic conditional correlation as well as the exponential GARCH model, with none of them being able to filter all the multivariate GARCH effects from the two time series.

[88] As noted in Francis et al. (2010), another reason for the difference in the results may stem from uncertainty in the estimated residuals of the VECM. However, we believe that this effect is of lower importance compared to the difference in power of the two approaches. We would like to thank Valentyn Panchenko for his helpful comments regarding this aspect.

Tabelle 6.10: Estimated multivariate GARCH model for ARA and RB Spot

Variables	Coefficient	t-statistic
$a(1)_{1,1}$	−0.190	−2.68 ***
$a(1)_{1,2}$	−0.114	−2.31 **
$a(1)_{2,1}$	0.167	3.22***
$a(1)_{2,2}$	0.367	6.52***
$a(2)_{1,1}$	0.319	4.99***
$a(2)_{1,2}$	0.154	2.85***
$a(2)_{2,1}$	−0.026	−0.37
$a(2)_{2,2}$	0.109	1.19
$b(1)_{1,1}$	0.893	61.44***
$b(1)_{1,2}$	−0.065	−2.39 **
$b(1)_{2,1}$	0.044	2.33**
$b(1)_{2,2}$	0.948	30.81***
Log likelihood	6377.46	

Notes: *** (** or *) Denotes significance at the 99%-level (95%-level or 90%-level). The multivariate GARCH models were estimated by quasi-maximum likelihood estimation using the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm. Standard errors robust to misspecification and heteroscedasticity were used (see Sadorsky, 2012).

In case of the two front-month futures price series, the nonlinear causality tests indicate a causal relationship in both directions (see Table 6.9). This result is generally confirmed by the estimated MGARCH model, as can be seen from the coefficients displayed in Table 6.11. In the short run, we only find evidence for a one-directional causal relationship going from Europe to South Africa. Looking at the b-coefficients, we find cross-volatility spillovers going from Europe to South Africa and vice versa. However, one needs to be cautious when interpreting the results of the MGARCH estimation, since despite trying various symmetric and asymmetric specifications of the BEKK-model as well as other MGARCH models none of them was able to capture all GARCH effects (as indicated by the significant ARCH-LM test in Table 6.12). Since the DPT as well as the estimated MGARCH model point in the same direction, we still conclude that nonlinear causality is bi-directional in nature as was the case for the spot prices. Furthermore, the estimates shown in Table 6.11 again confirm that own-volatility spillovers are of greater importance for the development of a time series' volatility than cross-volatility spillovers.

TABELLE 6.11: Estimated multivariate GARCH model for ARA and RB M+1

Variables	Coefficient	t-statistic
$a(1)_{1,1}$	0.268	4.47***
$a(1)_{1,2}$	−0.116	−1.61
$a(1)_{2,1}$	0.041	0.58
$a(1)_{2,2}$	0.442	5.40***
$a(2)_{1,1}$	0.161	1.72*
$a(2)_{1,2}$	0.160	2.23**
$a(2)_{2,1}$	0.035	0.45
$a(2)_{2,2}$	0.106	1.50
$b(1)_{1,1}$	0.886	46.85***
$b(1)_{1,2}$	0.283	12.64***
$b(1)_{2,1}$	−0.976	−16.07 ***
$b(1)_{2,2}$	−0.679	−14.46 ***
$b(1)_{2,2}$	0.661	33.69***
$b(2)_{1,2}$	0.064	4.56***
$b(2)_{2,1}$	0.064	2.61***
$b(2)_{2,2}$	0.680	31.76***
Log likelihood	6981.41	

Notes: *** (** or *) Denotes significance at the 99%-level (95%-level or 90%-level). The multivariate GARCH models were estimated by quasi-maximum likelihood estimation using the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm. Standard errors robust to misspecification and heteroscedasticity were used (see Sadorsky, 2012).

Again we close this subsection by presenting the results of the diagnostic tests that check as to whether the presented multivariate GARCH models capture all serial correlation and GARCH effects in the residuals of the VECM (see Table 6.12). While we find no evidence for serial correlation and GARCH effects on a 10%-significance level for the spot prices, the multivariate ARCH-LM test suggests that not all GARCH effects could be filtered out in case of the futures price series, a finding that was already discussed in the previous subsection.

TABELLE 6.12: Results of the diagnostic tests for the standardised residuals - interregional price formation

	Multivariate Ljung-Box	Multivariate ARCH-LM
ARA Spot & RB Spot	37.89	19.96
	0.57	0.83
ARA M+1 & RB M+1	56.49	63.07
	0.04**	0.00***

Notes: For each pair of time series the values in the first row are the respective test-statistics, whereas the second row displays the corresponding p-values. The chosen lag length m for the Ljung-Box Q-statistic is 10 since Tsay (2010) recommends to set $m = ln(N)$ or higher with N being the number of observations (here: $ln(974) \approx 7$). Concerning the Multivariate ARCH-LM test, it is recommended to set $m = P + Q$ in case of a GARCH-model, which in case of the spot prices is $m = 3$ and $m = 4$ in case of the futures prices.

6.6 Conclusions

The paper at hand analyses two interrelated aspects, namely price discovery and volatility spillovers both in an intertemporal and an interregional context using spot and futures prices, for two of the most important coal products in the international market for thermal coal, namely the import price of Northwestern Europe (Amsterdam, Rotterdam and Antwerp) and the South African export price at the Richards Bay Coal Terminal. To this end, tests for linear as well as nonlinear causality were applied to the spot and futures price returns for both trading hubs as well as between the two trading hubs, thereby accounting for the respective cointegration relationships. The estimation of volatility spillovers using multivariate GARCH models, particularly cross-volatility spillovers, may be useful for the interpretation of the findings of the nonlinear causality tests. First, one may use the GARCH models to filter the time series for multivariate GARCH effects, thereby allowing to test whether nonlinear causality is limited to the second moment or even takes place in higher moments. Second, investigating the existence of cross-volatility spillovers via the estimation of parametric MGARCH models allows to cross-check the results of the nonparametric nonlinear Granger causality test.

Concerning the empirical analyses presented in this paper, we, first, underline the results of previous analyses of the long-run equilibrium relationship between Europe and South Africa using data with a higher frequency and a different time period. Second, we extend the evidence found in other commodity markets that (linear) price discovery takes place in the futures market. Third, we find that price discovery in higher moments is bidirectional in nature - both in the intertemporal and -regional context. Furthermore, we – despite the results of the DPT for one pair of time series indicating otherwise – conclude that nonlinear causality is restricted to the second moment.

The finding that intertemporal price discovery mainly takes place in the futures market has the important implication that regulators should be interested in further fostering the liquidity of existing markets for coal derivatives as well as establishing new ones, since futures markets are beneficial to an efficient processing of information and allocation of ressources. To gain further insights into the interplay of derivatives and spot products and the importance of futures markets, it may be interesting to investigate the relationship of spot and forward prices as well as futures and forward prices, a task that suffers from a lack of data availability and is, hence, left for future research.

Anhang A

Supplementary material for Chapter 2

A.1 Details on the model

The model's spatial structure is formulated as a directed graph consisting of a set N of vertices and a set $A \subset N \times N$ of edges. The set of vertices can be subdivided into sources and sinks, where gas production facilities are modelled as sources and importing regions as sinks. The model's time structure is represented by a set $T \subset \mathbb{N}$ of points in time (months). This time structure is flexible and can be customised by the user, which means any year (y) until 2050 can be simulated with up to twelve months per year. An overview of all sets, decision variables and parameters can be found in Table A.1.

TABELLE A.1: Model sets, variables and parameters

Sets	
$n \in N$	all model nodes
$t \in T$	months
$y \in Y$	years
$p \in P \in N$	producer / production regions
$e \in E \in N$	exporter / trader
$d \in D \in N$	final customer / importing regions
$r \in R \in N$	regasifiers
$l \in L \in N$	liquefiers
$s \in S \in N$	storage operators
Primal Variables	
$pr_{e,p,t}$	produced gas volumes
$fl_{e,n,n1,t}$	physical gas flows
$tr_{e,d,t}$	traded gas volumes
$st_{s,t}$	gas stock in storage
$si_{s,t}$	injected gas volumes
$sd_{s,t}$	depleted gas volumes
Dual Variables	
$\lambda_{e,n,t}$	marginal costs of physical gas supply by exporter e to node n in time period t
$\sigma_{s,t}$	(intertemporal) marginal costs of storage injection
$\beta_{d,t}$	marginal costs / price in node n in time period t
$\mu_{e,p,t}$	marginal benefit of an additional unit of production capacity
$\phi_{n,n1,t}$	marginal benefit of an additional unit of pipeline capacity
$\epsilon_{s,t}$	marginal benefit of an additional unit of storage capacity
$\rho_{s,t}$	marginal benefit of an additional unit of storage injection capacity
$\theta_{s,t}$	marginal benefit of an additional unit of storage depletion capacity
ι_t	marginal benefit of an additional unit of LNG transport capacity
$\gamma_{r,t}$	marginal benefit of an additional unit of regasification capacity
$\zeta_{l,t}$	marginal benefit of an additional unit of liquefaction capacity
$\chi_{e,n,y}$	marginal costs of delivery obligation
Parameter	
$cap_{n,t/n,n1,t}$	monthly infrastructure capacity
$trc_{n,n1,t}$	transport costs
$(m)prc_{n,t}$	(marginal) production costs
$opc_{n,t}$	operating costs
$mdo_{e,n,t}$	minimal delivery obligation of exporter e
$dist_{n,n1}$	distance between node n and node $n1$ in km
$LNGcap$	initial LNG capacity
$speed$	speed of LNG tankers in km/h
cf_s	conversion factor used for storage injection & depletion capacity

A.1.1 Remaining capacity constraints

In Section 2.2.2, we skipped a few capacity constraints in order to keep the description of our model as brief as possible. These are listed in the following. Along the lines of Inequality 2.17, Inequality A.1 states that the sum over all transport flows (decided on by the traders) through the liquefaction terminal, i.e., all natural gas that is liquefied, has to be lower than the respective liquefaction capacity.

$$cap_{l,t} - \sum_{e \in E} \sum_{n \in A_{\cdot,l}} fl_{e,n,l,t} \geq 0 \quad \forall l, t \qquad (\zeta_{l,t}). \tag{A.1}$$

The same holds true for the restriction of gas volumes that are regasified and then transported to a demand node d in month t:

$$cap_{r,t} - \sum_{e \in E} \sum_{d \in A_{r,\cdot}} fl_{e,r,d,t} \geq 0 \quad \forall r, t \qquad (\gamma_{r,t}). \tag{A.2}$$

Finally, we account for a limitation of available LNG tankers. Hence, the sum of all gas volumes transported between liquefaction terminal l and regasification terminal r in month t is restricted by the available LNG transport capacity:

$$(LNGcap) * 8760/12 * speed - \sum_{e \in E} \sum_{l \in L} \sum_{r \in R} 2 * (fl_{e,l,r,t} * dist_{n,n1}) \geq 0 \quad \forall t \qquad (\iota_t) \tag{A.3}$$

where $speed$ is defined as the average speed of a LNG tanker (km/h), $dist_{n,n1}$ as the distance in km between node n and node $n1$ and $LNGcap$ as the number of existing LNG tankers times their average size in the initial model year. By using Inequality A.3, we take into account that each LNG tanker that delivers gas to a regasification terminal has to drive back to a liquefaction terminal in order to load new LNG volumes. Therefore, we simplify the model by assuming that each imaginary LNG tanker drives back to the liquefaction terminal from where it started.

A.1.2 First-order conditions of the model

A.1.2.1 Physical flows

Taking the first partial derivative of Equation 2.16 with respect to $fl_{e,n,n1,t}$ and accounting for the Inequalities (capacity constraints) 2.17, A.1, A.2 and A.3 results in:

$$\begin{aligned}\frac{\partial L_{eII}}{\partial fl_{e,n,n1,t}} = -\lambda_{e,n1,t} + \lambda_{e,n,t} + trc_{n,n1,t} + opc_{n,t}\\ + \phi_{n,n1,t} + \zeta_{l,t} + \gamma_{r,t}\\ + \iota_t * 2 * dist_{l,r} \geq 0 \quad \perp \quad fl_{e,n,n1,t} \geq 0 \qquad \forall e, n, n1, t.\end{aligned} \tag{A.4}$$

A.1.2.2 Production

The first-order condition for production is derived from the payoff function $\Pi_p(pr_{e,p,t})$ defined as

$$\max_{pr_{e,p,t}} \Pi_p(pr_{e,p,t}) = \sum_{t \in T} (\lambda_{e,p,t} * pr_{e,p,t} - prc_{e,p,t}(pr_{e,p,t})) \tag{A.5}$$

where $pr_{e,p,t}$ is the corresponding decision vector of p. The set of feasible solutions for $pr_{e,p,t}$ is restricted by the non-negativity constraint $pr_{e,p,t} \geq 0$. The first-order conditions of the producer's problem include Constraint 2.15 as well as the following partial derivative of the Lagrangian L_p:

$$\frac{\partial L_p}{\partial pr_{e,p,t}} = -\lambda_{e,p,t} + mprc_{e,p,t}(pr_{e,p,t}) + \mu_{e,p,t} \geq 0 \quad \perp \quad pr_{e,p,t} \geq 0 \qquad \forall p, t \tag{A.6}$$

A.1.2.3 Storage utilisation

The following derivatives derived from Equations 2.18 and 2.19 (as well as the respective capacity constraints) constitute the first-order conditions of the storage operator's optimisation problem:

$$\frac{\partial H_s}{\partial sd_{s,t}} = -\beta_{d,t} + \sigma_{s,t} + \theta_{s,t} \geq 0 \quad \perp \quad sd_{s,t} \geq 0 \qquad \forall s, t \tag{A.7}$$

$$\frac{\partial H_s}{\partial si_{s,t}} = -\sigma_{s,t} + \beta_{d,t} + \rho_{s,t} \geq 0 \quad \perp \quad si_{s,t} \geq 0 \qquad \forall s, t \tag{A.8}$$

$$-\frac{\partial H_s}{\partial st_{s,t}} = \epsilon_{s,t} = \Delta\sigma_{s,t} = \sigma_{s,t+1} - \sigma_{s,t} \leq 0 \quad \perp \quad st_{s,t} \leq 0 \qquad \forall s, t. \tag{A.9}$$

A.2 Data

TABELLE A.2: Nodes in the model

	Total number of nodes	**Number of countries**	**Countries with more than one node**	**Countries aggregated to one node**
Demand	84	87	Russia and the United States	Baltic countries and former Yugoslavian republics
Production	43	36	China, Norway, Russia and the United States	-
Liquefaction	24	24	-	-
Regasification	27	25	-	-
Storages	37	37	-	-

A.2.1 Production

For the majority of nodes, we model gas production endogenously. Only for very small gas producing countries and those with little exports do we fix production volumes to limit model complexity. Concerning endogenous production, we face the problem that there are only sources with data on historical production (i.e., IEA (2011a) but no single source that provides information about historical or current production capacities. We collect information from various sources listed in Table A.3. For the major LNG exporters (Qatar and Australia), we derive possible production capacities from the domestic demand assumptions and liquefaction capacities. In total, we assume a global production capacity of 3542 bcm in 2010 and 3744 bcm in 2012. Twelve to thirteen percent of that capacity is assumed to be fixed production. The usage of the remaining production capacity (87%) is optimised within the model.

TABELLE A.3: Assumptions and data sources for production

	Assumptions	**Sources**
Production	Exogenous production of small countries in 2010	IEA (2011a)
	Forecast on exogenous production of small-scale producing countries	ENTSOG (2011), IEA (2011a,b)
	Estimates of future production capacity in the USA	IEA (2011)
	Development of production capacities in Norway and Russia	Söderbergh et al. (2009, 2010)
	Forecasts for Saudi-Arabia, China, India, Qatar and Iran	IEA (2011a)
	Information which allow us to get an idea of production capacities in Africa, Malaysia, Indonesia and Argentina	IEA (2011b)

Concerning production costs, we follow an approach used in Golombek et al. (1995, 1998).[89] For the exporting countries, we estimate Golombek production functions by OLS regression, using various data sources such as Seeliger (2006) and OME (2001), or information on costs published in the *Oil and Gas Journal*.

A.2.2 Infrastructure

We consider the global gas infrastructure data aggregated on a country level. To reduce complexity, we bundle LNG capacities to one representative LNG hub per country. The same applies for storages and pipelines: Although, e.g., Russia and the Ukraine are connected via multiple pipelines in reality, we bundle pipeline capacity into one large pipeline "Russia-Ukraine". The Institute of Energy Economics at the University of Cologne (EWI) has its own extensive pipeline database that serves as the major source for current pipeline capacities and distances. New pipeline projects between 2010 and 2012 are based on publicly available data. The distances of the 196 LNG routes were measured using a port to port distance calculator.[90]

Tabelle A.4: Assumptions and data sources for infrastructure

	Assumptions	**Sources**
Infrastructure	Current and future capacities of LNG terminals	GIIGNL (2010), IEA (2011b)
	National storage capacities (yearly working gas volumes)	CEDIGAZ (2009), IEA (2011a)
	Underground storage capacities of China, Japan and South Korea	IGU (2003), Yoshizaki et al. (2009), Yuwen (2009)
	Onshore / offshore pipelines transportation costs (16 USD/kcm/1000 km and 26 USD/kcm/1000 km)	Jensen (2004), Rempel (2002), van Oostvoorn (2003)
	LNG liquefaction and regasification costs add up to 59 USD/kcm	Jensen (2004)
	Variable operating costs for storage injection of 13 USD/kcm	CIEP (2008)

We account for LNG transport distances by LNG tanker freight rates of 78000 USD/day (Drewry Maritime Research, 2011, Jensen, 2004). Based on our costs assumptions shown in Table A.4, the break-even distance between onshore pipelines and LNG transport is 4000 km, and around 2400 km for offshore pipelines.[91] This is in line with Jensen (2004) and Rempel (2002).

[89]Please refer to Subsection 2.2 for more details on the Golombek production function, in particular on the marginal cost function (its first derivative) that is used in our model.

[90]Please refer to http://www.searates.com/reference/portdistance/

[91]We assume that the average speed of a typical LNG vessel amounts to 19 knots and that the average capacity lies at circa 145000 cbm.

A.3 Cournot setting vs. perfect competition

The objective of this section is to justify our decision to model the gas market as an oligopoly. Therefore, we compare two market settings – perfect competition and Cournot competition with a competitive fringe – with respect to how well these simulations fit to the actual market outcomes in 2010. These two settings were chosen because, on the one hand, global gas markets are characterised by a relatively high concentration on the supply side. On the other, due to cost decreases in the LNG value chain, regional arbitrage has become a viable option, thereby potentially constraining the exercise of market power.

We start out by analysing the model outcomes of the perfect competition scenario. Figure A.1 compares the observed average prices in USD/kcm with the resulting average market clearing prices in the different market settings. Simulated prices in the perfect competition scenario are significantly lower than the actual prices in 2010 in almost every country depicted in Figure A.1, except for the US.

Figure A.2 displays the deviation of simulated total demand from actual demand realised in 2010 for the two different model settings. The deviation is shown as a percentage of the actual demand figures in 2010. Figure A.2 shows that endogenous demand in the perfect competition scenario strongly deviates from reality. The largest deviations were observed for Asia/Oceania and Europe, where the modelled demand exceeds the actual realised demand in 2010 by 3.7% and 9.7%, respectively. In contrast, simulated demand in North America resembles the actual demand quite well.

Figures A.3 and A.4 display production capacity (indicated by the bars), simulated production volumes and actual production in 2010 for five selected countries. Concerning the perfect competition case, the simulated production of the five producing countries

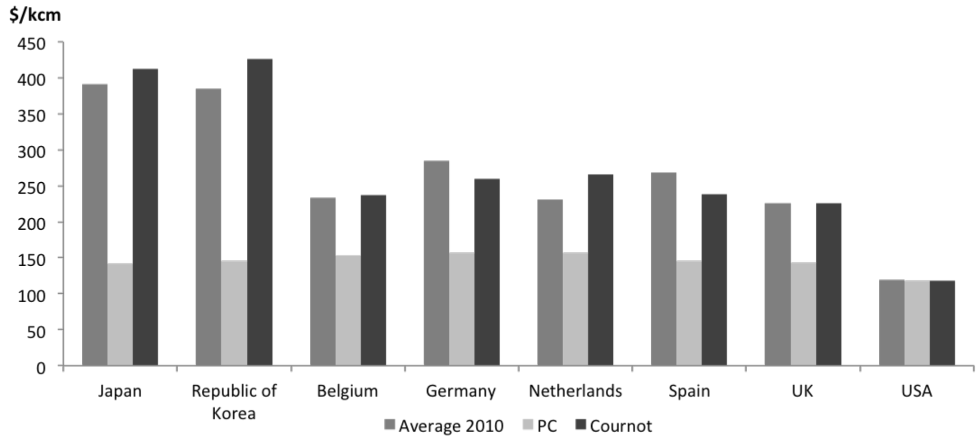

Abbildung A.1: Actual and simulated average prices (in USD/kcm)

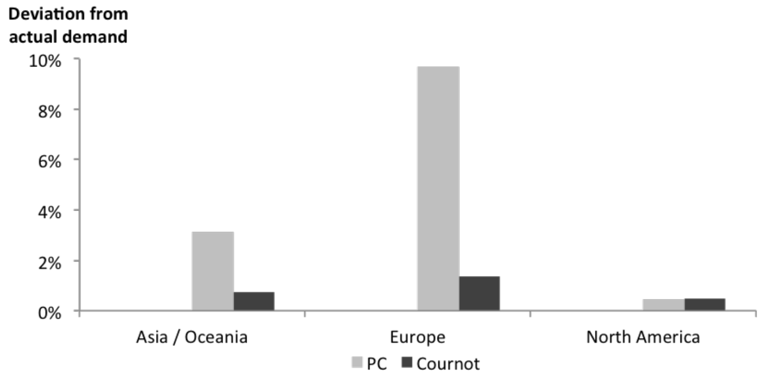

Abbildung A.2: Deviation of demand under different settings (in % of actual demand in 2010)

exceeds production volumes observed in 2010 (see Figures A.3 and A.4). From Figures A.1 to A.4, we conclude, that except for the North American natural gas market, the assumption of perfect competition does not fit well with actual market data. Therefore, we model the eight most important LNG exporting countries and the three most important pipeline exporters as Cournot players, thus allowing them to exercise market power by means of production withholding. All countries have almost all of their exports coordinated by one firm or consortium, e.g., Gazprom (Russia), Statoil (Norway) or Sonatrach (Algeria).

In comparison to the perfect competition setting, model results (i.e., demand, production and prices) in the Cournot setting seem to represent reality more accurately. Since the Cournot setting with a competitve fringe provides the closer fit to actual production, demand and price data such a setting is used for our analysis presented in Section 2.4.

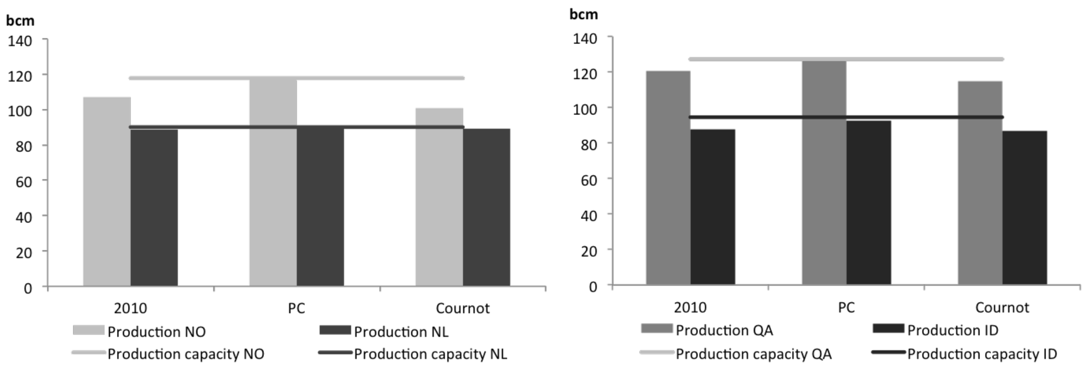

Abbildung A.3: Annual production and production capacities in four selected countries in the different market settings (in bcm)

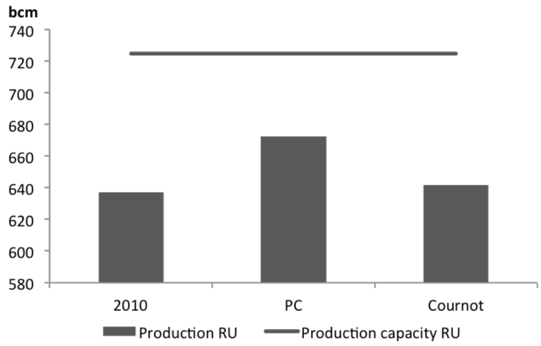

Abbildung A.4: Annual Russian production and production capacities in the different market settings (in bcm)

A.4 Sensitivity analysis

We analyse three alternative settings for the IP sector's demand elasticity, since this elasticity assumption is most important in determining overall demand elasticity in almost all countries. For example, we conduct one sensitivity analysis in which the elasticity in all countries is 50% higher (labeled "High"), i.e., -0.15 and -0.6 respectively, one in which it is 50% lower ("Low") and one in which the IP sector's demand elasticity is -0.4 in all countries ("Same").

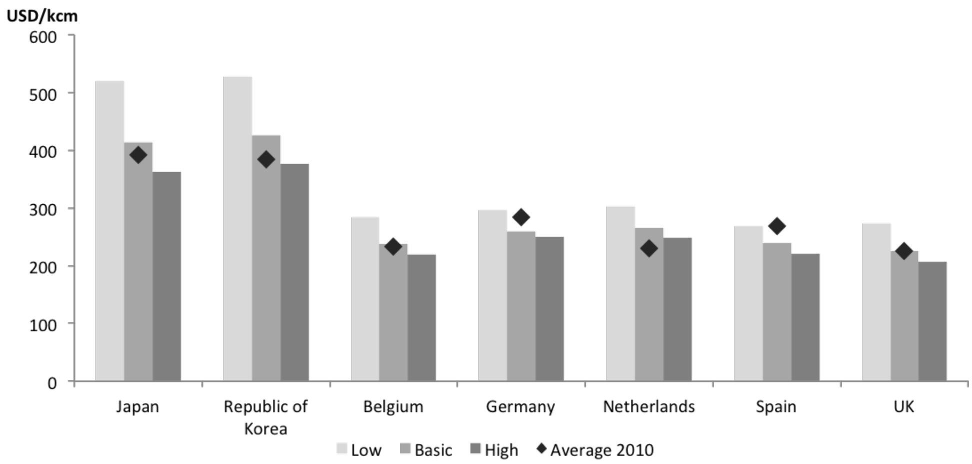

Abbildung A.5: Sensitivity analysis I - comparison of prices in selected countries with varying elasticity assumptions

We find that the elasticity assumptions ("Basic") used in our analysis provide the best fit with actual data. While prices in the sensitivity scenario "Lowßubstantially exceed actual prices (see Figure A.5, in particular in Japan and Korea), prices in the sensitivity scenario "Highündershoot prices in almost all countries (with the exceptions of Korea and the Netherlands). If we take a closer look at the scenario "Same"(Figure A.6), we see that by assuming the same demand elasticity in all countries, regional price differences are much lower than in reality (or in the scenario "Basic"). Therefore, given the elasticity assumptions used in this paper, we are able to obtain a reasonably good fit to the actual prices in 2010 and conclude that no other combination of elasticities could improve the accuracy of our model.

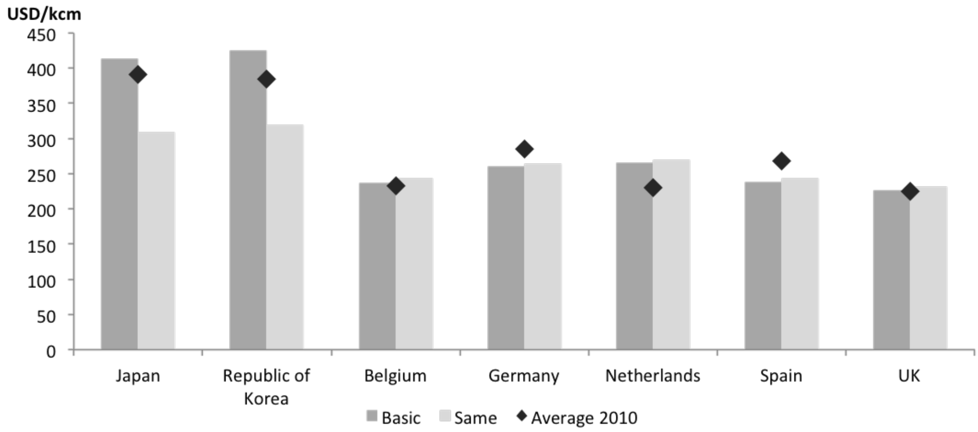

Abbildung A.6: Sensitivity analysis II - comparison of prices in selected countries with varying elasticity assumptions

Anhang B

Supplementary material for Chapter 3

B.1 Model overview

TABELLE B.1: Model sets, variables and parameters

Sets	
$y \in Y$	years
$f \in F$	factor inputs
$n \in N$	mining companies
$m \in M \in N$	mines
$d \in D \in N$	importing regions
Variables	
$pi_{d,y}$	pig iron demand / production in import region d
$tr_{n,f,m,d,y}$	transport of input f from mine m to import region d
$sa_{n,f,d,y}$	sales of input f to import region d
$sa^b_{n,d,y}$	sales of a bundle of inputs to import region d
$\lambda_{d,y}$	price of pig iron in import region d
$\rho_{f,d,y}$	price of factor input f in import region d
$v_{n,f,d,y}$	physical value of input f for company n to produce and to transport in import region d
$\mu_{n,f,m,y}$	marginal benefit of an additional unit of production capacity of input f at mine m
Parameter	
$cap_{n,f,m,y}$	annual production capacity of input f at mine m
$fin_{f,d,y}$	factor intensity of input f in crude steel production in import region d
$pco_{f,m,y}$	FOB costs of input f produced in mine m
$tco_{f,m,d,y}$	seaborne transport costs of input f (produced in mine m) to import region d
$cva_{n,y}$	company n's conjectural variation
$slo_{d,y}$	slope of linear pig iron demand function
$int_{d,y}$	intercept of linear pig iron demand function
sim_n	binary parameter indicating whether integrated company n optimises on a firm level

B.2 Oligopolistic market with a binding capacity constraint on one firm's output

We are interested in a setting where the integrated firm optimises output on a division level. However, this time we introduce a binding capacity constraint on one of the division's output, e.g., $\mathring{x}_i^1$. The first-order conditions of the divisions with no capacity limit are equivalent to Equation 3.5. Using the first-order conditions and inserting them in the price formulas yields:

$$\begin{aligned} p_c &= a - bx_c^1 - bx_c^2 - p_i = a - p_c - p_c - p_i \\ \Leftrightarrow p_c &= \frac{a - p_i}{3} \end{aligned} \tag{B.1}$$

and

$$\begin{aligned} p_i &= a - bx_i^1 - b\mathring{x}_i^1 - p_c = a - p_i - b\mathring{x}_i^1 - p_c \\ \Leftrightarrow p_c &= \frac{a - b\mathring{x}_i^1 - p_c}{2}. \end{aligned} \tag{B.2}$$

Using Equations B.1 and B.2 yields:

$$\begin{aligned} p_i &= \frac{3a - 3b\mathring{x}_i^1 - a + p_i}{6} \\ \Leftrightarrow p_i &= \frac{2a - 3b\mathring{x}_i^1}{5} \end{aligned} \tag{B.3}$$

and

$$p_c = \frac{a}{3} - \frac{2a - 3b\mathring{x}_i^1}{15} = \frac{a + b\mathring{x}_i^1}{5} \tag{B.4}$$

as well as

$$\begin{aligned} bx_c^n &= \frac{a + b\mathring{x}_i^1}{5} \\ \Leftrightarrow x_c^n &= \frac{a}{5b} + \frac{\mathring{x}_i^1}{5}. \end{aligned} \tag{B.5}$$

This allows us to derive the profit of the integrated firm optimising output division by division (i_1 and c_1) and one division has a binding capacity constraint, contingent on $\mathring{x}_i^1$:

$$\begin{aligned}
\pi^{i_1+c_1} &= \mathring{x}_i^1 \left(\frac{2a - 3b\mathring{x}_i^1}{5} \right) + \left(\frac{a}{5b} + \frac{\mathring{x}_i^1}{5} \right) \left(\frac{a + b\mathring{x}_i^1}{5} \right) \\
&= \frac{2a\mathring{x}_i^1 - 3b\left(\mathring{x}_i^1\right)^2}{5} + \frac{a^2 + ab\mathring{x}_i^1}{25b} + \frac{a\mathring{x}_i^1 + b\left(\mathring{x}_i^1\right)^2}{25} \\
&= \frac{10ab\mathring{x}_i^1 + ab\mathring{x}_i^1 - 15b^2\left(\mathring{x}_i^1\right)^2 + b^2\left(\mathring{x}_i^1\right)^2 + a^2 + ab\mathring{x}_i^1}{25b} \\
&= \frac{a^2 + 12ab\mathring{x}_i^1 - 14b^2\left(\mathring{x}_i^1\right)^2}{25b}.
\end{aligned} \tag{B.6}$$

B.3 Statistical measures

In order to assess the accuracy of our model, we compare market outcomes, such as production, prices and trade flows, to our model results. In comparing trade flows, we follow, for example, Kolstad and Abbey (1984), Bushnell et al. (2008) and more recently Trüby (2013) by applying three different statistical measures: A linear hypothesis test, Spearman's rank correlation coefficient and Theil's inequality coefficient. In the following, we briefly discuss the setup as well as some of the potential weakness of each of the three tests.

Starting with the linear hypothesis test, the intuition behind the test is that in case actual and model trade flows had a perfect fit the dots in a scatter plot of the two datasets would be aligned along a line starting at zero and having a slope equal to one. Therefore, we test model accuracy by regressing actual trade flows A_t on the trade flows of our model M_t, with t representing the trade flow between exporting country $e \in E$ and importing region $d \in D$, as data on trade flows is available only on a country level. Using ordinary least squares (OLS), we estimate the following linear equation:

$$A_t = \beta_0 + \beta_1 * M_t + \epsilon_t.$$

Modelled trade flows have a bad fit with actual data if the joint null hypothesis of $\beta_0 = 0$ and $\beta_1 = 1$ can be rejected at typical significance levels. One of the reasons why this test is applied in various studies is that it allows hypothesis testing, while the other two tests used in this paper are distribution-free and thus do not allow such testing. However, there is a drawback to this test as well, since the results of the test are very sensitive to how good the model is able to simulate outliers. To improve the evaluation of the model accuracy regarding the trade flows we apply two more tests.

The second test we employ is the Spearman's rank correlation coefficient, which, as already indicated by its name, can be used to compare the rank by volume of the trade flow t in reality to the rank in modelled trade flows. Spearman's rank correlation coefficient, also referred to as Spearman's rho, is defined as follows:

$$rho = 1 - \sum_{t}^{T} d_t^2/(n^3 - n)$$

with d_t being the difference in the ranks of the modelled and the actual trade flows and T being the total number of trade flows. Since Spearman's rho is not based on a distribution hypothesis testing is not applicable, but instead one looks for a large value of rho. However, Spearman's rank correlation coefficient does not tell you anything about how well the predicted trade flows compare volumewise to the actual trade flow volumes, since it could be equal to one despite total trade volume being ten times higher in reality as long as the market shares of the trade flows match.

Finally, we apply the normed-version of Theil's inequality coefficient U, which lies between 0 and 1, to analyse the differences between actual and modelled trade flows. A U of 0 indicates that modelled trade flows perfectly match actual trade flow, while a large U hints at a large difference between the two datasets. Theil's inequality coefficient is defined as:

$$U = \frac{\sqrt{\sum_t^T (M_t - A_t)}}{\sqrt{\sum_t^T M_t^2} + \sqrt{\sum_t^T A_t^2}}$$

B.4 Trade flows

Tabelle B.2: Realised values - iron ore and coking coal trade flows in million tonnes

Iron ore (2008)

Importers / Exporters	European Union	Other Europe	CIS	NAFTA	C. & S. America	Africa and ME	Asia	Oceania	**Total**
European Union		1.3	27.8	14.1	78.2	17.9	0.9	5.9	**146.1**
Other Europe	1.7		2.6	0.3	4.2	0.2	0.9	0	**9.9**
CIS	0	0		0.1	0.2	0	0	0	**0.3**
NAFTA	0.1	0	0		6.8	0	0	0	**6.9**
C. & S. America	0	0	0	1.5		0.1	0	0	**1.6**
Africa and ME	6.3	0	0	1.1	2.5		0.2	0	**10.1**
China	0	0	15.3	6.5	119.3	11.3	98.1	183.5	**434.0**
Japan	0	0	0	1.3	38.4	8.1	16.2	76.4	**140.4**
Other Asia	0	0	0	0.8	29.3	0.5	3.6	43.9	**78.1**
Oceania	0	0	0	0	0.4	0	1.7		**2.1**
Total	**8.1**	**1.3**	**45.7**	**25.7**	**279.3**	**38.1**	**121.6**	**309.7**	**829.5**

Coking coal (2008)

Importers / Exporters	**Australia**	**Canada**	**Russia**	**United States**	**Total**
Europe and Mediterranean	27	7	4.1	24.4	**62.5**
Japan	50.2	8.6	2	1.3	**62.1**
Korea	8.4	5.1	0.4	1	**14.9**
China	1.5	0.5	0.2	0	**2.2**
India	24.2	0	0	1.4	**25.6**
Other Asia	6.4	1.1	0	0.1	**7.6**
Brazil	3.9	1.4	0	5.5	**10.8**
Other	15.3	1.4	0.8	1.7	**19.2**
Total	**136.9**	**25.1**	**7.5**	**35.4**	**204.9**

Iron ore (2009)

Importers / Exporters	European Union	Other Europe	CIS	NAFTA	C. & S. America	Africa and ME	Asia	Oceania	**Total**
European Union		1	18	14.7	36.6	8.3	0.3	0.7	**79.6**
Other Europe	1.4		3.1	0.2	2.2	0	0	0	**6.9**
CIS	0	0		0	0	0	0	0	**0.0**
NAFTA	0.1	0	0.1		1.4	0.1	0	0	**1.7**
C. & S. America	0	0	0	1.2		0	0	0	**1.2**
Africa and ME	3.9	0	0	1.8	2.4		0.1	0	**8.2**
China	1.3	0	28.6	9.3	181.8	30.4	88	278.9	**618.3**
Japan	0	0	0.1	0.6	27.1	6.3	8.7	62.6	**105.4**
Other Asia	0	0	0.3	2.5	18.5	6.5	2.6	39.2	**69.6**
Oceania	0	0	0	0.3	0.6	0	0.1		**1.0**
Total	**6.7**	**1.0**	**50.2**	**30.6**	**270.6**	**51.6**	**99.8**	**381.4**	**891.9**

Coking coal (2009)

Importers / Exporters	Australia	Canada	Russia	United States	**Total**
Europe and Mediterranean	15.7	3.5	3.7	18.4	**41.3**
Japan	42.1	6.7	1.3	0.6	**50.7**
Korea	12.8	4.4	0.5	1.6	**19.3**
China	14.8	3.7	1.1	0.9	**20.5**
India	24	0	0	1.9	**25.9**
Other Asia	2.6	0.8	0.1	0.1	**3.6**
Brazil	4.1	0.9	0	6.7	**11.7**
Other	9.2	0.6	0	1.5	**11.3**
Total	**125.3**	**20.6**	**6.7**	**31.7**	**184.3**

Iron ore (2010)

Importers / Exporters	European Union	Other Europe	CIS	NAFTA	C. & S. America	Africa and ME	Asia	Oceania	**Total**
European Union		0.8	34.1	15.6	59.3	14.9	0.6	15.9	**141.2**
Other Europe	1.7		2.9	0.4	3.3	0	0	0	**8.3**
CIS	0	0		0	0	0	0	0	**0.0**
NAFTA	0.1	0	0.2		7.9	0	0	0	**8.2**
C. & S. America	0	0	0	1.9		0	0	0	**1.9**
Africa and ME	5	0	0	1.6	4.5		0	0	**11.1**
China	1.5	0	25.9	10.7	149.4	33.5	105.3	276.1	**602.4**
Japan	0	0	0.2	0.9	41	6.1	4.8	81.4	**134.4**
Other Asia	0	0	0.2	2.5	47.8	2.9	1.5	54.9	**109.8**
Oceania	0	0	0	0.2	1	0	0		**1.2**
Total	**8.3**	**0.8**	**63.5**	**33.8**	**314.2**	**57.4**	**112.2**	**428.3**	**1018.5**

Coking coal (2010)

Importers / Exporters	Australia	Canada	Russia	United States	**Total**
Europe and Mediterranean	20.7	4.8	4.3	27.7	**57.5**
Japan	45.8	8.7	2.1	2.7	**59.3**
Korea	17.4	5.3	1.3	2.7	**26.7**
China	21.9	4.3	2.5	3.8	**32.5**
India	32.3	0	0	2.3	**34.6**
Other Asia	7.4	0.6	0.1	0.2	**8.3**
Brazil	4.2	1.6	0.1	7.1	**13.0**
Other	5	0.7	0.1	1.2	**7.0**
Total	**154.7**	**26.0**	**10.5**	**47.7**	**238.9**

Tabelle B.3: Perfect competition - iron ore and coking coal trade flows in million tonnes (demand elasticity of -0.5)

Iron ore (2008)

Importers / Exporters	European Union	Other Europe	CIS	NAFTA	C. & S. America	Africa and ME	Asia	Oceania	**Total**
European Union	0.0	0.0	38.4	0.0	114.1	11.2	0.0	0.0	**163.7**
Other Europe	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.0**
CIS	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.0**
NAFTA	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.0**
C. & S. America	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.0**
Africa and ME	0.0	0.0	0.0	2.2	0.0	0.0	8.5	0.0	**10.7**
China	0.0	0.0	15.3	16.2	103.0	23.3	60.3	234.9	**453.0**
Japan	0.0	0.0	0.0	0.0	75.9	0.0	0.0	74.8	**150.7**
Other Asia	0.0	0.0	0.0	0.0	49.5	2.4	25.6	4.3	**81.8**
Oceania	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.0**
Total	**0.0**	**0.0**	**53.7**	**18.3**	**342.5**	**36.9**	**94.4**	**314.1**	**859.9**

Coking coal (2008)

Importers / Exporters	Australia	Canada	Russia	United States	**Total**
Europe and Mediterranean	25.4	7.0	2.1	35.9	**70.5**
Japan	54.9	9.6	3.0	0.0	**67.4**
Korea	16.2	0.0	0.0	0.0	**16.2**
China	0.0	0.0	0.0	0.0	**0.0**
India	34.1	0.0	0.0	0.0	**34.1**
Other Asia	8.7	0.0	0.0	0.0	**8.7**
Brazil	11.9	0.5	0.0	0.0	**12.4**
Other	2.4	6.1	0.0	0.0	**8.6**
Total	**153.7**	**23.3**	**5.1**	**35.9**	**218.0**

Iron ore (2009)

Importers / Exporters	European Union	Other Europe	CIS	NAFTA	C. & S. America	Africa and ME	Asia	Oceania	**Total**
European Union	0.0	0.0	25.0	18.2	36.7	10.3	0.0	0.0	**90.2**
Other Europe	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.0**
CIS	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.0**
NAFTA	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.0**
C. & S. America	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.0**
Africa and ME	0.0	0.0	0.0	1.5	4.3	0.0	0.0	0.0	**5.7**
China	0.0	0.0	28.6	0.0	190.9	34.3	84.0	372.0	**709.8**
Japan	0.0	0.0	0.0	0.0	110.7	0.0	0.0	0.0	**110.7**
Other Asia	0.0	0.0	0.0	0.0	55.5	3.8	0.0	15.0	**74.3**
Oceania	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.0**
Total	**0.0**	**0.0**	**53.6**	**19.7**	**398.1**	**48.4**	**84.0**	**387.0**	**990.6**

Coking coal (2009)

Importers / Exporters	Australia	Canada	Russia	United States	**Total**
Europe and Mediterranean	5.7	0.0	4.8	36.1	**46.6**
Japan	34.3	18.2	3.2	0.0	**55.7**
Korea	21.4	0.0	0.0	0.0	**21.4**
China	33.6	0.0	0.0	0.0	**33.6**
India	32.9	0.0	0.0	0.0	**32.9**
Other Asia	4.2	0.0	0.0	0.0	**4.2**
Brazil	10.0	0.6	0.0	3.0	**13.6**
Other	0.7	5.5	0.0	0.0	**6.2**
Total	**142.9**	**24.3**	**8.0**	**39.0**	**214.2**

Iron ore (2010)

Importers / Exporters	European Union	Other Europe	CIS	NAFTA	C. & S. America	Africa and ME	Asia	Oceania	**Total**
European Union	0.0	0.0	24.4	21.0	86.9	11.3	0.0	0.0	**143.7**
Other Europe	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.0**
CIS	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.0**
NAFTA	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.0**
C. & S. America	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.0**
Africa and ME	0.0	0.0	0.0	0.0	6.0	0.0	0.0	0.0	**6.0**
China	0.0	0.0	25.9	0.0	94.6	34.2	96.4	400.8	**651.9**
Japan	0.0	0.0	0.0	0.0	127.1	0.0	0.0	5.4	**132.5**
Other Asia	0.0	0.0	0.0	0.0	72.6	6.4	4.9	27.5	**111.4**
Oceania	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.0**
Total	**0.0**	**0.0**	**50.3**	**21.0**	**387.2**	**51.9**	**101.3**	**433.8**	**1045.4**

Coking coal (2010)

Importers / Exporters	Australia	Canada	Russia	United States	**Total**
Europe and Mediterranean	19.7	0.0	1.7	39.2	**60.5**
Japan	35.6	22.2	3.6	0.0	**61.4**
Korea	27.6	0.0	0.0	0.0	**27.6**
China	38.1	0.0	0.0	0.0	**38.1**
India	39.4	0.0	0.0	0.0	**39.4**
Other Asia	8.7	0.0	0.0	0.0	**8.7**
Brazil	2.8	0.8	0.0	10.3	**13.9**
Other	0.4	2.3	0.0	0.0	**2.7**
Total	**172.3**	**25.2**	**5.3**	**49.5**	**252.4**

Tabelle B.4: Division-level optimisation - iron ore and coking coal trade flows in million tonnes (demand elasticity of -0.5)

Iron ore (2008)

Importers / Exporters	European Union	Other Europe	CIS	NAFTA	C. & S. America	Africa and ME	Asia	Oceania	**Total**
European Union	0.0	0.0	38.4	0.0	48.5	14.3	6.5	47.1	**154.8**
Other Europe	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.0**
CIS	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.0**
NAFTA	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.0**
C. & S. America	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.0**
Africa and ME	0.1	0.0	0.0	2.2	1.2	0.0	4.1	2.1	**9.6**
China	8.1	0.0	15.3	16.2	166.1	12.5	38.7	188.4	**445.3**
Japan	3.7	0.0	0.0	0.0	28.5	6.1	42.1	53.6	**134.0**
Other Asia	0.8	0.0	0.0	0.0	24.2	3.9	24.3	23.0	**76.3**
Oceania	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.0**
Total	**12.8**	**0.0**	**53.7**	**18.3**	**268.6**	**36.8**	**115.8**	**314.1**	**820.0**

Coking coal (2008)

Importers / Exporters	Australia	Canada	Russia	United States	**Total**
Europe and Mediterranean	27.5	16.8	2.1	12.2	**58.7**
Japan	49.5	0.3	3.0	6.6	**59.4**
Korea	12.7	0.0	0.0	1.6	**14.3**
China	3.6	0.0	0.0	0.0	**3.6**
India	22.8	0.0	0.0	5.4	**28.2**
Other Asia	3.5	3.0	0.0	1.0	**7.5**
Brazil	4.0	0.0	0.0	6.2	**10.2**
Other	3.7	2.6	0.0	1.3	**7.6**
Total	**127.4**	**22.7**	**5.1**	**34.3**	**189.4**

Iron ore (2009)

Importers / Exporters	European Union	Other Europe	CIS	NAFTA	C. & S. America	Africa and ME	Asia	Oceania	**Total**
European Union	0.0	0.0	25.0	26.1	28.0	4.3	0.0	10.2	**93.6**
Other Europe	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.0**
CIS	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.0**
NAFTA	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.0**
C. & S. America	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.0**
Africa and ME	0.0	0.0	0.0	1.5	1.5	0.0	1.5	0.9	**5.4**
China	12.1	0.0	28.6	0.0	171.1	32.5	86.4	298.0	**628.9**
Japan	2.0	0.0	0.0	1.6	32.4	5.2	0.0	59.0	100.2
Other Asia	0.9	0.0	0.0	0.0	34.3	6.3	5.5	19.8	**66.8**
Oceania	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.0**
Total	**15.1**	**0.0**	**53.6**	**29.2**	**267.4**	**48.3**	**93.5**	**387.9**	**894.9**

Coking coal (2009)

Importers / Exporters	Australia	Canada	Russia	United States	**Total**
Europe and Mediterranean	16.6	10.9	4.8	7.9	**40.2**
Japan	30.8	10.2	3.2	4.8	**49.0**
Korea	16.6	0.0	0.0	2.0	**18.6**
China	13.5	0.0	0.0	4.8	**18.2**
India	22.8	0.0	0.0	5.9	**28.7**
Other Asia	2.0	0.9	0.0	0.6	**3.5**
Brazil	4.1	0.0	0.0	7.8	**11.9**
Other	2.6	1.7	0.0	0.8	**5.1**
Total	**108.9**	**23.8**	**8.0**	**34.6**	**175.3**

Iron ore (2010)

Importers / Exporters	European Union	Other Europe	CIS	NAFTA	C. & S. America	Africa and ME	Asia	Oceania	**Total**
European Union	0.0	0.0	32.5	8.0	50.6	9.0	0.0	58.1	**158.2**
Other Europe	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.0**
CIS	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.0**
NAFTA	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.0**
C. & S. America	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.0**
Africa and ME	0.1	0.0	0.0	0.0	3.9	0.0	0.7	1.2	**5.9**
China	12.2	0.0	25.9	0.0	188.8	23.3	102.7	264.7	**617.5**
Japan	4.4	0.0	0.0	14.1	36.3	8.2	0.0	65.9	**129.0**
Other Asia	2.6	0.0	0.0	0.0	42.1	11.2	5.3	45.3	**106.6**
Oceania	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.0**
Total	**19.3**	**0.0**	**58.4**	**22.0**	**321.7**	**51.7**	**108.7**	**435.3**	**1017.1**

Coking coal (2010)

Importers / Exporters	Australia	Canada	Russia	United States	**Total**
Europe and Mediterranean	22.6	12.2	4.9	16.0	**55.6**
Japan	39.9	8.4	3.6	5.4	**57.3**
Korea	23.4	0.0	0.0	2.4	**25.8**
China	24.2	0.0	0.0	8.7	**32.9**
India	31.1	0.0	0.0	5.1	**36.1**
Other Asia	3.1	4.0	0.0	1.0	**8.1**
Brazil	3.9	0.0	0.0	9.1	**13.0**
Other	1.8	0.0	0.0	0.6	**2.3**
Total	**149.9**	**24.5**	**8.5**	**48.3**	**231.2**

TABELLE B.5: Firm-level optimisation - iron ore and coking coal trade flows in million tonnes (demand elasticity of -0.5)

Iron ore (2008)

Importers / Exporters	European Union	Other Europe	CIS	NAFTA	C. & S. America	Africa and ME	Asia	Oceania	**Total**
European Union	0.0	0.0	38.4	0.0	46.9	16.3	1.4	57.7	**160.6**
Other Europe	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.0**
CIS	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.0**
NAFTA	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.0**
C. & S. America	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.0**
Africa and ME	0.1	0.0	0.0	2.2	1.3	0.0	3.5	2.7	**9.8**
China	8.7	0.0	15.3	16.2	171.4	6.2	61.3	163.8	**442.8**
Japan	4.0	0.0	0.0	0.0	30.5	9.9	27.8	64.4	**136.6**
Other Asia	0.9	0.0	0.0	0.0	25.0	4.6	19.7	27.0	**77.3**
Oceania	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.0**
Total	**13.7**	**0.0**	**53.7**	**18.3**	**275.1**	**36.9**	**113.7**	**315.6**	**827.1**

Coking coal (2008)

Importers / Exporters	Australia	Canada	Russia	United States	**Total**
Europe and Mediterranean	29.0	17.4	2.1	12.1	**60.6**
Japan	51.5	0.0	3.0	6.1	**60.6**
Korea	13.1	0.0	0.0	1.5	**14.6**
China	17.1	0.0	0.0	0.0	**17.1**
India	24.1	0.0	0.0	4.9	**29.1**
Other Asia	4.6	2.1	0.0	1.0	**7.7**
Brazil	4.9	0.0	0.0	5.6	**10.6**
Other	3.3	3.2	0.0	1.2	**7.7**
Total	**147.7**	**22.7**	**5.1**	**32.4**	**207.9**

Iron ore (2009)

Importers / Exporters	European Union	Other Europe	CIS	NAFTA	C. & S. America	Africa and ME	Asia	Oceania	**Total**
European Union	0.0	0.0	25.0	17.4	27.7	7.4	0.0	17.2	**94.6**
Other Europe	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.0**
CIS	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.0**
NAFTA	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.0**
Central and South America	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.0**
Africa and Middle East	0.0	0.0	0.0	1.5	1.5	0.0	1.3	1.1	**5.3**
China	12.1	0.0	28.6	0.0	178.4	24.4	86.5	302.4	**632.4**
Japan	2.0	0.0	0.0	9.9	37.3	8.5	0.0	44.1	**101.7**
Other Asia	0.9	0.0	0.0	0.0	31.2	8.1	4.4	23.0	**67.6**
Oceania	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.0**
Total	**15.1**	**0.0**	**53.6**	**28.7**	**276.2**	**48.2**	**92.1**	**387.8**	**901.7**

Coking coal (2009)

Importers / Exporters	Australia	Canada	Russia	United States	**Total**
Europe and Mediterranean	17.7	11.6	4.8	6.6	**40.7**
Japan	33.1	9.2	3.2	4.0	**49.5**
Korea	17.2	0.0	0.0	1.7	**18.8**
China	34.6	0.0	0.0	1.2	**35.8**
India	24.4	0.0	0.0	5.0	**29.3**
Other Asia	2.7	0.3	0.0	0.5	**3.6**
Brazil	4.5	0.0	0.0	7.5	**12.0**
Other	1.8	2.7	0.0	0.7	**5.2**
Total	**135.9**	**23.8**	**8.0**	**27.3**	**195.0**

Iron ore (2010)

Importers / Exporters	European Union	Other Europe	**CIS**	NAFTA	C. & S. America	Africa and ME	Asia	Oceania	**Total**
European Union	0.0	0.0	29.5	8.7	53.8	11.4	0.0	58.1	**161.5**
Other Europe	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.0**
CIS	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.0**
NAFTA	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.0**
Central and South America	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.0**
Africa and Middle East	0.1	0.0	0.0	0.0	3.9	0.0	0.7	1.2	**5.9**
China	12.4	0.0	25.9	3.0	201.2	17.0	101.5	263.9	**624.8**
Japan	4.4	0.0	0.0	12.4	39.3	10.6	0.0	64.8	**131.5**
Other Asia	2.6	0.0	0.0	0.0	41.9	12.8	4.1	46.9	**108.3**
Oceania	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.0**
Total	**19.5**	**0.0**	**55.4**	**24.0**	**340.2**	**51.7**	**106.3**	**434.9**	**1032.1**

Coking coal (2010)

Importers / Exporters	Australia	Canada	Russia	United States	**Total**
Europe and Mediterranean	26.7	13.2	3.7	13.7	**57.3**
Japan	41.8	8.7	3.6	4.4	**58.5**
Korea	24.4	0.0	0.0	2.0	**26.3**
China	30.6	0.0	0.0	5.7	**36.3**
India	33.1	0.0	0.0	4.1	**37.2**
Other Asia	5.4	2.1	0.0	0.8	**8.3**
Brazil	4.6	0.0	0.0	8.7	**13.3**
Other	1.2	0.7	0.0	0.5	**2.5**
Total	**167.9**	**24.7**	**7.3**	**39.8**	**239.7**

Anhang C

Supplementary material for Chapter 4

C.1 Input data[92]

Tabelle C.1: Reference demand [Mt] and price [US$/t]

	2008		2009		2010	
	demand	price	demand	price	demand	price
JP_KR	80	300	71	129	87	227
CN_TW	10	300	26	129	42	227
IN	26	300	26	129	35	227
LAM	16	300	15	129	17	227
EUR_MED	63	300	43	129	58	227
Other	18	300	10	129	7	227

Tabelle C.2: Production costs [US$/t]

	2008	2009	2010
Australia	67	71	73
Canada	100	101	104
China	91	114	117
Indonesia	110	112	113
New Zealand	72	73	75
Russia	162	163	156
South Africa	51	52	53
USA	117	108	113
Anglo American	67	69	70
BHP Billiton	76	77	80
Rio Tinto	78	79	82
Xstrata	63	65	67

[92]The input data are own calculations based on Trüby (2013). For more detailled information please refer to the appendix of Trüby (2013).

Tabelle C.3: Production capacities [Mtpa]

	2008	**2009**	**2010**
Australia	37.4	34.4	42.6
Canada	25.6	28.0	28.0
China	4.0	2.1	2.1
Indonesia	2.1	2.1	2.5
New Zealand	2.6	2.6	2.6
Russia	15.2	15.5	15.5
South Africa	0.8	0.8	0.8
USA	52.2	57.2	60.2
Anglo American	15.1	15.1	16.3
BHP Billiton	63.6	63.6	71.4
Rio Tinto	15.0	15.0	16.2
Xstrata	13.2	14.5	15.0

Tabelle C.4: Shipping costs [US$/t]

	CN_TW			EUR_MED			IN		
	2008	**2009**	**2010**	**2008**	**2009**	**2010**	**2008**	**2009**	**2010**
Australia	24.7	13.8	15.9	42.9	18.9	20.9	29.9	15.4	17.5
Canada	30.5	15.6	17.6	37.6	17.6	19.6	37.1	17.4	19.5
China	15.2	10.5	12.4	41.8	18.6	20.6	26.5	14.4	16.4
Indonesia	17.9	11.5	13.5	39.9	18.2	20.2	23.5	13.4	15.5
New Zealand	29.6	15.3	17.4	42.5	18.8	20.8	32.3	16.1	18.2
Russia	16.7	11.1	13.1	16.5	11.0	13.0	27.4	14.7	16.7
South Africa	31.6	15.9	18.0	32.7	16.2	18.3	25.1	14.0	16.0
USA	41.7	18.6	20.6	23.7	13.5	15.6	37.8	17.6	19.6
	JP_KR			LAM			Other		
	2008	**2009**	**2010**	**2008**	**2009**	**2010**	**2008**	**2009**	**2010**
Australia	24.8	13.9	15.9	36.2	17.2	19.2	33.7	16.5	18.5
Canada	26.4	14.4	16.4	36.4	17.2	19.3	41.2	18.5	20.5
China	15.1	10.4	12.4	42.5	18.8	20.8	32.1	16.0	18.1
Indonesia	22.2	13.0	15.0	37.7	17.6	19.6	26.9	14.5	16.6
New Zealand	29.2	15.2	17.3	32.3	16.1	18.1	36.2	17.2	19.2
Russia	12.4	9.3	11.2	33.0	16.3	18.4	27.2	14.6	16.7
South Africa	34.9	16.8	18.9	26.0	14.2	16.3	26.2	14.3	16.4
USA	39.2	18.0	20.0	27.9	14.8	16.9	36.5	17.3	19.3

C.2 Prices and statistical measures for trade flows

C.2.1 Prices

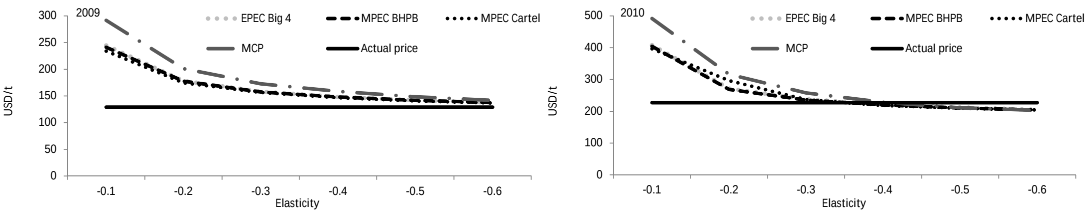

ABBILDUNG C.1: FOB Prices for a range of (abs.) elasticities - model results vs. actual benchmark price

C.2.2 Statistical measures for trade flows

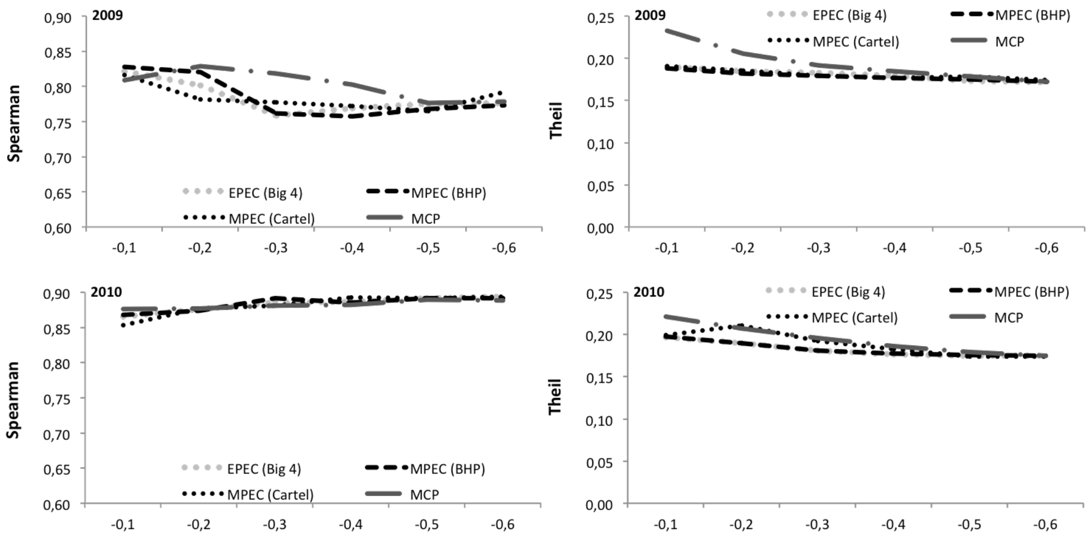

ABBILDUNG C.2: Spearman's rank correlation coefficients and Theil's inequality coefficients for a range of (abs.) elasticities

Anhang D

Supplementary material for Chapter 6

D.1 The Diks and Panchenko (2006) nonlinear Granger causality test

Diks and Panchenko (2006) test the null hypothesis of no nonlinear Granger causality between two time series by comparing their conditional distributions. Dropping the time index in the relationship

$$Y_t(h|\{X_s, Y_s|s \leq t\} \sim Y_t(h|\{Y_s|s \leq t\}, \tag{D.1}$$

and defining $Z = Y_t$ with $t = s + 1$, it must hold under the null that X and Z are independent conditionally on the past realisations of Y. More specifically, under the null the joint probability density function and their respective margins must satisfy the following equation:

$$\frac{f_{X,Y,Z}(x,y,z)}{f_Y(y)} = \frac{f_{X,Y}(x,y)}{f_Y(y)} * \frac{f_{X,Z}(x,z)}{f_Y(y)}. \tag{D.2}$$

As shown in Diks and Panchenko (2006) this implies that the null hypothesis of absent nonlinear Granger causality can be also be tested using

$$q \equiv E\left[f_{X,Y,Z}(X,Y,Z)f_Y(Y) - f_{X,Y}(X,Y)f_{Y,Z}(Y,Z)\right] = 0. \tag{D.3}$$

In contrast to Hiemstra and Jones (1994), the test by Diks and Panchenko (2006) proposes a modification of the test statistic in order to cure the tendency of the Hiemstra Jones Test to over-reject if the null hypothesis of no Granger causality is true (Diks and Panchenko, 2005). As this tendency is due to the possible variation in conditional distributions under the null hypothesis, the test statistic, $T_n(\epsilon_n)$, proposed by Diks and Panchenko (2006)

$$T_n(\epsilon_n) = \frac{n-1}{n(n-2)} * \sum_i \left[\hat{f}_{X,Y,Z}(X_i, Y_i, Z_i)\hat{f}_Y(Y_i) - \hat{f}_{X,Y}(X_i, Y_i)\hat{f}_{Y,Z}(Y_i, Z_i)\right] \quad \text{(D.4)}$$

automatically accounts for such variation. Thereby, $\hat{f}_W(W_i)$ denotes a local density estimator of a d_W-variate random vector $\mathbf{W}$ at W_i that is defined by

$$\hat{f}_W(W_i) = (2\epsilon_N)^{-d_W}(n-1)^{-1} \sum_{j,j\neq i} I^W_{i,j} \quad \text{(D.5)}$$

where $I^W_{i,j} = I(\|W_i - W_j\| < \epsilon_n)$ with $I(\cdot)$ being the indicator function and ϵ_n the bandwidth given the sample size n. Given a lag length of 1 and $\epsilon_n = Cn^{-\beta}$ with $C > 0$ and $\frac{1}{4} < C < \frac{1}{3}$, Diks and Panchenko (2006) were able to show that their test statistic's distribution converges to

$$\sqrt{n}\frac{T_n(\epsilon_n) - q}{S_n} \xrightarrow{D} N(0,1) \quad \text{(D.6)}$$

where S_n is the estimator of the asymptotic variance of $T_n(\cdot)$. We follow Diks and Panchenko (2006) by implementing a one-sided version of the test, rejecting the null hypothesis if the left hand-side of Equation D.6 is too large. Furthermore, we set C equal to 8 as suggesteed by Diks and Panchenko (2006). Knowing that the bandwidth that minimises the MSE of T_n is given by $\epsilon_n = C * n^{-\frac{2}{7}}$, the bandwidth in the empirical analysis is approximately 1.12.

D.2 Descriptive statistics of level time series

TABELLE D.1: Descriptive statistics of ARA and RB spot and futures price series (levels)

	Number of observations	Mean	Variance	Skewness	Kurtosis
ARA Spot	978	97.64	275.93	0.57	1.98
ARA M+1	978	97.80	266.15	0.54	1.97
RB Spot	978	95.43	232.26	0.49	2.02
RB M+1	978	96.05	230.89	0.48	1.99

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Professional Experience

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Refereed Journal Publications

Hecking, H. and Panke, T., 2015. The global markets for coking coal and iron ore – complementary goods, integrated mining companies and strategic behavior.
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