Charles University in Prague

Faculty of Social Sciences

Institute of Economic Studies

RIGOROUS THESIS

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Weather Risk in the Natural Gas Market

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Academic Year: 2009/2010

Prohlášení

Prohlašuji, že jsem rigorózní práci vypracoval samostatně a použil pouze uvedené prameny a literaturu.

Declaration

Hereby I declare that I compiled this rigorous thesis independently, using only the listed literature and sources.

Prague, 14 February 2010

Tomáš Vyležík

Acknowledgments

I would like to express my gratitude to Prof. Ing. Karel Janda, M.A., Dr., Ph. D. for supervising my thesis.

A special word of thanks belongs of course to my girlfriend, family and friends for their patience throughout the process of writing.

Bibliographic Evidence Card

Vyležík, Tomáš, *Weather Risk in the Natural Gas Market*, Prague: Charles University in Prague, Faculty of Social Sciences, Institute of Economic Studies, 2010, pages 102, Supervisor: Prof. Ing. Karel Janda, M.A., Dr., Ph. D.

Abstract

This thesis deals with the impact of weather on the natural gas market. We describe the development of the natural gas market in the recent past and its current structure. Both these contingencies contributed to the growing importance of hedging against weather risk.

Weather is unambiguously the primary determinant of demand in the natural gas market. For that reason, we build a model predicting consumption in the Czech natural gas market with respect to its temperature sensitivity.

Such an analysis frequently serves as the first indicator of the need for weather risk hedging, which is since the 90's commonly done with weather derivatives. Therefore we go through so called burn analysis that determines the fair price of an option with regard to past temperature measurements.

Keywords: natural gas, weather risk, regression model, weather derivatives

JEL class: C10, C20, G12, G13

Abstrakt

Tato práce se zabývá vlivem počasí na trh se zemním plynem. Popisujeme vývoj trhu se zemním plynem v posledních letech a také jeho současnou strukturu. Obojí přispělo k v dnešní době rostoucí důležitosti zajišťování proti riziku spojenému se změnami počasí.

Počasí je jednoznačně hlavním determinantem poptávky na trhu se zemním plynem. Proto vytváříme model, který predikuje spotřebu na českém trhu se zemním plynem s ohledem na jeho teplotní citlivost.

Takováto analýza často slouží jako první indikátor potřeby zajištění rizika změny počasí, které je od devadesátých let obvykle prováděno za pomocí weather derivátů. Proto provádíme takzvanou "burn analýzu", která určuje cenu opce na základě teplotních měření z minulosti.

Klíčová slova: zemní plyn, riziko spojené se změnami počasí, regresní model, weather deriváty

JEL class: C10, C20, G12, G13

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List of abbreviations

ACF	Autocorrelation function
CBOT	Chicago Board of Trade
CDD	Cooling Degree Days
CFO	Chief Executive Officer
CHMI	Czech Hydrometeorological Institute
CME	Chicago Mercantile Exchange
CORC	Cochrane-Orcutt iterative procedure
D-W	Durbin-Watson Statistics
EIA	Energy Information Administration
ERO	Energy Regulatory Office
EU	European Union
G	Daily gas consumption
GDP	Gross Domestic Product
GLS	Generalized Least Squares
GWh	Gigawatt Hour
HAC	Heteroskedasticity and Autocorrelation Consistent
HDD	Heating Degree Days
IEO	International Energy Outlook
LIFFE	London International Financial Futures and Options Exchange
LNG	Liquefied natural gas
mcf	Million cubic feet
MND	Moravské naftové doly, a.s.
MTI	Ministry of Industry and Trade
MVLUE	Minimum Variance Linear Unbiased Estimator
NGPA	Natural Gas Policy Act
NYMEX	New York Mercantile Exchange
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary Least Squares
OTC	Over-the-counter
PACF	Partial autocorrelation function
RWE TG	RWE Transgas a.s.
T	Daily average temperature
UK	United Kingdom
U.S.	United States of America
UNEP	United Nations Environment Programme
VIF	Variance Inflation Factor
WRMA	Weather Risk Management Association

♦ INTRODUCTION

"It is almost impossible to name a type of business that is insulated from the effects of the weather"

Lixin Zeng (2000)

Throughout history there have always existed many forces affecting economic life of the society. In this thesis we will focus on one of the strongest factors – the power of weather, which can not be physically influenced by anyone[1] and noticeably affects a broad range of activities. Weather highly influences our everyday life. It determines also what we do, wear or eat. Since continuous discussions on global warming are nowadays more and more intensive, interest in the relationship between weather, environment and economies is increasing all over the world.

Weather greatly affects economic performance of companies. Not only the short term extreme weather events such as hurricanes or heavy snow storms, but especially long term adverse weather conditions are often reflected in profits of companies in various businesses. For that reason, it is greatly in their interest to accurately predict sudden weather changes and to adopt arrangements to shield against their impacts. Although there have been achieved some improvements in weather forecasting over the past years leading to its higher accuracy and consistency, the predictability is still far from ideal. Inaccurate forecasts may cause, beside daily inconveniences for the ordinary life of people, also large financial losses in industry. There have been written numerous studies, for example Weatherbill Inc. (2008), Larsen (2006) or Dutton (2002b), that try to measure the share of economy vulnerable to weather. However,

[1] Here, we do not consider climate changes and the influence of people on climate that is subject to discussion over the whole world.

taking into account the fact that the weather impact varies with particular sectors of economy as well as with geographic regions, there is not easy to accurately assess weather impact.

Every year, companies in a wide range of industries blame adverse weather conditions for their poor financial performance and failures to meet sales or profit targets. Since this behaviour had been repeating for many years it received its own name even in the Wall Street - "the weather excuse". The situation has recently changed and more and more companies are apprehensive that weather usually implies a big-sized risk. Therefore, it becomes very difficult to ignore it and blame weather for bad financial performance. A successful weather risk management program can mean the difference between the profit and loss for many companies in different industries (see Ameko 2004). In view of adverse financial effects of more frequent weather-related events, an increasing number of companies become interested in weather risk management.

At a glance, it is obvious that especially the energy sector is an industry that is greatly affected by weather. Among the most significant evidences of the weather impact on the energy sector belong changes in the heating and cooling requirements of households. In order to minimize the effects of unfavourable outdoor temperatures, people decide to heat or cool to arrange comfortable environment for living. This behaviour is strongly reflected in consumption of both natural gas and electricity and consequently also in revenues of companies trading these commodities. Since the concept of protection against the consequences of adverse weather has highly changed during the last decade (Dutton 2002a), we try to apply recent findings to the actual situation in the Czech natural gas market.

The first chapter is concerned with the theory of weather risk. We introduce the definition as well as the basic approach to these questions in the world. Moreover, one part is devoted also to basic knowledge of hedging against weather threats and history of the weather risk market.

The second chapter deals with the natural gas market and its historical context. We show basic situations when market disturbances, among which belong also adverse weather events, might appear. In addition, main contingencies in the Czech natural gas market are presented, which is absolutely fundamental to the understanding of the situation in the market and therefore to further analysis of the impact of weather on the natural gas industry in the Czech Republic.

In the third chapter, we search for the relationship of temperature and natural gas consumption in the Czech market. Development of temperature and daily gas consumption over the period of nine years as well as the behaviour of these variables in particular months is demonstrated.

In spite of the fact that there are used various approaches to modelling the dependency of natural gas consumption on weather[2], we apply regression methods, which have been used e.g. by Fildes et al. (1997), Cao et al. (2004a), Abiodun (2002) or Gabbi and Zanotti (2003).

The dependency of natural gas consumption and weather varies across different countries and its level commonly corresponds to the structure of natural gas users in particular markets, i.e. may provide us information about the share of weather dependent demand. Due to this fact, the comparison of regression results may also indicate differences in natural gas usage in different countries.

The understanding and anticipation of the weather impact on natural gas demand is essential for companies' managements and analysts to create accurate expectations of sales and financial inflows. Also Feinberg and Genethliou (2005) state that: *"Accurate models for power load forecasting are essential to the operation and planning of a utility company."* Moreover, as there commonly large potential costs in the natural gas market linked to changeable weather, an accurate prediction of demand may greatly help to reduce the weather threat since it might help companies to prepare for inconvenient times. Since the 90s, financial derivatives started to be employed in the protection against adverse weather. Accordingly, a precise model may also greatly help as an indicator whether to hedge against adverse weather or not.

Hence, we deal with the two basic principles of protection against the risk of changeable weather in the natural gas market: offtake flexibility in contracts and weather derivatives. We will try to build a model that reflects as precisely as possible the temperature sensitivity of a given portfolio of natural gas consumers. Such model could be consequently employed in the prediction of natural gas consumption with respect to weather week-day sensitivity as well as in the protection against weather risk with the help of weather derivatives. Therefore, it could be helpful in securing stable financial inflow.

In the last chapter, that is rather descriptive than analytical, we deal with the contribution of financial markets to the protection against losses assigned to the risk of weather change. Hedging strategies with weather derivatives, on which are focused for example Cao et al. (2004a), Jewson (2004) or Jewson et al. (2005) and which are often employed abroad, are presented as an applicable instrument also in the Czech natural gas market.

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[2] These methods are usually based on weather forecasting, regression models or time series modeling.

1. WEATHER RISK

Nowadays, as the discussion on global climate change is gaining intensity, interest in the relationship between weather, or more generally said environment, and economy is spreading with enormous speed all around the world. There are dozens of authors that are trying to express in numbers the dependency of economy on weather and consequently evaluate the risks affiliated to weather. Since results are usually very miscellaneous, it is obvious that evaluation of these risks in not an easy task. Impacts of weather vary with economic sectors as well as with geographic regions and compared with other forces that bring some cost to economy, they have quite specific position.

We have to realize that weather is completely beyond human control. No one can influence, modify or manipulate it (regarding climate changes, it would be for a long discussion, of course). Moreover, no one can even forecast weather beyond the horizon of few days with enough accuracy. These aspects heavily contribute to the uniqueness of so called "weather risk". Reflecting the role of weather in economy, the main reasons for costs incurred by weather come out here.

1. 1. Impact of weather on the economy

In this thesis we focus mainly on weather related topics. However, due to the concern over global climate change around the globe today, also dozens of studies dealing with climate risks have been commissioned. Therefore, it is necessary to make a distinction between both terms - weather and climate. Even though the difference between them is quite obvious at the first sight, let us now define both terms to avoid possible misunderstandings. General definition[3] of weather says that it is *"... current, rather than average, atmospheric conditions; the object of study of synoptic meteorology. Weather variables include humidity, temperature,*

[3] According e.g. to: http://www.answers.com/topic/weather.

sunshine hours, cloud cover, visibility, and precipitation (fog, rain, snow, sleet, and frost)." The same source defines climate as follows: *"A summary of mean weather conditions over a time period; usually based on thirty years of records. Climates are largely determined by location with respect to land – and sea-masses, to large-scale patterns in the general circulation of the atmosphere, latitude, altitude, and to local geographical features."*

In other words, if you look out of your window, it will be weather you see anytime. But if you are repeating this for a month, quarter of a year or even years, you will be able to determine the climate outside. All definitions of these terms correspond to the general feeling that climate is much a long-run event.

1. 1. 1. Weather sensitivity

Precise assessing of weather sensitivity of various economic sectors is not an easy assignment. There have been published many papers, mainly in the United States (U.S.), dealing with the topic of weather sensitivity of economy. According to Larsen (2006) there do not exist any economic definitions of being economically sensitive to weather. However, one may find applicable definitions of sensitivity in the literature about climate. The United Nations Environment Programme (2001) defines sensitivity as: *"… the degree to which a system will respond to a change in climatic conditions."* Despite the fact that there are greatly diverse time horizons when talking about weather and climate, the definition of sensitivity is in general plausible for both cases. Therefore, if there is an adverse (or potentially beneficial) impact of weather on economic sectors, either direct or indirect, they are considered to be economically weather sensitive. Nevertheless it is important to define this sensitivity objectively as there usually exists the tendency to do it in a subjective way.

Larsen (2006) further claims that: *"A super-sector could be deemed objectively sensitive to weather (relative to another super-sector) if repeatedly drawing from a distribution of observed weather variables (e.g. temperature, precipitation) in a geographic region produces measurable changes in the variance of the dependent variable (e.g. sales of cars, agricultural yields, or some measure of sector output) estimated from a robustly fit regression equation."* He emphasizes the existence of a meteorologists' fraction which speculates that practically all sectors of the economy of the U.S. are weather sensitive. The U. S. is estimated to have total weather sensitivity of $2.5 trillion dollars, about 23 percent of the whole national economy.[4]

Dutton (2002b) supposes that about $3.9 trillion of the $9.9 trillion U.S. Gross Domestic Product (GDP) in 2000 was sensitive to weather. Expressed in percentages, 39.1% of the national GDP was affected by weather with the following components listed as weather sensitive:

- agriculture, forestry and fishing
- mining
- constructing
- transportation and public utilities
- retail trade
- finance, insurance and real estate
- services

"The conclusion is that some one-third of the private industry activities, representing annual revenues of some $3 trillion, have some degree of weather and climate risk. This represents a large market for atmospheric information, and it should represent a powerful force for advancing the cause of atmospheric observation and prediction," Dutton says.

Despite the fact that results of particular studies vary, it is obvious that a large portion of the U.S. economy is highly, directly or indirectly, affected by weather. Although this topic has been widely discussed in recent years, it is still very difficult to quantify the results objectively since authors tend to be in their analyses always subjective. Some level of subjectivity has to be generally used both in definition of:

- the manner of empirical testing at the national level
- the meaning of being sensitive

1. 1. 2. What is weather risk?

"Weather risk is the uncertainty in cash flow and earnings caused by weather volatility."

Jack Cogen (1998)

[4] Weatherbill Inc. (2008): *Global Weather Sensitivity: A Comparative Study*.

Dutton (2002b) defines weather and climate risk in a more comprehensive way as the possibility of injury, damage to property or financial loss due to severe or extreme weather events, unusual seasonal variations such as heat waves or droughts or long term changes in climate or climate variability.

Although we devote this thesis to weather and associated risks, also the discussion on climate and its change of course greatly helped to popularize the term "weather risk". We are interested in the topic of temporary weather changes that may mean even the period of a couple of months, even though continual changes of climate are not a topic of lower importance compared with short term weather variations. In the short term it is more obvious what the costs of a possible change are. It is the aim of all companies to quantify all possible weather threats and hedge against them in the best way that they are able to do.

Figure 1: Links between weather and financial risks

risk holder	weather type	risk
energy industry	temperature	lower sales during warm winters or cold summers
energy consumers	temperature	higher heating/cooling costs during cold winters and hot summers
beverage producers	temperature	lower sales during cold summers
building material companies	temperature/snowfall	lower sales during severe winters (construction sites shut down)
construction companies	temperature/snowfall	delays in meeting schedules during periods of poor weather
ski resort	temperature	lower revenue during winters with below-average snowfall
agricultural industry	temperature/snowfall	significant crop losses due to extreme temperatures or rainfall
municipal governments	temperature	higher snow removal costs during winters with above-average snowfall
road salt companies	temperature	lower revenues during low snowfall winters
hydro-electric power generation	precipitation	lower revenues during periods of drought

Source: Mitu, N. M. (2008)

As companies commonly use some normal weather patterns to build their business plans, contingent anomalies may cause an unwelcome surprise. All possible changes of weather affect consumed volumes of commodities. Thus, weather risk is commonly titled also as volumetric risk. Some of real-life weather impacts on volumes are listed in Figure 1. Even though volumes of consumed commodity are influenced at first, the price bears the heaviest impact in the end. With both prices and volumes being destabilized by weather, companies have to fight against those threats and manage their risk exposure.

Considering weather risk management, one may immediately imagine some kind of insurance against abnormal weather events. Even though it is a reasonable consideration as these types of coverage are quite popular, they represent just a small portion of weather risk management today, which has greatly developed and showed its enormous potential over the last ten years.

Weather-related insurance products have long been available. However, sharp increase of interest in weather risk came with the beginning of energy markets' deregulation that attracted also capital markets. Therefore new capital market products, called weather derivatives, appeared as an outgrowth of the liberalization of the energy industry.

♦ ***Risk on energy markets***

"Weather is a key driver for both electricity and natural gas demand."

Tom Ruck (2001)

In energy markets weather influences chiefly the demand side. Nevertheless, when there are highly unfavourable weather conditions like a huge storm or even a hurricane, also the supply side of the power network may be harmed as a commodity can not be delivered to customers. Severe weather conditions may for example lead to shut-downs of natural gas wells production, damages on gas pipelines or electricity network, which may be ideal candidates for event-studies. However, in this thesis we concentrate primarily on the impact of temperature on natural gas demand.

To have a basic notion how heavy the impact of weather on financial performance may be, let us now go through some experiences of particular companies suffering from changes on the demand side, which were listed in the presentation of RenRe Investment (2008).

- ***Enbridge Gas***:[5] *"Earnings for the year ended December 31, 2006 were \$61.8 million compared with \$111.9 million for the year ended December 31, 2005. Warmer than normal weather in 2006 reduced earnings by \$36.9 million compared with relatively normal weather in 2005 which did not significantly impact earnings."*

[5] Enbridge Inc. is the leader in energy transportation and distribution in North America.

- **Fortis**:[6] *"Electricity sales were 32 GWh, or 2.7%, lower than last year, primarily due to the impact of moderate weather conditions and the loss of an industrial customer in December 2005."*
- **Gazprom**:[7] *"Fiscal third-quarter net profit for Russian gas firm OAO Gazprom dropped 6.4% to $4.59 bil, due in part to increasing operating costs and unseasonably warmer weather."*

Ameko (2004) provides information on the decrease of revenues of Atmos by $0.20/share and the fall in the share price of Sears Canada by $0.06/share, both due to the non-employing of hedging strategies against adverse weather conditions.

Even though there were always acting also other factors, these cases unambiguously underline the danger linked to the threat of unstable weather. Whenever variations in weather reach extraordinary high levels, it is usually reflected in companies´ financial performances. Especially in the period of growing prices in the energy sector, factors influencing effort of these companies have more important sense than ever.

1. 1. 3. Managers' knowledge

Myers (2008) states that the most senior finance and risk managers in the U.S. realize that their businesses are notably affected by weather since *"… a stunning eight out of ten warn of a new risk: that the emergence of global climate change and accompanying volatile weather patterns will require changes to their business models in the decades ahead."* But the majority are still just at the beginning of the way to protect themselves from adverse weather effects.

Findings of another survey among 205 senior finance and risk managers at companies in weather-sensitive industries can be found in CME (2008). Based on these results, it is obvious that the U.S. companies, mostly in the energy industry, highly realize the effect of weather on their industries since:

- 59% of managers responded that their companies are highly or very exposed to weather volatility and that they need a protection against this threat

[6] Fortis Inc. is the largest investor-owned distribution utility in Canada, serving more than 2 million gas and electricity customers.
[7] Gazprom is the world's largest gas company focused on geological exploration, production, transmission, storage, processing and marketing of gas and other hydrocarbons.

- 43% of surveyed energy and agricultural companies perceives increased volatility of weather in recent years
- 74% of energy companies made a systematic attempt to quantify the impact of weather volatility on their business (while only 29% of retailers did so)
- 51% of all respondents realizes that their companies were not well prepared to cope with weather risk on an everyday basis
- 82% admits possible future changes in the long term business models in order to adjust them to increased weather volatility and climate changes
- from 10% of companies that have already used weather risk management tools (among energy companies it is even higher - 35%), 86 percent say that it was useful

Managers' inadequate knowledge, which has been limiting the growth of the weather risk market for a long time, is in some way understandable. During the period of global financial prosperity, companies did not have to worry so much about potential shortfalls in revenues (e.g. due to adverse weather conditions). Impacts of overlooked weather risks were easily offset by growing corporate profits and easily accessible bank loans.

Apart from the volatile behaviour of weather, there exists also another factor determining the absolute fundamentality of covering potential drop-outs in companies' earnings. As it is inconvenient in the period of financial crisis to compensate assorted financial losses due to lower cash reserves and bank's willingness to provide loans, ignoring weather risk is luxurious!

1. 2. History of weather risk management

"Weather risk markets are amongst the newest and most dynamic markets for financial risk transfers and include participants from a broad range of economic sectors such as energy, insurance, banking, agriculture, leisure and entertainment. Although the weather risk market is till very much based in the United States, new participants from Europe, Asia and Latin America are entering this market."

J. M. Geyser (2004)

1. 2. 1. Way to the weather risk market

Deregulation of energy markets in the U.S. was the primary catalyst in shaping the global weather risk market. Prior to deregulation, energy companies commonly used to act in many different roles in the market, e.g. as producers, distributors etc. This has changed with deregulation as companies had to separate their businesses, stopped to be monopolies and started to work in the competitive wholesale market.

The correlation between weather and energy consumption was always well known. However, the impacts of unpredictable seasonal weather patterns were for a long time absorbed and managed within monopoly environment. As soon as monopoly structures were dismantled in the energy industry and utility companies started to be funded by private investors, who were more severe in operating their investments than governments, new investors started to look towards instruments to hedge their weather exposure with the aim of assuring more stable revenue stream.

Many of monopolies were using so called “weather normalization adjustments” to cover additional costs or lower profits caused by illegitimate weather conditions. They were able to pass all these unexpected costs directly to the ratepayer. Since the beginning of deregulation, the situation has dramatically changed as energy companies were no longer able to avoid costs and risks of unpredictable weather behaviour.

There had been methods of transferring weather risk in different industrial or agricultural sectors even before the rise of the weather risk market. Agricultural companies used to sign contracts aimed at preventing possible losses, for example due to drought or hail, and there existed also temperature dependent agreements on power supply. Already in the early 80s Roger Wilcox from National Fuel Gas[8] proposed the concept of Heating Degree Days[9] to manage temperature risk. Some kinds of insuring against weather contingencies were used also by organizers of public events, as sporting events or music concerts are. However, all the contracts signed before 1997 had just a limited scope and none of them actually developed into a real market.

In addition to increasingly popular hedging of price risk applied in ensuring the stability of costs and revenues, energy companies became promptly aware of no possibility to protect against weather risk. As it was not possible to pass increased costs to customers in the case of adverse weather conditions, they had to find a way to hedge against weather variations that drive volumes demanded by customers. That is why several large energy companies in the

[8] National Fuel Gas is one of the earliest gas utility companies in the United States (founded in 1902).
[9] Let us define this term later (Chapter 4).

U.S. started to search for an alternative to offset their risk even in the capital markets, which eventually led to the development of weather derivatives in 1997.

1. 2. 2. Weather risk market's origin

The origin of the weather risk market dates back to the mid 90s, stemming chiefly at the side of energy companies in the U.S. Since energy companies promptly realized that weather conditions were in deregulated markets the main source of uncertainty in revenues, their aim was straightforward – to find instruments stabilizing earnings and thereupon transferring risks of adverse weather. This fact was soon stressed by the El Niňo[10] event, which forced many companies in the U.S. to hedge their seasonal weather risk since they were scared of possible significant declines of earnings due to the extremely warm winter of 1997.

Abnormally high winter temperatures in the U.S. during the El Niňo caused energy companies holding the risk by themselves to regret that they had not fully exploited the possibility of transferring the risk to someone else. Consequently, there were concluded three transactions with weather derivatives in the autumn of 1997. The first pair of transactions, which signified the beginning of the current weather risk market, was signed between Koch Industries, a privately held conglomerate with interests in energy and other commodities, and Enron Corporation. They were based on the temperature index for Milwaukee for the winter 1997/1998 and designed in the way that Koch would pay Enron $10,000 for every degree above normal temperature, while the opposite monetary flow would be invoked by temperatures below normal. Nevertheless, it is important to emphasize that none of these deals would have been signed without the convergence of capital markets and insurance markets proceeding in the 90s.

To sum up, according to the Weather Risk Management Association[11] (WRMA) the new weather risk market combined several features that had been already used before as it:

- provided index based risk transfer per measurable weather variables

[10] El Niňo is a warming of the surface water of the eastern and central Pacific Ocean. It occurs every 4 to 12 years and causes unusual global weather patterns. It mostly affects South America, Australia, and Indonesia, but even the U.S. may be sometimes impacted.

[11] WRMA was founded in 1999 by leading participants in the weather market as the industry association for the weather risk management business. Its purpose is to foster public consciousness of weather risk and its management as well as to promote the growth and general welfare of the weather risk market. [www.wrma.org]

- handled temperature, precipitation, snowfall, stream flow, wind speed, daylight hours, humidity or other weather variables
- transferred risk on the basis of aggregate measures (i.e. cumulated over a given period), frequency of appearance of a given weather feature or adverse event per closely related methodologies which integrate the market
- managed risk in ways compatible with both financial and insurance markets
- comprised the primary and secondary market in weather risk

The development of new products for other than energy companies started soon after the emergence of the new market. Since there were requests, e.g. from fertilizer, golf companies or breweries, for other products covering also risks linked to precipitation or wind, additional weather derivatives were created.

1. 2. 3. Development from the mid 90's

After the first two winters of the El Niňo, energy and utility corporations started to be increasingly active in the weather risk market. Their position as risk holders was subsequently delegated to insurers, banks or hedge funds. Although the trading of weather derivatives began as over-the-counter (OTC), i.e. as concluding privately negotiated agreements directly between two parties, this OTC aspect limited the attractiveness of weather derivatives as an investment vehicle. Therefore Chicago Mercantile Exchange[12] (CME) started to be actively involved in the weather derivatives market in 1999 when it started to list futures and options on temperature indices. From that time, weather derivatives are publicly traded on an open market in the form of standardized contracts.

Traded volumes at CME have experienced a rapid growth in recent years (as shown in Figure 2). Even though there were concluded 4,165 contracts in 2002 and 14,234 one year later, traded volumes reached 776,397 contracts in 2008 and almost incredible 1 million one year earlier. Rapid growth of the weather derivatives market declares also the increased number of cities on whose temperature indices were these instruments written. By the beginning of 2009, CME was already offering weather contracts based on aggregate temperatures in 45 cities[13] while there were only twenty cities used in designing contracts four years earlier.

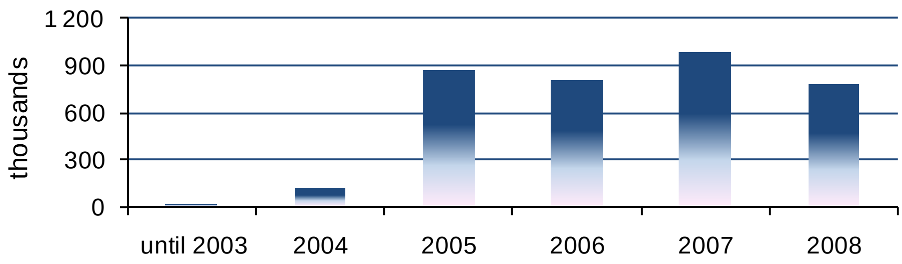
[12] Chicago Mercantile Exchange is an American financial and commodity derivative exchange founded in 1898 and based in Chicago. After its merger with the New York Mercantile Exchange in 2008, it creates the world's largest futures exchange.

[13] It included 24 cities throughout the U.S., 10 in Europe, 6 in Canada, 3 in Australia and 2 in Japan.

With regard to the range of offered products, CME has successively enlarged its supply also by listing products used to hedge risks associated with hurricanes, snowfall or frost. With the portion of economy vulnerable to weather, increased number of concluded deals and widened range of products, weather derivatives play today a highly important role in integrated risk management and diversification.

On the other hand, the total number of contracts signed at CME in 2008 reached 3.3 billion. In spite of the fact that weather affects such a high percentage of economy, weather derivatives still create just a fragment of total deals concluded at CME.

Figure 2: Number of weather derivatives contracts at CME



Source: CME Group and Storm Exchange (2008)

The weather risk market has moved forward really fast within just a one decade and spread from America also to other continents as it is largely functioning in the North America, Europe or Asia. In addition, it includes a large sphere of actions for e.g. energy industry, agriculture, construction or transportation to entertainment. From the beginning, weather conditions greatly helped to development of the market, with particular trades dominated chiefly by protection against the risk of warm winter. A prominent user of weather derivatives were from the beginning natural gas companies.

A successful hedging of weather risk has become a very important part of a quality risk management in a wide variety of business. Moreover, as weather is today able to change rapidly within few days or even hours, there is still open a large field for the weather risk market to expand. WRMA expects that after its very good start, the market has a presumption to essentially contribute to complex risk management that would affect even more than a third of the global GDP.

1. 3. Weather derivatives

"Since 1997, a financial strategy has emerged in the United States that allows companies to hedge weather-related risks with options based on weather variables. The instruments used to hedge weather risks are commonly called weather derivatives and are gaining wide acceptance in the energy industry as a primary mechanism for transferring weather risks to other parties."

John F. Dutton (2002)

Since various uncertainties have crept into the new competitive natural gas market, either the need for financial derivatives appeared.[14] They primary serve as instruments of transferring price risks to those that are willing and able to bear it.

A financial derivative is widely defined as a financial instrument whose characteristics and value depend on an underlying asset, by which is typically meant a commodity, bond, equity or currency. Even though derivatives' trading techniques might be quite risky and complicated, investors usually purchase or sell derivatives to:

1) manage risk associated with an underlying
2) protect against fluctuations in value
3) profit from periods of decline and financial losses

Apart from the main purpose of derivatives as hedging instruments, certain parties consider derivatives to have also the function of speculative instruments. In both cases, companies have to be very aware that incautious use of derivatives may lead to huge financial losses.

Beside traditional financial derivatives, there exist also their special sorts (with some unique attributes), among which belong also weather derivatives. Geyser (2004) defines weather derivatives as contracts between two parties that stipulate how a payment will be exchanged between parties, depending on certain meteorological conditions during the contract period.

Weather derivatives are today widely available to companies interested in insulating their financial results from variations in weather. With underlying variables as heating degree days, cooling degree days, average temperature, maximum temperature, minimum temperature, humidity, sunshine, or precipitation (both rainfall and snowfall), they are commonly written as weather swaps, futures or options. CME offers several weather derivatives products:

[14] After the first issue of a natural gas futures contract by NYMEX in 1990, financial derivatives became within few years an important product for all participants in the gas market.

- weather (temperature based) monthly and seasonal futures and options[15]
- frost day monthly and seasonal futures and options
- snowfall seasonal futures and options
- hurricane seasonal and event based futures and options

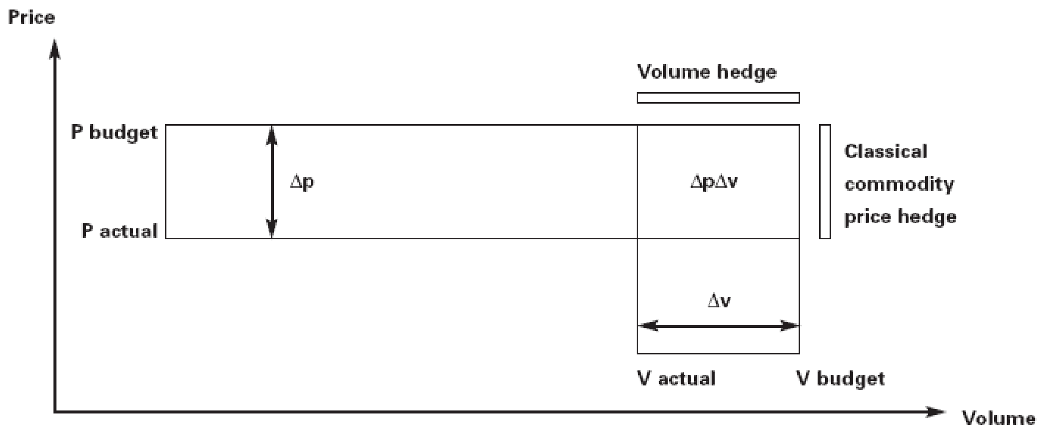
As highly structured financial products, weather derivatives are used in a dynamic management of weather risk and serve also as an instrument to diversify financial portfolios.

1. 3. 1. Weather derivatives' specifics

The main difference between weather derivatives and traditional financial derivatives consists in no existence of a traded underlying instrument, on which would be weather derivatives based. While an underlying of traditional derivatives is traded on a spot market, it is obvious that this is not the case of weather.

Since weather itself is not priced, it is impossible to put a monetary value to its variations. Thus, on the contrary to traditional derivatives, weather derivatives are not used to hedge the price of an underlying. The primary objective of weather derivatives is to hedge volumetric risk, i.e. influence of changes in consumed volumes on a company's financial performance.

Figure 3: Cross-sectional hedge for the sale of weather-sensitive products



Source: Müller and Grandi (2000)

Regarding the idea of weather hedges, weather sensitive sectors are frequently exposed to great volatility even though prices remain unchanged[16]. Hence, the objective of hedging is in this case just volume compensation. In contrast, there are industries where exists high impact

[15] Monthly and seasonal products are offered for Europe, Asia, Pacific or Canada, while even weekly for the U.S.

[16] To give a basic example, it would be the case of ice-cream sellers or swimming-pool runners.

of demand on price and therefore application of both price and volumes hedging is necessary to create a quality hedge. Such a hedge is called cross-sectional.

1. 3. 2. Weather derivatives vs. typical insurance

"The traditional market-based instruments for managing weather risk, e.g., insurance, are largely undeveloped and unavailable in most parts of the world. Given the growing interest in weather insurance markets, there are opportunities for innovation that have not been largely exploited."

J. M. Geyser (2004)

One might ask a question why to do not use common types of insurance. Since insurance contracts and weather derivatives are similar in many aspects, it may be confusing for a casual observer to find differences between these instruments.

It is relevant to say that weather derivatives have not emerged to replace traditional ways of insurance. Moreover, weather derivatives are not directly related to buyer's own financial costs as they are intended to profit from consequences of certain weather conditions. The payment is based on detected evolution of weather regardless of any impact on derivative's owner.

Insurance companies were involved in dealing with possible weather threats long time before the origin of weather risk market. And because weather derivatives are so specific and mostly have rather different intention, there is still a place for typical insurance contracts to stay in the market today. Both kinds of weather risk management techniques with their pros and cons serve to different purposes and it is not an exception that a company requires both of them to fulfil its specific needs.

According to Geyser (2004), highly specific weather derivatives differ from typical insurance contracts in several features listed below.

- Weather insurance contracts are designed to cover low-probability events with a high-risk such as hurricanes, storms, heavy rains or snowstorm blizzards, which may for example evoke cancellation of an outdoor sports or music event. In contrast, weather derivatives protect against higher probability events with lower risk as for example threat of warm winter or cool summer.

- Weather derivative's payout is designed to proportionally reflect the magnitude of a phenomenon while the payoff from a typical insurance contract has a form of one-term payment. In an insurance contract, the payout usually differs only slightly from the incurred loss. On the other hand, the fact that weather derivatives never properly match client's exposure is one of the most obvious restrictions to their expansion.
- When buying a typical insurance contract, an insured company must prove that suffered a financial loss in order to get the payment from insurance. On the other hand, if a weather event occurs, the payment from a weather derivative is made without proving anything. Therefore significant savings can be achieved on legal fees required to defend the payment.
- Since weather derivatives are traded securities, there is always a chance to re-sell these contracts that provides to companies increased flexibility in decision making. Based e.g. on updated weather forecasts, a company may decide to sell the derivative at some point of time before its maturity. When a company does not feel weather threat anymore, it may try to make some additional money on a derivative.
- Moral risk may be nearly removed in the case of weather derivatives as the reference is made to an index that none of counterparties can control. Since moral hazard is inherent in all insurance contracts, this feature also contributes to lower costs linked to weather derivatives.

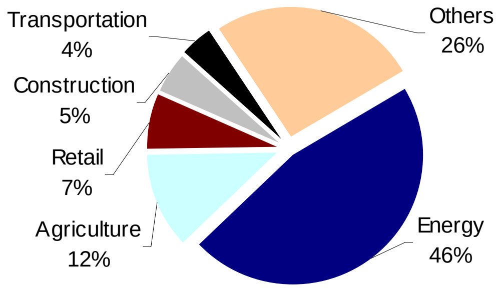
In a nutshell, since derivatives are less costly, do not require any demonstration of loss and provide protection from the uncertainty of changeable weather conditions, there exist strong reasons for giving priority to weather derivatives over typical kinds of insurance. Moreover, they might be used in both hedging against weather risk and making profits by speculation.

1. 3. 3. Trading weather derivatives

In general, there exist to standard ways how to trade weather derivatives. On the primary market are provided weather hedges for end-users that face weather risk in their business, e.g. utility and construction companies or agricultures (see Figure 4). In the U.S., the majority of derivatives is traded at CME – that is still the largest weather derivatives market in the world. In the CME are provided both options and futures for a wide range of the U.S. and European cities.

Beside the primary markets, there exists the opportunity to trade weather derivatives on secondary markets. According to Sytsma and Thompson (2002), several counter-parties, among which belong insurance companies, large energy companies, commercial banks or energy merchants, may be willing to assume the weather risk exposure of an energy company. Their aim is straightforward - achieving arbitrage profits by trading weather derivatives. Each single transaction in the primary market generally gives birth to several transactions within the secondary market.

Figure 4: Usage of Weather Derivatives by Industrial Sectors (2006)



Source: WRMA Survey (2006)

In contrast to insurance market, a participant that would make profit in the case of cold winter may meet in the weather derivatives' market a different company that prefers a gentle winter. Hereafter if these parties conclude a deal, both of them co be protected from their unique weather risk.

Despite the fact that the usage of weather derivatives in Europe is still limited, the situation has changed in the recent past. Buckley et al. (2002) discussed three possible reasons why there has been slower take up of weather derivatives in Europe in comparison with the U.S.:

- lack of reliable, standardised and cheap weather data in Europe
- less substantial extreme variations in weather in Europe
- deregulation of energy markets

Likewise, also less frequent usage of air-conditioning in Europe could have helped.

Since the middle of 90's, the primary market participants in Europe have been energy traders and insurance companies. With the beginning of new millennium, the weather derivatives' market entered also banks in several countries[17] and apart from administratively complicated OTC trades, an efficient management of risk was provided also by exchange-traded contracts.

The first attempt to trade weather derivatives on standardized exchanges in Europe was made in 2001 when LIFFE[18] launched trading of three temperature-based weather indices in London, Paris and Berlin. However, this activity stopped after the acquisition by Euronext. The next significant attempt dates to 2005 when Powernext, an European energy exchange based in France launched together with Meteo France the quotation of national temperature indices for 9 European countries (including France, Italy, United Kingdom, Belgium, The Netherlands, Portugal, Spain and Switzerland) with the focus mainly on energy companies.

The intention launched in 2005 further developed in 2007 by the development of Metnext – joint venture of Meteo-France and Euronext specialized in indices for weather risk management that even provides indices reflecting specific needs of individual firms with respect to their weather exposure (see Barrieu and Scaillet 2010).

Despite the global fall in trading weather derivatives in the last year,[19] there were concluded 34,068 contracts in Europe between April 2008 and March 2009 (according to internet pages of WRMA) that was about 9,000 contracts more than on the previous year. Nevertheless, the usage of weather derivatives in Europe is still of a low level.

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[17] E.g. Societe Generale in France, Deutsche Bank in Germany or Banca Nazionale del Lavoro in Italy.
[18] London International Financial Futures and Options Exchange (LIFFE) is a futures exchange based in London.
[19] For more info see http://www.energyrisk.com/public/showPage.html?page=860840.

2. NATURAL GAS MARKET

"Natural gas is believed by many to be the most important energy source for the future. The abundance of natural gas, worldwide as well as domestically, coupled with its environmental soundness and multiple applications across all sectors, means that natural gas will continue to play an increasingly important role in meeting demand for energy in the United States."

www.naturalgas.org* [*]

Although the composition of natural gas can widely vary, it is a mixture of hydrocarbons, primary formed by methane with other standard components such as ethane, propane, butane, pentane etc., that remain in the gas phase at standard temperature and pressure.[20] As a combustible gas it gives off a great deal of energy when burning. Unlike other fossil fuels natural gas burns cleanly and emits lower levels of potentially harmful by-products into the air.

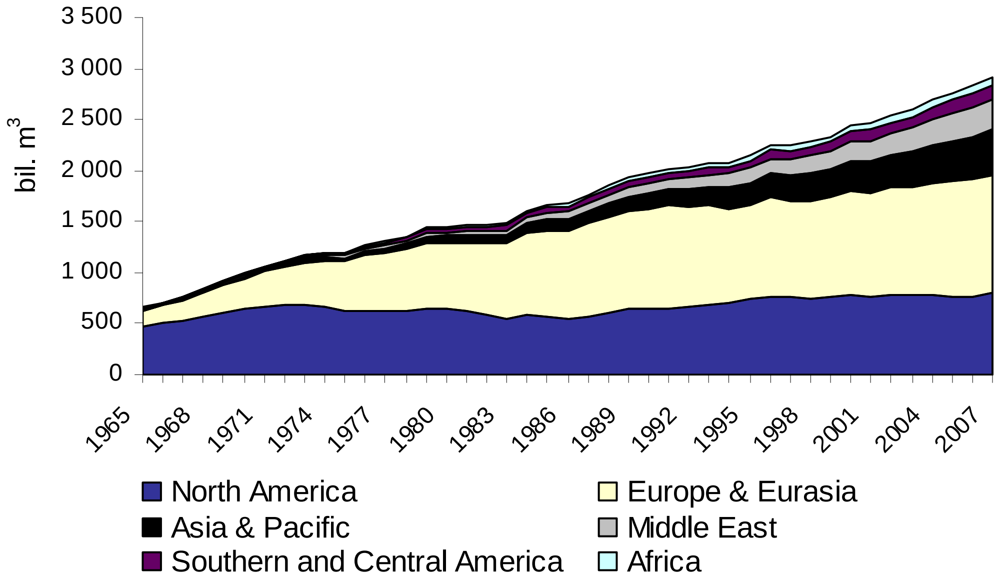
As global natural gas consumption has been steadily rising throughout 20th century (see Figure 5), the importance of natural gas as a clean and low-cost fuel helped in the 90's to further gross up of investments in facilities using natural gas, that declares also the fact that the vast majority of new electricity generation capacity build in the U.S. in the 90's is natural-gas fired (for more info see EIA 2008).

Energy Information Administration[21] (EIA) expects[22] "*… natural gas to replace oil wherever possible. Moreover, because natural gas combustion produces less carbon dioxide than coal or petroleum products, governments may encourage its use to displace the other fossil fuels as*

[*] Available at: http://www.naturalgas.org/business/demand.asp.
[20] This definition means weather conditions with the temperature of 20°C and atmospheric pressure.
[21] EIA is an independent agency within the U.S. Department of Energy that develops surveys, collects energy data on reserves, production, consumption, distribution, prices, technology or related information, and does analytical and modelling analyses of energy issues. Furthermore, the EIA publishes both long- and short- term energy forecasts.
[22] EIA (2008): *International Energy Outlook 2008*.

national or regional plans to reduce greenhouse gas emissions begin to be implemented." Consequently, EIA projects global consumption of natural gas to grow by 52% between 2005 and 2030.

Figure 5: World's natural gas consumption since 1965



Source: BP Statistical Review of World Energy June 2008

Concerning continuing trend of growing natural gas consumption, economies all over the world will become, and have been actually becoming even in recent past, more vulnerable to market disruptions.[23] Therefore business adjustments, e.g. in the form of hedging with financial derivatives, have to be done to avert potential financial losses.

Nowadays in highly energetically dependent world, natural gas as an energy source has elevated to an extreme level of importance with usage in four main areas:

- The principal use of natural gas is in *production of steel, glass, plastics or other products*.
- Through the use of gas and steam turbines, it is also a source for *electricity generation*. Since natural gas produces less carbon dioxide when burning, it is estimated to be widely spread in electricity power generation in future.
- It is widely used as a *heating source in manufactories*.

[23] For the information on the tight relationship of energy demand and GDP growth see BP (2008).

- And finally, what almost everybody knows from its own house, are deliveries of natural gas for heating and cooking in *residential domestic use*.

But there are also other and more recent alternatives of usage as for example:

- compressed natural gas is a cleaner alternative to typical automobile fuels – gasoline and diesel
- it can be also used to produce hydrogen which is valuable in the chemical industry, oil refineries and hydrogen vehicles
- other possible usage is in fertilizer production

With regard to weather sensitivity, it is straightforward that especially the dimension of residential heating and electricity generation is highly weather dependent. In conjunction with superior needs for manufacture heating during winters, absolute majority of the natural gas consumption is perceived as weather dependent.

2. 1. Market characteristics

Nowadays, there are two main forces shaping the European gas market (see Muir 2002):

- growing dependency on the non-EU suppliers
- continuing liberalization of the European market

Both of them have highly affected the supply side of the European gas market in the last decade. However, the natural gas market is beside these forces determined also by other phenomenon, which pressure companies in gas business to adapt to the actual situation in the market of the 21st century.

Sources of risks in the natural gas market, or generally in energy markets, might be distinguish with respect to their position; i.e. whether they lie on the supply, or demand side. With pressure on decreasing margins in the market and with the majority of sales being highly contingent on weather, the need of assuring coverage against possible risks will be increasingly important for companies in the gas business.

2. 1. 1. Deliveries of natural gas

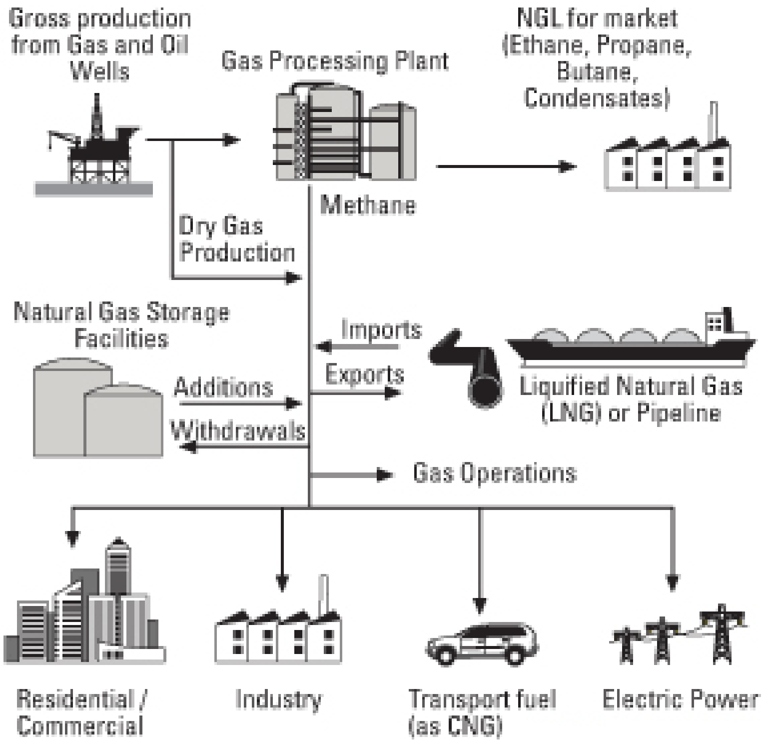
Natural gas supply stream, when the commodity is flowing from wells through pipelines as far as to burning places, never stops. Whole natural gas market functions as a uniform organism where all particular participants, functions and activities are in close connection in two segments (more detailed information about the segments provides Sturm 1997):

- exploration and production

- distribution and sales

In order to identify all possible sources of risk in the natural gas supply chain, let us now quickly go through Figure 6, where are components of this industry described more closely (as shown also by Augustine et al. 2006).

Figure 6: Natural gas flow from the well



Source: www.natgas.info[24]

- *Wellhead* - when a new natural gas field is discovered or there is associated gas in a crude oil reservoir, a production company drills for and extracts the crude commodity. The wellhead, into which the gas emerges when it comes up from the underground, funnels and controls the flow of gas to the surface.
- *Gas processing* - each wellhead is connected to the gathering system, a small-diameter pipeline system transporting gas to a central location, where is situated all necessary equipment required for delivering of a clean and saleable product. Volumes' processing can be characterized by extracting liquids and other by-products[25] in order

[24] See http://www.natgas.info/html/gaspipelines.html.
[25] There exists a specific active market for some of the by-products such as propane or butane.

to prepare a dry gas stream that meets industry standards for transportation through high-pressure pipelines.

- *Transport* - on the other side of the processing facility is located the receipt point where is the gas received by a larger-diameter pipeline, called the mainline. The natural gas is by these high-pressure pipelines commonly transported from regions of extraction into market areas and then to industrial end users, storage areas and local distribution companies. Because natural gas flows only from a high pressure area to an area of low pressure, compressor stations are set up along the mainline.
- *Liquefied natural gas (LNG)* – natural gas that is temporarily converted to liquid for ease of storage and transport is a special category. For example, this imported gas from overseas increases the supply in the U.S. by 3%. Of course, this can not be the case of the Czech Republic.
- *Storage* – natural gas system is not designed to produce and transport the full amount of natural gas demanded during peak-demand periods. Storage facilities are located along pipelines between gathering and market areas, mostly closer to final customers, to help in balancing receipts and deliveries of the commodity. The natural gas may be injected and withdrawn again to satisfy consumers' needs during a peak demand period, e.g. during cold winter days.
- *Local distribution company (LDC)* – usually owns and operates the network of pipes that carry natural gas from high-pressure pipes to end customers.
- *End customers* – mostly residential, industrial, commercial and ensuring electric power generation that are located at the end of pipeline systems.

Apart from all previously mentioned elements of the natural gas market and companies carrying given services, there is also other group of market participants that partially shapes the whole structure of the market - marketing companies. These companies, which are able to provide a various range of services, e.g. selling supplies or securing administrative services, are looking for profitable opportunities along a pipeline. Their most widely known role consists in functioning as *trading companies* that are buying and selling natural gas for creating a profit.

Many of trading companies that operate also as marketing companies may be, besides making a spread, i.e. margin as a difference between buy and sell prices, even seeking for other profitable occasions. With progressing deregulation, there have appeared many new market participants, which for example try to make profits on financial transactions. Also producers or local distribution companies are trying to take an advantage of these conveniences. Increasing number of market participants bearing on margins' decrease force companies to exploit all opportunities to sustain their profitable functioning.

2. 1. 2. Historical context - deregulation

In the middle of the 20th century, the natural gas industry was believed all over the world to be a "natural monopoly". As governments were afraid of setting unreasonably high prices for customers, regulation of this industry was for the first time established in 1938 in the U.S. But the structure of whole industry has gone through significant changes during last decades since it was hit by the process of deregulation and liberalization. Hence, the market left its limited flexibility with just few options for natural gas deliveries. In the following paragraphs, situation in the U.S. is employed as a benchmark case to show how this process looks like.[26]

- ***Regulated market***

In the natural gas market used to be a structure where exploration, production or trading companies were transporting natural gas to local distributors, which were selling the commodity mostly to end-customers. All prices were within this chain regulated by state governments; starting with prices of transport and ending with the prices for which traders were selling the commodity to regional distributors or even end-customers.

Structure of whole natural gas industry with regulated prices and established monopoly structures was very explicit with a very little space for competition and incentives to innovations and improvement of services. As an intention of various regulations was to ensure adequate supplies for customers at a fair price, sales were subject to government oversight at every single step of the way from a well-head to a burner-tip. Natural gas demand curve was highly inelastic. The basic presumption was that whole supply should be all the time able to cover demand at each location. This was a target that large state companies and monopolies with exclusive supply concession needed to meet.

As risks in the natural gas market have always lied primarily on the demand side, it was the role of national governments before liberalization to ensure that flexibility in gas production, which ensures the supply side to match the demand within a level that is not volatile too much, would be permanently sufficient. But within the U.S. this situation led in the end even to

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[26] For information on the history of regulation of the natural gas market see http://www.naturalgas.org or NYMEX (1998).

mismatch between the natural gas supply and demand, evoking shortages in the 70s and surpluses in the 80s. It was obvious that the structure of the natural gas market had to change. The regulation was no longer doing its job and competition in a free market was considered to be an alternative.

NYMEX (1998) states that before deregulation, the lack of incentives to drill for new supplies and reliable, readily accessible transportation both obstructed growth of the gas industry. The level of rigid regulation strongly declares also the fact that the liberalization of the natural gas market in the U.S., which started in 1978, resulted in a more significant increase in the production of natural gas than one would expect. Furthermore, a large extent for development of the market in natural gas futures and options was exploited by liberalization.

♦ ***Deregulation process***

Market structure has completely reversed during the recent past, mainly in the U.S. As a result, prices are no longer regulated and since the price of natural gas fully depends on interactions of supply and demand, the market is much more open to competition and therefore is functioning like other commodity markets. Hence, the market is accessible to opportunities as well as risks of competition.

Conditions in the natural gas industry were changing throughout the second half of the 20th century also due to the increasing importance of this commodity for the society. In the end, the idea of market deregulation with market based prices and competition emerged in the 80s and 90s. With shortages at the supply side in the U.S. reaching their peak in November 1978, the U.S. Congress enacted the Natural Gas Policy Act (NGPA)[27] that was aimed at abolishing of the American natural gas market regulation to:

- create a single national natural gas market
- equalize supply with demand
- allow market forces to establish the price on the market

Continuing gas market liberalization was ensured settlement of binding antitrust policy on volumes flowing into transport network and volumes sold to final costumers. This resulted in the decline of selling margins since new competitors were finally allowed to enter the market. With further progress in liberalization, major traders in the market faced increasingly higher competitive pressure that led to heightened stress on further margins' fall.

[27] For more detailed information on NGPA and its impacts, see for example http://www.eia.doe.gov/oil_gas/natural_gas/analysis_publications/ngmajorleg/ngact1978.html.

On the other hand, although the market may be fully liberalized, there could be still needed a national authority holding surveillance power on pricing. Its decision may limit the ability to increase costs for customers, chiefly tendencies of main players in the market to sell the commodity for inadequately high price to residential and commercial users.

♦ ***Consequences***

Lower prices for customers and new discoveries of natural gas fields were achieved as a consequence of deregulation in the U.S. Opening of the industry and avoidance from strict regulation brought also increased efficiency and motivation to technological improvements. Despite the fact that looking for new natural gas fields brings companies to hardly attainable places to meet increased demand requirements, ways to extract the commodity are today more efficient, cheap, and easy than before.

As price variations are common in deregulated markets, both producers and consumers react to these changes rationally. Since there are reasons, mostly technological, that force producers to continue producing at the same level even in a period of lower price, also consumers do not frantically change their demand with just a little change in prices.

2. 1. 3. Natural gas supply and demand

In a view of non-problematic commodity deliveries, the natural gas market heavily relies on resources available to extraction. As a petroleum by-product, natural gas is usually found wherever is located also crude oil, what means in reservoirs deeply under the land or oceans' floor.[28] According to the United States Energy Information Administration[29] (EIA), global natural gas reserves reached 6.168 trillion cubic feet by the beginning of 2008, what is sufficient enough cover world's demand in the near future without any troubles.[30]

The structure of natural gas supply and its determinants are very straightforward. Beside demand and occasional natural disasters, there is in general one other factor essentially affecting supply – price. Producers have with higher natural gas price more incentives to search for new reserves. To do not have maintenance and production costs exceeding sales

[28] Compared with oil, natural gas is considered to be easier to drill.

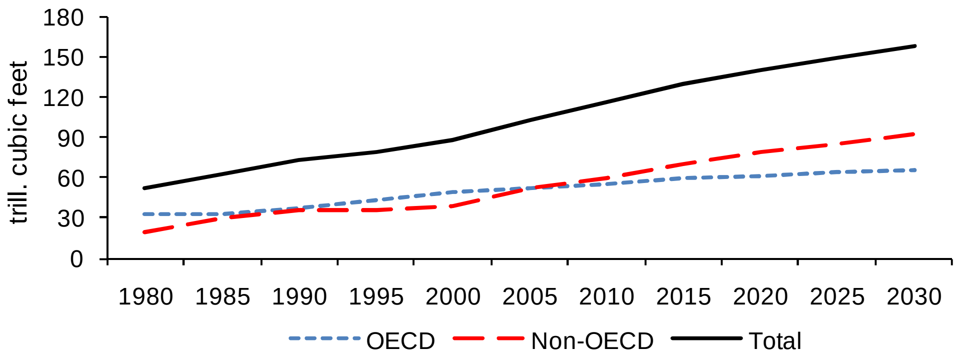
[29] EIA, established in 1977 by the U.S. Congress, is the independent statistical agency within the U.S. Department of Energy. It should provide policy-independent data, forecasts, and analyses on energy markets.

[30] EIA (2008): *International Energy Outlook 2008*.

revenues, it makes sense that with falling prices there comes up the producers' tendency to close down the least profitable wells.

Global natural gas demand continues to grow with power generation as the primary driver in the U.S. and Europe (for more detailed information see EIA 2008). Considering dependencies in the market, growing natural gas demand (as it is forecasted in Figure 7) should logically lead to higher commodity prices as well as natural gas supply.

Figure 7: Global natural gas consumption forecast until 2030



Source: International Energy Outlook 2008

Demand for natural gas has always been cyclical as it changes with various periods of a year as well as with different seasons. Because the primary driver of demand has always been the need for residential and commercial heating, demand is clearly highest during the coldest months of a year, reaching its peaks in January or February, whereas lowest in the warm summer moths as June and August. The situation has been recently partly changing over the world with enlarged usage of natural gas for electricity generation. Increased demand for electricity due to residential and commercial cooling leads to the higher requirements on supplies of natural gas even during warmer months. Consequently, there is today milder decrease in natural gas demand during summer months than what used to be.

♦ ***Determinants of the natural gas demand***

Beside the natural gas consumption cycle, there are three main drivers determining the short term demand, which may push the demand to be far from long term predictions.

1) ***State of economy*** may have a considerable effect particularly on the natural gas demand of industrial consumers in the short-term. In a period of economic expansion, demand for natural gas usually rises due to the growing industrial production. On the other hand, when the economy passes through bad times as it is actual situation in the world, demand for natural

gas decreases mainly due to restricted consumption of industrial plants or even because of closing down some of manufactories.

2) ***Price of natural gas***, which is created by interactions of supply and demand, can either affect the demand in a reverse way. Whenever the price is too high, there always exist some consumers, particularly industrial and power plants, which are able to switch from natural gas to other types of fuels.[31] Whenever there is a significant upward swing in the natural gas price, companies selling other fuels (electricity, coal, etc.) may compete and try to entice away customers from natural gas traders by setting a more feasible price.

In spite of the fact that residential customers may immediately adjust their thermostats when they are not interested in paying excessively high prices, natural gas demand is firstly influenced by the number of customers that are loosing interest in the commodity. This is a long term process as home-owners or commercial managers usually have to be convinced that the change of fuels will bring permanent and favourable alternation. Nevertheless, commercial customers with large consumption and possibility of a dual-fuel capacity may be an exception and therefore decide on switching fuels even in shorter time.

3) ***Weather*** is the third driver affecting natural gas demand. Since it may cause shifts in demand during any particular season, for example consumption's peak during an extremely cold winter may be more pronounced than usually due to weather.

2. 1. 4. Market disturbances

"… factors which influence gas demand include the gas price, the impact of energy conservation measures, general economic growth and in particular the weather, which is the main determinant of short term variations in gas demand."

Energy Markets Outlook[*]

Problems on the supply side might have various reasons. Apart from threats of natural disasters, there is a high chance of technical failure or political disputes that influence the natural gas market. Notwithstanding that the stability of the European gas market was

[31] For example switching to cheaper coal leads to lower demand for natural gas since especially relative prices between fuels, mainly in the long term, play a meaningful role.
[*] Department for Business, Enterprise & Regulatory Reform (2007): *Energy Market Outlook*.

previously tested on a number of occasions, there were never experienced any large disturbances in supply until 2009.

Before 2009, supply side problems were perceived as relatively minor threats. All major cases in the history of the European gas system were solved with help of storage facilities or other pipeline systems without any significant problems. De Joode et al. (2005) list several widely known problems with the European natural gas supply over the last twenty years:

- Strike among offshore workers in the United Kingdom and Norway in 1986 caused a loss of approximately quarter of total Norwegian supplies for several days.
- Bomb attack on the Trans-Mediterranean pipeline in Algeria in 1997. Because of the use of gas storage and alternative suppliers, there was not any significant impact on the market.
- As Ukraine demanded for crossing its area a transit fee by means of unauthorized diversions, it caused disturbances in the transit of natural gas from Russia few years ago. Even in this case did not arise any serious problems in Europe because of other opportunities to substitute the withdrawn supply.
- Transit difficulties in Turkey caused some physical shortages in 1994 and 1995.

Aside from Europe, there happened several disruptions also in parts of the world. The largest American one called the El Paso natural gas disruption occurred in 2000 in New Mexico. Also in this case were markets independently able to avoid severe gas shortages.

After a long time when supply in the European gas market, which the Czech market is a part of, had not been hit by any significant disruption, the “Russia-Ukraine gas dispute” appeared with the beginning of 2009.

When Europe’s gas dependency on Russia is so significant that some countries are reliant upon Russia even with 100% of their total natural gas supply, it is likely that problems on the supply side in the near future will arise especially due to similar political reasons.

The ability to deal with any supply side disturbances is today fully dependent on available alternative sources: usage of another pipeline, sufficient storage surplus or transport capacity in the system. When a gas-line breaks down or is cut off (e.g. due to political disputes), different source of natural gas or just another pipeline from the same source is usually used to cover the missing supply. These drop-outs are today usually solved without any long-term impact on the end-customers. Moreover, technical failures are often quite easy to repair and thus the commodity is flowing again through the same pipeline within a couple of hours.

However, current extreme dependency of countries mainly from Eastern Europe on Russia may under some circumstances, i.e. especially during winter, cause substantial problems for the whole economy.

Table 1: European countries' gas imports from Russia in 2004

country	from Russia (bil. cub. ft.)	% of domestic consumption	country	from Russia (bil. cub. ft.)	% of domestic consumption
Germany	1 290	39	Ukraine	850	35
Italy	855	31	Belarus	698	99
Turkey	506	65	Hungary	318	64
France	406	24	Czech Rep.	253	77
Austria	212	69	Slovakia	226	99
Poland	212	43	Poland	212	43
Netherlands	94	6	Finland	163	98
Greece	78	82	Romania	138	22
Sweden	39	< 0.5	Lithuania	103	100
Belgium	7	1	Bulgaria	99	99
Denmark	< 0.5	< 0.5	Moldova	77	100
Ireland	< 0.5	< 0.5	Latvia	62	100
Portugal	< 0.5	< 0.5	Georgia	39	100
Spain	< 0.5	< 0.5	Estonia	34	100
UK	< 0.5	< 0.5	Slovenia	20	52

Source: Gelb, B. A. (2007)

Since there were no big troubles in the past with natural gas supply in the majority European market, it seems that major risks have been related to demand fluctuations and the ability of supply to cope with them. In addition changeable prices, there are several other reasons affecting the level of demand for natural gas among which weather is of the highest importance.

2. 2. Czech natural gas market

In this part, we describe the situation in the Czech gas market and market structure with all contingencies.

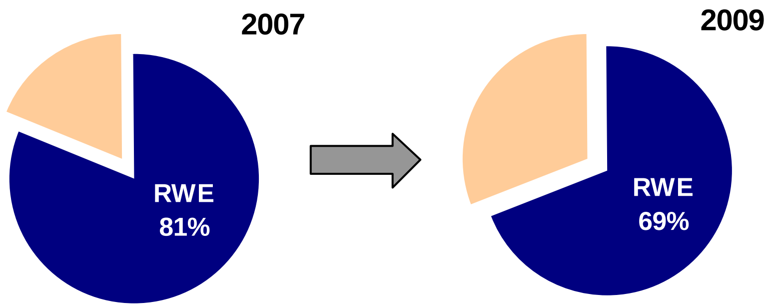
2. 2. 1. Liberalization

The situation in the Czech natural gas market started to change few years ago as European Union's (EU) directive no. 2003/55/EC, which is valid since 2004, installed an obligation of EU-member countries to implement remedies to improve the situation in the natural gas market (for more information about the liberalization of the European natural gas market see e.g. Muir 2002). As we have already mentioned the American natural gas market and its liberalized environment, the intention of EU is to get successively closer to the situation in the U.S through the free option to choose a supplier by wholesale customers (since 2004) as well as households (since 2007). At the same time, legal unbundling of runners of supply stream is demanded,[32] the role of national regulatory offices is reinforced and the public service commitment is assured. Expected consequences of liberalized EU natural gas market are:

- lower prices
- admission of new market participants
- increased competitiveness
- enhanced effectiveness
- higher level of provided services
- higher security of supplies

Until January 1, 2005 the Energy Regulatory Office (ERO) limited operators of transit and distribution networks in the Czech Republic and was setting tariffs for the entrance to the network. All deliveries were done through RWE Transgas, a.s. (RWE TG) with no change for customers to change the supplier. Sequential liberalization started in 2005. Based on the law no. 458/2000 Sb., the Czech natural gas market is since April 2007 administratively fully opened to competition in supplies to end-customers.

Figure 8: Dominant player's market share (sales to end-customers)



Source: RWE TG[33]

Despite the fact that in the Czech Republic have appeared about 60 new traders since the beginning of liberalization,[34] there are just 8 really significant new traders in the market.

[32] Particular companies in this stream are not the same legal objects what in the Czech natural gas market means that RWE TG, the main supplier in the market, is permitted to run the distribution network at the same time etc.
[33] Presentations: *RWE Group in the Czech Republic in 2007* and *RWE Group in the Czech Republic in 2008*.

Although these traders have so far taken just a limited market share, it was enough to result during a relatively short period in fall of market share of the main market player, RWE Group[35] (see Figure 8). Since end customers were allowed to change their supplier, RWE Group has since the beginning of liberalization lost 12% of its share in the market for end customers,[36] chiefly due to tough competition in the market for main industrial customers.

Price, as the main motive to the change of a supplier, is logically in the background of fall in the market share of the dominant player. As the price of natural gas in the Czech liberalized market consists of a regulated component set by ERO once a year,[37] price for structuring (storage), non-regulated component of price and a margin, it is straightforward that the pressure on margins' lessening and consequently lower profits of gas traders is much higher than before 2007.

2. 2. 2. Czech natural gas supply

As there has not been any failure of gas deliveries since 1990, the Czech natural gas market is, despite the fact that only some 1% of resources is indigenous[38], characterized by a high level of security of supplies. Based on the data provided by MIT (2008), natural gas was in 2007 delivered to the Czech Republic from two main sources:

- Russian federation (78%)
- Norway (22%)

Since imports of natural gas are crucial for the Czech Republic, long term import contracts belong to basic arrangements that contribute to the stability of the market. Given the contracts of RWE TG with its Russian and Norwegian suppliers, it is possible to import yearly 11.4 bil. m^3 of the commodity. According to the contract of another trader in the Czech market - VEMEX, s.r.o. with Gazprom, total possible volumes of natural gas that could be imported to the country overreach even 12 bil. m^3 (MIT, 2008).

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[34] According to the Czech Republic's *Report on the Security of Natural Gas Supplies in 2007*, there are in total 88 companies holding the permission to trade natural gas. In the retail market there are just 8 traders where each is supplying gas at least to 90 ths. customers.

[35] RWE Group in the Czech Republic operates in both wholesale market via RWE Transgas, a.s. and market for end-customers via its regional gas companies.

[36] It is necessary to distinguish between the market for end-customers, where RWE holds via its regional distribution companies' share of 69%, and wholesale market, where RWE holds 86.5% in 2009 mainly due to sales to Pražská plynárenská and E.ON.

[37] That in gas-business terminology embraces transport and distribution.

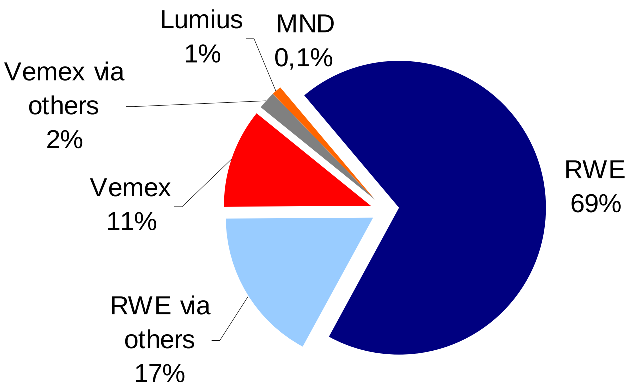
[38] With the main domestic supplier - Moravské naftové doly, a.s. (MND) in southern Moravia and marginally OKD Paskov in northern Moravia.

Considering the State Energetic Conception of the Czech Republic (2004) and the dispute of Ukraine and Russia in 2009, the goal of the country has to be to cut dependency on imports from Russia with the help of several new gas lines, which are currently being discussed across Europe.

Beside natural gas imports, there is obvious one more important factor significantly participating on gas supplies – gas storage. In order to assure non-problematic deliveries during periods with highest consumption requirements or to cover blackouts in imports as it happened in January 2009, the commodity flows into pipelines also from underground storages. Satisfactory storage space in the Czech Republic is one of the main reasons why there have not happened any disruptions in supplies during the last twenty years. Their importance underwrites also the fact that even during the warm year of 2008, there was extracted 1,830 mil. m^3 from underground storages, what equals to 21% of total yearly consumption in the Czech Republic.[39]

- ***Natural gas suppliers***

Figure 9: Czech natural gas wholesale market in 2009



Source: RWE TG and Balance Centre

As the market with assured non-problematic deliveries is nowadays opened to competition, there are several main players in the market engaged in deliveries of the commodity to customers (see Figure 9). As competition in the market becomes tougher, companies' profits are threatened what is also the case of the market leader.

[39] Similar volumes were also injected into storages mainly to balance supplies with demand requirements in the next heating season. See http://www.upd.cz/ for more data about the usage of natural gas storage.

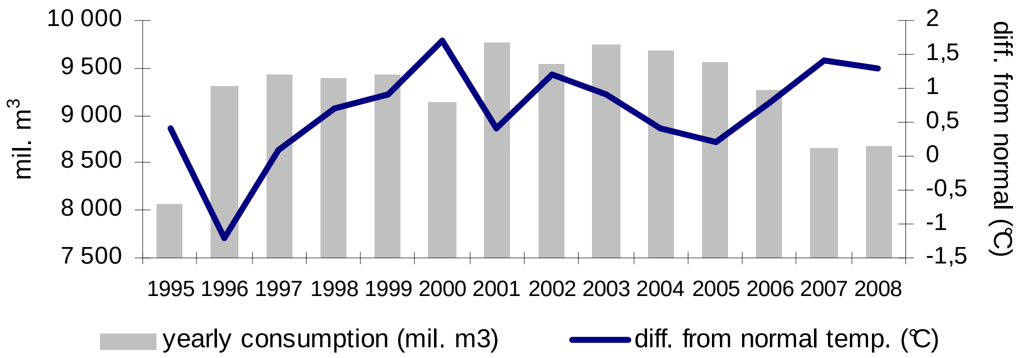
In 2009, there were 4 participants in the Czech wholesale market (with their own gas deliveries from abroad) and several others in the market for end-customers, e.g. Pražská plynárenská or E.ON, which were buying the commodity from two main traders – RWE Transgas, a.s. and Vemex, s.r.o and consequently provided supplies to end-customers.

2. 2. 3. Czech natural gas demand

"Natural gas consumption in the Czech Republic has been at a standstill since 1997 and in the previous years there happened even a mild fall in consumption. An exception is year 2007 when there was higher fall in natural gas consumption due to unusually high temperature during the heating season."

Ministry of Industry and Trade*

Figure 10: Yearly consumption and normal temperature



Source: BC

Natural gas consumption was steadily decreasing between 2003 and 2007. This trend stopped in 2008 when consumption reached 8,685 mil. m3, what was 0.4% more than in the previous year. Both Balance centre[40] (BC) and MIT consider above average temperatures in this period as a crucial reason for low consumption. As it is obvious from Figure 10, natural gas consumption is influenced whenever there is a significant difference from yearly normal temperature.[41]

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* MIT (2008): *Zpráva České republiky o bezpečnosti dodávek zemního plynu za rok 2007*.

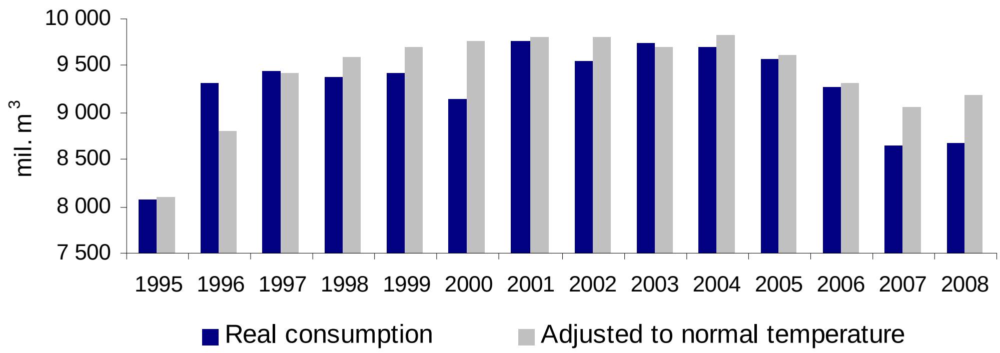
[40] Balance centre (BC) – in Czech "Bilanční centrum" is responsible for processing the data on the Czech natural gas market and handing them over to MIT, ERO and Czech Statistical Office.

[41] I.e. as the average temperature in 1996 was 1.2% below normal, meaningful increase in gas consumption occurred. On the other hand, highest above average yearly temperatures in 2000, 2007 and 2008 resulted in falls in gas consumption.

Nevertheless, consumption does not have to be far from expected values only due to temperature as there are other effects having an impact on consumption, e.g. economic cycle. Figure 11 transparently shows development of both real consumption and its values adjusted to the normal temperature.[42]

Even in the adjusted scenario is apparent decreasing trend in consumption since 2004 that is induced mainly by increasing prices and consequent tendency of customers to save money by lower consumption. Nevertheless, the impact of weather unambiguously displays the comparison with real consumption in a particular year as there occur big differences between adjusted and real consumption at the same time temperature highly differs from normal.

Figure 11: Real consumption vs. adjusted to temperature



Source: BC

♦ ***Customer segments***

There exist following four consumer segments (given their yearly consumption), according to gas business terminology, which participate on republic's overall consumption:[43]

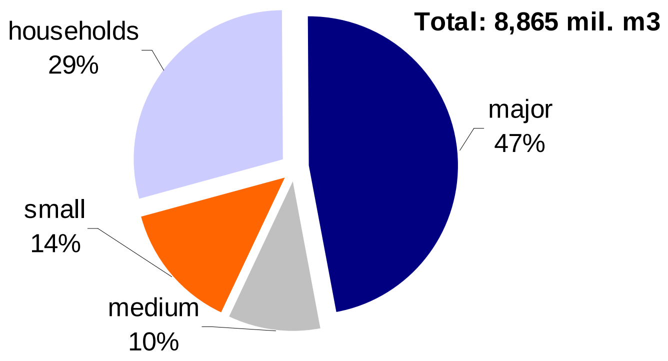
1) households
2) small customers (yearly consumption up to 630 MWh)
3) medium customers (up to 4,200 MWh)
4) major customers (over 4,200 MWh a year)

Since various segments are differently susceptible to weather changes, they comprise a significant feature in planning yearly consumption and especially its monthly structure. Given

[42] Normal temperature is a 30-years average of daily temperatures announced by the Czech Hydrometeorological Institute.
[43] More information about customers' segmentation see at http://www.liberalizace.cz/text/liberalizace-trhu-se-zemnim-plynem-v-cr.html.

monthly consumptions of particular customer segments, it is obvious that consumption of each particular group is influenced by temperature.[44]

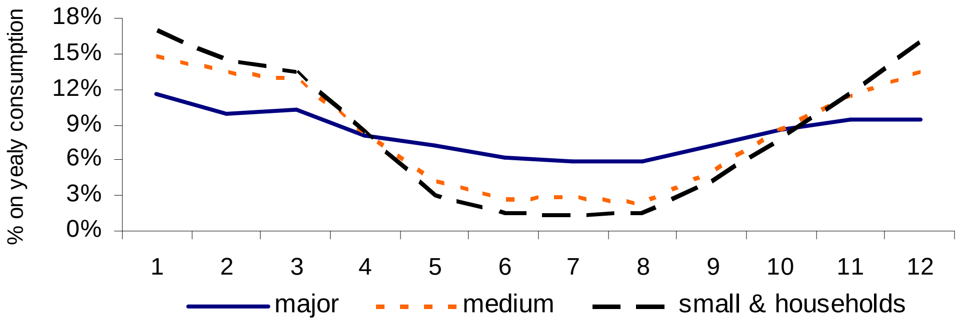
Figure 12: Customer segments in 2008



Source: BC

With regard to Figure 13, it is obvious that there is not such a significant fall in consumption of major customers during summer as in the case of small customers and households, which offtake the majority of their yearly volumes during winters.

Figure 13: Monthly consumption of customer segments in 2008



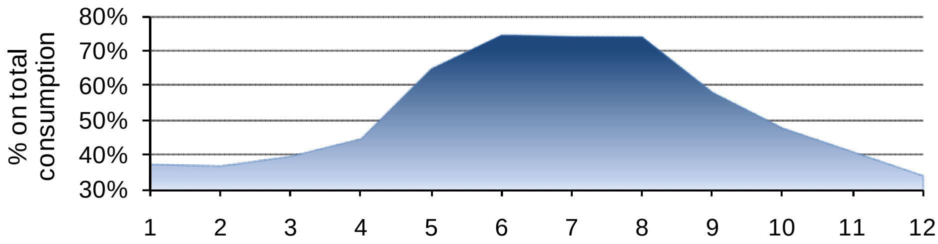
Source: BC

Small industrial customers and households, which comprise 43% share of yearly consumption in the Czech Republic and use the commodity principally for heating purposes, almost stop off-taking natural gas during summer. On the other hand, major customers that often use the commodity directly in production process, keep a relatively high level of consumption even during warm days (that is obvious from a relatively flat monthly profile of major customers shown in Figure 13). It is the segment of major customers who contributes the most to so

[44] Due to the fact that the consumption monthly profile of small customers and households was in 2008 approximately identical, I merged them in Figure 13.

called “base load demand” which is kept at a high level even during the warmest days in summer (see Figure 14).[45]

Figure 14: Share of major customers on total monthly consumption in 2008



Source: BC

A company has to be always aware of the structure of its portfolio of customers when considering impact of weather on natural gas consumption. Therefore one of initial activities of a company should be such analysis leading to identification of shares of particular customer segments on whole consumption and their resistance against weather changes. Considering the situation in the Czech Republic, it is obvious that at least 43% of end customers (households and small customers) are heavily susceptible to changes in temperature, what is very obvious from their summer consumption habits. Moreover, these customers are generally able to modify their heating within a relatively short period that determines their consumption during whole year.

♦ ***Gas demand forecasts***

Companies commonly work in predictions of future consumption with the normal temperature. In prognoses of the Balance Centre[46], national consumption is expected to rise between 0.6% and 4.2% a year until 2013 when considering average daily temperature in particular years to be 8°C. In the long term prediction of MIT (2008), natural gas demand is expected to rise between 0.5 and 1.2 percent a year until 2017 with assumption of long term price stabilization and emphasizing usage of natural gas as an ecological fuel. Although the reality may be in the end, with potentially noticeable impact of weather, pretty different from the plan, one should logically count with some normal temperature when creating expectations.

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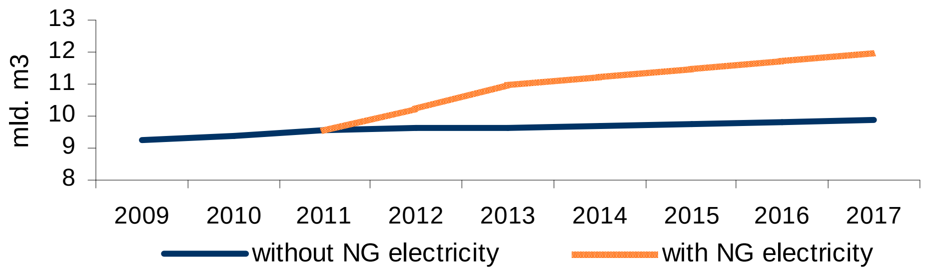
[45] As other customer segments almost do not offtake any gas during warm periods, the share of major customers on total monthly consumption substantially rises with warm weather (due to consumption of gas that is used in production – resistant against high temperatures).

[46] See http://www.upd.cz/upd_soubory/prognoza.html

Among other important factors influencing gas demand belong primarily long term economic development and building new steam and gas power plants. Since natural gas is used in the Czech Republic for electricity generation only insufficiently (according to the Austrian Energy Agency only 4.79% of electricity generation[47] in 2005), this commodity is employed in producing electricity about five times less than in countries of western Europe.

Figure 15: Natural gas consumption forecast until 2017



Source: MIT[48]

It is possible that consumption will rise in the near future primarily due to heightened interest in electricity generation from natural gas (see Figure 15), which could be consequently used in generation of some 20% of national electricity supply by 2017. Beside ČEZ, the main player in the Czech electricity market, also J&T and E.ON presented projects[49] on building new natural gas power plants in the Czech Republic.[50] Since the first plant could be started in 2012 at earliest, it is still a question what will be the final output from all these projections. But since this topic is nowadays highly discussed, it is likely that the share of natural gas on electricity generation will noticeably rise, what would in the end bring additional volumetric risk to the Czech natural gas market because weather could potentially influence also new volumes of the commodity demanded by these power plants.[51]

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[47] See http://www.energyagency.at/enercee/cz/supplybycarrier.en.htm.
[48] MIT (2008): *Natural Gas Consumption Outlook*.
[49] J&T is one of the most active investor groups in the Czech Republic and also Slovakia and is also an important long term investor in the energy industry. E.ON is one of the main players in whole European energy markets, trading both electricity and natural gas.
[50] Even though MIT still counts with gas electricity plants as a marginal electricity source, there have been announced projects with the total capacity about 2,000MW a year what is yearly output of nuclear power plant Temelín. For example, only ČEZ's intention is to build electricity plants in the northern Bohemia with the total capacity of 1,200MW.
[51] Since there is a portion of electricity generated for cooling requirements during summers. If the summer is colder than usually, it is reflected is lower electricity generation for cooling requirements and therefore also in lower natural gas demand. .

3. WEATHER IN THE CZECH GAS MARKET

The natural gas industry, in which profits of companies rely heavily on consumed volumes, is one of the most sensitive to weather. This dependency reaches its peak during the heating season when natural gas consumption is highly influenced by weather. Moreover, financial risks associated with fluctuations in consumption are further accompanied by the correlation between natural gas demand and prices because the sign of periods with high natural gas demand is also the presence of high commodity prices, whereas low natural gas loads are affiliated with lower prices. Hence, even more pronounced impact of weather on company's financial performance is present in the periods of high consumption.

Energy companies try to model natural gas or electricity demand with the help of various approaches, notwithstanding that *"there is no 'best' method of forecasting, even when the problem is as tightly defined as in these utilities."* (Fildes et al. 1997). Alfares and Nazeeruddin (2002), Piggott (2003), Feinberg and Genethliou (2005) or Taylor et al. (2006) give an overview of the most popular energy demand forecasting methods among which belong various regression types (simple linear, multiple or non-linear), Box-Jenkins method, Neural Networks, Expert Systems or Fuzzy Logic. Moreover, the list of potential "effectors" containing temperature, wind speed, snowfall, rainfall, time of year, holidays, demographic data, gas price etc. is provided.

The primary reason for the application of forecasting methods is obvious – reduction in costs. Fildes et al. (1997) state that: *"To counter the possible erosion of their profit margins, the companies, instead have looked to minimize their costs. On a daily basis, the companies can become more efficient by accurately predicting demand with a consequent reduction in storage and distribution costs."* In addition, we have to be aware that various approaches may contribute to substantial savings in different ways.

In this thesis, we discuss the threat of adverse temperature in the natural gas market. As we have already mentioned in the introduction, there exist two basic manners of protection against too high temperatures: (i) offtake flexibility bands set in contracts with customers, which may be based also on the results of a regression analysis, and (ii) weather derivatives. Hence, in the protection of company's financial performance, both kinds of protection might be applied.

Let us now imagine the situation that an extremely warm winter occurs. *"What will be then the impact on a company trading natural gas?"* Since there are costs linked to the fall in natural gas demand, the sellers generally specify yearly, monthly or daily offtake flexibilities in the contracts with their customers, which may be some smaller traders or even industrial end-customers. Once such minimum quantities are specified in the contracts, it serves, beside the cuts in costs due to the more predictable usage of gas storage, transportation system etc., also as the first protection of the seller from the loss of revenues that may arise due to adverse weather conditions or the fall in natural gas consumption because of lower industrial production or high energy prices. Moreover, the sellers are forced to use this feature in contracts also since it is common practice in the market that is applied by its own suppliers.

In the case that a customer does not offtake its minimum quantity stated in the contract, he is obliged to pay according to the provisions of a contract for volumes up to his pre-specified minimum offtake. Therefore, it is in the interest of customers in the competitive market to request flexibility conditions that the most precisely reflect their own needs in setting flexibility bands, i.e. reflect their temperature sensitivity or potentially some other factors relevant to their natural gas demand.

In this thesis, we try to model temperature sensitivity of gas consumption of a given customer portfolio. In addition, we also search for the impact of other factor – the day of a week. Consequently, we should be able to predict what should be the consumption of the portfolio on a given day with respect to some temperature profile and the day of a week. With respect to the contractual quantities, such an analysis may be consequently used just in the setting of maximum flexibility bands in contracts.

An alternative and potentially also additional way of hedging against weather risk is provided by weather derivatives. *"As any other derivative securities, weather derivatives serve the ultimate purpose of risk transfer."* (Cao et al. 2004a). Therefore, the analysis of relationship between natural gas consumption and weather may be used also in searching for the capability of companies in the Czech natural gas market to use weather derivatives. Similar investigation of the existence of a statistically significant relationship between energy consumption and various weather variables was performed for example by Gabbi and Zanotti (2003) for the Italian gas market, Fildes et al. (1997) for the British gas market or by de Dear and Hart (2004) for the Australian electricity market.

With regard to data for the Czech Republic, we discuss the dependency of consumption on only one weather variable - temperature, which has certainly the heaviest impact on the natural gas market, as it has been already proved by various studies[52] (see Gabbi and Zanotti 2003, Cao et al. 2004a or Piggott et al. 2000 etc.). This study should reveal how much of the variability in natural gas consumption may be explained by temperature and the presence of a particular day of a week. In addition, we discuss whether it could be favourable to use and how to use weather derivatives in the Czech natural gas market.

3. 1. Literature review

As we have already stated, there exist various approaches to modeling natural gas consumption and its dependency on weather. In this thesis, we apply regression models to assess two obvious features of natural gas consumption in the Czech gas market: (i) the relationship of consumption and temperature and (ii) lower consumption by industrial customers at weekends. We try to build up a model that should assign some level of consumption to the given customer portfolio with respect to the dependency on a given day of a week, its weather sensitivity and present temperature profile.

Let us now look at different studies dealing also with the weather sensitivity in the energy industry. Brief information about the dependency provide Cao et al. (2004a), who perform a basic linear regression to search for the dependency of monthly natural gas demand on temperature for Illinois residential customers for the period starting with January 1989 and ending with November 2002. Even with this basic statistical method, they reach the explanatory power (expressed by R-Square) of the model equal to 94% that corresponds to an extremely high impact of temperature on natural gas consumption.

Abiodun (2002) demonstrates some 5-6% impact of 1°C change in temperature on natural gas consumption in the U.S. Considering other weather variables, influence of consumption by

[52] Gabbi and Zanotti (2003) do not find weather variables as rain, humidity or air pressure statistically significant in the model predicting natural gas consumption.

snow, rain and wind reaches maximally 5%, respectively 2% and 0.5%. The effect of bank holidays is generally estimated to cause the fall in consumption between 5 and 20%.

Similar results provide also Piggott et al. (2000), who assess temperature as the key factor affecting the level of natural gas demand in the United Kingdom. As a rough estimate, the change in temperature by 1°C during winter is reflected in the change in gas demand of 5-6%. An interesting finding is also the fact that the dependency of natural gas demand on temperature is approximately linear for temperatures below 14°C. The impact of weather on consumption starts to weaken over this level and is insignificant for temperatures above 18°C.

Fildes et al. (1997) build a day-ahead natural gas demand forecast model with the usage of inter-day differences, which is consequently used to calculate the most efficient intake from the National Transmission System into the regional system that leads to more effective management of regional gas storage and reduced costs. They forecast the change in natural gas demand with respect to the change in temperature and addition of the factor, which adjust the demand on the days of industry shutdown. Based on the data provided by British Gas with average gas demand of 870 mil. cubic feet (mcf), they estimate that change in temperature by 1°C leads to the change in gas demand by 75.6 mcf. Thereunto, the decrease in demand by approx. 150 mcf is present at weekends. After the inclusion of autocorrelation term, R-Square of their model reaches 83%.

Gabbi and Zanotti (2003) search for the existence of statistically significant relationship between daily gas consumption in two Italian cities, Milano and Palermo, and more weather variables - temperature, rain, humidity or air pressure. They start with only a simple model and progressively add new factors to assess their impact on natural gas consumption separately. They also search for the influence of particular weather variables lagged up to two foregoing days and for the impact of presence of various days of a week or months during a year. In the final model, the impact of temperature on the present and two preceding days is assessed as significant as well as the impact of weekend days and holidays. After the inclusion of autoregressive process, the explanatory power (R-Square) reaches 97.5%.

To sum up, Gabbi and Zanotti (2003) demonstrate that temperature is the most significant explanatory variable in both cities while rain, humidity and air pressure are considered as statistically insignificant. In accordance with their expectations, there is present also high influence of seasonality. Such a model that predicts natural gas load might consequently serve as the first step leading to the hedging of weather risk.

Roustant et al. (2003) also try to capture the majority of features affecting natural gas demand with the model including several variables, e.g. temperature, trend, seasonality, volatility or consequently also price uncertainty. They show that the determination of a trend or seasonality might be beneficial for option pricing.

Tol (2000) investigates with regression methods the impact of weather volatility on more spheres of Netherlands' economy - international tourism, agriculture, water, natural gas and energy consumption. He sets a model predicting annual gas consumption that is applied to three customer segments: domestic, industrial and power plants. Temperature, natural gas price, lagged value of consumption and weather trend are included in the model as explanatory variables. The total R-Square of the regression reached 89.5% with the following results for particular customer segments:

- households – 96%
- industry – 81%
- power plants – 73%

Temperature plays a fundamental role in Tol's estimation as degree-days correctly indicate natural gas usage in the market. An interesting finding is also a fall in households' consumption with increasing price of the commodity. As there is no proven link between electricity generation and weather, he alleges that the usage of natural gas for power generation is not related to degree-days.

Several authors were interested also in the evaluation of risks linked to weather variability with the aim of consequent assessing of hedging opportunities. Campbell and Diebold (2005) believe that weather forecasting is crucial to all participants in the weather derivatives market. The mere fact that for example utilities or energy companies face weather fluctuations does not mean any significant weather risk if the variability is highly predictable. Weather risk is therefore seen to emerge from the unpredictable component of weather fluctuations – so called "weather noise". To determine hedging potential and formulate respective hedging strategy, it is essential to stipulate how much weather noise exists in the market.

3. 2. Summary of raw data

Both the deregulation process and current global financial situation further underlined the growing importance of cost and revenue control. Since companies usually build their business plans around some normal temperature, temperature's variability may cause, despite of highly improved accuracy of weather forecasts in recent past, perceptible changes in demand and subsequent significant financial losses.

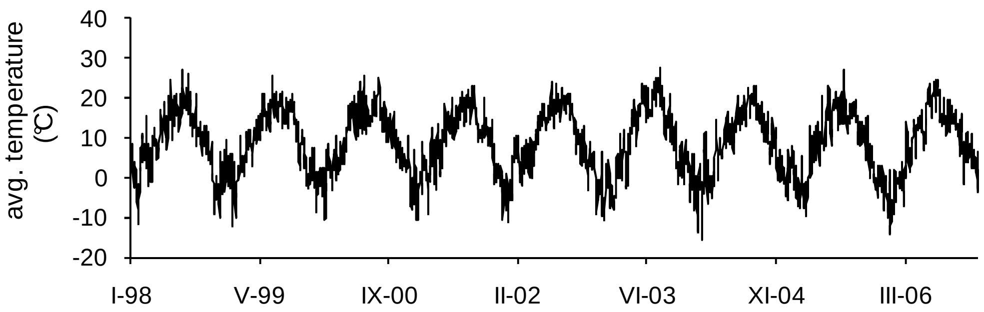
By reason that we are focused on the evaluation of weather risk, let us now introduce the data we are using. With the aim of consistency, we work with daily data for the period of 9 years; from January 1, 1998 to December 31, 2006 that counts in total 3,287 observations.

3. 2. 1. Data on temperature

Weather variables are commonly built on a weather index for a particular city. Thus it is reasonable to assume the weather index that considers temperature observations in Prague, as the biggest and best known city in the country, as the most plausible to be selected by companies providing weather insurance. Thus, we work with the data provided by the Czech Hydrometeorological Institute[53] (CHMI) on daily average temperatures at the measure point Prague – Ruzyně, which is both well suited and frequently used. We compute the daily average temperature as the mean of daily maximum and minimum, that is a common practice in derivatives' markets (see e.g. Mraoua et al. 2005 or Jones 2007).

$$T_{avg} = \frac{T_{\max} + T_{\min}}{2} \tag{1}$$

Figure 16: Daily average temperatures at Prague – Ruzyně since 1998



Source: Auhtor

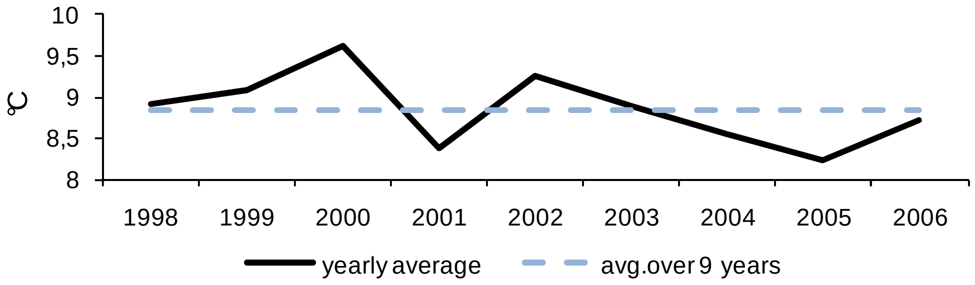
We use temperature measurements in Prague as a basis for whole country, although there might be observed climate diversities between particular regions. Nevertheless, the situation in the Czech Republic is completely different than in the U.S. or Italy.[54] Regarding both

[53] CHMI is the central State institute of the Czech Republic in the field of air quality, hydrology, water quality, climatology and meteorology.

[54] If we were for example in the U.S. where weather is completely diverse in the north than in the south, it would be essential to study weather impacts with regard to these miscellaneous weather conditions.

location and area of the Czech Republic, climatic conditions within the country are in general relatively stable and therefore Prague's temperature does not deviate from the republic's average.

Figure 17: Yearly average temperatures

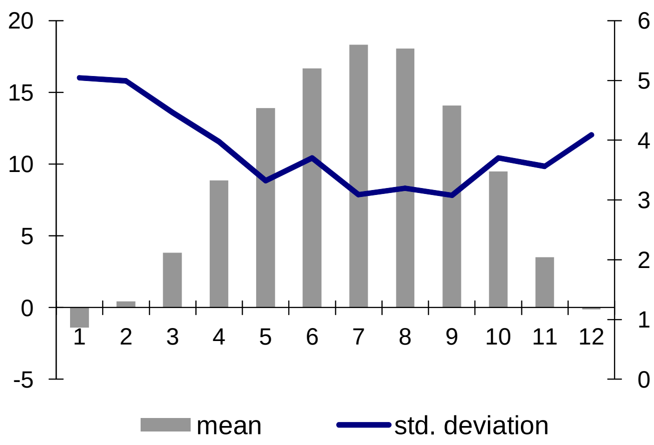


Source: Auhtor

Average daily values for the last eleven years plotted in Figure 16 reveal unsurprisingly strong seasonality in temperature, which corresponds with the general feeling that temperature moves repeatedly through periods of high and low levels as periods of the year are changing.

Figure 16 and Figure 17 show the development of temperature in the last 9 years. With respect to these figures, there does not seem to be any significant trend of increasing or decreasing average temperatures in the long term.

Figure 18: Daily temperatures per months – mean and standard deviation (°C)



℃	mean	std. deviation
January	-1.377	5.044
February	0.444	4.993
March	3.841	4.465
April	8.877	3.975
May	13.920	3.322
June	16.672	3.702
July	18.326	3.088
August	18.067	3.199
September	14.086	3.081
October	9.502	3.706
November	3.501	3.565
December	-0.129	4.090

Source: Author

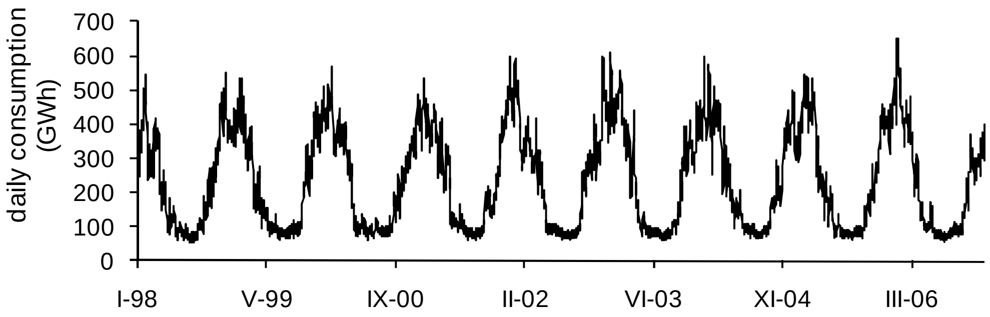
Apart from the yearly average temperature, more important for natural gas companies seems to be identifying of temperature variability over particular months. Since there is a significant impact of variations in temperature on natural gas consumption, it is important to identify, also for the purpose of potential hedging, when the variations in temperature reach their peak during the year.

With regard to Figure 18 it is facile to determine warm and cold periods (months) during the year and that temperature highly varies during periods when its monthly averages are low. Since the average daily temperature over the last eleven years was 9.0122 °C, the period from April to September could be labelled as warm, i.e. containing months with average temperatures above the yearly average, while the period from November to the end of March might be considered as cold.

3. 2. 2. Data on consumption

We work with consistent daily data on natural gas consumption in all geographic regions of the Czech Republic except from the southern Bohemia. We use large and consistent share of consumption, which may approximately represent even the whole Czech natural gas market.

Figure 19: Daily gas consumption since 1998

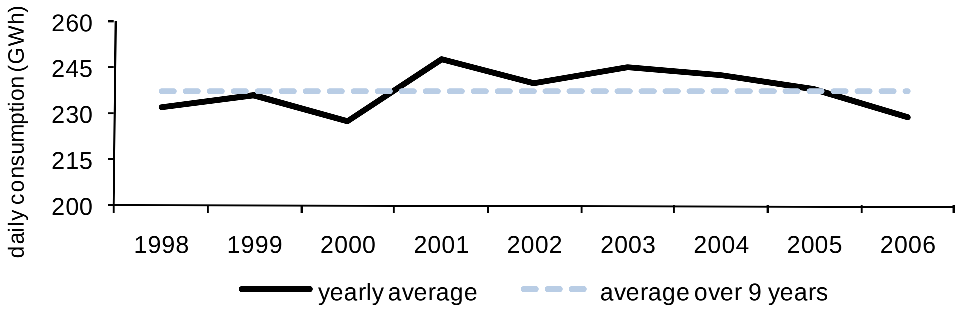


Source: Author

The behaviour of natural gas consumption over the last 9 years is outstandingly cyclic (as shown in Figure 19). Consumption reaches peaks in winters when temperature is the lowest, while it falls to the bottom during summers that are characterized by high temperatures. Therefore, the presence of a significantly negative correlation between temperature and consumption is evident.

The behaviour of the average daily natural gas consumption in recent years (as shown in Figure 20) in general correspond also to the development of temperature that is shown in Figure 17) High average daily temperatures in 2000, 2002 and 2006 (in comparison with preceding years) caused the average daily natural gas consumption to be low. On the other hand, the highest daily consumption was reached in 2001 when the average temperature sank to its bottom.

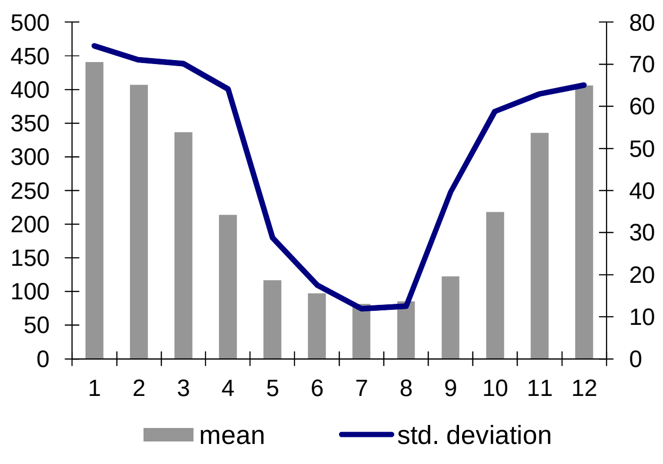
Figure 20: Average daily natural gas consumption (GWh)



Source: Author

In a similar way as it is done for temperature, we search for monthly patterns in natural gas consumption and for periods when its volatility is high. As both mean and standard deviation of daily consumption are the lowest from May to September, it may serve as an indicator that hedging against weather risk is not necessary for these months. In addition, also standard deviations of temperature are of low-levels during this period.

Figure 21: Monthly consumption – mean and std. deviation in GWh



GWh	mean	std. deviation
January	440.798	74.425
February	407.159	71.065
March	336.745	70.176
April	213.597	64.140
May	116.704	28.794
June	97.116	17.596
July	81.605	11.896
August	85.278	12.543
September	122.482	39.635
October	218.376	58.843
November	335.576	62.985
December	406.102	65.075

Source: Author

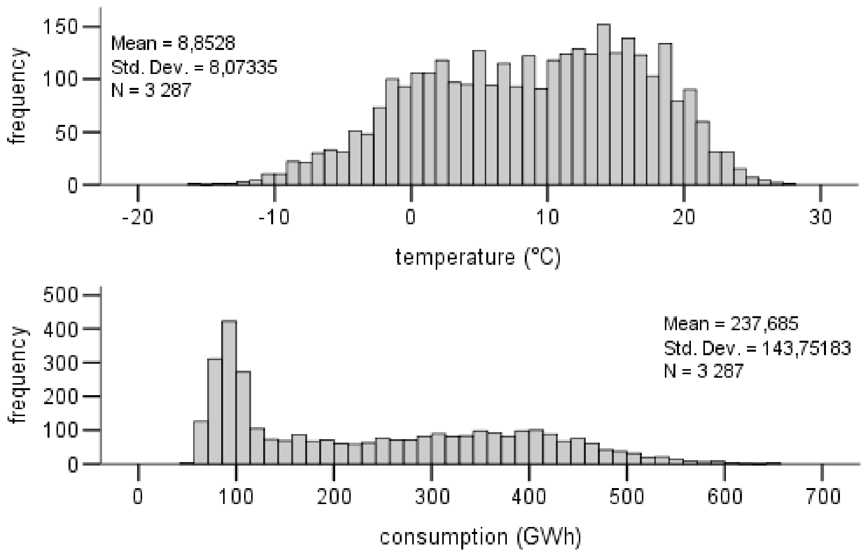
3. 2. 3. Empirical idea

Also with regard to the figures on cyclical development of consumption and temperature, a strong negative correlation between these two variables is evident in the Czech market. To make clear the background behind the notion of correlation, it is possible to look at cyclical behaviour of temperature and natural gas consumption also with the aid of histograms.

Figure 22 shows that the distribution of temperature is slightly bi-modal; with peaks in winter and summer that is quite usual for the majority of temperature distributions of countries with similar weather conditions to the Czech Republic. Temperature measurements at Praha – Ruzyně station, with the mean of about 8.9°C, seem to approximately follow the normal distribution. The majority of observations are situated somewhere between 0 and 20 °C.

With relatively few measurements above twenty degrees, the distribution becomes more skewed with increasing values which correspond to just a small number of tropical days in the Czech Republic. On the other hand, lower number of instances with temperatures below zero reflects characteristics of mild winters, which are usually relatively long but without any extreme temperature measurements.

Figure 22: Histograms of daily temperature and gas consumption (1998 – 2006)



Source: Author

The histogram of daily consumption indicates different behaviour than of temperature as the distribution is relatively stable. Since the highest frequency appears for low consumptions, it intuitively corresponds to the fact that consumption becomes stable (driven mainly by the base-load demand) with high temperatures.

3. 3. OLS regression methods

The understanding and adequate control of volatility in earnings should be an objective of all natural gas companies. In order to analyze hedging capabilities in the Czech natural gas market and consequently to find a valuable hedging strategy against volume risk, investigation of the dependency of natural gas consumption on weather (temperature) with assigned statistical analysis should be primary steps.

Larsen (2006) claims that the substitution of observed weather measures into a robustly estimated regression equation should produce observable distributions in the output of a given sector. According to Gil and Deferrari (2004) the most important factors affecting natural gas consumption of residential and commercial users are:

- temperature
- day of the week, i.e. effect of working days and holidays
- prevailing scenario of consumption

Results of such an analysis could be further improved by the addition of price into estimated models as there is generally present significant impact of price on natural gas consumption. For example Tol (2000) has proven that higher commodity prices lead to reduced natural gas consumption, especially by households.

In this thesis, we only search for temperature and week-day sensitivity of natural gas consumption of a given portfolio. It is common practice in the gas business that traders add into customers' contracts paragraphs regarding yearly, monthly or daily flexibility in off-takes that also serve as the first step in protection against weather risk. Especially in this highly weather dependent business, an accurate regression model may serve as a benchmark for setting up flexibility bands in contracts (instead of using just a plain percentage of volumes).

3. 3. 1. Linear dependency

It is obvious that temperature highly determines total consumed volumes of natural gas. The question in the Czech market is obvious: *"How much?"* In order to analyze this relationship, we start with a basic linear regression and the application of the ordinary least squares (OLS) method. Hereafter, we try to fit the model correctly to real-life observations also by addition of other variables than just temperature on a given day.

The model, in which daily gas consumption (G) is a dependent variable whereas temperature (T) is explanatory, looks as follows:

(2) $$G_t = c + \alpha \cdot T_t + \varepsilon_t$$

If we had information on natural gas prices, similar analysis could be performed also for companies' revenues instead of consumed volumes.

Regression results on the 5% level of significance are obtained with the help of SPSS econometric software. With regard to the results of the regression and R-Square reaching 89.7%, it is obvious that fluctuations in natural gas consumption can be greatly explained by variability in temperature. Moreover, all regression coefficients are significant with only low standard errors. Also the correlation coefficient between the explanatory and dependent variables of -94.7% indicates a strong negative linear relationship between consumption and temperature (see Figure 23). According to the results of this regression, daily natural gas consumption would rise by approximately 16.9 GWh with the fall in temperature of 1°C.

Table 2: Simple linear regression results

variable	coefficient	std. error	t-statistic	signif.	95% conf. interval lower	upper
const.	386.968	1.195	323.809	0.000	384.625	389.312
T_t	-16.863	0.100	-169.051	0.000	-17.058	-16.667
R-Square	0.897					
adj. R-Square	0.897					
std. error	46.164					
Durbin-Watson	0.586					
F- statistics	28 578.4					

Source: Author

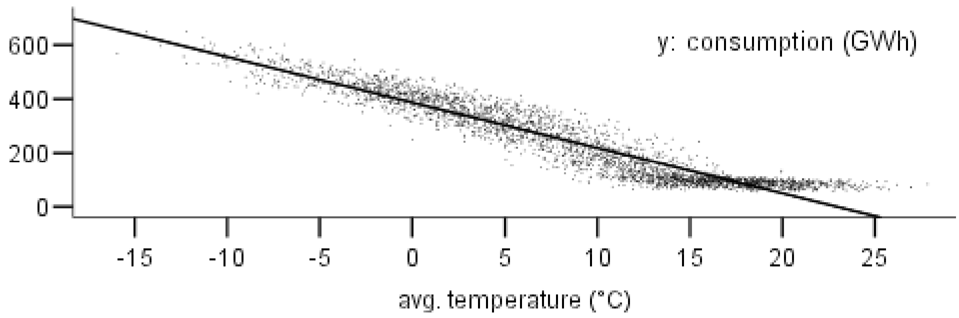
As shown in Figure 23, approximately linear relationship between consumption and temperature is abandoned when temperature rises above a threshold level that lies somewhere between 10°C and 20°C. Consumption starts to be highly inelastic in temperature at this point. Analogical feature is present also in the models of Gabbi and Zanotti (2003) for Italy, who consider the temperature of 18°C as this point, or of Piggott et al. (2000) for the United Kingdom who observe lower impact on gas consumption with temperatures over 14°C.

Considering the results of linear regression, consumption would reach zero with the temperature of approximately 22.95°C.[55] Nevertheless, there always exists some base-load consumption especially of industries, which use natural gas in the process of manufacture (e.g. glass producers) even during the warmest days of a year. Besides, there is always sustained

[55] And would be negative with even higher temperatures that is in contrast with the basic presumption about non-negative consumption.

some level of residential demand for the commodity that is further used in everyday life (cooking, heating of water etc.).

Figure 23: Linear regression – consumption dependency on temperature



Source: Author

3. 3. 2. Weekend factor

As another highly important factor determining natural gas demand is perceived the presence of weekends and holidays. Consumption is in general lower at weekends by reason that industrial production and therefore also energy consumption commonly decrease during weekends. Therefore we add into the model also the "weekend factor" that covers the presence of both public holidays and weekends.

(3) $$G_t = c + \alpha \cdot T_t + \beta \cdot WEEKEND_t + \varepsilon_t$$

Table 3: Linear regression with weekends

variable	coefficient	std. error	t-statistic	signif.	95% conf. interval lower	upper
const.	396.491	1.253	316.322	0.000	394.033	398.948
T_t	-16.909	0.095	-177.770	0.000	-17.095	-16.722
weekends	-30.550	1.678	-18.207	0.000	-33.840	-27.260
R-Square	0.906					
adj. R-Square	0.906					
std. error	44.003					
Durbin-Watson	0.555					
F- statistics	15 892.5					

Source: Author

Although weekend's consumption would be inherently included in time-series models, it has to be manually implemented into regression models. Since dummy variables are numerical variables used in regression analyses to represent subgroups of a sample, the application of dummies seems to be the most suitable way to model the "weekend factor". By reason that the purpose is to distinguish weekend patterns in consumption, the variable called '*WEEKEND*' has the value of 1 if a particular day is a weekend day or public holiday and equals 0 otherwise.

Results of the improved model correspond to our presumption. The presence of weekends and holidays leads to the fall in consumption by 30.55 GWh. Explanatory power (R-Square) has increased to 90.6%. If there was no such a factor in the regression, results would lead to regular underestimating of consumption on weekdays while overestimating at weekends.

3. 3. 3. Non-linear aspect of the model

♦ ***Setting a threshold on temperature***

Hereafter, we make the first attempt to catch the non-linearity in the relationship of natural gas consumption and temperature. Beside other regression types[56], there exists a way of dealing with nonlinearity also with linear regressions applied by us.

Because consumption tends to become stable with high temperatures, there might be set a cap on temperature that could catch with the regression only the weather dependent share of consumption.

$$T_t = \min(T_{real}; T_{threshold}) \tag{4}$$

This would correspond to the fact that consumption stays close to a constant level with temperatures reaching some threshold level of temperature and that there is almost no additional decrease in consumption with temperatures increasing above this level.[57] An empirical explanation is that the threshold level represents the daily temperature associated with minimum heating natural gas demand.

Consequently, we transform temperature measurements as shown by equation (4). Similar transformation is commonly done in derivatives' markets with application of so called degree days as we will show later in more detail (Chapter 4.1.1.). We analyze impacts of employing of various temperature levels as heating thresholds because determination of the most appropriate threshold level may greatly help also to set the most efficient hedging strategy.

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[56] See later in this chapter.

[57] Another manner to set a threshold for temperature could be the transformation into the degree day format, which has been chosen many times before, e.g. Gabbi and Zanotti (2003), de Dear et al. (2004) etc. This is not just a way how to deal with non-linearity in dependency, but it is also a change to the manner that insurance companies commonly use when provide hedging as I will show later. However, we use just plain cap on temperature measurements for the purpose of data analysis (and as it is more appropriate also for non-linear regression techniques).

It would be logical to proceed analogically also for very low temperatures. Since consumption increases due to growing heating demand when temperature goes down, it is obvious that the level of temperature where consumption becomes inelastic in temperature should exist with extremely low temperatures. The reasoning is straightforward since heating capacities meet at some point their maximum level and thus it is even technically impossible to further increase consumption. However, such a level does not seem to be reached in the Czech Republic in the past (as it is also obvious from Figure 23) because average temperatures are relatively high even during the coldest days.

As Figure 23 implies that the point where consumption starts to be approximately constant lies somewhere between 13°C and 18°C, we perform regressions with the weekend factor (see equation (3)) for particular thresholds varying between two considered values.

(5) $$G_t = c + \alpha \cdot \min(T_{real}; T_{treshold}) + \beta \cdot WEEKEND_t + \varepsilon_t$$

Table 4: Comparison of regressions with capped temperature

results	cap 13	cap 14	cap 15	cap 16	cap 17	cap 18
R-Square	0.917	0.928	0.934	***0.935***	0.933	0.930
adj. R-Square	0.917	0.928	0.934	***0.935***	0.933	0.930
std. error	41.485	38.658	37.062	***36.627***	37.093	38.167
Durbin-Watson	0.624	0.696	0.737	***0.742***	0.718	0.679
F-statistics	18 086.4	21 077.2	23 075.9	***23 666.3***	23 034.1	21 665.4

Source: Author

By performing these particular regressions, we have manually done something similar what generally do also robust statistical methods[58] that deal with influential observations (outliers). Nevertheless, there are three reasons why to use such a manual cap since:

- robust methods would limit us in further transformations of the model
- the manual method better demonstrates differences between various caps
- for the purpose of consequent hedging, we need to use integers what would not be the case of robust methods, which would simply choose the most appropriate value

(6) $$T_t = \min(T_{real}; 16°C)$$

The highest explanatory power of the model is reached with the cap set at 16°C. The regression curve with capped temperature better fits reality during months with highly weather dependent consumption. R-Square in these models highly accrues in comparison with

[58] For example Least Trimmed Squares.

the models without any cap, in the case of 16°C threshold even to 93.5% (compared with 90.6% when considering uncapped data). When comparing regression results with (Table 5) and without a cap (Table 3), there are higher constant term and impact of a change in temperature in the capped case.

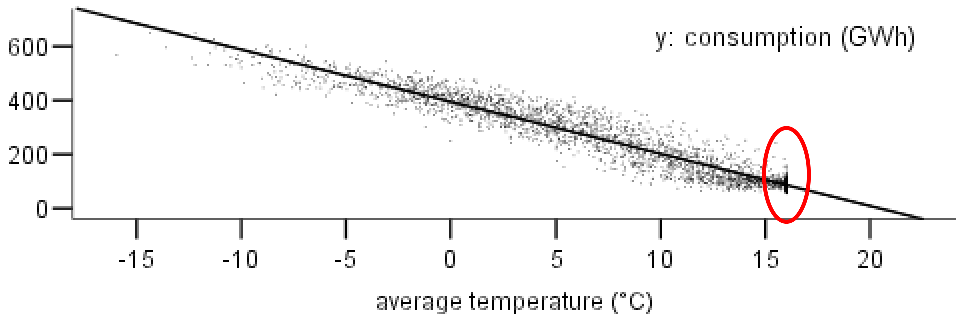
Table 5: Linear regression with temperature capped at 16°C

variable	coefficient	std. error	t-statistic	signif.	95% conf. interval lower	upper
const.	404.640	1.062	381.175	0.000	402.558	406.721
T_t (cap at 16°C)	-19.352	0.089	-216.953	0.000	-19.527	-19.177
weekends	-30.829	1.397	-22.073	0.000	-33.567	-28.090

Source: Author

By capping temperature at 16°C, the regression line (basic regression without the weekend factor) becomes steeper than in the uncapped case as there is not considered any additional impact of temperatures higher than the threshold. Consequently, there is a bunch of observations with the temperature of exactly 16°C since measurements with higher temperatures have been moved to the left to equal 16°C as well.

Figure 24: Simple linear regression with a cap (16°C)



Source: Author

The regression model with implemented cap better explains the area where consumption is highly dependent on temperature. The model is not biased by temperature observations above 16°C because there is almost no effect of weather on consumption on days with temperature higher than 16°C. Since Pearson correlation of daily consumption and actual temperature was -94.7% without any cap, it has amplified to -96.2% with temperature measurements capped at 16°C.

With respect to the results shown in Table 4 and Table 5, we have already proven that the weekend factor and cap on temperatures are greatly useful to improve the explanatory power of the model.

♦ ***Would another regression type be more appropriate?***

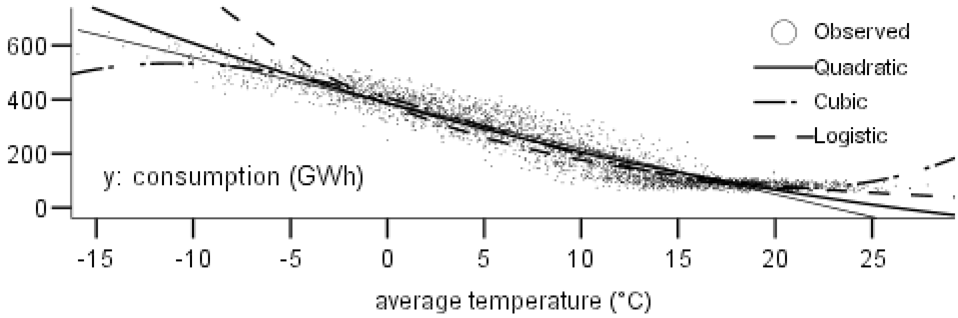
In order to capture the nonlinearity in the dependency differently than with capped temperatures, regressions with specific appearance of a curve could be applicable with satisfactory results as well. Despite the results of linear regression, the relationship between temperature and consumption might seem to follow a slightly curved line instead of straight. With regard to the nature of other regressions, quadratic (7), cubic (8) or logistic (9) regression could be in general more suitable for modelling the dependency.

(7) $$G_t = c + \alpha \cdot T_t + \beta \cdot T_t^2 + \varepsilon_t$$

(8) $$G_t = c + \alpha \cdot T_t + \beta \cdot T_t^2 + \gamma \cdot T_t^3 + \varepsilon_t$$

(9) $$G_t = \frac{1}{1 + e^{-(c + \alpha \cdot T_t)}} + \varepsilon_t$$

Figure 25: Other regression types



Source: Author

In view of regression curves shown in Figure 25 and results in Table 6, the cubic regression seems to be the most appropriate among considered alternative methods. The S-shaped cubic regression's curve resembles the straight line with inelastic consumption when temperature crosses thresholds on both sides of its scale.[59]

Therefore, if we take into account only the effect of actual day's temperature, the application of cubic regression might be considered as better even in the comparison with the linear form. And when cubic regression is further improved with the weekend factor, the obtained results (shown in Table 7) even slightly improve.

[59] If natural gas was highly used for electricity generation, the application cubic S-curve would be even more appropriate. From some level of temperature, consumption would be likely to increase again with rising temperatures due to high air-conditioning demand for electricity.

Table 6: Linear vs. nonlinear regression methods

regression	R-square	c	α (T)	β (T^2)	γ (T^3)
linear	0.897	386.968	-16.863		
quadratic	0.907	386.350	386.968	0.204	
cubic	0.927	405.805	-19.604	-0.415	0.028
logistic	0.875	0.003	1.080		

Source: Author

As it is obvious from Table 7, the cubic regression, as the best one among other regression types, leads to improved results in comparison with the basic linear regression (see Table 3). Nevertheless, capturing of the nonlinearity by implementation of the threshold level on temperature into the basic linear regression model highly improves the explanatory of the model which consequently reaches 93.5% that is similar R-Square as of the cubic regression. There is not too much value added by application of the cubic regression since it is possible to capture the nonlinearity of the model also with a quality linear regression model (e.g. given by equation (11) as we will see later).

Table 7: Cubic regression

variable	coefficient	std. error	t-statistic	signif.	95% conf. interval lower	upper
const.	415.222	1.201	345.813	0.000	412.867	417.576
T_t	-19.651	0.164	-119.787	0.000	-19.973	-19.329
T_t^2	-0.413	0.021	-19.357	0.000	-0.455	-0.371
T_t^3	0.028	0.001	31.890	0.000	0.026	0.030
weekends	-30.378	1.387	-21.909	0.000	-33.096	-27.659
R-Square	0.935					
adj. R-Square	0.935					
std. error	36.361					
Durbin-Watson	0.731					
F-statistics	12 019.4					

Source: Author

3. 3. 4. Impact of previous days

Even though the model with high explanatory power has already been reached, there remain other features that should be logically included. Gabbi and Zanotti (2003) relate lower R-Squares in their intermediate models to the presence of lagged effect of weather variables, i.e. the influence of past temperature observations.

Even unsophisticated logic lies in the background of this argumentation since the impact of past temperatures on present consumption can be partially explained for example by the thermal insulation of buildings. When temperature is very cold on two subsequent days, households generally adjust their consumption because houses do not need to be heated with the same intensity on the second day to reach desired effect. Similar justification holds for industrial customers as they adjust heating only if similar weather conditions take at least for several days.[60] Thus, consumption on two particular days with the same temperature, but in different periods of the year, is generally higher in winter.

Therefore we further consider several intuitive scenarios of impacts of past temperature measurements on consumption, including both the short and long term effects.

♦ ***Impact of prior days' temperatures***

It is very likely that apart from actual temperature on a given day, consumption is affected by temperatures on directly preceding days. Hereafter, we are intuitively concerned with impacts of daily lags up to six prior days, i.e. we are trying to capture short-term impact of temperatures within one week. We perform regression in which the weekend factor, actual and lagged temperatures (all capped at 16°C) act as explanatory variables (as shown by equation (10)).

(10)

$$G_t = c + \alpha \cdot T_t + \beta_1 \cdot T_{t-1} + \cdot \beta_2 \cdot T_{t-2} + \beta_3 \cdot T_{t-3} + \beta_4 \cdot T_{t-4} + \beta_5 \cdot T_{t-5} + \beta_6 \cdot T_{t-6} + \gamma \cdot WEEKEND_t + \varepsilon_t$$

With a view to the results of the regression, explanatory power of the model has further increased. However, there are two features that we need to be aware of. The results indicate that the fifth lag of temperature is not significant on 5% level of significance. However, we also need to be aware of a potential problem of multicollinearity of explanatory variables.[61] As the Variance Inflation Factor[62] (VIF) indicates this problem in our model, it corresponds to the intuitive notion that daily temperatures are likely to be correlated among each other. This may lead, besides unnecessarily high standard errors of particular regression coefficients, also to the incorrect consideration of significance of explanatory variables.

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[60] Gil and Deferrari (2004) apply this logic in their concept of effective temperature when modeling natural gas demand.

[61] Multicollinearity means that two or more explanatory variables may be explaining the dependent variable well but at the same time are closely mutually correlated. More information about this problem provides Greene (2002), pp. 56 - 59.

[62] VIF measures the impact of collinearity among the variables in a regression model. Even though there is no formal value of VIF that determines presence of multicollinearity, VIF exceeding 10 is generally perceived as a multicollinearity indicator.

Based on the results provided in Table 8, our model with short term lagged temperatures reaches R-Square of 96.7%. Regarding the impact on actual day's consumption, temperature on a given day higher by 1°C lowers consumption on that day by approximately 10.8 GWh. Increase in temperature by 1°C on directly preceding days has from five to ten times weaker impact.

We see that the impact of temperature is decreasing with observations more in the past. However, it is very interesting that the trend is turning with the last measurement since the sixth lag of temperature has the highest impact on actual day's consumption. Therefore, we can undoubtedly raise a question about the impact of long term temperature profile on natural gas consumption.

Table 8: Regressions with lagged temperature

variable	coefficient	std. error	t-statistic	signif.	95% conf. interval lower	95% conf. interval upper	VIF
const.	413.901	0.776	533.678	0.000	412.380	415.421	
weekends	-30.614	0.996	-30.735	0.000	-32.567	-28.661	1.003
T_t	-10.769	0.222	-48.522	0.000	-11.204	-10.334	12.234
T_{t-1}	-2.363	0.315	-7.509	0.000	-2.980	-1.746	24.597
T_{t-2}	-1.959	0.319	-6.145	0.000	-2.584	-1.334	25.220
T_{t-3}	-1.385	0.319	-4.337	0.000	-2.011	-0.759	25.305
T_{t-4}	-1.045	0.319	-3.277	0.001	-1.670	-0.420	25.221
T_{t-5}	-0.582	0.316	-1.842	0.066	-1.201	0.037	24.710
T_{t-6}	-2.390	0.223	-10.726	0.000	-2.827	-1.953	12.306
R-Square	0.967						
adj. R-Square	0.967						
std. error	26.053						
Durbin-Watson	0.448						
F-statistics	12 086.4						

Source: Author

♦ ***Long term lags***

As we have already mentioned, for two days with the same temperature where one is in winter and the other in summer, there is generally higher consumption on a winter day. It corresponds also to the fact that natural gas consumers (especially that industrial) do not adjust their heating devices unless weather remains alike at least for several days or even weeks. Consequently, we try to capture even the long term impact of temperature on consumption, which was previously indicated by the results shown in Table 8.

Beside the daily lags up to six foregoing days, we add in the model the long term average temperature for three other weeks, i.e. average temperature from the 7th up to 30th preceding day (the model is specified by equation (11)), which should reflect heating requirements in longer term (month), i.e. demand during the actual period of a year.

As we may see in the results in Table 8, VIF indicated a potential problem of multicollinearity in the model. To lessen this issue, transformation of daily data over more days into one variable could be a solution. Therefore, we implement only the long-term average of temperatures up to the 30th preceding day instead of temperatures on particular days and estimate the model as described by equation (11) with so called stepwise regression[63] in SPSS.

As it has not heavy impact on explanatory power of the model (R-Square remains in both cases at 96.9%), the stepwise regression method suggested the exclusion of the first, third and fifth lag from the model to press all VIF values below 10 and thus lessen the multicollinearity issue (for the results of the model with all lags see Appendix - Table A2). As a result, standard errors of particular coefficients decrease while estimated regression coefficients of temperature measurements increase (see Table 8).

$$G_t = c + \alpha \cdot T_t + \beta_1 \cdot T_{t-1} + \cdot \beta_2 \cdot T_{t-2} + \beta_3 \cdot T_{t-3} + \beta_4 \cdot T_{t-4} + \beta_5 \cdot T_{t-5} + \\ + \beta_6 \cdot T_{t-6} + \beta_7 \cdot T_{(t-7;t-30)} + \gamma \cdot WEEKEND_t + \varepsilon_t \tag{11}$$

Table 9: Linear regression with application of long term lag

variable	coefficient	std. error	t-statistic	signif.	95% conf. interval lower	95% conf. interval upper	VIF
const.	416.662	0.785	530.532	0.000	415.122	418.202	
weekends	-30.454	0.978	-31.137	0.000	-32.372	-28.536	1.004
T_t	-11.520	0.156	-73.724	0.000	-11.826	-11.213	6.255
T_{t-2}	-3.702	0.192	-19.289	0.000	-4.078	-3.326	9.444
T_{t-4}	-1.792	0.192	-9.340	0.000	-2.168	-1.416	9.456
T_{t-6}	-1.618	0.167	-9.663	0.000	-1.946	-1.290	7.212
$T_{(t-7 - t-30)}$	-2.201	0.148	-14.881	0.000	-2.491	-1.911	4.677
R-Square	0.969						
adj. R-Square	0.969						
std. error	25.494						
Durbin-Watson	0.557						
F-statistics	16 689.6						

Source: Author

The model with such a clear and understandable selection of temperature observations shows descending impact of changes in daily temperature when going back to the past. Nevertheless, even the average of daily temperatures lagged up to 30 days is still significant in the

[63] What means that the software automatically selects significant variables and performs several particular regressions whose results are consequently aligned according to their R-Squares.

regression with regard to its t-statistics and p-value (0.000). Furthermore, the explanatory power of the model with long term lags rises to 96.9% and there is not indicated any problem with multicollinearity. Therefore it is obvious that it is convenient to consider also the long term effect of weather on natural gas consumption, which is not a prevailing practice in similar studies (e.g. Gabbi and Zanotti 2003 count only with temperature measurements on two directly preceding days).

3. 4. Is OLS convenient?

It would not be an exception if the results from the previous chapter were sufficient for a natural gas trader and therefore applied in predictions of consumption. But beside just an economic point of view, we have to take into account also the statistical approach to interpret the results well.

We have quality data, there are no problems with outliers[64] or omitted variables and we have already dealt with multicollinearity issue in Chapter 3.3. Howeve, it is necessary to check potential troubles with residuals because for example Durbin-Watson statistics indicated autocorrelated residuals in the model. To interpret the results of our model (given by equation (11)) well, it is important that OLS assumptions about residuals are fulfilled.

3. 4. 1. Analysis of residuals

Herein, we investigate the presence of three most common problems with residuals in regression models that could in the end cause troubles in the interpretation of results.

♦ ***Normality***

With regard to the descriptive statistics shown in Table 10, it is obvious that residuals with a zero mean and values of skewness and kurtosis higher than -1, respectively lower than 1, fulfil the presumption of normality. Since residuals are normally distributed, estimated coefficients with OLS are not biased. Nevertheless, it does not mean that the estimator is efficient.

Table 10: Regression residuals

	sum	mean	skewness	kurtosis
residuals	0.000	0.000	-0.192	0.362

Source: Author

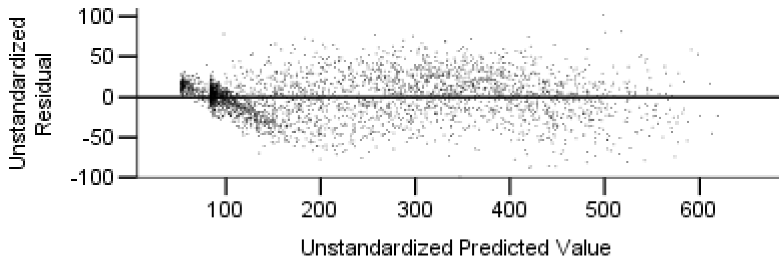
[64] Since there are just 15 observations with standardized residual's values higher than 3 what is commonly perceived as a sign of outlier. For more information about outliers see Appendix - Table A1.

♦ ***Heteroskedasticity***

Since we apply OLS method to time series data, there might generally appear two problems with residuals: heteroskedasticity and autocorrelation. If there is present any of these problems, it causes standard errors of estimated coefficients to be biased and thus the model is not efficient.

A notion on heteroskedasticity can be easily obtained even by plotting regression residuals into the same graph with e.g. predicted values of a dependent variable as it is done also in Figure 26. Since there is higher variance of residuals with increasing values of consumption, the presence of heteroskedastic residuals is indicated. It corresponds with the basic structure of daily consumption that highly varies especially in winters due to adjustments of heating devices. On the other hand, as the share of base-load consumption increases during warmer days, the variability of consumption greatly falls.

Figure 26: Residuals' variance



Source: Author

Consequently, standard White test for heteroskedasticity[65] of residuals is performed with the help of EViews[66] statistical software. Based on its results, the hypothesis on homoscedastic (homogenous) variance is rejected as F-statistic's value of 26.76 without any doubts crosses the critical value and thus the p-value is very low (see Table 11).

With present heteroskedasticity, the OLS estimate stays unbiased and consistent, but not asymptotically efficient. With regard to the nature of heteroskedasticity in this model[67], it is difficult to eliminate the problem with any transformation of data (e.g. using of natural

[65] Constant variance of residuals is tested by regressing square residuals from the model onto regressors, cross-products of regressors and squared regressors. For more information about White test see White (1980).
[66] EViews software can be used for general statistical and econometric analyses as time series, cross-section or panel data.
[67] It is obvious that consumption has higher variance during winters while it generally stays close to some constant value in summers.

logarithms). Thus, true variances are underestimated and t-statistics overestimated when using OLS in the model. As a result it would be even possible that we include into the model a non-significant variable due to biased standard errors.

Table 11: White test for heteroskedasticity

results	value	p-value
F-statistic	26.7635	0.0000
Obs*R-Square	270.9088	0.0000

Source: Author

Since a quality model for predicting daily natural gas consumption has been reached and regression coefficients are unbiased, OLS results are frequently employed, especially if we considers so large data sample as we have. The only accessory would be the application of White standard errors that reflect heteroskedasticity of residuals (for more information on this method see e.g. MacKinnon and White 1985 or Greene 2002).

White standard errors are commonly used by economists to fix heteroskedasticity problem even though the fix comes with a loss in efficiency. Thus, OLS is not the best linear unbiased estimator[68] anymore. Robust White estimators lead to higher standard errors and lower t-statistics of particular coefficients than application of common OLS statistics. Despite the fact that White standard errors are higher in comparison with OLS errors, there is no impact on the significance of variables in our model since all p-values stay very low even with application of robust standard errors (see Table 12).

Table 12: White robust estimator

variable	coeff.	std. error	t-stat.	std. error	t-stat.	p-value
		OLS std. errors		***White std. errors***		
const.	416.662	0.785	530.532	0.909	458.131	0.000
weekends	-30.454	0.978	-31.137	0.951	-32.022	0.000
T_t	-11.520	0.156	-73.724	0.184	-62.592	0.000
T_{t-2}	-3.702	0.192	-19.289	0.217	-17.098	0.000
T_{t-4}	-1.792	0.192	-9.340	0.213	-8.406	0.000
T_{t-6}	-1.618	0.167	-9.663	0.189	-8.557	0.000
$T_{(t-7\ -\ t-30)}$	-2.201	0.148	-14.881	0.168	-13.076	0.000

Source: Author

[68] Such estimate minimizes the variance of a chosen linear combination of the data subject to the constraint that the estimator must be unbiased.

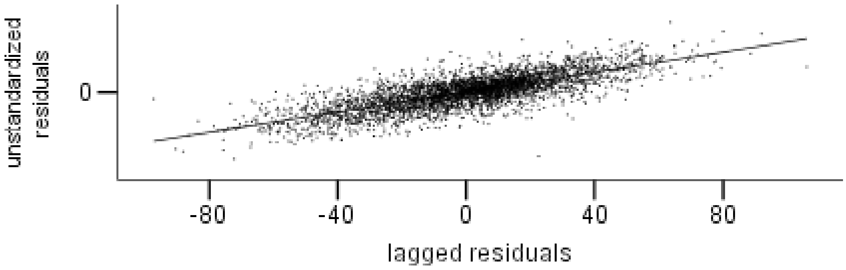
Since any transformation of data in this case would not help us to avoid heteroskedasticity, robust standard errors are the most appropriate way of dealing with this unwished feature. As the purpose is to predict daily natural gas consumption with respect to the temperature and week-day sensitivity, the model is highly explanatory with usage of OLS despite it is not the most efficient model. However, the loss in efficiency might be bearable in practical usage by natural gas companies because we have obtained greatly understandable results with OLS.

♦ ***Autocorrelation of residuals***

When working with data of time series origin, positive autocorrelation of residuals is not extraordinary since errors from one period of time are commonly carried over into future time periods. If it is weather (temperature) itself or natural gas consumption, which is highly dependent on temperature, trends in these variables generally tend to persist for some time. In all models that we have introduced, the Durbin-Watson statistics indicated serial correlation among residuals, which causes that estimated coefficients are, despite of still being unbiased, inefficient due to underestimated standard errors. As a consequence, also R-Square of the model is overestimated.

As an indicator of serial correlation among residuals is commonly used a plot showing the relationship of residuals and their lagged values. In Figure 27, by which is shown the dependency of regression residuals on their lagged values of the first order, is revealed strong autocorrelation of residuals in the model.

Figure 27: Autocorrelation of residuals



Source: Author

Since we have already demonstrated that the model suffers from both heteroskedasticity and autocorrelation of residuals, conventional OLS standard errors are wrong and accordingly robust standard errors have to be applied to interpret OLS results well. Since White robust standard errors assume that residuals of the estimated equation are serially uncorrelated, Newey and West (1987) proposed a more general covariance estimator that is consistent with the presence of both heteroskedasticity and autocorrelation of unknown form. The Newey-

West method is generally known as application of Heteroskedasticity and Autocorrelation Consistent (HAC) standard errors (for more detailed information on application of HAC standard errors see Newey and West 1987).

As shown in Table 13, HAC standard errors are higher than original OLS errors and consequently also t-statistics change. Nevertheless, calculation of HAC robust estimators reveals that all the coefficients in the model stay statistically significant as their p-values are still very low.

Table 13: HAC estimators

variable	coeff.	std. error	t-stat.	std. error	t-stat.	p-value
		OLS std. errors		*HAC std. errors*		
const.	416.662	0.785	530.532	2.012	207.120	0.000
weekends	-30.454	0.978	-31.137	0.859	-35.434	0.000
T_t	-11.520	0.156	-73.724	0.238	-48.481	0.000
T_{t-2}	-3.702	0.192	-19.289	0.179	-20.681	0.000
T_{t-4}	-1.792	0.192	-9.340	0.180	-9.928	0.000
T_{t-6}	-1.618	0.167	-9.663	0.231	-7.003	0.000
$T_{(t-7\ -\ t-30)}$	-2.201	0.148	-14.881	0.383	-5.752	0.000

Source: Author

Despite the fact that a quality model has been reached with OLS method, we have calculated robust standard errors to deal with both heteroskedasticity and autocorrelation. With application of HAC standard errors and t-statistics, one could interpret the estimated model in which all variables stay significant. Nevertheless, since the structure of residuals implies that OLS estimator is no longer efficient, it would be rewarding to find a more efficient model.

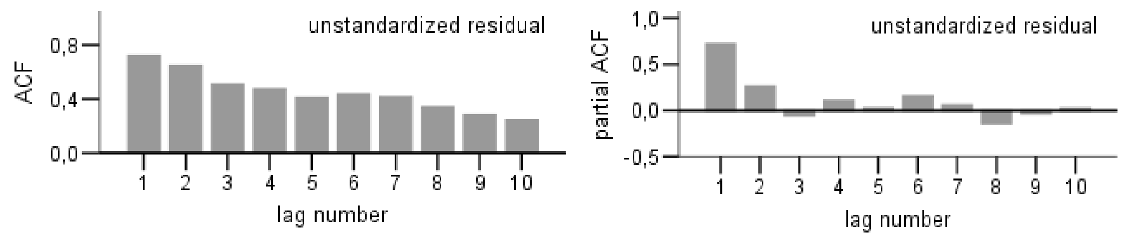
3. 4. 2. Generalized Least Squares

With the aim of finding an efficient estimator of the model, traditional OLS method is no longer satisfactory. Although OLS coefficients are not biased, standard errors and t-statistics tend to be underestimated with present autocorrelation. Thereby the Generalized Least Squares (GLS) method could be applied for such models. But prior to application of GLS, one should look at the structure of autocorrelation in more detail.

♦ ***Autocorrelation function***

Hereafter, we search for the form of autocorrelation with usage of autocorrelation functions. Autocorrelation function (ACF) and Partial autocorrelation function (PACF) are very helpful diagnostic tools in time series data analysis as they are estimated by calculation of the correlation coefficient between present and lagged values of a variable (see Box and Jenkins 1976). In view of Figure 28, the model of natural gas consumption seems to be primarily influenced by the autoregressive process of the first order (the correlation coefficient equals to 0.721 – for detailed information see Appendix - Table A3).

Figure 28: Correlation of residuals



Source: Author

Hereafter, GLS method is applied to the model to deal with the autocorrelation issue. To be more precise, we use one of GLS variations - the Cochrane-Orcutt (CORC) iterative estimation method. This method, which presumes the first order of autocorrelation structure - AR(1), is performed in several steps.

♦ ***Cochrane-Orcutt transformation***

The OLS estimate of the model (given by equation (11)) serves as a starting point in this method. Obtained OLS residuals $\hat{\varepsilon}$ (from equation (12)) are used to get an estimate of coefficient ρ stating the dependency among two subsequent residuals in the model (given by equation (13)).[69]

(12) $$Y_t = \beta_0 + \beta_1 X_{t1} + ... + \beta_k X_{tk} + \varepsilon_t$$

(13) $$\varepsilon_t = \rho \cdot \varepsilon_{t-1} + v_t \quad for\ t = 2, \ldots, N$$

The estimator of ρ is subsequently employed in the construction of transformed observations. Hereafter, OLS method is applied to the transformed model (in general form given by equation (15)).

(14) $$Y_t = X_t B + \varepsilon_t = X_t B + \rho \cdot \varepsilon_{t-1} + v_t = X_t B + \rho \cdot (Y_{t-1} - X_{t-1} B) + v_t$$

and thus:

[69] To introduce the method, we denote equations for GLS in their general form. However, one could easily install our variables into these general equations. For detailed information on this method see for example Cochrane and Orccutt (1949), Harvey (1990) or Greene (2002).

(15) $$Y_t - \rho \cdot Y_{t-1} = (X_t - \rho \cdot X_{t-1})B + v_t$$

However, ending with the first obtained value of coefficient ρ would not be accurate. Therefore Cochrane and Orcutt (1949) suggested an alternative procedure. When applying regression methods to the model given by equation (16), it is possible to get new residuals v_t for which is obtained new estimate of ρ. Transformation of the original model might be consequently repeated with new ρ. Based on the process stated by Jain and Wang (2003), iterations are repeated until a change in two subsequent coefficients ρ is not higher than 0.001. In the end, the final value of coefficient ρ is induced.[70]

(16) $$Y_t^* = \beta_0^* + \beta_1 X_{t1}^* + ... + \beta_k X_{tk}^* + v_t$$

where

$$Y_t^* = Y_t - \rho' \cdot Y_{t-1}, \; \beta_0^* = \beta_0 (1 - \rho') \; \textit{and} \; X_{ti}^* = X_{ti} - \rho' \cdot X_{(t-1)i}$$

for t = 2, 3, …, n and i = 1, …, k

Running CORC procedure, the total number of 10 iterations was reached. The transformed model is subsequently estimated with ρ' equal to 0.94819 (for detailed information on CORC results see Appendix - Table A4).

The coefficients estimated with GLS are different in comparison with that obtained by OLS. GLS method leads to the more pronounced coefficient of the long-term (monthly) temperature variable and decrease in the coefficient on actual day's temperature. Therefore, it is evident that autocorrelation in residuals in the original model led to the overestimated effect of actual day's temperature on current natural gas consumption. For that reason, regression coefficients of directly preceding days are lower in GLS and the sixth lag is not even statistically significant on 5% level.

When performing OLS, the Durbin-Watson statistics indicated strong positive autocorrelation of residuals, which caused R-Square of the model to be overestimated. With usage of GLS, the Durbin-Watson statistics already reaches satisfactory level that indicates remedy to autocorrelation. Due to corrected autocorrelation, non-overestimated R-Square falls to 63.9%,

[70] If ρ was known at the beginning, OLS could be directly applied to the model given by equation (16) to get efficient estimates. However, since ρ is unknown, one has to follow CORC iterative procedure that is stopped when reaching a predetermined level. The final coefficient ρ' is then applied to (16) in order to obtain an efficient estimator.

with the GLS method. Nevertheless, the presented model can still greatly explain variability in natural gas consumption.

Table 14: GLS regression results

variable	coeff.	coeff.	std. error	t-statistic	p-value
	OLS	Cochrane-Orcutt			
const.	416.662	378.583	0.392	50.028	0.000
weekends	-30.454	-25.671	0.502	-51.148	0.000
T_t	-11.520	-6.804	0.129	-52.759	0.000
T_{t-2}	-3.702	-1.355	0.130	-10.420	0.000
T_{t-4}	-1.792	-0.491	0.130	-3.791	0.000
T_{t-6}	-1.618	-0.219	0.128	-1.706	0.088
$T_{(t-7 - t-30)}$	-2.201	-7.534	0.664	-11.354	0.000
R-Square	0.969	0.639			
adj. R-Square	0.969	0.638			
std. error	25.494	15.083			
Durbin-Watson	0.557	2.000			
F-statistics	16689.642	957.167			

Source: Author

After dealing with autocorrelation (see residuals in Appendix - Table A5), heteroskedasticity is still present in the model estimated with GLS. Therefore, robust standard errors might be applied again. Based on the results shown in Table 15, there is just a slight difference between White and HAC standard errors and t-statistics. Since autocorrelation has been fixed with GLS, both types of robust estimators serve primarily as remedy to heteroskedasticity.

Table 15: Robust standard errors with Cochrane-Orcutt

variable	coeff.	s.e.	t-stat.	s.e.	t-stat.	s.e.	t-stat.
		OLS s.e.		*White s.e.*		*HAC s.e.*	
const.	378.583	0.392	50.028	0.466	42.136	0.450	43.553
weekends	-25.671	0.502	-51.148	0.533	-48.197	0.627	-40.966
T_t	-6.804	0.129	-52.759	0.182	-37.331	0.237	-28.690
T_{t-2}	-1.355	0.130	-10.420	0.145	-9.368	0.155	-8.759
T_{t-4}	-0.491	0.130	-3.791	0.143	-3.425	0.143	-3.444
T_{t-6}	-0.219	0.128	-1.706	0.146	-1.500	0.154	-1.425
$T_{(t-7 - t-30)}$	-7.534	0.664	-11.354	0.676	-11.151	0.634	-11.889

Source: Author

It is important to consider in similar models not only the economic point of view, but also the statistical. Since there are commonly present autocorrelated residuals, we should generally deal with this issue. In order to get an efficient estimator and avoid problems with interpretation of results, GLS should be applied to the final model. As we have seen overestimated R-Squares in previous chapters that were even higher than 90%, it was in all cases due to autocorrelation of residuals, which might lead to incorrect interpretation of OLS results.

3. 4. 3. Interpretation of results

With the help of GLS, we have assessed the impact of weather on daily natural gas consumption, which is not very different in comparison with similar studies. While the change in temperature by 1°C on a given day leads to the change in natural gas consumption in the Czech market by approx. 2.9%, if we compare the change with the average value of consumption, higher temperature by 1°C on all days of a directly preceding month causes the natural gas consumption on a given day to fall by approx. 6.9%.[71]

Our results correspond to the results from other countries since there is generally stated fall in consumption by some 5-10% due to the change in temperature by 1°C. If we look at the results provided by Gabbi and Zanotti (2003) for Italy, they show the change in natural gas consumption by 3.4% in Palermo and by 2.6% in Milano due to the change of temperature by 1°C on a given day. Moreover, they show the impact of change of temperature by 1°C on two directly preceding days equal to 1.5%, respectively 1.4% (in total for both days) of gas consumption. The lower impact of temperature on natural gas consumption in Milano reflects also its industrial background and the usage of natural gas in industrial production.

Our intention in this thesis was to state the level of consumption of a given customer portfolio with respect to its temperature and week-day sensitivity. Therefore we have corrected the model for present autocorrelation of residuals. However, it could be sometimes beneficial to work also with the autocorrelation process in the model (e.g. with AR (1)). If we want for example accurately forecast consumption in the short term, we need to be aware also of the autocorrelation term that might be covering the behaviour of industrial customers in the short-term, i.e. the gas usage with respect to the level of industrial production (this feature was covered also by Gabbi and Zanotti 2003).

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[71] Since we provide changes in percentages, we link them to the average consumption. We have already seen that there is approximately linear relationship between natural gas consumption and temperature, i.e. the impact of change in temperature by 1°C is in percentages is lower if consumption is already high. However, the change is in absolute values uniform independently from the current value of consumption.

Despite high R-Square of the model, is straightforward that temperature and the presence of weekends can not completely development of natural gas consumption. The level of explanatory power of such a model in general depends also on the share of weather sensitive natural gas demand in the market. As we already know, gas demand of households is in general highly predictable since it is composed of two basic parts – baseload demand used primarily for cooking on a day-to-day basis and the heating part of demand, which is highly temperature dependent. For that reason, unpredictable development of consumption is primarily causes by the industrial demand, which is not weather dependent and which may exhibit unexpected patterns due to decisions of particular companies about the level of production (e.g. based on its economic performance). Moreover, there might also act other factors in decisions of households and industries, e.g. the price of natural gas or economic performance of a country or a particular geographic region.

Moreover, building of such a model generally requires continuous actualization with respect to the current situation in the market. As a company may for example loose several significant manufactories that are temperature independent and that create a high portion of customer portfolio, its performance would become even more susceptible to weather.

To sum up, we have demonstrated that temperature greatly influences consumption of natural gas. If a company is not aware of potential threats linked to adverse weather conditions, it may in the end cause large financial losses. With regard to our results, a company may generally choose from two options to ensure stable financial performance:

- reflect new findings into contracts with customers[72]
- decide to hedge weather risk in the financial markets

Since the results reported by us serve as an evidence of the strong dependency of natural gas consumption on temperature. Therefore, it might be appropriate for particular companies to protect their businesses against weather risks with the help of weather derivatives, as it is a frequent practice in the world.

[72] Since companies frequently use off-takes' flexibility bands in contracts with their customers (i.e. that a customer has to off-take at least for example 85% of contracted volumes), some kind of a regression model may be implemented into contracts instead of just a plain percentage.

3. 5. Regression on differences

In the previous chapters, we have built the model stating the consumption of a given customers portfolio with respect to its temperature and week-day sensitivity. The model was estimated with the multiple regression method and consequently also with GLS that was applied to deal with autocorrelated residuals. We have found out that by employing present and past temperature observations, covering both the short and long term impact, and one dummy variable - day of a week as regressors, it is possible build a model greatly explaining variances in natural gas consumption.

Despite the fact that the estimation of natural gas consumption in absolute values with multiple regressions is frequent in the energy industry, as we have already seen, models based on differences could be also suitable since we work with the time series data. In order to forecast natural gas demand for gas of British Gas NW during the winter 1990/91, Fildes et al. (1997) provide just a model based on differences. We try to set up a similar model that is estimating the change in natural gas consumption in two consequent days with respect to the change in temperature and to the presence of a weekend day.

The transformation of data into differences (as shows equation (17)), which are used instead of absolute values, assures that we work with independent regressors and accordingly avoid problems of autocorrelation of residuals. We use the same presumption as in OLS and GLS regressions, i.e. that consumption tends to be inelastic with temperatures over 16°C.

$$\Delta G_t = \alpha \cdot \Delta Weekend_t + \beta \cdot \Delta T_t + v_t \tag{17}$$

where ΔX_t *means the difference between two consecutive observations of a given variable* $X_t - X_{t-1}$.

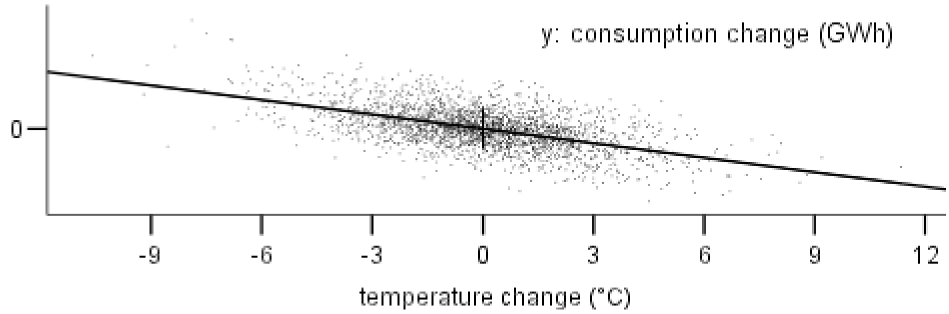
Table 16: Regression on differences

variable	coefficient	std. error	t-statistic	signif.	95% conf. interval lower	95% conf. interval upper
Week_change	-25.619	0.493	-52.015	0.000	-26.585	-24.653
Temp_change	-6.388	0.126	-50.685	0.000	-6.635	-6.141
R-Square	0.616					
adj. R-Square	0.616					
std. error	15.292					
Durbin-Watson	1.884					
F-statistics	2 637.3					

Source: Author

Results of the model based on differences as shown in Table 16 provide us similar information, with regard to the estimated coefficients as well as to the explanatory power, as the estimation with GLS. Regression on differences indicates that the inter-day fall in temperature by 1°C causes the consumption to rise by 6.388 GWh, whereas GLS provides us information that the change in temperature on a given day by 1°C leads to the variation in consumption by 6.804 GWh. The presence of weekend leads to the fall in consumption by 25.619 GWh according to the difference regression (see the impact without the weekend factor in Figure 29), while GLS indicated the change by 25.671 GWh.

Figure 29: Impact of change of temperature



Source: Author

We found out that the temperature dependency is lower than provided by Fildes et al. (1997) for England. With the average gas load equal to 870, they indicate the impact of temperature change of 1°C equal to 75.6, which is approx. 8.7% of the average consumption and of the weekend about 150, i.e. 18% of the average. However, we found out that the increase in temperature by 1°C causes the consumption to fall by approx. 6.4 GWh, which is only about 2.7% of the average load. Moreover, consumption on weekend days falls by 25.6 GWh that is only 10.8% of the average consumption. This comparison indicates higher usage of natural gas of British Gas for heating purposes. For that reason, we "only" get R-Square of the model equal to 61.6% in comparison with Fildes' model whose explanatory power reaches 83%.

With the usage of differences in the model we use differences, the past temperature are already reflected in the model. However, we have also demonstrated that the relationship between gas consumption and temperature is not completely linear. This feature was caught with lagged the application of lagged and capped variables. Therefore, with the model given by equation (18), let us look whether the impact of temperature changes on preceding days is directly observable on a given day.

(18) $$\Delta G_t = \alpha \cdot \Delta Weekend_t + \beta_0 \cdot \Delta T_t + \beta_! \cdot \Delta T_{t-1} + \beta_2 \cdot \Delta T_{t-2} + \beta_3 \cdot \Delta T_{t-3} + \beta_4 \cdot \Delta T_{t-4} + v_t$$

where ΔX_t *means the difference between two consecutive observations of a given variable* $X_t - X_{t-1}$, ΔX_{t-1} *means the difference* $X_{t-1} - X_{t-2}$, *etc.*

This model with the results provided by Table 17 corresponds to the long term impact of temperature. Despite the fact that the previous temperature changes have been already caught in the previous model (given by equation (17)), in the adjustment of heating devices is already reflected also the long term weather behaviour, as we already know.

Table 17: Regression with lagged differences

variable	coefficient	std. error	t-statistic	signif.	95% conf. interval lower	upper
Δ week$_t$	-25.544	0.466	-54.874	0.000	-26.457	-24.632
ΔT_t	-6.534	0.122	-53.760	0.000	-6.772	-6.296
ΔT_{t-1}	-2.199	0.122	-18.093	0.000	-2.437	-1.961
ΔT_{t-2}	-0.920	0.123	-7.481	0.000	-1.162	-0.679
ΔT_{t-3}	-0.733	0.122	-6.025	0.000	-0.971	-0.494
ΔT_{t-4}	-0.301	0.122	-2.469	0.014	-0.541	-0.062
R-Square	0.659					
adj. R-Square	0.658					
std. error	14.431					
Durbin-Watson	1.999					
F-statistics	1 055.1					

Source: Author

Therefore, we look if lagged temperature differences are statistically significant in our model. With respect to the results shown in Table 17, we see that that the differences up to the fourth lagged day are still significant on the 5% level in the model. It corresponds to the logical notion that the change in consumption for heating purposes is higher if some weather trend persists for more days. For example, if we have increase in temperature on a given day t, industrial consumers do not adjust much their heating devices if temperature was steadily falling on preceding days and rather wait for further development of weather. On the other hand, if temperature was stable or even rising on preceding days, it might be for several companies a stronger signal to switch off their heating systems.

By implementation of lagged differences, the explanatory power of the model has further increased to 65.9% that is slightly more than of the GLS model. As we have seen, all models presented by us indicate strong impact of temperature on natural gas consumption in the Czech Republic with the explanatory powers of models over 60%. Companies, which are generally aware of this dependency, should be willing to assess this dependency and consequently try to protect themselves against threats of adverse weather conditions.

4. HEDGING WITH WEATHER DERIVATIVES

"Weather hedges provide financial compensation for the buyer when adverse weather occurs. They can be structured to pay out against specific levels of precipitation, temperature or wind, or a combination of those and other weather variables."

Randy Myers (2008)

Wide flexibility in design of specific weather indices facilitates the development of innovative hedging structures that are used to manage a large scale of weather-related risks. Weather indices on temperature, precipitation, snowfall, wind or other weather features can be used for different locations as well as different time periods including days, weeks and months.

Ruck (2001) refers to several basic questions that should be answered before making a decision on hedging weather risks in order to help with the development of a successful strategy:

- How much weather risk can be tolerated?
- What is the minimum acceptable revenue, net income or unit sales level?
- How do the Board of Directors and senior management view hedging?
- Are premium payments acceptable, or must the hedge be cost less?
- Is there any accounting or tax implication associated with hedging weather risk?
- Are there any regulatory issues to consider?

With regard to other factors, such as the financial rating of counter-party or provided customer services, a company that is considering pros and cons of a potential hedge may get a notion that could greatly help to decide. Nevertheless, the decision is in the end usually based on a cost-benefit analysis that examines possible financial impact of a hedge.

A business with weather exposure may choose to buy or sell a futures contract, where one party is paid if degree days exceed a pre-determined level while another gets a payment in the opposite case. However, the majority of traded weather derivatives are put or call options, occasionally also combinations of both types.

Because we have already demonstrated the level of weather risk in the Czech market, we focus on the applicability of temperature-based derivatives in this chapter. According to Zeng (2000) or Mitu (2008), a weather derivative contract can be generally formulated by specifying several basic parameters listed below.

1) ***Reference weather station***. Almost all weather derivatives contracts are based upon one specified weather station, it may even happen that some use as a basis a combination of more stations.
2) ***Index*** defines when and how should be payments from the contract accomplished.
3) ***Term*** by which are defined days of beginning and termination of the contract.[73]
4) ***Structure***. As a weather derivative contract is based on standard financial derivatives' structures, its type (e.g. put, call, swap, collar etc.) has to be defined together with:
   a) Strike – specific threshold level when begin payments from the contract
   b) Tick – amount paid per one unit over the strike
   c) Cap (theoretical value) – maximum possible payment from the contract
5) ***Premium***. The buyer of a weather contract (option) pays a premium to the seller, usually between 10% and 20% of the theoretical amount of a contract.

Because weather hedges are most efficient when they are customized to buyer's specific needs and risk exposure, accurate quantification of potential impacts of weather with all associated risks is essential. It is generally recommended to correlate weather, sales and profit data for at least five years backwards. Hereafter an appropriate weather index has to be chosen in order to build a convenient derivative's structure. Since we do not have information on commodity prices, consumption (sales) of natural gas is used for the analysis of hedging capabilities.

4. 1. Weather options

4. 1. 1. Degree days options

Weather derivatives as contracts whose payoffs depend on weather have several possible weather measures that can be used as their basis. Garman (2000) estimates that some 98% of

[73] Very frequent are contracts with the duration from November, 1 to March, 31 for winter and from May, 1 to September, 30 in case of summers. However, with growing flexibility in contracts' conditions has increased also the number of monthly or even weekly contracts.

all weather derivatives are based on principal temperature indices that are often used in the energy industry and traded as weather derivatives:

- Heating Degree Days (HDD)
- Cooling Degree Days (CDD)
- Cumulative Average Temperature (CAT)[74]

With flexibility in using these indices today is facilitated also the development of innovative hedging structures to manage a wide range of weather-related risks.

HDD and CDD are by their nature quantitative indices derived from daily temperature measurements, which are designed to reflect the demand for energy needed to heat or cool houses and factories. The idea of HDD consists in the fact that heating is usually required when temperature drops below some reference level and thus energy expenditure is needed. Heating or cooling requirements for a given subject at a specific geographical location are commonly considered to be directly proportional to the number of degree days. For detailed overview of weather indices in use see also Barrieu and Scaillet (2010) or Cao et al. (2004b).

HDD is defined as the number of degrees by which the daily average temperature is below some base temperature, while CDD express the number of degrees by which the daily average temperature is above this value. Mathematically expressed, daily HDD and CDD structures look as follows:

(19) $$HDD = \max(0, T_{base} - T_{daily\_average})$$

(20) $$CDD = \max(0, T_{daily\_average} - T_{base})$$

The base approach in the energy sector, which has been previously used in numerous studies (see e.g. Cao et al. 2004a, Alaton et al. 2005 or Clemens et al. 2008), is to apply 18°C (= 65 degrees Fahrenheit) for HDD and 24°C (= 75 degrees Fahrenheit) for CDD as the base temperature.

Daily HDD and CDD are consequently accumulated over a period of time (usually of few months or whole season) that serves as an indicator of heating or cooling requirements for this period. Considering the interest of natural gas companies, increase in HDD corresponds with decreasing temperature, which is reflected in higher natural gas consumption. Since weather derivatives are applied for hedging of weather related risks over a long horizon, production of

[74] CAT is used only rarely since as primary indices are generally perceived HDD and CDD.

aggregate indices is needed. Campbell and Diebold (2005) demonstrate the importance of a cumulative HDD index (see equation (21)), which includes both nonlinear transformation of daily average temperature into HDD as well as further aggregation of daily indices because:

- weather derivatives are typically written on a cumulative sum of weather related outcomes
- November-March HDD contract is one of the most actively traded weather-related contracts and is also of a substantial interest to end users of weather models

(21) $$Cumulative\_HDD = \sum_{t=1}^{n} HDD_t = \sum_{t=1}^{n} \max(T_{base} - T_t, 0)$$

As we have already stated, the most commonly used weather derivatives are options, especially calls and puts[75] as well as their various combinations, e.g. collars[76]. With regard to intentions of particular hedges, a company generally decides on various option types shown in Table 18. Beside various purposes of particular options, this table introduces also simple drafts of payoffs that are generally based on the difference between the exercise and actual level of a weather index.

Table 18: Temperature options

option type	protection against	exercise when	payout
HDD call	overly cold winters	HDD > strike	tick*(HDD-strike)
HDD put	overly warm winters	HDD < strike	tick*(strike-HDD)
CDD call	overly hot summers	CDD > strike	tick*(CDD-strike)
CDD put	overly cold summers	CDD < strike	tick*(strike-CDD)

Source: Müller and Grandi (2000)

As we are primarily interested in fluctuations of natural gas consumption during winters, CDD are not considered in this thesis as this index corresponds especially to requirements for cooling energy.

In spite of wide flexibility available in designing weather derivatives, basic attributes are common for the majority of contracts. Therefore several basic features have to be specified to

[75] Just to remind, general definition of a call option says that it gives the right to buy (call in) an asset and thus make a profit when the price of an underlying increases. On the contrary, a put option gives the holder the right to sell an underlying asset to the writer of an option.
[76] Collar enables a market player to minimize his hedging costs by buying a put and selling a call with the same strike price.

determine the payoff from a HDD option. On the day following the end of a contract period, the payout from an option may be computed in compliance with equations (22) and (23).

- call option

(22) $$V = \min\left(\max\{0,(HDD - X)\}\cdot tick, cap\right)$$

- put option

(23) $$V = \min\left(\max\{0,(X - HDD)\}\cdot tick, cap\right)$$

where X means the strike level, HDD is an aggregate level of the index, Tick is the payment per one HDD and Cap is the maximum payment from an option.

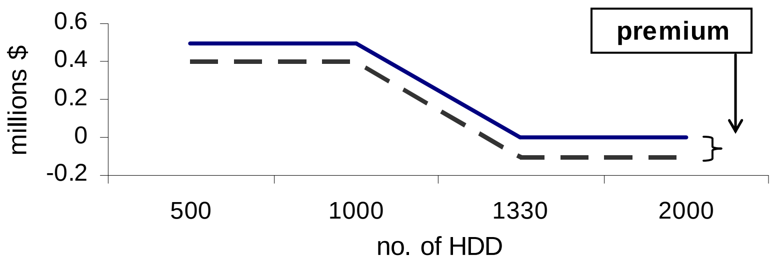
♦ ***Options used by companies trading natural gas***

Since revenues of natural gas companies decrease with warm weather especially during winters, these companies are primarily interested in hedging themselves against the case of lower number of HDD than the strike level. Therefore buying of a put HDD option is perceived to be an appropriate hedging strategy against warm weather.

Dutton (2002b) gives an illustrative example (see Figure 30) on the payoff structure of a long put option bought by Jefferson Gas as a protection against the risk of warm winter. The option was bought for the price (= premium) of $100,000 and with the following specifics:

- variable index – HDD
- cap - $500,000
- strike – 1,330 HDD
- rate of payment – $1,500/HDD

Figure 30: Payout diagram of a long put HDD option



Source: Dutton (2002b)

Consequently, the company would be paid up to the amount of $500,000 (the net revenue would reach $400,000) in the case of warm winter. On the other hand, if the cumulative number of HDD was higher than 1,330, the company would not be paid from the option and thus its net loss would be -$100,000 due to the premium payment.

4. 1. 2. Pricing techniques

"Due to the lack of widely accepted weather derivatives pricing methodologies, counterparties do not always agree on the right price to trade."

Garman et al. (2000)

As the predictability of earnings is for companies highly valuable, one of the major advantages of weather derivatives consist in ability to dramatically reduce volatility in earnings. Nevertheless, an analysis of financial favourableness of hedging eventuality has to be always executed. Buckley et al. (2002) or Tindall (2006) list several techniques of pricing weather derivatives based on:

- regression analysis and correlations
- de-trended time series
- burning analysis
- Monte Carlo simulations
- seasonal weather forecasting

Companies could easily use meteorological services to assess weather derivatives, but as the reliability of long term weather forecasts is limited, pricing techniques are more in hands of statisticians than of climatologists.

♦ ***Black-Scholes model***

Since weather as an underlying of weather derivatives is a non-tradable asset, the possibility of using standard evaluation techniques is limited. Therefore *the Black-Scholes* model as a traditional way of pricing financial derivatives is not convenient Garman et al. (2000) list even 4 reasons why it is not appropriate to use the Black-Scholes.

1) Weather does not follow the "random walk" like asset prices do as they tend to revert back to their historical prices and thus fluctuate within relatively narrow bands.
2) Weather is rather predictable in the short-term while approximately random in the long-run. Hence it behaves different according to the length of the period.
3) In contrast to the standard Black-Scholes options, weather derivatives are frequently capped, i.e. there exists some maximum level of payoff.

4) Since the underlying of weather derivatives is not the price, pricing can not be free of economy risk aversion factors.

Since temperature is mean reverting, i.e. usually tends to revert to normal levels within a couple of days, any models using the random walk are inadequate for modelling temperature.

♦ ***Monte-Carlo simulations***

Other method is *Monte-Carlo simulations method* that incorporates a computer-based generation of random numbers that may be used in the construction of weather scenarios. It generally consists of simulation of numerous weather scenarios (e.g. based on HDDs) to determine payoffs of an instrument. Consequently, the fair price is the average of all possible payoffs approximately discounted to account for the time value of money.

♦ ***Burn analysis***

Nelken (2000) shows a different way of evaluating weather derivatives, which is frequently used also in the insurance industry and determines their financial impact with regard to past temperature. This method is generally known as *the burning cost method* or *burn analysis*. The aim of this approach is to answer the question: "*What would have been the average payoff of the option in the past X years?*" Therefore Nelken suggests the following procedure:

1) collect the historical weather data
2) convert to degree days
3) make some corrections
4) determine what would have been paid out from the option for every year in the past
5) make an average of these amounts

The main advantage of burn analysis in comparison with other methods is that it does not include any form of weather (temperature) forecasting. Since this procedure is highly logic and relatively easy to set up, it is quite common that market participants use this method in order to get the first notion about the fair price of an option.

4. 2. Burn analysis

Burn analysis presumes the future development of weather corresponding to the average of its past behaviour. Thus, accordingly to reasonable but only relatively validated prediction, historical data can serve as a predictor of normal behaviour of temperature in the long-term. With regard to the easiness of this method, it may serve as an ideal starting point for a company that is considering purchasing of a weather derivative contract. To find the fair price of a potentially used HDD put option, we follow hereinbefore suggested Nelken's scheme.

Pricing of weather options needs a good source of historical temperature data and further application of statistical methods to fit distribution functions to this data. With the extended sample (until 2008) of temperature observations provided by CHMI that we have already used in Chapter 3, there is no problem with collection of daily temperature measurements. Therefore measurements at station Praha – Ruzyně might without any problems serve a basis for hedging.

♦ ***Transformation into HDD***

When transforming temperature measurements into HDD, one has to decide about the threshold level of temperature (see equation (19)). Despite the market convention of using 18°C, we would suggest, in accordance with the previous chapter, application of 16°C in the Czech natural gas market since it effectively captures heating demand and thus temperature dependent portion of consumption.

Table 19: Share of HDD in winter

year	1998	1999	2000	2001	2002	2003	2005	2006	2007	2008
total HDD	2 826	2 754	2 574	2 991	2 735	2 989	3 041	2 942	2 531	2 678
winter HDD	2 664	2 618	2 444	2 829	2 675	2 933	2 826	2 739	2 421	2 554
% of winter	94%	95%	95%	95%	98%	98%	93%	93%	96%	95%

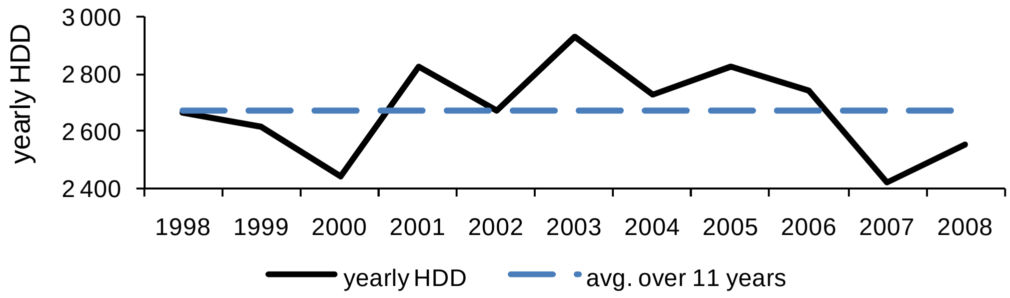
Source: Author

In order to build a cumulative HDD function, the risk exposure period, which is commonly considered to be a whole season or a particular month, has to be specified. HDD indices are commonly computed over the "winter season" what in most cases signifies the period from October to April, or November to March.[77]

With regard to Chapter 3.2.2 (Figure 21) and our regression results, it could be rewarding to do not use hedging with weather options for the whole year, but just for a part where consumption varies the most. Therefore an effective hedge is suggested to be applied only for the period of eight months, from September, 1 to April, 30. Moreover, if we transform temperature data into HDD (with application of 16°C as the base level), one might see in Table 19 that these eight months (labelled as "winter") contain the vast majority of yearly HDD.

[77] On the other hand, CDD indices are generally used during the "summer season".

Figure 31: Yearly number of HDD during the hedged period



Source: Author

Cumulative HDD index for a potentially hedged period (Figure 31) has been obtained by transformation of temperature data. The dashed line, representing the average quantity of HDD in the last eleven years, indicates that buying of HDD put options could have been appropriate in recent warm years. However, the profitability is in the end always a question of hedging costs.

♦ ***Payoff structure***

We show the payoff structure of a put option once more.

(24) $$V = \min\left(\max\{0, (X - HDD)\} \cdot tick, cap\right)$$

Because the number of HDD for each particular year is well known, especially the exercise level of an option has to be chosen properly. Roustant et al. (2003) suggest employing of the historical average temperature (HDD) index as a basic exercise level whereas e.g. Garcia and Sturzenegger (2001) suggest calculation as the average cumulative HDD minus ½ of its standard deviation. As another method, Platen and West (2005) apply as an exercise level the average cumulative HDD plus ½ of the standard deviation. Hereafter, playing with various levels close to the average HDD is recommended to find out the most appropriate alternative.

Considering temperature measurements over the last eleven years should be appropriate for choosing an exercise level, which is generally set in accordance with the normal climate conditions. Even though there are various approaches to this issue, the market usually takes as normal the average level over the past 10-15 years.[78] Because appropriate descriptive statistics

[78] Nevertheless, there might be exceptions, e.g. Considine (1999) mentions the case of Miami where 15-years average may not be appropriate as there has been substantial warming trend over the past 30 years.

for HDD (cumulated over 8 months) are listed in Table 20, one may show some of possible exercise levels of an option.

Table 20: Statistics on HDD in the Czech Republic (1998-2008)

	min.	max.	mean	std. dev.
HDD	2 421.3	2 932.7	2 675.6	159.9

Source: Author

Garman et al. (2000) suggest the calculation of an expected payoff for each year and consequent application of the average of those historical payoffs as the fair price. Hereafter, we determine the payoff of an illustrative HDD put option for the period of 8 months with the tick of EUR 1,000 per HDD and no payment's cap considered.

In Table 21 are displayed payoffs of the option with the application of exercise levels suggested by:

- Garcia and Sturzenegger (2001): exercise level = average HDD - ½ of std. dev.
- Roustant et al. (2003): exercise level = average HDD
- Platen and West (2005): exercise level = average HDD + ½ of std. dev.

Table 21: Various payoffs of the option

year	HDD	payoff (EUR)		
		X = 2 595.7	*X = 2 675.6*	*X = 2 755.6*
1998	2 664.3	0	11 300	91 300
1999	2 618.4	0	57 250	137 250
2000	2 444.0	151 700	231 600	311 600
2001	2 829.4	0	0	0
2002	2 675.3	0	300	80 300
2003	2 932.7	0	0	0
2004	2 727.5	0	0	28 150
2005	2 826.2	0	0	0
2006	2 739.3	0	0	16 311
2007	2 421.3	174 400	254 300	334 300
2008	2 553.7	42 000	121 900	201 900
average	*2 675.6*	*33 464*	*61 514*	*109 192*

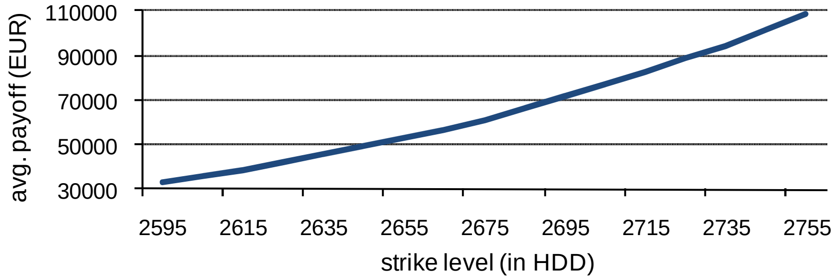
Source: Author

Calculation of average payoffs from the option in the past provides primary idea on value of the option. If a company is able to find such an option whose costs are similar of lower than above listed prices, it may be an indicator to look at that option in more detail. The logic of

HDD put option pricing is straightforward: with increasing exercise level (and no cap on payments considered) raises also the average payoff of the option (as shown in Figure 32).

Burn analysis is one of the primary steps on the way to hedging against weather risk. Both assessing of weather sensitivity of a business and searching for hedging possibilities, in which is frequently involved also burn analysis, should provide a notion whether it could be favourable to protect company's financial performance with weather derivatives.

Figure 32: Average payoff with regard to various exercise levels



Source: Author

However, when it is the time to make a final decision, more sophisticated methods are generally applied for pricing weather derivatives. Since a company determines the fair price of a hedge and is able to find such a financial instrument, which corresponds to this fair price level and satisfies all requirements of a company, the only question remains: *"How many weather options to buy?"* This question is generally answered with regard to size and weather sensitivity of company's revenues.

♦ CONCLUSION

Nowadays, in the period of liberalization of the natural gas market in Europe, companies become aware of controlling their revenues more than ever. Among the factors that have crucial impact on stability of revenues in the natural gas business belongs weather. Although companies in regulated markets were commonly adjusting prices to offset low revenues in the case of decreased demand for heating, the approach to this issue has greatly changed since the 90s as ongoing deregulation made increasing of consumer prices difficult.

Primarily, it was the interest of energy companies in the U.S. that helped the new weather risk market to emerge in the 90s. With the aim of staying competitive in liberalized markets, companies started to assess impacts of weather on their financial performance and consequently hedge against weather risk.

With more potential methods of protection against weather risk, energy companies commonly undertake analyses of weather sensitivity of their businesses and of the most favourable ways of hedging. This unambiguously holds for companies trading natural gas since consumption of this commodity is highly affected by changeable weather, especially by temperature. Among the most frequent methods of evaluating the dependency belong also regression methods.

In this thesis, we have shown two main models to which are applied OLS and GLS methods and that assess the impact of weather on natural gas consumption in the Czech Republic.

In the first model, that is modelling the absolute value of natural gas consumption of a given portfolio of customers with respect to its temperature sensitivity and a present temperature profile, we have been successively improving explanatory power by the addition of several useful features. Absolutely fundamental in the majority of similar studies is the application of two basic explanatory variables:

- actual day's temperature

- impact of weekends and bank holidays

Both increasing temperature on the actual day and the presence of weekend may cause significant fall in natural gas consumption. The explanation is straightforward because higher temperature is generally reflected in lower gas consumption due to the fall of heating requirements. Considering the impact of weekend, industries usually consume lower volumes during weekends due to limited production.

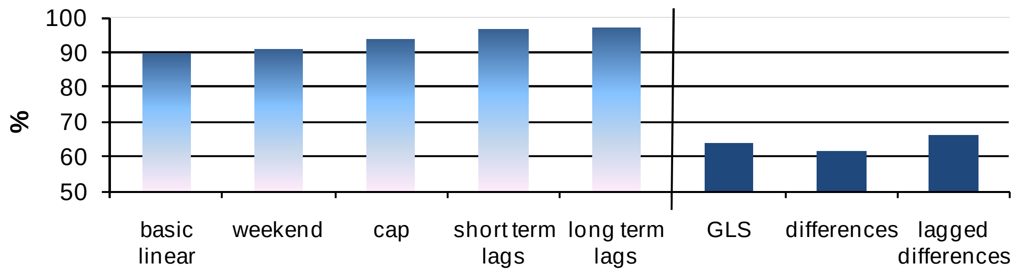
We have demonstrated that in the Czech market is present approximately linear relationship between natural gas consumption and temperature with the exception during warm periods of a year. Similar results provide also Fildes et al. (1997) for the British gas market and Gabbi and Zanotti (2003) for Italy. With temperatures above some threshold level, there generally remains only the base-load consumption, which is primarily shaped by the demand of industrial customers and which is not dependent on temperature. Such a feature is in various forms common for all natural gas markets. When comparing several levels of temperature, we have decided to set this cap on temperature at 16°C that should effectively reflect heating requirements. By this transformation, the model assigns to all observations with temperature higher than 16°C the same consumption, which corresponds to the fact that consumption stays with high temperatures close to mentioned base-load level.

The last characteristic that we implemented in the first model was the impact of past days' temperatures. It is a common practice that several lagged values of temperature are included in similar models, for example Gabbi and Zanotti (2003) used in their model two foregoing days, which primarily reflect the need for adjustment of heating devices in the short term. However, we have taken into account in our final model stating the absolute value of consumption also the adjustment of heating devices in the long term.

Since manufactories generally adjust (or even turn off) their heating devices with regard to some long term temperature profile, we have included in the model as an explanatory variable also monthly average of daily temperatures that is also a highly significant variable in the model. Therefore it should be rewarding for similar studies to count with the long term temperature profile to efficiently model natural gas consumption. Despite this fact, it is not a common practice in similar studies or even in analyses of natural gas companies.

When investigating the residuals in the first model, the presence of both autocorrelation and heteroskedasticity was revealed that caused the OLS estimator to be inefficient. Because the OLS estimator is unbiased, the model would be with application of robust standard errors, which deal with heteroskedasticity and autocorrelation, satisfactory for the majority of natural gas traders. Nevertheless, we have decided to use the generalized least squares method (with the Cochrane-Orcutt transformation) in order to deal with the autocorrelation of residuals and consequently get an efficient estimator, whose R-Square is 63.9% since the result of OLS was overestimated due to present autocorrelation. Furthermore, robust standard errors and t-statistics were applied as remedy to heteroskedasticity problem.

Figure 33: Comparison of applied methods (R-Square)



Source: Author

Such a model, which models the outcome of a given business with respect to its temperature sensitivity can be consequently applied for example in contracts with customers, e.g. to set effectively flexibility bands in customers' daily, monthly or yearly off-takes. Finally, evaluation of the dependency frequently serves also as the first step when considering hedging against weather risk, for which are commonly used weather derivatives.

Beside the first model predicting the absolute value of consumption with respect to weather sensitivity of a given portfolio, we have built also the second model based on differences. Similar model was applied also by Fildes et al. (1997) in the British gas market, which estimated the change in natural gas demand in two consecutive days with respect to the change in temperature and the day of a week. The results of this model primarily confirm our findings demonstrated by the first model about the impact of temperature and weekends on the natural gas consumption. Explanatory power of this model, which also covers non-linear aspect of the dependency with direct impact of past temperature differences on present consumption, reaches 65.9%. Both models demonstrate heavy influence of temperature on natural gas consumption, despite the fact that weather and lower industrial gas demand at weekends can not explain all variability in natural gas consumption. We are already aware that there are also other factors playing a role – one of the most significant is the current level of industrial production.

In the last chapter, we provided basic information on so called weather derivatives, which are often employed in hedging against weather risk. The most frequently applied instruments by natural gas companies are HDD put options that serve especially as a protection against abnormally high temperatures in winter. Beside some other factors, the final decision on hedging is commonly done with regard to the cost benefit analysis. Despite the fact that there exist even more sophisticated methods of assessing the fair price of an option, we have performed so called burn analysis that often serves as the first indicator of the fair price of an option. If revenues from the hedge are higher than costs, by which is meant an option premium, it is a good indicator that the hedge could be convenient. Therefore a company is generally looking such a hedge whose costs are below the fair price.

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♦ APPENDIX

Table A1: Outliers in the model

Case number	Std. residual	Consumption (GWh)	Predicted value	Residual
1092	-3.201	399.600	481.213	-81.613
1443	3.972	600.430	499.170	101.260
1804	3.141	580.530	500.444	80.086
1805	3.183	599.380	518.229	81.151
2191	-3.346	355.620	440.934	-85.314
2612	-3.097	463.270	542.232	-78.962
2621	-3.183	442.980	524.130	-81.150
2715	-3.025	122.280	199.401	-77.121
2865	-3.897	247.830	347.173	-99.343
2916	-3.040	327.540	405.033	-77.493
2970	-3.068	381.530	459.739	-78.209
2971	-3.408	334.950	421.829	-86.879
2972	-3.427	333.200	420.563	-87.363
2973	-3.392	362.200	448.666	-86.466
3224	3.058	175.670	97.699	77.971

Source: Author

Table A2: Regression with long term lags and multicollinearity of variables

variable	coefficient	std. error	t-statistic	signif.	95% conf. interval lower	95% conf. interval upper	VIF
const.	416.636	0.778	535.757	0.000	415.111	418.161	
weekends	-30.337	0.969	-31.320	0.000	-32.236	-28.438	1.004
T_t	-10.415	0.218	-47.855	0.000	-10.841	-9.988	12.377
T_{t-1}	-2.275	0.306	-7.437	0.000	-2.875	-1.676	24.483
T_{t-2}	-1.841	0.310	-5.948	0.000	-2.448	-1.234	25.066
T_{t-3}	-1.290	0.310	-4.162	0.000	-1.898	-0.682	25.149
T_{t-4}	-0.859	0.310	-2.774	0.006	-1.466	-0.252	25.128
T_{t-5}	-0.617	0.306	-2.012	0.044	-1.218	-0.016	24.624
T_{t-6}	-1.361	0.227	-6.003	0.000	-1.806	-0.917	13.489
$T_{(t-7\ -\ t-30)}$	-2.176	0.146	-14.852	0.000	-2.463	-1.888	4.681

R-Square	0.969
adj. R-Square	0.969
std. error	25.243
Durbin-Watson	0.438
F-statistics	11 356.6

Source: Author

Table A3: Autocorrelation of OLS residuals

lag	ACF	std. error	PACF	std. error
1	0.721	0.018	0.721	0.018
2	0.646	0.018	0.262	0.018
3	0.508	0.018	-0.055	0.018
4	0.474	0.018	0.106	0.018
5	0.409	0.018	0.025	0.018
6	0.435	0.018	0.155	0.018
7	0.416	0.017	0.059	0.018
8	0.340	0.017	-0.143	0.018
9	0.283	0.017	-0.036	0.018
10	0.244	0.017	0.024	0.018
11	0.242	0.017	0.072	0.018
12	0.242	0.017	0.043	0.018

Source: Author

Table A4: CORC iterations

Iteration	ρ (AR1)		D-W stat.
	value	***std. error***	
0	0.721	0.012	1.894
1	0.850	0.009	1.968
2	0.908	0.007	1.989
3	0.928	0.007	1.995
4	0.936	0.006	1.997
5	0.940	0.006	1.998
6	0.943	0.006	1.999
7	0.945	0.006	1.999
8	0.946	0.006	1.999
9	0.947	0.006	1.999
10	0.948	0.006	2.000

Source: Author

Table A5: Autocorrelation of GLS residuals

lag	ACF	PACF
1	-0.002	-0.002
2	-0.029	-0.029
3	-0.072	-0.072
4	-0.036	-0.037
5	-0.108	-0.114
6	0.044	0.035
7	0.214	0.206
8	0.010	-0.001
9	-0.084	-0.081
10	-0.076	-0.063
11	-0.027	-0.009
12	-0.076	-0.046

Source: Author