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Abstract

The aim of this paper is to develop a methodology for measuring the exercise of potential market power in liberalized electricity markets. We therefore investigate producer behavior in the context of electricity pricing with respect to fundamental time-dependent marginal cost (TMC), i.e. CO_2*- and fuel cost. In doing so, we do not - in contrast to most current approaches to market power investigation - rely on an estimate of the entire generation cost, which inevitably suffers from the lack of appropriate available data. Applying an analytical model of a day-ahead electricity market, we derive work-on rates, which provide information about the impact of TMC variations on electricity prices in the market constellations of perfect competition, quasi-monopoly and monopoly. Comparing these model-based work-on rates with actual work-on rates, estimated by an adjusted first-differences regression model of German power prices on the cost for hard coal, natural gas and emission allowances, we find evidence of the exercise of market power in the period* 2006 *to* 2008*. However, our results reveal that German market competitiveness increases marginally. We confirm our results by simulating a TMC-driven diffusion model of futures power prices estimated by maximum-likelihood.*

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1 Introduction

Even after the liberalization of its electricity market which started in 1998, German power consumers continue to face high electricity prices. This leads us to the issue of market power, which is defined by the ability to profitably shift prices above competitive levels, either by demanding a higher price than marginal cost or by withholding power plants that would be “in the money” [1]. Market power can be exhibited unilaterally, if the price-driven additional profit of the inframarginal power plants of one producer outweighs the quantity-driven decline in profits caused by a bid mark-up or capacity withholding. If unilateral market power abuse is not profitable, electricity generators might interact either explicitly (*collusion*) or implicitly (*tacit collusion*). The consequences of market power abuse are loss of wealth (*deadweight loss*), due to an inefficiently low output level, and a transfer of wealth from consumers to producers. Therefore, a thorough investigation of the exercise of market power is an essential element of monitoring market performance, after the restructuring of electricity markets, as was done in Germany in the late Nineties. While market power measurement methods have been investigated widely in the economic literature, the application in electricity markets is more complex due to its specific characteristics, such as grid-bound delivery, non-storability or its usually low price elasticity of demand.

In the power economics literature, there are basically three different approaches to analyzing market power: traditional concentration measures, market-level simulation models estimating cost functions in order to measure mark-ups of real prices, and oligopoly models explicitly modeling the strategic behavior of firms. Traditional concentration measures, such as the CR_n concentration ratio of n firms or the Hirschman-Herfindahl Index (HHI) are the simplest approaches to measuring market power potential in certain industries and have thus been applied to electricity markets by both researchers and regulators [2, 3, 4, 5]. However, these approaches entail significant shortcomings, such as measuring the potential, rather than the actual exercise of market power, as well as failing to consider supply and demand elasticities (see Borenstein *et al.* [6] for a further discussion of the applicability of traditional concentration measures to market power analysis in electricity markets).

The use of simulation models, which compute mark-ups of observed (ex-post) electricity prices on predicted competitive system marginal cost at ex-post quantities, are theoretically “best-practise” for measuring market power, as shown by Joskow and Kahn [7]. Hence, simulation models have been applied widely, particularly to the former England and Wales power pool [8, 9] and the Californian electricity market [10], where a broad set of cost data was available due to central planning by a (former) power pool manager. Cost simulation models have been applied to the German electricity market by Müsgens [11] as well as Schwarz and Lang [12]. While both reveal significant price-cost mark-ups in Germany from 2001 to 2003, the latter indicates that market power abuse was declining in 2004 and 2005. However, this approach entails two significant drawbacks. Firstly, simulation models generally lead to biased estimations of marginal cost and thus mark-ups by not accounting adequately for the complexity of electricity markets, such as the cost of flexibility (start up costs, ramp costs), fuel transport or operation and maintenance (O&M). Secondly, applying the approach to the German market in the absence of a pool manager having collected the necessary data, inevitably suffers from the lack of appropriate data.

Oligopoly models account explicitly for the abovementioned strategic behavior. Most of these approaches are equilibrium models, which assume a limited number of producers bidding either a single output quantity (*Cournot*) or a continuous supply function under the assumption that all other players keep their output constant (*Nash equilibrium*). The Cournot-Nash approach leads to prices which depend on the number of Cournot players and the potential threat of any existing competitive fringe. The computed oligopolistic prices are then compared to market clearing prices, in order to draw conclusions about the actual competitive situation. Due to its relative ease in computing, Cournot models have been widely used for the measurement of market power (e.g. [13] or [14]). Ellersdorfer [15] has applied a two-stage Cournot model to the German electricity market, finding that there is potential for the four dominant producers to exercise market power. Lise *et al.* [16] show that there is potential for strategic behavior in Germany, but it is lower than in the near-monopolies of France and Belgium. Because suppliers in real electricity markets face uncertain demand, supply function equilibrium (SFE) models assume that producers bid functions of quantity-price-combinations, rather than a single quantity as assumed in Cournot games. Being introduced by Klemperer and Meyer [17], SFE models have been applied to electricity markets in [18]–[21], all of which derive Nash equilibria, allowing for tacit collusion among the producers. Willems *et al.* [22] calibrate both a Cournot and an SFE model for the German electricity market on the basis of an identical set of data, revealing that each model explains an equal proportion of the observed price variation. Just like market-level simulation models, Cournot and SFE models rely on a detailed estimation of production cost, which is virtually impossible, due to the lack of available data.

In this paper, we introduce a novel approach for the measurement of electricity market power, that does not require an estimation of the entire marginal cost function. Instead, we investigate the impact of time-dependent marginal cost (TMC) on electricity prices, while ignoring time-independent elements of marginal cost, such as the cost of flexibility, transportation and O&M. The main electricity price-relevant TMCs are costs derived from the prices of hard coal, natural gas and carbon emission allowances offered by energy exchanges, such as the APX NL in Amsterdam or the European Energy Exchange (EEX) in Leipzig.

- Fuel cost: Due to the ability to resell the contracted fuel, the short-term exchange prices serve as references for electricity generation cost, irrespective of whether the power producers have short- or long-term contracts and whether they procure their fuel over-the-counter (OTC) or through exchanges.
- CO_2 cost: The emission of carbon has had a positive price, since the introduction of the European Union Emission Trading Scheme (EU ETS) in 2005. Since then, electricity producers are required to cover each ton of carbon dioxide (CO_2) emitted through the generation of power with a freely tradable European Union Allowance (EUA), the price of which constitutes the reference for carbon cost. Irrespective of whether EUA have been allocated free of charge on the basis of historical data (*grandfathering*) or have been auctioned, i.e. EUA are actually cash-relevant, a complete pass-through of EUA cost is essential and economically rational.

Summarizing, there *are* daily objective reference prices for the calculation of the main TMC.

In order to analyze the impact of TMCs on electricity pricing, we agree with Sijm [23], who defines the "work-on" rate (often referred to as relative price effect) as the share of producers' TMC variations which finds its way into electricity prices, i.e. "work on" electricity prices. Note that work-on rates for each kind of TMC must be identical, in accordance with economic rationality. Even though we consider the *simultaneous* analysis of all fundamental TMCs more reasonable, most approaches in the literature focus on electricity work-on rates induced by *EUA* costs. However, empirical results in the presence of market power are controversial. Wals and Rijkers [24], Sijm *et al.*[23] as well as Bonacina and Gullì [25] find that electricity prices increase more in competitive scenarios than under market power, whereas Lise *et al.* [16] and Newbery [26] state that the relationship is likely to be the other way around. These discrepancies result mainly from varying assumptions about and estimations of price elasticities. Fortunately, since 2004, the EEX provides anonymous hourly supply and demand bid curves for the day-ahead electricity market, so that we can work with real price elasticities in the wholesale market and do not rely on estimations in this context.

The basic idea underlying our approach is to simultaneously derive work-on rates for all TMCs and interpret them with respect to competition theory. We therefore develop a quasi-monopoly model of a dominant supplier facing a competitive fringe, and we calculate work-on rates for this model, as well as for the two extreme competition constellations of perfect competition and monopoly. The work-on rates are derived from EEX bid curves and the assumptions of the respective market constellation. We transfer these spot work-on rates to forward work-on rates by applying the spot-forward price relationship of commodity markets. The resulting model forward work-on rates are then compared to actual average work-on rates derived from an adjusted first-differences regression model of electricity futures prices on forward coal, gas and CO_2 cost, which takes advantage of the fact that work-on rates must be equal for each kind of TMCs. Because the actual work-on rates differ significantly from those calculated in perfect competition and monopoly, while still resembling the quasi-monopoly model rates, we find evidence of the exercise of market power in the German electricity market. These results are confirmed by a Monte Carlo simulation of power futures using a simple TMC-driven diffusion model estimated via maximum likelihood.

The remainder of the paper is structured as follows. Section 2 describes the setup of a spot market model and studies the work-on rates in several market constellations. In Section 3, the data is described, prepared and used for the calibration of a forward market model, which applies the theoretical spot-forward relationship. Section 4 compares the empirical results and presents the Monte Carlo simulation, while Section 5 concludes.

2 Spot market model

In the following investigation, we consider a day-ahead power market in which buyers and sellers submit hour-specific bids in double-sided sealed-bid auctions one day prior to power delivery. We examine this market within three differing competitive constellations. Both the generation facilities and the function of aggregated marginal cost are identical in all constellations. In the first constellation, demand is provided by a dominant group M and a passive competitive fringe F (quasi-monopoly $= QM$). In the second case, a single supplier (monopoly $= Mon$) balances demand, and in the third case, a large number of suppliers compete perfectly for consumers (perfect competition $= PC$).

2.1 Basic setup

The quasi-monopoly model can be described by the following characteristics.

1. In addition to some small producers F, which offer electricity at marginal cost prices, there are few large producers, which submit supply bid functions in accordance with profit-maximization. Since the auctions are repeated daily, the large producers are assumed to operate parallel and thus act as one aggregated supplier M (see Tirole [27] for repeated game settings).

2. Base load power plants are mainly in the hands of M. During intermediate and peak load peri-

ods, the market becomes more competitive by increasing fringe influence. Due to a broader diversification of the generation facilities of M relative to F, we have the piecewise differentiable marginal cost functions $MC_F(q_F) \geq MC_M(q_M) \geq 0$, where $MC_i'(q_i) \geq 0$ and $MC_i''(q_i) \geq 0$ for all $q_i \in \{\mathbb{R}^{\geq 0} | MC \in C^2(\mathcal{U}(q_i))\}$, $i \in \{F, M\}$.

3. Electricity demand in the day-ahead-market is $D(q) \geq 0$, where $D'(q) < 0$ and $D''(q) \geq 0$ for all $q \in \{\mathbb{R}^{\geq 0} | D \in C^2(\mathcal{U}(q))\}$.

Under these assumptions, the M determines the profit-maximizing price p^*. In doing so, M must consider that, depending on its chosen price, a component of demand will be met by the fringe. Hence, M has to calculate its relevant residual demand curve by subtracting the quantities $MC_F^{-1}(c)$ from the initial demand quantities $D^{-1}(p)$. Assuming fringe suppliers behave as price takers, we are able to derive market-clearing price-quantity combinations (p^*, q^*) in a quasi-monopoly. In order to determine optimal price-output-combinations in a monopoly and in perfect competition, we aggregate horizontally the marginal cost functions MC_M and MC_F to MC enabling a comparison of the three cases discussed above. In a monopolistic market, full capacity is provided by one producer which determines the profit-maximizing quantity q^* by equating its marginal cost MC to marginal revenues $MR = d(D(q) \cdot q)/dq$. In the case of perfect competition, all suppliers offer electricity such that price equals marginal cost.

2.2 What we *are* interested in

In order to understand the following investigation, it might be helpful to start with the things, we are *not* interested in. First of all, there is no need to estimate MC_F and MC_M. Besides specific marginal costs, which are firm- or plant-specific and consequentially difficult to compute, there are time-dependent marginal costs (TMCs). The TMCs are easier to compute, since they are closely related to the underlying reference prices, although costs differ from plant to plant. The "add-on" rate defines the share of TMC passed on to supply bids by electricity producers. As demonstrated in [28], the add-on rate of TMC is exactly 100 %, irrespective of the market constellation, since higher oligopoly prices are solely a result of the profit-maximizing calculus and not of larger add-on rates. This can be clarified in terms of a monopoly with zero marginal cost, but positive prices. So far so good, but we are *not* interested in the add-on rate of TMC. What then *are* we interested in?

In our investigation, we concentrate on the market-constellation-based relative price-effects of the TMC, the so called "work-on" rate. The classical (or strong) definition of the work-on rate Λ is

$$\Lambda = \frac{\Delta(p^*)}{\Delta(MC(q^*))}, \tag{1}$$

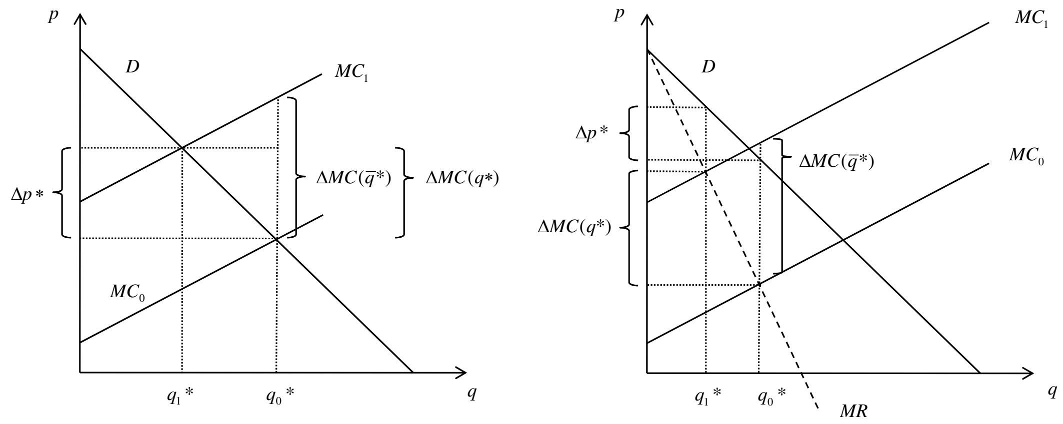

Figure 1: Weak and strong work-on rates in perfect competition (left) and in a monopoly (right).

where price-quantity combinations (p^*, q^*) vary with varying cost-quantity combinations $(MC(q^*), q^*)$. In a linear market model, Λ has a value of 1 by definition in competitive markets, and 0.5 in a monopoly. Unfortunately, it is difficult to calculate the *strong* work-on rate, because the equilibrium quantity is unknown, when marginal costs vary. In other words, in order to calculate the equilibrium quantities for all possible prices, it is necessary to know the marginal cost function. However, that is exactly what we claim being not possible.

Fortunately, it is possible to calculate a *weak* work-on rate λ. In a static setting, one can define

$$\lambda = \frac{\Delta(p^*)}{\Delta(MC(\overline{q^*}))} \tag{2}$$

where clearing price-quantity combinations vary with varying marginal cost, measured at one and the same quantity $\overline{q^*}$. In words, the *weak* work-on rate λ, unlike the *strong* work-on rate Λ, does *not* account for the quantity-induced decline in marginal cost, which results from the price elasticity of demand and marginal cost functions. $\Delta(MC(\overline{q^*}))$ can be interpreted as an average marginal cost add-on in a neighborhood of the clearing output q^*. For a simplified illustration of weak and strong work-on rates, see Figure 1. In a dynamic setting, the weak work-on rate

$$\lambda_t = \frac{\partial p^*/\partial t}{\partial MC/\partial t} \tag{3}$$

is more intuitive, where $\partial f/\partial t$ stands for the partial derivative of f with respect to time t. In appendix A.1 and A.2, we apply some simplified assumptions, in order to ensure the comparability of λ_t and λ as well as the comparability of λ and Λ. In the following spot market model investigation, we discuss λ, which are then computed by the use of static, non-differentiable EEX bid curves in Subsection 2.4. In Section 3, we derive λ_t for a forward market model via a regression analysis of forward price time series. Our intention is both to compare model and regression weak work-on rates, and to determine strong work-on rates from the model results, with the use of linear approximations of the bid curves.

2.3 Model-based work-on rates

There are two possible means of converting weak into strong work-on rates using linear approximation. First-order Taylor-expansion around the clearing point suffers from always being below the monotonic bid-curves. In order to more effectively capture the bid curves behavior around the clearing point, using polygons for piecewise approximation with identically distributed corners for demand and supply, therefore, seems much more appropriate. Applying the polygon approximation of the bid curves, we derive the three market constellation-based work-on rates of TMC

$$\begin{aligned} \lambda^{PC} &= \frac{b}{b+\gamma}, \\ \lambda^{QM} &= \frac{b}{b+v_{QM}}, \\ \lambda^{Mon} &= \frac{b}{2b+\gamma}, \end{aligned} \tag{4}$$

where b equals the absolute value of the demand polygon-derivative in the neighborhood of the clearing quantity q^*,

$$\gamma = \frac{v_F\, v_M}{v_F + v_M} \tag{5}$$

is the derivative of the resulting aggregated marginal cost function and

$$v_{QM} = v_F \cdot \frac{(k+1)b + v_F}{(2k+1)b + (k+1)v_F} \tag{6}$$

is the derivative of the resulting aggregated supply function S in the case of a quasi-monopoly (see Appendix A.1 for the derivation). Assuming bid functions are an outcome of a perfectly competitive market (benchmark PC), $v_F = (k+1)\cdot a$ is the derivative of the MC_F-polygon with $k = v_F/v_M$, while v_M is the derivative of the MC_M-polygon and a is the derivative of the supply bid function-polygon. On the other hand, assuming bid functions are an outcome of a quasi-monopoly setting (benchmark QM),

$$v_F = \frac{1}{2}\big(\sqrt{(b+k(b-a))^2 + 4kba} - (b + k(b-a))\big). \tag{7}$$

Weak work-on rate λ	Strong work-on rate Λ
$\lambda^{PC} = \dfrac{b}{b+\gamma} \geq \lambda^{QM}$ $\lambda^{QM} = \dfrac{b}{b+v_{QM}} \geq \lambda^{Mon}$ $\lambda^{Mon} = \dfrac{b}{2b+\gamma} \geq 0$	$\Lambda^{PC} = \dfrac{\lambda^{PC}}{1-\gamma\cdot\lambda^{PC}/b} = 1$ $\Lambda^{QM} = \dfrac{\lambda^{QM}}{1-\gamma\cdot\lambda^{QM}/b} \leq 1$ $\Lambda_{Mon} = \dfrac{\lambda^{Mon}}{1-\gamma\cdot\lambda^{Mon}/b} = 0.5$
with $\gamma = \frac{v_F\, v_M}{v_F+v_M}$ and $v_{QM} = v_F \cdot \frac{(k+1)b+v_F}{(2k+1)b+(k+1)v_F}$. **Benchmark** PC: $v_F = (k+1)\,a$ **Benchmark** QM: $v_F = \frac{1}{2}\big(\sqrt{(b+k(b-a))^2+4kba} - (b+k(b-a))\big)$	

Table 1: Weak and strong work-on rates.

In order to ensure that calculations are made with exactly the same aggregated marginal cost in all market constellations, the above differentiation of v_F is essential. We summarize our results in Table 1. Note that $\lambda^{PC} \geq \lambda^{QM} \geq \lambda^{Mon}$, $\Lambda^{PC} \geq \Lambda^{QM} \geq \Lambda^{Mon}$ and $\lambda^i \leq \Lambda^i$ for $i \in \{PC, QM, Mon\}$.

2.4 Empirical results

For the following empirical computations, we use data from the EEX day-ahead market from the period April 11, 2006 to July 17, 2008. In this market, physical contracts for the 24 hours of the following day are traded in a double-sided sealed-bid auction at 12.00 a.m. on each exchange trading day. The market area examined in this paper (EEX market area 1) comprises all four German balance areas, as well as the Austrian Power Grid (APG) balance area. Thus, physical delivery can be executed in one of these areas and is traded at a uniform price, since there is no transmission congestion between the areas. In order to procure or sell electricity in the auction, market participants submit hourly bids until 11.55 a.m. These bids allow for different buy and sell quantities to be placed simultaneously at different prices, ranging from 0 to 3000 €/MWh. The individual bid curves are then aggregated into market bid functions that determine the hourly market clearing price and quantity for the next day. Whereas the average of all clearing prices from the hourly auctions for one day is referred to as the Physical Electricity Index (Phelix) Base, the average of hourly prices during peak load times (08.00 a.m to 08.00 p.m. from Monday to Friday) is referred to as the Phelix Peak. The Phelix constitutes the reference power price in Germany and Austria, due to basic arbitrage principles.

In order to compute model-based work-on rates λ, we apply the aggregated hour-specific bid func-

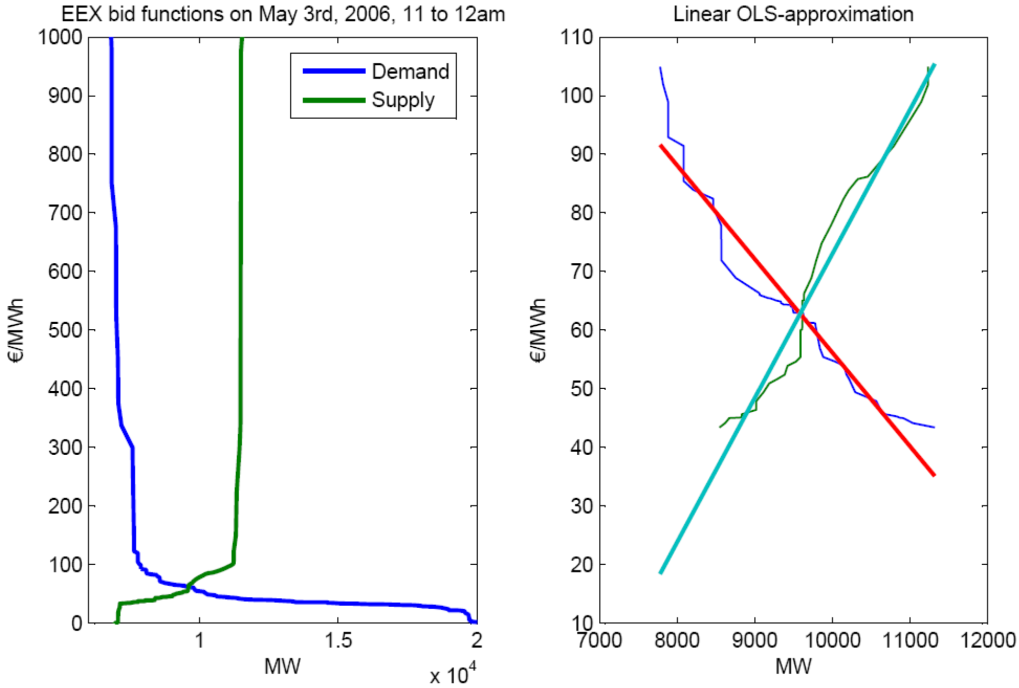

Figure 2: Exemplary EEX-bid curves approximation.

tions of electricity buyers and sellers. These discontinuous bid functions are captured by linear OLS-polygon approximations, or, expressed technically, by linear OLS-approximations in an appropriate neighborhood $\mathcal{U}(q_0)$ of the clearing output q_0. This is depicted in Figure 2 for an arbitrary peak hour in 2006.

We assume that the observed approximated supply function S is an outcome of either perfect competition (benchmark PC), that is, it equals the competitive supply function

$$S^{PC} : p(q) = u_{PC} + \gamma \cdot q = u_{PC} + \frac{v_F\, v_M}{v_F + v_M} \cdot q, \quad \forall q \in \mathcal{U}(q_0), \tag{8}$$

	BM QM Base	BM PC Base	BM QM Peak	BM PC Peak
PC	0.6877	0.4541	0.6801	0.4437
QM	0.5979	0.3893	0.6084	0.3918
Mon	0.4024	0.3069	0.4001	0.3019

Table 2: Mean of weak work-on rates λ for the three market constellations in 2006-2008.

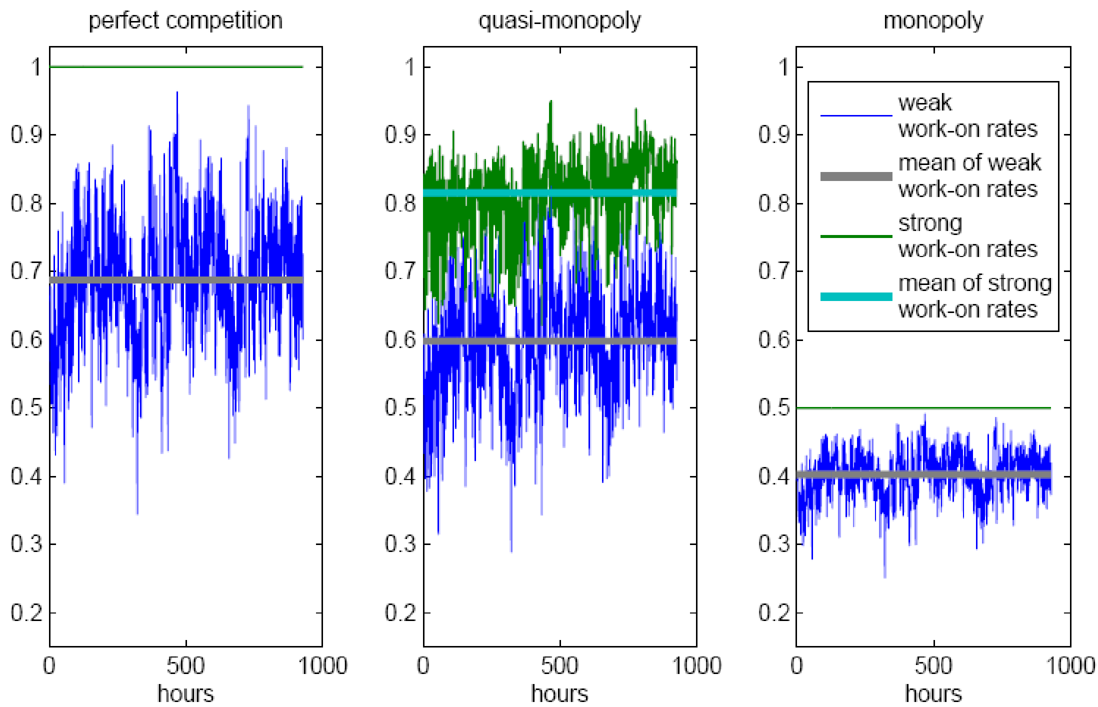

Figure 3: Weak (λ) and strong work-on rates (Λ) in BM QM for all market constellations.

or of a quasi-monopoly (benchmark QM), that is, it equals the strategic supply function

$$S^{QM}: p(q) = u_{QM} + v_{QM} \cdot q = u_{QM} + v_F \cdot \frac{(k+1)b + v_F}{(2k+1)b + (k+1)v_F} \cdot q, \quad \forall q \in \mathcal{U}(q_0). \tag{9}$$

Note that the values of v_F depend on the benchmark (see Table 1) and that there is no further need to determine the constants u_{PC} and u_{QM}. The functions $S^{PC,QM}$ then serve as benchmarks, which are required to determine the relevant market cost structure MC. Therefore, we can estimate $k = v_F/v_M$, which is exactly the quotient of the aggregated load factor of the four dominant German electricity producers EnBW AG, E.ON Energie AG, RWE Power AG and Vattenfall Europe AG and the aggregated fringe load factor (see Appendix A.3). We use a combination of a linear and a power function, in order to capture the decreasing load factors up to an intermediate load, where they reach a minimum level of one, and the increasing load factors during absolute peak hours. The function k depends on a percentage value $s_p = q_{bl}/q_{tot}$, given the ratio of the maximum base load quantity q_{bl} and the total bid quantity (q_{tot}) per hour. This results in a linear part from $l_1 = k(0)$ to $l_2 = k(s_p \cdot q_{tot}) = k(q_{bl})$ and a power function of second degree between $l_2 = k(q_{bl}), 1$ and $l_2 = k(q_{tot})$. For further information, see European Commission [29].

The empirical results are depicted in Tables 2 and 3 and Figure 3. The weak work-on rates are much higher in the case of benchmark QM than in the case of benchmark PC. We will come back to the benchmark question in the next Section. The strong work-on rates Λ^{QM} are, independent of the benchmark, significantly lower than 100 %. The rising strong work-on rates from 2006 to 2008 indicate that market competitiveness increases marginally. In addition, strong work-on rates during peak hours exceed those during base hours, thus indicating a load-dependent fringe influence. In the following Section, we focus on futures with base load delivery, since they are most suitable for a regression analysis.

3 Forward market model

In order to derive actual TMC work-on rates λ_t in the German electricity market, we investigate daily price variations of power and input prices at the less volatile forward market for future delivery (see Figure 4). Unfortunately, due to the lack of available supply and demand functions, it is impossible to compute strong work-on rates Λ in the forward market model. Nevertheless, we have to detect the remaining question of the adequate benchmark. Therefore, the forward market model is essential and helps us to dive deeper into electricity pricing.

3.1 Data Description and spot-forward relationship

Electricity prices stem from the EEX, which operates a forward market with financial futures for electrical power delivery in the current month, the next nine months, the next eleven quarters and the next six years. In our analysis, we focus on prices of Phelix year futures for 2007, 2008 and 2009 on trading days in the year prior to delivery (year-ahead futures). The delivery unit of one contract is 1 MW, prices are in €/MWh.

Forward markets can be regarded as insurance markets for risk-averse *hedgers* who physically produce or need electricity and aim at transferring spot price risks to insurers. *Speculators*, who intend to generate speculative profits by knowingly taking these price risks, act as insurers. As compensation, they demand a risk premium RP, which equals the difference between forward and expected

Year	BM QM Base	BM PC Base	BM QM Peak	BM PC Peak
2006	0.7893	0.7211	0.8176	0.7579
2007	0.8252	0.7527	0.8596	0.7928
2008	0.8420	0.7734	0.8824	0.8144

Table 3: Mean of strong work-on rates in the case of QM for 2006-2008.

spot prices, taking the expectation $\mathbb{E}^{\mathbb{P}}$ with respect to the physical measure $\mathbb{P}$. Unlike the spot market, in which temporary influences directly impact on supply and demand, the forward price F^P at time t for delivery period $[T_1, T_2]$ is determined by the risk premium and expected supply and demand during the delivery period. The main drivers are, therefore, the expected spot prices $P(T)$ for $T \in [T_1, T_2]$ on the basis of information $\mathcal{F}$ in t. Following Benth and Koekebakker [30], the value of a Phelix year future must be related to the value of a continuum of forward contracts

$$
\begin{aligned}
F^P(t, [T_1, T_2]) &= \int_{T_1}^{T_2} \left(\mathbb{E}^{\mathbb{P}}[P(T)|\mathcal{F}(t)] + RP(T-t)\right) \cdot \hat{\omega}(T, T_1, T_2)\, dT && (10)\\
&= \int_{T_1}^{T_2} \mathbb{E}^{\mathbb{Q}}[P(T)|\mathcal{F}(t)] \cdot \hat{\omega}(T, T_1, T_2)\, dT, && (11)
\end{aligned}
$$

where $\hat{\omega}(T, T_1, T_2) = \omega(T) / \int_{T_1}^{T_2} \omega(u)\, du$ for $0 \leq T \leq T_1 \leq T_2$ is the function describing the contract-specific capital lockup, i.e. $\omega(T)$ is equal to 1 if the futures is settled at maturity, whereas it is equal to $\exp(-rT)$ if settled continuously during the delivery period. In equation (11), expectation is taken under the risk neutral measure $\mathbb{Q}$ including the market price of risk, which can be estimated with the aid of derivative prices. While expected demand is influenced mainly by forecasts of weather, economic cycle, political frameworks and consumer behavior, primary impacts on supply are prospective fuel and carbon costs. As the latter are by far the most varying impacts over the medium- and long-term, fuel and carbon costs can be regarded as the main drivers of electricity futures prices, which is confirmed by the regression analysis in Subsection 3.4. Analogously to the above procedure regarding electricity futures, we consider the year-ahead futures of these TMCs. Due to its storability and in terms of basic arbitrage principles (see [31]), EUA, coal and gas futures are traded at prices in accordance with short-term prices $P(t)$, a mark-up for interest r and storage cost u (*cost of carry*) and a deduction y for availability at any point in time (*convenience yield*):

$$F^P(t, T) = P(t) \cdot e^{(r+u-y)(T-t)}. \tag{12}$$

EUA spot and futures prices are derived from the EEX, which established EUA spot and forward markets shortly after the introduction of the EU ETS in 2005. One EUA allows for the emission of one ton of CO_2 equivalent and is traded in €/t CO_2. Following a first EU ETS period between 2005 and 2007, a second period (*Kyoto-period*) runs from 2008 until 2012. Thus, we have to deal with two different EUA products in our investigation. One EUA 2005-2007 covers emissions in the first EU ETS period, whereas an EUA 2008-2012 allows for emissions in the second ETS period. This is an important distinction, because the price for EUA 2005-2007 declined almost to zero at the end of its trading period (December 2007), while futures prices for the second period remained stable

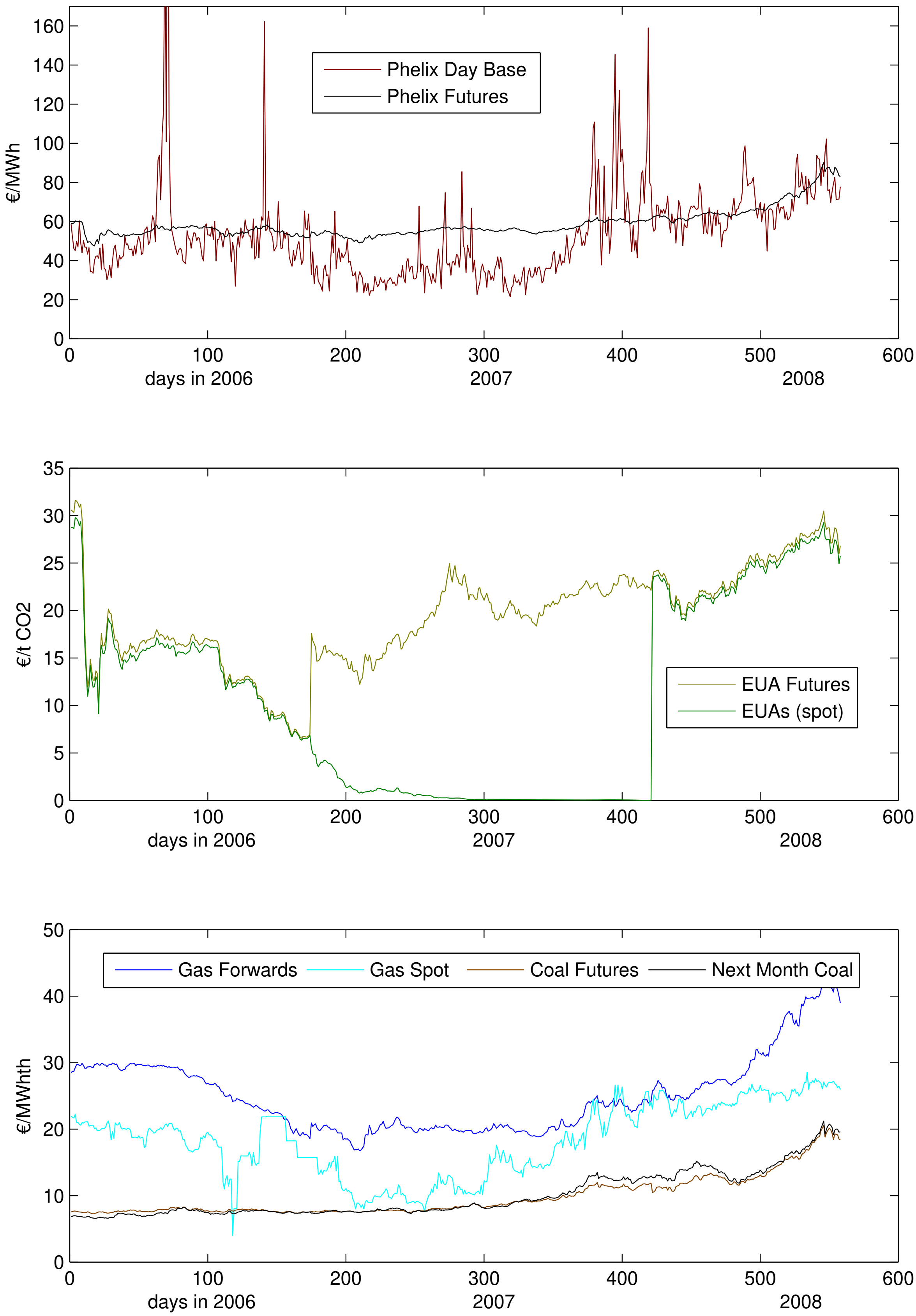

Figure 4: Spot and futures prices on trading days from April 11, 2006 to July 17, 2008.

above €20/MWh. This is due to a tighter total cap of emission allowances in the second period and a ban on transmitting first period EUA into the second period (*banking*). The First Period European Carbon Futures 2007 with delivery in December 2007 contributes the year-ahead carbon futures traded in 2006. Its underlying is an EUA 2005-2007. The underlying for the Second Period European Carbon Futures 2008 and 2009 is an EUA 2008-2012. Due to technical difficulties, a spot market for EUA has still not been established, either at the EEX or at other European exchanges. Therefore, we use the carbon futures with delivery in December 2008 as the indicator of the EUA spot price in 2008. However, this should not cause any problems with respect to our calculations, because the difference in EUA spot and futures prices is roughly equal to the interest rate. Because the allowances do not need to be available before April of the subsequent year, and the fact that credit risk is secured by the clearing house, theoretically, there is no benefit (*convenience yield*) in holding EUAs sooner. Hence, the buyer's advantage of a delayed transfer of money is what makes the futures slightly more expensive than the spot EUA.

Coal prices are also derived from the EEX. The delivery region is ARA (Amsterdam-Rotterdam-Antwerpen) and contracts are traded in US-$/metric tons. The examined year-ahead futures are the ARA Coal Year Futures Cal-07, Cal-08 and Cal-09 with delivery in 2007, 2008 and 2009 respectively. Since there is no real-time or day-ahead market for coal, the respective roll-over month-ahead ARA coal month futures at the EEX serve as short-term prices. In order to consider the cost of coal for German electricity producers, the coal time series are transformed in €/MWh_{th} with daily exchange rates for month futures and daily year-ahead exchange rates for year futures respectively (source: Barclays Bank).

There are two different sources of natural gas data. In the absence of a liquid gas trade in Germany, we obtain gas spot prices from the APX Gas NL, which was the first independent gas exchange in Continental Europe. Even if there is congestion in the transmission between Germany and the Netherlands, the gas price for delivery in the Title Transfer Facility (TTF) is a suitable indicator of natural gas price developments. We use the All-Day-Index, which is the average of all daily trades in €/MWh_{th}. The year-ahead forwards in 2006 and 2007 are OTC forward contracts for TTF delivery in 2007 and 2008 respectively. For the trading period from January to July 2008, we use the EEX Natural Gas Year Futures with delivery in the market area of Germany's leading gas transmission company E.ON Ruhrgas Transport (EGT). Natural gas trade at the EEX was introduced in July 2007 and trade volume has recently started to increase. Even if OTC gas trading volume is still higher, the exchange prices can serve as reference prices, due to the potential for arbitrage.

Because we wish to calculate the impact of input cost on electricity, we need to transform the input prices into relevant costs for power generators. We therefore require the power plant heat rates h which are defined in $\mathrm{MWh_{el}}$ /$\mathrm{MWh_{th}}$, thus yielding information about the generation efficiency of a certain plant. Even though plant efficiency data is sensitive and thus protected rather closely due to competitive sensitivity, fortunately, we have been able to rely on confidential data in this context. The heat rates of German lignite plants range from 28 % to 39 %, hard coal plants have heat rates of 31 % to 43 % and those of conventional gas plants and combined cycle gas turbines (CCGT), vary from 25 % to 58 %. In order to compute carbon costs, we apply fuel-specific emission factors $\bar{E}$ for lignite (407 g $\mathrm{CO_2/MWh_{th}}$), hard coal (341 g $\mathrm{CO_2/MWh_{th}}$) and natural gas (202 g $\mathrm{CO_2/MWh_{th}}$). Emission factor data stems from [32]. For the purpose of identifying the average marginal power plant, we use aggregated data for hourly generation and daily available capacity for the generation of hard coal and gas. The data are provided by electricity producers in Germany and Austria and have been reported to the EEX since April 11, 2006. It covers about 80 GW of installed capacity, more than 60 % of the total installed capacity in Germany and Austria.

3.2 Data preparation

After having computed the work-on rates with respect to our model, we now derive the actual market work-on rates λ_t to enable a comparison with the model rates λ. We focus on work-on rates for the cost of HC, natural gas and CO_2. Since the cost of lignite barely varies over time, it does not have much impact on power price dynamics, even if lignite-fired plants are likely to determine the spot price during off-peak periods. If one is interested in the general impact of input prices on electricity, a conventional linear multiple Ordinary-Least-Squares (OLS) regression is a suitable instrument. Problems of nonstationarity and autocorrelation are accounted for by using first-differences. The results of the regression of the Phelix base year-ahead futures on the year futures prices of coal, gas and emission allowances, traded from April 2006 to July 2008, are shown in Table 4. The power futures are measured in €/$\mathrm{MWh_{el}}$, coal and gas futures in €/$\mathrm{MWh_{th}}$ and the carbon futures in €/t CO_2.

However, we are interested in deriving *cost* work-on rates, rather than simple input price impacts. A work-on rate is nothing other than the ratio of TMC that finds its way into power prices. Since the price in the day-ahead auction is determined by the level of the last accepted supply bid (of the marginal power plant), we need to estimate the input-price-induced cost variation of that marginal plant.

Dependent Variable: d(power-baseload-price)

Included observations: 557

Variable	Coefficient	Std. Error	t-Statistic	Prob.
d(coal-price)	1.627656	0.120971	13.45490	0.0000
d(gas-price)	0.398558	0.055448	7.187949	0.0000
d(EUA-price)	0.479778	0.024446	19.62617	0.0000
R-squared	0.639214	S.E. of regression		0.436131
Adjusted R-squared	0.637911	Sum squared resid		105.3765
Akaike info criterion	1.183624	Durbin-Watson stat		2.086567

Table 4: Output of electricity year baseload futures prices on input prices, traded in the period from April 2006 and July 2008.

Initially, we compute hourly ratios g_i for hard coal (HC) and gas, which relates the actual generation to the respective available generation capacity. In order to account only for power price-related generation variations, we subtract each technology's minimum hourly generation quantity in a given year from the technology's generation per hour. We then compute the hourly fuel ratio $f = g_{HC}/g_{Gas}$ and assign weight functions $\rho_i(f)$, which determine the probability (see equation (20)) of being the marginal (price-setting) plant for both HC and gas:

$$\rho_{Gas} = \begin{cases} 0 & \text{if } f > f_{cap} \\ \frac{\log(f_{cap}+1-f)}{\log(f_{cap}+1)} & \text{else} \end{cases} \qquad \rho_{HC} = \begin{cases} 1 & \text{if } f > f_{cap} \\ \frac{\log(f+1)}{\log(f_{cap}+1)} & \text{else.} \end{cases} \tag{13}$$

This means that if relative residual hard coal generation exceeds relative residual gas generation by more than factor f_{cap}, gas generation is not relevant for price determination. However, the lower the f, i.e. the higher the share of residual gas generation, the more likely that gas-fired power plants set the electricity price. Assume that, if the hard coal-fired plant operation level converges to its upper limit, while the gas-fueled generation continues to increase, the probability of gas being the marginal plant grows. Lignite is treated different, since its costs do not impact on electricity price dynamics directly, but are essential for the level of average emission factors and thus impact on changes of average CO_2 costs. Hence, ρ_L is estimated by the optimization algorithm described later on and is treated as constant. For the purpose of transforming fuel prices [€/MWh$_{\text{th}}$] into cost [€/MWh$_{\text{el}}$] of the likely marginal plant, we divide prices by the hourly heat rates $h_{HC,Gas}$, which depend linearly on the hourly generation ratio $g_{HC,Gas}$ and vary between the respective upper and lower heat rate levels (see Subsection 3.1). Analogously, EUA prices [€/t CO_2] are multiplied by $e_i = \bar{E}_i/h_i$ for $i \in \{HC, Gas, L\}$, where $\bar{E}_i$ is the specific emission factor of i in g CO_2/MWh_{th}. By applying log functions to the calculation of ρ_i, we take into account that low-efficiency hard coal and high-efficiency gas-fueled plants (i.e. CCGT) are more likely to be the marginal plant in base hours.

Because the marginal power plant in a certain hour is a single plant, which we do not claim to be able to identify, and because coal, gas and EUA prices vary not hourly, but daily, we calculate daily averages of ρ_i, h_i and e_i. Subsequently, we compute fuel-independent daily emission factors

$$e = \frac{\sum_i e_i \cdot \rho_i}{\sum_i \rho_i}. \tag{14}$$

Additionally, we define heat rate-adjusted weights $\varrho_i = \rho_i/h_i$. Since all data and variables so far are obtained in the spot market, just as the model-based work-on rates λ in Section 2, it seems advisable to regress electricity spot prices on input spot cost for a comparison of model and actual work-on rates. However, such a procedure would fail, due to the stochastic nature of spot prices (see Figure 4). That is because in the spot market, TMC-induced impacts are outweighed by temporary influences on supply and demand, such as weather (wind intensity, temperatures, rainfall) or plant availability. Nevertheless, we can transform the spot market values e, ϱ_i and the model work-on rates λ into futures values e^{Fut}, ϱ_i^{Fut} and λ^{Fut} by employing spot and futures input prices. We therefore compute the daily ratio of short-term marginal cost of coal fired plants and gas fired plants

$$rat^P = \frac{\frac{P_{HC}}{h_{HC}} + P_{EUA} \cdot e_{HC}}{\frac{P_{Gas}}{h_{Gas}} + P_{EUA} \cdot e_{Gas}}, \tag{15}$$

where P_i are daily short-term prices. Subsequently, we compute four linear functions m, mapping the rat^P on the respective spot values e, $\varrho_{HC,Gas}$ and λ. Thereafter, we apply these fits to the ratio of the futures marginal cost of coal fired plants and gas fired plants

$$rat^{Fut} = \frac{\frac{F_{HC}}{\frac{1}{D}\sum_{d=1}^{D} h_{HC}(d)} + F_{EUA} \cdot \frac{1}{D}\sum_{d=1}^{D} e_{HC}(d)}{\frac{F_{Gas}}{\frac{1}{D}\sum_{d=1}^{D} h_{Gas}(d)} + F_{EUA} \cdot \frac{1}{D}\sum_{d=1}^{D} e_{Gas}(d)}, \tag{16}$$

where F_i are daily futures prices of hard coal, gas and EUA and D is the number of included trading days in a given year. By applying the functions m on rat^{Fut}, we obtain the yearly future values e_{Fut}, $\varrho_{i,Fut}$ and λ_{Fut}. We have, in fact, done nothing more than use the spot-forward relationship described by equation (12). If gas and coal had the identical forward effect resulting from the difference between inventory rate and convenience yield, the yearly future values would be consistent with the mean of the spot results. The fact that, for the majority of days, $rat^P > rat^{Fut}$, tells us that risk premiums are considerably higher for gas than for coal, which seems logical due to the usually higher volatility of natural gas. However, that is exactly what we need to consider when computing futures work-on rates. Furthermore, the spot-forward relationship guarantees that the level of exercised market power is identical in the spot and futures markets. In conformity with Stoft [1], a temporary, unequal exercise of market power enables arbitrage opportunities that are exploited immediately. Thus, we can continue with the analysis of future price work-on rates.

3.3 Calibration

Except for f_{cap} and ρ_L, we have so far prepared all the necessary data for a reliable estimation of work-on rates λ_t by regressing the first-differences of F^P on the first-differences of the TMCs, i.e.

$$c_i = F_i \cdot \sum_{d=1}^{D} \varrho_{i,Fut} \quad \text{and} \tag{17}$$

$$c_{EUA} = F_{EUA} \cdot \sum_{d=1}^{D} e_{Fut} \tag{18}$$

for $i \in \{HC, Gas\}$. Since economic rationality implies that work-on rates for all input factors must be equal, we calibrate the model for 2008 base data by solving the following optimization problem:

Let $\Delta F^P \in \mathbb{R}^n$ be the first-differences of power prices, where $n = D - 1$ is the number of observations, and let $\Delta C \in M^{n\times 3}(\mathbb{R})$ be a matrix depending on ρ_L and f_{cap}, where the columns of ΔC describe the first-differences of the TMCs c mentioned above. With the aid of the regression

$$\Delta F^P = \Delta C \cdot \beta + u, \quad u \sim N(0, \sigma),$$

we solve the optimization problem

$$\min_{\rho_L, f_{cap}} \left(|max(\hat{\beta}) - min(\hat{\beta})| \right), \tag{19}$$

Dependent Variable: d(power-price)

Included observations: 136

Variable	Coefficient	Std. Error	t-Statistic	Prob.
d(coal-cost)	0.619921	0.050882	12.18357	0.0000
d(gas-cost)	0.619934	0.122304	5.068794	0.0000
d(EUA-cost)	0.619919	0.087449	7.088932	0.0000
R-squared	0.794865	S.E. of regression		0.407531
Adjusted R-squared	0.791781	Sum squared resid		0.407531
Akaike info criterion	1.064410	Durbin-Watson stat		2.292962

Table 5: Output of electricity year baseload futures prices on TMCs, traded in 2008 (Jan-Jul).

where $\hat{\beta} = (\Delta C^T \Delta C)^{-1} \Delta C^T \Delta F^P$ *is the vector of OLS-estimated regression coefficients for TMCs.*

3.4 Empirical results

We obtain the unique solution of $f_{cap} = 3.4657$ and $\rho_L = 0.3918$. The former indicates that gas-fired power plants are not relevant for price determination, if residual coal-fired generation exceeds residual gas-fired generation by more than factor 3.4657. The latter implies that the mean probabilities of being the price-determining plant, defined by

$$prob_i = \frac{\sum_d \rho_i(d)}{\sum_{i,d} \rho_i(d)}, \tag{20}$$

are 47.47 % for hard coal, 28.83 % for natural gas and 23.70 % for lignite, which is a realistic base scenario, thus confirming the satisfactory performance of the model. The regression statistics confirm that the included TMCs are the main price drivers of F^P. The estimated uniform actual work-on rate λ_t for the Phelix Base Year Futures Cal-09 is 0.6199 and is significant at any conventional significance level (see Table 5).

4 Results

In order to evaluate the exercise of market power in the German electricity market, we are now going to integrate and visualize the results, derived in the previous Sections. Let us resume that model-based spot work-on rates λ have been derived in Section 2 and have been transformed to model-based forward work-on rates λ^{Fut} in Subsection 3.2. In addition, actual forward work-on rates λ_t have been obtained by the calibration of the forward market model in Subsection 3.3.

4.1 Comparison

The average values of λ in 2008 for the case of a quasi-monopoly in benchmark QM and the case of perfect competition in benchmark PC are $\lambda^{QM} = 0.5979$ and $\lambda^{PC} = 0.4541$ respectively (see Table 2), whereas $\lambda_t = 0.6199$. This refutes the hypothesis that the observed bid curves are an outcome of perfect competition (benchmark PC). In contrast, the bid curves seem to result from a quasi-monopoly setting (benchmark QM). The difference between the model and regression work-on rates of 0.0220 or 3.55 % might result from several sources. Besides the usual model-estimation errors and additional stochastic influences not captured by the regression, the difference is likely to occur due to the fact that we do not explicitly model competition between the players of the dominant group. In order to capture this, we could use an oligopoly model with a competitive fringe, rather than a quasi-monopoly model, but that would complicate the mathematics significantly. However, the gains might be rather small, as economic theory implies in the context of endlessly repeated games such as daily electricity auctions, which reinforces our results.

4.2 Simulation

We now conclude our results with some simulation paths for year-ahead futures of the last three years, depending on coal, gas and CO_2 costs, as well as the market-constellation-based work-on rates and a maximum-likelihood estimated diffusion part. The model is described by

$$dF_t^P = \mu\, dt + \lambda^{Fut} \cdot \sum_{i=1}^{3} dc_t^i + \sigma\, dW_t, \tag{21}$$

where futures price variations dF_t^P follow cost variations dc_t^i of the main price drivers coal, gas and CO_2. μ and σ represent the trend and volatility not caused by these TMCs, while λ^{Fut} is the average weak work-on rate, depending on the market constellation. Applying these model-based work-on rates, we re-simulate future prices, that is, in contrast to the popular use of stochastic models for

Year	μ	σ
2006	0.063	0.137
2007	-0.015	0.103
2008	-0.006	0.173

Table 6: ML-estimated parameters for the years 2006, 2007 and 2008.

derivative pricing, an ex-post analysis of futures prices. Firstly, we focus both on the current year, in which CO_2 prices have been stable above €20/t CO_2, and four weeks in April and May 2006, when CO_2 prices plummeted from €31.53/t CO_2 to €9.83/t CO_2 (see Figure 4), while setting $\mu = \sigma = 0$ and starting at the same point F_0^P for all market constellations. The latter is done to simplify the comparison between the performance of work-on rates in the three market constellations. However, this procedure ignores the fact that prices would be at higher and lower levels in a monopoly and under perfect competition respectively. The reason is that price levels inevitably result from the underlying price-formation mechanism, and not from different add-on rates (see Section 2). The simulation paths applying work-on rates obtained under the benchmark QM and the benchmark PC assumptions are depicted in Figures 5 and 6. As the values of average deviations of simulation paths and actual electricity price F^P reveal (see Table 7), the benchmark QM simulation performs much better. Thus, the result in the preceding subsection that quasi-monopoly is the correct benchmark is reconfirmed and we now focus on simulations in the benchmark QM.

The results of the ML-estimation illustrated in Table 6 reinforces the regression result that gas, coal and CO_2 are, in fact, the main power price drivers. However, the rather high value of μ for 2006 leads us to believe that there is an additional bullish effect in 2006. The remarkably volatile period in June and July 2008 is illustrated in Figure 5 and reflected in a relatively high value for σ in 2008. In Figure 7, we take into account that price levels must vary between the market constellations. Hence, several Monte-Carlo price simulation paths at "virtual" market-constellation levels, as well as the expected price path for the case of quasi-monopoly, are illustrated for 2006-2008. A remarkable result is that the CO_2-market-driven power price collapse in spring 2006 is reflected most effectively by the expectation of quasi-monopoly paths.

5 Conclusion

In this paper, our objective was to create a differentiated understanding of electricity price formation, subject to several time-dependent marginal costs (TMCs), and to investigate the relationship

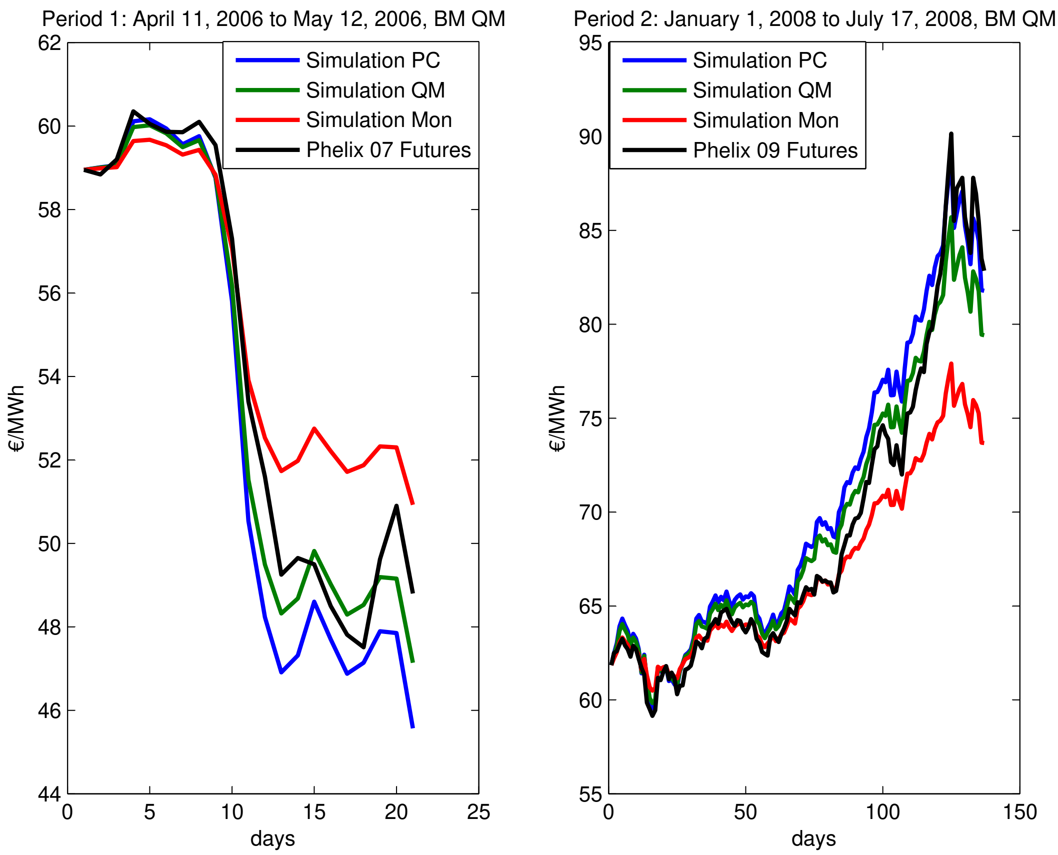

Figure 5: Futures price simulations with $\mu = \sigma = 0$, starting at F_0^P in all market constellations, benchmark QM.

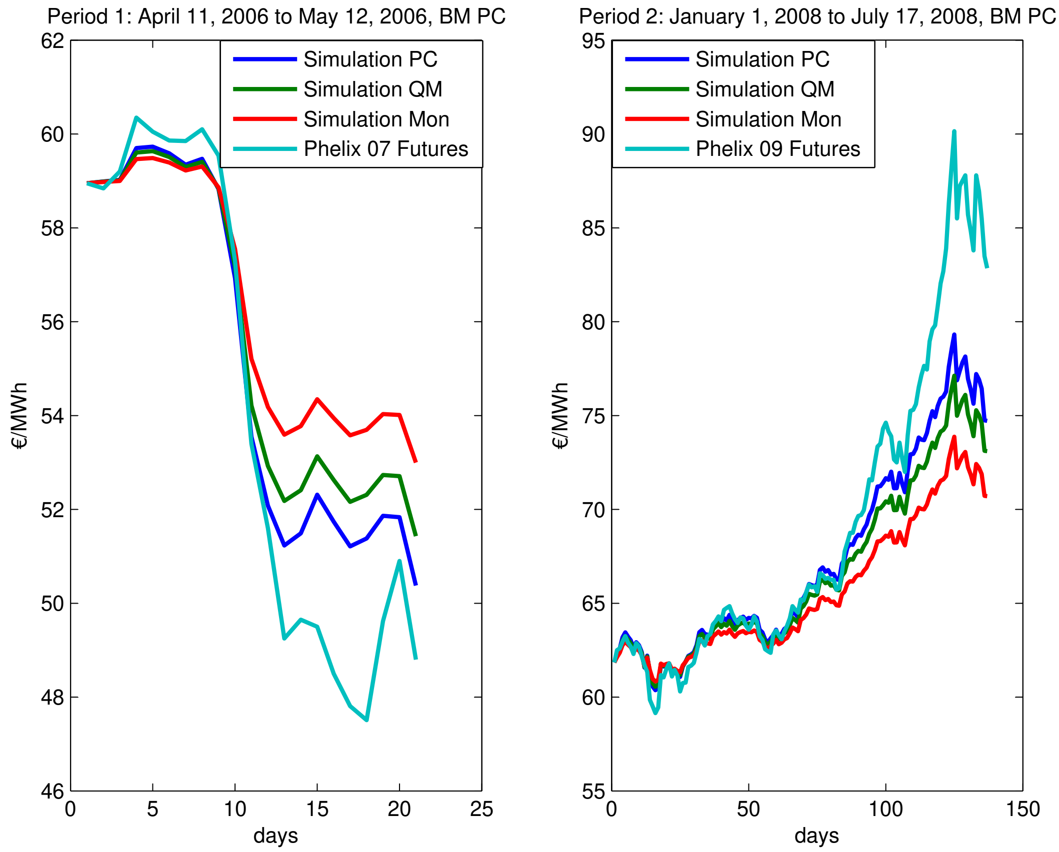

Figure 6: Futures price simulations with $\mu = \sigma = 0$, starting at F_0^P in all market constellations, benchmark PC.

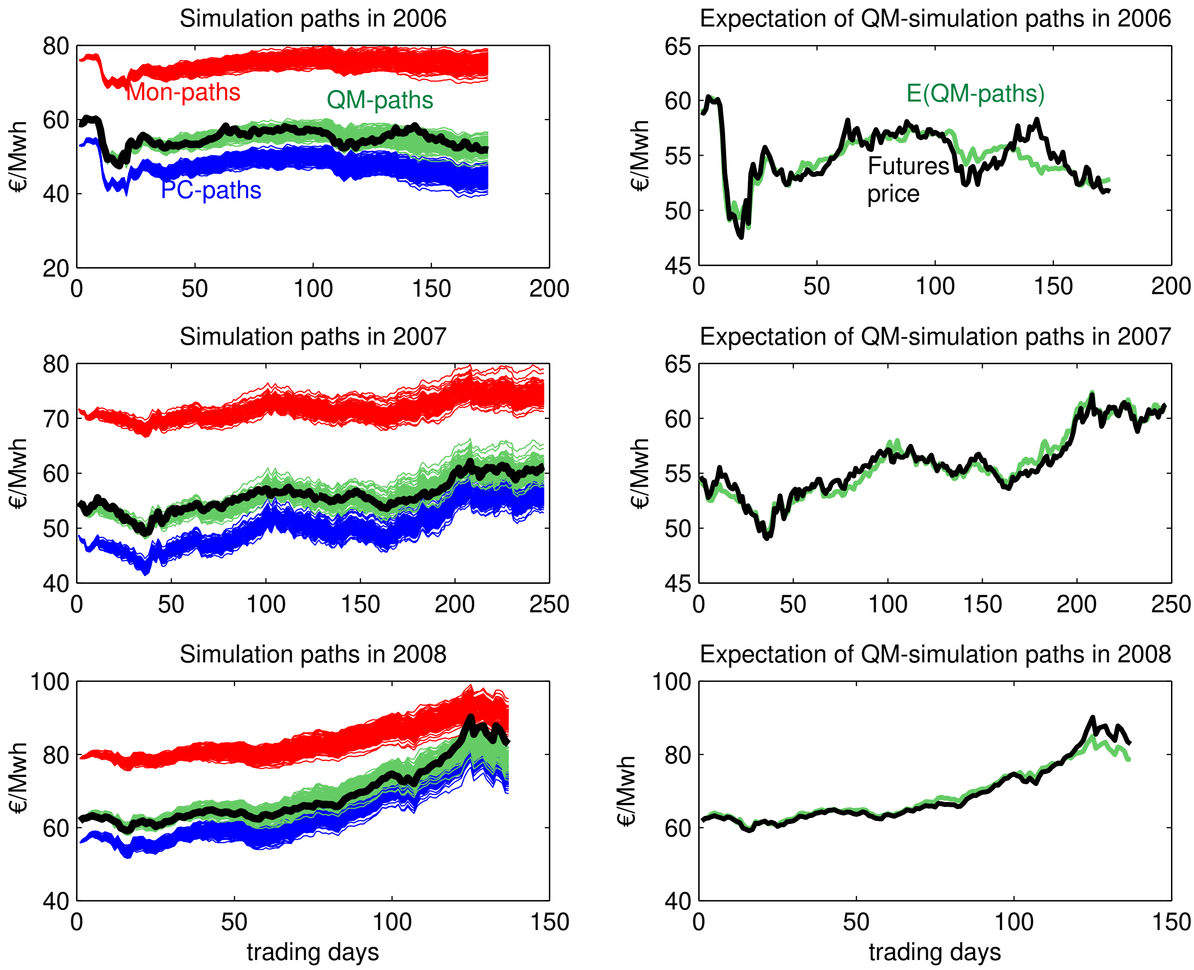

Figure 7: MC-simulation in different market constellations (left), Expectation of QM-paths (right)

	BM QM Period 1	BM QM Period 2	BM PC Period 1	BM PC Period 2
PC	1.2177	1.6647	1.2535	1.9245
QM	0.7381	1.3397	1.7241	2.4992
Mon	1.5042	2.2765	2.4487	3.4924

Table 7: Simulation performance in terms of average daily deviations for Period 1 (April 11, 2006 to May 12, 2006) and Period 2 (January 1, 2008 to July 17, 2008).

between such pricing and the degree of competition in a power market. Proving market-power-induced overpricing is a challenging objective in real markets, since we do not know suppliers' actual marginal cost, particularly firm- or plant-specific marginal cost. An easier way to investigate the existence of market power is to compare our results, derived from a quasi-monopoly model, with the coefficients for electricity futures regressed on its main influences, which we identify as TMCs. For the calibration of our model, we take advantage of the fact that the estimated coefficients in the case of linear regression must be equal. That is because the coefficients correspond precisely to weak work-on rates, which are, in accordance with economic rationality, defined as TMC-independent. Since the regression coefficients reflect our model results for a quasi-monopoly, we find indications of strategic bidding behavior above marginal cost levels in Germany over the period 2006-2008.

Fortunately, in a piecewise linear setting, it is possible to convert the computable *weak* work-on rates into the more intuitive, *strong* work-on rates, which range from 0.5 in a monopoly to 1 in a perfectly competitive market. While it is evident that strong work-on rates close to 100 % do not occur in the German electricity market, they have been increasing slightly since 2006 (2006 : 0.7893 %, 2007 : 0.8252 %, 2008 : 0.8420 %). Further research might investigate work-on rates in other electricity and commodity markets, in which the model assumptions are also applicable (e.g. the steel market), in order to develop a general measure of competitive intensity. That would enable a more accurate evaluation of the actual exercise of market power in electricity markets. The fact that German electricity prices seem to converge to competitive levels poses new problems, such as the issue of adequate generation capacity when market power rents decline. Future work could usefully focus on this issue in the context of efficiently designing competitive markets.

6 List of symbols and abbreviations

Symbols

M	dominant group

F	fringe
QM	quasi-monopoly
Mon	monopoly
PC	perfect competition
MC	marginal cost
q, p	price, quantity
D, S	demand, supply
Λ	strong work-on rate
λ	weak work-on rate
λ^P	model-based λ for the spot market
λ^F	model-based λ for the forward model
P	spot price
F^P	forward price
u	inventory rate
y	convenience yield
h	heat rate
$\bar{E}$	fuel-specific emission factor in $\mathrm{MWh_{th}}$
ρ	weight function
g	generation ratio
f	fuel ratio
f_{cap}, ρ_L	optimization variables
e	plant-specific emission factor in $\mathrm{MWh_{el}}$
ϱ	heat rate-adjusted weights ρ
rat	price ratio
c	time-dependent marginal costs (TMCs)
μ	trend
σ	standard deviation

W_t	standard Brownian motion

Abbreviations

TMC	time-dependent marginal cost
CO_2	carbon dioxide
O&M	operation and maintenance
EEX	European Energy Exchange
OTC	over-the-counter
EU ETS	European Union Emission Trading Scheme
EUA	European Union Allowance
BM	benchmark
HC	hard coal
L	lignite
CCGT	combined cycle gas turbines
ML	Maximum-Likelihood

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A Appendix

A.1

In order to derive the profit-maximizing price in a piecewise linear market model, M must consider that - depending on the level of its chosen price - a component of demand will be met by the fringe. Hence, its kinked demand curve is

$$D(q_M) = \begin{cases} \frac{av_F + bu_F}{b+v_F} - \frac{bv_F}{b+v_F} \cdot q_M & \text{for } q_M < \frac{a-u_F}{b} \\ \\ a - b \cdot q_M & \text{for } q_M \geq \frac{a-u_F}{b}, \end{cases}$$

where $MC_F(q_F) = u_F + v_F \cdot q_F$, $MC_M(q_M) = u_M + v_M \cdot q_M$ and $D(q) = a - b \cdot q$. The profit-maximizing price resulting from a Cournot principle is described by

$$p^*_{QM} = \begin{cases} \frac{a}{2} \cdot \frac{v_F}{b+v_F} + u_F \cdot \frac{b}{b+v_F} \cdot \left(1 - \frac{bv_F}{v_M(b+v_F)+2bv_F}\right) & \\ \qquad + u_M \cdot \left(\frac{bv_F}{v_M(b+v_F)+2bv_F}\right) & \text{for } q^*_M < \frac{a-u_F}{b} \\ \\ u_F & \text{for } q^*_M = \frac{a-u_F}{b} \\ \\ a\,(1 - \frac{b}{2b+v_M}) + u_M \cdot \frac{b}{2b+v_M} & \text{for } q^*_M > \frac{a-u_F}{b}. \end{cases}$$

In order to determine the price-output combinations in perfect competition as well as in a monopoly, we consider the aggregated marginal cost

$$MC(q) = \underbrace{\frac{v_M u_F + v_F u_M}{v_F + v_M}}_{\alpha} + \underbrace{\frac{v_F v_M}{v_F + v_M}}_{\gamma} \cdot q.$$

Therefore, the equilibrium price in perfect competition is

$$p^*_{PC} = a\,(1 - \frac{b}{b+\gamma}) + \alpha \cdot \frac{b}{b+\gamma},$$

whereas it is

$$p^*_{Mon} = a\,(1 - \frac{b}{2b+\gamma}) + \alpha \cdot \frac{b}{2b+\gamma}$$

in a monopoly.

A.2

For the comparison of λ and Λ, remember that in any piecewise linear static market model

$$\Delta q^* = \frac{\Delta p^*}{b} = \frac{\Delta MC(\overline{q}^*) - \Delta MC(q^*)}{\gamma},$$

irrespective of the market constellation. Thus

$$\frac{1}{\Lambda} = \frac{1}{\lambda} - \frac{\gamma}{b} \implies \Lambda = \frac{\lambda}{1 - \gamma/b \cdot \lambda}.$$

For the comparison of λ and λ_t, suppose an electricity forward market with time-independent demand but time-dependent supply, where EUA-cost variations do not cause any kind of fuel switches. In the case of perfect competition, we have

$$\lambda_t = \frac{\partial p^*/\partial t}{\partial MC/\partial t} = \frac{(\partial\alpha/\partial t) \cdot b/(b+\gamma)}{\partial\alpha/\partial t} = \lambda.$$

The equality for the other market constellations could be derived similarly. To summarize, we achieve the possibility of a comparison of weak and strong work on rates as well as the comparison of work-on rates in static (spot market model) and dynamic (forward market model) investigations.

A.3

By equalizing MC_F and MC_M, one can show that

$$k = \frac{q_M}{q_F} = \frac{q_M/(q_M + q_F)}{q_F/(q_M + q_F)},$$

since $v_F = kv_M$ and $u_M = u_F$. That means that k is exactly the quotient of the aggregated load factor of the four dominant German electricity producers $\big(q_M/(q_M + q_F)\big)$ and the aggregated fringe load factor $\big(q_F/(q_M + q_F)\big)$.