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Abstract

The prevalent market structures found in many resource markets consist of a high concentration on the supply side and a low demand elasticity. Market results are therefore frequently assumed to be an outcome of strategic interaction between producers. Common models to investigate the market outcomes and underlying market structures are games representing competitive markets, strategic Cournot competition and Stackelberg structures taking into account a dominant player acting first followed by one or more followers. Besides analysing a previously neglected scenario of the latter kind, we add to the literature by expanding the application of mathematical models by applying an Equilibrium Problem with Equilibrium Constraints (EPEC), which is used to model multi-leader-follower games, to a spatial market. We apply our model by investigating the prevalent market setting in the international market for metallurgical coal between 2008 and 2010, whose market structure provides arguments for a wide variety of market structures. Using different statistical measures and comparing model with actual market outcomes, we find that two previously neglected settings perform best: First, a setting in which the four largest metallurgical coal exporting firms compete against each other as Stackelberg leaders, while the remainders act as Cournot followers. Second, a setting with BHPB acting as sole Stackelberg leader.

Keywords: Applied industrial organisation, Stackelberg games (MPEC), multi-leader-follower games (EPEC), Cournot oligopolies (MCP), resource markets
JEL classification: C61, D43, L71, Q31

1. Introduction

Many resource markets suffer from a high concentration on the supply side and a low demand elasticity. Market results are therefore frequently assumed to be an outcome of strategic interaction between producers. A long tradition in the economic literature exists using mathematical models to analyse market outcomes to gain insides into the underlying market structures. Common models

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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 followers. We add to the literature by expanding the application of mathematical models by applying an Equilibrium Problem with Equilibrium Constraints (EPEC) to a spatial market, i.e., a set-up with multiple, geographically disperse demand and supply nodes. This model class is used to model multi-leader-follower games. This enables us to investigate more complex market structure that have been neglected in previous studies of 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.[1] 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 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's focus is on the time period from 2008 to 2010. Regarding the market structures, its author arrives at the conclusion that although assuming that the Big-Four jointly acting as a Stackelberg leader provides the best results compared to actual market outcomes, 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 under scrutiny. More specifically, we simulate one scenario in which the Big-Four compete against each other on a first stage, i.e., choose outpute 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 so far been omitted. As investigating

[1] 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 data set) that technically are thermal coals but can be used for metallurgical purposes as well, such as pulverised coal injection (PCI).

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 elasticities. In order 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 market outcomes. In case of the comparison of 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 organization and, more specifically, the analysis of the international market for metallurgical coal. We expand previous studies by the application of an Equilibrium Problem with Equilibrium Constraints (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. And, 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 on 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 it allows to assess different market structure. 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. Chapter 2 offers an overview of the relevant literature, while the methodology is described in Chapter 3. The fourth chapter briefly describes the numerical data used in this study. Chapter 5 is devoted to the analyses of the empirical results. Chapter 6 concludes.

2. Literature review

Commodity markets have often been subject to concerns regarding a too high concentration of the supply side, with several prominent examples being markets for energy resources such as the markets for oil, natural gas or metallurgical coal. Consequently, there has been substantial academic research trying to assess whether companies or countries have been able to exercise 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[2], 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 which specific market structure to assume or analyse. 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., do firms form a cartel or is there no explicit cooperation between the relevant firms.

Consequently, the use of mathematical programming models to analyse spatial markets has a long tradition in economics. Enke (1951) first described the problem of a spatial market 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) maximization 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), his 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 Nelson and McCarl, 1984; Harker, 1984, 1986). This has frequently been done since then, e.g., for steam coal markets (Kolstad and Abbey, 1984; Haftendorn and Holz, 2010; Trüby and Paulus, 2012), natural gas markets (Boots et al., 2004; Gabriel et al., 2005; Holz et al., 2008; Zhuang and Gabriel, 2008; Egging et al., 2010; Growitsch et al., 2013), wheat markets (Kolstad and Burris, 1986), oil markets (Huppmann and Holz, 2012) or for the markets of coking coal and iron ore (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 in 2008 to 2010 may be characterised by firms exercising market power, rejecting previous findings by Graham et al. (1999), although for a different time period since the latter focusses on 1996.

Most of the aforementioned models have in common that decisions by all players are taken simultaneously. This model type can be extended to represent bi-level games, the classical example

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

being Stackelberg games (Stackelberg, 1952). There are several applications for this type of problem, which can be modelled as a Mathematical Problem with Equilibrium Constraints (MPEC). MPECs are constrained optimization 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 non-linearities, 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 has to maximise leaders' profits 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 non-linearity, 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); Yao et al. (2008); Shanbhag et al. (2011) and Wogrin et al. (2013). Lorenczik et al. (2014) analyse investment decisions in the metallurgical coal market.

3. Methodology

3.1. Market Structures

Due to its market structure with few large producers and relatively low elasticity of demand, the metallurgical coal market is under suspicion of not being competitive. This suspicion was substantiated by a recent study showing that market outcomes can be reproduced rather by assuming strategic than competitive behaviour. Trüby (2013) found that in 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.[3] The paper's conclusion regarding the market structures is that, although assuming that the Big-Four jointly acting as a Stackelberg leader provides the best results compared to actual market outcomes, 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, which is the programming approach used to simulate 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 be in line with the methodology used in the corresponding literature.

[3] In the Cournot Cartel case, the Big-Four are assumed to engage in a cartel and, thus, jointly optimise their total supply. Trüby (2013) found 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 did 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).

However, 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 on the first stage and take into account the reaction of the other firms engaging in Cournot competition on the second stage (EPEC Big 4). We reason that this setting is interesting 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. Second, in the MPEC Cartel scenario simulated production volumes by the Big-Four do not match historic production volumes as well as the two additional settings proposed in this paper. Both reasons will be discussed in depth in Section 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 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

Figure 1: Overview of modelled market structures

To simulate the aforementioned different coking coal market settings, three different types of simulation models are used. The first calculates the expected market outcome in a Cournot oligopoly where 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 Mixed Complementary Problem (MCP). The second and third models are implemented as a Mathematical Problem with Equilibrium Constraints (MPEC) and an Equilibrium Problem with Equilibrium Constraints (EPEC), respectively.

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 like 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 will use general terms for the model description and notation to emphasise the applicability of our approach to other than the coking coal market. Table 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 describes what they stand for. Additional symbols are explained where necessary.

Table 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]

3.2.1. The MCP model

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

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

subject to

$$\begin{aligned}
& cap_m - x_m \geq 0, \;\; \forall m \in M_i \;\; (\lambda_m) \\
& \sum_{m \in M_i} x_m - \sum_j s_{i,j} \;\; \geq 0 \;\; (\mu_i) \\
& P_j = a_j - b_j \cdot (s_{i,j} + S_{-i,j}), \;\; \forall j \\
& s_{i,j} \geq 0, \;\; \forall j \\
& x_m \geq 0, \;\; \forall m \in M_i
\end{aligned}$$

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 greater than 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 to 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 related Karush-Kuhn-Tucker (KKT) conditions simultaneously for all players:

$$
\begin{aligned}
&0 \leq tc_{i,j} - P_j + b_j \cdot s_{i,j} + \mu_i \perp s_{i,j} \geq 0, \ \forall\, i, j \\
&0 \leq c_m + \lambda_m - \mu_i \perp x_m \geq 0, \ \forall\, m \in M_i \\
&0 \leq cap_m - x_m \perp \lambda_m \geq 0, \ \forall\, m \\
&0 \leq \sum_{m \in M_i} x_m - \sum_j s_{i,j} \perp \mu_i \geq 0, \ \forall\, i \\
&P_j = a_j - b_j \cdot (s_{i,j} + S_{-i,j}), \ \forall\, j \\
&s_{i,j} \geq 0, \ \forall\, i, j \\
&x_m \geq 0, \ \forall\, m,
\end{aligned}
$$

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.

3.2.2. The MPEC model

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

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

subject to

$$\begin{aligned}
&0 \leq tc_{i,j} - P_j + b_j \cdot s_{i,j} + \mu_i \perp s_{i,j} \geq 0, \ \forall \ i \neq l, j \\
&0 \leq c_m + \lambda_m - \mu_i \perp x_m \geq 0, \ \forall \ m \in M_{i \neq l} \\
&0 \leq cap_m - x_m \perp \lambda_m \geq 0, \ \forall \ m \in M_{i \neq l} \\
&0 \leq \sum_{m \in M_i} x_m - \sum_j s_{i,j} \perp \mu_i \geq 0, \ \forall \ i \neq l \\
&P_j = a_j - b_j \cdot (S_{-i,j} + s_{l,j}), \ \forall \ j \\
&s_{i,j} \geq 0, \ \forall \ i, j \\
&x_m \geq 0, \ \forall \ m
\end{aligned}$$

Thus, the leader decides on supply taking the equilibrium outcome of the second stage (which influences the market price) into account. The followers ($-i$) are taking 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 the existing non-linearities. Due to its simple implementation, for the complementary constraints we follow the approach presented by Fortuny-Amat and McCarl (1981) (for an alternative formulation see Siddiqui and Gabriel, 2013). For instance, the non-linear constraint

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

is replaced by the following linear constraints

$$\begin{aligned}
&0 \leq c_m - P_j + b_j \cdot s_{i,j} + \lambda_m \leq M \cdot u_{i,j} \\
&0 \leq s_{i,j} \leq M(1 - u_{i,j})
\end{aligned}$$

with M being a large enough constant (for hints on how to determine M see Gabriel and Leuthold, 2010).

For the remaining non-linear 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

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

where Δ_s represents the step size, i.e., the precision of the linear approximation, and k the number of steps. $b^s_{k,i,j}$ are binary variables. 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

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

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

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. Where MPECs are already difficult to solve due to their non-linear nature, it is even more difficult to solve EPECs. KKT conditions generally cannot be formulated for MPECs 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. Do 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 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 ran 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. Data

Modelling international commodity markets may be computational 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 computational challenging depends on which market structure one would like to analyse. While solvers for Mixed Complementary Problems such as PATH (see Dirkse and Ferris, 1995) can handle quite large systems of equations and variables, the same setup may be intractable when formulating it as a Mathematical Problem with Equilibrium Constraints (MPEC) or other more complex problems such as an Equilibrium Problems with Equilibrium Constraints (EPEC) due to their high non-linearity.

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.[4] To ensure comparability the same data setup 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 A for production and shipping costs as well as capacities).

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 which represent the remaining firms in the respective country. In addition to each of the four firms belonging to the Big-Four, i.e., BHP Billiton (BHPB), Rio Tinto, Anglo American and Xstrata, eight country supply nodes are included in the model of the international coking coal market (Table 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 were simply added up. Concerning production costs, we used the quantity-weighted average of the individual mines of a firm or country.

[4] 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.

Table 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	LAM	Latin America (mainly Brazil and Chile)
Australia		
Canada	EUR_MED	Europe and Mediterranean
China	Other	Africa and Middle East
Indonesia		
New Zealand		
Russia		
South Africa		
United States		

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 its minor importance in terms of share of total import volumes we included Africa and Middle East into one demand node despite the large area this demand node covers. Inverse demand functions are assumed to be linear (see Table A1 in Appendix A for the used market data). Since, it is a priori not clear which is the right elasticity, we run the market analyses for a range of elasticities, 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 in 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.

5. Results

In this section, the model results are presented and discussed. We start out by comparing prices under the different market settings to 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.

5.1. Prices

Figure 2 displays the actual 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 2, taking a look at the other years (see Figure C1 in Appendix C) confirms this conclusion.

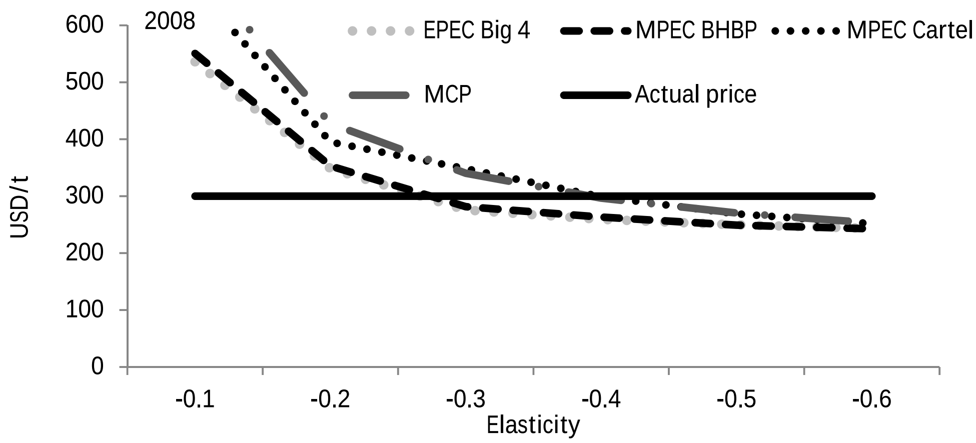

Figure 2: FOB Prices for a range of (abs.) elasticities - model results vs. actual benchmark price

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 firm of the followers 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 in the case the Big-Four form a cartel that acts as a Stackelberg leader, labelled MPEC Cartel, are below the prices in the Cournot oligopoly (MCP).[5] I.e., the output-increasing effect of becoming a leader is stronger than the output-decreasing effect of collusion (forming the cartel). Building on Shaffer

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

(1995) the intuition behind this finding can be explained by showing for the case of N identical firms, zero marginal costs and a linear demand that 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.[6] This is also in line with the results for the case in which BHPB acts as single leader (MPEC BHPB).

Finally, the higher the elasticity the more the simulated prices converge which can be explained by two effects: First, with increasing elasticity total production increases as well (along with decreasing prices). Thereby, the capacity utilization over all players increases from at minimum 79 % (MCP, eta -0.1) to around 97 % (all scenarios with eta -0.6) for 2008. This narrows the scope for differentiation between 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 severe 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).

5.2. Trade flows

In a first step, we investigate whether simulated trade flows under the different market structures match 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 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.[7]

Taking a closer look at Table 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 had plummeted compared to the previous year because of the financial crisis.

[6] In case of $k = N$, i.e., the cartel consists of all firms, N, in the market, the price in the market would equal the price a monopolist would ask.

[7] See Appendix C for more details on the methodology used in this subsection.

Table 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 3 depicts Spearman's rank correlation and Theil's inequality coefficient for the different market settings and the whole range of elasticities in 2008.[8] Both coefficients confirm the analysis of the linear hypothesis test since neither of the two indicators allows to discard one of the market settings when concentrating on the relevant range of elasticities.

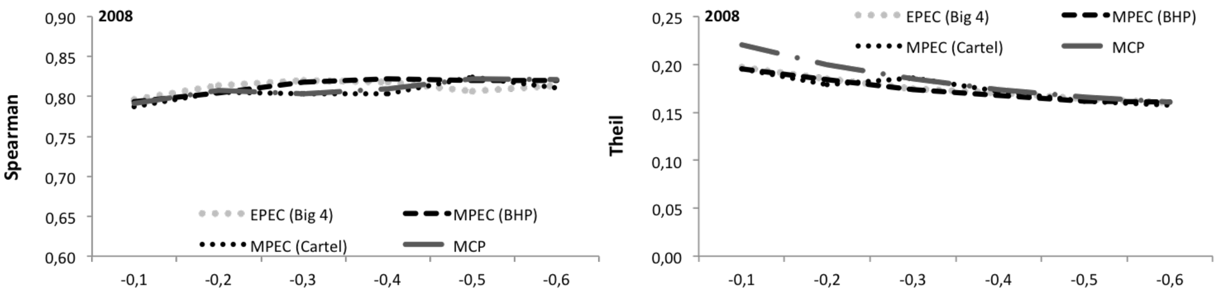

Figure 3: Spearman's correlation coefficients and Theil's inequality coefficients for a range of (abs.) elasticities

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 the others. Therefore, we take a closer look at two further aspects: revenues and production volumes of the Big-Four.

[8] Conclusions remain unchanged when focussing on the other two years as may be seen in Figure C2 in Appendix C.

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, in the MPEC Cartel setting the Big-Four make the largest profits. However, relative differences between the different market structures are negligible ($< 1\%$) as becomes obvious when comparing the bars in Figure 4.[9]

Thus, 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 the coordination of the firms inside the cartel.

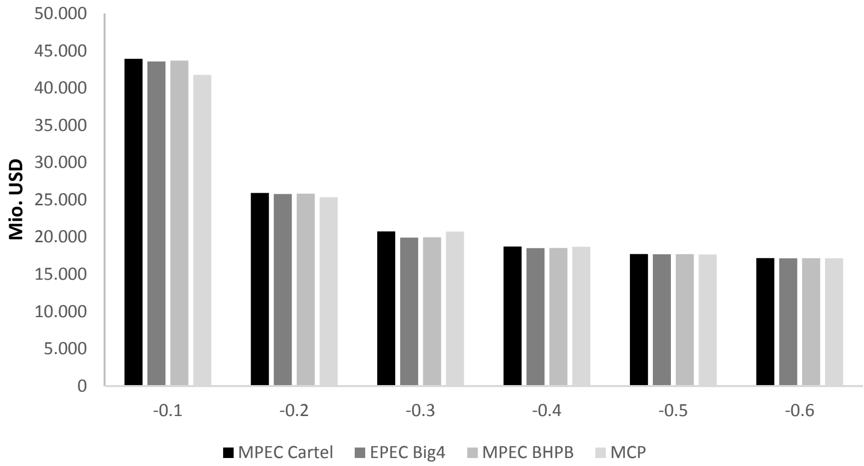

Figure 4: 2008's profits of the Big-Four in the three two-stage-games for the whole range of elasticities

Turning now to the production of the Big-Four, 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 of 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 5 for a demand elasticity of -0.4, which is the mean value of the range of elasticities found to be relevant (see Subsection 5.1). As can be seen in the left diagram, cumulated absolute differences to historic data lie in the range of 8% to 17%, with the MPEC Cartel setting performing worst and 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 responsible for this case' poor performance regarding squared deviations. In contrast, in the MPEC Cartel setting constantly overestimated the production of BHP Billiton and underestimates the one

9 The results for 2009 and 2010 are similar.

of Rio Tinto, with the reason being that this minimizes the overall production costs of the cartel. Concentrating on the two settings that perform best no striking patterns are observed.

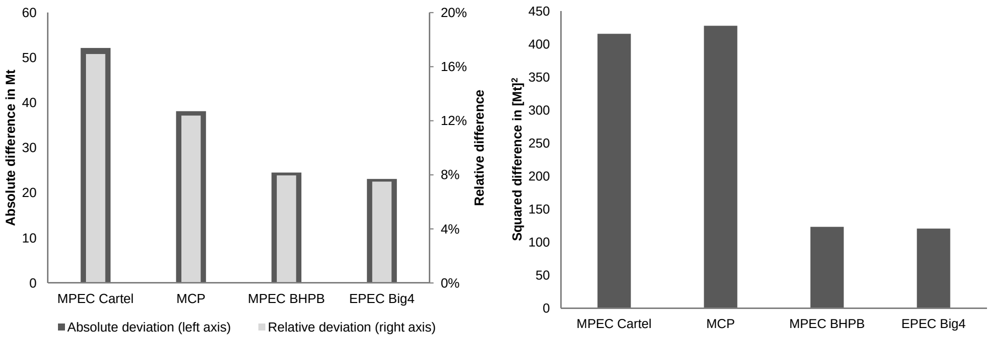

Figure 5: Cumulated absolute and squared difference in production volumes of the Big-Four to actual market outcomes at an elasticity of -0.4

In summary, three conclusions may be drawn from our analyses: i) We are able to support previous findings concluding 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 reproduce actual trade flows and prices well. 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 two settings with one or more leading firms reproduce actual trade flows and prices equally well as the cartel- as well as the Cournot-setting and, in addition, perform better than the former two settings with respect to the production volumes of the Big-Four. In particular, the in this paper introduced methodology representing multi-leader-follower games scored among the best results in all tests used in our analysis.

6. Conclusions

Previous analyses of the prevailing market structure in spatial resource markets mainly focused 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. By applying our model to the metallurgical coal market, which is especially suited as its market structure suggests a multitude of possible markets structures that have been neglected partly in previous analyses, 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 until 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 promoted 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 especially the computationally challenging non-linear 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 that detailed data were available. Unfortunately, neither mine-by-mine market results nor detailed profitability data on a firm level were available in our case.

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 may reflect collusive behaviour. Second, a market structure analysis solely based on market outcomes concerning price and trade flows may not be sufficient to decide on the actual market structure but has to be completed by additional analyses.

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Appendix A Input data

Table A1: 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

Table A2: 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

Table A3: 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

Table A4: 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

Appendix B Statistical measures[10]

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) as well as Hecking and Panke (2014) by applying three different statistical measures: a linear hypothesis test, the Spearman 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 data sets 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 on 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 $d_{i,j}$ 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

[10] This section has already been published in Hecking and Panke (2014) which is co-authored by one of the authors of this paper.

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 data sets. Theil's inequality coefficient is defined as:

$$U = \frac{\sqrt{\sum_t^T (M_t - A_t)}}{\sqrt{\sum_t^T M_t^2} + \sqrt{\sum_t^T A_t^2}}$$

Appendix C Prices and statistical measures for trade flows

Prices

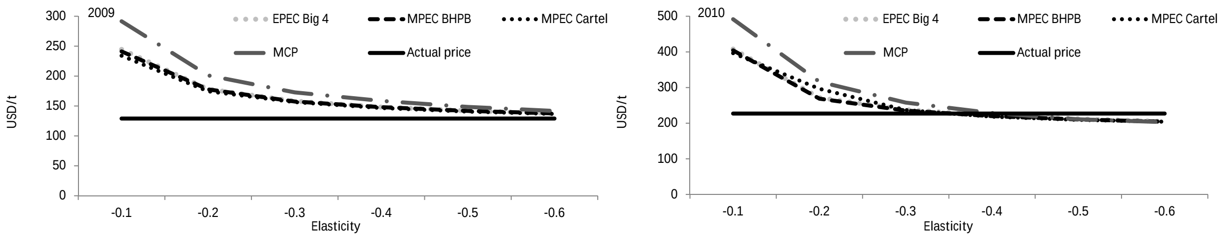

Figure C1: FOB Prices for a range of (abs.) elasticities - model results vs. actual benchmark price

Statistical measures for trade flows

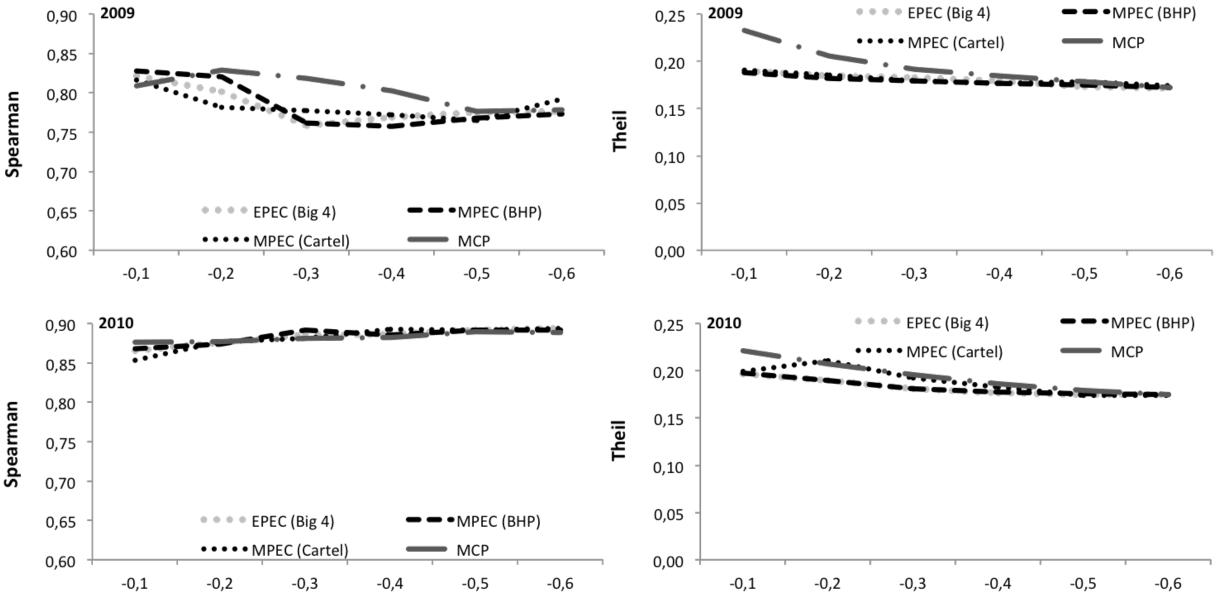

Figure C2: Spearman's correlation coefficients and Theil's inequality coefficients for a range of (abs.) elasticities