Empirical Essays on Energy Economics and Firm Performance Measurement

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Chapter 1

Introduction

1.1 Motivation

In most developed countries, policy makers have made significant efforts over the past decade to liberalize energy markets. The objective underlying the liberalization is to achieve gains in social welfare via an increase in competition and economic efficiency of the products and services provided (Aune et al., 2008). Within the European Union, the liberalization of both the electricity and the natural gas market has been enforced by directives of the European Parliament and the European Council (EU, 2003a,b, 2009a,b). In turn, the liberalization induced a change in paradigm since both markets have been historically dominated by protected regional monopolies in most member states. While the potential economic benefit of liberalized energy markets is considerable, it also brings about new challenges and raises new economic questions. The essays in this thesis thus seek to improve the understanding of some of these problems as they each address a specific economic question related to liberalized energy markets.

The liberalization of the European natural gas wholesale market has significantly changed pricing and business strategies in the natural gas industry. Historically, pricing of natural gas imports to continental Europe were based on crude oil prices or prices of crude oil derivatives, with long-term contracts (LTCs) being the prevalent institutional design between producers and wholesale market participants. LTCs were used by market participants because they allowed for a decrease in the risks implied in investments for gas producers in the development of gas fields and network infrastructure. The underlying economic rationale for the application of oil price indexation of natural gas prices within these LTCs was to ensure the competitiveness of natural gas as a fuel in the respective consumer market.

However, the traditional pricing model has been challenged by the liberalization that fostered competition in wholesale natural gas markets. The introduced third party access to natural gas infrastructure has spurred the emergence of trading hubs for natural gas in continental Europe. These hubs represent a virtual or physical area within the natural gas network where volumes are traded on a short-term (spot market) or long-term (futures market) basis. Prices of natural gas at these hubs are expected to reflect gas market-specific fundamentals such as weather conditions or infrastructure availability rather than exclusively the price of crude oil or crude oil derivatives.

Thus far, price determinants in liberalized natural gas markets have received limited attention, and existing research has focused on the US market (see, e.g., Brown and Yücel, 2008). However, knowledge of natural gas price determinants in liberalized markets is of high value for consumers and producers because it facilitates economic decision making and hedging. In order to improve the understanding of price determinants in the liberalized European natural gas market, the essay in Chapter 2 empirically investigates the effects of various fundamental variables on natural gas wholesale prices using econometric methods.

While the oil price indexation of natural gas prices has come under pressure, the need for LTCs may persist for the purpose of long-term risk sharing among gas producers and wholesale market participants. As a consequence, various market participants have proposed switching the price indexation of LTCs from crude oil prices to natural gas hub prices because they consider the latter to more adequately reflect the relevant demand and supply conditions. From an economic point of view, this proposal seems appealing at first glance since hub-based prices are expected to mirror a broader set of relevant market fundamentals. However, although the economic significance of the continental European hubs has grown steadily during the last years with rising trading volumes, liquidity at these hubs is still low and far below the British hub. Since sufficient trading liquidity is considered to be an important element in an efficient price formation process, the economic validity of prices at the rather illiquid continental European hubs has been recently questioned (see, e.g., Komlev, 2013). Within this context, the essay in Chapter 3 empirically analyzes the informational efficiency of spot and futures markets at European natural gas hubs. In specific, the essay compares price formation and intertemporal arbitrage dynamics between the rather illiquid trading hubs in continental Europe and the more mature British hub and therefore allows for an assessment of the informational efficiency of these markets and the role of liquidity.

Enforcing competition via an increased number of market participants as a core element of liberalization does not work for all market segments in the energy sector. Most importantly, the construction and the operation of energy transmission and distribution networks are characterized by high fixed costs and limited market size. Within this market segment, one supplier may thus provide the services at lower costs than multiple suppliers operating their own networks. The transmission and distribution of energy can therefore be classified as a natural monopoly, creating the need for regulation to ensure cost-efficient behavior of the system operator and the sharing of productivity gains between the supplier and customers (see, e.g., Joskow, 2008, Leland, 1974).

Historically, "rate of return regulation" has been applied by regulators to limit the economic rents that can be obtained by the network operator. However, this regulatory approach lacks cost efficiency incentives and may result in excessive investment behavior of the regulated firms (Averch and Johnson, 1962). In order to ensure a more cost-efficient behavior of natural monopolies, incentive-based regulation schemes that rely on so-called "yardstick competition" have been established by regulators in recent years. Yardstick competition is based on cost comparisons among the regulated firms and provides financial incentives for them to approach the best practice frontier (Shleifer, 1985). For the purpose of cost comparison, regulators frequently use empirical benchmarking techniques to assess the inefficiency of the regulated firms. Based on the outcome of the inefficiency assessment, firm-specific cost saving targets are derived by the regulator.

However, concerns have been raised that the current implementation, with a focus on operational performance, may negatively affect investments into the network and thus the quality of services provided by the system operator (Guthrie, 2006, Kwoka, 2009). Unfortunately, the impact of incentive-based regulation schemes on investment behavior is complex and empirical evidence is mixed (see, e.g., Cambini and Rondi, 2010, Nagel and Rammerstorfer, 2009, Roques and Savva, 2009, Vogelsang, 2010). The essay in Chapter 4 seeks to improve the understanding in this research area by incorporating dynamic aspects into benchmarking models applied by regulators within incentive-based regulation schemes and illustrates the impact of using dynamic versus static benchmarking models in an empirical application.

In contrast to the transmission and distribution sector, the European wholesale market for electricity is based on competitive elements as a result of market liberalization. Particularly in Germany, the induced competitive pressure combined with the political decision to prioritize the feed-in of power generation from renewable energy has weakened the economic viability of existing conventional power plants. This development has driven significant conventional generation capacity out of the market since these facilities have been unable to cover their variable cost of operation by revenue. The decline in reliable, i.e., non-intermittent, generation capacity in turn has aggravated the network stability in Germany (Bundeskartellamt and Federal Network Agency, 2012). Different measures to improve or maintain the reliability of electricity supply are currently intensively discussed, such as network extension or capacity remuneration mechanisms.

An economic assessment of such measures should be based on a comparison of the respective costs and benefits. While the costs of the different measures may be quantified despite significant uncertainties, the economic benefits of a reliable electricity supply seems less clear in the public debate. From an economic perspective, the value of an increase in the security of supply should equal the expected outage costs avoided by the respective measure. Thus, outage costs are of high relevance for the evaluation of security of supply measures. Surprisingly, this aspect has yet to receive attention in Germany despite security of supply measures being an important part of the national public debate. In this context, the essay in Chapter 5 quantifies sectoral and regional power interruption costs in Germany using a macroeconomic approach.

1.2 The Application of Econometrics in Economics - A Critical Discussion

Three out of the four essays in this thesis apply econometric methods to economic problems. Econometrics has emerged as a popular and frequently used tool in economic research but has also received significant criticism. The following paragraphs intend to provide a brief overview on the critical aspects as well as on the merits of the application of econometrics in economic research.

Econometrics can be defined as the quantitative analysis of economic variables such as quantities, prices or interest rates (Hendry, 1980). According to the Econometric Society, econometrics pursues the objective to advance economic theory in its relation to statistics and mathematics (Econometric Society, 1933). In current economic research, econometric methodology is mainly used for three purposes. First, econometric approaches are applied to empirically test established economic theory. Second, econometric models are specified for explorative studies, i.e., to investigate the relationship among economic variables without relying on established economic theory. Third, econometric methods are used to forecast economic variables.

The different application fields outlined above differ significantly with regard to the relationship between econometrics and economic theory. In the first field of application, there is a direct link between economic theory and the application of econometric methods as the quantitative analysis seeks to test an established economic theory. In contrast, explorative usage of econometric models is not directly backed by economic theory but rather based on economic intuition. However, explorative studies may be helpful in generating new economic insights and thus foster the advancement of economic theory, whereas the application of econometrics for forecasts usually neither relies on economic theory nor seeks to enrich it explicitly.

The adequacy of econometric models to investigate economic questions has been controversially discussed among economists. The seminal work of Tinbergen (1939) investigating fluctuations in the business cycle represents one of the first econometric applications that received significant attention but also raised a controversial debate on the role of econometrics in economic research. In response to Tinbergen's study, Keynes (1939) argues that some economic problems may not be properly addressed by econometric methods. In specific, Keynes had already begun to touch on some technical caveats in the application of time series econometrics that would receive increased attention in more recent research, for example the structural stability of estimated parameters, spurious correlation and problems arising from omitted variables.

Although many of these technical problems have been tackled by methodological enhancement such as the concept of cointegration (Engle and Granger, 1987) and the explicit consideration of time-varying volatility (Engle, 1982) as well as of structural breaks (Chow, 1960), the relationship between econometrics and economic theory has remained controversial among economists. Among others, the fact that the specification of econometric models requires more assumptions than economic theory can provide and the resulting flexibility in the model specification and the model selection process has been at the center of the debate. In addition, the widespread usage of time series econometrics that is usually not directly backed by economic theory has further increased the discrepancy of economic theory and empirical economic research. While Lucas (1976) argues that the discrepancies between economic theory and econometric models specified in empirical research render them inadequate for the purpose of policy evaluation, Pesaran (1988) emphasizes that despite their limitations, econometric models, including time series econometrics, are indispensable tools for the empirical evaluation of economic policy and for forecasting purposes.

This thesis takes on the approach of Pesaran (1988) and relies on econometric methodology because it allows for the empirical investigation of economic phenomena, while taking advantage of real world data. Dispensing econometric methods would in turn be equivalent to throwing away valuable information that may contribute to an improved comprehension of economic problems. Moreover, even explorative approaches that are not backed by economic theory have yielded meaningful economic insights that have stimulated the formulation of more advanced economic theory (Zellner, 1996). Nevertheless, the points raised by critics such as Keynes or Lucas are a valuable framework with regard to the interpretation of the empirical results obtained from econometric models. In specific, they call for sound methodological techniques to overcome technical difficulties and for a cautious economic interpretation, keeping in mind that the empirical approach and economic theory may not be fully aligned with each other. As a consequence of these limitations, econometric models should not be exclusively applied but rather be combined with alternative methods such as behavioral studies or theoretical models to achieve an increased methodological pluralism in economic research (Pinto, 2011).

1.3 Outline of the Thesis

This thesis comprises four empirical essays on energy economics. In Chapter 2, price determinants in liberalized natural gas markets are investigated with a special emphasis on the impact of supply interruptions. In specific, the price effect of various fundamental variables such as weather conditions, inventory, prices of substitutes and supply shortfalls are analyzed for the German natural gas wholesale market. The essay in Chapter 2 is based on a modified version of the working paper "What Drives Natural Gas Prices? - A Structural VAR Approach" (Nick and Thoenes, 2013). Stefan Thoenes co-authored the study, and contributions to all aspects of the essay were made in equal parts.

The essay in Chapter 3 investigates the informational efficiency of European natural gas hubs. The essay focuses on two aspects of informational efficiency, namely price formation and intertemporal arbitrage on spot and futures markets at the hubs in Germany, the Netherlands and the United Kingdom. This chapter draws upon an updated version of the working paper "Price Formation and Intertemporal Arbitrage within a Low-Liquidity Framework: Empirical Evidence from European Natural Gas Markets" (Nick, 2013), which is single-authored.

Chapter 4 deals with the regulation of natural monopolies in network industries. The essay in this section analyzes the impact of using static versus dynamic benchmarking models in the context of incentive-based regulation schemes. The effect of the consideration of investments on the benchmarking outcome is illustrated by an empirical application to a dataset of US electricity distribution and transmission firms. The essay is based on the working paper "The Hidden Cost of Investment: Adjustment Costs and their Impact on Firm Performance Measurement and Regulation" (Nick and Wetzel, 2014) which is a joint work with Heike Wetzel, who equally contributed to all parts of the study as co-author.

The economic assessment of power interruption costs is at the center of the essay in Chapter 5. Within this essay, economic costs of power interruptions in Germany are approximated by losses in economic output. A revised version of the working paper "The Costs of Power Interruptions in Germany - an Assessment in the Light of the Energiewende" (Growitsch et al., 2013) is the underlying work of this essay. It is joint work with Christian Growitsch, Raimund Malischek and Heike Wetzel. All co-authors contributed in equal parts to all aspects of the paper.

The subsequent paragraphs briefly outline the research questions, the methodological framework and the findings of the four essays included in this thesis. Limitations and methodological caveats are also addressed.

In the essay "What Drives Natural Gas Prices? - A Structural VAR Approach", the price determinants in liberalized wholesale natural gas markets are analyzed with special focus on supply interruptions. The determinants of natural gas prices within liberalized markets have only received limited attention. Most research has focused on the natural gas prices in the US and their relationship to crude oil prices and some fundamental variables such as inventory and weather conditions (see, e.g., Brown and Yücel, 2008, Hartley et al., 2008). Concerning European gas prices, the empirical approaches focus exclusively on crude oil prices as the explanatory variable (see, e.g., Panagiotidis and Rutledge, 2007).[1] The aforementioned studies generally suffer from two shortfalls. First, they lack the consideration of important price determinants such as coal prices or trade flows of liquefied natural gas (LNG). Second, the authors impose strict exogeneity assumptions on the explanatory variables. While these assumptions are valid for weather conditions, it seems to be a flaw with regard to inventory as changes in natural gas inventory, i.e., withdrawal and injections of natural gas in the network by storage operators, cannot be regarded as independent from changes in the market price for natural gas.

In order to overcome both shortfalls, the essay in Chapter 2 specifies a structural vector autoregressive (VAR) model for the German natural gas market. The VAR framework allows to both incorporate a rich set of fundamental variables in the model and avoid imposing invalid exogeneity assumptions.[2] The fundamental variables included in the model comprise various supply and demand drivers of natural gas. In specific, natural gas supply disruptions, LNG imports, meteorological conditions, prices of coal and crude oil as well as natural gas inventory data are used to empirically assess the determinants of wholesale natural gas prices. In addition, due to its capability to capture endogenous

[1] An exception is the work of Regnard and Zakoian (2011), which incorporates weather related data into the econometric model. However, this study primarily analyzes volatility dynamics of gas price returns rather than determinants of natural gas price levels.

[2] VAR models have been extensively used in macroeconomic applications. For a technical introduction to the methodological framework, see e.g., Sims (1980).

interaction among the model variables, the VAR approach allows for insights into the behavior of gas storage operators with regard to changes in natural gas prices or weather conditions. The econometric model is based on weekly data since this allows for an explicit modeling of weather conditions and inventory data. The sample covers the period from January 2008 to June 2012 and is restricted by the availability of hub prices in Germany before this period.[3]

The innovative approach of a structural VAR model for the German gas market comes at the cost of some caveats. First, the missing supply volumes have to be approximated using a heterogeneous set of data sources. Second, the modeling framework is unable to reflect physical network characteristics and infrastructure constraints that may also affect the impact of supply disruptions on natural gas prices. While the first shortfall is reduced by due diligence and frequent consistency checks with available literature, the second aspect has to be kept in mind when interpreting the empirical results derived from the structural VAR model.

A further methodological challenge within the structural VAR approach is the identification of the structural model from its reduced-form representation. The reduced-form interpretation ignores the instantaneous interaction among the variables included in the model. Thus, these interdependencies are captured by the error terms, rendering a distinctive economic interpretation of the reduced-form error term impossible. To allow for an economic interpretation of the VAR residuals, a structural form has to be derived such that the instantaneous interaction of the variables is explicitly accounted for. By doing so, error terms with a diagonal variance-covariance matrix allow for a distinctive economic interpretation. Unfortunately, the identification of the structural form requires assumptions to be imposed on the data analyzed. Different methodological approaches have been proposed, such as restrictions on the interaction of model variables in the long run, in the short run or sign restrictions.[4] Within this essay, restrictions on the instantaneous interaction of the model variables are imposed to obtain the structural VAR representation. The selection of this identification strategy is motivated by two arguments. First, the usage of weekly data implies that short-term restrictions are not as restrictive compared to models that are based on monthly or quarterly data. Second, some of the model variables, e.g., weather effects, exhibit exogenous character with regard to some other model variables, thus facilitating the selection of the restrictions.

Drawing upon the structural VAR model, three econometric techniques are used to give insight into price determinants and the impact of fundamental shocks to wholesale

[3]Natural gas inventory data for Germany is only available on a weekly basis prior to 2011.

[4]For a technical discussion, see e.g., Lütkepohl (2005) and Amisano and Giannini (1997).

natural gas prices in Germany. First, so-called "impulse response functions" are computed. The impulse response functions allow for the analysis of the effects of structural shocks, i.e., unexpected changes in a certain variable, on the other variables within the system. Second, the "forecast error variance decomposition" is used to derive shares of changes in the explained variable that can be attributed to other model variables. Thus, forecast error variance decompositions allow for an assessment of the importance of certain variables for the development of another variable. Third, the parameter estimates of the structural VAR model are used to generate "historical decompositions" of price changes. The historical decomposition enables the disentangling of the effects of explanatory variables on the variable of interest during a certain time period.

The empirical findings of the study allow for comprehensive insights into price determinants of natural gas markets. The response functions of the natural gas price to shocks of the included variables are in line with economic intuition. With regard to demand-sided price effects, extraordinarily cold temperatures cause an immediate increase in gas prices, reflecting an increase in natural gas demand for heating. In addition, the responses of the natural gas price to structural shocks in oil and coal prices are positive. This suggests that there is a distinctive relationship between these commodities that may be the result of common price drivers, e.g., the macroeconomic climate, or substitutability, e.g., the competition between coal and gas in the electricity sector.

Concerning supply-sided price effects, an unforeseen cut in gas deliveries leads to higher gas prices because the missing volumes have to be replaced by more expensive supply options, or gas consumers have to be driven out of the market by price signals. Positive storage shocks, i.e., storage injection that is higher than expected or storage withdrawal that is lower than expected, also have positive effects on natural gas prices. This finding is plausible since positive storage shocks represent additional demand or a reduction in supply on the spot market. Interestingly, the response of storage flows to positive gas price shocks is significantly negative. This is consistent with the economic intuition that storage operators withdraw natural gas in the case of an unexpected rise in spot prices. The forecast error variance decomposition shows that the natural gas price is heavily affected by weather conditions and supply disruptions in the short run. However, both price effects are only of transitory nature. In contrast, the effects of coal and crude oil price shocks on natural gas prices fully unfold only with a certain delay.

In a further step, the structural VAR model is used to analyze the impact of three major supply interruptions to the German natural gas market by carrying out a historical decomposition for the respective periods. In particular, the Russian-Ukrainian gas dispute in January 2009, the reduced natural gas supplies from Libya during the "Arab Spring" in 2011 and the cut in Russian gas deliveries during the cold spell in February 2012 are analyzed. Overall, the results of the historical decompositions suggest that all three supply disruptions coincided with other fundamental impacts on natural gas demand. Therefore, assigning the observed market price reactions exclusively to the cut in natural gas deliveries would be misleading since demand-side effects either mitigate or aggravate the impact of supply interruptions on wholesale natural gas prices.

With regard to the Russian-Ukrainian dispute in January 2009, the price increase caused by the supply disruption was partially mitigated by the weak economic climate as a result of the global financial crisis. Without the corresponding drop in natural gas demand, the historical decomposition suggests that a price increase of about 30% instead of the actual price spike of 15% would have occurred as a consequence of the supply shortfall. The historical decomposition for the period of the Libyan civil war suggests that the actual price spike of 15% can be disentangled into two sources. First, the missing volumes directly increased market prices by about 5%. Second, precautionary gas injection by storage operators who anticipated future scarcity of supply as a consequence of the political unrest in North Africa created additional demand on the spot market and therefore increased natural gas spot prices by about 10%. Concerning the cut in Russian gas deliveries to Germany in February 2012, the impact of the missing supply volumes on natural gas prices in Germany is even smaller compared to the two other events analyzed. According to the historical decomposition of the respective period, the actual price increase of approximately 40% can be mostly attributed to the extraordinarily cold weather conditions, resulting in a sharp increase in natural gas demand.

The empirical results of the study suggest that policy makers should not exclusively focus on purely supply-sided measures in order to increase the security and the competitiveness of European gas supply as the historical decompositions emphasize that gas prices are to a large extent driven by demand fundamentals. In fact, attention should also be paid on flexibility options on the demand side in order to limit abrupt demand spikes in case of extraordinary cold weather conditions as well as to the functioning of the storage market since these facilities are of special importance for smoothing out transitory imbalances in the gas market.

Besides price determinants, the liberalization of European natural gas wholesale market and the subsequent emergence of natural gas trading hubs in continental Europe have raised other relevant economic questions. In particular, the low liquidity of continental European gas hubs has created doubts among market participants and policy makers regarding the validity of their price signals (see, e.g., Komlev, 2013). In order to add insights in this area of research, the essay in Chapter 3 addresses the informational efficiency of the natural gas hubs in Germany, the Netherlands and the United Kingdom.

The efficiency of the relatively immature continental European trading hubs for natural gas has only been incompletely addressed thus far. Empirical research has been carried out to assess the efficient exhaustion of regional price arbitrage opportunities by investigating regional price convergence among the European hubs (see, e.g., Growitsch et al., 2012, Robinson, 2007). These studies generally suggest a high level of regional integration of wholesale prices, thus indicating rather efficient regional arbitrage activities.

However, the informational efficiency of European natural gas hubs within an intertemporal framework has not yet been explored.[5] In addition, the price discovery process of European natural gas hubs has received only very limited attention in previous empirical research on natural gas markets. However, in the debate surrounding the possible price indexation of LTCs on hub prices, knowledge about the informational efficiency is valuable for the market participants affected. To bridge the research gap described above, the essay in Chapter 3 empirically investigates the price formation process and the efficiency of intertemporal arbitrage activity at the European natural gas hubs using econometric approaches on daily spot and futures market price data for the period from October 2007 to August 2012. Daily data is preferred to weekly or monthly frequency because this enables a better assessment of the short-term informational efficiency of the markets investigated.

In the first part of the essay, the price formation process at European natural gas hubs is analyzed. The underlying motivation is to investigate if either the spot or the futures market is informationally superior and thus functions as the leader for price discovery. Fama (1970) states that equally efficient markets for the same underlying asset should reflect relevant information simultaneously. Thus, a potential systematic lead-lag relationship between spot and futures markets is an indication that one market is more informationally efficient than the other.

From a methodological perspective, Granger causality testing is applied in order to investigate whether one market dominates the price discovery process or if both markets react simultaneously to new information.[6] The standard Granger causality test is a valuable methodology to infer whether a certain variable has explanatory power for future values of another variable. However, the standard test suffers from two shortfalls. First, instantaneous causality is not accounted for. Second, it assumes linearity in the causality relationship. With regard to the empirical application of the essay, the first shortfall is mitigated by the fact that the goal is to test for a systematic lead-lag pattern between spot and futures markets and not for an instantaneous interaction between the

[5] A notable exception is the study of Stronzik et al. (2009). The authors investigate whether the theory of storage holds at three major European gas hubs between 2005 and 2009. However, they do not directly address the price formation process and the efficiency of intertemporal arbitrage activity.

[6] For an extensive discussion on the concept of Granger causality, see Granger (1969).

markets. The second weakness deserves more attention since there is empirical evidence of significant nonlinearities in the relationship of commodity spot and futures markets (see, e.g., Bekiros and Diks, 2008, Chen and Lin, 2004, Silvapulle and Moosa, 1999). This finding is usually attributed to the nonlinearity of transaction costs, asymmetric information and heterogeneous expectations of market participants (Arouri et al., 2013). There are good reasons to assume that these drivers of nonlinear interaction are relevant for the continental European gas hubs since the low liquidity at these hubs may foster market frictions such as transaction and information costs. To overcome the caveat of imposing linearity assumptions on the interaction of natural gas spot and futures markets, nonlinear interaction between the markets is explicitly accounted for by using the nonlinear causality test proposed by Diks and Panchenko (2006).

The second part of the essay seeks to assess how efficiently intertemporal arbitrage opportunities between spot and futures markets at the European gas hubs are exhausted. The theory of storage states that spot and futures markets should share a stable long-run equilibrium since intertemporal arbitrage prevents deviations from this equilibrium to be persistent (Working, 1949). Such a stable long-run economic equilibrium can be empirically tested for using cointegration techniques.[7] Moreover, the efficiency of intertemporal arbitrage, i.e., the speed at which deviations from the intertemporal equilibrium are corrected, can be empirically analyzed using vector error correction models (VECM).

A shortfall in measuring the efficiency of intertemporal arbitrage based on spot and futures prices in this essay is that storage costs cannot be explicitly considered due to to the lack of daily data. While the time-constant effect of storage costs does enter the estimated long-run equilibrium relationship and is therefore accounted for, information contained in the variation of storage costs is lost. However, the variation of storage costs over time is expected to be small because there is only little short-term trading of storage capacities at European hubs. For this reason, the shortfall arising from the inability to explicitly account for storage costs seems limited.

While VECMs represent an intuitive and frequently used approach to measure the efficiency of arbitrage, a potential shortcoming is the assumption of linearity in the error correction process. Assuming linearity in this context implies that error correction starts instantaneously even for small deviations from the equilibrium and hence does not consider transaction costs resulting from market frictions. In the context of European natural gas hubs, the lack of liquidity as well as the physical characteristics of the market, e.g., restricted withdrawal and injection capacities of gas storages, may affect

[7] The concept of cointegration states that two economic variables share a common stochastic trend and thus a long-run equilibrium. For a detailed technical discussion, see Engle and Granger (1987) and Johansen (1988).

arbitrage dynamics between the spot and the futures market. Within the essay, such frictions are thus addressed by estimating a nonlinear threshold VECM (TVECM). The TVECM enables the identification of regimes that exhibit different arbitrage dynamics depending on the magnitude of the deviation from the long-run equilibrium. Comparing the error correction mechanisms of the different regimes therefore provides an opportunity to assess the magnitude of market frictions that impede intertemporal arbitrage activity at European natural gas hubs.

Market liquidity as a potential driver of arbitrage efficiency has changed significantly during the sample period at all hubs analyzed. In particular, the German and Dutch hubs have experienced remarkable growth in liquidity. Thus, a static VECM with the underlying assumption of structural stability may not fully capture the arbitrage dynamics. In order to account for structural changes in the arbitrage efficiency over time, a VECM with time-varying coefficients is estimated using the Kalman filter technique.[8] This state-space approach allows for the analysis of whether the increase in liquidity has fostered the short-run informational efficiency of the two continental European gas hubs throughout the sample period.

The empirical results of the essay allow for insights regarding the informational efficiency of the European natural gas hubs. Causality testing reveals that price formation takes place on the futures market at all hubs. This finding is in line with the hypothesis that futures market participants react more efficiently to information than their spot market counterparts (Bohl et al., 2012, Silvapulle and Moosa, 1999). It seems plausible to attribute this finding to the broader scope of market participants on the futures market, where contracts can be traded for the purpose of hedging and speculation without taking physical delivery of the commodity. With regard to hub-based pricing of internationally traded gas, an indexation on futures market prices rather than on spot market prices thus promises to provide more valid price signals.

The theory of storage seems to hold for all hubs in the long run. Moreover, the hypothesis of long-run informational efficiency, i.e., full convergence of spot and futures prices, cannot be rejected. Nevertheless, the sticky error correction process points toward frictions impeding intertemporal arbitrage activities and thus significant informational inefficiency in the short run. The results of the nonlinear TVECM suggest the existence of a "band of no arbitrage" for the German and the British hub. Although none of the hubs considered can be regarded as fully informationally efficient, intertemporal arbitrage opportunities seem to be most efficiently exploited at the British hub once the deviation from the long-run equilibrium crosses a certain threshold. However, the difference in the degree of arbitrage efficiency compared to the other hubs is rather small.

[8]For a technical discussion of the Kalman filter, see Kalman (1960).

The state-space VECM approach shows convergence in the short-run informational efficiency among the hubs within the sample period. Interestingly, only the short-run informational efficiency of the German hub seems to have benefited from the increase in liquidity. With regard to the validity of price signals of the continental European hubs, the convergence in intertemporal arbitrage efficiency implies that the informational superiority of the British hub has diminished over time. Concerning the hub price indexation of LTCs, this finding suggests that a price indexation based on continental European hub prices as opposed to British hub prices is not expected to cause significant economic disadvantages.

Overall, the empirical results suggest that policy makers and regulators should seek to increase the short-run informational efficiency at the European natural gas hubs. Beside fostering liquidity, regulators and competition authorities should carefully assess whether the access of market participants to storage or network capacities is free of discrimination in order to ensure an efficient functioning of the European natural gas wholesale market.

The essay in Section 4 deals with different concepts of inefficiency measurement used in the context of incentive-based regulation schemes applied to natural monopolies. The need for regulation of natural monopolies is common knowledge in economic theory.[9] Historically, the rate of return regulation has been applied by regulators to firms of network industries such as telecommunication, railway or energy transmission. Under rate of return of regulation, the regulator allows the utility to cover its operating costs and to earn a specified rate of return on its invested capital. While rate of return regulation effectively limits the rent of the regulated firms (Joskow, 2008), it does not provide incentives for cost efficiency. Moreover, it may incentivize firms to overinvest in capital. The latter shortfall is known as the Averch-Johnson effect (Averch and Johnson, 1962).

In order to overcome the shortcomings of rate of return regulation, alternative regulatory approaches have been developed and implemented by regulators. The seminal work of Shleifer (1985) laid the groundwork for incentive-based regulation schemes. This regulatory approach is based on cost comparisons among comparable firms, following the idea of "yardstick competition". Incentive-based regulatory regimes have since then found their way into regulatory practice. For the purpose of cost comparison, empirical benchmarking techniques are commonly applied in incentive-based regulation schemes to assess firm-specific inefficiency relative to the firm's peers. Firm-specific "X-factors", reflecting cost saving targets imposed by the regulator, can subsequently be obtained from the inefficiency estimates of the benchmarking model. The objective of these

[9] For an in-depth discussion on the regulation of natural monopolies see, e.g., Schmalensee (1979).

"X-factors" is to move inefficient firms towards the efficient frontier defined by the best-practice firms. Benchmarking models currently used in regulatory practice are static measures of inefficiency. This means that they focus on a single "snapshot" combination of inputs and outputs for a certain period in order to determine firm-specific inefficiency.

However, firms are expected to optimize their input usage over a dynamic multi-period framework rather than on a period-to-period basis. For this purpose, firms will invest in assets that will reduce costs in the long run. Such investments, however, may lead to a transitory increase in inefficiency. For instance, the economic benefit of investing in a new, efficient software system may go along with significant costs for the implementation, staff training or reorganization. These costs are referred to as adjustment costs. However, the regulator is unable to disentangle the corresponding transitory inefficiency caused by investments from the "true" inefficiency because adjustment costs can usually not be capitalized by the investing firm. Thus, firms that carry out investments in line with long-run cost minimization may be classified as inefficient by static benchmarking models. As a consequence, firms aware of this effect may be incentivized to cut their investments in order to avoid being penalized by X-factors that are too strict.

Overcoming the regulatory problem outlined requires explicitly accounting for the dynamic nature of inefficiency caused by adjustment costs. Following this line of argumentation, different approaches to measure inefficiency in a dynamic context have emerged. Within one of this research strands, the studies of Sengupta (1994, 1999) and Silva and Stefanou (2003, 2007) represent the theoretical framework for the incorporation of adjustments costs into the economic rationale of firms within every period.[10]

The essay in Chapter 4 draws upon the concept of dynamic inefficiency measurement introduced by Silva and Stefanou (2003) and Silva and Stefanou (2007). Using a data set of US electricity transmission and distribution firms covering the period 2004 to 2011, the essay investigates how the inclusion of investments and their adjustment costs into the benchmarking model affects firm-specific and industrial inefficiency estimates and thus the X-factors imposed by the regulator. The incorporation of both transmission and distribution firms in the model increases the heterogeneity of the sample and thus represents a potential obstacle for an exact measurement of inefficiency. However, the resulting shortfall may be rather small for two reasons. First, nonparametric data envelopment analysis (DEA) is used. This methodological approach avoids imposing a restrictive functional form on the data as opposed to parametric methods. Second, rather than assessing the actual inefficiency of the industry, the essay seeks to contrast the outcomes of static versus dynamic inefficiency measures. Thus, the difference in

[10]Another strand of literature is dynamic network DEA in which the initial outputs are allowed to be treated as inputs in the subsequent periods (Burger and Geymüller, 2007, Färe and Grosskopf, 1997, Geymüller, 2007, Nemoto and Goto, 1999, 2003).

inefficiency estimates obtained from the different measures is at the center of interest rather than the inefficiency level itself, and this difference should not be significantly affected by heterogeneous sample firms.

In the methodological framework applied in the essay, dynamic technical inefficiency is assessed by the firm's ability to simultaneously contract the usage of variable inputs and expanding gross investments. In contrast, static measures focus exclusively on variable input contraction. The inclusion of investments resolves the problem that arises in the measurement of technical inefficiency in the presence of adjustment costs, namely the inability of firms with high investments to contract variable input usage to the same extent as their competitors with low investments. As a consequence, the dynamic measure provides a more valid estimate of a firms actual technical inefficiency than the static measure in the presence of adjustment costs.

Since adjustment costs automatically enter the cost data used in the benchmarking process, the benchmarking costs have to be modified by subtracting the long-run savings implied in the investments of the respective period. In doing so, the immediate costs as well as the long-run benefit of investments are considered. This long-run benefit can be approximated using the marginal value of capital, the so-called "shadow value of capital". Obtaining reliable estimates for the shadow value of capital is methodologically challenging. This is because the shadow value of capital represents a scarcity indicator for this input and thus depends on the initial capital stock, outputs and prices of inputs of the respective firm (Oude Lansink and Silva, 2013). From a theoretical perspective, this endogeneity calls for a simultaneous determination of cost inefficiency and the firm-specific shadow value of capital (Oude Lansink and Silva, 2013). However, a simultaneous determination translates into a nonlinear problem with severe numerical difficulties.

For this reason, two alternative approaches have emerged to sequentially approximate the firm-specific shadow value of capital and dynamic cost inefficiency. Within these sequential procedures, the shadow value of capital is determined in a first step and subsequently incorporated into the computation of dynamic cost inefficiency. One option to derive the shadow value of capital is an econometric estimation based on historical cost data, while the second option is to derive the shadow value from first-order conditions in a nonparametric framework. A potential caveat of the econometric estimation is that it requires imposing a functional form on the cost function. A second shortfall may arise from the fact that the sample used for the econometric estimation may not be characterized by efficient investment behavior of firms. Thus, the estimated shadow values may reflect in part either the effects of underinvestment or excessive capital stock expansion. However, the econometric approach represents a more feasible way to obtain estimates of firm-specific shadow values than solving the nonlinear optimization problem and is therefore used in the empirical application of the essay. In addition, the econometric estimation allows to avoid the unrealistic assumption of dynamic allocative efficiency that is implied in the nonparametric sequential approach.[11]

The empirical results emphasize that the consideration of investments and the corresponding adjustment costs significantly affects the inefficiency estimates on an industrial and firm-specific level. The average dynamic technical inefficiency of the sample firms is approximately 26%. In contrast, technical inefficiency amounts to 40% in a static framework, i.e., when investments are ignored. The differences in technical inefficiency estimates are most pronounced for firms with large investments. With regard to cost inefficiency, the dynamic and static approaches yield average values of 37% and 40%, respectively. Similar to the case of technical inefficiency, firms with high investments perform significantly better when the dynamic cost inefficiency measure is applied. This suggests that firms with high investment activity are penalized by the application of static benchmarking models in regulatory practice.

The theoretical considerations as well as the empirical application of the essay illustrate the potential benefit of using dynamic inefficiency measures in the context of incentive-based regulation. By applying dynamic inefficiency measures, regulators may derive X-factors that are in line with long-run cost minimization and hence avoid misleading incentives to cut investments. Thus, regulatory authorities should carefully assess the benchmarking models used with respect to their ability to account for adjustment costs. In particular, regulators may try to assess the economic relevance of adjustment costs for the regulated firms in order to develop an understanding about the distortion of X-factors that arises when static benchmarking models are applied. If the regulator concludes that adjustments costs are of relevance for the respective industry, switching to a dynamic benchmarking model would appear to be warranted.

The essay in Chapter 5 focuses on the economic costs of power interruptions. Public interest in the assessment of power interruption costs has grown steadily in Europe during the last years. This is mainly a result of the ongoing transition of the European electricity sector, with many European countries trying to decarbonize their electricity sectors by increasing the share of renewable energies within the overall power production. Since the electricity feed-in of these sources is at least for some technologies intermittent, the shift from fossil to renewable resources may have negative effects on the stability of the electricity system. Significant research efforts have centered around the assessment of the technical feasibility and the economic efficiency of measures that seek to integrate

[11] The econometric approach to derive the shadow value of capital is in line with similar studies (see, e.g., Fernandez-Cornejo et al., 1992).

stochastic power generation into the electricity grid (see, e.g. EWI et al., 2010). The main assumption underlying these efforts is that power interruptions cause high economic costs.

Thus far, power interruption costs have been quantified for some European countries such as Austria, the Netherlands, Ireland and Spain (see, Bliem, 2005, de Nooij et al., 2007, 2009, Leahy and Tol, 2011, Linares and Rey, 2013). For Germany, research on outage costs is scarce, although the country is the largest electricity consumer in Europe (IEA, 2012a).[12] Thus, the essay in Chapter 5 seeks to improve the understanding of power interruption costs in Germany. Besides its size, Germany's regional diversity makes the German electricity market particularly interesting for an empirical assessment of outage costs. Since the federal states in Germany are substantially different in terms of economic structure, outage costs may heavily depend on the region affected. In addition, outage costs are expected to differ across sectors and industries as a result of different production technologies. In order to account for the regional and sectoral heterogeneity, the essay quantifies interruption costs on both the federal state level and for a broad range of industries.

Three methodological approaches have been applied in previous research to obtain estimates of the economic costs caused by interruptions in power supply. The first methodological approach uses data from historical blackouts to approximate outage costs (see, e.g., Corwin and Miles, 1978, Serra and Fierro, 1997). While case studies have the advantage that the assessment of outage costs is based on actual supply interruptions, they can hardly be generalized due to the specific nature of the actual power interruption (Linares and Rey, 2013). Surveys are used as the second methodology to assess power interruption costs by investigating the willingness to pay of different economic subjects for avoiding a power interruption (see, e.g., Balducci et al., 2002, LaCommare and Eto, 2006). Compared to case studies, this approach has the advantage that it can be applied irrespective of any historical power outage. However, there is the shortcoming that the interviewed persons may either under- or overstate their willingness to pay due to a lack of information or strategic behavior. The third methodological option for the empirical assessment of power interruption costs is the so-called "macroeconomic approach". This approach treats electricity as an input in the value-adding process of both firms and private households. Within this methodological framework, the economic costs of power interruptions are quantified by the losses in output resulting from the outage.

Unfortunately, the macroeconomic approach suffers from various drawbacks. First, the approach exclusively quantifies losses in output, while it abstains from considering one-off

[12] A notable exception is the study by Praktiknjo et al. (2011). However, the authors focus on estimating the power interruption costs of private households and only shortly address the welfare losses of commercial sectors at a high level of industrial and regional aggregation.

damages caused by the outage. Second, it assumes linearity among the usage of the input factor electricity and the generated output. While the first shortcoming suggests that the approach understates real interruption costs, the latter may lead to an overestimation. This is because the output in at least some economic sectors is less than proportionately related to the consumption of electricity. Despite its caveats, the essay in Chapter 5 relies on the macroeconomic approach because it represents a more general measure than the alternative methodologies. In addition, the macroeconomic approach allows for an estimate of outage costs based on publicly available data. However, the empirical results of the essay should be interpreted as a rough approximation of outage costs rather than as precise estimates.

For firms, the economic costs of electricity outages are approximated by the loss in gross value added induced by the interruption in power supply. Dividing the gross value added by the electricity consumption yields the "Value of Lost Load" (VoLL). The VoLL thus represents the loss in output caused by one unit of electricity not supplied to the respective customer. In the case of private households, the output generated is assumed to be leisure activity valued in monetary terms. Thus, the VoLL of the residential sector is calculated as the ratio of the monetary value of electricity-based leisure time and power consumption of private households. According to microeconomic theory, leisure time may be evaluated based on the opportunity costs, i.e., marginal wages (Becker, 1965). Since data on marginal wages is not available, the study uses average net wages instead. In addition, the empirical approach accounts for the fact that not all leisure activities are based on electricity consumption and that non-employed people may have lower opportunity costs of leisure. For this reason, an electricity dependence of leisure of 50% and opportunity costs for non-employed people of 50% of the average net wage are assumed. Clearly, these assumptions are shortcomings in the sense that they are based on intuition rather than on empirical evidence. However, they are in line with similar studies (e.g., Bliem, 2005) and enable to quantify at least a rough estimate of the power interruption costs within the residential sector. Moreover, a comprehensive sensitivity analysis is carried out with respect to the electricity dependence of leisure and the opportunity costs of non-employed persons.

The empirical results reveal an average national VoLL of about 7.4€/kWh. The interpretation of this estimate is that, averaged over the year and all sectors, one kWh not supplied causes losses in economic output of approximately 7.4€. Due to the different role of electricity in the value adding process of the sectors considered, large differences between the sectoral VoLL estimates can be observed. In industries with a high ratio of electricity consumption relative to value added, such as the pulp and paper industry or the chemical industry, the VoLL ranges between 1€/kWh and 2€/kWh. In contrast, in the service sector, a kWh of electricity not supplied causes output losses of approximately 11€. With regard to absolute outage costs, the results of the macroeconomic approach emphasize significant fluctuations in output losses over time. In almost all sectors covered, outage costs vary considerably with regard to the time of the day, weekdays and seasons. Generally speaking, outage costs are high at noon and in the evening, while rather low during the night. In addition, outage costs are higher in the winter than during the other seasons, reflecting an increase in electricity consumption in this season. On a national level, the average economic costs of a one-hour interruption of total power supply causes losses in output of about 430 Mio €, while a missing gigawatt hour on average causes economic costs of 7.6 Mio €. Throughout the year, almost half of the output losses can be assigned to the residential sector, emphasizing that private households are also subject to substantial welfare losses in the case of power outages.

The insights gained from the empirical analysis may be used in various ways. The first field of application is the assessment of interruptible electricity supply contracts. The disaggregated VoLL estimates represent an approximation of the welfare losses induced by one unit of electricity not supplied and can thus be regarded as an indication as to in which sectors and regions the establishment of interruptible electricity supply contracts may be cost-efficient. The controversial concept of "rational rationing" represents the second area of application. This concept follows economic theory, suggesting that load shedding, if necessary, should be applied to the customer suffering the lowest welfare losses. It thus recommends to carry out load shedding, given supply shortages, based on the VoLL of the different consumers. However, the approach seems to be problematic from a social point of view, and an application may hardly be feasible due to network constraints and regional interdependencies in the electricity grid. It should therefore be assessed with care. The third field of application is the economic evaluation of measures to maintain or improve the reliability of electricity supply. The costs of such measures should be compared to the increase in expected outage costs if the measure is not undertaken. The estimates of power interruption costs in this essay can therefore provide guidance for regulators, network operators and policy makers in assessing the economic efficiency of measures that intend to increase the security of electricity supply.

Chapter 2

What Drives Natural Gas Prices? - A Structural VAR Approach

2.1 Introduction

The price of natural gas is of significant economic interest for various stakeholders. Not only does gas play a crucial role as a primary fuel in the residential and commercial heating market, but it also serves as an important input for industrial applications and electricity generation. Consequently, understanding the drivers of natural gas prices is relevant from both a macro and firm-specific perspective. However, the price formation at liberalized natural gas hubs is complex since these markets are faced with a variety of fundamental demand and supply influences such as meteorological conditions, business cycles, international trade flows and substitution effects among energy commodities. Moreover, unforeseen disruptions in gas supply may induce significant repercussions in these markets. This holds true especially for the continental European natural gas market, which recently has been exposed to supply disruptions due to the Russian-Ukrainian gas transit dispute of January 2009, production outages caused by the Libyan civil war in the spring of 2011 and the cut in Russian gas deliveries in February 2012.

In this study, we focus on Germany, one of the largest European natural gas markets, which is heavily dependent on natural gas imports via pipelines and therefore provides an interesting setting for the investigation of the impact of supply disruptions on the gas price. For this purpose, we develop a structural vector autoregressive model (VAR) to investigate the effects of various fundamental variables on gas prices. The natural gas-related variables analyzed in this study include gas supply disruptions, weather conditions, storage activity and imports of liquefied natural gas (LNG). Moreover, the model yields insights into the relationship of the natural gas price and the prices of coal and crude oil, which we use as proxies for the substitution relationship between the different energy commodities.

The impulse responses provided by the VAR are consistent with economic theory and suggest that the natural gas price reacts to the underlying supply and demand characteristics. The natural gas price rises in reaction to supply interruptions and due to extraordinarily cold temperatures increasing the heating demand. The response to structural shocks of storage follows the idea that storage flows either serve as additional demand or additional supply in the respective period. Whereas coal prices have an immediate and persistent impact on natural gas prices, the crude oil price only affects natural gas prices after a substantial delay. The decomposition of the forecast error variance of the natural gas price highlights that supply disruptions and unexpected meteorological conditions have an important, but transitory, effect on gas prices. For medium- and long-term horizons, gas prices are mainly affected by both coal and crude oil prices.

To better understand the effects of natural gas supply interruptions, we use our VAR model to disentangle the historical structural shocks affecting the German gas market during the three recent supply shortfalls. Our results show that the positive price impact of the Russian-Ukrainian transit dispute of January 2009 was partly offset by the negative price pressure of the coinciding financial crisis and economic slowdown. The structural effects on gas prices during the Libyan civil war suggest that the increase of German wholesale gas prices was rather induced by precautionary demand of storages than by the actual supply shortfall to the European gas market. Furthermore, the sharp price spike in February 2012 was caused to a greater extent by the extremely low temperatures compared to the sudden shortfalls in Russian supply.

A major contribution of our research is the identification of the distinct influences that affect gas prices in critical market situations. By disentangling the respective structural shocks, we are able to infer how the main fundamental variables interact in case of supply interruptions. Hence, we can distinguish the contribution of the different variables on gas prices. This is especially valuable since the observed natural gas price increases are caused not only by the supply shock, but also by various coinciding shocks of all variables. The proposed model therefore helps to provide new empirical insights into the security of supply for the European natural gas market.

Our finding that coal prices have a significant impact on the natural gas market challenges the conventional opinion of crude oil being the primary explanatory variable for cross-commodity effects on gas prices, which is common in most of the empirical gas market research.[13] Economic reasons for a decoupling of oil and gas prices could be the increasing production of shale gas in the United States or the rise of liquid spot markets in Europe fostering gas-to-gas competition and therefore a slow but steady decline in oil-indexed contracts. We also add to the literature as our structural VAR approach allows for endogeneity of fundamental gas market variables, such as storage and LNG supplies. Most approaches treat gas inventories as exogenous with respect to gas prices.[14] The assumption of exogenous gas inventories implies that storage operators do not adjust flows according to market prices, which is a restrictive assumption for liberalized gas markets.

The remainder of this study is structured as follows: We give an overview about the related literature in Section 2.2. Section 2.3 describes the data used for our analysis. The structural VAR framework and the identification of our model are given in Section 2.4. The results of the impulse response analysis as well as the decomposition of forecast error variance are presented and discussed in Section 2.5. Section 2.6 provides a brief overview of the three recent gas supply interruptions affecting the German natural gas market and also contains the event studies of these situations. Section 2.7 concludes.

[13]See for example Hartley et al. (2008), Panagiotidis and Rutledge (2007) and Brown and Yücel (2008).

[14]See for example Brown and Yücel (2008), Erdos (2012), Mu (2007) or Ramberg and Parsons (2012).

2.2 Literature Review

Our study combines the VAR methodology frequently used in macroeconomic applications with different strands of commodity market research. The subsequent section provides an overview on the related literature and positions our study within the existing literature.

There is a large amount of empirical literature investigating the interaction between crude oil prices and macroeconomic aggregates. Using a structural VAR methodology, Kilian (2009) and Lippi and Nobili (2012) argue that oil price movements are driven by a range of different macroeconomic and oil-specific shocks. Depending on the source of the oil price fluctuation, the effect on the economy may be very different, as argued by Kilian (2008) in the context of exogenous oil supply shocks. The structural VAR models can also be used to analyze certain unusual situations and scenarios, such as political events leading to supply shocks. Our study applies this idea, promoted for the crude oil market by Baumeister and Kilian (2012) as well as by Kilian and Murphy (2013), to the European natural gas market and draws upon the methodology commonly used in the area of oil market research.

Most studies investigating natural gas markets focus on the interaction between gas prices and the prices of other energy commodities. Hartley et al. (2008) and Brown and Yücel (2008) use a cointegration framework and specify error correction models to capture the mechanisms among the markets for natural gas and crude oil both in the short run and the long run. Both studies use natural gas inventory data, heating degree days and shut-in gas production in the models and show that natural gas and crude oil prices in the United States are closely tied together. However, the stability of the cointegration relationship has been questioned by Ramberg and Parsons (2012) as there seems to be a decoupling of oil and gas prices. They find that the cointegration relationship between oil and gas prices in the United States is not stable over time and argue that the price of oil has only weak explanatory power for short-term gas price fluctuations. Erdos (2012) shows that the cointegration link between natural gas and crude oil prices in the United States only lasted until the year 2009, when the increasing production of shale gas led to a decoupling. In his study, shut-in natural gas production, storage and weather are included as exogenous variables. Considering coal, oil and natural gas markets, Bachmeier and Griffin (2006) also find that the prices of these three primary energy carriers are at most weakly integrated. Accounting for the macroeconomic conditions and their implications on the US natural gas market, Mu (2007) focuses on returns and volatilities using equity market and treasury bill rates as proxies for economic conditions.

Our study is innovative as it introduces a comprehensive econometric model of the European natural gas market.[15] Probably due to a lack of available data, fundamental variables are often not used when analyzing the European natural gas market. Most studies focus solely on price dynamics or the relationship to crude oil prices. For example, Panagiotidis and Rutledge (2007) analyze the cointegration properties of natural gas and oil prices in the UK without considering additional variables. Regnard and Zakoian (2011) include temperatures in addition to crude oil prices in their analysis of natural gas price volatility properties at the Zeebrugge hub. Stronzik et al. (2009) analyze the storage behavior in the European natural gas market indirectly by testing no-arbitrage conditions between the spot and forward prices. Another line of research, including Renou-Maissant (2012) and Growitsch et al. (2012), establishes the increasing integration of the different national European natural gas markets by analyzing the cointegration properties with time-varying parameter models. Asche et al. (2013) consider the relationship between different European monthly spot natural gas prices, German contract-based natural gas import prices and Brent crude oil prices. The study shows that the contract-based price is indeed based on oil prices. Furthermore, the European natural gas prices are found to be relatively well integrated with each other and they are also correlated with the the oil price in the long run. However, Asche et al. (2013) are not able to distinguish whether the link between deregulated natural gas and oil prices is based on economic effects such as substitution or on the traditional contract-based oil indexation.

[15] Brown and Yücel (2008), Mu (2007), Ramberg and Parsons (2012), Hartley et al. (2008) and Maxwell and Zhu (2011) all focus on the natural gas market in the United States.

In contrast to the aforementioned empirical gas market research, our model does not exclusively focus on a single price determinant, but rather allows for a more comprehensive assessment of the interactions in the European gas market. Moreover, in contrast to most of the referenced studies, we allow for endogeneity between the variables of interest and therefore generate more realistic and accurate insights into the drivers of natural gas prices.

Additionally, our structural model provides a coherent framework to analyze both the determinants and the impact of LNG imports in the European market. In this area, the research is still in the early stage as there are only few studies that explicitly account for LNG imports. Maxwell and Zhu (2011) employ a reduced-form VAR and Granger causality tests to investigate the interdependency of LNG imports and the gas market in the United States. More research, such as Neumann (2009), has been devoted to the role of LNG as a driver of cross-continental market integration. These studies generally employ cointegration analysis using the prices of major gas hubs, but do not explicitly account for LNG shipments. Thus, the argument of LNG being the main force behind this development is based on economic rationale rather than on empirical evidence. Brown and Yücel (2009), who use a similar cointegration approach, therefore argue that the coordination of natural gas prices between the markets in the United States and Europe may be driven by crude oil prices rather than physical shipments of LNG. Siliverstovs et al. (2005) use a principal components analysis and a cointegration framework to show that up to the year 2004, the integration between the European, Japanese and North American natural gas markets was very limited.

2.3 Data

Our data set comprises weekly data within the period from January 2008 to June 2012.[16] It consists of the NetConnect Germany (NCG) natural gas price, the Brent crude oil price, the North-Western-European coal price, the deviation from historical average heating degree days in Germany, German natural gas storage data, shortfalls of natural

[16]The first observation is the week ending on Friday February 1st, 2008 and the last observation is the week ending on Friday June 1st, 2012.

gas supplies to the European market and European LNG import data.[17] Figure A.1 in the Appendix displays all time series used for the analysis and Table 2.1 summarizes the definition of the variables used in this study. In the following, detailed descriptions concerning data sources and the construction of variables are provided.

TABLE 2.1: Variable Definitions

Variable	Description	Unit	Source
Heating degree days deviation (Temperature)	Deviation from historical heating degree days during the respective week	Degrees celsius	Deutscher Wetterdienst (DWD), German Meteorological Service
Supply Shortfall	Missing natural gas supply volumes due to specific events	Billion cubic meters (bcm)	Own estimates based on various sources
Price of Brent crude oil	Europe Brent spot crude oil price	Euro per barrel	Energy Information Administration (EIA)
Price of coal	Coal price for North-Western-Europe	Euro per ton	McCloskey
LNG imports to EU-27	Linearly detrended LNG import volumes for all EU-27 countries	Million cubic meters (mcm)	Eurostat
Storage	Difference between historical and actual weekly changes in the German natural gas storage utilization rate	Percentage points	Gas Infrastructure Europe (GIE)
Natural gas price	NetConnect Germany (NCG) day-ahead natural gas price	Euro per Megawatt hour	European Energy Exchange (EEX)

Notes: All time series are transformed to weekly data within the period from January 2008 to June 2012

The data set for the econometric analysis is rather comprehensive with seven variables included. The decision of variable selection is justified by the diversity of fundamental impacts on gas prices, which do not allow a more parsimonious model specification. As reference prices for the German gas market, we use day-ahead prices of the market area NCG quoted at the European Energy Exchange (EEX).[18] We rely on spot prices as we expect that some short-term impacts of crucial interest for our research question, such as temperature induced demand spikes or unexpected supply shortfalls, are reflected to a greater extent in the day-ahead than in the futures market. We focus on spot prices

[17] For cases in which time series are available on a daily level, we generally construct five-, respectively seven-day averages (depending on the number of trading days per week).

[18] Available at `https://www.eex.com/de/marktdaten/erdgas/spotmarkt/ncg#!/2014/04/07`

at NCG rather than at Gaspool because liquidity within the NCG market area is higher and therefore prices in this market should represent more valid signals.[19]

We specify our model in weekly frequency since this allows both for an inclusion of storage data, which is only available on a weekly frequency before 2011, and the incorporation of short-term meteorological conditions. The choice of an appropriate frequency with respect to weather and storage activity has the consequence that we cannot rely on macroeconomic data on the degree of capacity utilization, industrial production or gross domestic product as an approximation for the business cycle. Weekly data is mainly available for financial data including stock prices and behavioral indicators such as investor or consumer sentiment indices. However, these measures are highly complex in their formation and lack physical linkage to the industrial natural gas consumption. We therefore abstain from incorporating these indices because we think that they do not adequately approximate industrial demand for natural gas.

However, spot prices of Brent crude oil may be interpreted as a proxy for the macroeconomic environment as outlined by He et al. (2010).[20] In addition, the oil price captures the substitution relationship of oil and gas in the residential heating market as well as the still prevailing oil indexation of German gas imports. Beside crude oil prices, spot prices of coal for delivery in North-Western Europe, as published by McCloskey, are used in the model.[21] The price of coal is included to capture the interaction of gas and coal within the electricity sector and therefore represents cross-commodity effects related to fuel substitution.

Some of our variables may be non-stationary or cointegrated. However, since it is well known that unit root tests have low power in the case of near-unit root processes (see Elliott, 1998), we do not know with certainty whether some of our series do actually contain a unit root. We tested for long-run relationships among our variables using

[19]In March 2012, the trading volume for H-gas was approximately 85,500 gigawatt hours (GWh) at the Gaspool Hub, while approximately 116,600 GWh were traded at NCG in the same period. The respective churn rates were 3.02 for Gaspool and 3.51 for NCG. This data is available at `http://www.gaspool.de/hub_handelsvolumina.html` and `http://datenservice.net-connect-germany.de/Handelsvolumen.aspx?MandantId=Mandant_Ncg`

[20]The oil price data is available at `http://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=RBRTE&f=D`.

[21]Available at `http://cr.mccloskeycoal.com/story.asp?sectioncode=164&storyCode=34769`

the cointegration testing procedure suggested by Johansen (1988) but did not find robust statistical evidence of a cointegration vector among some of our series.[22] More importantly, the estimates of our impulse response functions are consistent even when unit roots or a cointegration relationship are ignored, whereas falsely imposing a unit root or cointegration would yield inconsistent estimates (see Kilian and Murphy, 2013, Lutkepohl and Reimers, 1992, Sims et al., 1990, Toda and Yamamoto, 1995). Thus, we specify our structural VAR model by using natural logarithms of the commodity prices to avoid inconsistent impulse response estimates. This procedure is in line with similar applications of structural VAR models, such as Kim and Roubini (2000), Kilian (2009), Kilian (2010), Kilian and Murphy (2013) and Abhyankar et al. (2013).

We also account for the fact that gas demand, especially in the residential space heating sector, is highly sensitive to temperature. However, in a liberalized gas market, storage operators are expected to exploit predictable seasonal demand variations. Therefore, only unexpected shifts in gas demand, which are caused by extraordinary short-term weather conditions, are expected to be relevant for the gas price formation. Consequently, we focus on deviations from the average seasonal meteorological pattern as a determinant of gas prices. Thus, in a first step, we construct the historical average seasonal series of heating degree days (HDD) using temperature data from the German Weather Service for Frankfurt am Main during 1949-1999.[23] In a second step, we calculate the deviations of observed HDD and their historical averages in order to estimate the effects of unexpected temperature conditions on gas prices.

We include storage data because storage operators are both part of the supply side (storage withdrawal) and the demand side (storage injection). Existing German underground gas storage sites can be split into two categories.[24] On the one hand, pore storages balance out the seasonal divergence of supply and demand during winter and summer months. Due to technical restrictions, they are rather inflexible in their operation and hence many of them may be unable to respond to short-term price signals.

[22]The test results are provided in the Appendix.

[23]Available at `http://www.dwd.de/bvbw/appmanager/bvbw/`

[24]In addition to underground gas storages, many above ground gas storages exist in Germany. However, since the working gas volume is relatively small, they are of less importance compared to underground gas storage facilities.

On the other hand, more flexible cavern storages offset short-term imbalances between gas supply and demand. The most straightforward modeling approach would be to only consider flows of sufficiently flexible storages, which can quickly adapt their withdrawal and injection activity according to price fluctuations. Unfortunately, storage flow data is neither available on a site-specific nor on a category-specific level for Germany as only aggregated storage data is published. Therefore, we take an alternative approach to separate the two aforementioned categories. Accounting for the fact that inflexible storages follow a rather strict seasonal pattern, whereas flexible storages do not, we first construct an average seasonal pattern of storage utilization based on data published by Gas Storage Europe.[25] We consider utilization rates instead of absolute volumes to control for changes in the total storage capacity. In a second step, we take the first differences of the average weekly utilization. These values are the changes in average utilization for each calender week, measured in percentage points of total storage volume, and represent the seasonal storage flows. Finally, we take the difference between these average seasonal changes in utilization and the actual change in each week as a proxy for the flows related to flexible storages.

As the supply side is concerned, natural gas production data with monthly or weekly frequencies is not available. However, we account for the gas supplies with a supply shortfall variable, which represents gas volumes that are unexpectedly not delivered to the continental European market. Thus, the variable is equal to zero when no supply interruption occurs and amounts to the missing volumes, measured in billion cubic meters (bcm), during periods of supply shocks. We consider the impact of the Russian-Ukrainian transit dispute of 2009, the supply shortfalls caused by the civil war in Libya in 2011 and the lack of Russian gas supplies in February 2012.[26]

Beyond capturing supply interruptions via the supply shortfall approach presented above, we also draw upon the EU-27 LNG-imports provided by Eurostat as an indicator of current supply conditions.[27] Unfortunately, the import data is only available on a monthly frequency. Therefore, we apply linear interpolation to the data as we argue that any

[25] Available at `https://transparency.gie.eu.com/`

[26] Details about the crises and the calculation of the missing supply volumes are given in Section 2.6.

[27] Available at `http://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=nrg_124m&lang=en`

resulting errors from this procedure are expected to be rather small compared to the benefit of modeling LNG volumes entering the European gas market. Since the EU-27 LNG-imports exhibit a significant growth over time, we linearly detrend the variable by regressing the interpolated series against time.

The major European gas markets are highly interdependent, as shown by Robinson (2007) and Growitsch et al. (2012). Based on the empirical findings of these studies, we conclude that changes in supply volumes, no matter in which market area they originally occur, induce repercussions in other continental European gas markets. Therefore, we refer to supply shortfalls and LNG-imports on a European rather than only on a national level.

2.4 A Structural VAR for the German Natural Gas Market

We employ a structural vector autoregression for modeling the interdependencies between the main gas market fundamentals in order to explicitly examine the relevant transmission channels affecting the natural gas price. Accounting for the exogeneity of some variables, we constrain certain feedback-effects by restricting their coefficients to zero.

The model in its reduced-form representation can be written as

$$y_t = v + A_1 y_{t-1} + \ldots + A_p y_{t-p} + u_t \tag{2.1}$$

where $y_t = (y_{1t}, \ldots, y_{Kt})'$ is a vector of K endogenous variables and p is the number of lags included in the model. The vector v is an intercept vector with K rows and the A's are $K \times K$ coefficient matrices. Furthermore $u_t = (u_{1t}, \ldots, u_{Kt})$ is a K-dimensional vector of reduced-form errors with the properties $E(u_t) = 0$, $E(u_t u_s') = \Sigma_u$ and $E(u_t u_s') = 0$ for $s \neq t$, where Σ_u is an invertible $K \times K$ variance-covariance matrix. We specify the VAR model to have a lag length of two lags as indicated by the Schwarz Information

Criterion. However, since u_t reflects the instantaneous causality among the variables not accounted for in the reduced-form model, this representation does not allow an economic interpretation of the error term. For this purpose, the structural model has to be identified. The structural VAR has the representation

$$Ay_t = A_1^* y_{t-1} + \ldots + A_p^* y_{t-p} + \epsilon_t \tag{2.2}$$

or equivalently, adding $(I_k - A)y_t$ to both sides of the equation,

$$y_t = (I_K - A)y_t + A_1^* y_{t-1} + \ldots + A_p^* y_{t-p} + \epsilon_t \tag{2.3}$$

where I_K represents the identity matrix of order K, A is an $K \times K$ matrix of instantaneous interaction among the variables and A_i^* is equal to AA_i for $i = 0, \ldots, p$. Moreover, $\epsilon_t = (\epsilon_{1t}, \ldots, \epsilon_{Kt})'$ is a row-vector of dimension K representing structural errors with variance-covariance matrix Σ_ϵ. As the instantaneous causality of the variables is captured by A, Σ_ϵ is diagonal. Hence, the errors of the structural representation can be assigned to a single variable and therefore have economic meaning. The identification of the structural form is based on restrictions placed on the instantaneous coefficient matrix A. To derive the structural representation, a total of $K(K-1)/2$ restrictions must be imposed. We choose a recursive identification structure as the starting point for our model. However, in case the recursive identification diverges from our economic expectations, we deviate from the recursive ordering and impose restrictions that are more appealing from an economic point of view. The instantaneous restrictions imposed for the identification of the structural VAR model are summarized in Table 2.2.

Since weather is apparently exogenous with respect to the other included variables, deviations from historical heating degree day averages are ordered first within the matrix of instantaneous interaction. The supply shortfall variable, accounting for absent gas deliveries to the European market, also exhibits exogenous character. However, historical evidence suggests that supply shortfalls of Russian gas are more likely during peak

TABLE 2.2: Identification of the Contemporaneous Matrix

	Temp-erature	Supply Shortfall	Crude Price	Coal Price	LNG	Storage	Gas Price
Heating degree days deviation	$\star$	0	0	0	0	0	0
Supply Shortfall	$\star$	$\star$	0	0	0	0	0
Price of Brent crude oil	$\star$	$\star$	$\star$	0	0	0	0
Price of coal	$\star$	0	$\star$	$\star$	0	0	$\star$
LNG imports to EU-27	$\star$	$\star$	0	0	$\star$	$\star$	$\star$
Storage	$\star$	$\star$	$\star$	$\star$	0	$\star$	$\star$
Natural gas price	$\star$	$\star$	$\star$	$\star$	$\star$	$\star$	$\star$

Notes: Each row of this table indicates an equation in the VAR model with the respective dependent variable. Each column indicates the instantaneous impact of a variable in each equation. The $\star$ denotes that a parameter is estimated from the data and that the model allows for an instantaneous relationship, whereas a 0 indicates that the according parameter is restricted to zero.

demand periods.[28] Consequently, we leave the instantaneous influence of temperature deviations on supply shortfalls unrestricted. As the price of crude oil is concerned, it appears intuitive to let it instantaneously react to the supply shortfall variable as gas supply disruptions frequently go hand in hand with a shortened supply of crude oil. A recent example of this phenomenon is the case of the civil war in Libya in 2011, which affected both natural gas and crude oil production. Furthermore, extraordinarily cold weather periods increase the demand for heating oil in Europe and possibly increase the price of Brent crude oil through this channel. Therefore, we do not restrict the impact of heating degree days on the crude oil price. The price of coal is assumed to be instantaneously affected by weather conditions (via an increase in power demand). Additionally, accounting for the role of crude oil as a global benchmark commodity and the character of gas as a substitute for coal, it seems reasonable to assume a contemporaneous impact of oil and gas prices on the price of coal.

The first variable directly related to the German gas market is the EU-27 import of LNG. Unexpected weather conditions as well as supply shocks are likely to evoke significant changes in natural gas market fundamentals and hence the demand for LNG volumes. Therefore, we do not place any restrictions on the respective coefficients. Furthermore, LNG imports are expected to be affected by gas prices and storage flows. Regarding the necessary restrictions for identifying this equation, we argue that the instantaneous

[28]The experienced shortfalls of Russian gas supply to Western Europe in 2009 and 2012 both occurred during extraordinarily cold weather conditions. This may be a consequence of Gazprom's priority to satisfy domestic demand.

impact of coal and oil prices are of less, if any, relevance. Hence we restrict these coefficients to zero.

It is necessary to account for the endogeneity of storage flows with respect to changes in gas prices. Gas storages are likely to react instantaneously to changes in gas prices since intertemporal price arbitrage is the economic rationale of any commercial storage operator. Additionally, storage flows are expected to balance temporary divergence of supply and demand caused by any unforeseen shifts in market conditions, e.g., weather, supply surprises or cross-commodity effects. Thus, we allow for the direct effects of gas prices, coal prices, oil prices, unexpected temperatures and supply shortfalls on storage flows. Finally, since the German gas price is of main interest to our research, no restrictions are placed on the equation of this variable. This allows for a comprehensive analysis of the instantaneous impacts of all variables considered in the model on the price of natural gas.

As the instantaneous restrictions required for identification are based on economic theory, we use them also for lagged relationships with the following exceptions: First, the supply shortfall variable is set to be strictly exogenous, i.e., not affected by lagged temperature changes. Second, we allow for cross-commodity price effects in all directions because, from our perspective, there is no need to impose strict exogeneity to crude oil prices a priori. Third, the process of heating degree days is modeled as a first-order autoregressive process and has no lagged influence on crude oil and coal prices. We argue that temperature effects on commodity prices exhibit short-term character. Additionally, we allow LNG imports, storage and natural gas prices to depend on lags of all other variables. Table 2.3 summarizes the parameter restrictions on the lagged relationships.

The restrictions placed on lagged relationships imply different regressors within the VAR-framework. The existence of different explanatory variables makes the ordinary least squares estimator inefficient, as pointed out by Zellner (1962), because the error term of the reduced-form representation contains instantaneous correlation among the variables. Accordingly, we explicitly account for the correlation between the variables when estimating the reduced-form model using feasible generalized least squares (FGLS).

Table 2.3: Lag Restrictions in the VAR Model

	Temperature	Supply Shortfall	Crude Price	Coal Price	LNG	Storage	Gas Price
Heating degree days deviation	$\star$/0	0	0	0	0	0	0
Supply Shortfall	0	0	0	0	0	0	0
Price of Brent crude oil	0	$\star$	$\star$	$\star$	0	0	$\star$
Price of coal	0	0	$\star$	$\star$	0	0	$\star$
LNG imports to EU-27	$\star$	$\star$	$\star$	$\star$	$\star$	$\star$	$\star$
Storage	$\star$	$\star$	$\star$	$\star$	$\star$	$\star$	$\star$
Natural gas price	$\star$	$\star$	$\star$	$\star$	$\star$	$\star$	$\star$

Notes: Each row of this table indicates an equation in the VAR model with the respective dependent variable. Each column indicates a lagged impact of a variable in each equation. The $\star$ denotes that a parameter is estimated from the data, whereas a 0 indicates that the according parameter is restricted to zero.

The estimation of the structural model in the second step is based on the variance-covariance matrix of the reduced-form residuals estimated via FGLS. The structural-form parameters are nonlinear with respect to the reduced-form parameters and therefore only iterative algorithms, instead of a closed-form solution, can be applied. Hence, we estimate the structural-form parameters using the scoring algorithm of Amisano and Giannini (1997), as proposed by Lütkepohl (2005).

2.5 Empirical Results

The structural moving average (MA) representation of our model can be used to infer impulse response functions. Dropping the intercept term as it is of no interest for the analysis, allows the structural MA-form to be written as

$$y_t = \sum_{i=0}^{\infty} \Theta_i \epsilon_{t-i} \tag{2.4}$$

where ϵ has the properties as described in Section 2.4. The Θ_i-matrices can be calculated using the previously estimated structural coefficient matrices and contain the dynamic multipliers within the system. Hence, the response of variable j, i periods after an impulse of variable k is reflected in $\theta_{jk,i}$, the jk-th element of Θ_i. The impulses have the size of one standard deviation as we use the square roots of the estimated structural variance-covariance matrix for the calculation of responses. Following Lütkepohl (2005), who emphasizes the problematic finite sample properties of asymptotic confidence intervals for impulse responses, we rely on numerical resampling methods to derive error bands. We refer to Hall's 95-percentage bootstrap intervals using 1000 draws (see Hall, 1995). We generate responses of the natural gas price on impulses of all other variables, thus exploring the dynamic effects of gas market fundamentals on the price development. Figure 2.1 presents the estimated impulse response functions for the natural gas price.

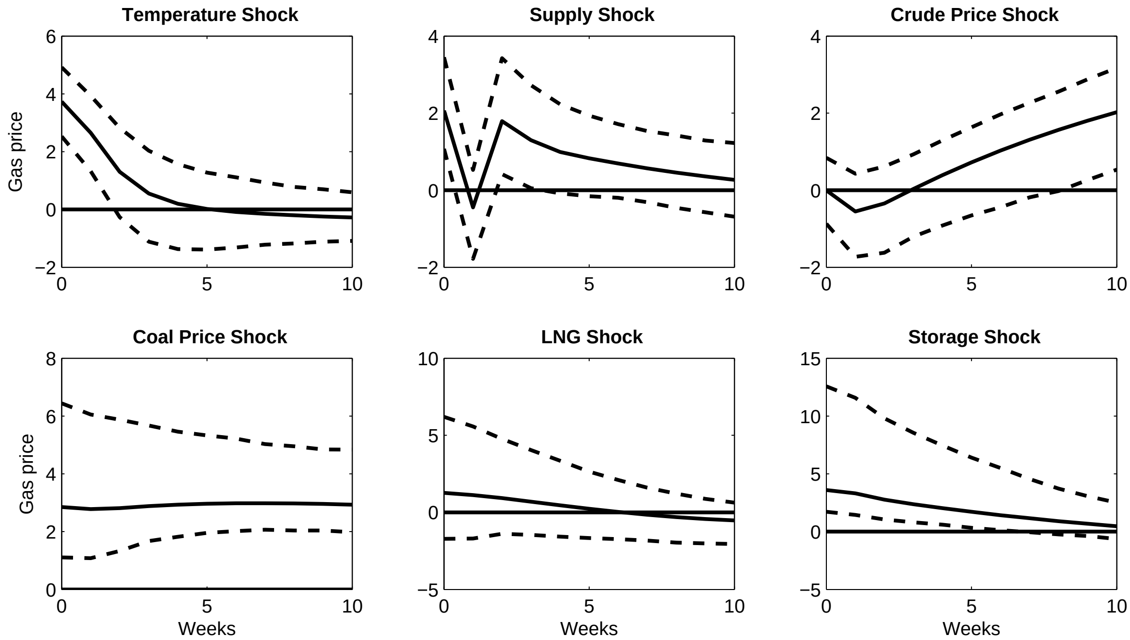

FIGURE 2.1: Responses of the Natural Gas Price

Notes: The impulse responses (solid lines) are based on one standard deviation of the respective structural shock. They can be interpreted as the percentage change in the natural gas price as a reaction to a standardized shock of the respective variable. Confidence intervals (dashed lines) are bootstrapped as Hall's 95-percentage bootstrap interval using 1000 draws.

The impulse responses of the natural gas price are consistent with economic reasoning. Extraordinarily cold weather results in an immediate and strong increase in the natural gas price. This increase is significant but lasts only for two weeks, indicating that temperature deviations have rather short-term effects on gas prices. Supply disruptions, approximated by the structural innovations of the supply shortfall variable, also cause a rise in the natural gas price. This result is consistent with both historical market conditions, e.g., the price spikes in January 2009 and February 2012, and economic intuition. The missing volumes are replaced by more expensive sources of supply to satisfy the rather price-inelastic gas demand. Furthermore, the impact on the natural gas price could also be attributed to the uncertainty of future supply conditions resulting in spot purchases (e.g., storage injection as a consequence of anticipated price increases).

The derived structural response functions of the natural gas price, with respect to oil and coal prices, provide evidence of significant interdependencies among the different energy commodities. The price of gas responds positively to shocks of both oil and coal prices. However, the pattern with which oil and coal influence the natural gas prices is fundamentally different. The impact of coal prices on gas prices occurs instantly and remains stable over time. In contrast, oil prices only affect natural gas prices after a substantial time delay.[29]

The strong interdependency of coal and gas prices can be attributed to different features of European energy markets. First, the fuel competition of the primary energy carriers gas and coal in the electricity sector may induce a positive cross-price elasticity for these commodities. Consequently, a rise in coal prices implies an increased demand for gas and therefore a resulting price increase. Second, since the spot prices used in this study comprise the North-Western European coal price and the German natural gas price, they reflect the same regional economic dynamics. Both aforementioned effects are reflected in the response function of the natural gas price with respect to coal prices since our model setup does not allow separating the pure substitution effect from the shared regional macroeconomic effects.

In contrast, the physical link between crude oil and natural gas exhibits rather long-term character since direct substitution is effectively limited to the residential heating sector. However, in the long run, as oil-indexed long-term contracts still prevail in German gas imports, a certain degree of long-run correlation between these two commodity prices seems plausible. While oil price indexation has decreased in relevance during the sample period, it may still cause an additional linkage between both commodity price series in continental Europe compared to markets without oil-indexed long-term contracting such as the US market. Unfortunately, our data does not allow for a distinction whether

[29]This finding is also supported by the correlations of price returns. While the returns of gas and coal prices have a correlation coefficient of 0.2088, the correlation of oil and gas returns is 0.0486 and statistically insignificant. The two-tailed 5% critical value is 0.1305 for 226 observations.

macroeconomic factors, the actual physical substitution or the impact of long-term contracts establishes the link between crude oil prices and natural gas prices. We refer to Asche et al. (2013) for a further investigation of contractual natural gas import prices into Germany

Next, the influence of the endogenous gas market variables on the natural gas price is discussed. There is no clear effect of a LNG import shock on the natural gas price, which may be caused by the use of interpolated monthly LNG import data. The German gas market is only indirectly affected by LNG imports to its neighboring countries (especially Belgium and the Netherlands) and subsequent cross-border trades as Germany itself does not have an LNG import terminal. Therefore, the volatile character of LNG deliveries to Europe as well as potential bottlenecks in the cross border capacity may prevent us from identifying a significant price effect in our model setting.

A positive structural storage shock contributes to rising gas prices as the injected volumes increase the spot market demand. Intuitively, a positive structural storage shock can be interpreted as an abnormal storage injection or as a storage withdrawal that is smaller than presumed for the current market situation. The price effect of inventory in natural gas markets has also been subject to previous econometric research. Brown and Yücel (2008) estimate a significant negative impact of inventory deviations from historical averages on gas prices in the United States. Using the same inventory variable as Brown and Yücel (2008), Ramberg and Parsons (2012) cannot find a significant effect on US gas prices for a more recent sample. Erdos (2012) also relies on the deviation from average storage utilization and does not find a significant price influence of this variable on neither UK nor US gas prices. Taking the first difference of his inventory variable, however, reveals a significant negative price effect in the US market. Following a slightly different approach, Mu (2007) constructs a variable representing storage surprises using a Fourier transformation to control for the seasonal pattern in natural gas inventory. His econometric estimations show that positive storage surprises, i.e., a higher rise in inventory than anticipated by market participants, affect the prices of US gas futures contracts negatively.

All of these studies share the strong assumption that the storage variable is exogenous with respect to the gas price. However, we argue that this assumption is invalid for liberalized natural gas markets since storage operators are expected to adjust the storage operations to current market conditions, i.e., to changes in gas prices. Thus, the aforementioned studies may suffer from an endogeneity bias resulting in inconsistent parameter estimates with regard to the price impact of gas inventory. In contrast, our approach to treat storage in a VAR framework explicitly allows for endogeneity between storage and other variables such as gas prices. Hence, we avoid any endogeneity bias and therefore generate more reliable estimates of the price effect of gas inventory. Our results are qualitatively similar to those of Brown and Yücel (2008) and Mu (2007). However, a direct comparison is not adequate since these studies rely on unexpected deviations from average storage level rather than on deviations from average changes in utilization.

Although our focus is on the determinants of the natural gas price, we briefly discuss the structural responses of LNG imports and storage since they are a novelty in econometric research on European gas markets. The respective impulse responses are presented in the Appendix. The endogenous treatment of our storage variable enables us to infer on how storage operators adjust their flows to changing market conditions including unexpected changes in spot market prices or temperature shocks.

The impulse response analysis shows that extraordinarily low temperatures lead to storage withdrawals. This relationship is caused by an increase in the temperature-sensitive natural gas demand in the residential and commercial heating sector. The additional demand has to be satisfied by gas withdrawal from storage facilities. The reaction of storage flows to supply disruptions is rather volatile and does not reveal a clear pattern. The response of storage flows to structural shocks in the natural gas price is consistent with the economic objectives of storage operators because higher natural gas prices incentivize storage operators to withdraw natural gas. Our empirical finding that storage operators react to price, temperature and supply shocks by withdrawing natural gas stresses their economic importance for smoothing out gas consumption and supply in extraordinary circumstances. The determinants of LNG imports are estimated with large error bands. Thus, there seems to be no clear pattern how the included fundamental gas market variables influence the amount of imported LNG.

In the following discussion, we return to the investigation on the impact of different fundamental influences on the natural gas price. In order to analyze the relative contribution of the variables considered in the modeling framework, we perform a forecast error variance decomposition using the results of the estimated structural VAR model. Based on the structural MA-representation of the VAR model, the contribution of innovations in variable k to the error variance of an h-step forecast of variable j can be written as

$$\omega_{jk,h} = \sum_{i=0}^{h-1} e_j' \theta_i^2 e_k / MSE[y_{j,t}(h)] \tag{2.5}$$

with

$$MSE[y_{j,t}(h)] = \sum_{i=0}^{h-1} \sum_{k=1}^{K} \theta_{jk,i}^2 \tag{2.6}$$

as the mean squared error (MSE) of h-step forecasts for variable j and e_k as the k-th column of an identity matrix of order K. Consequently, in our model framework, $\omega_{7k,h}$ represents the fraction of gas price variance that can by explained by the structural innovations of another variable included in the model.

Table 2.4: Forecast Error Variance Decomposition for the Natural Gas Price

Forecast Horizon	Weather	Supply Shortfall	Crude Price	Coal Price	LNG	Storage	Gas Price
1	0.26	0.08	0.00	0.15	0.03	0.24	0.24
2	0.23	0.05	0.00	0.17	0.03	0.26	0.25
4	0.16	0.07	0.00	0.22	0.03	0.26	0.26
8	0.11	0.06	0.02	0.33	0.02	0.23	0.23
12	0.09	0.05	0.07	0.39	0.02	0.19	0.19
26	0.05	0.02	0.30	0.37	0.02	0.12	0.12
52	0.04	0.02	0.39	0.26	0.01	0.14	0.14

Table 2.4 shows the estimated shares of the variance of the natural gas price accounted for by the structural innovations of each variable. The results are both intuitive and

consistent with the economic arguments provided above. In the short run, supply disruptions and unexpected temperature deviations are of major importance for the natural gas price and explain 34% of its fluctuation. However, the impact of these effects is rather short lived and hence, their influence diminishes over time. For longer horizons, the forecast errors of gas prices can be explained more precisely by developments related to the coal and oil markets. The variation in coal prices reaches its maximum explanatory power in medium-term horizons (12 to 26 weeks), while the long-term gas price development (up to 52 weeks) is heavily affected by variations in oil prices. With a forecast horizon of half a year, the aggregated effects of changes in coal and oil prices account for 67% of the gas price variance. Furthermore, our results indicate that storage flows have an important short-term influence on gas prices, a finding that is consistent with the fact that storage facilities balance the demand and supply fluctuations occurring in the natural gas market. In contrast, the explanatory power of LNG imports on the gas price is weak for all time horizons.

Both the impulse response analysis and the decomposition of the forecast error variance indicate that coal prices are more relevant than crude oil prices in explaining the natural gas price in the short term. While recent literature, for example Brown and Yücel (2008), Ramberg and Parsons (2012) and Hartley et al. (2008), focuses on the relationship between crude oil and natural gas prices, our results highlight that for an improved understanding of gas price dynamics, attention should also be paid to the interdependencies of gas and coal markets.

2.6 Event Studies of Supply Interruptions: Historical Decomposition

In this section, we examine the price impact of the three major interruptions in gas supply since the year 2008. First, we analyze the import disturbances from Russia in January 2009, which were caused by a dispute between Russia and Ukraine about the conditions of gas transit. Second, the Libyan production outage in the spring of 2011 due to a civil war is investigated. Third, we explore the withheld exports by Russia in February 2012.

Two difficulties regarding our analysis are that the nature of these supply shocks is not perfectly equivalent and that the gas infrastructure also changes over time. For example, the Russian-Ukrainian gas transit dispute could have a different impact if it occurred after the commissioning of the Nord Stream pipeline.[30] In order to harmonize the impact of these different disruptions, we attempt to objectify the magnitude by calculating approximative values for the volumes of supply shortfall. Taking into account the high degree of integration among European national gas markets, as shown by Robinson (2007), Renou-Maissant (2012) and Growitsch et al. (2012), we argue that one unit of production or import shortfall to the European market results in similar economic effects for all cases and locations of the gas shortage. The method has the advantage that the estimated effect of supply shocks, as derived from our model, has a generalizable interpretation. This property is desirable because future supply shocks are inherently uncertain with respect to the time and location of their occurrence.

The proposed structural VAR model is able to disentangle the different fundamental effects during the supply disruptions described above. The technical procedure of our analysis is generally the same for all three event studies of the respective supply shocks. We determine the first week in which the specific situation begins and calculate the impact of the relevant structural shocks on the natural gas price. For this purpose, we do not only use the shock in the first week, which would be similar to an impulse-response analysis, but extract the actual sequence of the relevant structural shocks to infer the accumulated impact in each period. As an indicative benchmark, we also show the actual development of the natural gas price in each plot.[31]

[30]The Nord Stream pipeline directly connects Russia with Germany through the Baltic Sea and therefore bypasses the transit route of the Ukrainian corridor. Thereby, Russia increases its own bargaining position towards transit countries as pointed out by Hubert and Ikonnikova (2011).

[31]The actual change in the natural gas price also depends on structural shocks before the time period analyzed. However, in the historical decomposition of the event studies, these shocks prior to the event are not included in the relative contribution of each influence during the specific event considered. Therefore, the relative influences during the crisis itself do not necessarily provide an optimal fit of the actual change in the natural gas price, which is therefore only included for illustrative purposes.

2.6.1 The Russian-Ukrainian Gas Conflict of 2009

The Russian-Ukrainian gas dispute of 2009 is one of the most prominent examples of political supply risks related to natural gas imports from Russia. In January 2009, natural gas transits from Russia into Western Europe were disrupted for about two weeks as Russia and the Ukraine could not find an agreement on transit charges. According to Lochner (2011), who analyzes this crisis in detail, Russia at this time accounted for 25% of the natural gas supplies to the European Union, 65% of which were transported through Ukraine. Our estimates of the supply shortfalls during this crisis are based on the supply statistics of Naftogaz Ukrainy reprinted in Pirani et al. (2009). The transit volumes declined from 318.4 million cubic meters (mcm) on January 1$^{\text{st}}$, 2009 to a complete stop on January 7$^{\text{th}}$. The gas flows were interrupted until January 20$^{\text{th}}$ and regained normal levels on January 22$^{\text{nd}}$. In order to calculate the volume of missing deliveries, we take the volume of gas transported on January 1$^{\text{st}}$ as a reference case and consider volumes below that level as supply shortfall. To measure losses between January 20$^{\text{th}}$ and January 22$^{\text{nd}}$, we linearly interpolate to the pre-crisis volumes to be reached on January 22$^{\text{nd}}$.

Following this procedure, the calculated lacking transit volumes amount to 4932.1 mcm in total. To test for robustness, we compare this estimate with the Eurostat Russian natural gas exports to EU-27 countries. The exports reported in January 2009 are 4585.9 mcm lower than in January 2008, 4793.7 mcm lower than in January 2010 and 5119.2 mcm lower than in January 2011. This comparison indicates that our estimates are of reasonable magnitude. As a second robustness test of our approach, we compare our estimates of lacking deliveries with the simulation-based estimate derived by Lochner (2011). According to that analysis, the affected daily gas transits via Ukraine account to 303.5 mcm on a normal winter day, which is close to the value found using our methodology.

Figure 2.2 shows the fundamental drivers of gas prices during the Russian-Ukrainian dispute of January 2009 and for a period of 12 weeks. The shortfall of natural gas supplies accounts for an increase in the gas price of more than 30% and is therefore the main driver of the observed price spike. Increased demand due to unusually low

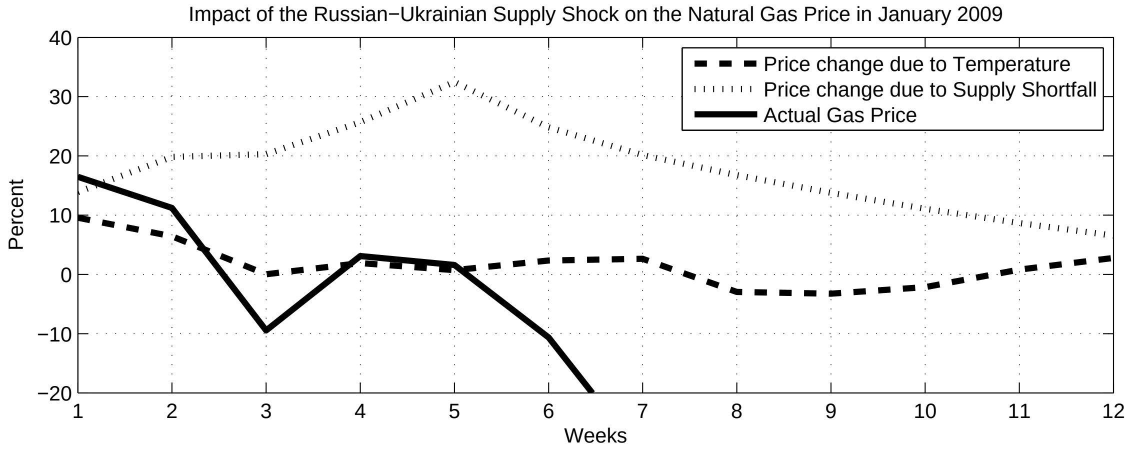

FIGURE 2.2: Historical Decomposition of Structural Influences During the Russian-Ukrainian Gas Dispute

Notes: Week 1 refers to the week ending on Friday January 9$^{\text{th}}$, 2009

temperatures accounts for 10% of the price increases and is especially of importance during the first two weeks. To summarize, the natural gas price follows the fundamental signals both from supply (interruption of imports) and demand (extraordinarily low temperatures) closely.

However, the actual increase in the gas price was less than what would have been implied by the sudden supply shortfall and extreme temperature when setting all other influences to zero. This is due to the fact that the Russian-Ukrainian gas dispute occurred during the financial crisis and the natural gas price was already following a negative trend. During this time, the financial crisis and the global economic downturn constituted a distinctive influence on all commodity markets. Therefore, we investigate the price impact during a longer period surrounding the supply disruption. Figure 2.3 shows the weekly development of the natural gas price for the six months after the bankruptcy of Lehman Brothers on September 15$^{\text{th}}$, 2008. In this figure, the spike in natural gas price in week 17 is driven by the start of the Russian-Ukrainian dispute in January 2009. The extended time window illustrates that while the short-term impact of the supply shock is substantial, it only had a short-lived impact on the overall downward sloping trend of the natural gas price. The results of this event study confirm our previous finding that the long-term development of the natural gas price crucially depends on the economic climate and closely follows the benchmark commodity prices of oil and coal.

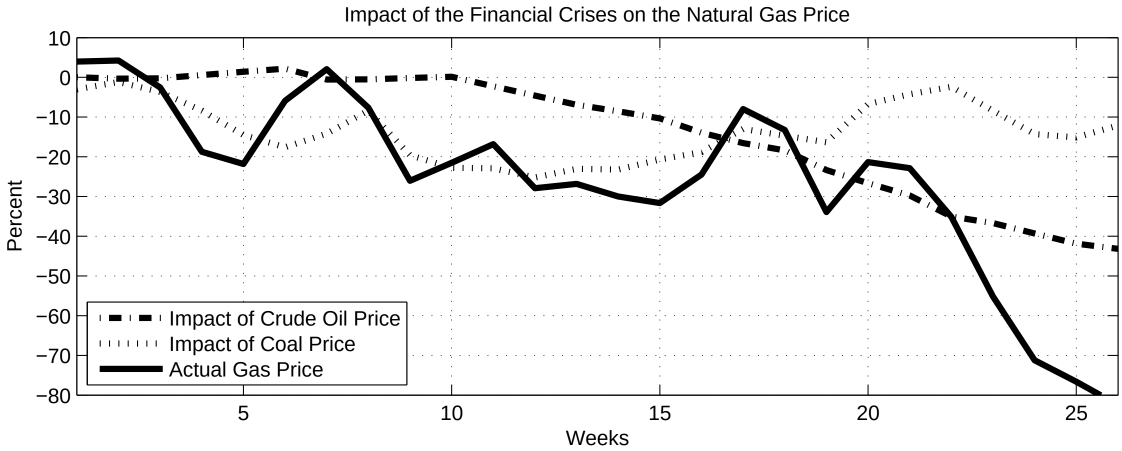

FIGURE 2.3: Historical Decomposition of Structural Influences During the Financial Crisis

Notes: Week 1 refers to the week ending on Friday September 19th, 2008. The price increase in week 17 reflects the beginning of the Russian-Ukrainian gas dispute of January 2009.

2.6.2 The "Arab Spring" and the Civil War in Libya 2011

In February 2011, the civil unrest of the so-called "Arab Spring" spread to Libya and resulted in a civil war with foreign military intervention. This turmoil led to an interruption of natural gas production in Libya. Lochner and Dieckhöner (2012) point out that Italy, the main recipient of Libyan gas deliveries, compensated for the Libyan imports by using storage withdrawals and additional imports via Austria and Switzerland, highlighting the integration of European natural gas markets. The shortfall of Libyan production therefore indirectly affects the German natural gas market because natural gas flows from Russia were diverted to Southern Europe and could consequently not be delivered to German consumers.

In order to estimate the supply shortfall, we use monthly Eurostat export data from Libya to Italy, which is Libya's main customer in the EU. We linearly interpolate from monthly to weekly frequency and define the supply shortfall as the difference between the actual exports and the exports before the interruption. According to Lochner and Dieckhöner (2012), delivery via the Greenstream pipeline to Italy was interrupted from February 22nd to October 13rd, 2011. This period is consistent with Eurostat data indicating no exports to the EU between March and September 2011. As Italy was able to compensate the Libyan supply shortfalls by additional imports from Russia, we only consider the missing Libyan gas volumes until the mid of April 2011 as a shock.[32]

In addition to the actual supply shortfall, there were also other indirect effects on the natural gas market. First, there was an additional risk that the Arab Spring could spread to Algeria and thus disrupt the Algerian natural gas production. In this case, as Lochner and Dieckhöner (2012) point out, the consequences for the European natural gas market would have been more severe. Second, the Arab Spring also affected the crude oil market both directly and indirectly. Libya is a relevant crude oil exporter and the market, according to news coverage, accounted for the risk that the Arab Spring could spread to other more important crude oil producers in the Middle East. Baumeister and Kilian (2012) discuss how the supply shock in Libya, as well as a precautionary demand shock driven by the political unrest resulting in a stocking up of crude oil, contributed to the increase in oil prices.

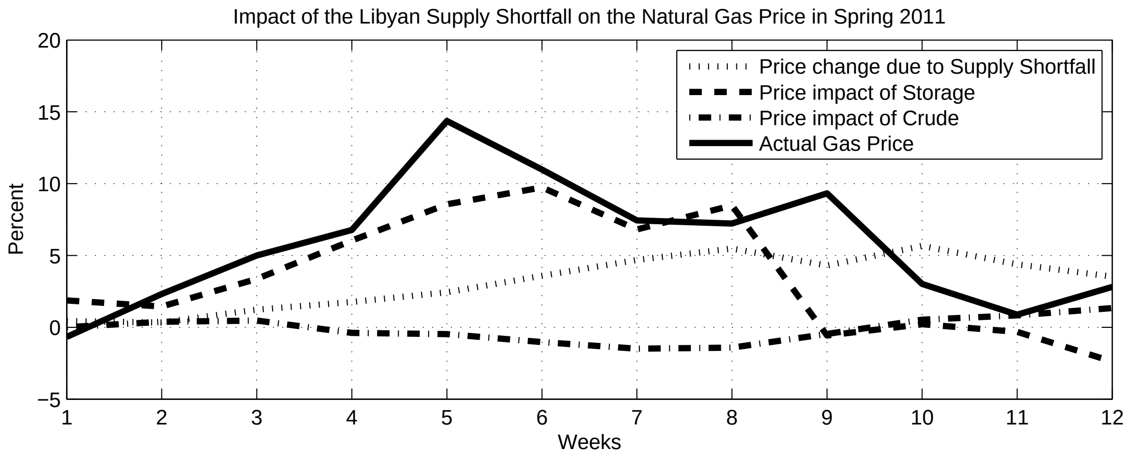

Figure 2.4: Historical Decomposition of Structural Influences During the Supply Shortfall After the Libyan Civil War

Notes: Week 1 refers to the week ending on Friday February, 18^{th}, 2011

Figure 2.4 shows the impact of the Libyan supply shortfalls in Spring 2011. Due to the relatively small amount of supply shortfalls, the direct impact on the gas price is rather weak. Furthermore, our analysis indicates that the development of the crude oil price does not seem to be a major explanatory factor for the German gas price increase during

[32]Lochner and Dieckhöner (2012) argue that the lack of imports from Libya were mainly compensated by increased imports via the Austrian TAG pipeline carrying Russian natural gas deliveries. However, as it takes approximately two weeks for Russian gas to be physically transported to Italy, the compensation mechanism of delivering additional gas via pipelines from Russia was mainly relevant after the first few weeks of the interruption.

the Libyan civil war in 2011. Yet, due to the political instability and risks associated with Algeria as a larger natural gas exporter, the increased precautionary demand for storage leads to increased gas prices. Such behavior is typical for energy markets during situations of uncertainty or turmoil in supplying countries, as shown by Kilian and Murphy (2013) using the Iranian Revolution in the year 1979 as one example.

2.6.3 Supply Interruptions of Russian Gas Deliveries in February 2012

In late January 2012, unusually low temperatures increased the domestic Russian gas demand for a sustained period of time. As the cold weather spread to Central and Western Europe, Russia found itself unable to meet its export commitments and thereby induced supply shortages and price spikes at various European gas hubs. However, there is a lack of quantitative estimates regarding the amount of the shortfall of supply during February 2012. In order to calculate a reasonable estimate, we draw upon different sources including the Dow Jones TradeNews Energy, the ICIS Heren European Gas Markets report and a report by Henderson and Heather (2012). Details regarding the information in these sources is given in the Appendix. The estimates of supply interruptions are mostly in the range of 10% to 30%, but vary depending on the date, geography or company considered. Given this wide range of estimates, we assume a shortfall of 20% in the first two weeks of February 2011 and assume a normal weekly delivery volume of 2.5 bcm to the EU as indicated by Eurostat data.

In Figure 2.5, we analyze the period of reduced Russian supplies in February 2012 coinciding with extraordinarily cold temperatures. Our results indicate that the abnormally low temperatures can explain a larger share of the actual price increase than the relatively small amount of supply shortfall. Consequently, we conclude that the price increase was rather driven by a positive demand shock than by the temporary cut in gas supplies.

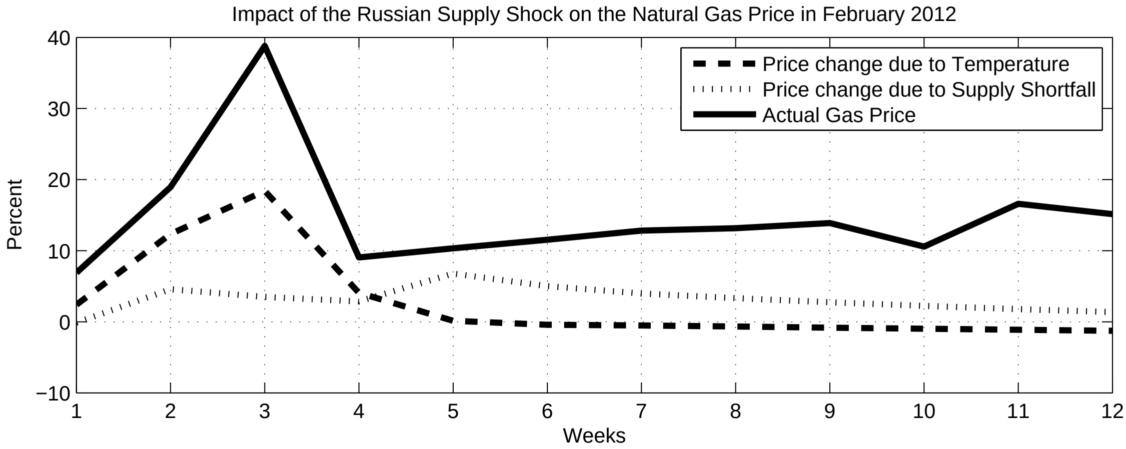

FIGURE 2.5: Historical Decomposition of Structural Influences During the Russian Supply Shortfall in February 2012

Notes: Week 1 refers to the week ending on Friday January 27$^{\text{th}}$, 2012

2.7 Conclusion

In this study, we introduced a novel approach to model the economics of natural gas prices. Our structural model allows us to appropriately account for the dynamics within the natural gas market as well as for the relationship to other commodity markets. The empirical results for Germany show that abnormal temperatures and supply shocks affect the natural gas price in the short term. However, in the long term, the price development is closely tied to crude oil and coal prices, indicating a high importance of cross-commodity effects.

The structural model allows us to perform a historical decomposition of the shocks affecting the natural gas price. We focus on the three major recent supply interruptions, namely the Russian-Ukrainian gas dispute of 2009, the Libyan supply shortfall in the spring of 2011 and the withheld Russian exports in February 2012. We explicitly analyze the specific contribution of the main fundamental variables on gas price development in these periods. Our findings can be used to draw conclusions about how the security of gas supply can be improved by different measures. The results of our structural model indicate that while supply shortfalls have a significant impact on the German gas market, their effect on gas prices may be overestimated since some of the discussed shortfalls occurred simultaneously with extraordinary demand conditions. These conditions comprise both extremely low temperatures and precautionary demand resulting from the anticipation of further supply interruptions, as pointed out in Section 2.6.

Consequently, the objective to improve the security of German gas supplies should not only focus on supply-sided measures such as a diversification of gas imports, but could also address flexibility options on the demand side of the market such as temperature-indexed interruptible contracts for industrial customers. Moreover, storage facilities as an important measure to smooth out temporary supply and demand imbalances deserve special attention from regulators and policy makers. Our model provides a solid framework for further research on more specific economic mechanisms within gas markets. Additionally, it could be easily extended to a European scope or other geographical regions. However, the current application is still restricted by the limited data available for the European gas markets.

Chapter 3

The Informational Efficiency of European Natural Gas Hubs: Empirical Evidence on Price Formation and Intertemporal Arbitrage

3.1 Introduction

The price signals of commodity spot and futures markets are of economic significance for market participants and various stakeholders as they tend to ensure an efficient allocation of resources. However, the extent to which commodity spot and futures prices fulfill their function crucially depends on the informational efficiency of the respective market. Economic theory suggests that sufficient market liquidity facilitates the processing of information into valid price signals. Thus, the efficiency of markets that are still immature and suffer a lack of liquidity may be questioned. This holds true for the natural gas wholesale markets within continental Europe. Spot markets for immediate delivery of natural gas as well as futures markets have emerged rather recently as a consequence of the natural gas directives of the European Parliament (EU, 2003b, EU, 2009b), aiming towards an integrated and competitive European gas market. Liquidity on these markets, though rising, is still low compared to the mature gas markets in the UK or the US. The limited liquidity of both spot and futures markets at continental European gas hubs has entered the scientific debate as European gas pricing is currently undergoing a transition phase from traditional oil indexed pricing of long-term contracts (LTC) to an increase in the significance of hub-based pricing.[33]

The shifting towards hub-based pricing of natural gas in continental Europe is based on the assumption that the respective hubs are capable of providing valid price signals. In this context, this study seeks to shed light on the informational efficiency of European gas hubs by empirically investigating two areas that allow for insights with regard to market efficiency: The price discovery process at spot and futures markets for the same underlying asset and the efficiency of intertemporal arbitrage between these two markets. It draws upon econometric approaches for the German hub "NetConnect Germany" (NCG), the Dutch hub "Title Transfer Facility" (TTF) and the British "National Balancing Point" (NBP), where the mature and liquid British hub serves as a benchmark for the other hubs.[34]

This paper extends research on natural gas markets in various ways: Foremost, it analyzes the informational efficiency of the European gas hubs through the investigation of the price formation process and the efficiency of intertemporal arbitrage. Second, it explicitly addresses the specific characteristics of the European gas market, namely low liquidity and technical constraints, by nonlinear econometric approaches. Third, it provides an insight into the evolution of informational efficiency at European gas hubs over time.

The empirical results of this study yield multiple insights into the informational efficiency of European natural gas markets. First, they show that the futures market is more

[33]For an elaborated discussion of the economics fostering the transition from oil indexation to hub-based pricing, see Stern and Rogers (2010). A real-life illustration are the current renegotiations of LTCs between various continental European gas importers with their suppliers (ICIS, 2013).

[34]Although the British gas hub may be considered as an appropriate benchmark for pricing European gas imports in terms of liquidity, the limited cross-border transportation capacity between mainland Europe and the UK as well as the implied currency risks for European gas traders carrying out transactions at this hub suggest the need for a continental European gas price benchmark.

informationally efficient than the spot market and that price discovery exclusively takes place on the futures market. Second, the analysis of intertemporal arbitrage reveals that there is a stable long-run equilibrium between spot and futures markets, but short-run equilibrium deviations can be quite persistent, pointing towards significant frictions in intertemporal arbitrage trading. Third, the increase in liquidity seems to have improved informational efficiency only at one of the three hubs considered.

The remainder of the paper is organized as follows: Section 3.2 discusses the underlying economic theory and relevant previous research. Section 3.3 provides information with regard to market liquidity and the flexibility potential of gas storages at the hubs considered. Section 3.4 presents the data used in this study and preliminary statistical tests. In Section 3.5, price discovery at European gas hubs is investigated using linear and nonlinear causality testing while Section 3.6 analyzes the efficiency of intertemporal arbitrage. A state-space approach to capture the evolution of arbitrage efficiency over time is specified in Section 3.7. Section 3.8 concludes.

3.2 Theoretical Considerations and Previous Research

Informationally efficient markets are expected to process relevant information instantaneously (Fama, 1970). Within an intertemporal context, this implies that informationally efficient spot and futures markets should react simultaneously to news that affect both markets. Consequently, there should be no systematic lead-lag relationship between the two markets (Zhang and Jinghong, 2012). This is in line with the Fama (1970) weak-form efficiency hypothesis stating that excess returns on efficient markets should be unpredictable as otherwise risk-free profits may be generated (Arouri et al., 2013). However, if one of the markets is more efficient in processing information, this market may become the leading market. In that case, price discovery takes place at the leading market and the price signal is subsequently transmitted to the following market.

There are various hypotheses with regard to the differences in informational efficiency of spot and futures markets and the resulting systematic relationship. Silvapulle and Moosa (1999) and Bohl et al. (2012) suggest that futures prices may react quicker to the arrival of information because informationally efficient speculators are only active in this market. As a result, information processing and price discovery occur in the futures market and spot prices adjust accordingly until an arbitrage-free equilibrium is achieved. In contrast, Moosa and Al-Loughani (1995) argue that the spot market should lead the futures market because arbitrageurs react to spot price movements by engaging in futures market positions.

Empirical research on price discovery on natural gas spot and futures markets is scarce. Dergiades et al. (2012) explore causality relationships between spot and futures prices at the US gas hub. Their econometric approach based on a frequency domain causality test provides evidence of causality running from the month-ahead futures market to the spot market. Focusing on the northwest US natural gas market, Gebre-Mariam (2011) tests for causality among spot and futures market prices and market efficiency by drawing upon cointegration techniques. The empirical results of the study suggest that there is no general pattern in causality between spot and futures prices as the direction of causality depends on the maturity of the futures contracts considered. In specific, futures contracts with a maturity of more than one year seem to significantly influence spot prices, while spot prices in turn affect the short-term futures market. Concerning the European gas market, empirical research has centered on the assessment of market integration and the efficiency of regional arbitrage (e.g., Neumann et al., 2006, Growitsch et al., 2012), whereas the price formation process at the European spot and futures markets has thus far been neglected.

The theory of storage suggests that spot and futures markets for storable commodities are linked through transactions of market participants optimizing their portfolios intertemporally, resulting in a stable long-run relationship between these markets (Working, 1949). The corresponding cost-of-carry condition is characterized by the equivalence of the price of a futures contract in period t with the delivery in period $t+k$, $F_{t+k|t}$, and the spot price compounded with the respective interest rate $r_{t+k|t}$, $S_t(1+r_{t+k|t})$, plus the storage costs $w_{t+k|t}$ adjusted for the economic benefit of physical ownership, the so-called "convenience yield" $c_{t+k|t}$. This condition can be stated as

$$F_{t+k|t} = S_t(1 + r_{t+k|t}) + w_{t+k|t} - c_{t+k|t}, \tag{3.1}$$

Deviations from the intertemporal equilibrium may trigger arbitrage activity by market participants. In this context, arbitrage can be considered as the economic activity of generating risk free profits by taking advantage of the substitutability between commodity spot and futures markets (Schwartz and Szakmary, 1994). As outlined by Huang et al. (2009), a long arbitrage position, i.e., buying the commodity on the spot market and selling a futures contract, is profitable if the basis $b_t = F_t - S_t$ exceeds the difference of warehouse costs and convenience yield, adjusted for the interest rate r:

$$b_t - S_t r_{t+k|t} > w_{t+k|t} - c_{t+k|t}. \tag{3.2}$$

In contrast, a short arbitrage position, i.e., selling the commodity on the spot market and buying a futures contract, generates profits if

$$b_t - S_t r_{t+k|t} < -(w_{t+k|t} - c_{t+k|t}). \tag{3.3}$$

The theory of storage has been empirically analyzed for different commodity markets by Fama and French (1987), and more recently by Considine and Larson (2001) and Huang et al. (2009). With regard to the European natural gas market, Stronzik et al. (2009) find significant deviations from the theory of storage for three European hubs for the period 2005 to 2008 using indirect testing procedures. However, the efficiency of intertemporal arbitrage activity at European gas hubs has not yet been addressed in the existing literature.

3.3 The Role of Liquidity and Storage Capacity

The spot and futures markets of the gas hubs considered in this study differ significantly with respect to their liquidity. While the NBP hub can be considered as mature and liquid, the younger hubs NCG and TTF suffer from low liquidity despite steadily increasing trading volumes during the last years. The churn rate, defined as the ratio between the number of traded contracts and the number of contracts that result in physical delivery of the underlying asset, can be used to assess the degree of financialization of commodity markets. Table 3.1 illustrates the differences among the three hubs with regard to their trading volumes, measured in billion cubic meters (bcm), and their churn rates as of 2011. The historical development of traded volumes is presented in Figure 3.1. There is no agreement as to which churn rate is required for a market to be considered as sufficiently liquid. However, a churn rate in the range from eight to fifteen is frequently regarded as critical (IEA, 2012b). As can be seen in Table 3.1, only the churn rate of NBP is situated within this range. Based on the superior liquidity of the British hub, information processing is expected to be more efficient at NBP compared to the continental European hubs.

Table 3.1: Liquidity at European Gas Hubs

	Physical Volume (bcm)	Traded Volume (bcm)	Churn Rate
NCG	35.5	108.5	3.1
TTF	35.6	151.7	4.3
NBP	79.6	1137.2	14.3

Source: IEA (2012b), Gasunie (2011), NCG (2011). The figures presented refer to the total hub trades (sum of trades in the "Over The Counter" (OTC) market and those via exchanges).

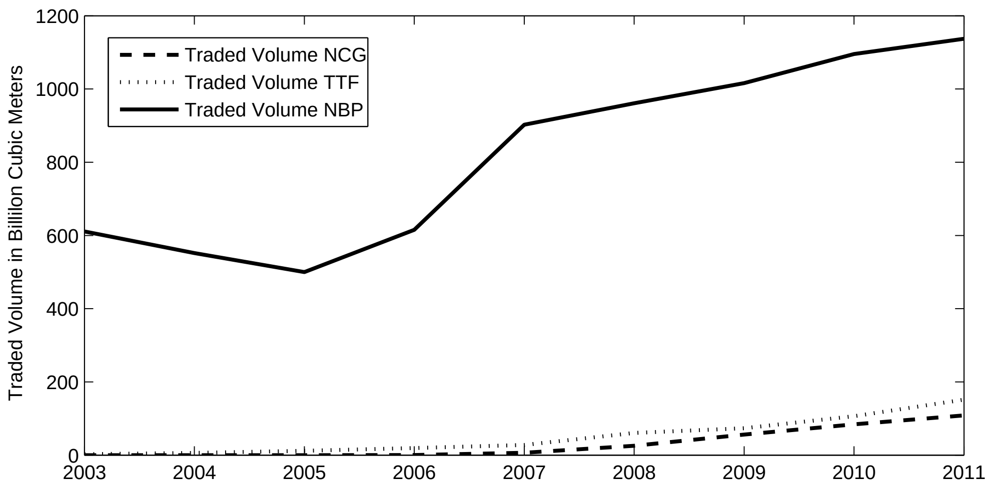

Figure 3.1: Trading Volumes at European Gas Hubs

Source: IEA (2012b)

Beside the frictions resulting from illiquid spot and futures markets, the efficiency of intertemporal arbitrage activity may be restricted by technical constraints. In particular, scarcity in storage capacity may prevent efficient arbitrage trading at least in the short run since the construction of additional storage facilities requires significant amount of time. A first indicator for the availability of sufficient storage capacity is the ratio of aggregated working gas volume to annual gas consumption. In addition, the flexibility potential of the existing storage capacities is crucial for an efficient adjustment of storage flows in order to exploit arbitrage opportunities. Frequently used measures for the degree of gas storage flexibility are the shares of aggregated injection capacity (IC) and aggregated withdrawal capacity (WC) on aggregated working gas volume (WGV). Table 3.2 presents data on WGV, natural gas consumption (C) and the three flexibility indicators for Germany[35], the Netherlands and the UK as of 2011.

Table 3.2: Storage Capacity and Flexibility Potential

	WGV (bcm)	C (bcm/a)	WGV/C	WC / WGV	IC / WGV
Germany	20.1	77.6	0.2590	0.0215	0.0111
Netherlands	5.1	47.9	0.1065	0.0410	0.0112
UK	4.5	82.6	0.0545	0.0195	0.0055

Source: IEA (2012c), GIE (2011).

The data emphasize the ample storage capacity of the German gas market. In contrast, storage capacity in the UK is rather scarce in a physical sense since the WGV only amounts to approximately 5% of annual gas consumption. The Netherlands range between Germany and UK in terms of this indicator. With regard to operational flexibility, Dutch gas storages seem most capable of adjusting operations to changing market conditions in the short run, while UK storage facilities are fairly inflexible. From a technical point of view, the indicators thus suggest that the storage market in the UK is less supportive of efficient intertemporal arbitrage activity compared to NCG and TTF.

Beside the physical capacity constraints discussed above, contractual congestion may hamper intertemporal arbitrage activity. However, the regulators in all the countries considered generally opted for a negotiated, rather than a regulated, third party access model in order to implement the third European natural gas directive (EU, 2009b).

[35] Currently, there are two market areas in Germany, NCG and Gaspool. Therefore, total national gas consumption and storage capacity cannot be fully allocated to NCG. However, the national consumption-to-storage ratio is used here as an approximation for this hub.

Thus, the regulatory approach to ensure third party acces to storage facilities may not be expected to fully explain potential differences in the efficiency of intertemporal arbitrage between the hubs investigated.

3.4 Sample Description and Preliminary Data Analysis

The sample comprises daily spot, one month-ahead (m+1), two month-ahead (m+2) and three month-ahead (m+3) futures prices for the hubs NCG[36], TTF and NBP[37] during the period October 2007 to August 2012.[38] All prices represent the settlement prices of the respective trading day. The selection of the two continental European hubs is motivated by the steady rise in trading activity during the last years, suggesting that at least one of these hubs will emerge as the leading continental European trading area (Heather, 2012). The NBP hub, as the most mature and liquid hub in Europe, serves as benchmark to assess the informational efficiency of NCG and TTF. Monthly futures contracts are preferred to quarterly or seasonal products to account for the tendency towards the trading of monthly contracts with short maturity (NMA, 2012). Descriptive statistics of the price return series, computed as the differences in the logarithms of two consecutive daily settlement prices, are provided in Table 3.3.

TABLE 3.3: Descriptive Statistics of Gas Price Returns

	Observations	Mean	Variance	Skewness	Kurtosis
NCG Spot	1228	1.88e-04	0.0023	-0.5081	12.3466
NCG m+1	1228	1.45e-04	0.0008	1.8054	21.6685
NCG m+2	1228	1.53e-04	0.0007	2.1349	25.2165
NCG m+3	1228	1.11e-04	0.0006	2.3307	23.7995
TTF Spot	1228	2.81e-04	0.0018	-0.1175	8.9574
TTF m+1	1228	1.51e-04	0.0008	1.3689	14.1179
TTF m+2	1228	1.55e-04	0.0007	1.5960	19.2947
TTF m+3	1228	1.29e-04	0.0006	1.9247	20.0573
NBP Spot	1268	2.23e-04	0.0062	-0.2147	18.9689
NBP m+1	1268	2.36e-04	0.0011	2.5508	27.0689
NBP m+2	1268	1.93e-04	0.0009	1.8292	19.7212
NBP m+3	1268	2.13e-04	0.0007	1.5505	18.2572

[36]For NCG, spot and futures prices were obtained from the European Energy Exchange, available at `http://www.eex.com/de/marktdaten/erdgas`

[37]For TTF and NBP, spot prices were obtained from Endex (`http://www.iceendex.com/`), futures prices from the Intercontinental Exchange (`https://www.theice.com/natural_gas.jhtml`).

[38]The beginning of the sample has been restricted by the availability of NCG prices which were not available before October 2007.

All price return series have means close to zero. The Samuelson Hypothesis, stating that the variance of price returns decreases with the maturity (Samuelson, 1965), is confirmed by the data as spot market returns have the greatest variance, while fluctuations gradually decline from the m+1 to the m+3 contracts. All return series exhibit excess kurtosis, reflecting a fat-tailed distribution that is frequently observed in commodity market return series. For the subsequent econometric analysis, the stationarity properties of all price series are investigated using the Augmented Dickey Fuller (ADF) test and the nonparametric Phillips-Perron test to avoid misleading statistical inference. For all price series, the null hypothesis of a unit root in the log-level cannot be rejected, which is the case for the first differences, i.e., the daily returns.[39] Thus, the intertemporal equilibrium between the spot and futures market at the hubs considered can be investigated using cointegration analysis.

The concept of cointegration was developed by Engle and Granger (1987) and implies that two or more time series share a stable long-run equilibrium. In technical terms, it states that for two time series, both integrated of order n with $n \geq 1$, there exists a linear combination of these series that is integrated of order $n-1$. Following Lütkepohl (2005), the cointegration relationship can be investigated based on a k-dimensional VAR model of order p:

$$y_t = A_1 y_{t-1} + ... + A_p y_{t-p} + u_t, \tag{3.4}$$

where cointegration of rank r implies that the matrix

$$\Pi = -(I_k - A_1 - ... - A_p) = \alpha\beta', \tag{3.5}$$

is of rank r. In Equation (3.5), α and β represent the loading matrix and the cointegration matrix, respectively, and are of dimension (k x r) and of rank r. To determine the rank of Π, the procedure proposed by Johansen (1988) is applied. The null hypothesis of absent cointegration between spot and futures prices can be rejected for all hubs. Thus, there is empirical evidence of an intertemporal equilibrium between the spot and

[39]The results of the unit root tests are provided in the Appendix.

futures markets at the hubs considered. Table 3.4 presents the results of the Johansen cointegration tests for the spot and the month-ahead prices at the hubs considered.[40]

Table 3.4: Results of the Johansen Cointegration Test (Spot and m+1)

Hypothesis	Eigenvalue	Trace Statistic	Critical Value (95%)	p-Value
NCG r=0	0.0611	78.694	20.262	0.0000
NCG r$\leq$ 1	0.0013	1.5589	9.1645	0.8627
TTF r=0	0.0548	70.511	20.262	0.0000
TTF r$\leq$ 1	0.0012	1.5125	9.1645	0.8712
NBP r=0	0.0450	60.508	20.262	0.0000
NBP r$\leq$ 1	0.0019	2.3415	9.1645	0.7092

3.5 Price Formation: Linear and Nonlinear Causality Testing

This section investigates the price discovery process on the spot and futures markets of the European gas hubs. Econometric tests are applied to investigate whether the hypothesis of simultaneous information processing (Fama, 1970) holds for the spot and futures markets under consideration. The idea of simultaneous information processing implies that there should be no systematic, i.e., no causal, relationship between price changes on spot and futures markets. Thus, linear Granger causality testing (Granger, 1969) can be applied to analyze information transmission and price formation. A process x_t is said to cause a process y_t in the sense of Granger if

$$\Sigma_z(h|\Omega_t) < \Sigma_z(h|\Omega_t \backslash (x_s|s \leq t)) \text{ for at least one } h = 1,2,...,\text{N}, \tag{3.6}$$

where $\Sigma_z(h|\Omega_t)$ is the optimal mean squared error of an h-step forecast based on the information set Ω_t reflecting all past and current information (Lütkepohl, 2005).

The test is carried out for the price returns within a vector error correction (VECM) framework. Thereby, the cointegration relationship between spot and futures prices is

[40] In the following, this study focuses on the month-ahead contracts rather than on futures contracts with longer maturity. This is in line with the fact that the trading of futures contracts at the European gas hubs is centered on the month-ahead contract. However, the choice of maturity does not significantly affect the findings and the empirical results for futures contracts with longer maturity are provided in the Appendix.

explicitly accounted for to avoid misleading inference.[41] In addition, the VECM-filtered residuals are tested for any remaining linear causality pattern. Table 3.5 contains the results of the linear Granger causality tests for the spot- and month-ahead return series. For the unfiltered return series, the null hypothesis of absent Granger causality can be rejected for the direction from futures to spot markets at all three hubs. This means that the change in the month-ahead futures price has explanatory character for the next day's spot price change, violating the Fama (1970) weak-form efficiency hypothesis that is based on the unpredictability of price returns.[42] Consequently, information is not processed simultaneously by spot and futures market participants.

In fact, information is first processed within the futures market and subsequently transmitted to the spot market. Thus, the month-ahead market seems to be the dominant market in terms of price discovery. The finding of the futures market providing price discovery for the spot market is noteworthy in the context of natural gas markets, where the information sets of spot and futures markets partially differ from one another. Most notably, short-run influences such as weather conditions or infrastructure outages are expected to affect spot market returns significantly, whereas their impact on the futures market should be limited. However, despite these specific characteristics of the purely physical spot market, the futures market still has significant explanatory power for the subsequent outcome of the spot market.

The informational superiority of the futures market may result from the broader scope of participants on this market. The opportunity to trade futures contracts multiple times before maturity and thus close out the trading position without taking physical delivery makes the futures market attractive for hedgers and speculators without interest in physical delivery of the underlying asset. These additional market participants may cause a greater efficiency of information processing of the futures market compared to the one of the spot market, as suggested by Silvapulle and Moosa (1999) and Bohl et al.

[41] Ignoring an existing cointegration relationship may lead to invalid results of linear and nonlinear Granger causality tests, as outlined by Chen and Lin (2004).

[42] The finding of Granger causality from futures market price returns to spot market price returns at all hubs remains unchanged when controlling for conditional heteroskedasticity of the price return series within a GARCH(1,1)-framework. The results of the Granger causality tests for the spot market and longer-maturity futures markets are presented in the Appendix. For all hubs, there is empirical evidence of futures markets leading the spot market.

(2012). Overall, the empirical evidence of the month-ahead natural gas futures market leading the corresponding spot market is in line with the findings of Dergiades et al. (2012) for the US natural gas market. For the VECM-filtered series, the null hypothesis of absent Granger causality cannot be rejected in any direction for all hubs.[43] This suggests that all linear causality is captured by the VECM-model.

Table 3.5: Pairwise Linear Causality Tests for Gas Price Returns

Direction	Chi-sq-Statistic
NCG Spot on NCG m+1	0.1193
NCG m+1 on NCG Spot	5.7441**
TTF Spot on TTF m+1	2.8416
TTF m+1 on TTF Spot	306.06***
NBP Spot on NBP m+1	2.1940
NBP m+1 on NBP Spot	8.6832**

Notes: *** (**) Denotes significance at the 99 (95)%-level. Granger causality has been investigated within the VECM-framework, explicitly accounting for the cointegration relationship.

The econometric methodology as applied thus far is only capable of investigating linear relationships. However, there is empirical evidence suggesting nonlinearities in the relationship of commodity spot and futures markets, which is usually attributed to the nonlinearity of transaction costs and market microstructure effects such as minimum lot sizes (Bekiros and Diks, 2008, Chen and Lin, 2004, Silvapulle and Moosa, 1999). Additionally, asymmetric information and heterogeneous expectations of market participants may also induce nonlinearities in the relationship between commodity spot and futures prices (Arouri et al., 2013). There are good reasons to believe that these drivers of nonlinearity are relevant for the continental European gas hubs because the low liquidity at these hubs may foster market frictions such as significant bid-ask spreads and information costs.

Following this reasoning, the nonlinear causality test proposed by Diks and Panchenko (2006) is applied to investigate nonlinear dynamics among the considered spot and futures markets. The testing procedure of Diks and Panchenko (2006) is based on the Hiemstra Jones Test (Hiemstra and Jones, 1994). The null hypothesis of absent nonlinear Granger causality between two series is tested using their conditional distributions.

[43]Test statistics are provided in the Appendix.

Assuming stationarity, the null hypothesis of Y with respect to X implies that the conditional distribution of a variable Z given its past realization $Y = y$ equals the conditional distribution of Z given $Y = y$ and $X = x$. Thus, the joint probability functions and their marginals can be used to state the null hypothesis as

$$\frac{f_{X,Y,Z}(x,y,z)}{f_Y(y)} = \frac{f_{X,Y}(x,y)}{f_Y(y)} \cdot \frac{f_{Y,Z}(y,z)}{f_Y(y)}. \tag{3.7}$$

Diks and Panchenko (2006) show that the null hypothesis can be reformulated as

$$q \equiv E\left[f_{X,Y,Z}(X,Y,Z)f_Y(Y) - f_{X,Y}(X,Y)f_{Y,Z}(Y,Z)\right] = 0. \tag{3.8}$$

As outlined by Diks and Panchenko (2005), the test statistic has to be corrected for possible size bias resulting from time-varying conditional distributions. Diks and Panchenko (2006) show that the adjusted test statistic is

$$T_n(\epsilon_n) = \frac{n-1}{n(n-2)} \cdot \sum_i (\hat{f}_{X,Z,Y}(X_i,Z_i,Y_i)\hat{f}_Y(Y_i) - \hat{f}_{X,Z}(X_i,Y_i)\hat{f}_{Y,Z}(Y_i,Z_i)), \tag{3.9}$$

where $\hat{f}_W(W_i)$ is the estimator of the local density of a d_w-variate random vector W_i with

$$\hat{f}_W(W_i) = (2\epsilon_n)^{-d_W}(n-1)^{-1} \sum_{j,j\neq i} I_{ij}{}^W, \tag{3.10}$$

where ϵ_n is the bandwidth depending on the sample size n and $I_{ij}{}^W = I(\|W_i - W_j\| < \epsilon_n)$ is an indicator function. Diks and Panchenko (2006) demonstrate that the distribution of the test statistic equals

$$\sqrt{n}\frac{(T_n(\epsilon_n) - q)}{S_n} \xrightarrow{d} N(0,1), \tag{3.11}$$

for a lag length of 1 and $\epsilon_n = Cn^{-\beta}$ with $C > 0$ and $\frac{1}{4} < \beta < \frac{1}{3}$. S_n is the estimator of the asymptotic variance of $T_n(\cdot)$ (Bekiros and Diks, 2008). Furthermore, Diks and

Panchenko (2006) show that the optimal bandwidth minimizing the mean squared error of T_n is

$$\epsilon_n^* = C^* n^{(-2/7)}. \tag{3.12}$$

The nonlinear causality testing procedure is applied to the VECM-filtered residuals to ensure that any detected causality can be attributed to nonlinear interaction of the spot and futures markets. Following Diks and Panchenko (2006), the constant term C^* of the bandwidth ϵ_n is set to 8.[44] Inserting C^* into Equation (3.12) results in a bandwidth ϵ_n of approximately 1.[45]

As can be seen in Table 3.6, the null hypothesis of absent nonlinear Granger causality among spot and month-ahead return series can be rejected in both directions for all three hubs.[46] This suggests that there is a bidirectional nonlinear interaction between the spot and futures markets investigated. However, as outlined by Bekiros and Diks (2008), these nonlinear interdependencies may stem from volatility effects. As a consequence, a multivariate GARCH model is applied to capture the dynamics in the second moment of distribution in both markets, filtering out time-varying volatility effects. The diagonal BEKK GARCH model of Engle and Kroner (1995) is applied to explicitly control for conditional heteroskedasticity.[47] Subsequently, the nonlinear causality test of Diks and Panchenko (2006) is used for the BEKK GARCH-filtered VECM residuals.

For all hubs, the nonlinear causality from spot to futures markets disappears after BEKK-GARCH filtering. This suggests that any predictive power of spot return distributions for subsequent distributions of futures market returns results from volatility effects rather than from informational superiority. Interestingly, except for TTF, there remains no more causality from the futures market to the spot market after filtering out linear causality and volatility effects. Thus, the interaction between spot and futures

[44] Similar values of C^* have been used for comparable empirical approaches (e.g., Bekiros and Diks (2008) set C^* equal to 7.5).

[45] As a robustness check, the test has been conducted with smaller and larger bandwidths within the range of 0.9 and 1.1. However, the results are not very sensitive to the choice of bandwidth.

[46] The results of the nonlinear causality tests for the other pairs of return series are presented in the Appendix.

[47] BEKK refers to the first letters of the names of Baba, Engle, Kroner and Kraft, who jointly developed the model.

markets at NCG and NBP seems limited to the first and the second moment of distribution. To sum up, the performed causality analysis suggests that price formation takes place on the more informationally efficient futures markets with the less informationally efficient spot markets adjusting accordingly.

TABLE 3.6: Pairwise Nonlinear Causality Tests for Gas Price Returns

	Direction	t-Statistic
VECM-filtered Data	NCG Spot on NCG m+1	4.219***
	NCG m+1 on NCG Spot	5.520***
	TTF Spot on TTF m+1	3.965***
	TTF m+1 on TTF Spot	7.703***
	NBP Spot on NBP m+1	3.305***
	NBP m+1 on NBP Spot	3.222***
BEKK GARCH-filtered Data	NCG Spot on NCG m+1	-1.944
	NCG m+1 on NCG Spot	-0.477
	TTF Spot on TTF m+1	-0.711
	TTF m+1 on TTF Spot	5.698***
	NBP Spot on NBP m+1	1.016
	NBP m+1 on NBP Spot	0.939

Notes: *** Denotes significance at the 99%-level.

3.6 The Efficiency of Intertemporal Arbitrage: Linear and Threshold Error Correction

The finding of cointegration for the spot and futures market price series at all hubs in Section 3.4 suggests that the theory of storage holds in the long run. The long-run relationship can be written as

$$S_t = c + \beta F_t + \epsilon_t. \tag{3.13}$$

Here, S_t and F_t are the spot and the futures prices, respectively. The coefficient β represents the degree of price convergence in the long run and ϵ_t captures the deviations from the long-run relationship.[48] As pointed out by Arouri et al. (2013), cointegration between the spot market and the futures market is a necessary but not a sufficient

[48]With regard to the cost-of-carry relationship, the intercept in Equation 3.13 contains the time-invariant spread between futures and spot prices that can be assigned to the convenience yield, storage costs and the interest rate. Assuming time-invariant carrying parameters, ϵ_t represents the deviation from the cost-of-carry relationship, triggering arbitrage trading between spot and futures markets. One should keep in mind that in case of time-varying carrying parameters, e.g., fluctuations of storage costs, ϵ_t may not completely reflect deviations from the cost-of-carry condition.

condition for informational efficiency in the long run. In fact, long-run informational efficiency implies full price convergence (β=1). This hypothesis can be empirically assessed by testing the respective coefficient restriction.

However, even if the market is informationally efficient in the long run, arbitrage opportunities and thus short-run inefficiencies may exist (Arouri et al., 2013). In order to assess the short-run informational efficiency of spot and futures markets, the short-term behavior of the spot and futures price series is therefore of special interest. Since these series are cointegrated, their short-run behavior can be modeled by a VECM (Engle and Granger, 1987). The bivariate VECM for the analysis of the spot and futures market price return series behavior has the following representation:

$$\begin{aligned} \Delta f_t = &\quad \alpha^f \epsilon_{t-1} + \sum_{k=1}^{k=n} \gamma_k^f \Delta f_{t-k} + \sum_{k=1}^{k=n} \delta_k^f \Delta s_{t-k} + \eta_t^f, \\ \Delta s_t = &\quad \alpha^s \epsilon_{t-1} + \sum_{k=1}^{k=n} \gamma_k^s \Delta f_{t-k} + \sum_{k=1}^{k=n} \delta_k^s \Delta s_{t-k} + \eta_t^s, \end{aligned} \tag{3.14}$$

where α is the adjustment coefficient representing the error correction of the series in case of any deviation from the long-run equilibrium (Lütkepohl, 2005) and n denotes the number of lags included in the model. The γ and δ coefficients account for autoregressive behavior of the series. To asses the short-run informational efficiency, the α coefficients are of central interest because they measure the speed of error correction. The greater the value of the adjustment coefficient in absolute terms, the more informationally efficient are the market participants in exhausting arbitrage opportunities. For the assessment of both the long-run and the short-run informational efficiency of the markets analyzed, linear VECMs are estimated as proposed by Johansen (1988) in order to obtain estimates of β and α simultaneously . Table 3.7 presents the estimated cointegration vector of the long-run relationship and the short-run adjustment coefficients for the spot price and the month-ahead futures price. As to the long-run informational efficiency, the estimated β coefficients are close to unity. A likelihood ratio test (LR test) is carried out to test the hypothesis of long-run informational efficiency, i.e., $\beta = 1$. The null hypothesis cannot be rejected for all hubs (see Table 3.8). Thus, long-run informational efficiency in terms of full price convergence cannot be rejected.

TABLE 3.7: Normalized Cointegration Vectors and Error Correction Coefficients

	Parameter	Standard Error	t-Statistic
c_{NCG}	-0.0276	0.0761	-0.3621
β_{NCG}	0.9836	0.0203	38.849***
$\alpha_{NCG,spot}$	-0.1329	0.0176	-7.5461***
$\alpha_{NCG,m+1}$	0.0107	0.0106	1.0021
c_{TTF}	-0.0368	0.0816	-0.4509
β_{TTF}	0.9809	0.0272	36.005***
$\alpha_{TTF,spot}$	-0.1111	0.0130	-8.5230***
$\alpha_{TTF,m+1}$	0.0036	0.0105	0.3453
c_{NBP}	-0.0665	0.1520	-0.4375
β_{NBP}	0.9758	0.0394	24.858***
$\alpha_{NBP,spot}$	-0.1538	0.0196	-7.8323***
$\alpha_{NBP,m+1}$	0.0044	0.0088	0.5035

Notes: *** Denotes significance at the 99%-level. A lag length of 1 for the VECM is selected based on the Schwarz Information Criterion for NCG and TTF, while the same criterion suggests to include 2 lags for NBP.

TABLE 3.8: Results of the Likelihood Ratio Test on the Cointegration Vector

	Chi-sq-Statistic	p-Value
NCG	0.4036	0.5252
TTF	0.4726	0.4918
NBP	0.3605	0.5482

Notes: The test was applied to the cointegration vector of the spot and the month-ahead futures prices. The null hypothesis of the LR test is: β =[1;-1].

With regard to the short-run informational efficiency, the adjustment coefficient is statistically significant in all spot price return equations. Hence, deviations from the long-run relationship are corrected within the spot market at all hubs. In contrast, the futures price return series do not react to deviations from the equilibrium. This finding is in line with Huang et al. (2009), who obtain similar results for crude oil spot and futures markets in the period 1991 to 2001. The insignificant adjustment coefficient in all futures return equations suggests that these series are weakly exogenous with respect to the corresponding spot price series (Urbain, 1992).[49] The small absolute values of the

[49] Similar results are obtained from the VECM estimation for the interaction of spot prices and futures prices with longer maturity. The respective test statistics are presented in the Appendix.

adjustment coefficients imply a rather low efficiency of intertemporal arbitrage and suggest significant informational inefficiency in the short run.[50] Although this means that none of the considered hubs can be regarded as fully informationally efficient, arbitrage seems to be most efficiently exploited at NBP. This finding is noteworthy as technical storage flexibility is smaller in the UK than in Germany and in the Netherlands (see Table 3.2) and may be a result of the superior liquidity of the British hub. However, the difference in the speed of adjustment and hence in the degree of arbitrage efficiency compared to NCG and TTF is fairly moderate.

The specified VECMs assume linearity in the adjustment process. This implies that error correction starts instantaneously in case of any, arbitrarily small, deviation from the long-run equilibrium, thus neglecting any kind of market frictions. However, the exhaustion of arbitrage opportunities at European gas hubs may be constrained by significant transaction costs resulting from the low liquidity on the respective spot and futures markets and by physical constraints such as limited injection and withdrawal capacity of storage facilities. Thus, arbitrage may only be triggered if the deviation from the intertemporal equilibrium exceeds a certain threshold, such that the arbitrage traders are compensated for the incurred transaction costs (Li, 2010), resulting in a so-called "band of no arbitrage" around the long-run equilibrium. Therefore, the threshold vector error correction model (TVECM) proposed by Granger and Lee (1989) is applied in the following to explicitly address market frictions resulting from low liquidity or from physical characteristics of the gas market. TVECMs have proved to be a useful approach for capturing arbitrage dynamics among spot and futures markets for financial assets (e.g., Anderson, 1997) and various commodities (Li, 2010, Huang et al., 2009, Root and Lien, 2003) by explicitly accounting for market frictions.

[50]For instance, the absolute value of the adjustment coefficient of the NCG spot return series implies a half-life period of error correction of about five days.

The bivariate TVECM of order n applied to the system of spot and futures market returns used in this study has the representation

$$\begin{aligned}\Delta f_t = & \quad (I-1)\alpha_h^f \epsilon_{t-1} + I\alpha_l^f \epsilon_{t-1} + \sum_{k=1}^{k=n} \gamma^f \Delta f_{t-1} + \sum_{k=1}^{k=n} \delta^f \Delta s_{t-1} + \eta_t^f, \\ \Delta s_t = & \quad (I-1)\alpha_h^s \epsilon_{t-1} + I\alpha_l^s \epsilon_{t-1} + \sum_{k=1}^{k=n} \gamma^s \Delta f_{t-1} + \sum_{k=1}^{k=n} \delta^s \Delta s_{t-1} + \eta_t^s,\end{aligned} \tag{3.15}$$

where I denotes the regime indicator stating whether the lagged deviation from the long-run equilibrium is below or above the threshold (in absolute terms). The coefficient α_h (α_l) represents the error correction dynamic for the case in which the absolute value of the deviation is higher (lower) than the threshold (Enders and Siklos, 2001).

The model of Equation (3.15) is estimated using different thresholds. The thresholds are assumed to be symmetric and their size is defined in terms of the standard deviation of ϵ_t, the error term of the cointegration regression.[51] This approach reveals the magnitude of the deviation from the long-run equilibrium that is necessary to trigger arbitrage activity by investigating the statistical significance of α_l, the adjustment coefficient in the "lower regime", for different thresholds. Table 3.9 contains the estimates for the regime-specific adjustment coefficients of the TVECM.

Table 3.9: Estimates of Threshold Vector Error Correction Models

		NCG		TTF		NBP	
Threshold	Regime	α_{spot}	α_{m1}	α_{spot}	α_{m1}	α_{spot}	α_{m1}
$0.5\sigma_\epsilon$	high	-0.1359***	0.0238	-0.1101***	0.0012	-0.1603***	0.0042
$0.5\sigma_\epsilon$	low	-0.0834	0.0094	-0.1312***	0.0421	-0.0465	0.0078
σ_ϵ	high	-0.1358***	0.0148	-0.1092***	0.0080	-0.1835***	0.0033
σ_ϵ	low	-0.1203***	-0.0144	-0.1212***	-0.0243	-0.0196	0.0094

Notes: *** (**) Denotes significance at the 99%-level. The estimation is based on OLS using robust standard errors as proposed by Newey and West (1987). A lag length of 1 for the VECM is selected based on the Schwarz Information Criterion for NCG and TTF, while the same criterion suggests to include 2 lags for NBP.

[51]The standard deviations of ϵ_t are 0.08 for NCG and TTF, and 0.11 for NBP. The thresholds selected for the TVECM estimation are $0.5\sigma_\epsilon$ and σ_ϵ. In general, smaller and greater thresholds can be used to investigate the regime-dependent arbitrage dynamics. However, these threshold choices result in a small sample for one of the regimes with large standard errors of the estimated coefficients, hindering valid statistical inference. The same problem occurs when estimating the thresholds endogenously following the procedure of Balke and Fomby (1997).

In the TTF spot price return equation, the adjustment coefficient is always statistically significant in both regimes. Thus, for the threshold values tested, there is no empirical evidence of a "band of no arbitrage" at the TTF hub. In contrast, arbitrage at NCG and NBP does not start until the deviation from the long-run equilibrium exceeds a certain threshold, i.e., α_l is insignificant for at least one of the specifications. Surprisingly, although NBP is the most liquid hub in the sample, it exhibits a rather broad "band of no arbitrage", indicating frictions impeding instantaneous intertemporal arbitrage. Interestingly, the TVECM seems not to improve the model fit substantially compared to the linear VECM. In general, the sum of squared residuals is almost identical in both settings. Moreover, Wald tests carried out on the adjustment coefficients in the TVECM reveal that the hypothesis of equal adjustment behavior in the two regimes, i.e., linearity, can only be rejected for NBP.[52] Thus, even the linear VECM may be regarded as an adequate framework to investigate the interaction of the natural gas spot and futures markets considered in this study.

To sum up, the theory of storage holds for all hubs in the long run. Moreover, the hypothesis of long-run informational efficiency, i.e., full price convergence of the spot and the futures markets, cannot be rejected. However, there is empirical evidence of significant short-run informational inefficiencies as deviations from the long-run equilibrium are only slowly exploited by intertemporal arbitrage activity. Comparing the different hubs, intertemporal arbitrage starts most instantaneously at TTF but is executed most efficiently at NBP once the deviation from the intertemporal equilibrium crosses a certain threshold. The first finding is in line with the high flexibility of Dutch gas storage (see Table 3.2), while the latter may be attributed to the superior liquidity of NBP (see Table 3.1).

[52] The results of the Wald tests are provided in the Appendix.

3.7 The Evolution of Intertemporal Arbitrage Efficiency: A Kalman Filter Approach

Various political and regulatory measures have been introduced to foster the liquidity of the continental European gas hubs.[53] As a consequence, one may expect informational efficiency at these hubs to have increased over time. To test this hypothesis, a dynamic state-space approach is applied to capture the evolution of intertemporal arbitrage efficiency over time. Time-varying coefficient models have been used for the European gas market in different applications. Neumann et al. (2006) draw upon a state-space approach to investigate regional price convergence. Growitsch et al. (2012) estimate a time-varying VECM to assess the evolution of regional price arbitrage efficiency over time. However, in contrast to the aforementioned studies, this paper applies the state-space methodology within an intertemporal context to the European natural gas market. In doing so, the intertemporal arbitrage dynamic is investigated by estimating Equation (3.16) in order to assess the development of the adjustment coefficients over time.

$$\begin{aligned} \Delta f_t = &\quad \alpha_t^f \epsilon_{t-1} + \sum_{k=1}^{k=n} \gamma_k^f \Delta f_{t-k} + \sum_{k=1}^{k=n} \delta_k^f \Delta s_{t-k} + \eta_t^f, \\ \Delta s_t = &\quad \alpha_t^s \epsilon_{t-1} + \sum_{k=1}^{k=n} \gamma_k^s \Delta f_{t-k} + \sum_{k=1}^{k=n} \delta_k^s \Delta s_{t-k} + \eta_t^s, \end{aligned} \tag{3.16}$$

with

$$\alpha_t = \alpha_{t-1} + \zeta_t, \tag{3.17}$$

where α_t represents the time-varying adjustment coefficient following a random walk as specified in Equation (3.17) and ϵ_{t-1} is the lagged error term of the linear cointegration regression. The recursive procedure suggested by Kalman (1960) is applied to estimate

[53] Most notably, the Third Gas Market Directive of the European Union from 2009 comprises various efforts to improve access to gas infrastructure and thus facilitates the development of liquid natural gas hubs (EU, 2009b).

the state-space model.[54] Based on the hypothesis of increasing short-run informational efficiency at the continental European hubs due to the rise in liquidity, the absolute values of the respective adjustment coefficients are expected to increase over time. Figure 3.2 presents the estimated time paths for the adjustment coefficients in the spot return equation.[55] Some of the spikes in the plotted series can be attributed to the economic downturn in autumn 2008, and gas market-specific shocks such as the extraordinary supply interruptions resulting from the Russian-Ukrainian crisis in January 2009 and the cold spell in February 2012.[56] There is a distinctive pattern in the evolution of the relative short-run informational efficiency of the hubs considered over time, as can be inferred from the time-varying coefficient estimates. As of the beginning of 2008, NCG is the least informationally efficient hub. However, the absolute value of the adjustment coefficients grows towards the end of the sample period, indicating an increase in short-run informational efficiency. In contrast, the absolute value of the adjustment coefficient of NBP decreases over time, indicating a decline in the efficiency of intertemporal arbitrage. For the Dutch TTF hub, short-run informational efficiency is at a rather low level and decreases slightly during the sample period.[57] Overall, there is convergence in the degree of short-run informational efficiency of the hubs considered and only the short-run informational efficiency of NCG seems to have moderately benefited from the increase in liquidity. Thus, as of 2012, the differences in informational efficiency between the hubs considered appear significantly reduced.

[54] As initial value of α, zero is selected assuming informational inefficiency at the beginning of the sample period. The variance of the respective spot return series, σ^2_{rspot}, is selected as initial variance of η_t and ζ_t is set to $\sigma^2_{rspot}/1000$. In line with the linear VECM specified above, one lag is included for NCG and TTF, while two lags are used in the specification for NBP.

[55] The evolution of the adjustment coefficient in the futures return equation is neglected due to statistical insignificance.

[56] In the latter two periods, it seems reasonable to infer that the strong increase in spot price represents an immediate reaction to the physical supply and demand imbalance, independent from the futures market price. For a more detailed discussion of the economic impact of these events on German gas prices, see Nick and Thoenes (2013).

[57] The visual impression of increasing (decreasing) short-run informational efficiency at NCG (NBP and TTF) is confirmed when fitting the respective time-varying adjustment coefficient estimates against a constant and a linear trend. For TTF and NBP, the trend coefficients are slightly positive and statistically significant, while a negative and significant trend coefficient is obtained for NCG. However, since the left-hand side variable of this regression is itself an estimated value, the statistical inference has to be interpreted cautiously.

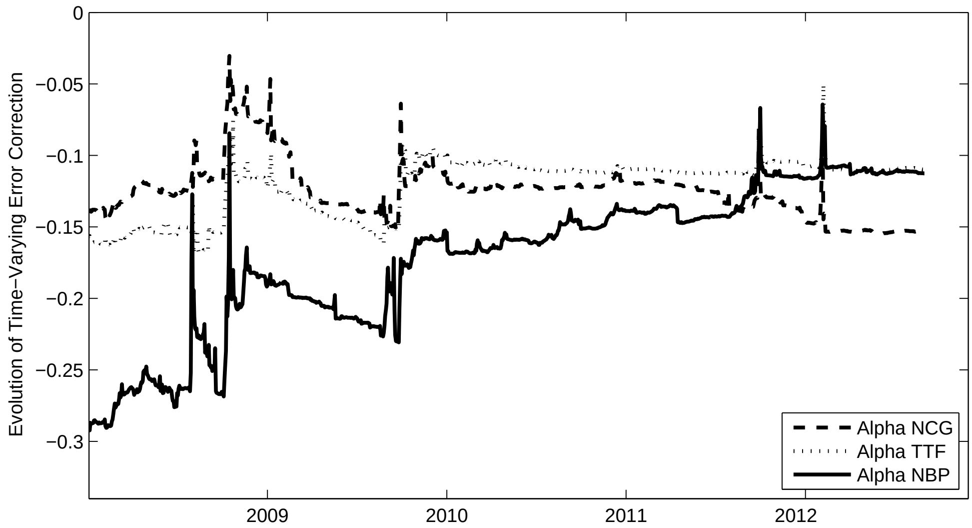

Figure 3.2: Time-Varying Adjustment Coefficients of Spot Price Return Series

3.8 Conclusion

The objective of the paper was to analyze the informational efficiency of different European gas hubs by empirically investigating price discovery and arbitrage activity between spot and futures markets. For this purpose, linear and nonlinear econometric approaches were specified to explicitly account for the low-liquidity environment and the physical characteristics of the gas market.

Causality testing reveals that price formation takes place on the futures market at all hubs. This finding is in line with the hypothesis that futures market participants react more efficiently to information than spot market traders (Silvapulle and Moosa, 1999, Bohl et al., 2012) and may be assigned to the broader scope of market participants on the futures market. The opportunity to trade the contract multiple times before maturity, and thus to close out the trading position without taking physical delivery, enables their use for hedging and speculation. Thus, in contrast to the purely physical spot market, the futures market is easily accessible for traders without interest in physical delivery. Apparently, this structural difference between both markets yields the futures market to be significantly informational superior compared to the spot market. In the light of hub-based pricing of internationally traded gas, an indexation on futures market prices rather than on spot market prices therefore promises to provide more valid price signals.

The theory of storage seems to hold for all gas hubs considered in the long run, indicating the existence of significant arbitrage between the respective spot and futures markets. Moreover, the hypothesis of long-run informational efficiency, i.e., complete convergence of spot and futures market prices, cannot be rejected. However, the error correction process is rather sticky, suggesting frictions impeding intertemporal arbitrage activity and thus a low level of short-run informational efficiency. From a dynamic perspective, the state-space estimations reveal a convergence in short-run informational efficiency across the hubs during the sample period.

With regard to the role of liquidity, the empirical results provide mixed evidence. On the one hand, intertemporal arbitrage opportunities are most efficiently exploited at the liquid NBP once the deviation from the intertemporal equilibrium is sufficiently large. In addition, the rise in liquidity seems to have slightly fostered arbitrage efficiency at NCG. On the other hand, the detected frictions in the price formation process and arbitrage activities are similar for all hubs, regardless of their liquidity. Therefore, it seems reasonable to attribute the limited short-run informational efficiency at least partly to specific characteristics of the gas market such as limited storage flexibility or inefficient allocation of storage and network capacity, rather than exclusively to market liquidity.

The empirical findings of these studies suggest that regulators and policy makers may think about measures to improve the short-run informational efficiency of the European natural gas market. Besides fostering liquidity, attention should also be paid to the functioning of the third party access to storage or network infrastructure in order to facilitate arbitrage activity. A promising field for further research on the short-run informational efficiency of the European gas market could be the extension of the analysis to intraday data and thus the investigation of the interaction between spot and futures markets at an even higher time resolution. This approach, however, suffers from the lack of data availability and is therefore left for future research ventures.

Chapter 4

The Hidden Cost of Investment: The Impact of Adjustment Costs on Firm Performance Measurement and Regulation

4.1 Introduction

Allocating the costs and benefits of economic decisions to certain time periods represents an important element in everyday economic life. In specific, the effects of an investment in capital assets have to be distributed over time by accountants in order to allow stakeholders to gain an assessment of the firm's performance within a certain period. However, an adequate allocation of the true economic costs and benefits of an investment over time is hindered by the fact that the measurable costs and benefits considered in the bookkeeping may diverge from the actual economic costs and benefits. This phenomena is referred to as an allocation problem of financial accounting (Thomas, 1969).

For an illustrative example of this accounting problem, consider a firm investing into a new, more efficient software system. In the initial period, the implementation of the new system will cause significant adjustment costs for installation, training and reorganization that are reflected in the firm's operational expenditures. In contrast, the measurable economic benefits of the new system will unfold only later in the following periods. As a consequence, the firm will appear less profitable for investors, regulators and other stakeholders during the installation period although it is implementing an investment decision that increases the performance of the company in the long run.

This work addresses a specific version of such an allocation problem in accounting, namely the mismatch between the benchmarking methods used in the context of incentive-based regulation schemes and the multi-period optimization behavior of the regulated firms. Current benchmarking practice usually ignores the intertemporal linkage of investments outlined above by relying solely on static inefficiency measures. These inefficiency measures focus on input and output data (costs or quantities) for a certain period and do not control for adjustment costs of investments that affect the observable combination of variable inputs and output in the respective benchmarking period. Thus, the regulator ignores the fact that the measured inefficiency may reflect short-term adjustment costs from investments necessary for long-run cost minimization rather than the "actual" inefficiency. As a result, firms with high investments in the benchmarking period may be worse off when compared to peers with lower investments. In contrast, firms with low investments may operate far from the dynamic optimum but may be deemed as fully efficient from a static perspective. This distortion in the outcome of static benchmarking exercises may not even be reversed in the benchmarking process for the subsequent regulatory period since the economic lifetime of capital assets in network industries is expected to heavily exceed the duration of one regulatory period.

Following this line of argumentation, the need for dynamic benchmarking approaches in order to explicitly address the intertemporal character of long-term input decisions made by firms has been widely acknowledged. However, there is only limited empirical research on the application of dynamic inefficiency estimation in the presence of adjustment costs. Moreover, the regulatory implications of applying dynamic rather than static inefficiency measures have yet to be addressed. This paper seeks to fill this research gap. Using a data set of US electricity transmission and distribution firms for the period 2004 to 2011, we assess the firms' dynamic technical inefficiency explicitly accounting for changes in the capital stock and their implied adjustment costs. Drawing upon dynamic data envelopment analysis (DEA), we compute a dynamic directional distance function that enables us to analyze the dynamic technical inefficiency of our sample firms. Nonparametric DEA is applied rather than parametric estimation techniques in order to avoid imposing a restrictive functional form on our heterogeneous sample of firms. We use the established duality between the dynamic directional distance function and the current value of the optimal value function of the intertemporal cost minimization problem in order to compute the dynamic cost inefficiency and the dynamic allocative inefficiency in an adjustment cost framework. We compare our derived dynamic inefficiency estimates to their static counterparts, i.e., the inefficiency estimates obtained by ignoring the adjustment costs of changes in the capital stock. This allows us to assess the impact of applying dynamic inefficiency measures on the outcome of benchmarking exercises, both on a firm-specific and industrial level.

This study provides two main contributions to empirical research in the field of inefficiency measurement: First, our paper illustrates the impact of the methodological choice of static versus dynamic inefficiency measures on the outcomes of benchmarking exercises frequently carried out in regulatory practice. In doing so, we discuss the incentives implied in both methodologies with regard to long-term investments for the firms under regulation. Second, we provide new insights into the dynamic inefficiency of the US electricity transmission and distribution industry, explicitly controlling for the adjustment costs of investments.

Overall, our empirical findings suggest that investments in capital assets and their implicit adjustment costs should be accounted for by the regulator in order to avoid biased firm-specific cost saving targets and misleading incentives to cut investments. We find that the average dynamic technical inefficiency of the US electricity transmission and distribution industry is around 26% during the sample period. The dynamic approach yields on average lower technical inefficiency scores than the corresponding static inefficiency estimates focusing exclusively on variable input contraction (40%). Dynamic cost inefficiency of the industry amounts on average to 37% and is 3 percentage points lower than the corresponding static measure. On a firm-specific level, the application of dynamic inefficiency measures has even stronger implications on the inefficiency estimates. Thus, the economic impact of biased inefficiency factors derived from static benchmarking procedures for the firms under regulation is expected to be severe.

The paper is structured as follows: Section 4.2 provides the theoretical background and Section 4.3 discusses relevant previous research. The methodology is outlined in Section 4.4. Section 4.5 presents the data, while empirical results are discussed in Section 4.6. Section 4.7 concludes.

4.2 Theoretical Background

The need for regulation of natural monopolies in network industries such as telecommunication, railway or energy distribution and transmission has been extensively discussed (see, e.g., Joskow, 2008, Leland, 1974). As emphasized by Jamasb and Pollitt (2007), regulatory measures applied to these industries aim to provide incentives for an efficient operation of the regulated firms and to ensure a sharing of productivity gains between firms and customers. Historically, "cost-of-service" (rate of return) regulation has been used by regulators. Under rate of return of regulation, the regulator sets the price which the utility can charge in such a way that the utility can cover its operating costs and additionally is allowed to earn a specified rate of return on its capital employed. Although the rate of return regulation is effective in terms of "rent extraction" (Joskow, 2008), it lacks cost reduction incentives and provides incentives to overinvest in capital. The latter shortfall is widely known as the Averch-Johnson effect (Averch and Johnson, 1962).

In order to avoid the aforementioned economic inefficiencies, the seminal work of Shleifer (1985) proposes an alternative regulatory approach that promises a more efficient outcome based on cost comparisons among comparable firms, the so-called "yardstick competition". Incentive-based regulatory regimes reflecting the idea of yardstick competition are nowadays common practice in the regulation of natural monopolies, usually implemented via a price or revenue cap mechanism.[58] As the price or revenue cap is fixed

[58] See, e.g., Joskow (2008) for a review on incentive-based regulation in electricity networks.

for a certain period, any cost reductions translate into additional profit for the firms, thereby providing a strong incentive for cost-efficient behavior of the regulated firms.

In order to determine the socially-optimal price or revenue cap, empirical benchmarking techniques such as DEA or stochastic frontier analysis (SFA) are frequently applied. These techniques measure a firm's inefficiency relative to its peers. Firm-specific cost saving targets, the so-called "X-factors", are then derived from the benchmarking outcome. The X-factor specifies the inefficiency decrease for a certain firm within a regulatory period required by the regulator in order to force the firm back to the efficient frontier. It is then incorporated into the adaption of the price or revenue cap for the next regulatory period (Joskow, 2008):

$$P_{1,i} = P_{0,i}(1 + RPI - X_i) \tag{4.1}$$

In Equation (4.1), RPI denotes the inflation of input prices (rate of input price increase), X_i denotes the firm-specific rate of inefficiency decrease, and $P_{0,i}$ and $P_{1,i}$ are the initial and the adjusted firm-specific price or revenue caps, respectively (Joskow, 2008).

Changes in the capital stock and the corresponding costs can cause various problems when static benchmarking models are applied to derive the X-factors within incentive-based regulation schemes. Increases in capital costs directly transfer into measured inefficiency if total costs enter the static benchmarking model as input data. That way, firms with high investments are penalized by significant X-factors. To avoid misleading incentives to reduce investments, capital costs are frequently excluded from the benchmarking model (Joskow, 2008). However, even if only operational costs are subject to benchmarking, adjustment costs such as expenditures for reorganization, investment support or staff training may distort the validity of static benchmarking outcomes since these costs are reflected in the operational expenditures.

The regulatory problem arising from adjustment costs can be illustrated using a simple example. Consider two homogeneous firms i and j subject to incentive-based regulation where static benchmarking on operational costs is carried out at the beginning of the regulatory period. For the upcoming regulatory period, both firms have the option to either minimize their long-run costs by choosing a combination of contracting the variable input usage and expanding the capital stock via investments or to focus exclusively on contracting their variable input usage, i.e., solely minimize their short-run costs. If, in the presence of adjustment costs, firm i decides to stick to long-run cost minimizing behavior and therefore invests in its capital stock, it will be unable to contract the usage of variable inputs to the same extent as firm j that exclusively focuses on contracting variable input usage. As a consequence, firm j will be deemed as fully efficient by the static benchmarking outcome. In contrast, firm i is classified as inefficient due to the adjustment costs implied in the investments and reflected in the operational costs, although it sticks to the socially-optimal minimization of long-run costs. Even if the benefits from the changes in the capital stock of firm i unfold later on, the relative disadvantage of firm i against firm j in terms of the assigned X-factor may not be (fully) mitigated in the subsequent benchmarking since the economic lifetime of capital assets usually heavily exceeds the duration of one regulatory period.[59]

The example places emphasis on two interesting effects: First, firms that carry out investments consistent with long-run cost minimization may be classified as inefficient by static benchmarking methods since they suffer from adjustment costs that translate into higher operational costs. In contrast, firms that deviate from the long-run cost minimizing behavior by cutting investments may be deemed as fully efficient in the static benchmarking process. Second, firms may have an incentive to cut investments. The second effect results from the first since firms try to avoid being classified as inefficient although they minimize their long-run costs.[60] To sum up, the X-factors derived from static benchmarking measures are inconsistent with long-run cost minimization in the presence of adjustment costs and may thus encourage firms to deviate from the optimal input decision path by cutting investments. The source of this problem is that the static benchmarking models used by regulators are based on a "snapshot" combination

[59] CEPA et al. (2010) estimate the economic lifetime of capital assets in the electricity transmission and distribution industry to vary between 10 and 140 years. The weighted average is calculated to be around 50 years for electricity transmission and around 70 years for electricity distribution. In contrast, a typical regulatory period within incentive-based regulation schemes comprises three to eight years (Ernst & Young, 2013).

[60] Beside cutting investments, firms may also have an incentive to defer investments into other periods than the benchmarking period. However, the effectiveness of this approach depends on the persistence of the adjustment costs induced by the respective investment.

of input and output without taking into account the intertemporal effect of investments on inefficiency. The usage of this "snapshot" without controlling for adjustment costs in static benchmarking models makes it impossible to distinguish between "true" operational inefficiency and transitory inefficiency caused by changes in capital assets. Thus, regulators that rely on static benchmarking models ignore the fact that the measured inefficiency may be partly caused by investments that are necessary for the minimization of long-run costs. The regulatory problem is illustrated in Figure 4.1 using the example outlined above.

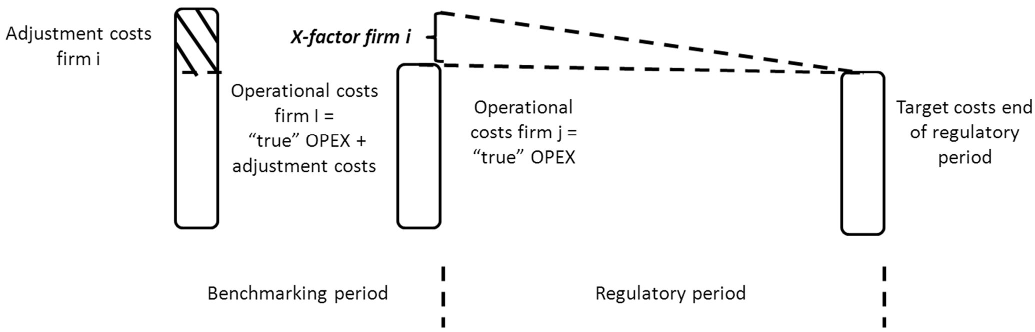

FIGURE 4.1: Bias in X-Factors Derived From Static Benchmarking in the Presence of Adjustment Costs

Overcoming the bias in X-factors derived from static benchmarking results requires accounting for the adjustment costs induced by investments in capital assets. In Section 4.4, we discuss a dynamic approach to inefficiency measurement that is able to do so. Prior to that, Section 4.3 shortly reviews relevant previous research concerning the impact of incentive-based regulation on the investment activity of the regulated firms as well as the application of benchmarking within this context.

4.3 Previous Research

The relationship between investment and incentive-based regulation has been intensively discussed in the literature (see, e.g., Guthrie, 2006, Kwoka, 2009). While economic theory initially suggested that incentive-based regulation is generally associated with underinvestment, some recent theoretical and empirical studies draw a more comprehensive picture. In particular, they indicate that investment decisions within an incentive-based regulatory regime highly depend on the way in which regulation is handled in practice (Vogelsang, 2010). In a study from 2009, Roques and Savva show that a relatively high price cap can speed up investment, while a low price cap can be a disincentive for investment. Nagel and Rammerstorfer (2009) obtain similar results. They find that a stringent price cap encourages firms to lower investments. Furthermore, in an empirical application to a sample of EU energy utilities from 1997 to 2007, Cambini and Rondi (2010) show that the investment behavior of incentive-regulated firms is negatively related to the level of the X-factor set by the regulatory authority.

With regard to benchmarking, a number of studies deal with nonparametric approaches to dynamic inefficiency measurement. One strand of this literature uses dynamic network DEA (Färe and Grosskopf, 1997, Nemoto and Goto, 1999, 2003). An interesting application of this methodological approach on the inefficiency of European electricity transmission system operators are the studies of Burger and Geymüller (2007) and Geymüller (2007). Within this methodological framework, intertemporal behavior is modeled by allowing outputs from the initial period to be used as inputs in the following periods (Fallah-Fini et al., 2013).

Within another strand of the literature, introduced by Sengupta (1994, 1999) and Silva and Stefanou (2003, 2007), intertemporal behavior among subsequent periods is captured via model constraints within a dynamic formulation of the conventional DEA framework (Fallah-Fini et al., 2013). In particular, Silva and Stefanou (2003, 2007) define an intertemporal cost minimizing problem in which the decision making unit in every time period is required to minimize its discounted flow of costs over time. Building on this theoretical framework, Silva and Oude Lansink (2009) and Oude Lansink and Silva (2013) measure dynamic inefficiency in the presence of adjustment costs via a directional distance function approach. Moreover, they establish duality between the primal representation of the adjustment cost production technology, the dynamic directional distance function, and the current value of the optimal value function of the intertemporal cost minimization problem.

In this paper, we follow the approach developed by Silva and Oude Lansink (2009) and Oude Lansink and Silva (2013) and apply dynamic DEA to a sample of US electricity distribution and transmission companies. Furthermore, we compare the derived dynamic inefficiency measures to their static counterparts in order to assess how the consideration of economic costs and benefits induced by investments affects the outcome of empirical benchmarking approaches. Our paper is innovative in the sense that applies this concept of dynamic inefficiency measurement to a sample of firms within the electricity distribution and transmission sector. Moreover, it relates an empirical application of dynamic inefficiency measures to existing benchmarking practice in the context of incentive-based regulation schemes.

4.4 The Model

In this section, we present and discuss the dynamic inefficiency measurement model formulated by Silva and Oude Lansink (2009) and Oude Lansink and Silva (2013). We review the main elements of the model using Oude Lansink and Silva's notation and provide some additional explanations and economic interpretation, also with a graphical illustration.

4.4.1 Dynamic Technical Inefficiency and the Dynamic Directional Distance Function

To model a production technology within an adjustment cost framework, assume that $y \in \Re_{++}$ denotes a vector of outputs, $x \in \Re_{+}$ denotes a vector of variable inputs, and $K \in \Re_{++}$ denotes a vector of initial capital stocks or quasi-fixed inputs that can be adjusted by a vector of gross investments $I \in \Re_{+}$. Following Silva and Stefanou (2003), the input requirement set can then be specified as:

$$V(y : K) = \{(x, I) : (x, I) \text{ can produce } y \text{ given } K\}, \tag{4.2}$$

where $V(y : K)$ represents all the combinations of variable inputs x and gross investments I that can produce the output vector y given the initial capital stock vector K. The set $V(y : K)$ is nonempty, compact and satisfies the standard properties of no free lunch, possibility of inaction and strong disposability of variable inputs and outputs (see, e.g., Färe and Primont, 1995).

Furthermore, in order to incorporate the economic concept of adjustment costs in the production technology, Silva and Stefanou (2003) suggest three additional properties. First, we assume negative monotonicity of $V(y : K)$ in I. That is,

$$\text{if } (x, I) \in V(y : K) \text{ and } I' \leq I, \text{ then } (x, I') \in V(y : K). \tag{4.3}$$

This property explicitly accounts for the adjustment costs within the intertemporal framework. It states that an adjustment of quasi-fixed inputs through gross investments decreases the production level of the outputs given a certain level of the variable inputs. Or, in other words, an increase in the level of gross investments requires, other things being equal, an increase in the level of inputs to produce the same level of outputs.

Second, we assume that a higher initial capital stock increases the level of outputs given a certain level of the variable inputs. In other words, the same level of output can be achieved with lower variable input given a greater capital stock. Formally,

$$\text{if } K' \geq K, \text{ then } V(y : K) \subset V(y, K'). \tag{4.4}$$

Together, the properties defined in (4.3) and (4.4) reflect the trade-off within the intertemporal economic calculus of firms regarding the optimal level of gross investments: Gross investments decrease the current output levels through adjustment costs but increase future output levels via an increase in the future capital stock (Oude Lansink and Silva, 2013, Silva and Stefanou, 2003).

Finally, we assume $V(y : K)$ to be strictly convex. That is,

$$\begin{gathered} \text{if } (x, I) \in V(y : K) \text{ and } (x', I') \in V(y : K) \text{ then} \\ (\mu x + (1-\mu)x', \mu I + (1-\mu)I') \in V(y : K) \text{ for all } \mu \in [0, 1]. \end{gathered} \tag{4.5}$$

This property implies increasing marginal adjustment costs and therefore is consistent with gradual rather than one-off investment behavior.

As shown by Silva and Oude Lansink (2009), an input requirement set that satisfies these assumptions can be represented by a dynamic directional distance function. This input-orientated dynamic directional distance function can be specified as:

$$\vec{D}(y, K, x, I; g_x, g_I) = max\{\beta \in \Re : (x - \beta g_x, I + \beta g_I) \in V(y : K)\}, \tag{4.6}$$

where $g = (g_x, g_I) \in \Re_{++} \times \Re_{++}$ and β represent the direction and proportion to which the input combination (x, I) is scaled, respectively, to reach the boundary or frontier of the input requirement set $V(y : K)$. The directional distance function value β is bounded below by zero. A value of zero identifies the observed input combination as located on the frontier and, hence, as being technically efficient. Values greater than zero belong to input combinations within the frontier, indicating technical inefficiency. Thus, the dynamic directional distance function is a measure of dynamic technical inefficiency.

A graphical illustration of the relationship between dynamic technical inefficiency and the dynamic directional distance function is provided in Figure 4.2. The vertical axis shows the usage of variable input x, while the horizontal axis shows the gross investments I. The set $V(y : K)$ is the area of all the combinations of x and I that can produce the output vector y given the initial capital stock vector K. Points A, B and C represent efficient production points located on the frontier of the input requirement set, while point D above the frontier indicates an inefficient production point. Using the directional vector $g = (x, I)$, the dynamic directional distance function then measures the proportion to which the original input combination (x, I) at point D can be simultaneously contracted in x and expanded in I to reach the efficient input combination $(x - \beta\, x, I + \beta\, I)$ at point C.

In contrast, from a static perspective, the input requirement set $V(y : K)$ reduces to the line segment $0D'$ on the vertical axis since investments are neglected. Within the static framework, A' represents the efficient variable input level of production point A, and D' represents the inefficient variable input level of production point D. Hence, the static directional distance function measures the proportion in which the original variable input level at point D' can be reduced to reach the efficient variable input level at point A'.

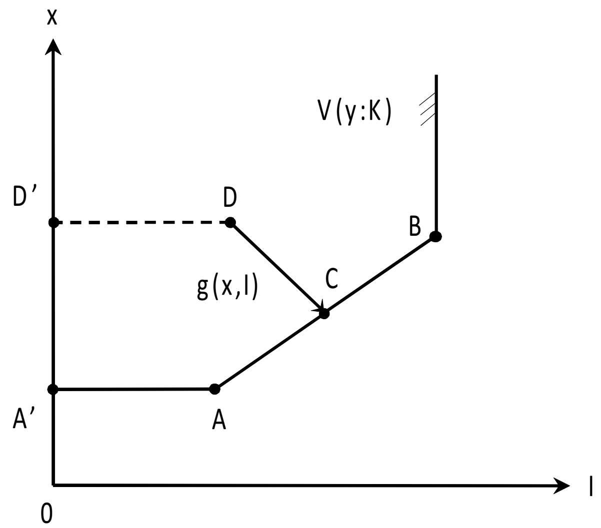

FIGURE 4.2: Dynamic Directional Distance Function

As proposed by Silva and Stefanou (2003, 2007), the input-orientated dynamic directional distance function presented in Equation (4.6) can be determined by dynamic DEA. Given a sample of J firms with M outputs, N variable inputs and F quasi-fixed inputs, the dynamic directional distance function $\vec{D}$ for each observation i is obtained by solving the following optimization problem:

$$
\begin{aligned}
\vec{D}(y^i, K^i, x^i, I^i; g_x, g_I) = \max_{(\beta^i,\gamma^j)} \beta^i & & & \\
s.t. \quad \sum_{j=1}^{J} \gamma^j y_m^j &\geq y_m^i, & m = 1, \ldots, M, & \quad (i) \\
\sum_{j=1}^{J} \gamma^j K_f^j &\leq K_f^i, & f = 1, \ldots, F, & \quad (ii) \\
\sum_{j=1}^{J} \gamma^j x_n^j &\leq x_n^i - \beta^i g_{x_n}, & n = 1, \ldots, N, & \quad (iii) \\
\sum_{j=1}^{J} \gamma^j I_f^j &\geq I_f^i + \beta^i g_{I_f}, & f = 1, \ldots, F, & \quad (iv) \\
\gamma^j &\geq 0, & j = 1, \ldots, J, & \quad (v)
\end{aligned}
\tag{4.7}
$$

where γ^j are intensity variables assigning a weight to each observation j when constructing the dynamic frontier. The inequality constraints in (i)-(iv) ensure that observation i is located within the feasible production region, while the non-negativity constraints on the intensity variables in (v) indicate that constant returns to scale are assumed. The solution to this program, the maximum value of β^i, shows to what extent the variable inputs and the gross investments of observation i can be proportionally contracted and expanded relative to the efficient benchmark on the frontier at given outputs and given capital stocks.

4.4.2 Dynamic Cost Inefficiency and the Intertemporal Cost Minimization Problem

Given that the dynamic directional distance function defined in Equation (4.6) is a valid representation of the input requirement set specified in Section 4.4.1, a firm's intertemporal cost minimization problem at any base period $t \in [0, \infty)$ can be specified as:

$$\begin{aligned} W(y, K_t, w, c, r, \delta) = \underset{(x,I)}{min} \int_t^{\infty} & e^{-r(s-t)}[w'x(s) + c'K(s)]ds \\ & s.t. \\ & \dot{K}(s) = I(s) - \delta K(s), K(t) = K_t \\ & \vec{D}(y, K, x, I; g_x, g_I) \geq 0, s \in [t, +\infty], \end{aligned} \tag{4.8}$$

where W denotes the value function, $y \in \Re_{++}$ is a vector of outputs in the base period and $K_t \in \Re_{++}$ represents a vector of initial capital stocks (Oude Lansink and Silva, 2013). The vectors of the current input prices for the variable input vector $x(s) \in \Re_{++}$ and the capital stock vector $K(s) \in \Re_{++}$ are represented by $w \in \Re_{++}$ and $c \in \Re_{++}$, respectively. The time-invariant discount rate is $r > 0$, and δ is a diagonal matrix of depreciation rates $\delta_f > 0, f = 1, \ldots, F$. Finally, I and $\dot{K}$ are vectors of gross and net investments, respectively (Oude Lansink and Silva, 2013, Silva and Oude Lansink, 2009).

The intertemporal cost minimization problem defined in Equation (4.8) requires a firm to minimize the discounted flow of cost over time subject to two restrictions that have to hold in every time period s. The first restriction states that a change in a quasi-fixed factor can only be achieved via investments and is therefore accompanied by adjustment costs. The second restriction requires the combination of variable inputs and investments to be located within the input requirement set $V(y : K)$.

To derive the combination of variable inputs and gross investments that leads to the current value of the optimal value function within a certain period, the Hamilton-Jacobi-Bellmann (H-J-B) equation can be applied. Oude Lansink and Silva (2013) show that the H-J-B equation for the intertemporal cost minimization problem in Equation (4.8) can be written as:

$$rW(y, K, w, c) = \min_{(x,I)} \left\{ w'x + c'K + W'_K(I - \delta K) : \vec{D}(y, K, x, I; g_x, g_I) \geq 0 \right\}, \quad (4.9)$$

where $W'_K = W_K(y, K, w, c)'$ is the vector of shadow values of the quasi-fixed factors. The long-run savings implied in investments are explicitly incorporated in the H-J-B equation, as the shadow value W_{K_f} of the quasi-fixed factor f measures the decrease in the long-run costs if the initial capital stock K_f is increased by a marginal unit.[61]

[61] Obtaining reliable estimates for the shadow values of the quasi-fixed factors is methodologically challenging. This is because each shadow value represents a scarcity indicator for the respective quasi-fixed factor and thus depends on the initial capital stock vector, output quantities and input prices. This endogeneity calls for a simultaneous determination of optimal firm-specific input quantities and the firm-specific shadow values of the quasi-fixed factors (Oude Lansink and Silva, 2013). However, a simultaneous determination translates into a nonlinear problem with severe numerical difficulties. For this reason, we use an alternative sequential approach to determine the shadow value of the quasi-fixed factor within our empirical application (see Section 4.6).

Similar to the dynamic directional distance function, Equation (4.9) can be represented by a dynamic DEA model. The corresponding optimization problem for a sample of J firms with M outputs, N variable inputs and F quasi-fixed inputs is given by:

$$
\begin{aligned}
rW(y^i, K^i, w^i, c^i) = & \min_{(x,I,\gamma^j)} \quad [w^{i\prime} x + c^{i\prime} K^i + W_K^{i\prime}(I - \delta K^i)] \\
s.t. \quad & \sum_{j=1}^{J} \gamma^j y_m^j \geq y_m^i, && m = 1, \ldots, M, && (i) \\
& \sum_{j=1}^{J} \gamma^j K_f^j \leq K_f^i, && f = 1, \ldots, F, && (ii) \\
& \sum_{j=1}^{J} \gamma^j x_n^j \leq x_n, && n = 1, \ldots, N, && (iii) \\
& \sum_{j=1}^{J} \gamma^j I_f^j \geq I_f, && f = 1, \ldots, F, && (iv) \\
& \gamma^j \geq 0, && j = 1, \ldots, J, && (v) \\
& x_n \geq 0, && n = 1, \ldots, N, && (vi) \\
& I_f \geq 0, && f = 1, \ldots, F, && (vii)
\end{aligned}
\tag{4.10}
$$

where $W_K^{i\prime}$ represents a vector of firm-specific shadow values of the quasi-fixed factors. The inequality constraints (i)-(v) have the same interpretation as in Equation (4.7). The constraints in (vi) and (vii) ensure the non-negativity of variable inputs and gross investments.

By using duality theory, Silva and Oude Lansink (2009) and Oude Lansink and Silva (2013) show that a firm-specific dynamic cost inefficiency (CIE) measure can be derived from the solution of Equation (4.10) as follows:

$$
CIE = \frac{w'x + c'K + W_K'(I - \delta K) - rW(y, K, w, c)}{w'g_x - W_K' g_I} \geq \vec{D}(y, K, x, I; g_x, g_I). \tag{4.11}
$$

That is, firm-specific CIE is the deviation of the observed total shadow cost of the actual input choices from the minimum total shadow cost of the optimal input choices, divided by $w'g_x - W_K' g_I$ to construct a unit-free measure.[62] The right-hand side of Equation

[62] For a detailed discussion on the duality between the dynamic directional distance function and the current value of the optimal value function of the intertemporal cost minimization problem, see Oude Lansink and Silva (2013).

(4.11) denotes the firm-specific dynamic technical inefficiency (TIE), represented by the dynamic directional distance function. As a consequence, the difference between CIE and $\vec{D}(y, K, x, I; g_x, g_I)$ yields a measure for firm-specific dynamic allocative inefficiency ($AIE \geq 0$). The obtained dynamic allocative inefficiency scores provide an indication as to whether the trade-off between variable input contraction and capital stock extension is optimal in terms of long-run cost minimization.

The relationship between dynamic TIE, CIE and AIE is illustrated in Figure 4.3. As in Figure 4.2, points A, B and C denote technically efficient production points located on the frontier of the input requirement set $V(y : K)$, while point D above the frontier indicates a technically inefficient production point. The distance between D and C measures the dynamic TIE of production point D.

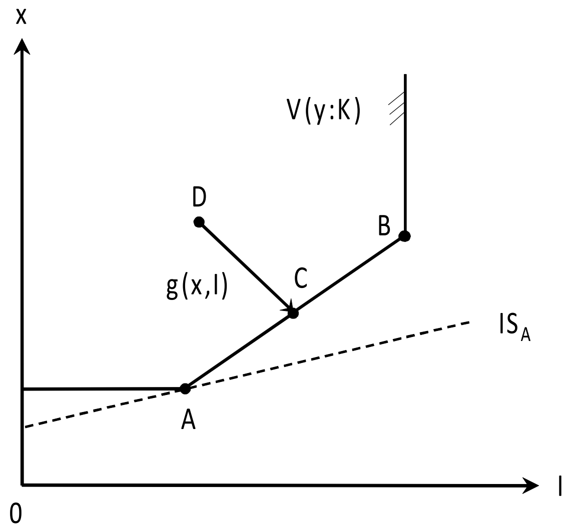

FIGURE 4.3: Dynamic Inefficiency Estimates

Further, in order to illustrate dynamic CIE, an isocost line IS_A is mapped. The slope of the isocost line is given by the negative ratio of the shadow value of the quasi-fixed factor W_K and the price of the variable input w: $-W_K/w$, with $W_K < 0$. Thus, the slope represents the ratio of the savings obtained from variable input contraction and from investing in the capital stock. Isocost lines with higher intercepts represent higher long-run costs. Consequently, only point A, at which the frontier is a tangent to the isocost line IS_A, represents a dynamic cost-efficient production point. Points B and C denote technically efficient but allocatively inefficient production points with higher costs. Within the illustration, B and C should invest less and focus more on variable input contraction given the relationship between the shadow value of capital and the price of the variable input. Point D, in contrast, suffers from both technical and allocative dynamic inefficiency.

4.5 Data for Empirical Application

We apply the methodology outlined and discussed in Section 4.4 to a sample of firms within the electricity sector. The sample comprises US electricity transmission and distribution companies for the period 2004-2011. The data is obtained from the FERC Form No.1. After correcting for outliers and eliminating all firms with missing observations during the period considered, the sample consists of an unbalanced panel of 61 firms covering 8 years with 464 observations in total.

Table 4.1 presents descriptive statistics on the model variables. The choice of output variables for electricity transmission and distribution firms is not straightforward. Different measures, such as peak load of the system, network length, number of customers and total electricity delivered are summarized in Jamasb and Pollitt (2001). In this study, we argue that the total number of customers, aggregated over all segments, and the total electricity flow through the network most appropriately reflect the economic output of our sample firms. We choose two outputs rather than one to account for the heterogeneity of our sample, comprising firms with a focus on either distribution or transmission of electricity.

We select the operational expenditure (OPEX) as the variable input. To adjust the variable input expenses for changes in input prices, we deflate OPEX using a weighted average of a labor cost index for the electricity transmission and distribution industry on the state level (LCI)[63] and the producer price index for the electricity transmission and

[63] The index is calculated from the average annual pay data obtained from the Quarterly Census of Employment and Wages, which is published by the Bureau of Labor Statistics: `http://www.bls.gov/cew/cewind.htm#year=2010&qtr=1&own=5&ind=10&size=0`.

Table 4.1: Descriptive statistics

Variable	Mean	Std. Dev.	Minimum	Maximum
Total Number of Customers (in millions)	1.05	1.07	0.12	5.25
Total Flow of Electricity (in MWh)	33.88	28.19	1.37	122.51
OPEX (in million 2002 US$)	136.12	139.54	15.34	645.16
Capital Stock (in billion 2002 US$)	3.19	3.37	0.27	20.24
Gross Investments (in billion 2002 US$)	0.27	0.33	0.01	2.01
Labor Cost Index	1.21	0.16	0.88	1.70
Producer Price Index	1.22	0.15	0.96	1.64
Consumer Price Index	1.16	0.06	1.05	1.25

Notes: Information on the components used to compute the figures presented as well as their FERC Form No.1 definitions can be found in the Appendix.

distribution industry (PPI)[64]. The quasi-fixed input, i.e., the capital stock, is approximated by the balance sheet value of the network assets. The capital stock is deflated by the PPI. Gross investments are computed by taking the sum of net investments (changes in the deflated capital stock) and the deflated depreciation on these assets in the respective year. For the computation of dynamic cost inefficiency and dynamic allocative inefficiency, we use the same deflators outlined above as an approximation for the price of the variable input and the price of capital. However, in order to generate real monetary values, we adjust both input prices for inflation using the consumer price index (CPI).[65] Finally, capital expenditure (Capex) is given by the sum of the deflated annual depreciation and the required annual return on the balance sheet value of the network assets. Following Nillesen and Pollitt (2010), we assume a rate of return of 6 percent for all assets.

4.6 Empirical Results

This section presents and interprets the results of applying the dynamic inefficiency measures outlined in Section 4.4 to our sample of US electricity distribution and transmission firms. The derived average inefficiency values per year are reported in Table 4.2.

[64] Obtained from the Bureau of Labor Statistics: `http://data.bls.gov/timeseries/PCU221122221122`.

[65] Obtained from the Bureau of Labor Statistics: `http://www.bls.gov/cpi/data.htm`.

Table 4.2: Average Dynamic and Static Inefficiency Scores

Year	TIE Dynamic	CIE Dynamic	AIE dynamic	TIE/CIE static
2004	0.29	0.44	0.15	0.42
2005	0.29	0.37	0.08	0.42
2006	0.26	0.36	0.10	0.41
2007	0.28	0.38	0.10	0.43
2008	0.26	0.39	0.13	0.33
2009	0.29	0.37	0.08	0.41
2010	0.25	0.33	0.08	0.45
2011	0.19	0.30	0.11	0.36
Mean	0.26	0.37	0.10	0.40

The average dynamic technical inefficiency (TIE) of our sample firms ranges between 19% and 29% for the years considered. On average, industrial dynamic technical inefficiency amounts to 26%, indicating that there is substantial potential for the industry to move towards the dynamic technical efficiency frontier by simultaneously contracting variable input usage and expanding gross investments.

We compare and contrast our dynamic technical inefficiency estimates with their static counterparts to assess the impact of considering changes in the quasi-fixed inputs in the benchmarking process. For this purpose, static technical inefficiency is computed for our sample firms by applying DEA to a restricted version of the linear program stated in Equation (4.7). In this specification, the investment (iv) and capital (ii) constraints are ignored and the directional vector is set to $g = (x, 0)$. Thus, the efficient static frontier can be achieved by exclusively contracting variable input usage, disregarding changes in the quasi-fixed input. The resulting static benchmarking model is in line with regulatory practice, where the focus frequently lies on benchmarking operational costs.

The average static technical inefficiency values per year are also reported in Table 4.2. The average technical inefficiency of our sample firms is higher when applying the static measure compared to the dynamic approach. This finding is not surprising as the dynamic approach to technical inefficiency allows for an additional dimension in the benchmarking process (namely the expansion of gross investments) besides the contraction of variable inputs. On average, dynamic technical inefficiency is around 14 percentage points below the static technical inefficiency. This finding emphasizes that the assessment of the industrial technical inefficiency is significantly altered when adjustments of quasi-fixed inputs via investments are accounted for. The differences in the distribution of technical inefficiency scores between the static and the dynamic approach are illustrated in Figure 4.4 using kernel density estimates. Clearly, the mean of the dynamic technical inefficiency distribution is smaller than the corresponding static value. Moreover, applying the dynamic measure results in a larger number of fully technically efficient observations, while the number of observations with very high dynamic technical inefficiency scores is rather low.

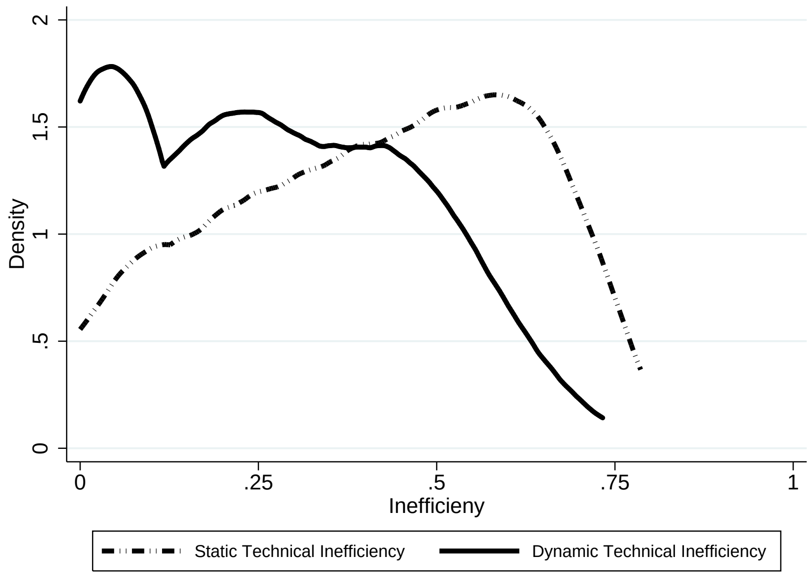

FIGURE 4.4: Distribution of Dynamic and Static Technical Inefficiency

Note: Kernel density estimate based on an Epanechnikov kernel.

For the assessment of dynamic cost and allocative inefficiencies, we first approximate the firm-specific long-run cost savings induced by a marginal increase in the capital stock by estimating a quadratic dynamic cost function. Differentiating this function with respect to the capital stock yields firm-specific shadow values of capital.[66] Subsequently, in a second step, these values are incorporated into the dynamic DEA model, as described in Equation (4.10). We rely on this sequential approach in order to circumvent the numerical problems present in a simultaneous determination of optimal firm-specific

[66]A detailed description of the parametric approximation of the firm-specific shadow values of capital is provided in the Appendix.

input quantities and firm-specific shadow values of capital. In addition, the sequential parametric approach avoids imposing the unrealistic assumption of dynamic allocative efficiency that is inherent in an alternative sequential nonparametric approach. The median of the estimated shadow values of capital is about -0.21, suggesting that one additional monetary unit of capital leads to long-run cost savings of about 0.21 monetary units on average.

We find that the dynamic cost inefficiency (CIE) of our sample firms is considerably large, with an average dynamic cost inefficiency of 37% (see Table 4.2).[67] This finding indicates notable potential for savings in long-run costs for the US electricity distribution and transmission industry. The significant level of allocative inefficiency (AIE) in most of the sample years suggests that firms may face problems when choosing the mixture of variable and quasi-fixed inputs given the respective input prices. This means that their trade-off between variable input contraction and capital stock expansion is not in line with the ratio of the variable input price and the shadow value of capital, i.e., the economic benefits of both choices.

Comparing dynamic and static cost inefficiency in our empirical application is complicated by the fact that the dynamic cost inefficiency incorporates allocative inefficiency, while the static cost inefficiency does not.[68] The application of the dynamic cost inefficiency measure yields an average cost inefficiency that is 3 percentage points lower compared to the static measure. In particular, more observations are deemed to be fully cost-efficient when the dynamic input and the shadow value of capital are controlled for. Thus, considering adjustment costs and long-run cost savings induced by investments does affect the outcome of cost inefficiency measurement, although the effect is not very pronounced in our application. With regard to benchmarking carried out in regulatory practice, this suggests that X-factors derived from static benchmarking models may deviate from long-run cost minimization targets of the firms under regulation.

[67] For a limited number of observations, we find dynamic cost inefficiency values greater than one. This is the case when actual and optimal investments show a huge difference. Considering these observations as extreme cases, we denote them as outliers and do not include them in our further analysis.

[68] Since we use only one variable input measured in monetary terms (OPEX) in our empirical application, the obtained results on the static technical inefficiency can also be interpreted as a static cost inefficiency measure, i.e., inefficiency due to over-usage in cost.

The methodological choice of applying either static or dynamic inefficiency measures is expected to most severely affect firms with large investments due to the fact that these firms may face high adjustment costs through changes in the capital stock. Thus, we find it promising to analyze the inefficiency scores obtained from static and dynamic measures for firms with different investment activity. For this purpose, we sort our observations according to their investment shares, defined as the ratio of gross investments and capital stock, and compare the static and dynamic inefficiency scores of different percentiles. The average inefficiency scores for the percentiles considered are reported in Table 4.3.

Table 4.3: Average Dynamic and Static Inefficiency Scores for Investment Ratio Percentiles

Cumulative Percentile of Investment Ratio	Observations	TIE Dynamic	CIE Dynamic	AIE Dynamic	TIE/CIE Static
Total Sample	464	0.26	0.37	0.11	0.40
5	441	0.25	0.36	0.11	0.40
25	348	0.22	0.33	0.11	0.39
50	232	0.21	0.33	0.12	0.41
75	116	0.17	0.28	0.11	0.44
95	24	0.07	0.20	0.13	0.44

The comparison reveals that firms with high investment ratios suffer heavily when investments are neglected in the assessment of inefficiency. While the static inefficiency values differ only slightly among the different percentiles, the dynamic technical and dynamic cost inefficiency values show significant variation. For instance, dynamic average technical inefficiency of the upper investment ratio quartile is 27 percentage points lower than its static counterpart. For the case of the upper fifth percentile, the difference in technical inefficiency between the dynamic and static measure even increases to 37 percentage points. In contrast, firms with small investment shares are less exposed to the choice of the technical inefficiency measure. With regard to cost inefficiency, a similar pattern arises. For the case of the upper fifth percentile, the difference in cost inefficiency between the dynamic and static measure amounts to 24 percentage points, while for the total sample the difference is only 3 percentage points.

4.7 Conclusion

The objective of this study was to investigate the impact of using static versus dynamic inefficiency measures in the context of benchmarking used for incentive-based regulation schemes. We therefore applied the concept of dynamic inefficiency developed by Silva and Oude Lansink (2009) and Oude Lansink and Silva (2013) to a sample of US electricity distribution and transmission firms in order to obtain dynamic technical and dynamic cost inefficiency estimates using dynamic DEA. We then compared our dynamic inefficiency estimates with their static counterparts.

Most importantly, our empirical results reveal that the consideration of investments and the corresponding adjustment costs significantly affect the outcome of benchmarking exercises, both in terms of technical and cost inefficiency. In specific, firms with large investments are extremely vulnerable to the choice of the inefficiency measure underlying the benchmarking process and suffer from X-factors that are too strict when static benchmarking models are applied by the regulator. As a result, firms subject to X-factors derived from static benchmarking models may have incentives to deviate from the long-run cost minimization by cutting investments.

This finding emphasizes that the application of dynamic inefficiency measures in the context of incentive-based regulation may be beneficial. Dynamic inefficiency measures have the advantage that they are consistent with the multi-period optimization of firms and explicitly address adjustment costs from changes in quasi-fixed inputs. Thus, X-factors derived from dynamic benchmarking models can resolve the mismatch between benchmarking methods used in regulation and the optimization of firms with regard to the time horizon of decision making. Moreover, the dynamic approach allows for a comparison of the optimal and the actual mix of static and dynamic factor usage via estimating dynamic allocative inefficiency. This enables the regulator to shift incentives in the regulatory design towards the desired direction.

In addition, our empirical findings point towards a significant potential for long-run cost savings for the US electricity distribution and transmission industry. The computation of the dynamic directional distance function reveals an average dynamic technical inefficiency of 26%, while average dynamic cost inefficiency amounts to 37%. The rather high level of dynamic inefficiency may be attributed to a lack of efficient regulation within the industry considered. For instance, incentive-based regulation of electricity transmission and distribution firms is not in place in many states in the US (Kwoka, 2009). However, when interpreting the results of our inefficiency measures, one should keep in mind that our sample firms are rather heterogeneous. We therefore recommend a cautious interpretation of the inefficiency scores obtained.

Our study has generated various insights into the application of static and dynamic measures of inefficiency and the implicit consequences on derived X-factors in incentive-based regulatory schemes. Nevertheless, different extensions of our research seem promising, such as the application of dynamic inefficiency measurement to other industries in which the role of adjustment costs is expected to be different. Another interesting opportunity for further research would be to apply the static and dynamic methods to a more homogeneous sample and to draw concrete conclusions with regard to the financial effects for the firms under incentive-based regulation schemes.

Chapter 5

The Costs of Power Interruptions in Germany - a Regional and Sectoral Analysis

5.1 Introduction

The availability of cheap and reliable electricity supply is a key element of economic competitiveness and prosperity. At first glance, affordability and reliability of electricity supply may appear to be a trade-off. However, the economic costs of electricity supply go beyond the electricity sector and include the risk of insufficient electricity supply for society and the resulting welfare losses in the case of blackouts. This risk can be separated into two aspects: technical and economical. The technical aspect can be described as the technical probability of a service interruption. The economic aspect relates to the economic damage a customer has to take in the case of interruption. This damage is equivalent to the opportunity costs of alternative (economic) activity or the Value of Lost Load (VoLL). In this paper, we estimate the costs of potential power interruptions based on the VoLL in Germany. Given Germany's regionally heterogeneous population, industry structure and demand patterns, we place special focus on regional economic vulnerability imposed by potential power interruptions. Therefore, we estimate the costs of potential power interruptions for different German regions and sectors. This approach allows us to assess the economic risk of potential power interruptions on a very disaggregated regional and sectoral level.

Methodologically speaking, three different approaches have been applied in previous research to derive the economic costs of power interruptions. First, some studies draw upon historical blackouts to infer outage costs from available data (see, e.g., Corwin and Miles, 1978, Serra and Fierro, 1997). The advantage of such case studies is that real, as opposed to hypothetical, interruptions are examined. However, as each interruption is specific in terms of place, time and duration, case studies suffer from a lack of generalization (Linares and Rey, 2013). Second, surveys are often used to investigate the willingness to pay for avoiding an interruption among different groups of customers (see, e.g., Balducci et al., 2002, LaCommare and Eto, 2006). While the obvious advantage of this methodology is the independence from actual power outages (which are rare in developed countries), a clear shortfall is that surveys rely on subjective rather than objective measures. Consumers may both under- or overstate their willingness to pay either due to a lack of information or as a result of strategic response behavior. Moreover, surveys are exceptionally time and cost intensive. The third methodology used to obtain estimates of welfare losses caused by interruptions in electricity supply is the macroeconomic approach. Within this framework, electricity is interpreted as an input factor both for firms and for private households. The approach seeks to derive economic costs of electricity outages from the loss in output generated by these two groups.

As the macroeconomic approach relies on publicly available data, it represents a more feasible approach than studies based on historical outages. However, the benefits of the macroeconomic methodology also come at a cost since the approach only captures losses in output while disregarding instantaneous damages caused by the supply interruption. Another critical aspect of the macroeconomic approach is the implied assumption of linearity among electricity input and generated output. An immediate consequence of this supposition is that the relation between outage duration and interruption costs is also characterized by linearity. This may be considered a shortfall, as any adjustment by electricity customers to outages is neglected.

Overall, each methodology has its own assets and drawbacks. As historical outages are rare and comprehensive survey data is not available for Germany, we rely on the macroeconomic approach. Using a rich data set on industry and households, we first estimate regional- and sector-specific VoLLs, defined as the loss in output resulting from failing to supply one unit of electricity and measured in Euro per kilowatt hour (€/kWh). We then multiply these VoLLs with hourly regional and/or sectoral demand (in KW) to obtain hourly costs of power interruption. Furthermore, we choose four typical hours, each representing a distinctive load structure, and compute the national and regional outage costs for the case in which one GWh is not supplied. Notwithstanding the aforementioned shortcomings of the macroeconomic approach, this process allows us to derive at least a rough estimate of the regional and sectoral distribution of power interruption costs in Germany. In addition, in order to account for the uncertainties in the assumptions that have to be made, e.g., on the degree of electricity dependence of residential leisure time, we conduct a number of sensitivity analyses.

The remainder of the paper is structured as follows: Section 5.2 discusses previous research. Section 5.3 presents the methodological approach. Results from the empirical analysis are discussed in Section 5.4. Section 5.5 concludes.

5.2 Previous research

Several studies have relied on the macroeconomic approach to determine the economic value of a secure electricity supply. Bliem (2005) investigates the economic costs of power interruptions for Austria. He derives VoLLs for both households and economic sectors based on electricity-dependent leisure activities and sector-specific gross value added. Beyond the sectoral disaggregation, the research also accounts for demographic and economic structures of various regions through the derivation of regional VoLL figures. Overall, Bliem concludes that the outage costs within the residential sector and the aggregated outage costs within the economic sectors have comparable magnitude. On a national average, the VoLL amounts to 8.60€/kWh.

De Nooij et al. (2007) analyze the economic value of supply security in the Netherlands. They calculate sectoral VoLLs accounting for day-of-the-week effects and construct estimates of aggregated hourly outage costs. On a national average, they estimate the economic cost of one kWh electricity not supplied to be 8.56€. In an extension of this work, de Nooij et al. (2009) advocate the superiority of rational rationing, i.e., curtailing regions with low VoLLs first, to minimize the social costs per unit of electricity not supplied, compared to a random selection of curtailed regions in case of an outage. Following a similar approach, Leahy and Tol (2011) investigate the value of secure electricity supply in Northern Ireland and the Republic of Ireland. They estimate the economic costs of a one-hour blackout with respect to different times of day, days of the weeks and groups of customers. Their findings reveal that the residential sector exhibits the greatest VoLL across all sectors in both countries. Linares and Rey (2013) explore national as well as regional outage costs in Spain. Their study stresses both the regional and sectoral heterogeneity of power interruption costs. On an aggregated level, they estimate the average VoLL for Spain to be 6.35€/kWh. Moreover, the authors argue that electricity market regulation in Spain does not provide appropriate incentives to prevent electrical power outages. Thus, they conclude that the Spanish level of electricity system reliability is not optimal from a welfare point of view.

In the context of Germany's nuclear phase out, Praktiknjo et al. (2011) estimate the economic value of supply security within Germany for the residential sector. The authors rely on numerical simulation and are therefore able to account for uncertainty regarding consumer preferences, marginal wages and time use. The result of their Monte Carlo approach yields a right-skewed distribution of residential VoLL estimates, with average economic costs of 15.70€/kWh electricity that is not supplied to the customer. Moreover, they investigate the additional economic costs that would arise if the German System Average Interruption Duration Index (SAIDI) was increased to the European average. Praktiknjo et al. (2011) conclude that such a decrease in the level of service reliability in Germany would cause significant economic costs.

However, previous research on outage costs in Germany has neglected the investigation on a disaggregated sectoral level as well as the combined effects of regional and sectoral effects. Our paper contributes to the existing literature by identifying sectoral as well as regional VoLLs and outage costs, thereby giving insight into the regional- and sector-specific economic value of a reliable electricity system.

5.3 Methodological Approach

In the case of firms, we measure the economic costs in the event of power interruptions by the loss in gross value added. Dividing the gross value added by the electricity consumption yields the VoLL, representing a measure of economic output generated by inputting one unit of electricity. Another way to look at the VoLL is to interpret it as the loss in output and hence the economic costs caused by one unit of electricity not supplied. The macroeconomic approach assumes that the value adding process of firms fully depends on electricity consumption. As noted by de Nooij et al. (2007, 2009), this linearity assumption may lead to an overestimation of the outage costs. On the other hand, as costs from losses in goods and materials or restarting costs are not included, an underestimation may also occur. Therefore, our estimated outage costs should be seen rather as a rough estimate than as an absolute exact figure.

Just as the role of electricity in production processes varies significantly across economic sectors, the same holds true for the VoLL. Hence, the accuracy of estimates regarding economic costs of power interruptions crucially depends on the extent of sector-specific granularity. Following this argumentation, we investigate power interruption costs on a disaggregated sectoral level and calculate VoLLs and time-varying outage costs for a number of economic sectors. Beyond the sector-specific differences, power interruption costs may also depend on the regional economic structure as well as the technologies that are regionally available. Therefore, we additionally differentiate between federal states in our calculations, allowing the obtained VoLL estimates to be more credible since we account for both regional and sectoral heterogeneity. Consequently, the VoLL of sector s in federal state f is

$$VoLL_{s,f} = \frac{GVA_{s,f}}{EC_{s,f}}, \tag{5.1}$$

where $GVA_{s,f}$ and $EC_{s,f}$ are the (annual) gross value added and the (annual) electricity consumption of sector s in federal state f, respectively. The VoLL, as calculated in Equation (5.1), is by construction a static value as it normalizes the annual output to the use of one unit of electricity. However, the gross value added by firms is unarguably not equally distributed throughout time. Thus, outage costs differ with respect to the moment at which the interruption occurs. Moreover, actual economic interruption costs are also determined by the absolute amount of power not supplied. Therefore, for an absolute and time-varying estimate of outage costs, the static VoLL (measured in €/kWh) is not sufficient. In fact, the static VoLL of an economic sector s within a federal state f has to be multiplied by its power consumption $EC_{s,f,t}$ in hour t to yield a proper estimate of time-varying costs. The time-varying outage costs within sector s in federal state f at a specific hour t are

$$OC_{s,f,t} = \frac{GVA_{s,f}}{EC_{s,f}} \times EC_{s,f,t} = GVA_{s,f} \times lf_{s,t}. \tag{5.2}$$

In other words, the hourly outage costs represent the respective VoLL multiplied by current power consumption. This is equivalent to the annual output scaled by the hourly load factor $lf_{s,t}$. The load factor represents the share of electricity consumption in a respective hour in overall annual electricity consumption. It can be obtained from an appropriate standard commercial load profile, which is a representative mapping of electrical load over time.[69]

For the derivation of electrical power outage costs within the residential sector, it is important to consider the kind of output generated by households. People gain utility from leisure activities. However, the relationship between availability of electricity and leisure activities is not straightforward. While some leisure activities directly or indirectly depend on electricity, e.g., watching television, others do not, e.g., reading in times of daylight. This reasoning suggests that the correlation of leisure-induced welfare and electricity consumption may neither be zero nor one, but rather in the range between these two values. Since substitutability between electricity-based leisure activities and non-electricity-based leisure activities is likely to exist, we follow the approach as

[69] The assignment of load profiles to the different commercial sectors is discussed in Section 5.4.2.

advocated by Bliem (2005) and assume a coefficient of electricity dependency equal to 0.5. In other words, power outages reduce the amount of welfare households gain from leisure activities by 50%.[70]

In order to determine the amount of time households dedicate to leisure activities, we take advantage of labor market data and available information regarding the time allocated by households to different activities. Computing the annual amount of leisure across all households and multiplying by the factor of substitutability yields the time spent for electricity-based leisure activity. However, an economic value has yet to be assigned to leisure. The work of Becker (1965) provides an economic framework to derive a monetary value for leisure time. In his model, Becker argues that households gain utility from the consumption of goods and from leisure activities. The money for consumption is earned by working. Furthermore, since the marginal utility of both consumption and leisure activities decreases with each additional unit, there is an optimal amount of working and non-working hours. Within this equilibrium, the household is indifferent between an additional hour of work and an additional hour of leisure. That is, the value of an additional hour of leisure is equal to the income from an additional hour of work.[71]

However, Becker's approach may not apply to people that are not employed, i.e., unemployed, children, pensioners, sick or disabled persons, as their opportunity costs of leisure are no longer equal to the hourly income. Since leisure time, in this case, is less scarce than for employed people, valuing leisure by the hourly income may be an overestimation. On the other hand, leisure time is still valuable. In order to capture the different opportunity costs of leisure for employed and non-employed people, we assume that an hour of leisure is worth half the hourly income to the group of non-employed. This approach is in line with the methodology proposed by de Nooij et al. (2007, 2009) and followed by Linares and Rey (2013). Once the economic value of leisure is obtained, the VoLL of the residential sector can be calculated as the ratio of this value

[70] In Section 5.4.4, we compute sensitivities on this and other parameters as household parameters are most likely prone to uncertainty.

[71] However, one has to keep in mind that this equilibrium holds only in a fully flexible labor market, while frictions in this market may yield deviations from this optimum. Moreover, since data on marginal wages is not available, we refer to average wages in the empirical part of the paper.

and the electricity consumption. Since hourly wages and average working hours vary significantly among federal states in Germany, the opportunity costs of leisure as well as the amount of time that is available for leisure activities are expected to be regionally heterogeneous. Hence, we specify the residential VoLL-calculations not on a nationally aggregated level, but rather on a state-specific level, explicitly accounting for regional labor market conditions.

The VoLL of the residential sector r in federal state f can be stated as

$$VoLL_{r,f} = \frac{VL_{r,f}}{EC_{r,f}}, \tag{5.3}$$

where $VL_{r,f}$ is the federal state's (annual) economic value of leisure and $EC_{r,f}$ is the federal state's (annual) residential electricity consumption. Consequently, the time-varying outage costs can be expressed as

$$OC_{r,f,t} = \frac{VL_{r,f}}{EC_{r,f}} \times EC_{r,f,t} = VL_{r,f} \times lf_{r,t}, \tag{5.4}$$

where $lf_{r,t}$ denotes the load factor in hour t.

5.4 Empirical results

5.4.1 Value of Lost Load

The estimated VoLLs, i.e., the losses in output caused by one unit of electricity not supplied, are presented in Table 5.1. The values are sectorally and regionally disaggregated into 15 economic sectors and one residential sector and 16 federal states of Germany. To calculate values, we collect data on electricity consumption from the energy balances for both Germany entirely and each state individually. In a limited number of cases, missing values are replaced by values from Eurostat's energy statistics.[72] The data on gross value added is drawn from the regional economic accounts of the federal states

[72] The accounting policies for the energy balances of the federal states are defined by the Länderarbeitskreis Energiebilanzen in close cooperation with the Arbeitskreis Energiebilazen e.V., which is responsible for the preparation of the overall energy balance of Germany.

provided by the Statistical Office of Baden-Württemberg (2011). The reference year is 2007. A detailed overview on the utilized electricity consumption and gross value added data is provided in the Appendix.

The gaps shown in Table 5.1 result from missing data on electricity consumption and/or gross value added for some sectors in some states. For four states, namely Berlin (BE), Brandenburg (BB), Saxony (SN), and Thuringia (TH), data for the manufacturing sector was only available on an aggregate level. However, as none of these states are characterized by an exceptionally large or highly industrialized manufacturing sector, we consider any bias that may be included in the aggregated manufacturing VoLL of these states as negligible. Furthermore, for the agriculture and fishing as well as the construction and services sectors, disaggregated data on electricity consumption was only available on the federal level (D). However, the technological heterogeneity across regions for these sectors can be assumed to be rather low. Hence, we do not consider the lack of regional disaggregated VoLLs for these sectors as a problem. In fact, in order to include these sectors in our regional outage cost calculations, we use the sectors' federal VoLLs and the sectors' regional disaggregated data on gross value added to calculate the sectors' regional disaggregated electricity consumption. By doing so, we are able to calculate regional outage costs that, in terms of gross value added, account for at least 90% of all economic sectors in the federal states.[73]

The data on electricity consumption for the household sector is taken from the same sources as for the economic sectors. To calculate the value of leisure $VL_{r,f}$, we use data on the labor market provided by the regional economic accounts of the federal states and Eurostat, as well as time use data provided by the Federal Statistical Office of Germany. The labor market data includes information on employed and unemployed persons, number of actual hours worked per employee per year and labor costs per hour on the regional level. A detailed overview on this data is provided in the Appendix. The time use data of the Federal Statistical Office of Germany indicates that the average German person spends around 11 hours per day on personal care such as sleeping, eating, washing and dressing (Destatis, 2003).

[73] As can be seen the Appendix, the data on gross valued added accounts for 90% of all economic sectors in Rhineland-Palatinate (RP). For all other federal states, a higher percentage is given.

TABLE 5.1: Value of Lost Load in €/kWh (2007)

Sector	BW	BV	BE	BB	HB	HH	HE	MV	NI	NW	RP	SL	SN	ST	SH	TH	D
Agriculture and fishing																	2.49
Manufacturing																	
• Food, beverages and tobacco	2.00	2.58			2.04	2.43	2.61	1.75	1.80	2.05	2.25	2.01		1.42	2.42		2.08
• Textile and leather	3.65	2.42					4.26	11.98	3.71	2.62	2.02			0.62			
• Wood and wood products	2.11				7.81		2.51	0.75	1.24	1.22	1.61	0.57		0.78			
• Pulp, paper and print	1.11	1.06			6.95	19.07	2.26	2.34	0.98	1.15	1.07			0.69	1.41		1.40
• Chemical and petro-chemical	3.25	1.11			2.43	2.94	2.27	1.74	0.48	0.80		0.28		0.51	1.32		1.07
• Rubber and plastic	2.04	1.90			5.21	1.78	1.99	1.77	1.65	1.97	1.17	1.06		1.06			1.75
• Non-metallic minerals	1.32	1.46			0.52		1.74	2.01	1.18	0.75	1.24	2.46		0.81	1.14		1.09
• Basis metals and fabricated metal products	2.30	2.26			0.86	0.29	2.27	2.77	0.77	1.03	1.59	1.32		1.74	3.58		1.30
• Machinery and equipment n.e.c.	7.73	7.26			16.99	13.12	9.76	5.42	8.56	8.46	9.83	5.01		5.22	8.60		7.97
• Electrical and optical equipment	7.16	6.77			24.39	9.30	6.05	6.14	5.25	3.11	9.02	6.37		4.99			
• Transport equipment	4.84	5.95			5.46	6.51	3.12	3.56	3.84	3.49	3.83	3.91		2.98	3.30		4.55
• Manufacturing n.e.c. and recycling	6.33					5.32	3.69	3.96	3.53	4.11			1.85				
Manufacturing total	3.58	2.81	4.65	1.06	2.44	2.23	3.04	2.18	1.58	1.51	2.13	1.87	1.91	1.06	2.21	1.77	2.19
Construction																	102.93
Services																	11.04
Households	14.53	13.77	17.37	12.53	11.96	11.70	14.96	12.40	12.11	13.12	11.93	13.00	12.77	10.86	10.23	9.50	11.92
Total	8.73	8.85	12.35	6.63	7.92	8.81	9.67	8.92	6.67	6.50	8.34	6.58	7.57	5.46	8.73	6.39	7.41

[a]The state codes represent Baden-Württemberg (BW), Bavaria (BV), Berlin (BE), Brandenburg (BB), Bremen (HB), Hamburg (HH), Hesse (HE), Mecklenburg-Vorpommern (MV), Lower-Saxony (NI), North Rhine-Westphalia (NW), Rhineland-Palatinate (RP), Saarland (SL), Saxony (SN), Saxony-Anhalt (ST), Schleswig-Holstein (SH), Thuringia (TH), and Federal Republic of Germany (D). [b]The sector classification follows the Statistical Classification of Economic Activities in the European Community (NACE Rev.1.1). [c] The reference year for Lower-Saxony is 2006. Source: Own calculations

The first step in determining our value of leisure requires the derivation of the employees' net hourly income. Given that the employer's average rate of social security contributions amounts to approximately 22% of the labor costs per hour (Destatis, 2008) and that the employees' average rate of income tax and social security contributions amounts to approximately 33% of the gross hourly income (OECD, 2012), we calculate a regional net hourly income equal to around half of the respective regional labor cost per hour.[74] Using the information described above, the annual value of leisure for all employed persons in the federal state f can be calculated as

$$\begin{aligned} VL_{e,f} = &((8760 - 365 \times 11 - hours\ work_f) \times net\ hourly\ income_f) \\ &\times number\ of\ employed\ persons_f \times 0.5, \end{aligned} \tag{5.5}$$

where 0.5 reflects the assumed substitutability between electricity-based leisure and non-electricity-based leisure as defined in Section 5.2. Similarly, assuming that the hour of leisure for unemployed persons is worth half the net hourly income of that of the employed (see Section 5.2), the annual value of leisure for all unemployed persons in the federal state f is calculated as

$$\begin{aligned} VL_{u,f} = &((8760 - 365 \times 11) \times 0.5 \times net\ hourly\ income_f) \\ &\times number\ of\ unemployed\ persons_f \times 0.5, \end{aligned} \tag{5.6}$$

Together, $VL_{e,f}$ and $VL_{u,f}$ add up to the residential value of leisure in the federal state f, $VL_{r,f}$. This value divided by the household's electricity consumption in a given state yields the residential VoLL in the federal state f, $VoLL_{r,f}$.

As can be seen in Table 5.1, the VoLLs vary significantly between the sectors and the federal states. First, with respect to sector level, the highest federal VoLL is observed for the construction sector with 102.93€/kWh. This value is much higher than all other

[74] Due to the lack of data on marginal wages, we rely on average wages in our empirical application. The labor cost data used is provided in the Appendix.

VoLLs, which results from a relatively higher gross value added than the level of electricity consumed in this sector. In other words, the construction sector is characterized by an exceptionally low electricity intensity (kWh/€) compared to other sectors.[75] At the federal level, the construction sector accounts for approximately 4% of gross value added but only for approximately 0.2% of total electricity consumption in all economic sectors considered (see data provided in the Appendix).

The federal VoLLs for the service sector and for the households amount to 11.04€/kWh and 11.92€/kWh, respectively. Both sectors are large electricity consumers and generate a large amount of output. At the federal level, the service sector accounts for approximately 36% of total electricity consumption and generates approximately 69% of gross value added in all economic sectors considered. In absolute numbers, electricity consumption and value added of the households are even higher compared to those of the service sector. Expressed in shares and taking households and all economic sectors together, households account for approximately 27% of overall electricity consumption and for approximately 43% of total value added (see data provided in the Appendix). In contrast, the federal VoLLs of the agriculture and total manufacturing sectors are relatively low (2.49€/kWh and 2.19€/kWh, respectively). Compared to the service sector, the manufacturing sector consumes even more electricity – approximately 62% of total electricity consumption in all economic sectors considered – but it creates only approximately 24% of gross value added. Finally, for the agricultural sector, both numbers are low. At the federal level, the agricultural sector accounts for approximately 2% of total electricity consumption in all economic sectors considered and generates approximately 1% of gross value added (see data provided in the Appendix).

Overall, our sector results are in line with the results from studies of other countries (see, e.g., Bliem, 2005, de Nooij et al., 2007, Linares and Rey, 2013). All studies indicate relatively low VoLLs for the agricultural and manufacturing sectors compared to relatively high VoLLs for the construction, service and household sectors. On the

[75] Although the result that the construction sector has the highest VoLL among all sectors is in line with the results from other studies, the amount is rather high. For example, Bliem (2005) calculates a value of 42.4€/kWh for Austria and Linares and Rey (2013) calculate a value of 33.37€/kWh for Spain. In order to check whether our high VoLL for the construction sector is a result of a one-year effect in the year 2007, we also calculated VoLLs for the construction sector in the years 2001 to 2009. In all years considered, the VoLL remains quite stable around 100€/kWh.

regional level, the VoLLs for the federal states indicate a large heterogeneity among states. In particular, the city-states Berlin, Hamburg and Bremen show VoLLs in some sectors that differ significantly from the corresponding VoLLs of the other states. This is due to the fact that in small states, one or just a couple firms with a specific VoLL have a high sectoral impact. For example, the sector pulp, paper and print in Hamburg consists mainly of printing and publishing firms rather than any huge pulp or paper production plants. Since printing and publishing has significant lower electricity intensity than pulp and paper production, Hamburg's VoLL for this sector is much higher than in other federal states with a different sectorial structure. Similar arguments can be applied to other sectors such as the machinery and equipment sector and the electrical and optical equipment sector. Overall, the heterogeneity in the regional VoLLs shows that there exist large differences in the economic structures of the federal states and it is therefore important to differentiate between regions in order to obtain credible estimates of regional outage costs.

The derived VoLLs constitute a valuable framework to assess the relative economic efficiency of systematic marginal load shedding within different sectors and regions. Economic theory suggests that, in case of a supply shortage, it is welfare-optimal to curtail the customer with the lowest VoLL first since this minimizes the social costs caused by the loss of one unit electricity. The potential welfare gains of such a rational rationing, i.e., curtailing regions and sectors with low VoLL first compared to a random selection, have been advocated by de Nooij et al. (2009). The authors use regionally disaggregated VoLL values for the Netherlands (de Nooij et al., 2007) and find that an efficient regional rationing can reduce social costs by 42 to 93% compared to a random rationing, i.e., a rationing which does not take into account regional differences. However, one has to keep in mind that rational load shedding requires technical feasibility, such as transmission constraints, as well as social and political acceptance. The latter cannot be ignored in particular for many public services such as hospitals. Hence, the sectoral VoLLs found in our study could be used rather as indications of the sectors in which interruptible electricity contracts are comparatively efficient as opposed to a strict sectoral ranking for load shedding.

5.4.2 Time-Varying Outage Costs

Since output generated by the sectors is not equally distributed over seasons, weeks, and days, the outage costs vary significantly over time. Given the assumed linearity among electricity input and generated output, we scale each sectoral output along the standard load profile that most appropriately reflects the power consumption patterns of the specific sector. For this purpose, we rely on the residential and commercial standard load profiles for 2012, as specified by the German Association of Energy and Water Industries and published by E.ON (2012).

For the residential sector, the choice of a suitable load profile is straightforward since a standardized profile for households exists. The same holds true for the agricultural sector.[76] The identification of suitable profiles for the other economic sectors is more challenging. For sectors that do not fit to one of the existing specific load profiles, we choose the most general standard commercial load profile. However, if we assume continuously producing enterprises to prevail within a certain sector, we can then assign standard load profiles specifically designed for these kinds of firms to the respective sector.[77]

Figure 5.1 displays the mean-, maximum-, and minimum-hourly total national outage costs in € Mio occurring each day throughout the year. The u-shaped curvature of average outage costs illustrates their seasonality, as the costs of interruptions are higher during the winter compared to the summer months. Moreover, the intra-weekly fluctuations are reflected in the weekly drops in average outage costs, stressing that the average outage costs are higher on working days compared to weekends. Maximal national outage costs per hour amount to more than 750 € Mio on a Monday in December between 1 p.m. and 2 p.m., while the lowest costs, around 168 € Mio, arise on an early Sunday morning between 3 a.m. and 4 a.m. in September. On average, a nationwide one-hour power interruption causes a welfare loss of more than 430 € Mio.

[76] There exist various standard load profiles for the agricultural sector, depending on the type of agriculture. Since we do not have any detailed information on the agricultural structure in Germany, we choose the most general standard load profile for agriculture, "L0".

[77] We assign profiles for continuously producing enterprises to the following sectors: Pulp, paper and print, chemical and petrochemical, basis metals and fabricated metal products, machinery and equipment and transport equipment.

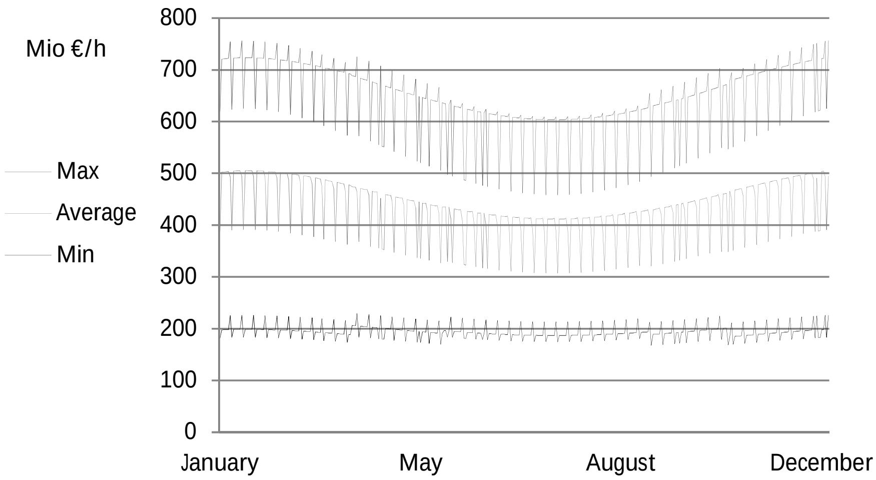

FIGURE 5.1: Total National Outage Costs (€ Mio/h)

Beyond the calculation of aggregated national outage costs, it seems promising to investigate the distribution of outage costs among the different sectors. Therefore, we calculate hourly costs of power interruptions on a sectoral level. Table 5.2 contains minimum, maximum and average values of sector shares based on total hourly outage costs as well as information on the moment when the extreme values of sector shares occur.[78]

TABLE 5.2: Time-Varying Shares of Sectoral Outage Costs

	Residential	Agriculture	Manufacturing[a]	Commercial and Public Services
Min Share	31%	0%	8%	18%
Time	Sep/Sat/4 a.m.	Jan/Sat/2 p.m.	Jan/Sun/11 a.m.	Jan/Sun/11 a.m.
Max Share	74%	2%	23%	53%
Time	Dec/Sun/11 a.m.	Nov/Thu/8 a.m.	Jul/Sun/5 a.m.	Nov/Fri/11 a.m.
Average Share	46%	1%	15%	39%
Median Share	43%	1%	14%	39%

[a]Including construction. Source: Own calculations

On average, the residential sector accounts for 46% of total hourly outage costs. The service sector ranks second as it captures on average 39% of all hourly welfare losses resulting from power interruptions. Aggregated hourly costs in the manufacturing sector (including construction) represent on average 15% of total interruption costs, whereas the

[78] The maximum and minimum values of the sector shares may occur several times throughout the year. The information provided refers to the first time within the year that the respective value can be observed. For the sake of simplicity, a brief notation is used in Table 5.2: For instance, "Sep/Sat/4 a.m." indicates that the extreme value occurs on a Saturday in September from 4 a.m. to 5 a.m.

welfare losses in the agricultural sector are comparatively small. However, a remarkable feature of the national outage cost structure is that the sectoral shares based on total outage costs vary over time: Approximately 74% of aggregate hourly outage costs can be assigned to the residential sector on a Sunday at noon in December, whereas the share decreases to 31% of total hourly costs during nights in September. Within the commercial sectors, the cost share of the service sector varies between 18% and 53%. Our finding of heavily time-dependent sectoral cost shares stresses the fact that without knowing the exact moment of a power interruption, it cannot be known a priori which sector bears the greatest welfare losses from the outage.

Our extensive data set allows for a more elaborate analysis of the costs arising from an interruption in power supply within the manufacturing sector. We calculate time-varying outage costs for a variety of manufacturing sectors using the standard load profiles discussed above. Based on these sectoral cost estimates, we compute the sectoral shares of total outage costs in the manufacturing sector as well as of total national outage costs for each hour of the year. Descriptive statistics on these shares are shown in Table 5.3. The majority of outage costs within the manufacturing sector can be

Table 5.3: Time-Varying Shares of Outage Costs in the Manufacturing Sector

Sector	Share in Manufacturing Costs[a]			Share in Total National Costs		
	Average	Min	Max	Average	Min	Max
Food, beverages and tobacco	6%	3%	7%	0.78%	0.37%	1.01%
Textile and leather	2%	1%	2%	0.23%	0.11%	0.32%
Wood and wood products	1%	0%	1%	0.11%	0.05%	0.12%
Pulp, paper and print	6%	4%	7%	0.82%	0.45%	1.57%
Chemical and petrochemical	9%	7%	11%	1.29%	0.71%	2.49%
Rubber and plastic	4%	2%	5%	0.57%	0.26%	0.78%
Non-metallic minerals	2%	2%	3%	0.35%	0.16%	0.47%
Basis metals and fabricated metal products	13%	10%	16%	1.93%	1.07%	3.73%
Machinery and equipment n.e.c.	16%	12%	20%	2.31%	1.28%	4.46%
Electrical and optical equipment	9%	6%	12%	1.32%	0.61%	1.80%
Transport equipment	16%	13%	21%	2.42%	1.34%	4.67%
Manufacturing n.e.c. and recycling	1%	1%	2%	0.20%	0.09%	0.27%
Construction	16%	10%	21%	2.25%	1.04%	3.06%

[a]Including construction. Source: Own calculations

assigned to four sectors, namely transportation equipment, machinery and equipment, basic metals and fabricated metal products and construction. On average, these sectors account for approximately 61% of total hourly outage costs within the manufacturing sector. Their average cumulative share in national hourly costs is about 9%.

The outage cost estimates provided thus far assumed a total blackout on a national level. However, since a complete breakdown of the electricity system represents an extreme event, smaller supply shortages may be considered as more realistic in real life. As a consequence, we focus on power outages for the case in which one GWh is not supplied. The choice of magnitude seems appropriate as it is in line with the outage of one large power plant that would be needed to satisfy electricity demand. In order to assess outage costs induced by a missing GWh in electricity supply, we use the following procedure. In a first step, we choose four typical hours that each represent a distinctive load structure: The hour between noon and 1 p.m. on a working day (Monday) and on the weekend (Sunday) during both winter (January) and Summer (July). We then compute the sectoral structure of power consumption within these specific hours and split the missing GWh proportionally between the affected sectors, ending up with the amount of electricity not supplied to each respective sector. In the next step, the amount of electricity not delivered to each respective sector is multiplied by its VoLL in order to obtain the sectoral outage costs induced by a missing GWh on a national level. The national outage costs for the case in which one GWh is not supplied are presented in Table 5.4.

TABLE 5.4: National Outage Costs (One GWh Outage) in € Mio

	Outage cost in € Mio/GWh	Agriculture	Manufacturing	Services	Residential
Weekend Winter	8.98	1%	7%	20%	73%
Working Day Winter	6.65	0%	17%	50%	33%
Weekend Summer	8.23	1%	9%	27%	63%
Working Day Summer	6.68	0%	16%	49%	34%

Source: Own calculations

On average, national outage costs resulting from a missing GWh range from 6 € Mio to 9 € Mio. Interestingly, costs are higher on weekends compared to working days because private households, with their comparatively high VoLL, represent a larger proportion of the overall load. As a consequence, private households account for 63% and 73% of total national costs on weekends in the summer and winter, respectively. In contrast, their share in total costs decreases to around 33% on working days. On working days, the service sector is most affected by the GWh not supplied, with costs of around 3.3 € Mio.

In addition to the presented sectoral heterogeneity, outage costs may also vary significantly across regions. Hence, a more regional, disaggregated analysis on the federal state level is provided in the following section.

5.4.3 Regional Focus on Outage Costs

Descriptive statistics on the time-varying pattern of total hourly outage costs on the federal state level are provided in Table 5.5. The numbers are calculated using the detailed regional data described in Section 5.4.1 and according to the method from Section 5.4.2. Again, we find significant seasonal, intra-weekly, as well as intra-daily patterns of fluctuations in interruption costs.[79]

Overall, the descriptives emphasize the dominance of North Rhine-Westphalia, Bavaria and Baden-Württemberg on national outage costs as their average cumulative share in national outage costs amounts to around 55% (equal to around 238 € Mio per hour). The eastern part of Germany and the federal state Saarland exhibit significantly lower costs from power interruptions. The regional distribution of outage costs reflects the relative economic strength and the population size of the aforementioned regions.

In line with our approach in Section 5.4.2, we also calculate the outage costs induced by failing to supply one GWh on the regional level. The results are presented in Table 5.6. First, the numbers emphasize that in federal states with relatively high electricity consumption, a one GWh outage represents a relatively minor incident. For example, in North Rhine-Westphalia, the loss of one GWh results on average in around 7 € Mio outage costs. This is less than 10% of the average costs of a total one hour breakdown (see Table 5.5). In contrast, since electricity consumption in one hour in Bremen is on average lower than one GWh, the calculated outage costs for one GWh not supplied in

[79] The time-varying structure of regional outage costs are qualitatively similar to the structure of national outage costs analyzed in Section 5.4.2.

TABLE 5.5: Descriptive Statistics on Regional Outage Costs (€ Mio/h)

Federal State	Mean	Median	Min	Max	Standard Deviation
BW	64.8	66.0	26.3	111.1	23.7
BV	74.8	75.5	29.3	129.5	28.2
BE	15.8	16.2	5.6	28.2	6.3
BB	9.1	9.4	3.2	16.2	3.6
HB	4.3	4.3	1.7	7.5	1.7
HH	13.5	13.1	5.1	23.5	5.3
HE	39.0	39.3	14.9	68.0	15.0
MV	6.6	6.6	2.4	11.5	2.6
NI	38.1	39.0	14.6	66.3	14.4
NW	98.3	100.2	38.3	170.8	37.0
RP	19.4	20.1	7.3	34.1	7.4
SL	5.6	5.7	2.2	9.5	2.0
SN	15.0	15.3	5.3	26.6	5.9
ST	9.5	9.7	3.6	16.6	3.6
SH	13.2	13.5	5.0	23.2	5.1
TH	7.8	8.0	2.8	13.8	3.1

[a] The state codes are the same as in Table 5.1. Source: Own calculations

Bremen are on average even higher than the calculated outage cost for a one hour total breakdown in Bremen. The same applies to the federal states Mecklenburg-Vorpommern and Saarland. Not surprisingly, as private households represent a large proportion of the overall load, the highest costs for one missing GWh are observed for states with the highest VoLL values for the residential sector, namely Berlin, Baden-Württemberg and Hesse. Nevertheless, the seasonal and daily patterns also show that the absolute numbers vary significantly depending on the time of the interruption.

5.4.4 Sensitivity Analysis: Residential Sector

Several parameters that are relevant for the computation of residential outage costs are subject to a high degree of uncertainty. Therefore, we conduct sensitivity analyses for this sector by systematically varying the input parameters described in Section 5.3 and Section 5.4.1. We thus create a robust range for the outage costs of private households, explicitly accounting for the main uncertainties induced in the computation of residential outage costs. The sensitivity analysis is carried out subject to the following parameters:

TABLE 5.6: Regional Outage Costs (One GWh Outage) in €Mio

Federal state	Mean	Weekend winter	Working day winter	Weekend summer	Working day summer
BW	9.05	10.78	7.78	9.82	7.82
BV	8.89	10.43	7.76	9.58	7.80
BE	12.68	14.50	11.30	13.57	11.34
BB	6.87	8.53	5.66	7.59	5.69
HB	8.07	9.29	7.19	8.60	7.21
HH	8.86	9.82	8.15	9.29	8.17
HE	9.97	11.63	8.75	10.72	8.78
MV	8.98	10.06	8.17	9.47	8.21
NI	6.96	8.55	5.81	7.66	5.84
NW	6.92	8.70	5.64	7.67	5.67
RP	8.18	9.53	7.17	8.82	7.20
SL	6.99	8.76	5.72	7.74	5.75
SN	7.73	9.31	6.57	8.43	6.61
ST	5.69	7.16	4.62	6.31	4.65
SH	8.46	9.11	7.96	8.78	7.98
TH	6.43	7.47	5.66	6.91	5.68

[a] The state codes are the same as in Table 5.1. Source: Own calculations

- The substitutability between electricity-based leisure activities and leisure activities independent from the availability of electricity (i.e., the degree of electricity dependence of residential leisure time).

- The valuation of leisure time for non-employed persons.

The impact of the parameter variations on average residential outage costs and average total outage costs is illustrated in Figure 5.2. Increasing the dependency parameter from 0.5 (the standard assumption) to 0.75 (0.95) implies a rise in the monetary value of electricity-based leisure time and thus a higher VoLL of the residential sector. As a consequence, the level of interruption costs for this sector is shifted upwards, while the seasonal and intraday patterns of outage costs remain unaffected. Assuming a dependency parameter of 0.75 (0.95), average outage costs of the residential sector amount to 302 €Mio/h (382 €Mio/h) compared to 201 €Mio/h in the standard setting. In contrast, a reduction of the electricity dependency of leisure activities, reflected in a coefficient of 0.25 (0.05), induces a drop in average residential outage costs to 101 €Mio/h (20 €Mio/h). Since the average outage costs in the other sectors are not affected by the parameter variation, average total outage costs increase (decrease) accordingly with increasing (decreasing) electricity dependency of leisure.

An increase in the dependency parameter to 0.75 (0.95) implies a rise in the residential share in total outage costs to 56% (62%) compared to 46% in the Reference Scenario. Thus, our findings can be regarded as quite robust with regard to a moderate increase in the dependency parameter, whereas a more extreme increase in this parameter significantly alters our results. In contrast, a moderate decrease in the dependency parameter to 0.25 causes a significant drop in the residential share in total outage costs to 30% and the extreme scenario, i.e., a dependency parameter of 0.05, yields a share of only 8%. We therefore conclude that our findings are fairly robust with regard to increases in the dependency parameter while moderate decreases in this parameter have a significant impact on our empirical results. However, keeping in mind the extensive usage of electricity-based technology in private households, we regard a decrease in the dependency parameter to 0.25 as a rather extreme and hence unlikely scenario.

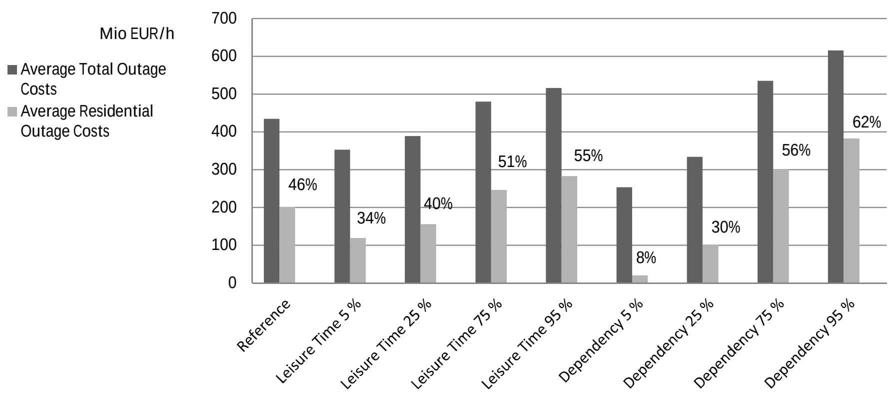

FIGURE 5.2: Average Residential Outage Costs (€ Mio/h)

We observe a similar impact on residential outage costs when the valuation of leisure time for non-employed people is varied. Again, only the level of outage costs is shifted while the characteristic patterns remain the same. Increasing the valuation of leisure time for non-employed persons from 50% (the standard assumption) to 75% (95%) of the average net wage of employed persons leads to a higher monetary value assigned to the leisure time of private households (see Equation 5.6). Thus, the residential VoLL rises (see Equation 5.3), resulting in higher outage costs throughout the year (see Equation 5.4) and average hourly outage costs of 247 €Mio/h (283 €Mio/h). A decrease in the valuation of leisure time for non-employed people to 25% (5%) of the average net wage has the opposite effect on the residential VoLL and the outage costs of this sector. The average hourly outage costs amount to 156 €Mio/h (119 €Mio/h). Again, average outage costs in the other sectors are not affected by the parameter variation and hence average total outage costs increase (decrease) accordingly with increasing (decreasing) valuation of leisure time for non-employed persons. Analyzing the share of average residential outage costs in total average outage costs, we see that our results are rather robust to moderate variations in the valuation parameter as the share varies only between 40% and 51% for a valuation parameter of 0.25 and 0.75, respectively. A more extreme variation in the valuation parameter, in turn, has a more pronounced effect on our results. Assuming a valuation parameter of 0.05 (0.95) leads to a residential share in total outage costs of 34% (55%). Overall, we conclude from the sensitivity analysis that the assumptions made on electricity dependency are of higher relevance for the computation of residential outage costs than the assumptions made with regard to leisure time valuation of non-employed persons.

The impact of the parameter variations on average total outage costs in the case of a one GWh outage is illustrated in Table 5.7. Increasing the electricity dependency of leisure, as discussed above, leads to a higher VoLL in the residential sector and thus to higher outage costs in this sector given a one GWh outage. In addition, with outage costs in the other sectors remaining constant along the parameter variation, the residential sector's share in average total outage costs increases. The share increases from 54% in the reference to 64% (69%) for a dependency parameter of 0.75 (0.95). Average total outage costs increase from 7.63 €Mio to 9.68 €Mio (11.33 €Mio). Decreasing the electricity dependency reduces total average outage costs and the share of residential outage costs in total average outage costs. Total average outage costs decrease to 5.57 €Mio (3.93 €Mio) in the case of a dependency parameter of 0.25 (0.05). The residential sector's share in average total outage costs in the case of a one GWh outage decreases to 37% (10%).

Table 5.7: Sensitivity Analysis: National Outage Costs (One GWh Outage) in €Mio

	Average outage costs of four type days	Agriculture	Manufacturing	Services	Residential
Reference	7.63	1%	12%	34%	54%
Leisure Time 5%	5.96	1%	15%	44%	41%
Leisure Time 25%	6.70	1%	13%	39%	47%
Leisure Time 75%	8.56	0%	10%	30%	59%
Leisure Time 95%	9.30	0%	10%	28%	62%
Dependency 5%	3.93	1%	23%	66%	10%
Dependency 25%	5.57	1%	16%	47%	37%
Dependency 75%	9.68	0%	9%	27%	64%
Dependency 95%	11.33	0%	8%	23%	69%

Source: Own calculations

Similar effects can be observed when the valuation of leisure time for non-employed people is varied. Increasing the value of leisure time leads to a higher VoLL and hence to higher outage costs for the residential sector in the case of a one GWh outage. This in turn leads to higher average total outage costs and, as the other sectors are not affected by the parameter variation, to a higher share of residential outage costs in total outage costs. An increase in the parameter to 75% (95%) leads to a share of residential outage costs in total outage costs equal to 59% (62%) and average total outage costs of 8.56 €Mio (9.30 €Mio). In contrast, decreasing the value of leisure time leads to lower average total outage costs in the case of a one GWh outage and a lower share of residential outage costs in total outage costs. A reduction in the valuation parameter to 25% (5%) leads to a residential share of 47% (41%) in total outage costs and average total outage costs of 6.70 €Mio (5.96 €Mio).

5.5 Conclusions

In this study, we quantified the economic costs of power interruptions in Germany. Drawing upon a macroeconomic approach, we derived the VoLLs and outage costs in different German regions and sectors, accounting for regionally heterogeneous economic structures and federal state-specific labor market conditions.

On a national level, our empirical findings reveal average total German outage costs of around 430 €Mio per hour, peaking at 750 €Mio per hour on a Monday in December between 1 p.m. and 2 p.m. A missing gigawatt hour creates average outage costs of about 7.6 €Mio. On average, national outage costs are approximately equally split across commercial and residential electricity customers, although the sectoral shares in total costs vary significantly over time. Sensitivity analyses for the VoLL and the outage costs of residential customers generally support our findings. However, the sensitivity analyses show that both VoLL and outage costs for Germany heavily depend on the assumptions made on the way in which residential consumers use electricity in their leisure time. Concerning the regional heterogeneity of outage costs within Germany, we find that southern and western Germany face high welfare losses if these regions are subject to a one hour interruption in electricity supply. If, however, electricity supply is decreased by just one GWh, Berlin will suffer the highest losses of around 12.86 €Mio on average.

Our empirical results shed light on the economic efficiency of different approaches in dealing with electricity supply shortages. Economic theory suggests that load shedding, if necessary, should be applied to customers who suffer the lowest economic cost from one unit of electricity not supplied. Thus, our estimates of disaggregated VoLLs can be used to assess the economic efficiency of curtailing customers within different sectors and regions. However, a pure economic rationing would be socially or politically unacceptable. Nevertheless, our estimations can serve as a starting point to optimize load shedding. After an evaluation of the first best solution from a social preferences perspective, a system operator could shed load in a second best optimum. Although the practical feasibility of such a concept should be considered carefully due to social and political as well as technical restrictions, our findings of strictly heterogeneous VoLLs across different sectors and regions provide an idea about how large the potential welfare gains of an efficient power curtailment may be compared to the benchmark of random load shedding.

The investigation of regional outage risks from a more technical perspective could be a promising branch for further research within the area of welfare losses induced by electricity supply interruptions. A special emphasis should be put on transmission constraints. On the one hand, transmission constraints aggravate the problem of necessary load shedding in certain areas. On the other hand, these constraints may influence the technical feasibility of the merit order of optimal load shedding as shedding load upstream of constrained transmission lines may be technically and, by that, economically without any effect. The results could then be combined with the disaggregated outage cost estimates of this work to derive reliable expected regional welfare losses from electricity supply interruptions. Moreover, an investigation of one-off outage costs for both industrial and residential customers could complement our research since this cost component cannot be accounted for within the macroeconomic methodology used in this study.

Appendix A

Supplementary Material for Chapter 2

Table A.1: Summary Statistics

	Temp-erature	Supply Shortfall	Crude Price	Coal Price	LNG	Storage	Gas Price
Mean	-1.383	0.031	64.412	76.265	0.000	0.000	19.985
Min	-10.762	0.000	25.880	42.844	-1158.726	-0.060	7.320
Median	-0.728	0.000	63.192	74.499	-172.721	0.001	22.006
Max	9.302	2.229	96.329	139.217	2438.632	0.050	31.510
Std Dev	3.124	0.200	17.130	21.433	753.823	0.016	5.835
t	227	227	227	227	227	227	227

Table A.2: Results of the Johansen Cointegration Test

Hypothesis	Eigenvalue	Trace Statistic	Critical Value (95%)	p-Value
Coal - Crude Oil r=0	0.0298	7.9670	20.262	0.8270
Coal - Crude Oil r$\leq$ 1	0.0053	1.1827	9.1645	0.9260
Coal - Natural Gas r=0	0.0665	19.8383	20.262	0.0571
Coal - Natural Gas r$\leq$ 1	0.0196	4.4367	9.1645	0.3510
Crude Oil - Natural Gas r=0	0.0789	19.9140	20.262	0.0558
Crude Oil - Natural Gas r$\leq$ 1	0.0067	1.5110	9.1645	0.8714

Table A.3: Summary of Sources, Russian Supply Shortfall of February 2012

Source	Publication Date	Time Period	Affected Location	Supply Disruption	Original Source
DJ Tradenews	02/02/12	01/31/12	Europe	1.5% less	Gazprom Employee
DJ Tradenews	02/03/12		E.ON Ruhrgas, Germany	None	Company
DJ Tradenews	02/03/12		Italy	11.6% less	
DJ Tradenews	02/03/12		Italy, Poland, Slovakia	8% to 10% less	Speaker of Günther Oettinger, European Commission
DJ Tradenews	02/03/12		Hungary, Czech Republic	Less	
DJ Tradenews	02/03/12		RWE Supply & Trading, Germany	30% less	Company
DJ Tradenews	02/03/12		Wingas, Germany	Less	Company
DJ Tradenews	02/03/12		OMV, Hub Baumgarten, Austria	30% less expected	Company
DJ Tradenews	02/06/12		PGNiG, Poland	7% less	Company
DJ Tradenews	02/06/12		E.ON Ruhrgas, Germany	One third less	Company
DJ Tradenews	02/06/12	02/02/12	Austria	30% less	Speaker of Günther Oettinger, European Commission
DJ Tradenews	02/06/12	02/02/12	Italy	24% less	Speaker of Günther Oettinger, European Commission
DJ Tradenews	02/06/12	02/02/12	Poland	8% less	Speaker of Günther Oettinger, European Commission
DJ Tradenews	02/06/12	Currently	Italy, Greece, Austria, Poland, Slovakia, Hungary, Bulgaria, Romania	Less	Speaker of Günther Oettinger, European Commission
DJ Tradenews	02/07/12		Germany, Romania, Italy	Less	Speaker of Günther Oettinger, European Commission
DJ Tradenews	02/07/12		Bulgaria, Slovakia, Hungary, Poland, Austria, Greece	No disruptions	Speaker of Günther Oettinger, European Commission
DJ Tradenews	02/08/12	Previous week	Europe	15% less	Alexander Medvedev, Gazprom
DJ Tradenews	02/13/12		E.ON Ruhrgas, RWE and Wingas, Germany	Less deliveries	Company
ICIS Heren EGM	02/15/12		Europe	About 10% below contractual levels	Gazprom
ICIS Heren EGM	02/15/12	Beginning of February	GDF Suez, France	30% less	Company
ICIS Heren EGM	02/15/12	02/06/12	GDF Suez, France	20% less	Company
ICIS Heren EGM	02/15/12	01/31/12	Slovakia	8% to 10% less	
ICIS Heren EGM	02/15/12	02/02/12	SPP, Slovakia	36% less	Company
DJ Tradenews	02/21/12		Europe	No disruptions anymore	Alexander Medvedev, Gazprom
Henderson and Heather (2012)	April 2012	02/02/12 to 02/07/12	Italy	11% - 29% less	Snam Rete Gas

Notes: DJ Tradenews refers to the Dow Jones TradeNews Energy publication available at `http://www.dowjones.com/commodities/TradeNews-Energy.asp`. ICIS Heren EGM refers to the ICIS Heren European Gas Market report available at `http://www.icis.com/energy/gas/europe/`.

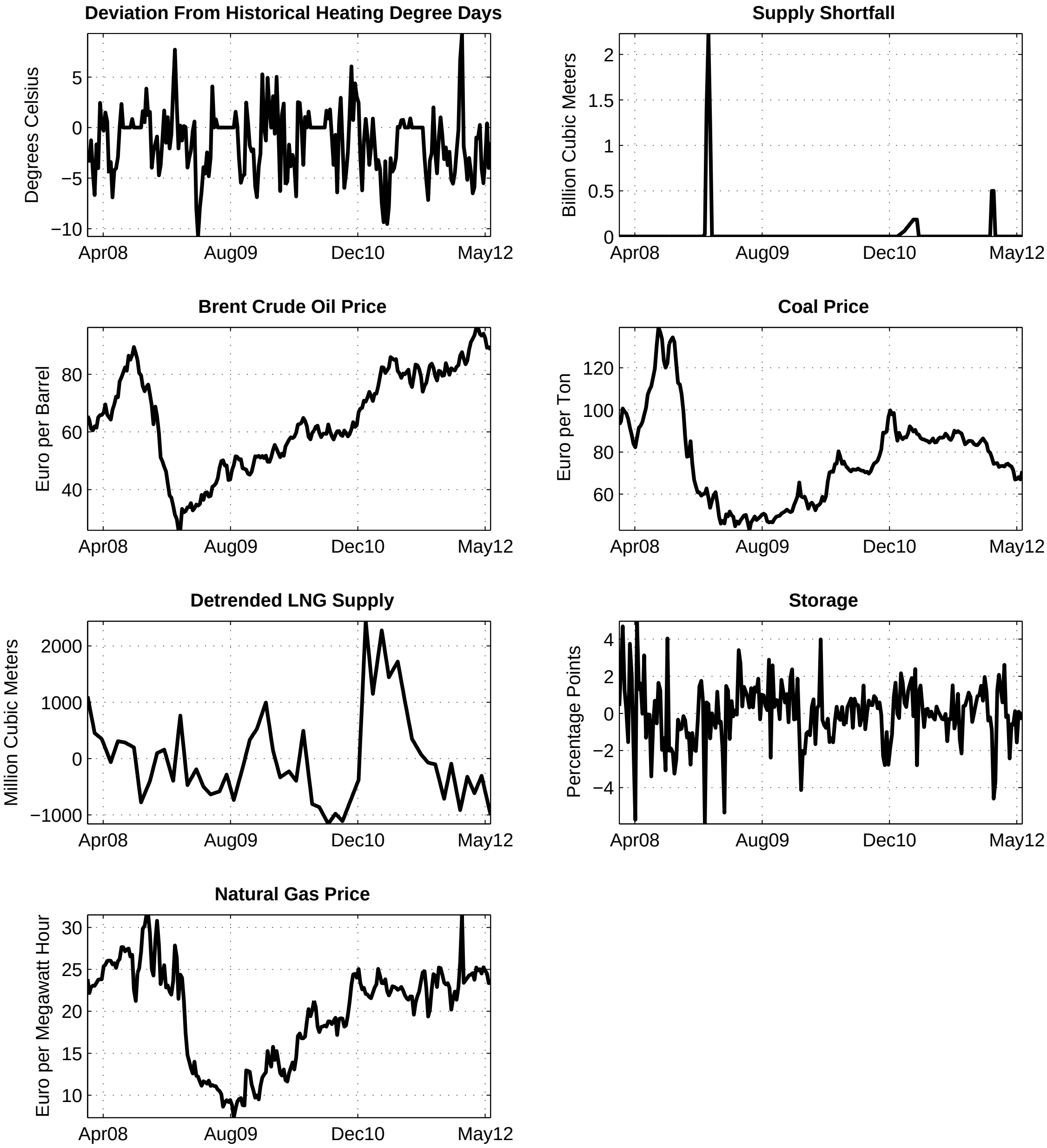

Figure A.1: Plots of the Time Series Used for the Analysis

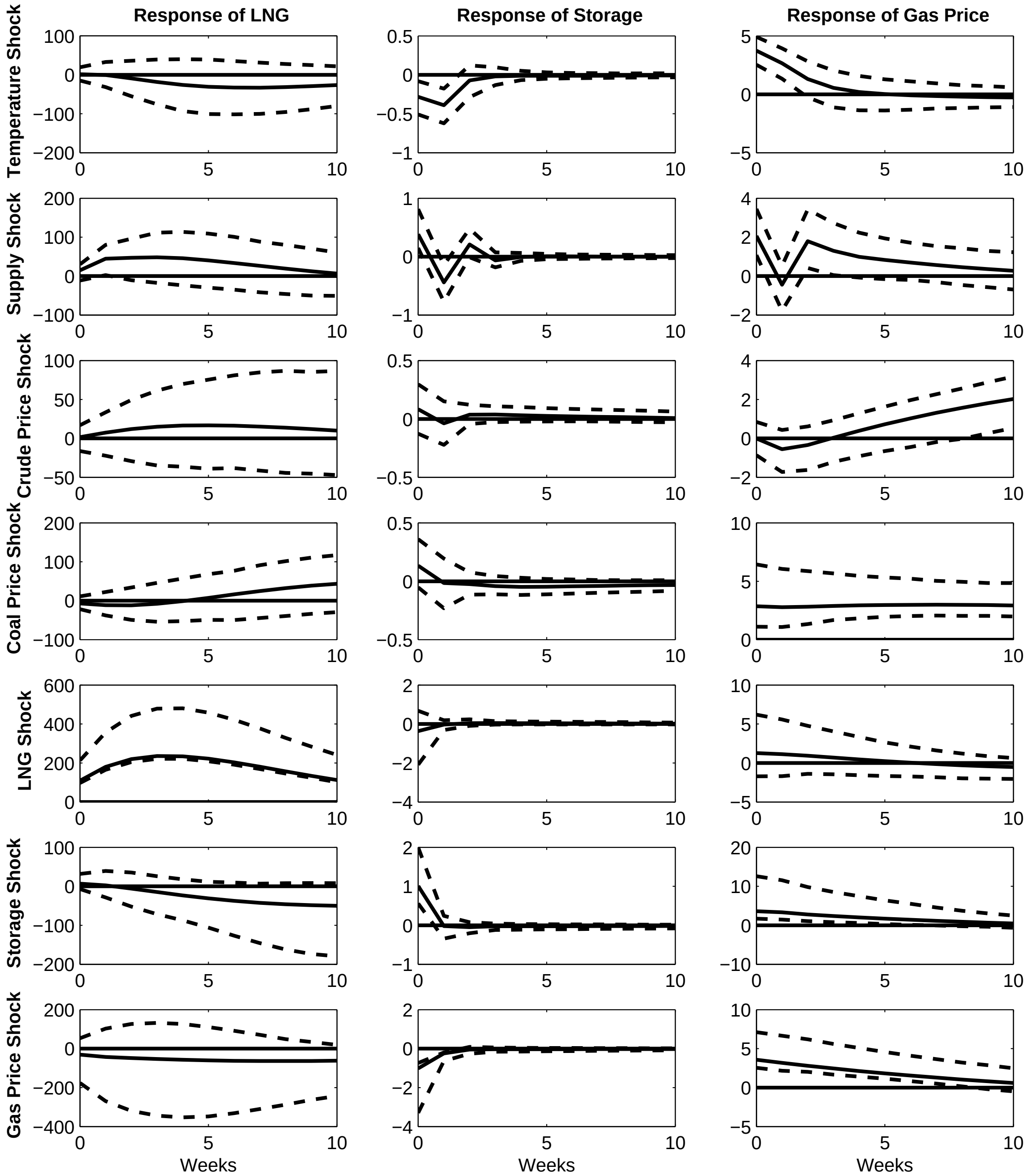

FIGURE A.2: Responses of LNG, Storage and the Natural Gas Price

Notes: The impulse responses (solid lines) are based on one standard deviation of the respective structural shock. The response of LNG is measured in million cubic meters (mcm), the response of deseasonalized storage utilization is measured in percentage points and the response of the natural gas price is measured in percent. Confidence intervals (dashed lines) are bootstrapped following Hall's 95-percentage bootstrap interval using 1000 draws.

Appendix B

Supplementary Material for Chapter 3

Table B.1: Results of the Unit Root Tests

	t-Statistic ADF	p-Value ADF	t-Statistic PP	p-Value PP
NCG Spot	-1.5307	0.5178	-1.9745	0.2938
NCG m+1	-1.3782	0.5943	-1.3513	0.6073
NCG m+2	-1.8279	0.3671	-1.3083	0.6276
NCG m+3	-1.1575	0.6945	-1.2410	0.6585
TTF Spot	-1.5473	0.5093	-2.1754	0.2156
TTF m+1	-1.3514	0.6072	-1.3401	0.6126
TTF m+2	-1.4541	0.5567	-1.2593	0.6502
TTF m+3	-1.1283	0.7065	-1.2117	0.6714
NBP Spot	-1.6091	0.4776	-3.2456	0.0177
NBP m+1	-1.4889	0.5391	-1.6794	0.4415
NBP m+2	-1.5543	0.5057	-1.6491	0.4570
NBP m+3	-1.4122	0.5776	-1.4726	0.5474
ΔNCG Spot	-13.2306	0.0000	-40.8718	0.0000
ΔNCG m+1	-12.7497	0.0000	-32.7785	0.0000
ΔNCG m+2	-6.3319	0.0000	-33.9596	0.0000
ΔNCG m+3	-5.0573	0.0000	-33.8859	0.0000
ΔTTF Spot	-13.1479	0.0000	-34.7274	0.0000
ΔTTF m+1	-10.8880	0.0000	-34.3284	0.0000
ΔTTF m+2	-9.9450	0.0000	-33.2840	0.0000
ΔTTF m+3	-5.2044	0.0000	-32.7979	0.0000
ΔNBP Spot	-10.2739	0.0000	-62.3198	0.0001
ΔNBP m+1	-20.7571	0.0000	-35.1039	0.0000
ΔNBP m+2	-22.2504	0.0000	-34.8534	0.0000
ΔNBP m+3	-21.9632	0.0000	-34.0489	0.0000

Notes: The unit root tests are specified with a constant but without a linear trend as a time trend seemed inappropriate from the first investigation of the price series. The optimization of the lag length included for the ADF test equation was conducted with respect to the Akaike Information Criterion. The selection of the bandwidth for the Phillips-Perron test was based on the Newey-West procedure using a Bartlett kernel.

Table B.2: Results of the Johansen Cointegration Test (Spot and m+2)

Hypothesis	Eigenvalue	Trace Statistic	Critical Value (95%)	p-Value
NCG r=0	0.0256	33.6016	20.262	0.0004
NCG r$\leq$ 1	0.0013	1.5655	9.1645	0.8615
TTF r=0	0.0227	29.6522	20.262	0.0019
TTF r$\leq$ 1	0.0012	1.5023	9.1645	0.8730
NBP r=0	0.0226	31.4289	20.262	0.0010
NBP r$\leq$ 1	0.0020	2.5516	9.1645	0.6673

Table B.3: Results of the Johansen Cointegration Test (Spot and m+3)

Hypothesis	Eigenvalue	Trace Statistic	Critical Value (95%)	p-Value
NCG r=0	0.0167	22.0623	20.262	0.0280
NCG r$\leq$ 1	0.0013	1.5672	9.1645	0.8612
TTF r=0	0.0149	19.8639	20.262	0.0566
TTF r$\leq$ 1	0.0012	1.5087	9.1645	0.8718
NBP r=0	0.0226	31.4289	20.262	0.0010
NBP r$\leq$ 1	0.0012	1.5087	9.1645	0.8718

Table B.4: Pairwise Linear Causality Tests for NCG Returns

	Direction	Chi-sq-Statistic
Raw Data	NCG Spot on NCG m+2	0.0593
	NCG m+2 on NCG Spot	12.974***
	NCG Spot on NCG m+3	2.6556
	NCG m+3 on NCG Spot	10.8730***
	NCG m+1 on NCG m+2	3.6889
	NCG m+2 on NCG m+1	0.0989
	NCG m+1 on NCG m+3	3.7935
	NCG m+3 on NCG m+1	1.1040
	NCG m+2 on NCG m+3	3.2389
	NCG m+3 on NCG m+2	2.2918
VECM-filtered Data	NCG Spot on NCG m+1	0.0001
	NCG m+1 on NCG Spot	0.0115
	NCG Spot on NCG m+2	0.0010
	NCG m+2 on NCG Spot	0.0273
	NCG Spot on NCG m+3	0.0111
	NCG m+3 on NCG Spot	0.0234
	NCG m+1 on NCG m+2	0.0086
	NCG m+2 on NCG m+1	0.0000
	NCG m+1 on NCG m+3	0.0308
	NCG m+3 on NCG m+1	0.0002
	NCG m+2 on NCG m+3	0.0148
	NCG m+3 on NCG m+2	0.0040

Notes: *** (**) Denotes significance at the 99 (95)%-level. For the raw return series, Granger causality was investigated within the VECM framework, explicitly taking into account the cointegration relationship. For the VECM-filtered residuals, causality testing is based on a VAR-model of the residuals, where the number of lags is optimized with respect to the Schwarz information criterion, suggesting the inclusion of one lag.

Table B.5: Pairwise Linear Causality Tests for TTF Returns

	Direction	Chi-sq-Statistic
Raw Data	TTF Spot on TTF m+2	5.1896
	TTF m+2 on TTF Spot	347.91***
	TTF Spot on TTF m+3	6.3281**
	TTF m+3 on TTF Spot	349.45***
	TTF m+1 on TTF m+2	0.0001
	TTF m+2 on TTF m+1	0.8102
	TTF m+1 on TTF m+3	0.2332
	TTF m+3 on TTF m+1	0.9347
	TTF m+2 on TTF m+3	0.4150
	TTF m+3 on TTF m+2	4.1041**
VECM-filtered Data	TTF Spot on TTF m+1	0.0294
	TTF m+1 on TTF Spot	0.0381
	TTF Spot on TTF m+2	0.0859
	TTF m+2 on TTF Spot	0.0067
	TTF Spot on TTF m+3	0.1358
	TTF m+3 on TTF Spot	0.0116
	TTF m+1 on TTF m+2	0.0025
	TTF m+2 on TTF m+1	0.0002
	TTF m+1 on TTF m+3	0.0020
	TTF m+3 on TTF m+1	0.0063
	TTF m+2 on TTF m+3	0.0233
	TTF m+3 on TTF m+2	0.0118

Notes: *** (**) Denotes significance at the 99 (95)%-level. For the raw return series, Granger causality was investigated within the VECM framework, explicitly taking into account the cointegration relationship. For the VECM-filtered residuals, causality testing is based on a VAR-model of the residuals, where the number of lags is optimized with respect to the Schwarz information criterion, suggesting the inclusion of one lag.

Table B.6: Pairwise Linear Causality Tests for NBP Returns

	Direction	Chi-sq-Statistic
Raw Data	NBP Spot on NBP m+2	2.7163
	NBP m+2 on NBP Spot	33.872***
	NBP Spot on NBP m+3	3.2826
	NBP m+3 on NBP Spot	38.780***
	NBP m+1 on NBP m+2	162.84***
	NBP m+2 on NBP m+1	0.1249
	NBP m+1 on NBP m+3	23.098***
	NBP m+3 on NBP m+1	0.8021
	NBP m+2 on NBP m+3	0.4293
	NBP m+3 on NBP m+2	0.9533
VECM-filtered Data	NBP Spot on NBP m+1	0.0073
	NBP m+1 on NBP Spot	0.0009
	NBP Spot on NBP m+2	0.0016
	NBP m+2 on NBP Spot	0.0218
	NBP Spot on NBP m+3	0.0357
	NBP m+3 on NBP Spot	0.0288
	NBP m+1 on NBP m+2	0.0031
	NBP m+2 on NBP m+1	0.0133
	NBP m+1 on NBP m+3	0.0115
	NBP m+3 on NBP m+1	0.0000
	NBP m+2 on NBP m+3	0.0143
	NBP m+3 on NBP m+2	0.0063

Notes: *** (**) Denotes significance at the 99 (95)%-level. For the raw return series, Granger causality was investigated within the VECM framework, explicitly taking into account the cointegration relationship. For the VECM-filtered residuals, causality testing is based on a VAR-model of the residuals, where the number of lags is optimized with respect to the Schwarz information criterion, suggesting the inclusion of one lag.

Table B.7: Cointegration Vectors and Error Correction Coefficients (Spot and m+2)

	Parameter	Standard Error	t-Statistic
c_{NCG}	-0.0658	-0.0658	-0.3478
β_{NCG}	0.9605	0.0621	15.4605***
$\alpha_{NCG,spot}$	-0.0630	0.0114	-5.52501***
$\alpha_{NCG,m+2}$	-0.0052	0.0066	-0.7735
c_{TTF}	-0.0760	0.1925	-0.3949
β_{TTF}	0.9571	0.0635	15.0659***
$\alpha_{TTF,spot}$	-0.0486	0.0087	-5.6054***
$\alpha_{TTF,m+2}$	-0.0060	0.0063	-0.9532
c_{NBP}	-0.2412	0.3205	-0.7526
β_{NBP}	0.9214	0.0819	11.2517***
$\alpha_{NBP,spot}$	-0.0807	0.0137	-5.8978***
$\alpha_{NBP,m+2}$	-0.0059	0.0056	-1.0503

Notes: *** (**) Denotes significance at the 99 (95)%-level. A lag length of 1 for the both VECMs is selected based on the Schwarz Information Criterion for NCG and TTF, while the same criterion suggests to include 2 lags for NBP.

Table B.8: Cointegration Vectors and Error Correction Coefficients (Spot and m+3)

	Parameter	Standard Error	t-Statistic
c_{NCG}	-0.1865	0.3334	-0.5595
β_{NCG}	0.9134	0.1086	-8.4090***
$\alpha_{NCG,spot}$	-0.0377	0.0086	-4.4097***
$\alpha_{NCG,m+3}$	-0.0045	0.0046	-0.9814
c_{TTF}	-0.1852	0.3384	-0.5472
β_{TTF}	0.9142	0.1108	8.2498***
$\alpha_{TTF,spot}$	-0.0280	0.0066	-4.2222***
$\alpha_{TTF,m+3}$	-0.0040	0.0044	-0.9098
c_{NBP}	-0.5174	0.4971	-1.0408
β_{NBP}	0.8448	0.1260	6.7045***
$\alpha_{NBP,spot}$	-0.0531	0.0110	-4.8353***
$\alpha_{NBP,m+3}$	-0.0047	0.0041	-1.1493

Notes: *** (**) Denotes significance at the 99 (95)%-level. A lag length of 1 for both VECMs is selected based on the Schwarz Information Criterion for NCG and TTF, while the same criterion suggests to include 2 lags for NBP.

Table B.9: Results of the LR Test on the Cointegration Vector (Spot and m+2)

	Chi-sq-Statistic	p-Value
NCG	0.3727	0.5415
TTF	0.4178	0.5180
NBP	0.8239	0.3640

Notes: The test was applied to the cointegration vector of the spot and the month-ahead futures prices. The null hypothesis of the LR test is: β =[-1;-1].

Table B.10: Results of the LR Test on the Cointegration Vector (Spot and m+3)

	Chi-sq-Statistic	p-Value
NCG	0.5498	0.4584
TTF	0.5187	0.4714
NBP	1.2812	0.2577

Notes: The test was applied to the cointegration vector of the spot and the month-ahead futures prices. The null hypothesis of the LR test is: β =[-1;-1].

Table B.11: Results of the Wald Test for Linear Error Correction

	Threshold	Chi-sq-Statistic	p-Value
NCG	$0.5\sigma_\epsilon$	0.6986	0.4033
NCG	σ_ϵ	0.0818	0.7752
TTF	$0.5\sigma_\epsilon$	0.2217	0.6377
TTF	σ_ϵ	0.0859	0.7695
NBP	$0.5\sigma_\epsilon$	3.1297	0.0769
NBP	σ_ϵ	9.1698	0.0025***

Notes: *** (*) Denotes significance at the 99%-level. The test was applied to the TVECM specified in Equation (3.15). The null hypothesis of the Wald test is: $\alpha_h = \alpha_l$.

Appendix C

Supplementary Material for Chapter 4

C.1 Parametric Approximation of the Firm-Specific Shadow Values of Capital

The dynamic cost function in a quadratic functional form is given by

$$
\begin{aligned}
W_{it} = {} & \alpha_0 + \alpha_{QE}\, QE_{it} + \alpha_{QC}\, QC_{it} + \alpha_K\, K_{it} + \alpha_w\, w_{it} + \alpha_c\, c_{it} \\
& + \frac{1}{2}\alpha_{QE,QE}\, QE_{it}\, QE_{it} + \frac{1}{2}\alpha_{QC,QC}\, QC_{it}\, QC_{it} + \frac{1}{2}\alpha_{K,K}\, K_{it}\, K_{it} \\
& + \frac{1}{2}\alpha_{w,w}\, w_{it}\, w_{it} + \frac{1}{2}\alpha_{c,c}\, c_{it}\, c_{it} + \alpha_{QE,QC}\, QE_{it}\, QC_{it} + \alpha_{QE,K}\, QE_{it}\, K_{it} \\
& + \alpha_{QE,w}\, QE_{it}\, w_{it} + \alpha_{QE,c}\, QE_{it}\, c_{it} + \alpha_{QC,K}\, QC_{it}\, K_{it} + \alpha_{QC,w}\, QC_{it}\, w_{it} + \alpha_{QC,c}\, QC_{it}\, c_{it} \\
& + \alpha_{K,w}\, K_{it}\, w_{it} + \alpha_{K,c}\, K_{it}\, c_{it} + \alpha_{w,c}\, w_{it}\, c_{it} + \alpha_t\, t_t + \frac{1}{2}\alpha_{t,t}\, t_t^2,
\end{aligned}
\tag{C.1}
$$

where the subscripts i and t denote the firm and year, respectively; W represents long-run costs; QE is the flow of electricity; QC is the number of customers; K is the capital stock; t is a time trend; and c and w are the price of capital and the price of the variable input, respectively.

Representing the dynamic cost function by $g(\cdot)$, we estimate the parameters of Equation C.1 by solving the following minimization problem:

$$\begin{aligned} & min \sum_{t=1}^{T} \sum_{i=1}^{N} \epsilon_{it}^2 \\ s.t.\ & W_{it} = g(\cdot) + \epsilon_{it} && && \forall i, t, && (i) \\ & \partial\, g(\cdot)/\partial\, QE_{it} && \geq 0 && \forall i, t, && (ii) \\ & \partial\, g(\cdot)/\partial\, QC_{it} && \geq 0 && \forall i, t, && (iii) \\ & \partial\, g(\cdot)/\partial\, w_{it} && \geq 0 && \forall i, t, && (iv) \\ & \partial\, g(\cdot)/\partial\, c_{it} && \geq 0 && \forall i, t, && (v) \\ & \partial\, g(\cdot)/\partial\, K_{it} && \leq 0 && \forall i, t, && (vi) \end{aligned} \tag{C.2}$$

The problem minimizes the sum of the squared residuals of the quadratic dynamic cost function subject to a set of inequality constraints that impose monotonicity required by economic theory. The shadow value of capital is then approximated by the first derivative of the cost function with respect to the capital stock:

$$\frac{\partial\, g(\cdot)}{\partial\, K_{it}} = \alpha_K + \alpha_{K,K}\, K_{it} + \alpha_{QE,K}\, QE_{it} + \alpha_{QC,K}\, QC_{it} + \alpha_{K,w}\, w_{it} + \alpha_{K,c}\, c_{it}. \tag{C.3}$$

C.2 Data Sources

Table C.1: Data Sources

Variable	Source
Total Number of Customers (in millions)	
= avg. no. customers per month	FERC Form No.1: 301 - 12 (g)
Total Flow of Electricity (MWh)	
= sales of electricity	FERC Form No.1: 301 - 12 (d)
+ transfer of electricity received	FERC Form No.1: 329 - TOTAL (i)
- transmission of electricity by others	FERC Form No.1: 332 - TOTAL (d)
OPEX (in million 2002 US$)	
= transmission expenses for electric operation and maintenance	FERC Form No.1: 321 - 112 (b)
+ distribution expenses for electric operation and maintenance	FERC Form No.1: 322 - 156 (b)
Capital Stock (in billion 2002 US$)	
= transmission plant balance (begin of year)	FERC Form No.1: 206 - 58 (b)
+ distribution plant balance (begin of year)	FERC Form No.1:206 - 75 (b)
Gross Investments (in billion 2002 US$)	
= gross investments in transmission	
= transmission plant balance (end of year)	FERC Form No.1: 207 - 58 (g)
- transmission plant balance (begin of year)	FERC Form No.1: 206 - 58 (b)
+ transmission plant depreciation expenses	FERC Form No.1: 336 - 7 (b)
+ gross investments in distribution	
= distribution plant balance (end of year)	FERC Form No.1: 207 - 75 (g)
- distribution plant balance (begin of year)	FERC Form No.1: 206 - 75 (b)
+ distribution plant depreciation expenses	FERC Form No.1: 336 - 8 (b)
Labor Cost Index	Bureau of Labor Statistics
Producer Price Index	Bureau of Labor Statistics
Consumer Price Index	Bureau of Labor Statistics

Appendix D

Supplementary Material for Chapter 5

TABLE D.1: Gross Value Added in €Mio and in Percentages of All Economic Sectors (2007)

Sector	BW		BV		BE		BB		HB		HH	
Agriculture and fishing	2,315	0.7	4,077	1.0	98	0.1	932	2.0	52	0.2	143	0.2
Manufacturing												
• Food, beverages and tobacco	3,426	1.1	6,525	1.7					877	3.7	1,060	1.4
• Textile and leather	1,912	0.6	1,839[e]	0.5								
• Wood and wood products	1,110	0.3							31	0.1		
• Pulp, paper and print	5,714	1.8	5,699	1.5					139	0.6	1,354[j]	1.8
• Chemical and petro-chemical	6,744	2.1	6,239	1.6					61	0.3	821	1.1
• Rubber and plastic	4,107	1.3	4,506	1.2					52	0.2	263	0.4
• Non-metallic minerals	1,787	0.6	3,691	0.9					42	0.2		0.0
• Basis metals and fabricated metal products	12,159	3.8	8,291	2.1					909	3.8	746	1.0
• Machinery and equipment n.e.c.	24,841	7.7	17,186	4.4					731	3.0	1,377	1.8
• Electrical and optical equipment	17,062	5.3	8,60[f]	2.2					171[i]	0.7	1,321	1.8
• Transport equipment	26,077	8.1	22,734	5.8					1,980	8.3	2,257	3.0
• Manufacturing n.e.c. and recycling	2,402	0.7										
Manufacturing total[b]	107,342	33.4	85,313	21.9	9,755[h]	12.6	6,976[h]	14.6	4,993	20.8	9,199	12.2
Construction	13,935	4.3	15,792	4.1	2,552	3.3	2,487	5.2	651	2.7	1,655	2.2
Services[c]	190,708	59.4	260,751[g]	66.9	63,730	82.6	34,816	73.0	17,508	73.0	61,768	82.2
Total	314,300	97.9	365,933	93.9	76,135	98.7	45,210	94.8	23,204	96.8	72,766	96.8
All economic sectors	321,189	55.9	389,522	57.4	77,160	51.7	47,690	53.4	23,984	61.8	75,190	62.5
Households[d]	253,196	44.1	289,201	42.6	72,037	48.3	41,561	46.6	14,805	38.2	45,079	37.5
All economic sectors and households	574,385		678,723		149,198		89,251		38,789		120,269	

TABLE D.2: Continued

Sector	HE		MV		NI[k]		NW		RP		SL	
Agriculture and fishing	1,138	0.6	862	2.8	2,783	1.5	3,002	0.6	1,410	1.5	64	0.2
Manufacturing												
• Food, beverages and tobacco	2,122	1.1	991	3.2	4,907	2.7	7,030	1.5	1,652	1.8	410	1.5
• Textile and leather	430	0.2	24	0.1	579	0.3	2,357	0.5	334	0.4		
• Wood and wood products	431	0.2	261	0.8	423	0.2	1,346	0.3	410	0.4	73	0.3
• Pulp, paper and print	2,381	1.2	248	0.8	2,451	1.4	6,849	1.4	1,393	1.5		
• Chemical and petro-chemical	7,678	4.0	236	0.8	3,239	1.8	15,602	3.3			122	0.5
• Rubber and plastic	2,293	1.2	140	0.4	2,942	1.6	5,311	1.1	1,660	1.8	322	1.2
• Non-metallic minerals	653	0.3	163	0.5	1,315	0.7	3,118	0.7	1,354	1.4	206	0.8
• Basis metals and fabricated metal products	4,191	2.2	440	1.4	4,398	2.4	26,854	5.6	3,104	3.3	2,815	10.4
• Machinery and equipment n.e.c.	5,024	2.6	314	1.0	4,271	2.4	19,575	4.1	3,067	3.3	882	3.3
• Electrical and optical equipment	5,991	3.1	455	1.5	3,538	2.0	11,282	2.4	1,381	1.5	560	2.1
• Transport equipment	4,198	2.2	520	1.7	11,379	6.3	7,935	1.7	2,517	2.7	2,409[l]	8.9
• Manufacturing n.e.c. and recycling	649	0.3	103	0.3	761	0.4	3,149	0.7	481	0.5		
Manufacturing total[b]	36,041	18.7	3,895	12.5	40,203	22.3	110,408	23.2	17,353	18.6	7,799	28.9
Construction	6,652	3.5	1,692	5.4	7,514	4.2	16,126	3.4	4,105	4.4	1,049	3.9
Services[c]	145,126	75.3	24,293	77.7	123,135	68.3	330,944	69.5	61,264	65.5	17,308	64.1
Total	188,958	98.0	30,743	98.4	173,635	96.3	460,481	96.6	84,132	90.0	26,221	97.1
All economic sectors	192,796	55.8	31,247	53.9	180,247	53.0	476,458	54.3	93,470	52.0	27,007	54.7
Households[d]	152,712	44.2	26,706	46.1	159,781	47.0	400,678	45.7	86,119	48.0	22,373	45.3
All economic sectors and households	345,508		57,953		340,028		877,135		179,589		49,380	

TABLE D.3: Continued

Sector	SN		ST		SH		TH		D	
Agriculture and fishing	934	1.1	875	1.9	1,047	1.6	716	1.6	20,940	1.0
Manufacturing										
• Food, beverages and tobacco			1,394	3.0	1,322	2.1			35,525	1.6
• Textile and leather			48	0.1		0.0				
• Wood and wood products			186	0.4		0.0				
• Pulp, paper and print			542	1.2	1,192	1.9			31,351	1.4
• Chemical and petro-chemical			1,970	4.3	1,500	2.3			55,929	2.6
• Rubber and plastic			554	1.2		0.0			24,665	1.1
• Non-metallic minerals			689	1.5	368	0.6			15,410	0.7
• Basis metals and fabricated metal products			1,582	3.4	733	1.1			73,619	3.4
• Machinery and equipment n.e.c.			840	1.8	1,987	3.1			85,483	3.9
• Electrical and optical equipment			794	1.7		0.0				
• Transport equipment			545	1.2	534	0.8			89,274	4.1
• Manufacturing n.e.c. and recycling			214	0.5		0.0				
Manufacturing total[b]	17,463[m]	20.8	9,358	20.2	7,636	11.9	10,260[m]	23.3	513,266[n]	23.5
Construction	5,248	6.3	2,640	5.7	2,420	3.8	2,591	5.9	87,490	4.0
Services[c]	57,094[g]	68.0	31,106[g]	67.2	48,854	75.9	28,976[g]	65.7	1,502,430	68.9
Total	80,739	96.2	43,979	94.9	59,957	93.1	42,543	96.5	2,124,126	97.4
All economic sectors	83,969	55.4	46,319	54.2	64,398	53.5	44,075	55.2	2,180,730	56.6
Households[d]	67,654	44.6	39,120	45.8	56,021	46.5	35,704	44.8	1,671,484	43.4
All economic sectors and households	151,623		85,439		120,419		79,780		3,852,214	

[a]The state codes and the sector classifications are the same as in Table 1. [b]Excluding the manufacture of coke, refined petroleum products and nuclear fuel. [c]Including the collection, purification and distribution of water. [d]For the Households, the numbers represent value of leisure. [e]Excluding manufacture of leather. [f]Only manufacture of electrical machinery and apparatus n.e.c.. [g]Excluding the collection, purification and distribution of water. [h]Including other mining and quarrying. [i]Only manufacture of medical, precision and optical instruments, watches and clocks. [j]Only publishing, printing and reproduction of recorded media. [k]The reference year for Lower-Saxony is 2006. [l]Excluding the manufacture of other transport equipment. [m]Including the manufacture of coke, refined petroleum products and nuclear fuel. [n] Including the subsectors for which the data is not given at the disaggregated level. Source: Statistical Office of Baden-Württemberg (2011), own Calculations.

Table D.4: Electricity Consumption in GWh and in Percentages of All Economic Sectors (2007)

Sector	BW		BV		BE		BB		HB		HH	
Agriculture and fishing[b]	928	1.9	1,636	2.9	39	0.5	374	3.7	21	0.6	57	0.6
Manufacturing												
• Food, beverages and tobacco	1,711	3.5	2,528	4.5					431	11.8	436	4.4
• Textile and leather	524	1.1	760[f]	1.4								
• Wood and wood products	527	1.1							4	0.1		
• Pulp, paper and print	5,149	10.7	5,382	9.7					20	0.5	71[j]	0.7
• Chemical and petro-chemical	2,073	4.3	5,603	10.1					25	0.7	279	2.8
• Rubber and plastic	2,010	4.2	2,378	4.3					10	0.3	148	1.5
• Non-metallic minerals	1,354	2.8	2,535	4.5					82	2.2		
• Basis metals and fabricated metal products	5,278	10.9	3,674	6.6					1,061	29.0	2,602	26.6
• Machinery and equipment n.e.c.	3,215	6.7	2,368	4.2					43	1.2	105	1.1
• Electrical and optical equipment	2,383	4.9	1,270[g]	2.3					7[i]	0.2	142	1.4
• Transport equipment	5,386	11.1	3,819	6.9					363	9.9	347	3.5
• Manufacturing n.e.c. and recycling	380	0.8										
Manufacturing total[c]	29,991	62.1	30,317	54.4	2,098[h]	26.4	6,599[h]	65.0	2,046	55.9	4,130	42.1
Construction[b]	135	0.3	153	0.3	25	0.3	24	0.2	6	0.2	16	0.2
Services[b,d]	17,276	35.7	23,621	42.4	5,773	72.8	3,154	31.1	1,586	43.3	5,595	57.1
Total	48,331		55,727		7,935		10,151		3,659		9,798	
All considered economic sectors	48,331	73.5	55,727	72.6	7,935	65.7	10,151	75.4	3,659	74.7	9,798	71.8
Households	17,427[e]	26.5	21,003[e]	27.4	4,148	34.3	3,316	24.6	1,238[e]	25.3	3,853	28.2
All considered economic sectors and households	65,758		76,730		12,083		13,467		4,897		13,651	

Table D.5: Continued

Sector	HE		MV		NI[k]		NW		RP		SL	
Agriculture and fishing[b]	456	1.8	346	8.0	1,117	3.0	1,204	1.2	566	4.0	26	0.4
Manufacturing												
• Food, beverages and tobacco	812	3.2	566	13.0	2,728	7.2	3,432	3.3	734	5.1	204	3.5
• Textile and leather	101	0.4	2		156	0.4	899	0.9	165	1.2		
• Wood and wood products	172	0.7	348	8.0	341	0.9	1,102	1.1	255	1.8	128	2.2
• Pulp, paper and print	1,052	4.1	106	2.4	2,506	6.6	5,974	5.7	1,307	9.1		
• Chemical and petro-chemical	3,380	13.2	136	3.1	6,810	18.0	19,527	18.7			442	7.6
• Rubber and plastic	1,152	4.5	79	1.8	1,781	4.7	2,693	2.6	1,418	9.9	305	5.3
• Non-metallic minerals	374	1.5	81	1.9	1,118	3.0	4,165	4.0	1,092	7.6	84	1.5
• Basis metals and fabricated metal products	1,845	7.2	159	3.7	5,702	15.1	26,150	25.1	1,954	13.6	2,133	36.9
• Machinery and equipment n.e.c.	515	2.0	58	1.3	499	1.3	2,315	2.2	312	2.2	176	3.0
• Electrical and optical equipment	990	3.9	74	1.7	674	1.8	3,628	3.5	153	1.1	88	1.5
• Transport equipment	1,345	5.3	146	3.4	2,942	7.8	2,272	2.2	657	4.6	616[l]	10.7
• Manufacturing n.e.c. and recycling	122	0.5	28	0.6	192	0.5	893	0.9	117	0.8		
Manufacturing total[c]	11,860	46.5	1,783	41.0	25,449	67.3	73,050	70.0	8,164	57.0	4,176	72.2
Construction [b]	65	0.3	16	0.4	73	0.2	157	0.2	40	0.3	10	0.2
Services[b,d]	13,146	51.5	2,201	50.6	11,154	29.5	29,979	28.7	5,550	38.8	1,568	27.1
Total	25,527		4,346		37,793		104,390		14,320		5,780	
All considered economic sectors	25,527	71.4	4,346	66.9	37,793	74.1	104,390	77.4	14,320	66.5	5,780	77.1
Households	10,209	28.6	2,154	33.1	13,191	25.9	30,549	22.6	7,220	33.5	1,721[e]	22.9
All considered economic sectors and households	35,736		6,500		50,984		134,939		21,540		7,501	

TABLE D.6: Continued

Sector	SN		ST		SH		TH		D	
Agriculture and fishing[b]	375	2.5	351	2.9	420	5.0	287	3.3	8,400[m]	2.2
Manufacturing										
• Food, beverages and tobacco			979	8.1	546	6.6			17,056	4.5
• Textile and leather			78	0.6						
• Wood and wood products			238	2.0						
• Pulp, paper and print			781	6.5	845	10.2			22,351	6.3
• Chemical and petro-chemical			3,870	32.1	1,139	13.7			52,470	13.8
• Rubber and plastic			525	4.4					14,082	3.7
• Non-metallic minerals			854	7.1	324	3.9			14,152	3.7
• Basis metals and fabricated metal products			911	7.6	205	2.5			56,669	14.9
• Machinery and equipment n.e.c.			161	1.3	231	2.8			10,726	2.8
• Electrical and optical equipment			159	1.3						
• Transport equipment			183	1.5	162	1.9			19,639	5.2
• Manufacturing n.e.c. and recycling			116	1.0						
Manufacturing total[c]	9,123	62.0	8,855	73.5	3,452	41.5	5,785	66.3	234,259[n]	61.7
Construction[b]	51	0.3	26	0.2	24	0.3	25	0.3	850[m]	0.2
Services[b,d]	5,172	35.1	2,818	23.4	4,426	53.2	2,625	30.1	136,100[m]	35.9
Total	14,721		12,050		8,321		8,722		379,609	
All considered economic sectors	14,721	73.5	12,050	77.0	8,321	60.3	8,722	69.9	379,609	73.0
Households	5,299	26.5	3,602	23.0	5,478	39.7	3,758	30.1	140,200	27.0
All considered economic sectors and households	20,020		15,652		13,799		12,480		519,809	

[a] The state codes and the sector classification are the same as in Table 5.1. [b] Estimated via the federal VoLL and the federal states' gross value added. [c] Excluding manufacture of coke, refined petroleum products and nuclear fuel. [d]Including collection, purification and distribution of water. [e] Estimated via the number of households in the state and the average electricity consumption per household at the federal level. [f] Excluding manufacture of leather. [g] Only manufacture of electrical machinery and apparatus n.e.c.. [h] Including other mining and quarrying. [i] Only manufacture of medical, precision and optical instruments, watches and clocks. [j] Only publishing, printing and reproduction of recorded media. [k] The reference year for Lower-Saxony is 2006. [l] Excluding manufacture of other transport equipment. [n] Including the subsectors for which the data is not given at the disaggregated level. [m] Drawn from energy statistics provided by Eurostat. Source: Energy balances of the Federal States; Energy balance of the Federal Republic of Germany (2007); Eurostat.

TABLE D.7: Labor Market Statistics on the Regional Level

Federal State	Population	Employed persons	Unemployed persons	Number of hours actually work per employee per year	Labor costs per hour	Net hourly income
BW	10,746.3	5,520.2	5,226.1	1,638.0	31.33	17.21
BY	12,504.6	6,540.2	5,964.4	1,647.0	30.73	16.88
BE	3,407.6	1,604.0	1,803.6	1,641.0	28.45	15.62
BB	2,541.6	1,034.5	1,507.1	1,685.0	22.54	12.38
HB	663.3	388.4	274.9	1,639.0	29.13	16.00
HH	1,761.7	1,087.9	673.8	1,639.0	33.12	18.19
HE	6,072.5	3,081.7	2,990.8	1,650.0	33.57	18.44
MV	1,686.7	727.2	959.5	1,688.0	21.70	11.92
NI	7,979.4	3,550.2	4,429.2	1,662.0	27.23	14.95
NW	18,012.0	8,272.4	9,739.6	1,651.0	30.08	16.52
RP	4,049.5	1,828.7	2,220.8	1,656.0	28.84	15.84
SL	1,040.0	507.9	532.1	1,607.0	28.64	15.73
SN	4,234.4	1,940.5	2,293.9	1,678.0	21.71	11.92
ST	2,427.6	1,008.0	1,419.6	1,669.0	22.11	12.14
SH	2,835.3	1,252.1	1,583.2	1,657.0	26.87	14.76
TH	2,300.1	1,022.1	1,278.0	1,687.0	21.20	11.64

Sources: Statistical Office of Baden-Württemberg (2011), Destatis (2003), Eurostat (2008), own calculations.

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Curriculum Vitae

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2005	**University Entrance Examination (Abitur)** Mörike Gymnasium Göppingen, Germany

PROFESSIONAL EXPERIENCE

2012 – 2014	**Research Associate** Institute of Energy Economics at the University of Cologne, Germany
2011	**Diploma Student** BayernLB, Germany
2011 – 2011	**Intern** EnBW Trading GmbH, Germany
2009 – 2010	**Student Research Assistant** Chair of Corporate Finance at the University of Stuttgart, Germany

ACADEMIC CONFERENCES & SUMMER SCHOOLS

- “The Changing World of Natural Gas”, 2013, Moscow
- 28th Annual Congress of the European Economic Association, 2013, Gothenburg
- 13th European Workshop on Efficiency and Productivity Analysis, 2013, Helsinki
- 13th European IAEE Conference, 2013, Düsseldorf
- 8th Conference on Energy Economics and Technology, 2013, Dresden
- Summer school “Dynamic Efficiency Analysis”, 2013, Wageningen
- Summer school “Productivity and Efficiency Analysis”, 2013, Helsinki

WORKING PAPERS

- The Hidden Cost of Investment: The Impact of Adjustment Cost on Firm Performance Measurement and Regulation (EWI Working Paper 14/03, with H. Wetzel)
- Price Formation and Intertemporal Arbitrage within a Low-Liquidity Framework: Empirical Evidence from European Natural Gas Markets (EWI Working Paper 13/14)
- The Costs of Power Interruptions in Germany - an Assessment in the Light of the “Energiewende” (EWI Working Paper 13/07, with C. Growitsch, R. Malischek, H. Wetzel)
- What Drives Natural Gas Markets? - A Structural VAR Approach (EWI Working Paper 13/02, with S. Thoenes)