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Forecasting Japan's spot LNG prices using Bayesian Structural Time Series

By

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I hope that prosperity of shipping industry with the beautiful oceans.
Best wishes for everyone who interacted with me through MEL.

Ai Kitamura

Abstract

Japan's spot LNG prices may affect Japanese power utilities' profitability. This study proposes better models to forecast Japan's spot LNG prices in the short run and in the long run by applying Bayesian Structural Time Series (BSTS) model.

For the short-term forecasting, BSTS model performs better than a classical model, Autoregressive Integrated Moving Average (ARIMA) model. BSTS model captures dynamically changing patterns under the limited historical data (51 observations). The results show that Japan's spot LNG price of June 2018 is estimated to be $9.0/MMBtu.

For the long-term forecasting, BSTS model with a regression component performs better than Single BSTS model. To select the important variables, Spike and Slab prior is derived from Google search data. We consider the 11 potential variables influencing Japan's spot LNG prices: oil price, coal price, natural gas price, upstream investment in oil and gas, investment in LNG liquefaction plant, Japan's LNG spot market utilisation rate, global LNG spot market utilisation rate, natural gas production, natural gas consumption, global LNG trade, Japan's LNG import. The best-performing BSTS model includes Japan's LNG import in volume as the highest inclusion probability. The results show that Japan's spot LNG price is estimated to be $7.9/MMBtu in 2030.

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List of Abbreviations

ACE	Alternating Conditional Estimation
AIC	Akaike Information Criterion
ANN	Artificial Neural Network
AR	Autoregressive
ARCH	Autoregressive Conditional Heteroscedasticity
ARFIMA	Autoregressive Fractionally Integrated Moving Average
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive Moving Average
BATS	Bayesian Time Series Analysis
bbl	Barrel
bcm	Billion Cubic Metres
BP	British Petroleum
BSTS	Bayesian Structural Time Series
FOB	Free On Board
FY	Fiscal Year
GIIGNL	International Group of Liquefied Natural Gas Importers
HH	Henry Hub
IEA	International Energy Agency
LNG	liquified natural gas
MA	Moving Average
MAPE	Mean Absolute Percentage Error
METI	Japan’s Ministry of Economy, Trade and Industry
MMbtu	Million British Thermal Unit
MPTA	Million Tonne Per Annum
MT	Million Ton
VECM	Vector Error Correction model
VLGC	Very Large Gas Carrier
WTI	West Texas Intermediate

Chapter 1 Introduction

1.1 Background

Natural gas plays a crucial role as an energy supply, an electricity generator and a feed stock for industry. Global natural gas demand is expected to increase, because it has an environmental advantage compared to the other fossil fuels. It produces relatively low greenhouse gas emissions and contributes to higher air quality. Recent natural gas trade is more dynamic and globalised due to the shale gas revolution and the expansion of liquified natural gas (LNG). The shale gas revolution produces new natural gas supply locations in the world. LNG shipping allows flexible deliveries to meet demand and supply in the global basis.

Japan is the world largest LNG importer and Japanese companies have participated in the LNG export projects for 50 years. They are not only traditional LNG buyers but also important participants in the LNG supply chain. Japan's demand for LNG soared after the nuclear plant accident caused by the earthquake and tsunami in 2011. Before 2011, there were 54 nuclear reactors producing 30 % of Japanese power. In 2014, all nuclear reactors became offline. Japanese utilities increased rapidly the short-term LNG procurements. It prompted the surge in East Asian LNG spot prices and contributed to the shape of the dynamic spot LNG trades.

1.2 Problem Statements

Power utilities industry in Japan is undergoing dramatic changes and faces huge risks. It is difficult to reach the equilibrium of supply and demand for LNG, because the domestic LNG demand is fulfilled with uncertainty and LNG supply based on the long-term contracts is inflexible.

The LNG domestic demand as a fuel would be influenced by three factors such as: decreasing the domestic power demand in the long run, growing the solar capacity in the medium run and nuclear returning in the short run. On the other hand, the LNG supply market has inflexible characteristics which include long-term contracts and destination restrictions. However, developing liquidity in the LNG market has been seen. LNG spot trades boost and the U.S. became a LNG exporter due to the shale gas revolution. The LNG from the U.S. is flexible to destination. It means that it is possible to resell LNG from the U.S. to another destination.

Japanese power utilities face a problem to optimise their LNG procurement, because it is difficult to anticipate the domestic demand exactly. Moreover, it is anticipated that the LNG supply will have shortage because the increase in global LNG demand and the decrease in the final investment decision for the LNG upstream facilities.

In order to meet domestic demand and supply, there are three options. The first option is to buy the exact amount of LNG to meet the domestic demand by utilising the spot market. The second option is to resell the LNG which does not have destination restrictions in the long-term contract in case of excess supply in Japan. The third option is to trade LNG to make a profit and adjust the domestic procurement. Japanese power utilities choose the best combination of the LNG procurements in the long-term contracts, in the short-term contracts and from the spot market.

In this thesis, we limit the scope of the first option. Because the LNG trading is not a straight forward strategy to minimize the procurement costs but also more aggressive strategy to make profits. Moreover, the reselling the LNG is not necessarily if they can adjust the LNG supply from the short and the spot market. However, it is always better to have a back-up plan.

Therefore, to optimise the procurement costs, Japan's spot LNG prices are important. Although the volume of the LNG procurement could be adjusted from the spot market, the spot price is fluctuated. The spot LNG price forecasting could be useful for the power utilities to determine a budget for the cost in the near future.

1.3 Research Questions

With regards to the problem statements, this study answers the following main research question:

"How can we forecast Japan's spot LNG prices?"

This main research question comes from the situation that Japanese power utilities would increase the volume of LNG procurement from the spot market up to around 50% of the total by 2030. The LNG procurement from the spot market has increased due to the combination of the urgent LNG procurement in 2011 and the uncertainty of the future LNG demand. The LNG spot price could influence their procurement costs.

To answer the main research question, the following sub-research questions are formulated.

1. Who are LNG exporters and importers in the world (Chapter 2)?
2. What is the characteristic of LNG trade agreements (Chapter 2)?
3. How has the LNG market changed recently (Chapter 2)?
4. What is the characteristic of the global LNG spot market (Chapter 2)?
5. What determines the LNG demand in Japan (Chapter 3)?
6. What determines the LNG supply in Japan (Chapter 3)?
7. How do Japanese power utilities make use of the spot market (Chapter 3)?
8. What method is available to forecast Japan's spot LNG prices (Chapter 4)?

1.4 Research Methodology and Structure

This study uses both qualitative and quantitative methods to forecast Japan's spot LNG prices in the short run and in the long run.

In the qualitative part, we analyse global and Japan's LNG market to determine the potential variables which might influence Japan's spot LNG prices. The focal point is the LNG spot market. In the quantitative part, we use Autoregressive Integrated Moving Average (ARIMA) model and Bayesian Structural Time Series (BSTS) model for the short-term forecasting. we use BSTS without a regression component and BSTS with a regression component for the long-term forecasting.

This study is structured as follows.

Firstly, Chapter 2 analyses global LNG market focusing on the development of global LNG spot market. Chapter 3 analyses Japan’s LNG market focusing on the development of Japan’s LNG spot market. The results from Chapter 2 and 3 are used as variables of BSTS with a regression component for the long-term forecasting.

Secondly, Chapter 4 describes literature review to have ideas about the choices of this study methods. Chapter 5 analyses the characteristics of this study combined with the literature review and verifies the choices of this study methods. Chapter 6 describes notations of ARIMA and BSTS, the data set and the process of the implementations in the statistic software, R, for the short-term forecasting and long-term forecasting.

Thirdly, Chapter 7 describes results and analysis for forecasting Japan’s spot LNG prices. we use errors as a guidance to determine a model performance. Then, we compare the short-term results to the data published by Japan’s Ministry of Economy, Trade and Industry (METI) and long-term results to the data published by the World Bank.

Finally, Chapter 8 describes the key findings in terms of model performance and the forecast accuracy. We recommend BSTS to commercial people in their dairy work based on the overall results. In addition, limitations of this study and suggestions for further research are stated.

Chapter 2 Global LNG market

2.1 Introduction

Japan's spot LNG prices would be influenced by various factors. Most of commodity prices are affected by their demand and supply. In this chapter, we focus on the global LNG market. Because the Japanese LNG price is affected by the global LNG market. Firstly, we analyse demand for natural gas and LNG in 2.2 and LNG exporters and importers in 2.3. Secondly, we describe the characteristic of traditional LNG trade agreements to analyse how the LNG contracts were inflexible in 2.4. Finally, we analyse the LNG market development and a possible future opportunity about the spot market in 2.5.

2.2 Demand for natural gas and LNG

Global natural gas consumption has increased, and it would be a part of main energy sources due to its technical and economic advantages (Kumar, et al., 2011). The natural gas share accounts for 21 % of the worlds' total primary energy demand in 2014 right behind oil and coal with 31% and 29% respectively (IEA, 2017b). Global demand for natural gas is anticipated to rise by 2 % per year between 2017 and 2035, with demand for LNG expected to increase at 4 % per year (Royal Dutch Shell PLC, 2017). LNG expected demand is higher than natural gas demand, as LNG is more flexible and transported by LNG vessels to the locations, where pipeline facilities are not provided. Therefore, the LNG market is more globalised and increasing in volume.

Figure 1 shows Global LNG trade from 2007 to 2018. The LNG trade in volume increased sharply from 2009 to 2011. Although the volume decreased slightly from 2011 to 2012, the volume increased gradually from 2012 to 2014. Then, the LNG trade increased sharply again from 2015 to 2017.

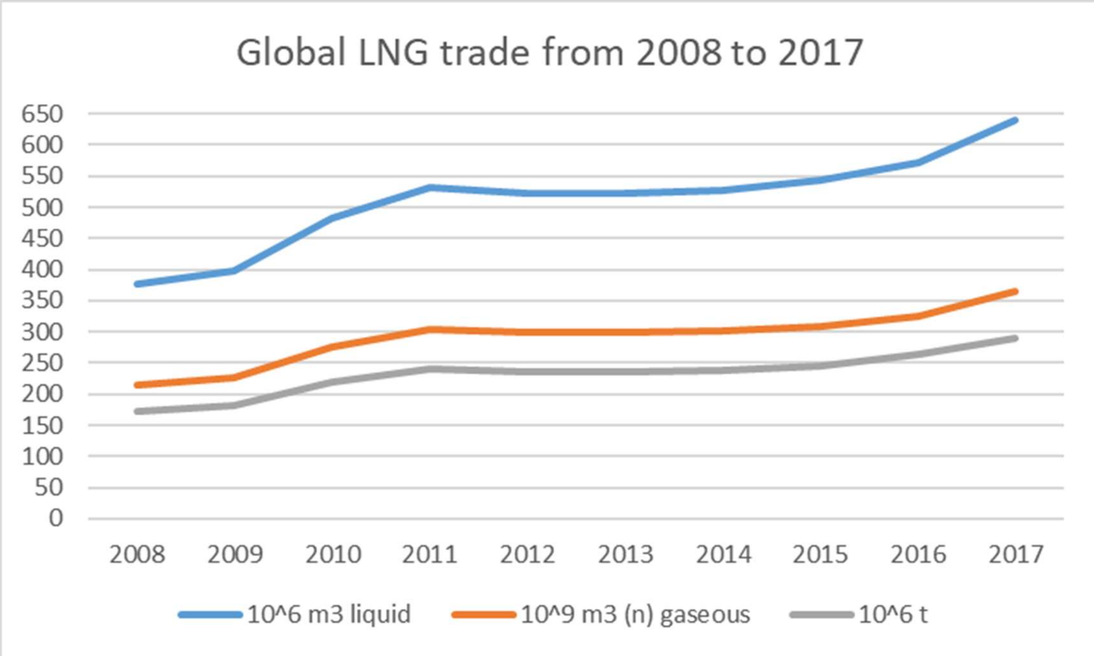


Figure 1 Global LNG trade

Source: Author via (GIIGNL, 2008, 2009, 2010, 2011, 2012,2013,2014,2015,2016,2017)

2.3 LNG exporters and importers

LNG global trade accounts for almost one third of total natural gas trade. According to BP (2018), global natural gas trade movements by pipeline in 2016 were 737.5 billion cubic metres (bcm) and LNG trade movements in 2016 were 346.6 bcm. There are specific LNG exporters and importers in a similar way to the other fossil fuels.

Regarding exporters, there are three types of LNG exporters. The first one is a natural gas producer which has excess supply in their countries after exports by pipeline. The second one is a producer surrounded by oceans such as Australia. The last one is a producer which has no or few pipelines towards neighbour countries because the neighbour countries do not consume much natural gas.

Meanwhile, three different conditions are applicable to LNG importers. The first condition is that there is LNG shortage within the country after imports by pipeline such as China. The second condition is a country has LNG shortage surrounded by oceans such as Japan. The third condition is a consumer which has no or few pipelines across the border.

Figure 2 shows World LNG exporters in 2016 and 2017. According to the BP (2018), the total LNG trade in 2017 was 393.4 bcm. The LNG exports by top 5 countries, Qatar, Australia, Malaysia, Nigeria and Indonesia were 264.9 bcm accounting for 67 % of the market share. The U.S. increased the LNG export from 4.4 bcm in 2016 to 17.4 bcm in 2017. Figure 3 shows LNG importers in 2016 and 2017. Top 5 importers, Japan, China, South Korea, India and Taiwan handled 266 bcm which shared 67 % of the market. China replaced South Korea and became the second largest LNG importer in 2017. They increased the LNG import from 34.3 bcm in 2016 to 52.6 bcm in 2017.

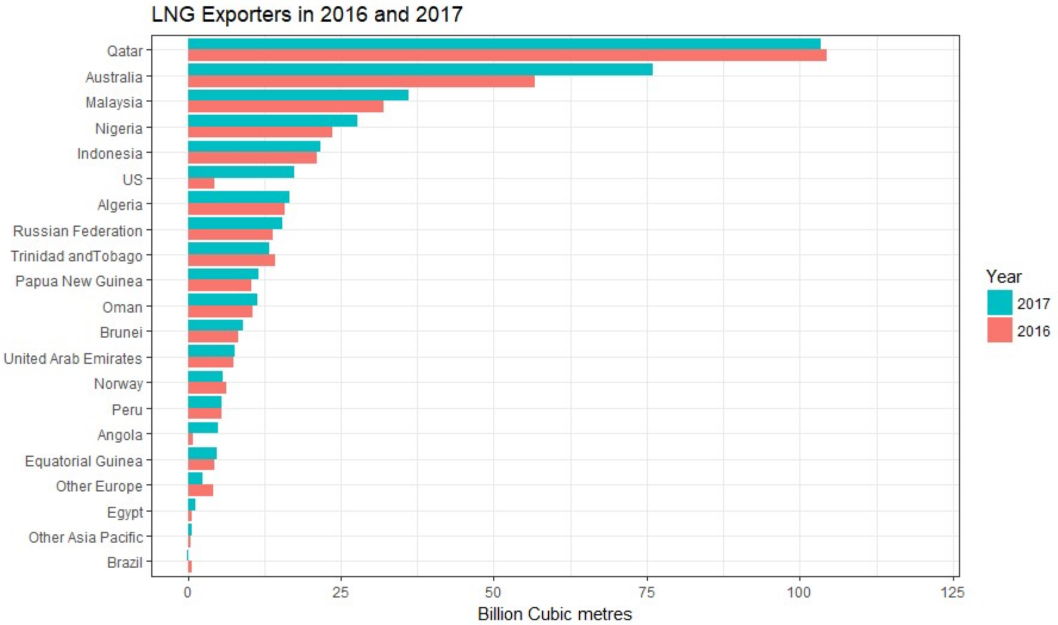


Figure 2 World LNG Exporters

Source: Author via (BP, 2018)

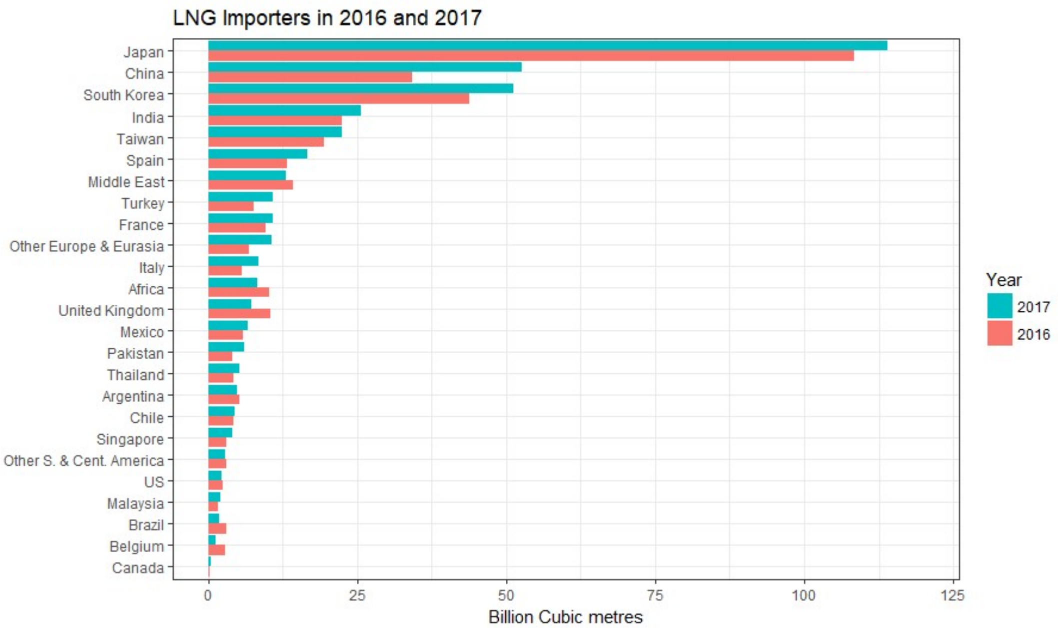


Figure 3 World LNG importers

Source: Author via (BP, 2018)

2.4 Characteristics of traditional LNG trade agreements

Traditional LNG sales and purchase agreements have long-term contracts, oil-price indexations and inflexible clauses. It is because there were specialised supply conditions and different types of demand in the specific regional LNG markets.

Traditionally, LNG trades were mainly dominated by the three markets: the first market was Japan and South Korea whose suppliers were mainly Indonesia, Australia, Malaysia and the Middle East, the second market was OECD Europe whose suppliers were mainly Norway, Russia and Algeria, and the third market was North America whose suppliers were mainly Canada and Mexico [Siliverstovs, et al., 2005].

Firstly, long-term contracts dominated traditional LNG trade agreements between importers in resource scarce areas and exporters [Olive, 2016]. The long-term contracts played key roles for covering large capital costs to extract and liquefy natural gas. The long-term contract allowed lenders to expect the future cash flows from the LNG project and worked as a security for financial contracts [Wolter, 2016]. Neumann et all (2015) investigated 426 LNG contracts from 1965 to 2014. They found that typical contract durations were 20 to 25 years from start dates of deliveries though the number of shorter contracts, 5 to 10 years, increased from 2000 or later. At the same time, deal tenors about LNG project finance transactions were in the range from 10 years to 20 years [De saint Gerand, 2013]. Thus, the long-term contract could cover the duration of repayments.

Secondly, the oil-price indexations influenced traditional price determinations. LNG price is highly correlated to crude oil price and crude oil products. LNG price is determined by the base price and the index which is mainly linked to crude oil price [Stern, 2014]. In Japan, LNG prices were determined by the Japanese Crude Cocktail, which is a basket of imported crude oils and adjusted monthly [Cornot-Gandolphe, 2005]. In Europe, LNG prices were connected to prices of gasoil and heavy fuel oil, with adjustment from six months to one year [Cornot-Gandolphe, 2005].

Thirdly, in the contracts, there were other inflexible clauses such as Renegotiation clause, Take-or-pay clause, and Destination clause. Renegotiation clause exists as the market would have significant economic changes during the long-term contract periods. Buyers and sellers normally agree to do price reviews within the contract periods. However, Asian buyers more focus on the negotiation to obtain lower gas prices at the beginning of the contract and sometime do not review the prices because the contracts are under English or American law, therefore, the renegotiation would take place in London or New York [Braaksma, et al., 2014]. Take-or-pay clause means there are minimum volumes for buyers to take in the certain period, if they do not meet the volume, the buyers shall pay for the volume deficiency. The take-or-pay clause sometime becomes by following provisions, where a specific percentage of the minimum volumes and the extension of the certain period are mentioned as well as a Make-Up clause and a Carry-Forward clause [Namikawa, 2003]. Destination clause is that buyers are restricted to deliver LNG at the specific port and are not allowed to sell the LNG outside of the specific geographical area.

2.5 LNG market development

The current LNG markets became more diversified and fragmentated due to the liquidity [Carriere, 2018]. The trade contracts have become more flexible. The short-term trade agreements and the development of the spot market contribute to the liquidity.

New LNG importers and the new LNG exporter, the U.S., support the diversification and fragmentation. New liquification facilities, mainly in the U.S. and Australia, will add 200 billion cubic metres (bcm) by 2022 and new 9 countries and territories are anticipated to import LNG by 2022 (IEA, 2017a). Especially, China increased their LNG imports by 42 % from the year 2016 because the Chinese government changed the policy about energy mix to change coal to gas in order to decrease air pollution (GIIGNL, 2018).

2.5.1 The development of the LNG trade agreement

The LNG trade agreements have become more flexible. The current LNG contract has smaller size of volume, shorter contract length, and more flexible destination [IEA, 2016]. It also has the other characteristics such as less oil-linked indexation and more FOB shipping modes.

The Global Gas Security Review (2016) compared the change about the LNG trade agreement before and after 2010. The contracts singed until 2009 had the following characteristics. Annual contract quantities were 1.75 bcm. The average lengths were 18 years. Regarding the price indexation, 76% of the contracts was oil-linked and 24 % of the contracts had gas to gas index. 33% of the contracts had flexible destinations and 41 % of the shipping modes were FOB. On the other hand, the contracts signed after 2010 had the following characteristics. Annual contract quantities were 1.55 bcm. The average lengths were 13 years. Oil-linked contracts were 49.5% and Gas to gas contracts were 50.5%. 51% of the contracts had flexible destinations and 54.0% of the shipping modes were FOB.

The U.S. would be a main contributor for the increase of the flexible contracted volumes in the world because the contracted LNG from the U.S. is destination flexible. By 2022, the flexible volume would reach 247 bcm, where 93 bcm out of 247 bcm mainly would come from the U.S. [IEA, 2017a].

Figure 4 shows the number of LNG contracts between 2006 and 2011. Figure 5 shows the number of LNG contracts between 2012 and 2017. The number of the world total contracts increased sharply from the batch of 2006-2011 to the batch of 2012-2017. Both graphs show 20 years contracts were the most popular duration, however the contracts between 2012 and 2017 indicated more varieties. Especially, the increased number of contracts with the duration of 5 years in Figure 5 explains the trend. As a result, these figures show that the LNG contracts have had smaller volumes and shorter contract lengths.

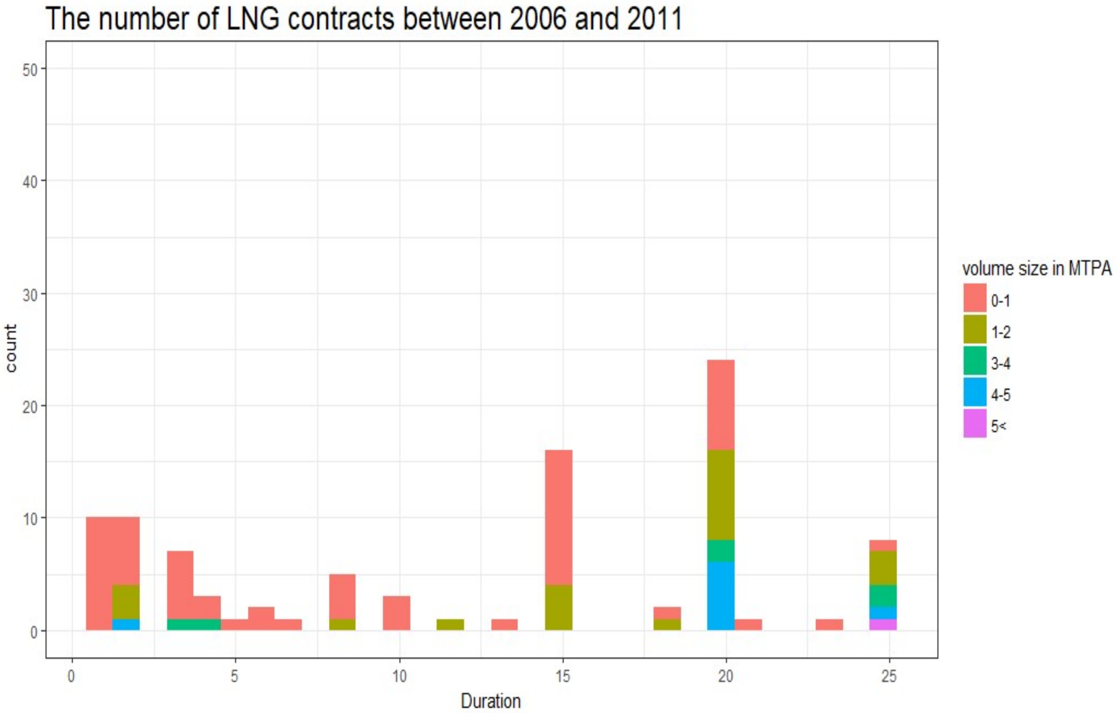


Figure 4 The number of LNG contracts between 2006 and 2011

Source: Author via (GIIGNL, 2006, 2007,2008,2009,2010,2011)

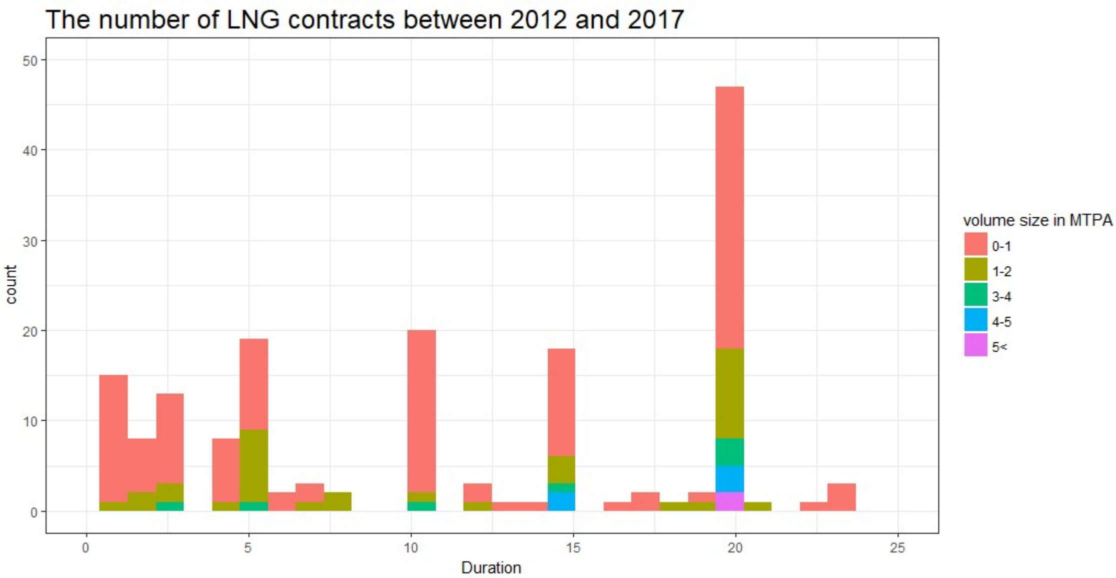


Figure 5 The number of LNG contracts between 2012 and 2017

Source: Author via (GIIGNL, 2012,2013,2014,2015,2016,2017)

2.5.2 The development of the LNG spot market

The LNG spot and short-term contracts have increased strongly during the last decade. The development of the market was not only in favour of buyers but also allowed the new participants to enter the market. Oil companies and investment banks joined the market and East Africa (Mozambique and Tanzania) started to participate in the market in addition to the traditional LNG buyers and suppliers [Norton Rose Fulbright, 2012].

Figure 6 shows comparison between LNG total trade and the quantity traded in the spot and short market. The LNG purchased from the spot and short market was 77.55 MT accounting for 27 % of the total imported LNG in 2017. In 2005, 13 % of LNG was purchased from the spot and short market. The growth rate in the short and spot market from 2005 to 2017 was higher than the growth rate in the total imported LNG. It means that the LNG spot and short market has a stage of great promise.

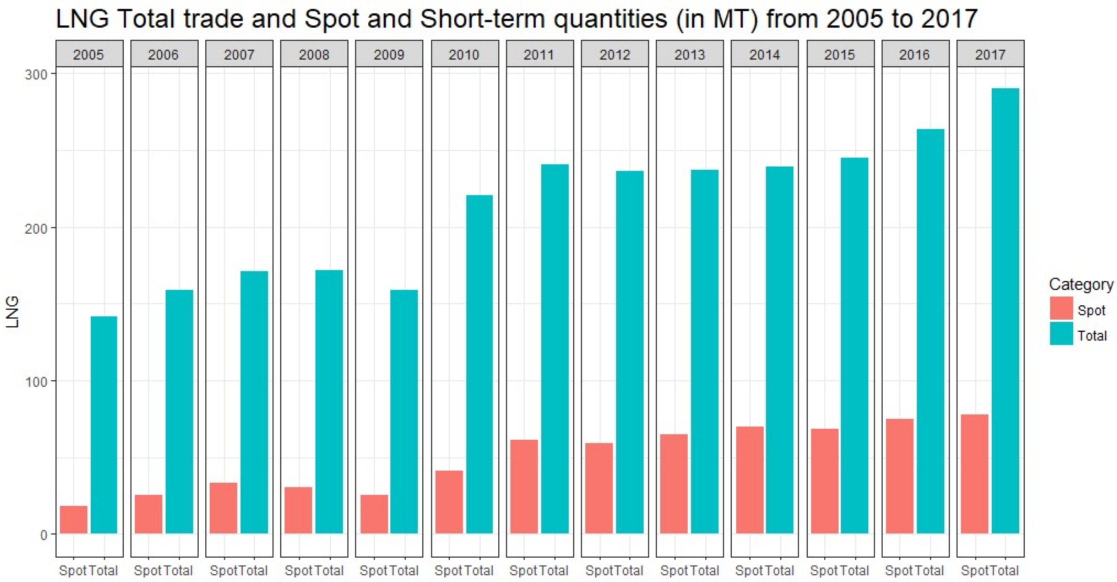


Figure 6 LNG total trade and Spot and Short-term quantities

Source: Author via (GIIGNL, 2006-2018)

2.6 Conclusion

The global LNG market used to have the limited number of players and inflexible characteristics. However, the emerging players in the LNG market and the more flexible LNG trade agreements contribute to the increase of liquidity of the world LNG market. Although the LNG spot market has developed gradually, the increase of the liquidity would cause more utilisation of the LNG spot market.

Chapter 3 Japan’s LNG market

3.1 Introduction

Japan has played a role in the LNG Industry since 1969. In 1964, the first commercial LNG trade began from Algeria to the UK. In 1969, Japan started to import LNG from Alaska. Since then, LNG has been one of the most important energy sources in Japan. Especially, the LNG has played a pivotal role for Japanese energy mix after the nuclear plant accident in 2011.

In this chapter, we explain the recent trend in Japan’s LNG market and the importance of the LNG spot price forecasting. Firstly, we introduce the recent LNG demand and supply and analyse Japan’s LNG prices in 3.2. Secondly, we analyse the difficulty of the LNG demand forecasting in 3.3 and the future LNG demand and supply towards 2030 in 3.4. It includes the uncertainty about LNG demand based on the government energy mix outlook. Finally, we propose a strategy to meet the future LNG demand analysing the characteristics of Japanese LNG trade agreements and the developing LNG spot market in 3.5.

3.2 The LNG demand and supply

The LNG demand in Japan would be influenced by the reactivate nuclear plants in the short run. The majority of LNG is used to generate electricity. Hence, it became hard to anticipate the demand for domestic LNG after the nuclear plant accident in 2011. After the accident, all nuclear plants became offline to meet more stringent regulatory requirements. They need to obtain the government approvals and local consents for the restarts.

3.2.1 LNG Demand in volume and in value

Commodity prices are fluctuating due to the change in demand and supply. The price of LNG is also volatile. However, Japan’s LNG price would be affected by another factor, the price of oil because the majority of their long-term LNG trade agreements have oil price indexations.

Figure 7 shows the total LNG import in million ton and in billion USD from 2008 to 2017. The amount of LNG rose by more than 10 % each year from 2010 to 2012. It reached a peak of 88 million ton in 2014 and fell to 83 million ton in 2017. Japan still imported 13 million ton more than the LNG imported in 2010. Although the procurement cost for LNG also reached a peak of 71 billion USD in 2014, the cost fluctuated largely. It more than doubled from 2010 to 2014. Then the cost halved to 30 billion USD from 2014 to 2016.

As we mentioned in Chapter 2, one of characteristics of LNG trade agreements is oil indexation pricing. Japanese LNG prices are highly correlated to crude oil price with a time-lag of a few months. Figure 8 shows crude oil, natural gas and LNG prices from 2008 to 2017. Japanese LNG price decreased from 14.81 $/mmbtu to 7.33 $/mmbtu from 2014 to 2016. In the same time, the average crude oil price decreased from 88.9 $/bbl to 45.53 $/bbl. The decrease rates were 51% and 41 % respectively. On the other hand, US natural gas decreased by 35% from 4.04

$/mmbtu to 2.65 $/mmbtu from 2014 to 2016. Thus, Japanese LNG still keeps oil indexation pricing.

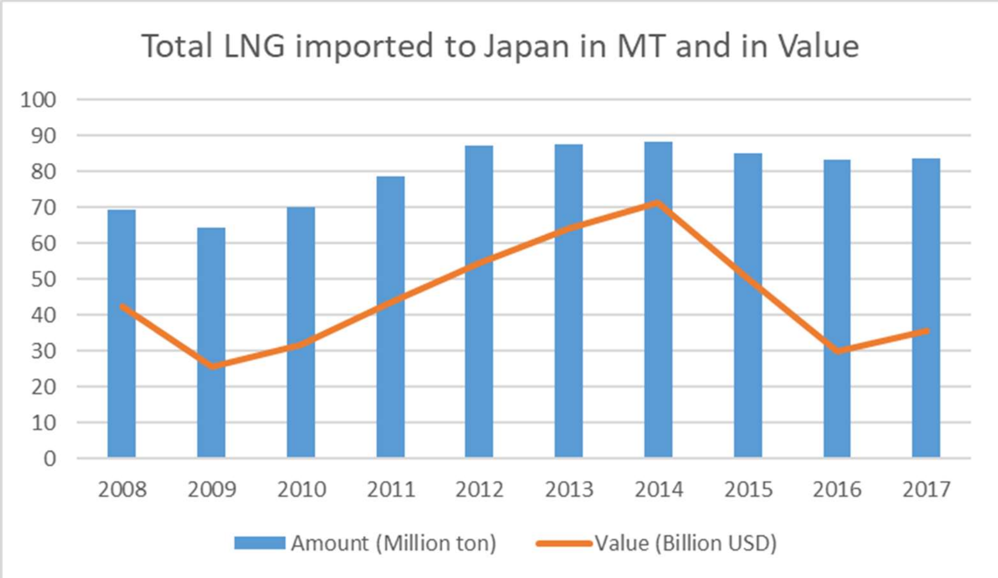


Figure 7 Total LNG imported to Japan

Source: Author via [Trade Statistics of Japan, 2017]

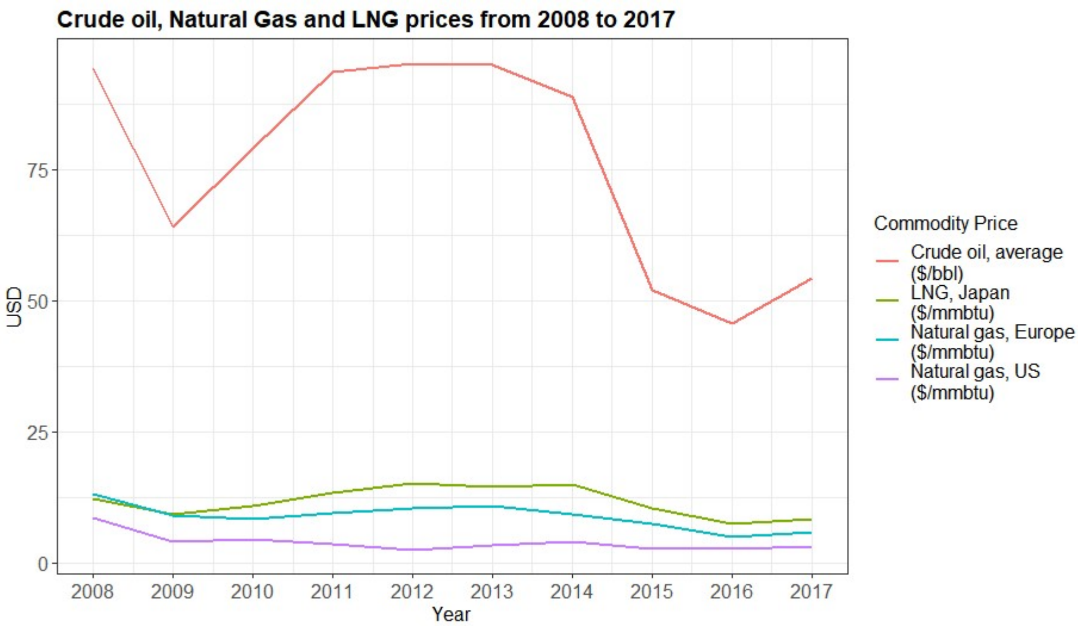


Figure 8 Crude oil, Natural Gas and LNG prices

Source: Author via [World Bank, 2018]

Meanwhile, there are some related prices in the LNG industry such as vessel charter rate and new building prices. The charter rates could be related to Japanese LNG prices, because LNG is delivered to Japan by LNG vessels. The new building price could also be related to Japanese LNG prices, because transportation costs might be reduced by more LNG carriers. Figure 9 shows very large gas carrier

(VLGC) s' time charter rates and LNG carrier newbuilding prices from 2008 to 2018. VLGC time charter rate increased from 2011 and peaked at close to 74,000 USD per day in 2015. It decreased sharply to less than 16,000 USD per day in 2016. The increase of the charter rate from 2011 to 2015 was in line with the increase of the global LNG trade. However, the decline of the rate from 2015 to 2016 was the opposite movement of the global LNG trade. This implies that the time charter rate could be influenced by the LNG market and LNG shipping market, however the Japanese LNG price would not be affected by the charter rate. Regarding new building price, it was stable at about 185 million USD from 2010 to 2013 then soared up to 200 million USD in 2014. LNG carriers are so expensive that ship owners need to prove the secure repayments by showing a long-term charter contract when they borrow money from banks. So, the new building LNG carrier requires a huge capital investment. The new building price would be affected by the shipping market. The LNG market, especially demand would affect the shipping market. However, Japanese LNG price is irrelevant to the LNG carrier Newbuilding price.

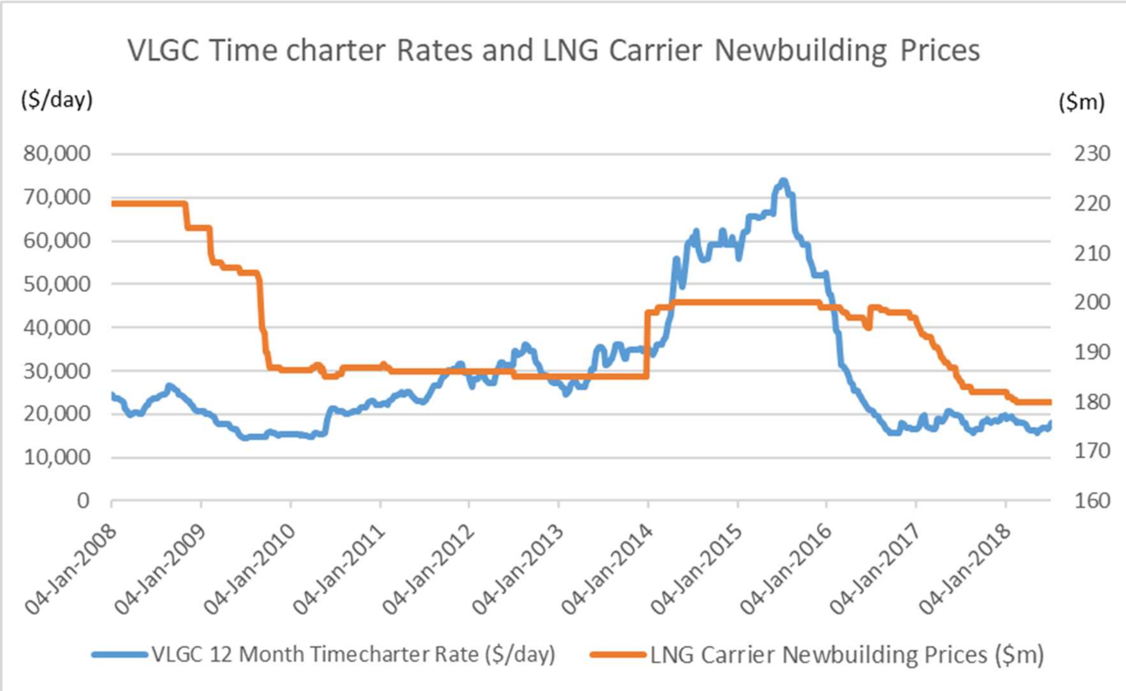


Figure 9 VLGC time charter rates and LNG carrier newbuilding prices

Source: Author via [Clarkson Research Services Limited, 2018]

In conclusion, Japanese LNG in value is more fluctuated than LNG in volume. Japanese LNG price is more correlated to the crude oil price than the natural gas price in U.S.

3.2.2 LNG supply by country

Japan has tried to diversify its energy resources since the oil crisis in 1970s. The offline of the nuclear plants led Japan to rely on more fossil fuels. The resource-poor country was forced to realise the importance of energy security with the limited fossil fuels. So, Japan needs to diversify not only energy mix but also countries of the

LNG suppliers. In this section, we analyse the Japanese LNG import in MT and in value by country and the diversification of the LNG suppliers.

Figure 10 shows Japanese LNG import amount by country from 2008 to 2017. Australia, Malaysia and Qatar have been the LNG stable suppliers. Within the top 5 countries, the import from Indonesia in 2017 was lower than the amount in 2010. Figure 11 shows Japanese LNG import in value by country from 2008 to 2017. As we concluded the LNG import in value is more volatile than the LNG import in volume in 3.2.1, the LNG import in value by country is also fluctuated.

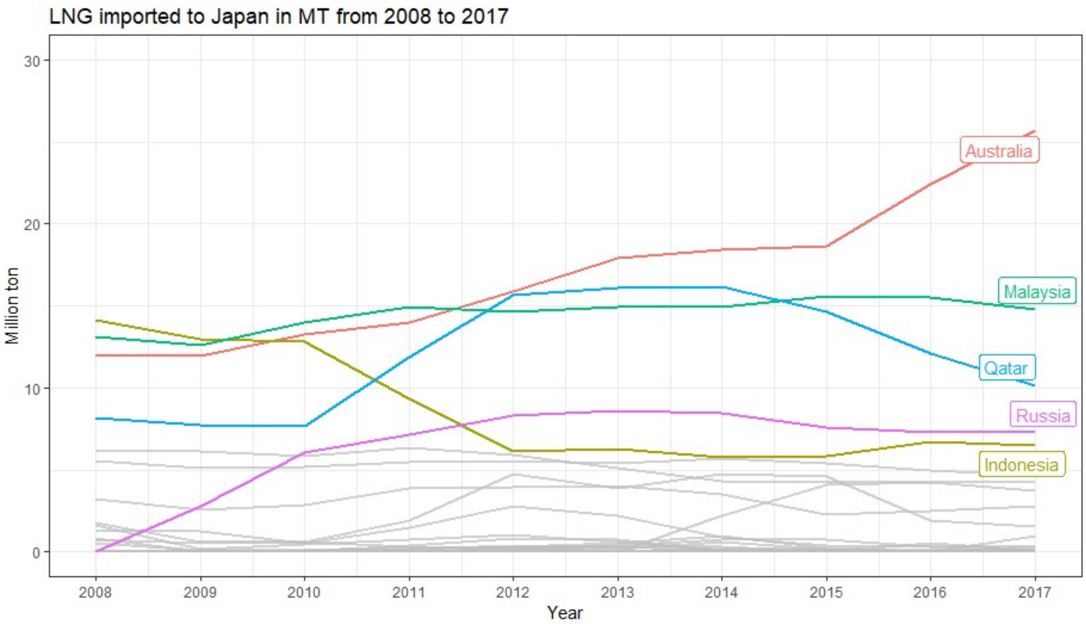


Figure 10 LNG imported to Japan in MT by country

Source: Author via [Trade Statistics of Japan, 2017]

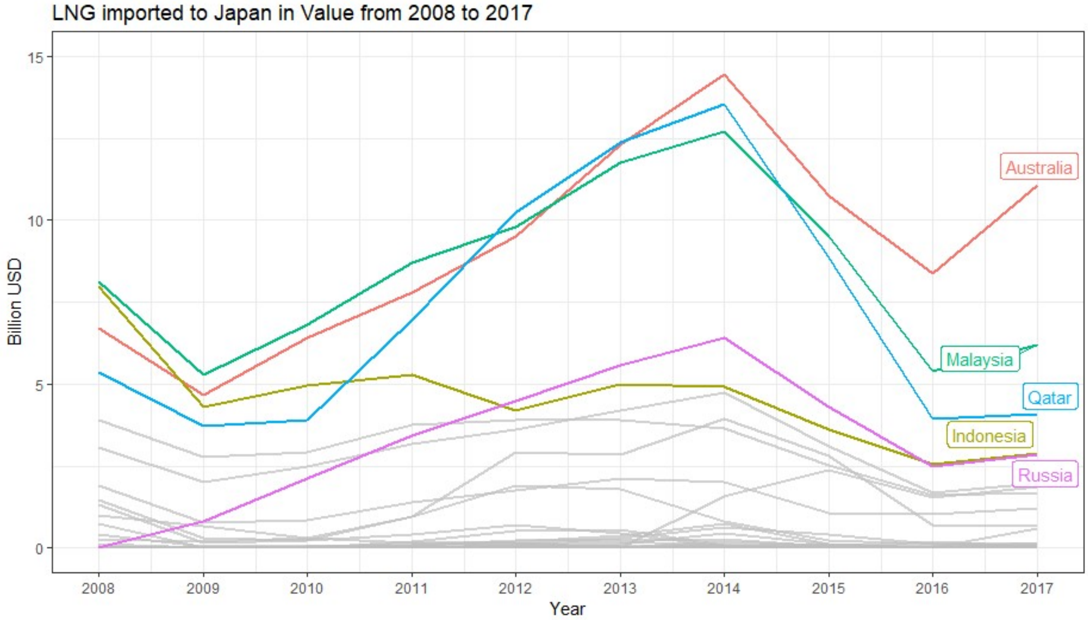


Figure 11 LNG imported to Japan in value by country

Source: Author via [Trade Statistics of Japan, 2017], 1USD=110JPY

Figure 12 shows LNG sources by country in 2008, 2014 and 2017. In the number of countries wise, although Australia, Malaysia and Qatar dominated the market, Japanese gas and utilities diversified the importing countries from 13 countries in 2008 to 20 counties in 2017. Meanwhile, in the volume wise, Japan still highly relies on the top 3 countries. In 2008, the share of the top 3 countries, Indonesia, Malaysia and Australia was 57%. In 2017, the top 3 countries Australia, Malaysia and Qatar accounted for 61 %. The reliance rate on the top 3 LNG suppliers in 2017 was higher than in 2008 due to the increase LNG import from Australia. In terms of the energy security, it was not a preferable situation.

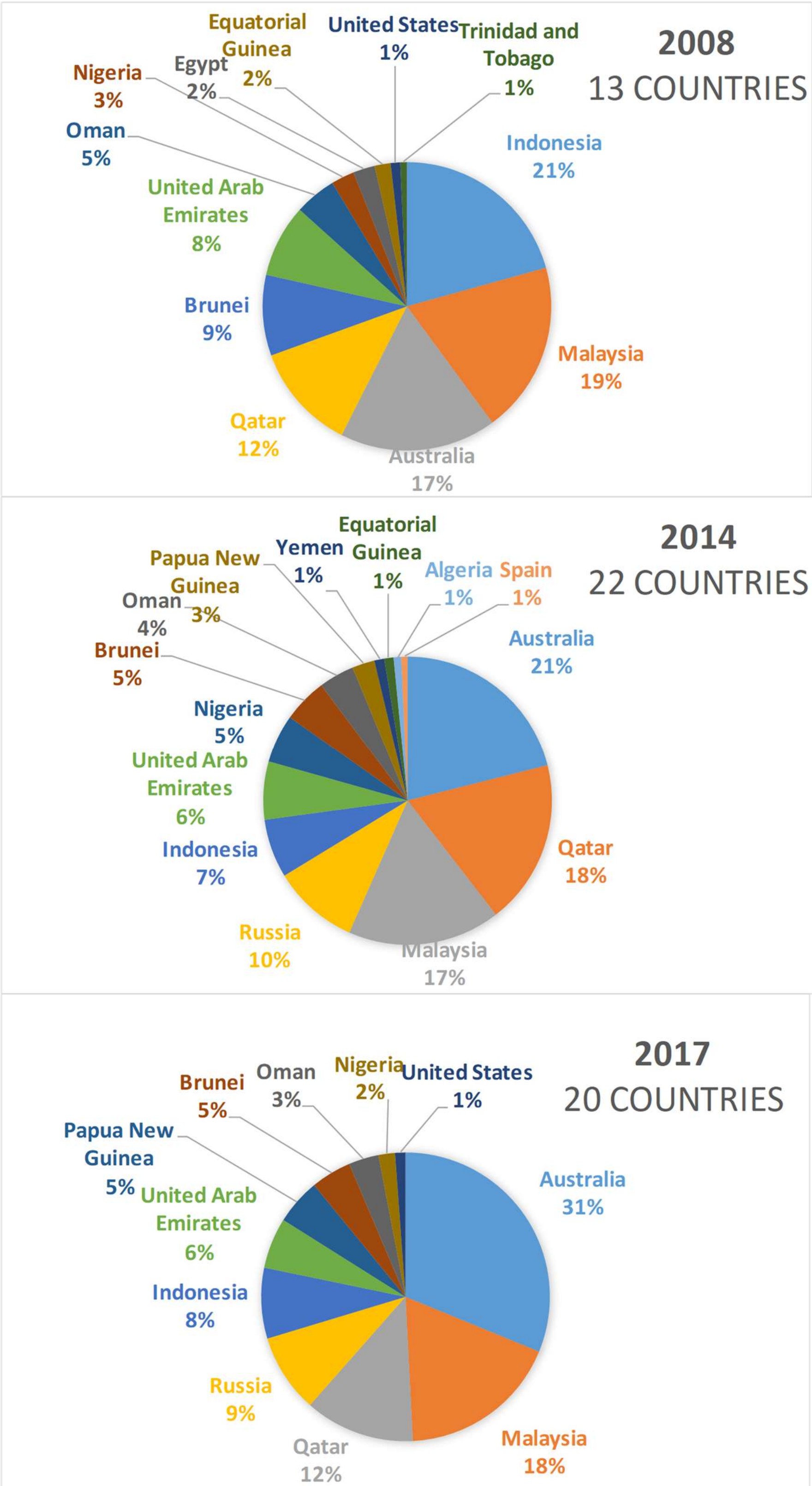


Figure 12 LNG sources by country

Source: Author via [Trade Statistics of Japan, 2017] *excluded importing countries of less than 1 %.

3.2.3 LNG usage in Japan

Japanese LNG demand would be affected by the domestic energy consumption. In this section, firstly, we analyse the energy demand and supply from LNG. Secondly, we focus on the energy from power generation and analyse the different types of electrical energy generation. Finally, we focus on thermal power plants and analyse the types of fuels to be used to generate electricity.

Energy supply from LNG increased along with the increase of Japanese LNG import. We break down the energy by the usage. Figure 13 shows Energy supply from LNG from April in 2009 to March in 2016. The shape of the bars is a similar shape of Japanese LNG import in volume in Figure 7. Figure 14 shows Energy demand from LNG by use from April in 2009 to March in 2016. A major usage of LNG was to generate electricity. More than 65 % of LNG was used for power generation in the fisical year 2016. Gas conversion remained stable between April 2011 and March 2016. On the other hand, demand for power generation in the fisical year 2011 shot up to 3,119 PJ. The trend of total energy supply in Figure 13 followed the shape of the line of Power generation in Figure 14. Therefore, the total demand and supply for LNG are influenced by the demand to generate electricity.

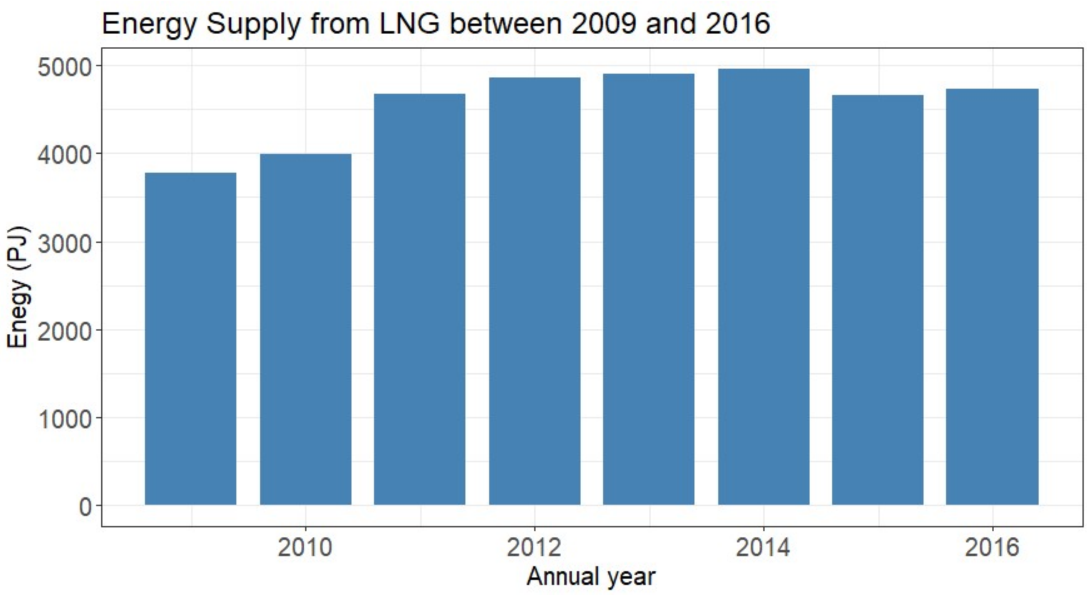


Figure 13 Energy supply from LNG

Source: Author via [Agency for Natural Resources and Energy, 2009-2016]
* The Japanese fiscal year is starting in April and ending in May.

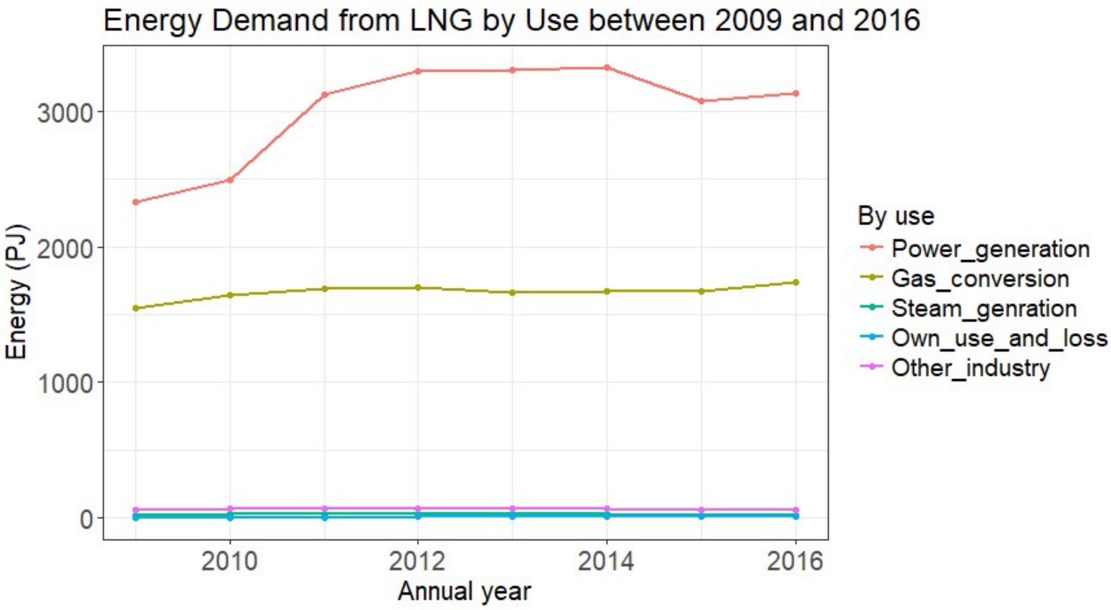


Figure 14 Energy demand from LNG by use

Source: Author via [Agency for Natural Resources and Energy, 2009-2016]
* The Japanese fiscal year is starting in April and ending in May.

According to Figure 13 and 14, we found that a majority of the imported LNG is used for power generation and the amount of energy soared from 2010 to 2011. Next, we investigate the electrical power generation which produced electricity. Figure 15 shows the breakdown of generated and received electrical energy from 2009 to 2015. The total electricity generated has decreased steadily to 864 billion kWh from 2010 to 2015. The electricity production from thermal plants in 2015 was greater than in 2010 by 118 billion kWh. The electricity generation from nuclear plants became 0 billion kWh in 2014. Figure 16 shows the percentage of electrical generation by types of power generators. The share of thermal generation peaked at 72.92 % in 2013. These two figures show that after the 2011 accident, thermal plants took over nuclear plants.

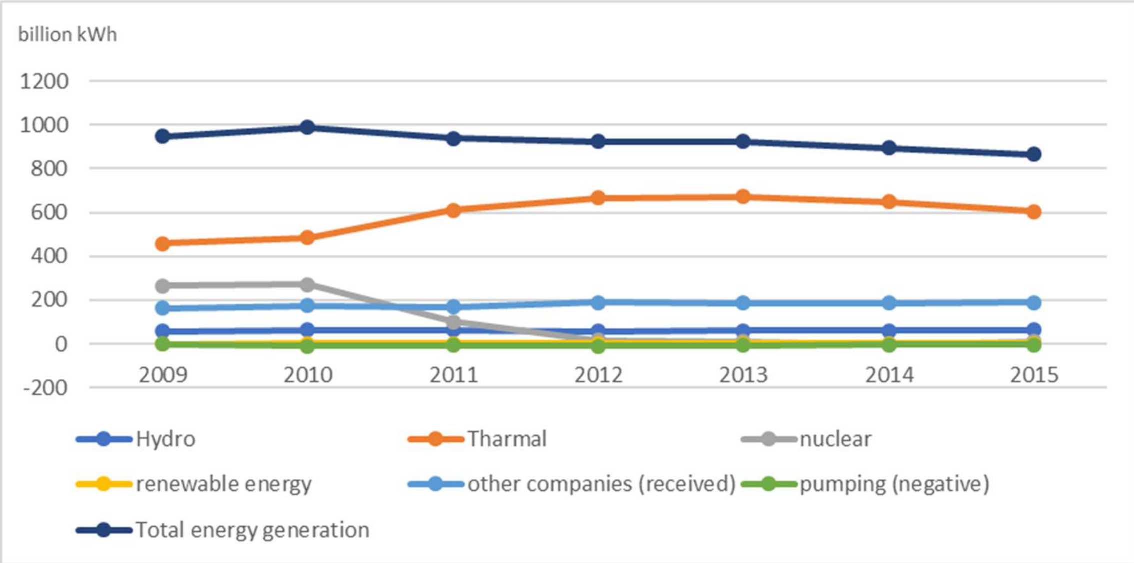


Figure 15 Breakdown of generated and received electrical energy

Source: Author via [The Federation of Electric Power Companies of Japan, 2009-2015]
* The Japanese fiscal year is starting in April and ending in May. This collected data is for 10 major electric companies

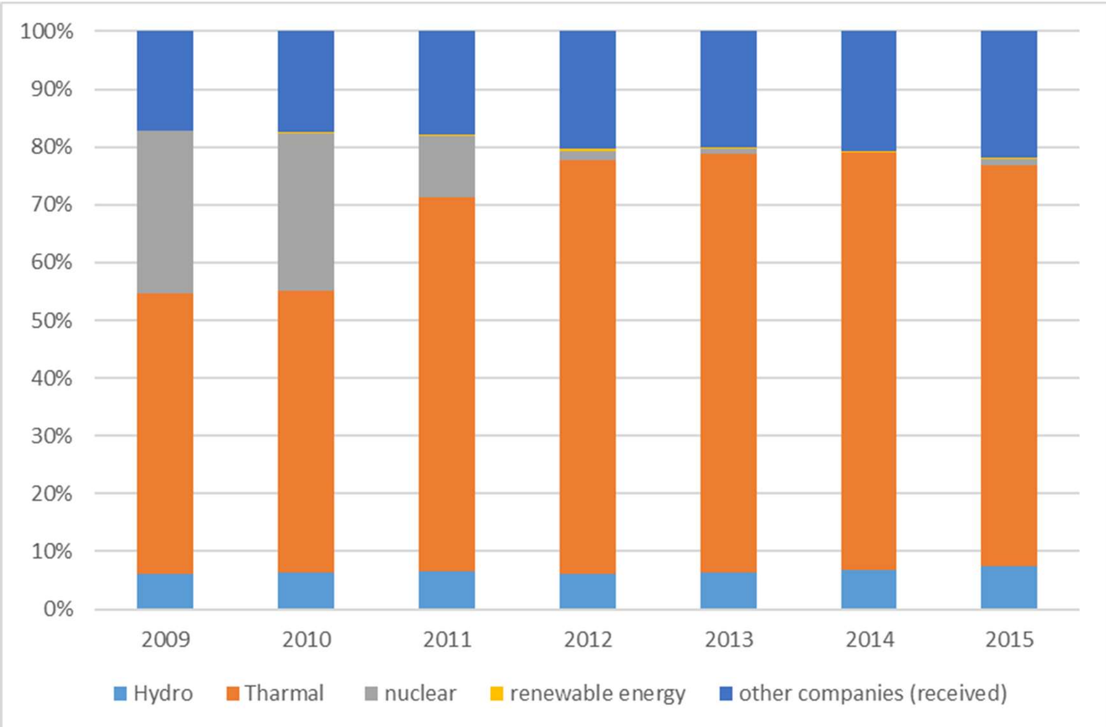


Figure 16 The percentage of electrical generation by types of power generator

Source: Author via [The Federation of Electric Power Companies of Japan, 2009-2015]
* The Japanese fiscal year is starting in April and ending in May. This collected data is for 10 major electric companies

According to Figure 15 and 16, we found that the thermal plants were the main electricity generator and the share of thermal plants increased sharply from 2010. Next, we investigate the fuels to be used for the thermal generation. Figure 17 shows fuels used by thermal power plants. LNG increased from 2010 to 2014. The LNG used as a fuel in 2015 was still greater than in 2010 by 10.5 million ton. Compared their volume in 2015 to 2010, the percentage in increase of each fuel, Coal, LNG and Oil was 15.2%, 25.2% and 15.4% respectively. The amount of these fuels would be affected by the price of each commodity. But LNG usage showed the highest increase rate.

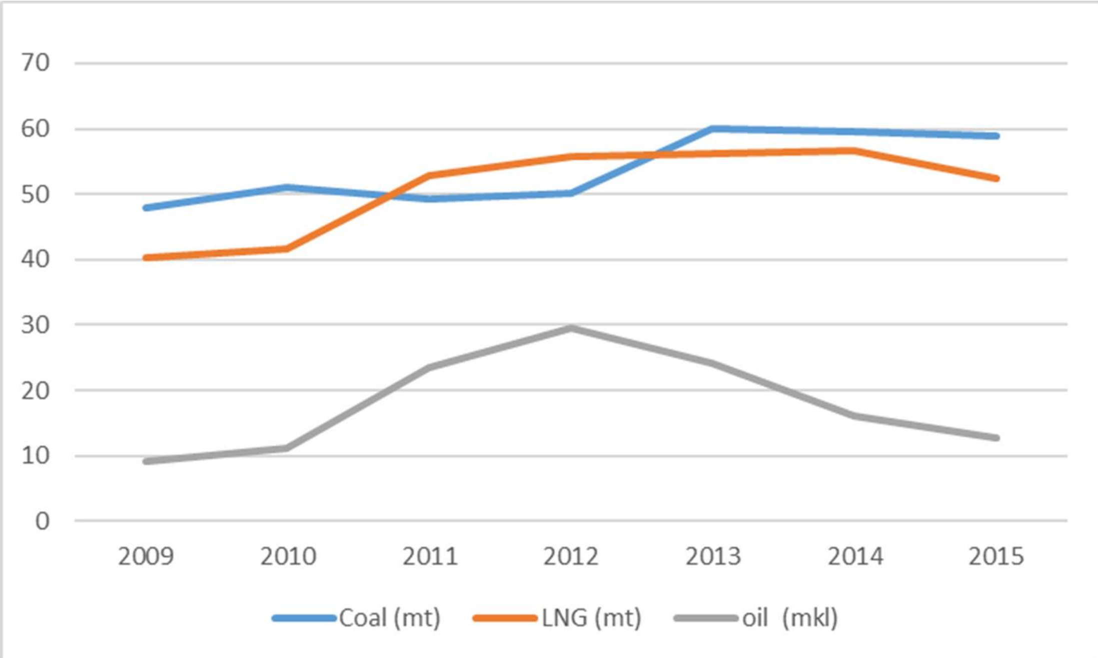


Figure 17 Breakdown of thermal power fuels

Source: Author via [The Federation of Electric Power Companies of Japan, 2009-2015]
* The Japanese fiscal year is starting in April and ending in May. This collected data is for 10 major electric companies

In conclusion, the absence of nuclear plants increased Japanese LNG demand because thermal plants replaced the nuclear plants in terms of electricity generation. Although the more LNG was used as a fuel for the thermal plants in the absence of nuclear plants, the amount of LNG in need would be influenced by the balance of the commodity prices and markets of coal, oil and LNG.

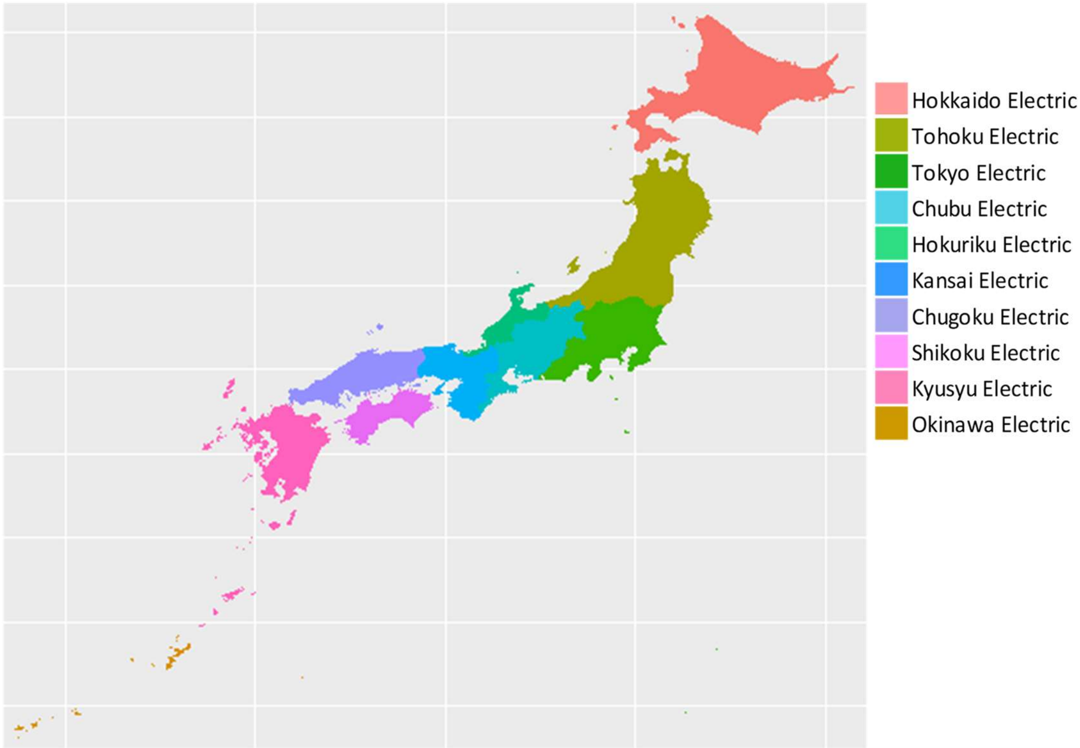
3.3 The difficulty to forecast the future LNG demand

Reactivation of nuclear plants would influence the LNG demand. During the absence of nuclear generation, the coal and oil markets and their commodity prices affect the LNG demand. These two factors make the LNG demand forecast difficult. Moreover, the electricity liberalization in Japan made forecasting the future LNG demand more difficult. In this section, we explain Japanese electricity market before the electricity liberalization. Then we analyse the electricity demand and supply after the liberalization.

Japan deregulated the electricity market in 2016 due to following reasons. Firstly, the nuclear accident in 2011 exposed monopolistic characteristics of the power utilities. Figure 18 showed the service areas of 10 power utilities before the deregulation. There was little electricity transmission beyond areas, little competition, price control by the regional monopolists, and resisting to increase renewable energy in their energy mix [Yamazaki , 2015]. Secondly, the reform achieved public consensus. The offline of the rest of nuclear reactors raised the cost of fossil fuels for thermal plants. It had negative impacts on the power utilities' financial results. The electric bills between 2010 and 2014 increased both for households and for industry, by 25.2% and by 38.2% respectively [Yamazaki , 2015].Thirdly, CO_2 emissions increased along with an increase of fossil fuels usage. CO_2 emissions produced by the sector of general electricity utilities rose by 110 million ton from the fiscal year 2011 to 2013. [Yamazaki , 2015].

Meanwhile, the demand areas for electricity differ from the supply areas. Figure 19 shows demand for electricity per prefecture and Figure 20 shows supply for electricity by thermal plants per prefecture. Within Japan, the high demand areas for electricity are different from the electricity generation areas by thermal plants. As a result of the electricity deregulation, the share of new entrants at the retail sector increased to 10 % in 2017 [METI, 2018a]. The capacity of renewable energy increased by average 26% annually from the fiscal year 2012 to 2016 [METI, 2017].

Therefore, the market deregulation made it difficult for each electric utility to forecast the electricity demand from customers. The electricity demand would affect the thermal plants' operations and the demand for LNG as a fuel. The increase of electricity supply from renewable energy would also affect the thermal plants' operations. The future LNG demand forecast is difficult due to the above reasons.



* The service area was colored by prefecture. We choose one company when one prefecture had two electric suppliers. Electricitiy was supplied by Chubu Electric west of the Fuji river in Sizuoka prefecture. But we categorised Sizuoka prefecture as Tokyo Electric area.
Map: the GADM database (www.gadm.org), version 2.5, July 2015
Source: These power companies' websites.

Figure 18 Service Area of Power utilities before the liberalization

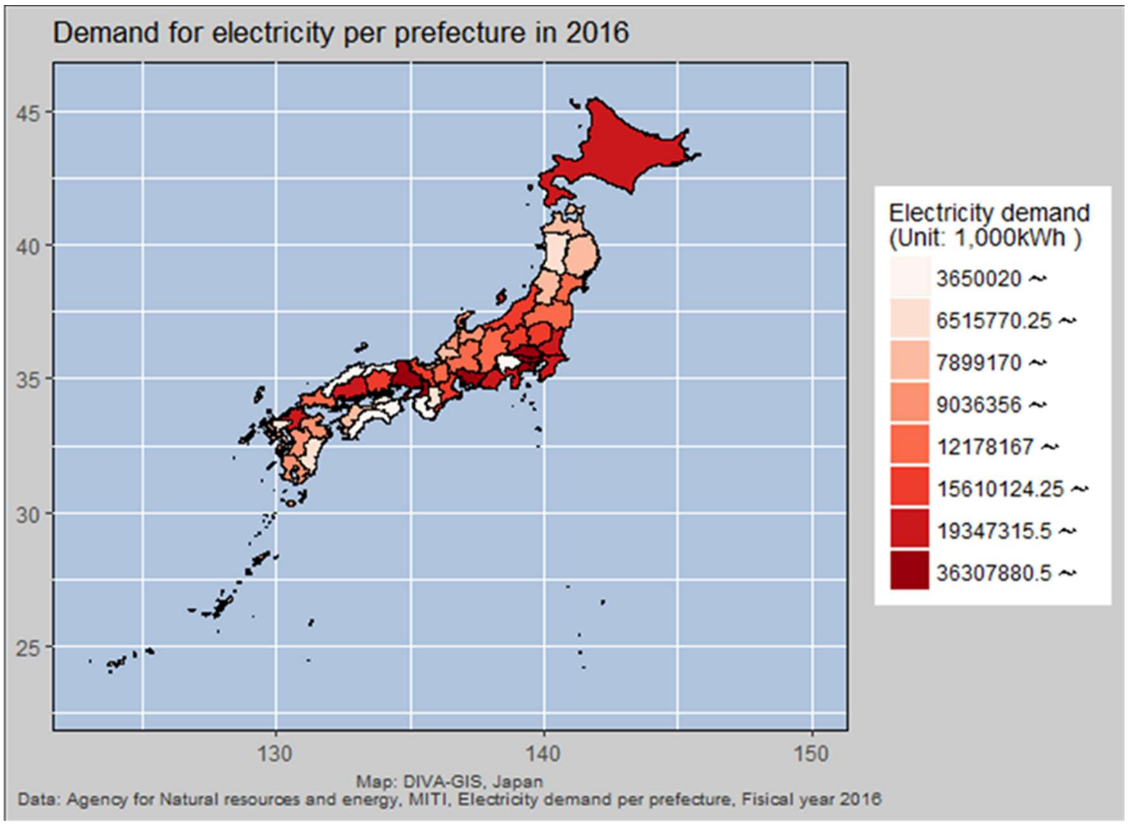


Figure 19 Demand for electricity per prefecture

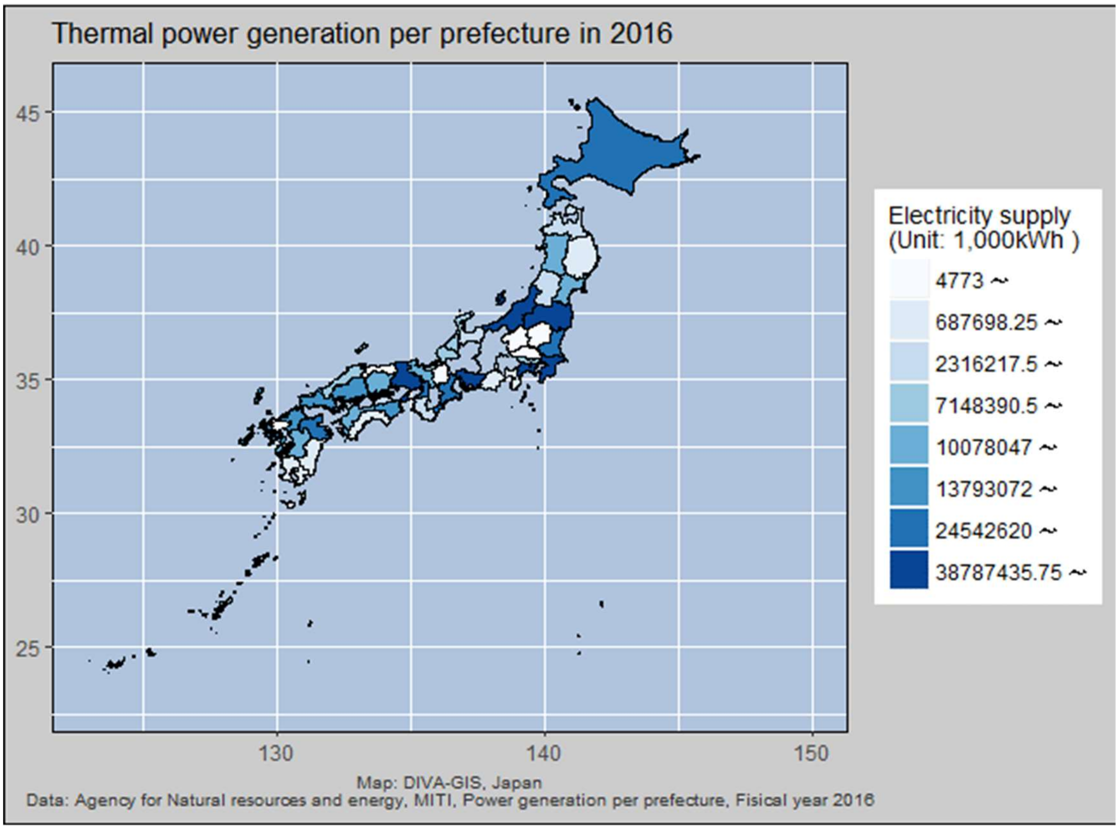


Figure 20 Thermal power generation per prefecture

3.4 The LNG demand towards 2030

Japanese LNG demand has much of uncertainty because of the commodity market and price, the reactivation of nuclear plants and the progress of renewable energy. At the same time, the government revealed the power source mix towards 2030. In this section, we analyse the past power sources by comparing with the government policy.

Japanese utilities will reduce LNG procurements towards 2030 due to falling LNG demand. Ministry of Economy, Trade and Industry disclosed Long-term Energy Supply and Demand Outlook in 2015. It estimated that electric power demand and the power source mix towards FY2030. According to the outlook, electric power demand in FY2030 will remain almost at the same level as FY2013, even with 1.7 % annual economic growth, due to the increase of energy efficiency and conversion. The percentage of the electric power supplied by nuclear plants would decreased from approx. 30 % in FY2010 to approximately 20% to 22 % in FY2030 [METI, 2015]. They estimated the total power generation would be 1,065 billion kWh and LNG would account for 27% of the structure. Thus, LNG would produce 287 billion kWh in FY2030.

Table 1 shows Power source mix from 2010 to 2016. The 287 billion kWh in 2030FY is smaller than 334 billion kWh in 2010FY. It means Japanese power utilities would decrease the amount of LNG procurements at least at the level of 2010. Figure 21 shows LNG demand in MT by use between 2009 and 2016. The LNG used as a fuel to generate electricity in 2010 and 2016 were 45.7 million tons and 57.6 million tons respectively. Therefore, the LNG procurements for thermal plants would be decreased by 12 million tons.

Table 1 Power source mix

(billion kWh)

FY	2010	2011	2012	2013	2014	2015	2016
Nuclear Power	288	102	16	9	0	9	18
Coal	320	306	334	357	354	355	337
LNG	334	411	432	443	455	425	441
Oil	98	158	189	158	118	102	97
Hydroelectric Power	84	85	77	79	84	87	79
Solor power	4	5	7	13	23	35	46
Wind power	4	5	5	5	5	6	6
Geothermal power	3	3	3	3	3	3	2
Biomass power	15	16	17	18	18	19	18
Total power generation	1,149	1,090	1,078	1,085	1,059	1,041	1,044

Source: Author via [Agency for Natural Resources and Energy , 2010-2016]

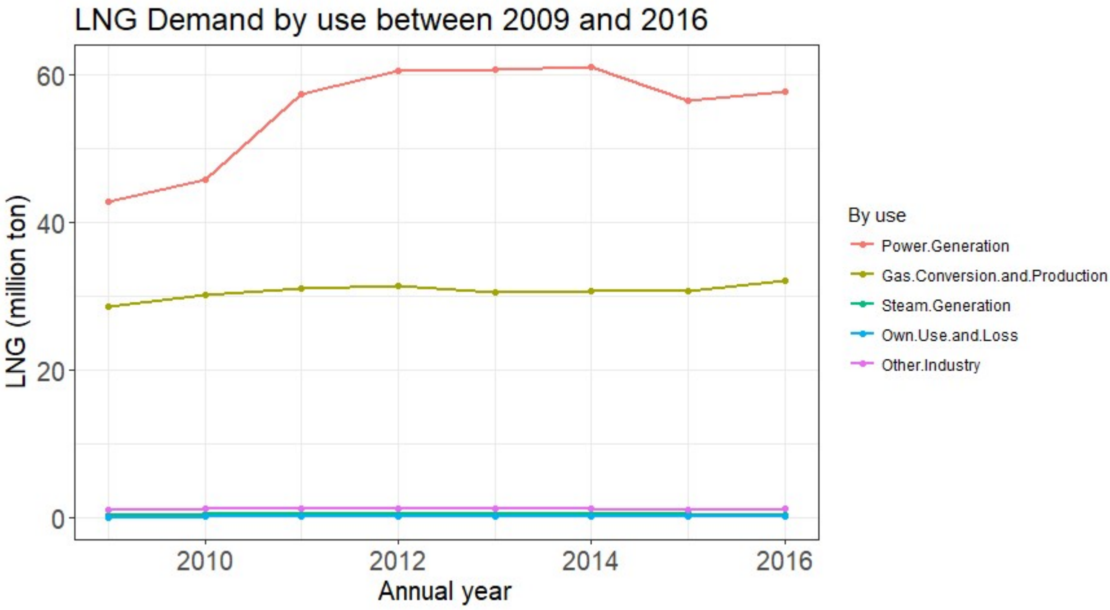


Figure 21 LNG demand by use

Source: Author via [Agency for Natural Resources and Energy, 2009-2016]
* The Japanese fiscal year is starting in April and ending in May.

In conclusion, Japanese LNG demand would decrease by 12 million tons towards 2030 if Japanese power utilities follow the government power mix outlook. It also includes much of uncertainty.

3.5 Strategy to meet the future LNG demand

So, how would Japanese power utilities reduce the 12 million tons? In this section, we suggest a possible solution to meet the LNG demand towards 2030. We also introduce an example about one electric power utility's plan towards 2030.

3.5.1 LNG procurement contracts

One solution is to utilise flexible contracts. Japanese power utilities have achieved more flexible LNG procurement contracts than the past. Figure 22 is the list of contracts signed between suppliers and Japanese power utilities between 2006 and 2017. As we explained the characteristics about the current global LNG contracts in Chapter 2, the LNG contracts of Japanese power utilities had similar characteristics such as smaller volume and shorter durations. Some LNG contracts are agreed on the cargo basis. 3 cargoes are approximately 0.2 MPTA (GIIGNL, 2017).

year	Export country	Exporter	Buyer	ACQ(MTPA)	Duration(Year)	Start date	Delivery Format
2006	Malaysia		Chubu Electric	0.54	20	2011	DES
2006	Russia		Tohoku Electric	0.42	20	2010	FOB
2006	Oman		Tokyo Electric	0.8	15	2006	DES
2007	Russia - Sakhalin 2		Chubu Electric	0.5	15	2011	DES
2007	Australia - NWS		Chugoku Electric	1.4	12	2009	
2007	Australia - Pluto		Kansai Electric	2	15	2010	FOB/DES
2007	Australia - NWS		Kyushu Electric	0.73	8	2009	
2007	Malaysia		Shikoku Electric	0.42	15	2010	
2008	Australia		Chubu Electric	0.5	7	2009	DES
2009	Australia		Chubu Electric	1.44	25	2014	DES
2009	Australia		Kansai Electric	0.4	8	2009	DES
2009	Indonesia		Tohoku Electric	0.12	15	2010	
2009	Australia		Tokyo Electric	0.3	8	2009	FOB
2009	Papua New Guinea		Tokyo Electric	1.8	20	2013	
2009	U.S.A		Tokyo Electric	0.34	2	2009	DES
2010	Indonesia (Tangguh LNG)		Chubu Electric	0.25	2	2011	DES
2010	Indonesia (Tangguh LNG)*		Chubu Electric	0.5	3	2013	DES
2011	Australia & BG Portfolio		Chubu Electric	0.41	21	2014	DES
2011	Qatar (QATARGAS)		Chubu Electric	0.2	6	2014	DES
2011	Australia (APLNG)		Kansai Electric	1	20	2016	DES
2011	Australia (Ichtys)		Kansai Electric	0.8	15	2017	FOB
2011	Australia (Gorgon		Kyushu Electric	0.3	15	2015	DES
2011	Australia (Wheatstone)		Kyushu Electric	0.7	20	2017	FOB
2011	Australia (Ichtys)		Kyushu Electric	0.3	15	2017	FOB
2011	Australia (Wheatstone) The		Tokyo Electric	3.1	20	2017	
2011	Australia (Ichtys)		Tokyo Electric	1.05	15	2017	FOB
2012	BP portfolio	BP portfolio	Chubu Electric	0.5	16	2012	DES
2012	QATAR	Qatargas	Chubu Electric	1	15	2013	DES
2012	ALGERIA	Eni Portfolio	Chubu Electric	0.2	5	2013	
2012	AUSTRALIA (Ichthys)		Chubu Electric	0.5		2017	FOB
2012	QATAR	Qatargas	Kansai Electric	0.5	15	2013	DES
2012	AUSTRALIA	APLNG	Kansai Electric	1		2016	FOB
2012	QATAR	Qatargas	Tokyo Electric	1	10	2012	DES
2012	AUSTRALIA (Wheatstone)		Tokyo Electric	0.4	20	2017	
2012	AUSTRALIA (Wheatstone)		Tokyo Electric	0.7	20	2017	
2013	AUSTRALIA/Wheatstone	Chevron	Chubu Electric	1	20	2017	FOB
2013	INDONESIA	Tangguh PSC	Kansai Electric	1	22	2014	DES
2013	AUSTRALIA/Wheatstone	Chevron	Tohoku Electric	0.9	20	2017	DES
2013	BRUNEI	Brunei LNG Sendirian	Tokyo Electric	2	10	2013	DES
2014		Shell	Chubu Electric	12 CARGOES	20	2014	DES
2014		GDF SUEZ	Chubu Electric	1.47	2.25	2015	DES
2014	USA	Mitsui & Co., Ltd	Kansai Electric	0.4	20	2017	DES
2014	MALAYSIA	Malaysia LNG	Tohoku Electric	0.4	10	2016	DES
2014	QATAR	Qatargas 3	Tohoku Electric	0.18	15	2016	DES
2014		GDF SUEZ	Tohoku Electric	0.27	2.5	2014	DES
2014		BP	Tokyo Electric	1.2	18	2017	DES
2015	Portfolio	ENGIE	Chubu Electric	20 CARGOES	2	2016	DES
2015	MALAYSIA	MALAYSIA LNG	Chugoku Electric	0.24	3	2015	DES
2015	MALAYSIA	MALAYSIA LNG	Chugoku Electric	0.24	3	2015	DES
2015	Portfolio	Kansai Electric	Hokkaido Electric	0.2	10	2018	DES
2015	MALAYSIA	Malaysia LNG	Hokuriku Electric	0.38	10	2018	DES
2015	Portfolio	BP	Kansai Electric	0.56	23	2015	DES
2015	Portfolio	Chubu	Tohoku Electric	0.3	20	2023	DES
2015	USA	ENGIE	Tohoku Electric	0.27	20	2018	DES
2016	Portfolio	Petronas	Hokuriku Electric	6 cargoes	10	2018	DES
2017	potfolio	Total	Chugoku Electric	0.25	17	2019	DES
2017	Malaysia	MLNG/Petronas	Hokkaido Electric	0.13	10	2018	DES
2017	potfolio	Kansai Electric	Hokkaido Electric	0.2	10	2018	DES

Figure 22 List of contracts signed between suppliers and Japanese power utilities

Source: Author via (GIIGNL, 2006-2018)

3.5.2 The LNG spot market for Japan

The other solution is to utilise the LNG spot market. Japanese LNG buyers utilise the spot market less than the global standard, although we explained the development of the global LNG short and spot market in Chapter 2. Figure 23 shows the total LNG imported to Japan and Spot and Short-term quantities from 2005 to 2017. the short and spot market increased by 20% in 2011 from the year 2010 because of the sudden demand by closing nuclear plants. It contributed to increase the liquidity of the LNG market. However, the utilization of the short and spot market for Japan was not as high as the global LNG standard. The LNG purchased from the short and spot market was 12.27 MT accounting for 14.69 % of the total imported LNG in Japan in 2017. It was smaller compared to the global percentage of LNG volume from the short and spot market, 27% as described in Chapter 2. Thus, there are room to utilise more the short and spot market.

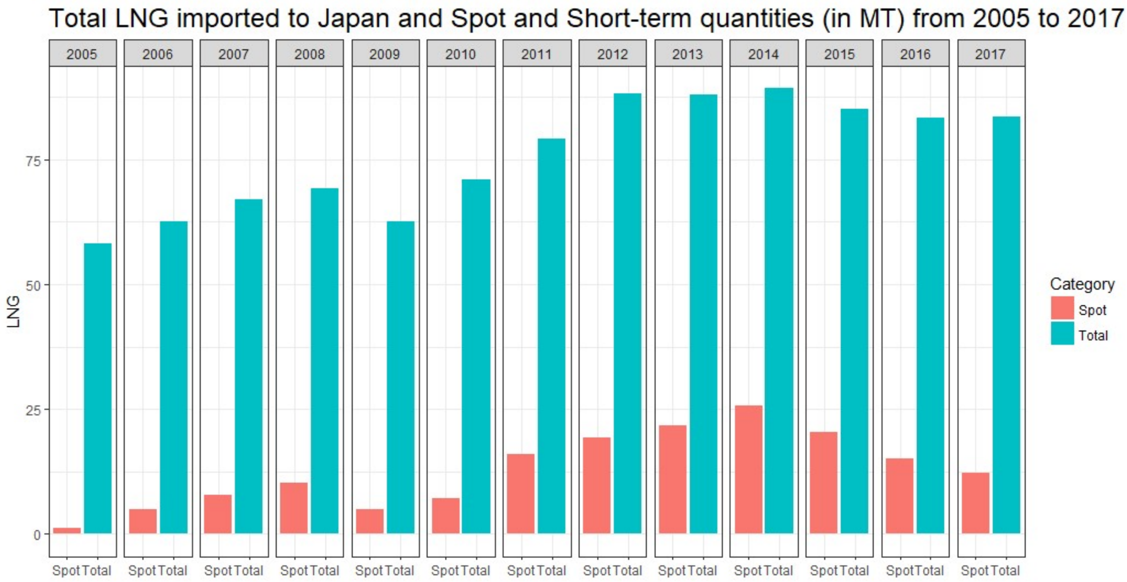


Figure 23 Total LNG imported to Japan and Spot and Short-term quantities

Source: Author via (GIIGNL, 2006-2018)

Meanwhile, the utilization ratio of the spot and short market in Japan is highly likely to increases. Because Japanese power utilities revealed their business plan to focus on more the spot market in response to the change for LNG demand.

For example, under the government outlook towards 2030, the largest LNG importer, JERA published the business plan in 2030. JERA is a joint-management company between Tokyo Electric Power Company and Chubu Electric Power Company. It handles their fuel procurements for power generation. In 2016, the amount of LNG procurements was 40 MTPA (35 MTPA from long-term offtake commitments, 5 MTPA from short-term or spot contracts) [JERA, 2016]. It was almost 70 percent of LNG procurement in power utilities in Japan.

JERA would have 15 MTPA from long-term offtake commitments in 2030 [JERA, 2016]. The long-term contracts will expire by the early 2020s by 10 MTPA and JERA will make long-term agreements by 5 MTPA to keep 20 MTPA in 2030 [Tsukimori, 2016]. The business plan in 2030 anticipated the total LNG procurements would be from 30 MTPA to 40 MTPA. Thus, JERA will optimise LNG portfolio to make the procurements between 10 MTPA to 20 MTPA by the short-term contracts and from the spot market. JERA's LNG procurement will be more flexible as 4.6 MTPA out of the existing 15 MTPA contracts are the destination flexible LNG, which starts in 2018 and lasts for 20 years, produced in the U.S. However, there is still uncertain about purchasing LNG through the short-term contracts and from the spot market in 2030 and about the costs of the LNG which would influence power utilities' profits.

3.6 Conclusion

Japanese LNG market has full of uncertainty. However, the utilization of the LNG spot market is a key to adjust the change of Japan's domestic LNG demand. Moreover, Japan's utilisation rate of the LNG spot market is less than Global utilisation of the LNG spot market. Therefore, future development would be expected.

In addition, based on the global LNG market analysis in Chapter 2 and the Japan's LNG market analysis in Chapter 3, we could consider the following 12 variables which might influence Japan's spot LNG prices in the long run. The 12 variables are natural gas price, crude oil price, coal price, natural gas production and natural gas consumption, LNG trade in volume, Japanese LNG demand, the global LNG spot market utilisation rate, Japanese LNG spot market utilisation rate, LNG upstream costs for natural gas, Investment in LNG liquification plants and geographical events.

Although we analyse the 12 variables in Chapter 5, here we briefly mention why we choose the variables as the potential regressors. First of all, LNG is a liquid form of natural gas. As we discussed in 3.2.1, Japan's LNG price is more correlated to the crude oil price. Coal is one of the thermal power fuels and the price of coal might affect LNG demand of Japanese power utilities. Natural gas production and consumption would affect natural gas prices. LNG trade in volume would affect LNG prices. Japanese LNG demand might affect Japan's LNG prices. The global and Japanese LNG spot market utilisation rates would influence the spot LNG prices. Natural gas upstream costs might affect natural gas prices. Investment in LNG liquification plants might affect LNG prices. Finally, geographical events would affect every commodity price.

In conclusion, Japan's spot LNG prices might be affected by the various factors. We analyse them deeply in Chapter 5 and choose the variables to be included into our model for the long-term forecasting.

Chapter 4 Literature Review

4.1 Introduction

The research of Japanese LNG market in Chapter 3 concluded that Japanese power utilities would utilise the LNG spot market to adjust the change of the domestic LNG demand in a timely manner. In this chapter, we analyse various methods to be used for price forecasting. Regression models are referred in 4.2 and Time series regression analysis are introduced in 4.3. Then, we provide a summary of the literature in 4.4.

4.2 Regression models

Regression models are utilised, as quantitative analytical tools, in order to understand the relationship between variables, forecast the future and analyse scenarios (Welc, et al, 2018).

Yoshida (2014) evaluated that how did the joint-purchase of LNG by Japanese power utility companies reduce costs of LNG procurement by using a fixed variable regression analysis. The results showed possibility to obtain discount from LNG suppliers by the increase of the quantities of the LNG purchases. Although the joint-purchase is an effective approach to tackle LNG procurement optimization, JERA would need procure LNG between 30 mpta and 40 mpta from short-term contracts or the spot market in 2030. Forecasting Japan's spot LNG prices would catch these power utilities interests. Because the spot LNG prices will affect their profitability.

As we discussed in Chapter 2 and 3, LNG trade agreements have oil price indexations. It is reasonable that LNG price and crude oil price have correlation. On the other hand, many studies have been conducted about natural gas price. Brigida (2014) showed a cointegrating relationship between natural gas and crude oil price by using Markov-switching cointegrating equation. Ramberg and Parsons (2012) also found the cointegrating relationship between Henry Hub (HH) natural gas prices and the West Texas Intermediate (WTI) crude oil price by using Vector Error Correction model (VECM). There are many studies to show the cointegration relationship between gas price and oil price. However, Mishra (2016) examined the linkage of natural gas prices to crude oil prices using the Conditional Error Correction mechanism in VECM with HH and WTI datasets from January 1999 to June 2016. He found that the relationship between natural gas price and oil price became weaker after 2008 and other external factors influenced the price of natural gas.

4.3 Time series regression analysis

Time series regression analysis plays a key role to describe the past mechanism and forecast the future (Ostrom, 1990). The commonly used data-driven methods to forecast commodity prices are Autoregressive Moving Average (ARMA), Autoregressive Conditional Heteroscedasticity (ARCH), Artificial Neural Network (ANN) and Support Vector Regression (Salehnia et al, 2013).

Paul et al, (2015) used the Autoregressive Fractionally Integrated Moving Average (ARFIMA) model to forecast the spot price of mustard. The reasons they used

ARFIMA was because time series data of agricultural commodity prices had long memory and ARIMA was not able to describe the long memory accurately. They found ARFIMA is applicable to the daily spot market of mustard in Munbai. Chaâbane (2014) used the new hybrid model of ARFIMA and artificial neural network model (ANN) to forecast electricity prices. The author argued that linear models were not able to capture non-linear components. Then the author used AFRIMA to capture linier components of the time series data and ANN to capture non-linear components of the time series data. The author showed the hybrid model outperformed.
Jadevicius and Huston (2015) used ARIMA model to forecast Lithuanian house price. Although the author recognised critics about ARIMA such as inaccuracy for long term forecast and weakness about turning point predictions, ARIMA was chosen based on the enormous success records of ARIMA. The author introduced the reliable assessment of ARIMA, which evaluated that the model was especially suitable for short term forecasting. As the result of the Lithuanian house price forecast, ARIMA was evaluated as a useful method to capture the price changes broadly. Munim and Schramm (2017) used ARIMA and autoregressive conditional heteroscedasticity model (ARCH) to forecast container shipping freight rates in the Far East. They included ARCH because of the nature of the freight rates. Freight rates are highly volatile, fluctuate and have cyclicality. According to the authors, ARCH is able to reflect recent changes due to the freight market volatility. The authors conducted short-term shipping freight rates forecasting on weekly and monthly basis. As a result, two AFRIMA models and two ARIMA models were selected as four best-performing models. The above ARIMA related studies: Paul et al, (2015), Chaâbane (2014), Jadevicius and Huston (2015), and Munim and Schramm (2017) used one variables. However, Misha (2012) used not only one variable but also independent variables to forecast the U.S. natural gas price. The models used by the author were ARIMA and a nonparametric regression called Alternating Conditional Estimation (ACE). The reason the author used ACE was because oil and gold price are not related to the natural gas price as a linear function. The author obtained Time series data of three models for crude oil price, gold average price and natural gas price by using ARIMA. Then the author forecasted Natural gas price from independent variables: crude oil price and gold price by using the time series data modified by ACE. The result shows reasonable degree of confidence.

However, traditional time series analysis, Bayesian models have been more popular recently. Bayesian structural time series models are more suitable to forecast values with good accuracy, when the datasets have less sufficient amount [Larsen, 2016]. Spedding and Chan (2000) used Bayesian time series analysis(BATS) to forecast future manufacturing demand. The forecasted horizons were next 15 weeks and 27 weeks and one variable (demand) is used. The authors made use of the model's advantage because the number of historical data was limited (less than 100 observations). The authors compared BATS to ARIMA and found that BATS had less error than ARIMA. The authors concluded that ARIMA's forecasting time frame is short-medium, however BATS is suitable for any forecasting time frames. Lee and Huh (2017) used a Bayesian Model with Informative Priors to forecast long-term crude oil prices. The authors included WTI Spot Price, World oil demand, World oil supply, Financial factor, and Upstream cost as independent variables. As a result, the crude oil was predicted to rise to $169.3/Bbl by 2040 and the model captured the volatility of the oil prices and showed better performances.

4.4 Conclusion

Table 2 shows the summary of the literature review listing models used, dependent and independent variables, targets and results. In regression models, natural gas price is a dependent variable and crude oil price is an independent variable. In order to forecast Japan's spot LNG prices, there are mainly two models: such as ARIMA group and Bayesian group. ARIMA group is suitable for short term forecasting and Bayesian group is suitable for short-medium-long term forecasting. In the literature, ARIMA included only one variable. However, Bayesian included one variable when the forecasting time frame was relatively short. When the forecasting time frame was relatively long, many independent variables were deployed in the model.

Table 2 Summary of the literature review

Author	Year	Model		Dependent variable	Independent variable	Target	Result
Regression model							
Brigida	2014	Markov-switching		Natural Gas P_{HH}	Crude Oil P_{WTI}	Cointegration	YES
Ramberg and Parsons	2012	VECM		Natural Gas P_{HH}	Crude Oil P_{WTI}	Cointegration	YES
Mishra	2016	VECM		Natural Gas P_{HH}	Crude Oil P_{WTI}	Cointegration	YES
Short-term Forecasting							
Paul et al.	2015	ARFIMA		Masturd Price	Masturd Price	Better Forecasting Model	ARFIMA could be used for modelling and forecasting the daily spot market of mastard in Mumbai market
Chaâbane	2014	ARFIMA and ANN		Electlicity Price	Electricity Price	Better Forecasting Model	New model, a combination of ARFIMA and ANN perfomed better than the existing models.
Jadevicius and Huston	2015	ARIMA		House Price	House Price	Investigation of Price Changes	ARIMA could used for assessing market price changes and forecasting prices.
Munim and Schramm	2017	ARIMA and ARCH		Freight Rate	Freight Rate	Better Forecasting Model	4 best-performing forecast models: 2 from ARIMARCH model and 2 from ARIMA model
Mishra	2012	ARIMA and ACE	Time Series	Natural Gas Price	Natural Gas Price	Better Forecasting Model	New model, a combination of ARIMA and ACE showed reasonable degree of confidence.
			ARIMA	Crude Oil Price	Crude Oil price		
				Gold Price	Gold Price		
			Regression	Natural Gas Price	Crude Oil Price		
			ACE		Gold price		
Short-medium-long-term Forecasting							
Spedding and Chan	2000	Bayesian Time Series		Demand	Demand	Better Forecasting Model	BATS could be applicable to short-medium-long term forecasting. It had relatively less error than ARIMA.
Lee and Huh	2017	Bayesian Regression		Oil Price	WTI Spot Price	Better Forecasting Model	The crude oil price was predicted to rise to $169.3/Bbl by 2040.
					World Oil Demand		
					World Oil Supply	Long term Price Forecasting	The proposed Bayesian model outperformed and explained the volatility of the Oil price.
					Financial Factor		
					Upstream Cost		This research provided not only short-term forecasting but also long-term forecasting.
					Geographical Event		

Source: Author via the literature

Chapter 5 Theoretical Analysis

5.1 Introduction

Chapter 2 gave an overview of the global LNG market and the current development. In Chapter 3, we described the Japanese LNG market and explore LNG demand towards 2030. In this chapter, based on the analysis in Chapter 2 and 3 and with the literature review in Chapter 4, we conduct theoretical analysis to forecast Japan's spot LNG prices in the short run in 5.2 and in the long run in 5.3. Regarding the shot-time frame forecasting, we use one variable. However, regarding the long-time frame forecasting, we consider various variables which would influence Japan's spot LNG prices. We suggest two hypotheses: the hypothesis about model performances comparing ARIMA to Bayesian model for the short-term forecasting in 5.2 and the hypothesis about Bayesian model performances with or without the variables for the long-term forecasting in 5.3.

5.2 Short-term forecasting

Based on the literature review, only one variable, Japan's spot LNG price would be used with applications of both ARIMA and Bayesian models, especially, Bayesian Structural Time Series (BSTS) model. Because the short-term forecasting price would be influenced strongly by the price of the previous time point. It is supposed to run the model regularly reflecting the new data in order to obtain more reliable forecasting price. Japan's spot LNG price published by METI is monthly basis. It is not reasonable to obtain other variables each month. METI started the publication of Spot LNG price statistics in 2014. This data has a limitation as the number of observations is 51. Therefore, we generate the following hypothesis:

Hypothesis 1
H_0: BSTS model performs better than ARIMA model in Japan's LNG spot market for the short-term forecasting.

5.3 Long-term forecasting

Long-term forecasting with accuracy is difficult because of uncertainty in the future. Present actions or events influence the future. Meanwhile, based on the literature review, Bayesian model would be applicable for the long-term forecasting. One advantage of BSTS model is capability to use spike-and-slab priors which reduce the number of related variables and make the model simple and powerful [Larsen, 2016]. Thus, we use BSTS models with one variable and various variables. One variable is Japan's spot LNG price. However, there are various variables which could influence the spot LNG price. In this section, we analyse the independent variables.

We consider the 12 variables: natural gas price, crude oil price, coal price, natural gas production and consumption, LNG trade in volume, Japanese LNG demand, the global LNG spot market utilization rate, Japanese LNG spot market utilization rate, natural gas upstream costs, Investment in LNG liquification plants and geographical events.

As LNG is liquified natural gas price, natural gas price would influence LNG price. The literature review show natural gas price and crude oil price are cointegrated. Plaquet' cointegration analysis (2015) concluded there are cointegration relationships among natural gas, crude oil and coal prices. Japanese LNG demand is affected by LNG usage for thermal plants. The component of fuels are natural gas, oil and coal. We consider Australian coal prices as an independent variable because majority of coal imported to Japan comes from Australia. Figure 24 shows monthly natural gas and LNG prices from 2014 to 2018. The actual-based Japanese spot LNG price followed the trend of the contract-based Japanese spot LNG price. These Japanese spot prices seems to be correlated to the prices of US and Europe at the area of Spike 1, 2 and 3 in Figure 24. The average price of LNG imported to Japan (plot in green) seems not to be correlated or the correlation is too weak to be observed. Figure 25 shows monthly crude oil and coal prices from 2014 to 2018. Comparison of the Figure 24 and 25 shows the gaps of between European gas price and US gas price are wider than the three oil indexes.

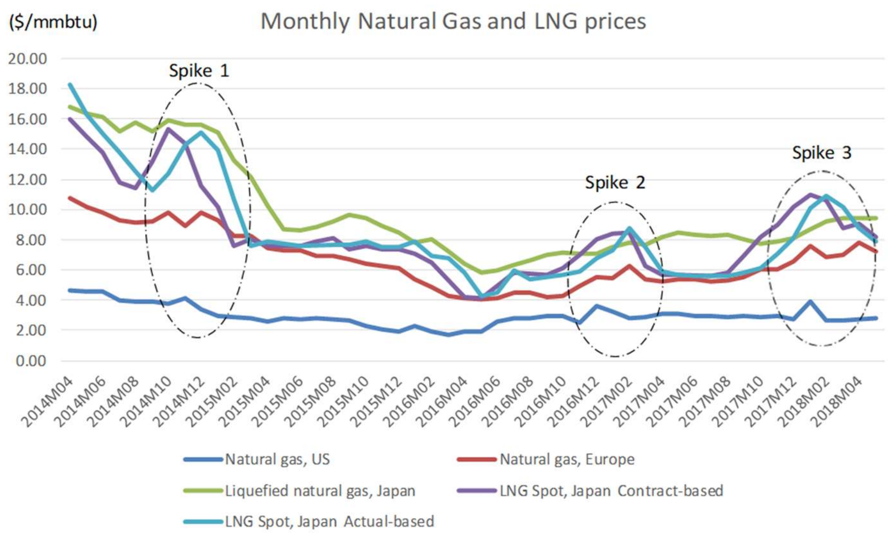


Figure 24 Monthly natural gas and LNG prices

Source: Auther via (World Bank and MITI, 2018)

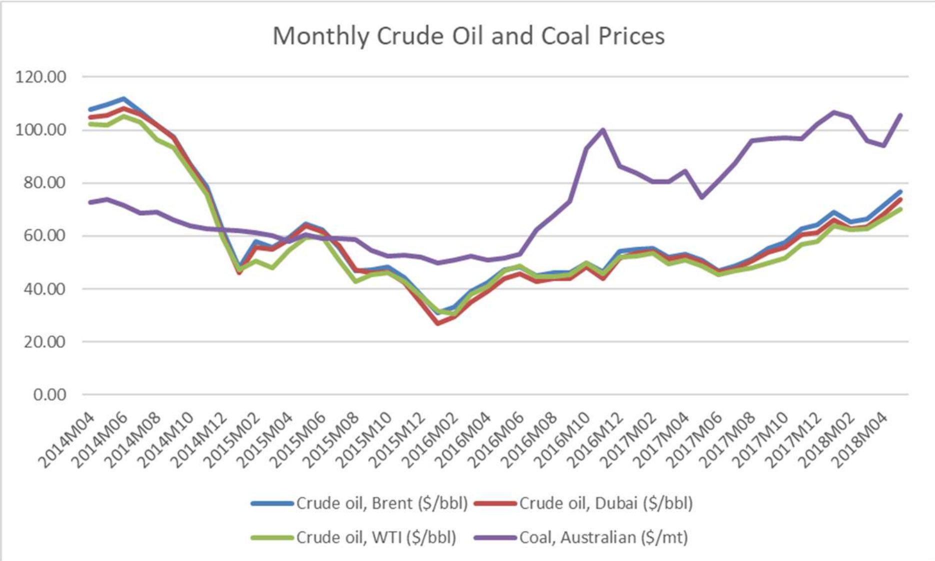


Figure 25 Monthly crude oil and coal prices

Source: Auther via [World Bank , 2018]

Natural gas production and natural gas consumption, global LNG trade in volume, and Japanese LNG demand are also considered as factors which would influence Japan's spot LNG price. As a basic economic theory, demand and supply affect price and quantity of the good. Figure 26 show Natural gas production and consumption have increased over time. Figure 1 in Chapter 2 shows global LNG trade and Figure 7 in Chapter 3 shows LNG imported to Japan. These factors also would be considered.

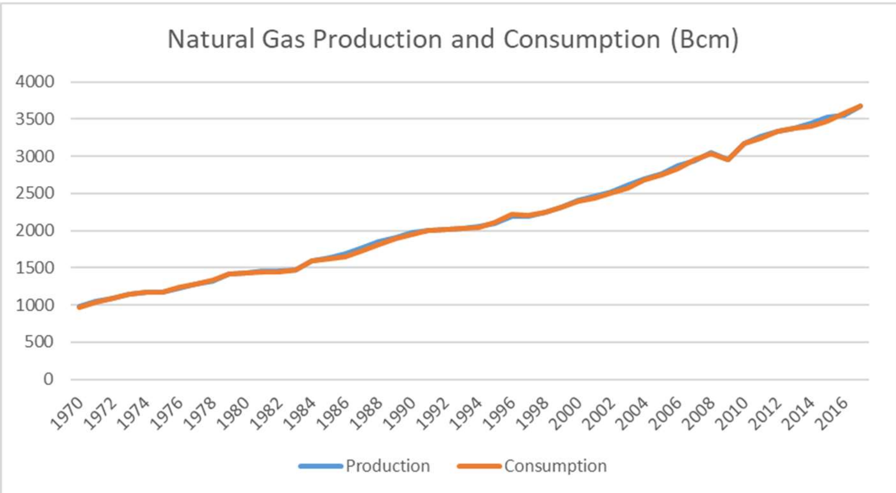


Figure 26 Natural gas production and consumption

Source: Auther via [BP, 2018]

Based on the analysis about the development of the global LNG spot market in Chapter 2, the increase of liquidity could influence the price of the global LNG spot market. Figure 27 shows LNG spot market utilisation rates of the world and Japan. Although the utilisation rate of Japan reached the peak of 29 % in 2014, it decreased from 2014 to 2017. As we discussed the less utilisation of Japanese LNG spot market and Japanese buyers' willingness to increase more LNG procurements from the spot market in Chapter 3, there are room for the Japanese spot market to be developed. Thus, these utilisation rates could affect Japan's spot LNG price.

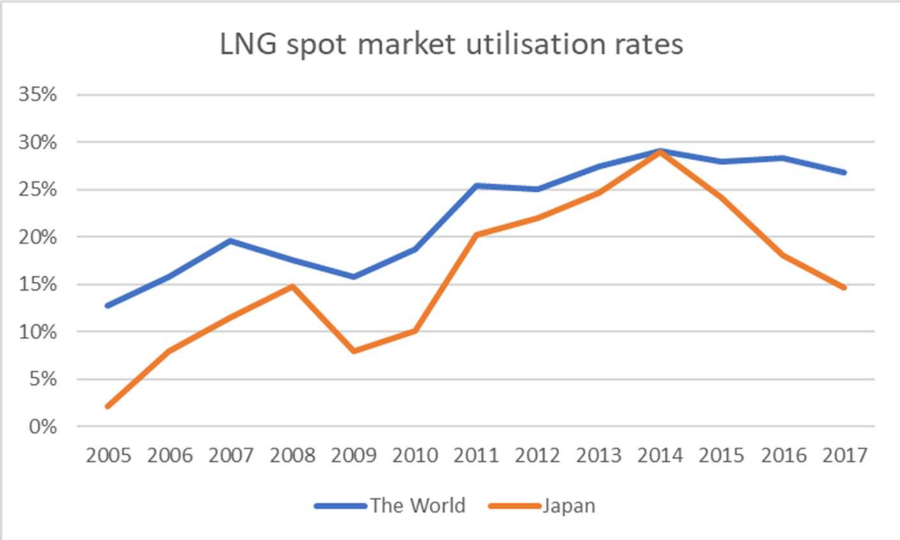


Figure 27 LNG spot market utilisation rates

Source: Author via (GIIGNL, 2005-2017)

Upstream costs for LNG and investment in LNG liquification plants would also be considered. Because large capital is needed for the LNG supply chain. LNG is delivered by shipping from production areas to consumption areas. The shipping is one part of the LNG supply chain from upstream to downstream. Before LNG is used as a fuel for energy generation, there are many steps to go through such as: exploring and drilling, production and liquefaction, shipping, regasification and energy generation. Every step requires large capital investments. As we discussed the LNG trade agreements in Chapter 2, one of the reasons why the long-term contracts dominated the LNG market was because gas production companies needed to raise capital and obtain loans from banks to cover the large capital costs to extract and liquify natural gas. Within the gas project financing process, the long-term trade agreements are reliable information for gas production companies to be able to manage their finance in their repayment terms. Moreover, LNG new building is relatively expensive in comparison to the other type of vessels. Figure 9 in Chapter 2 shows the cost range of new building was from 180 to 200 million USD per one vessel for the past 10 years. Regarding LNG shipping in operation, the high safety and security standard and special care are needed, because of LNG's characteristics, where LNG is transformed from the gas into a liquid with one-600th of its volume in a gaseous by being cooled to a temperature of minus 162 degrees Celsius.

Figure 28 shows the global investment in upstream oil and gas, and investment in LNG liquefication plants. Regarding the global investment in upstream oil and gas, the investment hit the low in 2016 and slightly recovered to 450 billion USD in 2017. The main driving force was US, reflecting the increase in the shale industry's capital spending [IEA, 2018]. Regarding the Investment in LNG liquefication plants, the investment has decreased reflecting the decline of foreign direct investments for the

LNG project in Australia and US [IEA, 2018]. Development of exploring and drilling is the starting point of the LNG supply chain and influences the amount of gas production. Liquification plants play a role to transform natural gas to LNG, thus the trend of the investment affects global LNG trade in volume and would influence the price of global LNG. Therefore, these variables should also be considered.

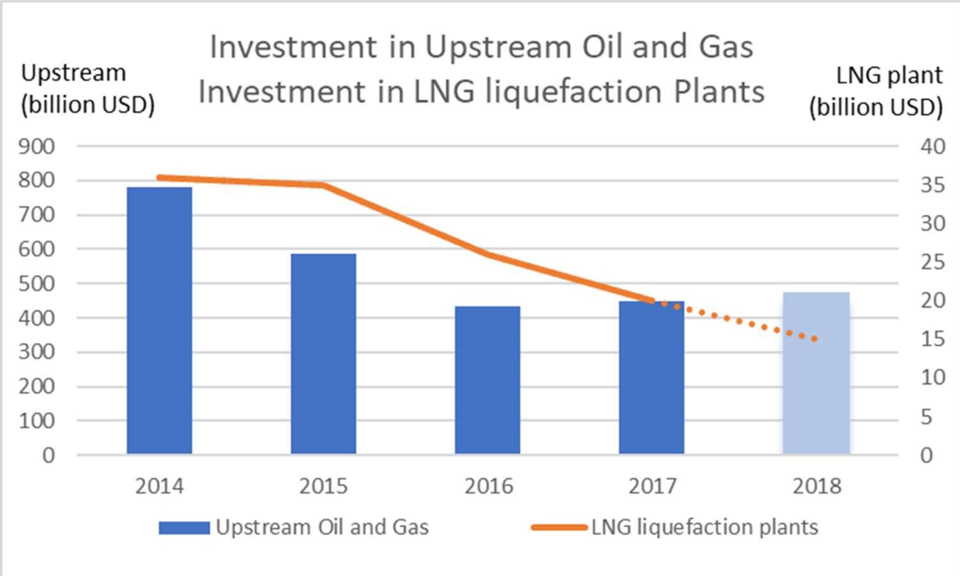


Figure 28 Investment in upstream oil and gas, and LNG liquefication plants

Source: Auther via (IEA, 2017c, 2018)

Finally, geographical events could affect Japan's spot LNG price. Figure 29 shows crude oil, natural gas and LNG prices from 1960 to 2017. The oil crises in 1970s seems to affect European natural gas price and Japanese LNG price. The financial crisis from 2007-2008 seems to influence every commodity price. Meanwhile, the strong correlation of Japanese LNG price and crude oil price is also observed in Figure 29. Japanese LNG price and crude oil price in Dubai had similar shapes from 2008 to 2016. And besides, regional events could also affect Japan's spot LNG price. Figure 30 shows US Natural gas, European Natural gas and Japanese LNG prices from 1977 to 2017. The Great East Japan Earthquake in 2011 seems to influence Japanese LNG price and partially European Natural Gas price. However, US Natural gas price seems not be affected by the regional event.

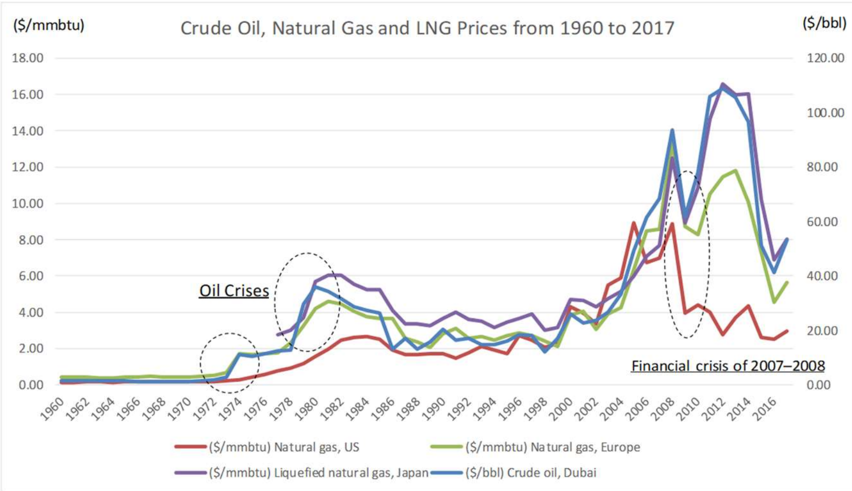


Figure 29 Crude oil, natural gas and LNG prices

Source: Auther via (World Bank, 2018)

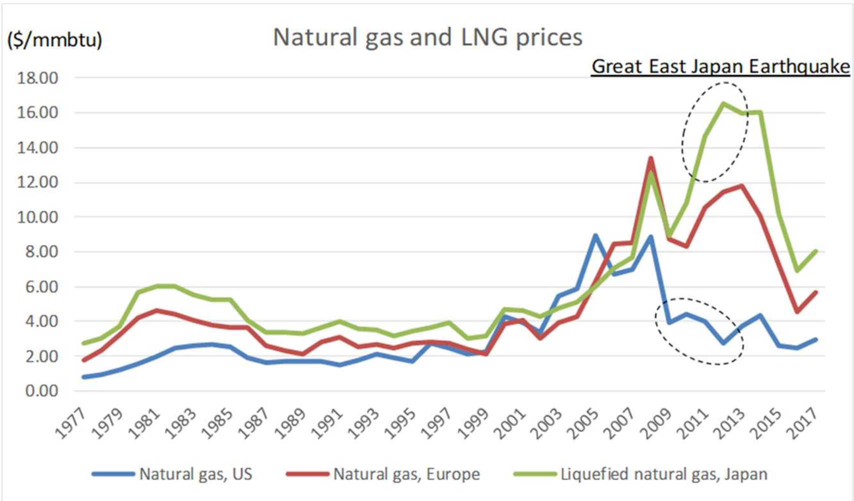


Figure 30 Natural gas and LNG prices

Source: Auther via (World Bank, 2018)

To sum up, Japanese LNG spot price would be influenced by the following variables.

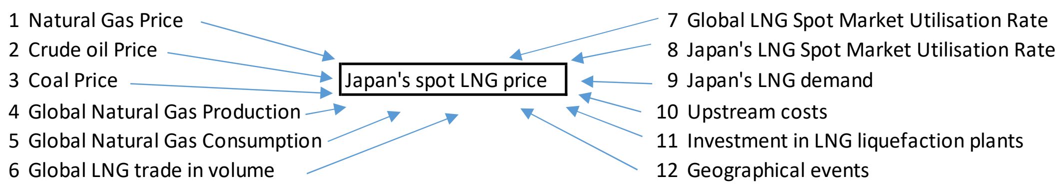


Figure 31 Variables influencing Japan's spot LNG Prices

Source: Author

Therefore, we generate the following hypothesis.

Hypothesis 2
H_0: BSTS model with various variables performs better than Single BSTS model in Japan's LNG spot market for the long-term forecasting.

5.4 Conclusion

We use ARIMA model and BSTS model to forecast Japan's spot prices in the short term. Meanwhile, we use Single BSTS model and BSTS model with the variables, which would affect Japan's spot LNG prices, for long-term forecasting.
We set the two hypotheses and conduct this study. Our two hypotheses are as follows:
Hypothesis 1
H_0: BSTS model performs better than ARIMA model in Japan's LNG spot market for the short-term forecasting.
Hypothesis 2
H_0: BSTS model with various variables performs better than Single BSTS model in Japan's LNG spot market for the long-term forecasting.

Chapter 6 Methodology

6.1 Introduction

We propose ARIMA model and BSTS model for Japan's spot LNG price forecasting in the short run. Then, we compare the suggested spot prices to the METI's published data. After that, we conduct the long run Japan's spot LNG price forecasting by Single BSTS model and BSTS model with a regression component. We use the various variables as discussed in Chapter 5. Then, we compare the suggested spot prices to the World Bank's Japanese LNG price forecast. In this chapter, we introduce ARIMA model in 6.1, a Bayesian model, especially, Bayesian Structural Time Series (BSTS) model in 6.2. We propose steps for the analysis to be implemented in 6.3 and describe the data set to be used for the analysis in 6.4.

6.2 ARIMA model

ARIMA or ARIMA group is one of the most popular methods to forecast commodity prices in the short run as discussed in Chapter 4. Here, we describe general notations of ARIMA and a common methodology to apply ARIMA.

Firstly, ARIMA is a combination of Autoregressive model and Moving average model with differentiation. The mathematical structure of ARIMA models is as follows:

Autoregressive (AR) model

$Y_t = a_0 + a_1 Y_{t-1} + \varepsilon_t,\ where, \varepsilon_t = NID(0, \sigma_\varepsilon^2)$
Y_t is a function of its previous value, Y_{t-1} and a stochastic error, ε_t.
ε_t is normally distributed with mean 0 and variance σ_ε^2. This is an autoregressive model of order 1. It means that the value of the period t is determined by the value of the previous period (t-1).
$Y_t = a_0 + a_1 Y_{t-1} + a_2 Y_{t-2} + a_3 Y_{t-3} + \cdots \ldots + a_p Y_{t-p} + \varepsilon_t,\ where, \varepsilon_t = NID(0, \sigma_\varepsilon^2)$
If Y_t is a function of its previous values, Y_{t-1}, Y_{t-2}, Y_{t-3}...., Y_{t-p}, it is called an autoregressive model of order p.

Moving Average (MA) model

AR model shows the random error ε_t. MA model is considered that Y_t is determined by the random error.
$Y_t = b_1 Y_{t-1} + \cdots + \varepsilon_1$
$Y_{t-1} = b_2 Y_{t-2} + \cdots + \varepsilon_2$
....
$Y_{t-q} = b_q Y_{t-q} + \cdots + \varepsilon_q$
$Y_t = \varepsilon_t + b_1 \varepsilon_{t-1} + b_2 \varepsilon_{t-2} + \cdots \ldots + b_q \varepsilon_{t-q}\ where, \varepsilon_t = NID(0, \sigma_\varepsilon^2)$
If Y_t is a function of its previous white noise error, it is called a Moving Average model of order q.

Autoregressive Moving Average(ARMA) model

ARMA model is combination of AR and MA model. It depends on the past value and the error term. Therefore, it is represented below:
$Y_t = a_0 + a_1 Y_{t-1} + a_2 Y_{t-2} + \cdots + a_p Y_{t-p} + b_1 \varepsilon_{t-1} + b_2 \varepsilon_{t-2} + \cdots + b_q \varepsilon_{t-q} + \varepsilon_t$
This is ARMA model of order (p, q)

Autoregressive Integrated Moving Average (ARIMA) model

AR, MA and ARMA are applicable if the data is stationary. In the case of the data is non-stationary, we need to differentiate the data to eliminate the non-stationarity. To forecast a time series $Y_t = (Y_1, \ldots\ldots Y_t)$ in the ARIMA model (p, d, q). p is the number of order from AR model, d is the number of differences needed to eliminate the non-stationarity, and q is the number of the errors from MA model.
If d=0, $y_t = Y_t$
If d=1, $y_t = Y_t - Y_{t-1}$
If d=2, $y_t = (Y_t - Y_{t-1}) - (Y_{t-1} - Y_{t-2}) = Y_t - 2Y_{t-1} + Y_{t-2}$

The general forecasting model is below:

$\hat{y}_t = a_0 + a_1 y_{t-1} + \cdots + a_p y_{t-p} - b_1 \varepsilon_{t-1} - \cdots - b_q \varepsilon_{t-q}$

Secondly, we use partially Box-Jenkins(B-J) methodology: (1) Identification, (2) Estimation and (3) Diagnostic checking to apply ARIMA. The R software helps to conduct trials and errors to forecast the prices. The basic B-J methodology is as follows:

(1) Identification
We observe the dataset and find the characteristics such as: Stationarity and Seasonality.

(2) Estimation
Based on the identification, we choose an appropriate ARIMA model (p, d, q) with Akaike information criterion.

(3) Diagnostic checking
Before applying the model, we check the validity of the model.

Diagnostic checking

(a) Akaike information criterion(AIC)
We determine the ARIMA (p, d, q) to choose the lowest AIC because AIC is a goodness of fit measure.

(b) Ljung-Box test
We conduct Ljung-Box test to research if there is autocorrelation of the residuals from the proposed ARIMA model. If P-value is more than 0.05, we can assume there is no autocorrelation, thus we can run the model.

6.3 A Bayesian Structural Time Series Model

Bayesian group has an advantage to apply for short and long-term forecasting as discussed in Chapter 4. However, most of models involve complicated mathematics and it is almost impossible for the author who does not have strong mathematical background to conduct forecasting. Meanwhile, BSTS allows us to conduct this study with some lines of R code. Thus, we choose BSTS. In this section, we introduce basic idea about BSTS which was built by Scott and Varian (2014).

BSTS is Structural time series in Bayesian framework. The basic notation is as follows:

Structural time series model (State space form)

There are two components of a structural time series model: (1) Observation equation and (2) Transition equation.

y is the observed data. α_t is a vector of latent variables (state variables). $Z_t$and H_t are structural parameters. Observation equation shows y_t comes from state variable, α_t. Meanwhile, level of α_t is shown previous state variable plus noise term in Transition equation. T_t, R_t and R_t, are structural parameters.

$$y_t = Z_t^T \alpha_t + \varepsilon_t \quad \varepsilon_t \sim \mathrm{N}(0, H_t) \qquad (1)$$

$$\alpha_{t+1} = T_t \alpha_t + R_t \eta_t \quad \eta_t \sim \mathrm{N}(0, Q_t) \qquad (2)$$

Trend, seasonal and regression could be added into the state vector α_t.

Basic Bayesian Statistics

Bayesian theorem is that Posterior distribution = Prior distribution × Likelihood and it is used to update probabilities.

$$\mathrm{P}(A|B) = P(A) \times \frac{P(B|A)}{P(B)}$$

A and B are two events. $P(A)$ is the prior probability of A. $\mathrm{P}(B|A)$ is the likelihood function. $\mathrm{P}(A|B)$ is the posterior probability.

Combination of Structural Time series and Bayesian frameworks

Bayesian technic simulates the state α from its posterior distribution given the data, $\mathrm{P}(\alpha|y)$. In order to obtain the posterior distribution, the Kalman filter and a Markov Chain Monte Carlo algorithm are used. In BSTS with a regression component, Spike and Slab prior is used to specify the prior distribution by selecting regressors and promoting sparsity.

BSTS

BSTS uses Google search data to determine the prior distribution using the method called Spike and Slab prior. Due to the time limitation and the author's less mathematical background, it is not able to explain how BSTS works. However, Scott and Varian (2014) concluded Google Trends and Google Correlate data was useful to "nowcast" economic time series. Moreover, the R package "bsts" built by Scott automatically conducts the mathematical computation. Therefore, we use BSTS for this study.

6.4 Implementation of ARIMA and BSTS in R

We use "forecast" package and "BSTS" package of the statistic software, R to conduct the analysis. The procedure of the implementation is as follows:

<u>(1) Short-term forecasting</u>

(a) Comparison of ARIMA model and BSTS model with the mean absolute percentage error (MAPE)
(b) Forecast of Japan's spot LNG prices for the next three months
(c) Evaluation of the two models and results

<u>(2) Long-term forecasting</u>

(a) Comparison of Single BSTS model and BSTS with multiple regressors model with cumulative absolute error
(b) Forecast of Japan's spot LNG price until 2030
(c) Evaluation of the two models and results

6.5 Data set

We describe the data sets to be used for the short-term and long-term forecasting and their sources.

<u>(1) Short-term forecasting</u>

Spot LNG Price Statistics (March 2014 to May 2018) published by Japan's Ministry of Economy, Trade and Industry (METI). The data is monthly and have 51 observations. The number of data is small because METI started to publish the prices from March 2014 and the LNG spot market is under development.

<u>(2) Long-term forecasting</u>

Main data to be used is the same data of the short-term forecasting plus the data of June and July in 2018. Although the price of July in 2018 is preliminary, we include it and use the average price of each year (2014 to 2018).

Regarding the variables, as mentioned in 5.3, there are 12 variables might influence Japan's spot LNG prices. However, geographical events happen suddenly thus, we consider the other variables excluding the geographical events. The data and their sources are shown in Table 3.

Table 3 List of variables

Data	Period	Source
Crude oil price (WTI)	1982-2017	World Bank Commodity Price Data, Annual prices (Nominal)
Coal price (Australia)	1982-2017	World Bank Commodity Price Data, Annual prices (Nominal)
Natural gas (HH)	1982-2017	World Bank Commodity Price Data, Annual prices (Nominal)
Upstream investment for oil and gas	2000-2018	Author's visual Estimation via IEA, World energy investment 2017-18
Iinvestment in LNG Liquefaction plant	2014-2018	Author's visual Estimation via IEA, World energy investment 2017-18
Japan's LNG spot market utilization rate	2005-2017	Auther via GIIGNL, annual report 2005-2017
Global LNG spot market utilization rate	2005-2017	Auther via GIIGNL, annual report 2005-2017
Natural gas production	1982-2017	BP Statistical Review of World Energy
Natural gas consumption	1982-2017	BP Statistical Review of World Energy
Global LNG trade in volume	2008-2017	Auther via GIIGNL, annual report 2008-2017
Japan's LNG import in volume	1988-2017	Trade Statistics of Japan

Source: Auther

6.6 Conclusion

In summary, we forecast Japan’s spot LNG prices in short-term and long-term with the following procedure. Our focal point is not to find the best fitting model but to predict Japan’s spot LNG prices with higher accuracy.

Table 4 Model processing framework

	Short-term	Long-term
Step 1	Data observation	Data observation
Step 2	Model building (ARIMA, BSTS)	Forecast without a regression component
	Inc. Diagnostic checking	Inc. Single BSTS model building
Step 3	Applying the models	Identifying the contribution of regressors
Step 4	Comparison with MAPE	Estimation of the future values of each regressor
Step 5	Forecasting the prices (June-August 2018)	Forecasting the prices until 2030
Step 6	Analysis of the results	Analysis of the results

Source: Auther

Chapter 7 Results and Analysis

7.1 Introduction

In this chapter, we segregate the results and analysis into four parts. Firstly, we describe the results and analysis of the short-term forecasting Japan's spot LNG prices in 7.2. Secondly, we mention the steps we made to forecast the prices in 7.3 Thirdly, we describe the results and analysis of the long-term forecasting Japan's spot LNG prices in 7.4. Finally, we mention the steps we made to forecast the prices in 7.5.

7.2 Results and Analysis of the short-term forecasting

In this section, we present results of forecasting the LNG price using ARIMA and BSTS. Table 5 shows the results from the four different proposed models: ARIMA (0,1,1), ARIMA (2,1,0) with log-transformation, BSTS, and BSTS with log-transformation. The result of BSTS with log-transformation model is closer to the price of June 2018 which METI (2018b) published.

Table 5 Short-term Japan's spot LNG price forecasts

	ARIMA			BSTS			METI
	ARIMA (0,1,1)	Log Transformation ARIMA (2,1,0)			Log Transformation		(Unit: USD/MMBtu)
Month	Value	log10	Value	Value	log10	Value	Contract-based price
Jun-18	7.1931810	0.8395433	6.9110383	8.4782550	0.9559786	9.0360495	9.3*
Jul-18	6.8038290	0.8110755	6.4725513	8.5074530	0.9859648	9.6819938	10**
Aug-18	7.2033390	0.8452865	7.0030383	8.8654670	1.0018175	10.0419372	

METI: Trend of the price of spot-LNG (Preliminary Figures for July 2018), published on August 9, 2018
*Detailed ** Preliminary

However, ARIMA with log-transformation model shows the lowest MAPE value as the result of the examinations among two different forecasting periods: the next 1 year and 5 months (January 2017- May 2018) and the next 5 months (January 2018 – May 2018). Table 6 shows comparison of MAPE values among four models with two different durations. These MAPE are not the errors of the results during the model building periods but the errors of results during the forecasting periods. In the forecasting period, from January 2018 to May 2018, the lowest MAPE is 8.14% of the ARIMA with log-transformation model and the second best MAPE is 12.88 % of the BSTS model.

Table 6 Comparison of MAPE values

Models	Period			
	Building model Mar2014- Dec2016	17months Forecasting Jan2017-May2018	Building model Mar2014-Dec2017	5months Forecasting Jan2018-May2018
		MAPE (Unit: %)		MAPE (Unit: %)
ARIMA		24.09		25.01
ARIMA Log Transformation		16.66		8.14
BSTS		17.53		12.88
BSTS Log Transformation		23.45		25.8

In summary, although MAPE of BSTS with log-transformation model for the next 5 months forecast shows the worst value, the real forecasted value from the model is closer to the real value (June 2018). Therefore, in this case, BSTS with log-transformation model outperforms.

7.3 Model building process for the short-term forecasting

We represented the results and analysis in 7.2. In this section, we describe how we reached the results by following steps discussed in Chapter 6.

Step 1 Data Observation

Missing values

The data of 51 observations has 5 missing values of May 2015, March 2016, June 2016, August 2016 and June 2017. Due to limitation of time, we used the linear interpolation, which is the mean of the values of the closest months to the target month, although there are other ways to interpolate values such as: the spline interpolation and the Stineman interpolation.

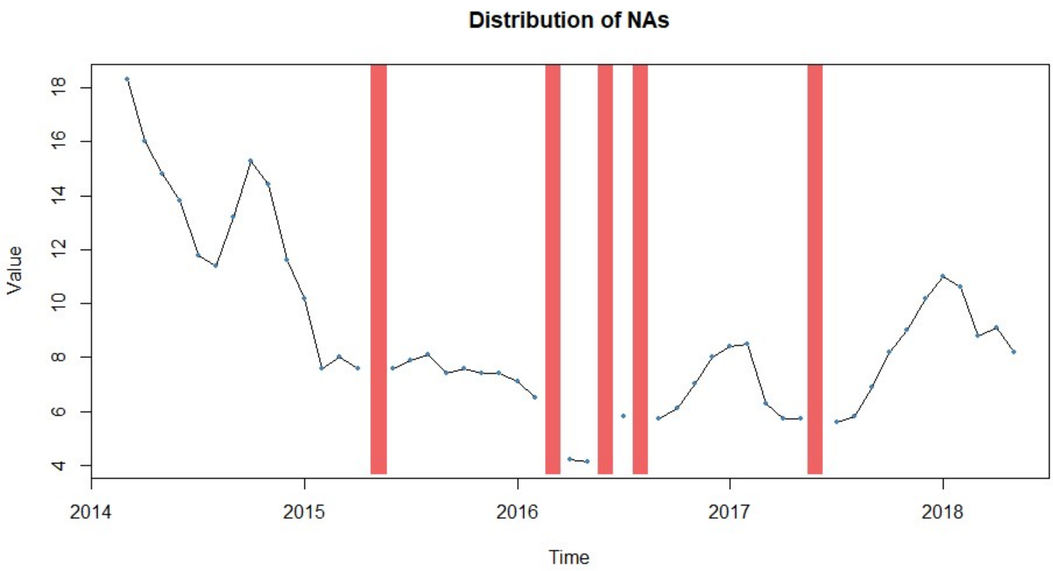


Figure 32 Missing values of the data set

Stationarity

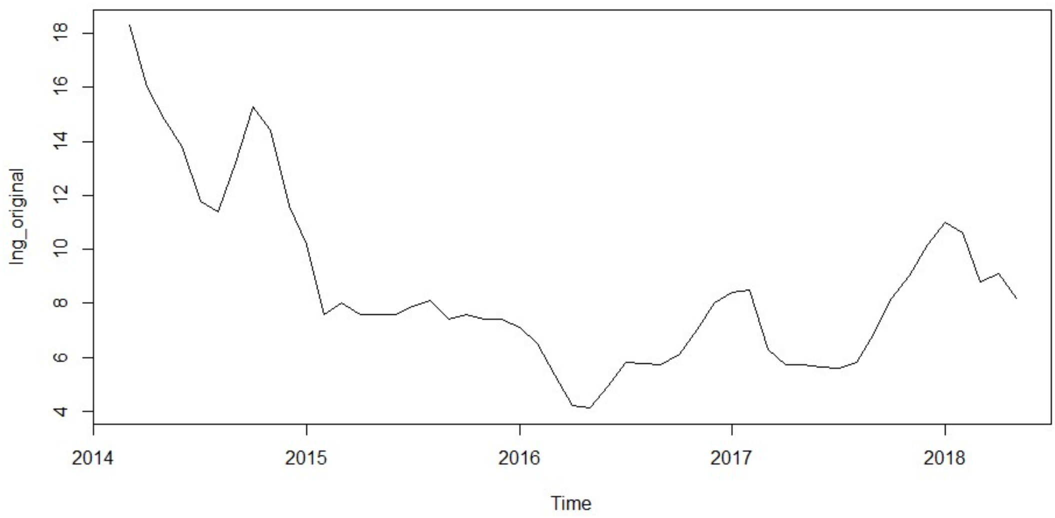


Figure 33 Original data set

The original data plot looks non-stationary and Dickey-Fuller Test also shows p-value is 0.5872. Thus, the original data is non-stationary.

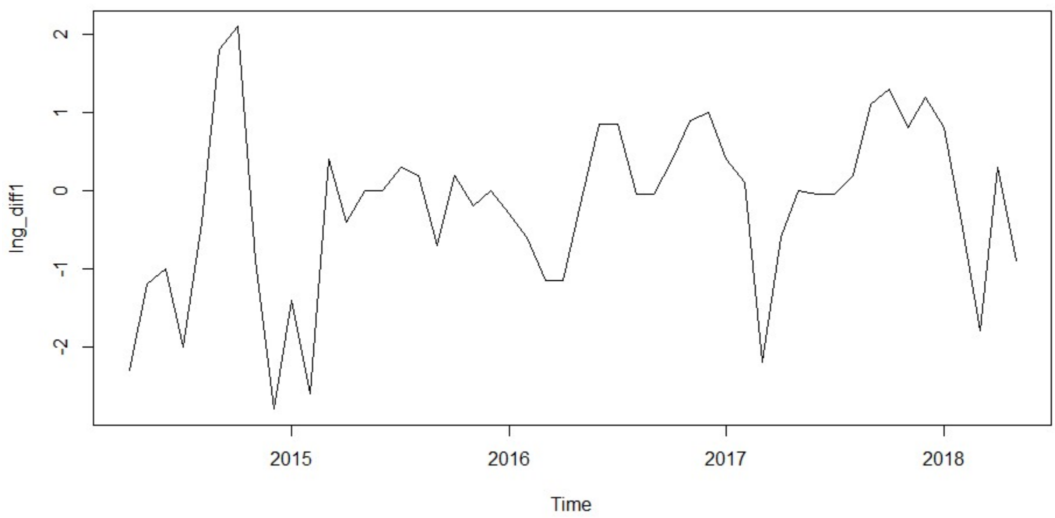


Figure 34 The first difference of the original data

The first difference of the original data set looks stationary and Dickey-Fuller Test also shows P-value is 0.01. Thus, the first difference of the original data set is stationary. We can assume d=1 for ARIMA (p, d, q) models.

Autocorrelation

In order to forecast the future values, the data should have some kind of relationships between one value and one value behind in time.

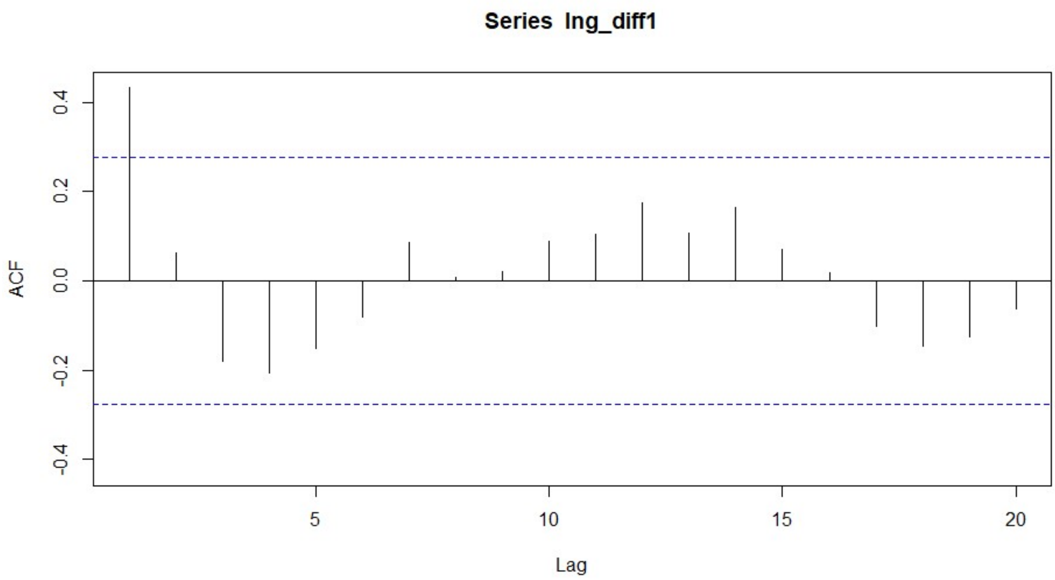


Figure 35 ACF plots of the first difference of the original data

There is autocorrelation because the value of 0.433 at the lag1 is out of the bound. We can assume q=1 for ARIMA (p, d, q) models.

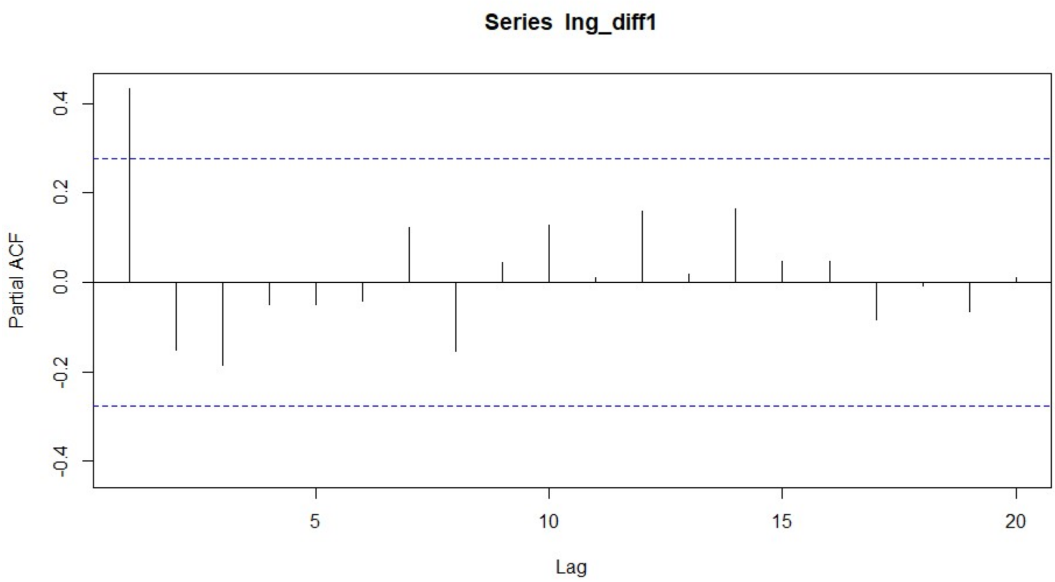


Figure 36 PACF plots of the first difference of the original data

There is partial autocorrelation because the value of 0.433 at the lag1 is out of the bound. It shows correlation between a variable and its lags, which is not captured by ACF. We can assume p=1 for ARIMA (p, d, q) models.

<u>Seasonality</u>

Seasonal component, trend component and cycle component would affect the results. Both the original data and the first difference of the original data have seasonal and trend components. Since this is the monthly data, we assume seasonal peaks at lag 12.

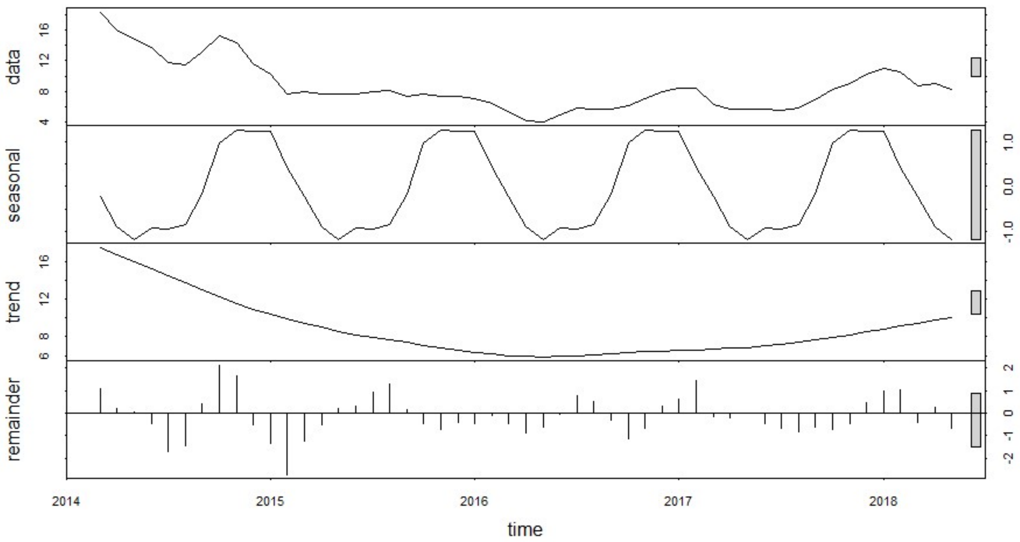


Figure 37 Decomposition of the original data

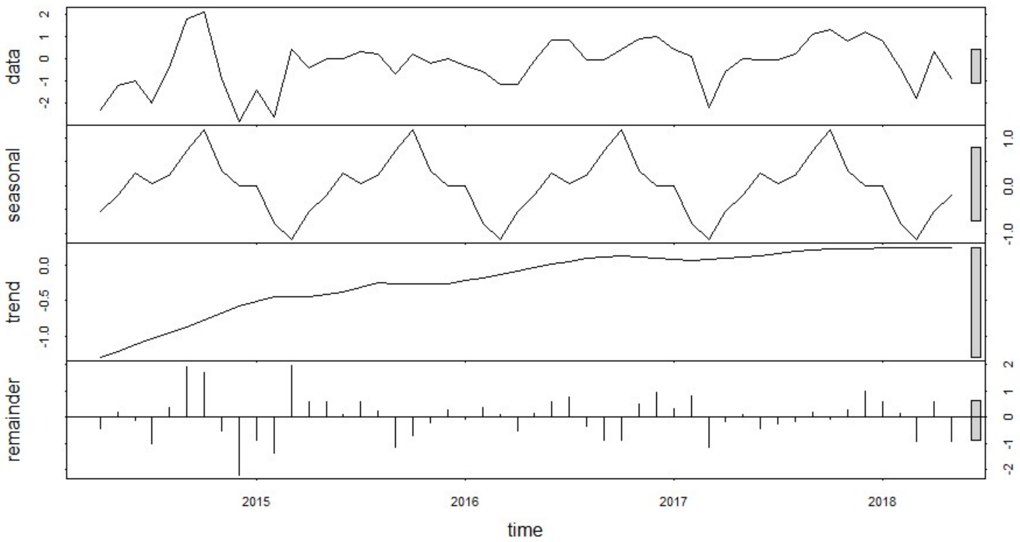


Figure 38 Decomposition of the first difference data

In conclusion, the original data is applicable for both ARIMA model and BSTS model. The data has autocorrelation to predict the future values. The original data is non-stationary. However, ARIMA and BSTS are able to handle the non-stationary data because ARIMA has a differencing process and BSTS assumes a structural change in time series, where the mean and variance of the time series could change. We also consider seasonal components at lag 12 and trend components.

Step 2 Model building

ARIMA

The following model includes seasonal component, period=12.

ARIMA for the next 17 months forecasting:
Auto.arima suggested ARIMA (0,1,2). We added ARIMA (0,1,1) for reference. We conducted AIC and Ljung-Box test and selected ARIMA (0,1,1) model.

	AIC	P-value (Ljung-Box)
ARIMA (0,1,2)	78.83439	0.816400
ARIMA (0,1,1)	75.81740	0.816400

ARIMA for the next 5 months forecasting:
Auto.arima suggested ARIMA (1,2,1). We added ARIMA (0,1,1) for reference. We conducted AIC and Ljung-Box test and selected ARIMA (1,2,1) model.

	AIC	P-value (Ljung-Box)
ARIMA (1,2,1)	83.57223	0.321400
ARIMA (0,1,1)	104.66220	0.615100

ARIMA for the real forecasting (June-August 2018):
Auto.arima suggested ARIMA (0,1,1) and ARIMA (0,0,1). We conducted AIC and Ljung-Box test and selected ARIMA (0,1,1) model.

	AIC	P-value (Ljung-Box)
ARIMA (0,1,1)	116.10650	0.477800
ARIMA (0,0,1)	213.95380	0.000000

ARIMA with log-transformation for the next 17 months forecasting:
Auto.arima suggested ARIMA (0,1,1) and ARIMA (1,1,0). We conducted AIC and Ljung-Box test and selected ARIMA (0,1,1) model.

	AIC	P-value (Ljung-Box)
ARIMA (0,1,1)	-105.09880	0.47100
ARIMA (0,1,0)	-99.19313	0.03244

ARIMA with log-transformation for the next 5 months forecasting:
Auto.arima suggested ARIMA (2,1,0) and ARIMA (0,1,0). We conducted AIC and Ljung-Box test and selected ARIMA (2,1,0) model.

	AIC	P-value (Ljung-Box)
ARIMA (2,1,0)	-144.62410	0.90630
ARIMA (0,1,0)	-135.00680	0.01893

ARIMA with log-transformation for the real forecasting (June-August 2018):
Auto.arima suggested ARIMA (0,1,1) and ARIMA (0,1,0). However, we added ARIMA (2,1,0) based on the results of 5 months forecasting model. We conducted AIC and Ljung-Box test and selected ARIMA (2,1,0) model.

	AIC	P-value (Ljung-Box)
ARIMA (0,1,1)	-109.56190	0.100900
ARIMA (0,1,0)	-108.76220	0.004826
ARIMA (2,1,0)	-112.2445	0.815100

BSTS

Although ARIMA needed to specify ARIMA (p, d, q) and conduct diagnostic checking, BSTS offered a good fit model with Markov chain Monte Carlo methods (MCMC). According to Scott (2017), the BSTS package finds the best fit model to estimate parameters using a MCMC algorism.

To build a model, firstly, we chose a state specification from the BSTS package to specify a vector of latent state variable α_t. Then, we added a local linear trend component and a seasonal state component with 12 seasons into the state specification. We set the number of MCMC iterations 500.

As with the ARIMA models, we built 6 BSTS models such as: BSTS for the next 17 months forecasting, BSTS for the next 5 months forecasting, BSTS for the real forecasting (June-August 2018), BSTS with log-transformation for the next 17 months forecasting, BSTS with log-transformation for the next 5 months forecasting and BSTS with log-transformation for the real forecasting (June-August 2018).

We can see the contents of the fit model. For example, our BSTS with log-transformation for the real forecasting has the following contents:

```
 [1] "sigma.obs"                 "sigma.trend.level"         "sigma.trend.slope"
 [4] "sigma.seasonal.12"         "final.state"               "state.contributions"
 [7] "one.step.prediction.errors" "log.likelihood"           "has.regression"
[10] "state.specification"       "prior"                     "timestamp.info"
[13] "model.options"             "family"                    "niter"
[16] "original.series"
```

Meanwhile, Figure 39 shows posterior distribution of the model state and Figure 40 shows individual state components of the model. Actual data points are showed as blue circles. The unclear lines include the marginal posterior distribution of each point.

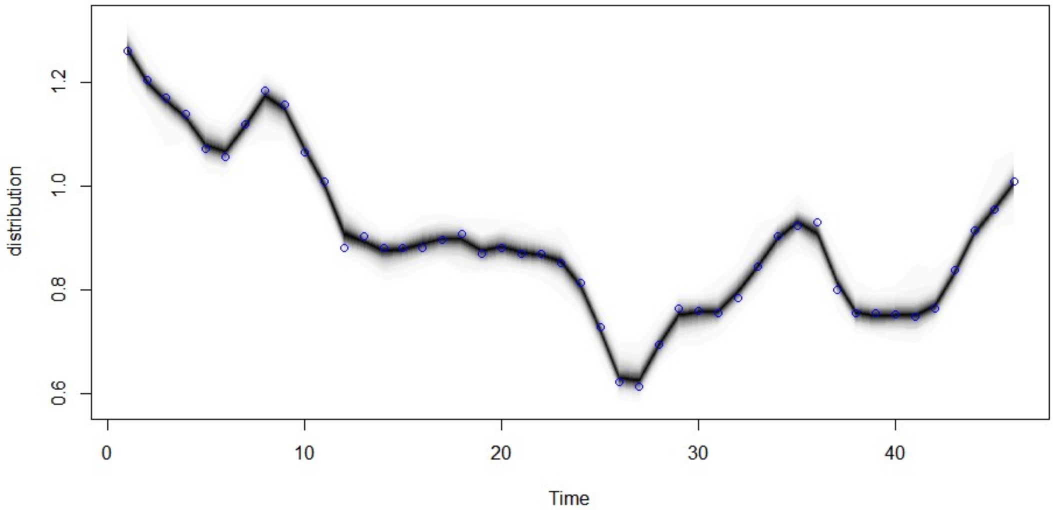


Figure 39 Posterior distribution

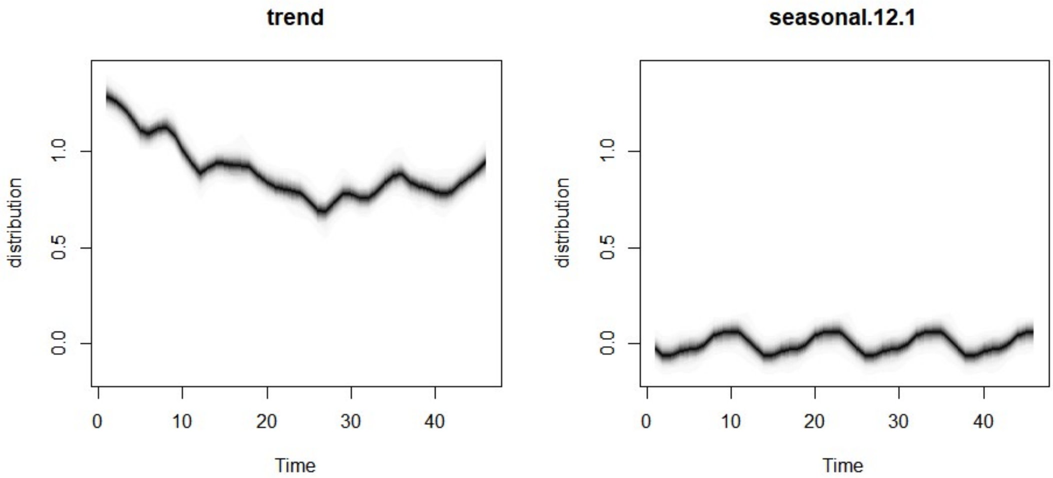


Figure 40 Individual state components

Step 3 Applying the models

We run the models in R studio and analyse them in the Step 4, Comparison with MAPE.

Step 4 Comparison with MAPE

We compared the proposed models by using Mean Absolute Percentage Error (MAPE) between model fitted data and actual data, because it is commonly used to analyse a model performance. We used the MAPEs of the forecasting parts for the comparison.

<u>Model comparison for the next 17 months forecasting (Jan 2017- May 2018)</u>

ARIMA with log-transformation showed the lowest MAPE, 16.66 % in Figure 42. However, ARIMA showed the worst MAPE, 24.09 % in Figure 41. These ARIMA models could capture the movements with high accuracy from 2014 to 2015 but the differences of the model were observed from 2015 to 2017. Especially, the ARIMA model failed to forecast in Figure 41, because it just showed a straight line from 2017 to 2018. On the other hand, BSTS models captured the flow of the data. Although there were no exactly fitted periods, BSTS plotted the overall flow from 2017 to 2018. In this comparison, the ARIMA failed the forecast and the ARIMA with log-transformation outperformed.

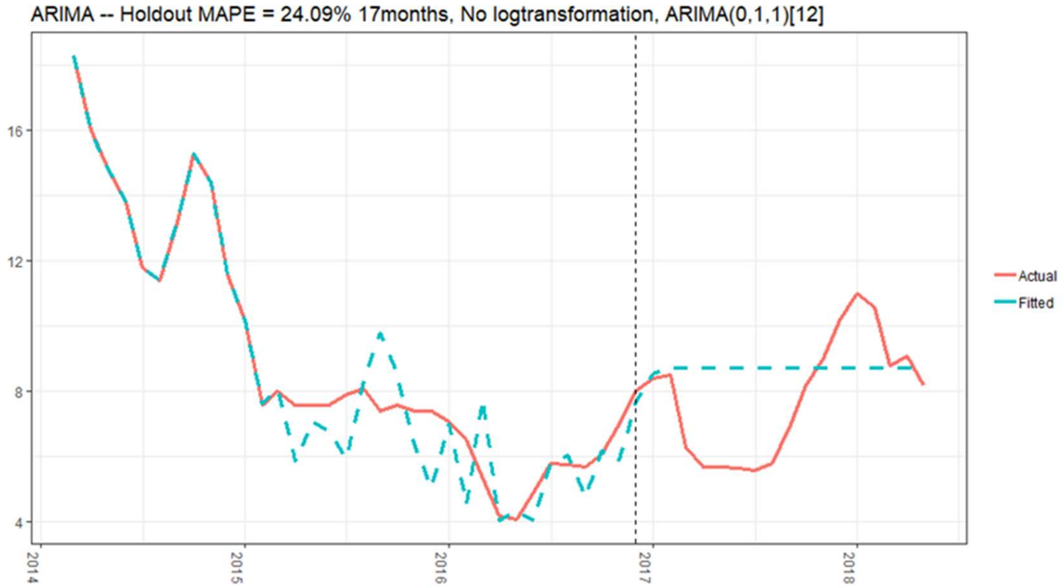


Figure 41 MAPE of ARIMA for the next 17 months forecasting

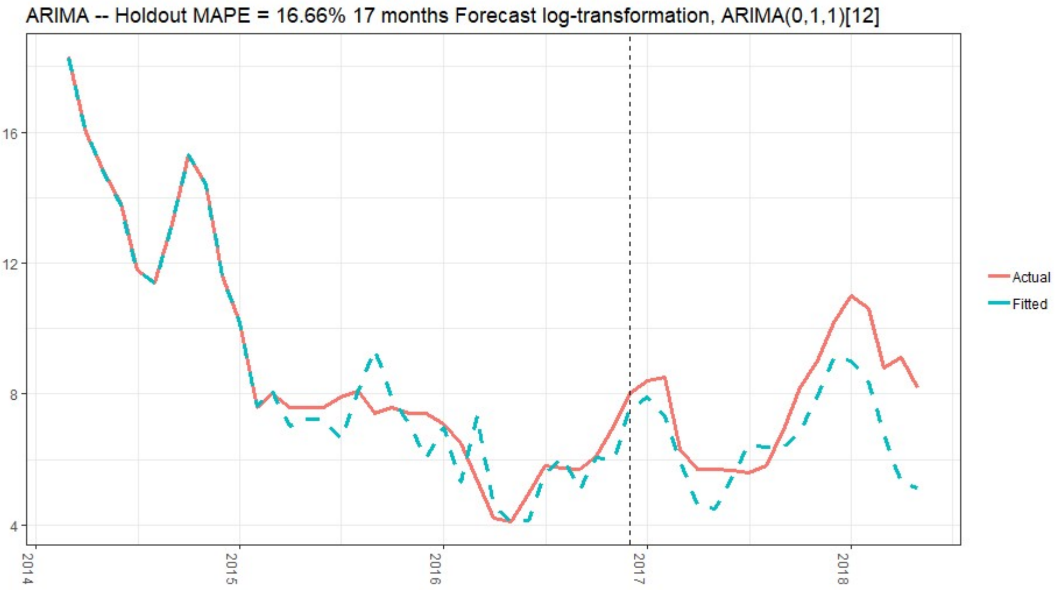


Figure 42 MAPE of ARIMA with log-transformation for the next 17 months forecasting

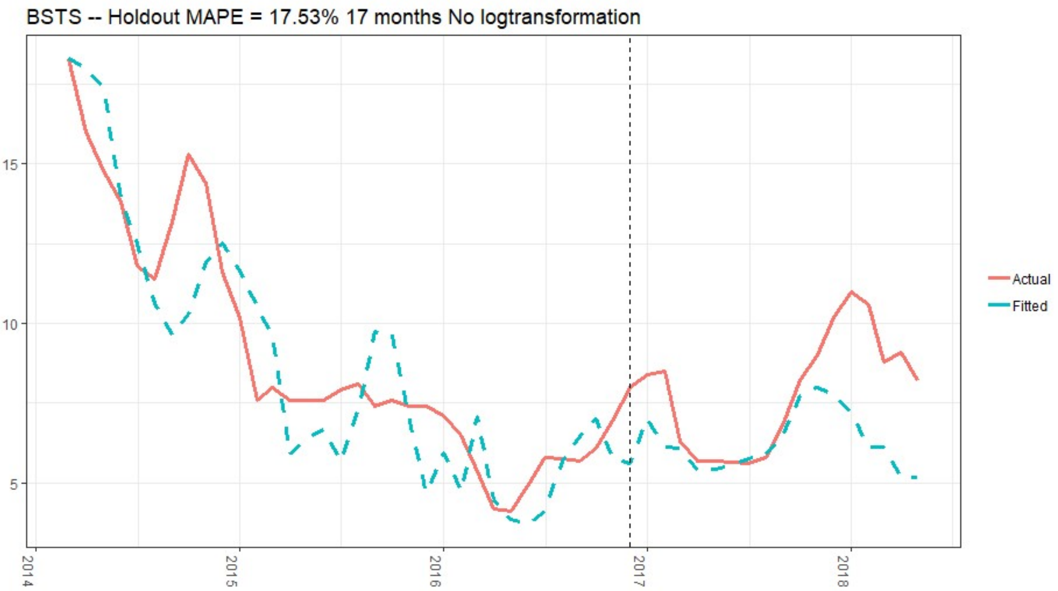


Figure 43 MAPE of BSTS for the next 17 months forecasting

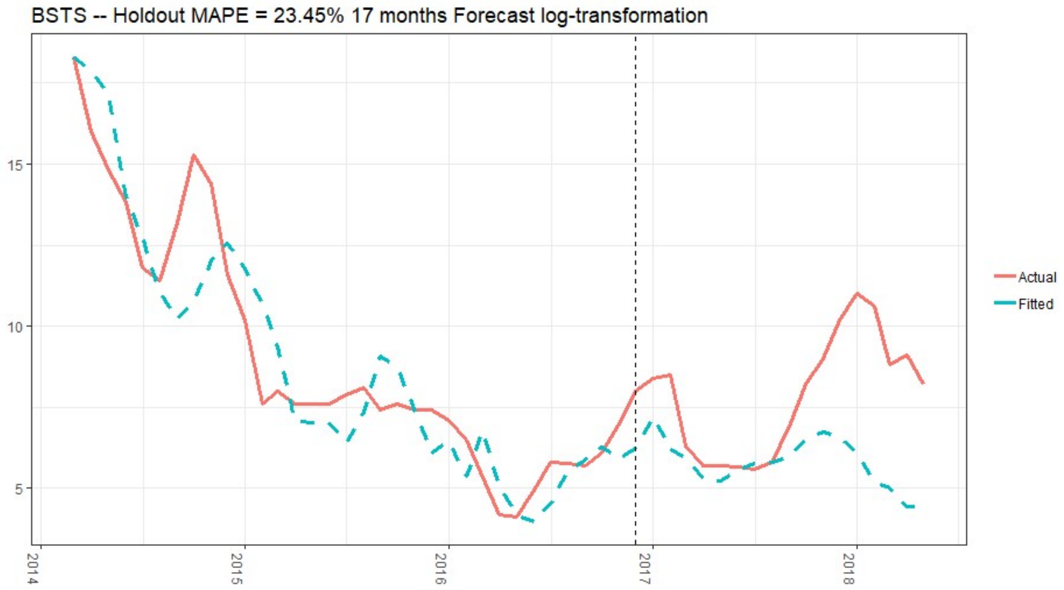


Figure 44 MAPE of BSTS with log-transformation for the next 17 months forecasting

<u>Model comparison for the next 5 months forecasting (Jan 2018- May 2018)</u>

Generally, the ARIMA models fitted well the first part of the time series. The ARIMA model failed the forecast because the fitted line went up, the opposite direction of the actual line in Figure 45. However, at least, the ARIMA model forecasted something not showing the straight line which we observed in Figure 41. As a result, we could support the idea from previous studies that ARIMA is a good model for the short-term forecasting. The ARIMA with log-transformation had the best MAPE, 8.14 % and looked to forecast the next 5 months well. Meanwhile, generally, the BSTS models followed the actual lines. The BSTS model captured the flow of the forecasting period in Figure 47. However, the BSTS with log-transformation failed to forecast because the fitted line went up, the opposite direction of the actual line in Figure 48. In this comparison, the ARIMA and the BSTS with log-transformation failed the forecast. The ARIMA with log-transformation outperformed.

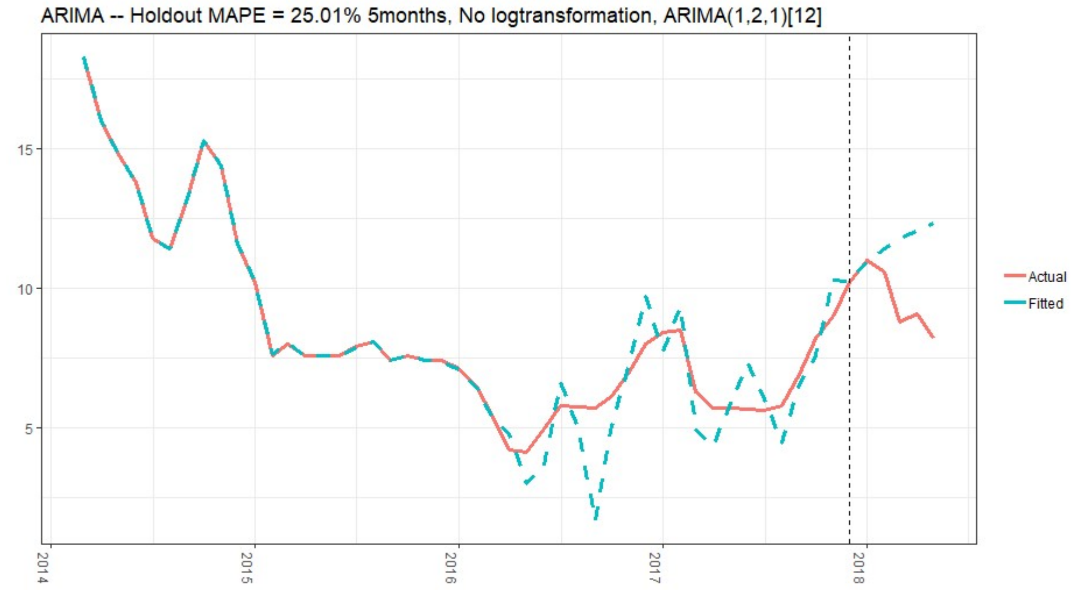


Figure 45 MAPE of ARIMA for the next 5 months forecasting

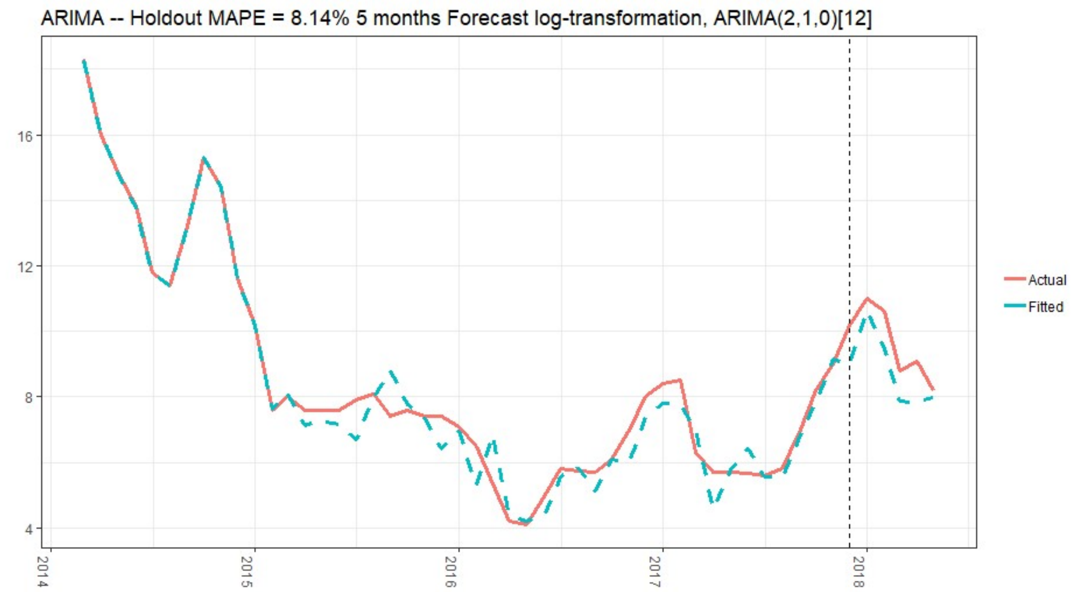


Figure 46 MAPE of ARIMA with log-transformation for the next 5 months forecasting

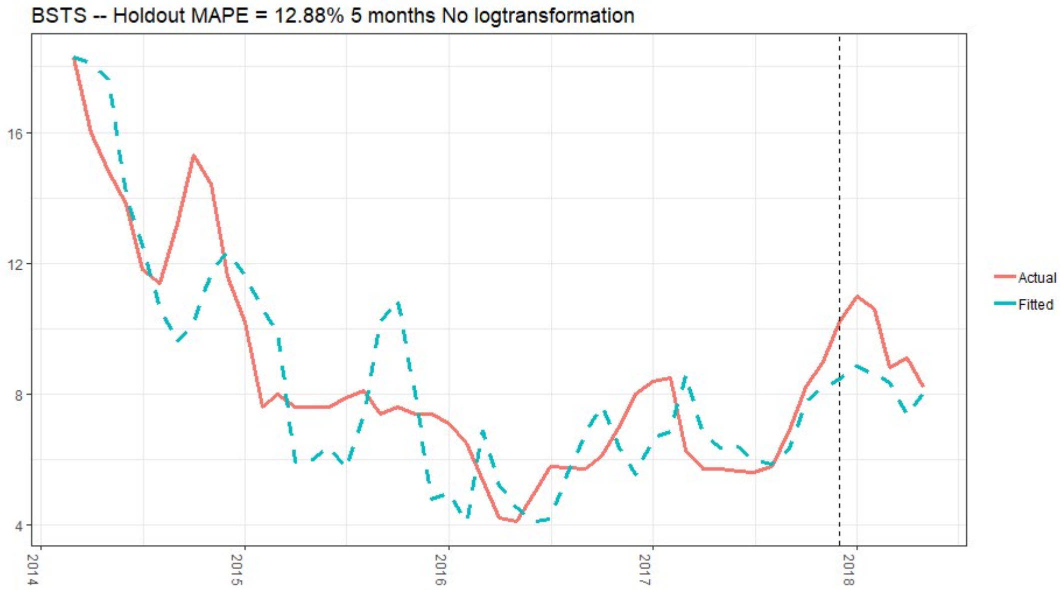


Figure 47 MAPE of BSTS for the next 5 months forecasting

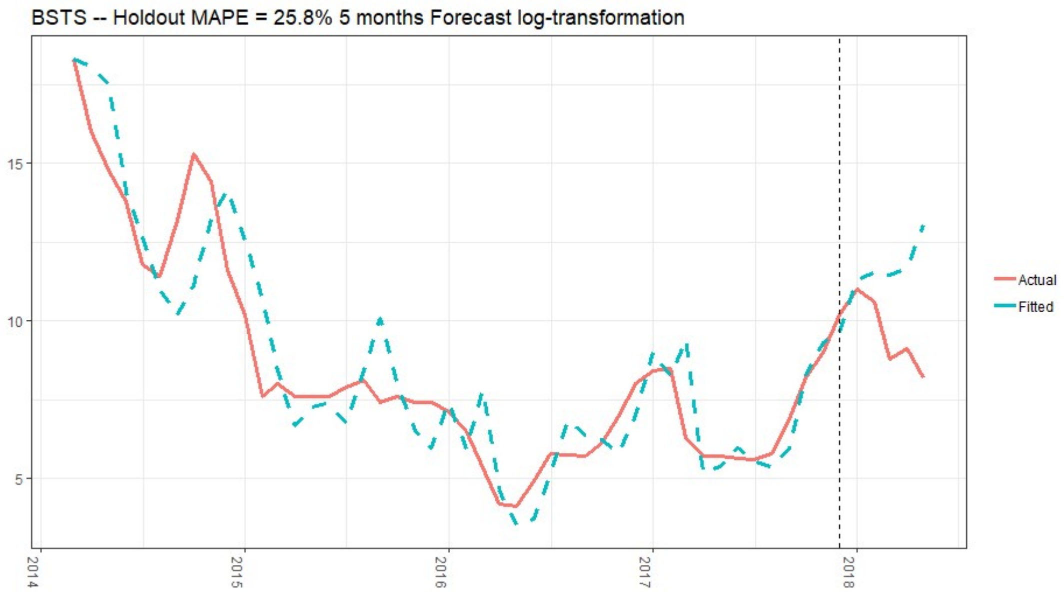


Figure 48 MAPE of BSTS with log-transformation for the next 5 months forecasting

Step 5 Forecasting the prices (June -August 2018)

Generally, the following models captured the upward trend. However, there were time lags to capture the trend among the models. The ARIMA models predicted the prices with downward trend for lag 2 and then predicted the price of August with upward trend. Meanwhile, the BSTS models predicted the prices with upward trend at the beginning of the forecasting.

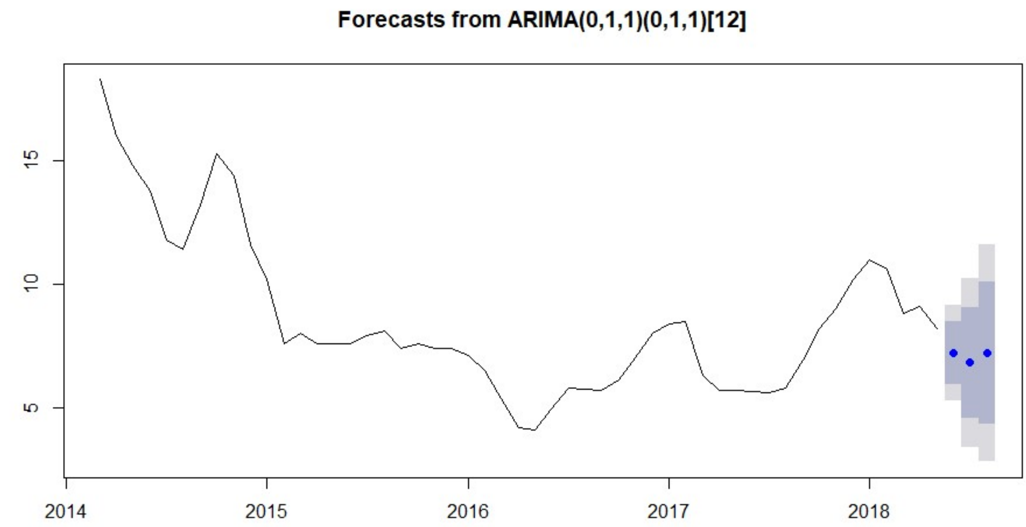


Figure 49 Forecasts (June – August 2018) from ARIMA

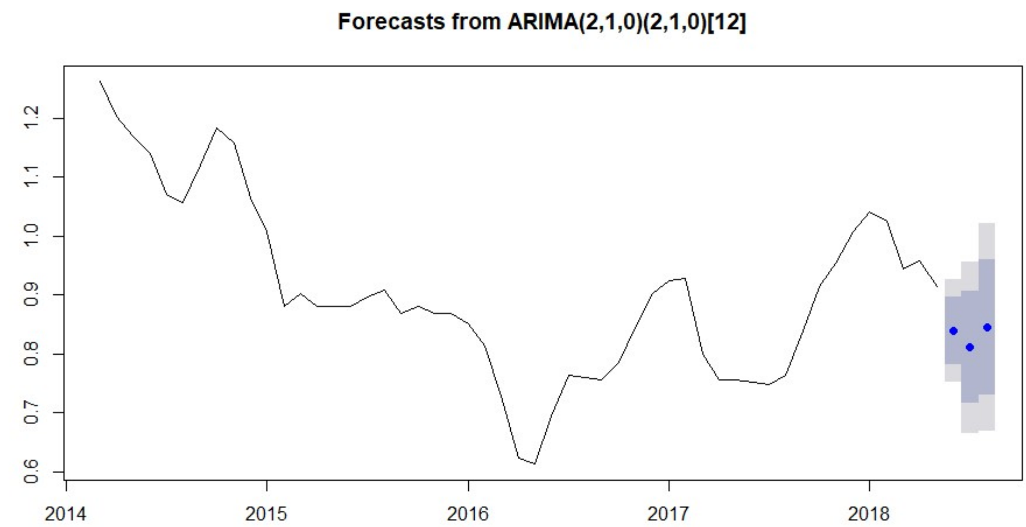


Figure 50 Forecasts (June – August 2018) from ARIMA with log-transformation

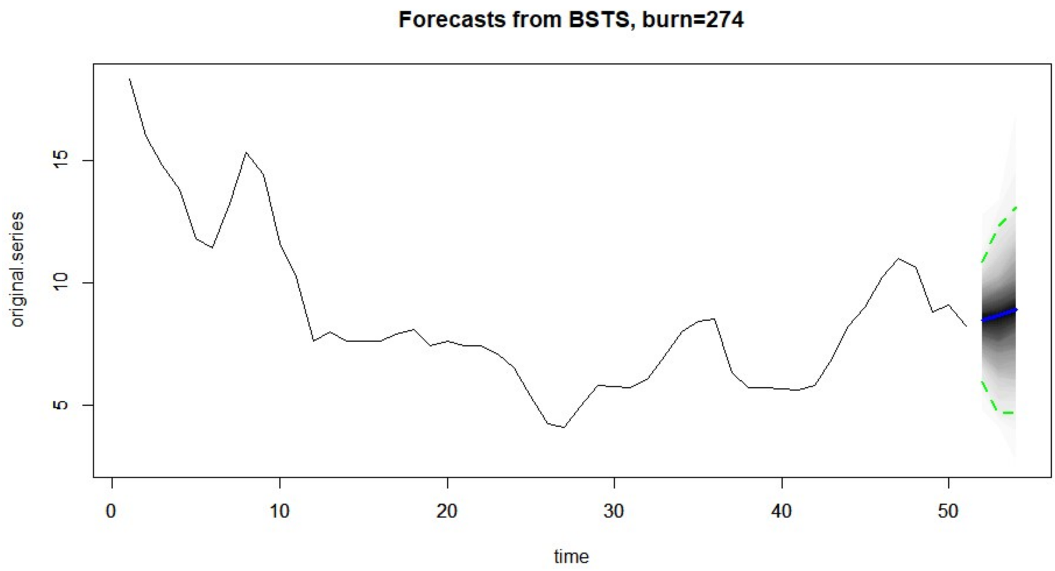


Figure 51 Forecasts (June – August 2018) from BSTS

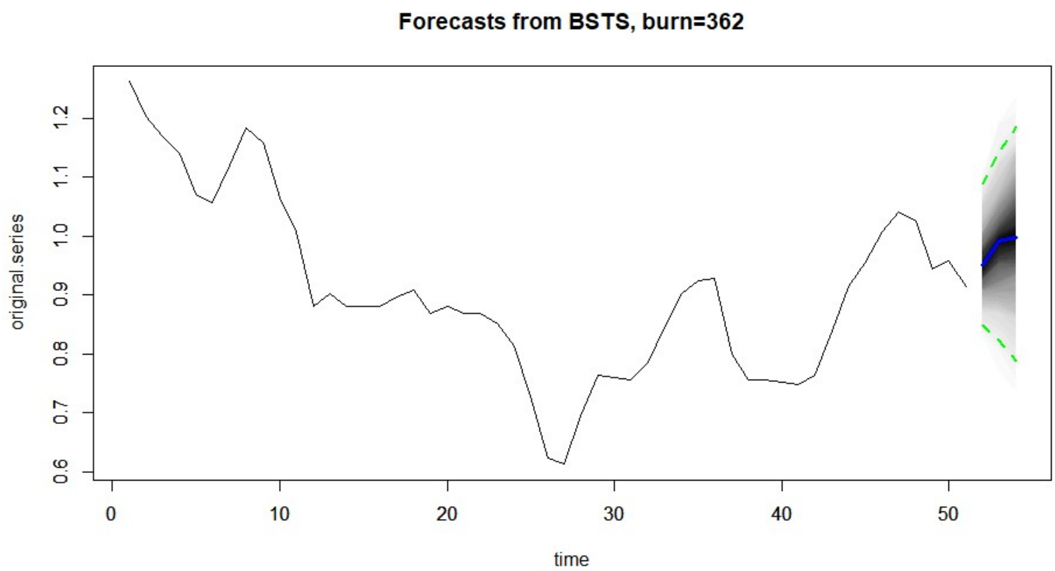


Figure 52 Forecasts (June – August 2018) from BSTS with log-transformation

Step 6 Analysis of the results

Analysis of the results was discussed in 7.2.

7.4 Results and Analysis of the long-term forecasting

In this section, we present results of forecasting the LNG price using BSTS and BSTS with multiple regressors. Table 7 shows the results from single BSTS and BSTS with multiple regressors, more specifically, the estimated model size of 8. The values are estimated means for the posterior distribution. We explain why we chose the estimated model size in 7.5.

The single BSTS model forecasted that the price would decrease up to 3.22 USD/MMBtu. However, the values are too small to take account for the transportation costs which are necessary for Japan to import LNG by vessel. The results from BSTS with multiple regressors are closer to the World Bank forecasts. Please note the World Bank forecasts show the average Japan's LNG prices.

Table 7 Long-term Japan's spot LNG price Forecasts

	BSTS Single	BSTS Multiple regressors	World Bank Natural gas LNG, Japan
Year	Spot	Spot	Average
2019	8.44	9.81	8.9
2020	8.31	10.18	9.1
2021	7.61	10.06	9.3
2022	7.08	10.10	9.4
2023	6.41	10.10	9.6
2024	5.85	10.01	9.7
2025	5.35	9.82	9.9
2026	4.84	9.50	
2027	4.39	9.17	
2028	3.94	8.79	
2029	3.51	8.45	
2030	3.22	7.90	10

World Bank : Commodities Price Forecast (nominal US dollars), released on April 24, 2018
Unit: USD/MMBtu

Furthermore, the BSTS with multiple regressors had less cumulative absolute error shown in Figure 53. The BSTS model included Japan's LNG import in volume as the highest inclusion probability.

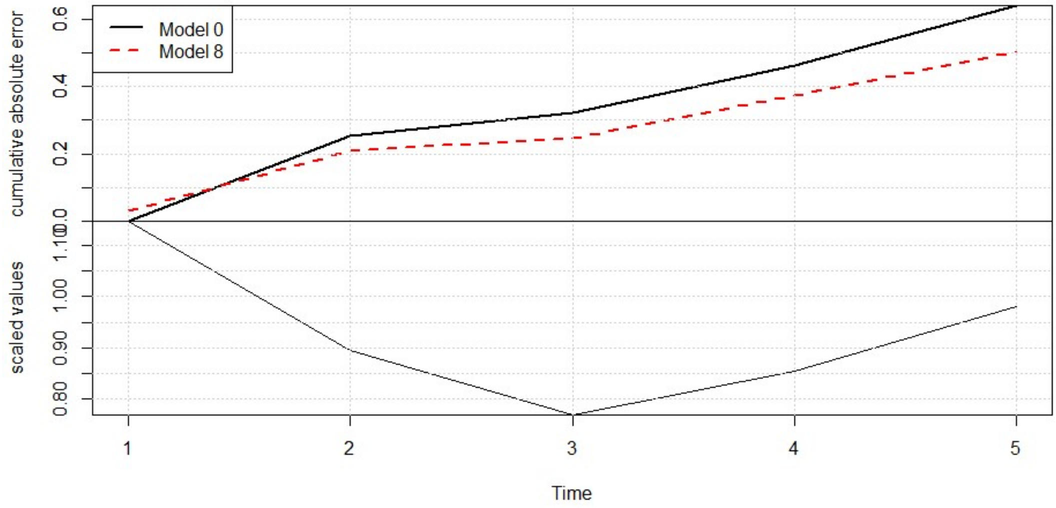


Figure 53 Comparison of cumulative absolute error between single BSTS and BSTS with regressors

In summary, based on the cumulative absolute errors, the BSTS model with multiple regressors would perform better than the single BSTS model. However, the long-term forecast predicts the future values and we do not know what happens in the future. Therefore, we could conclude that the BSTS model would outperform with uncertainty.

7.5 Model building process for the long-term forecasting

Step 1 Data Observation

Our original data was very poor, because only 5 observations were available. However, Bayesian statistics could apply the case that the number of observations is less than the number of estimations. Due to the poor number of data set, we used the annual mean of the recent Japan's spot LNG prices, including the preliminary price of July 2018, published by METI on 9th August 2018.

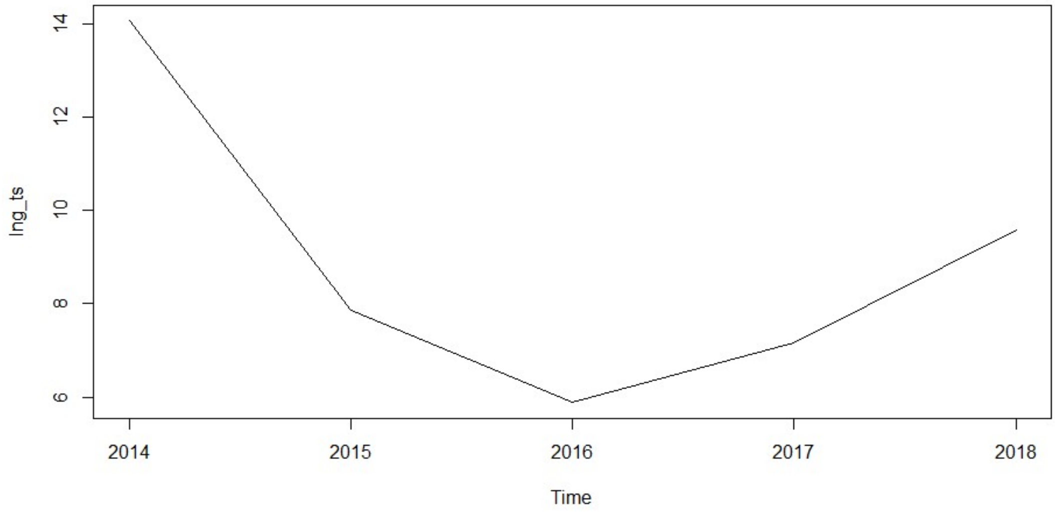


Figure 54 Original data set for long-term forecasting

<u>Step 2 Forecast without a regression component</u>

As conducted in 7.2 and 7.3, we chose a state specification. We compared a local linear trend or a semilocal linear trend component to select the state specification. Our observed data was annual, thus there was no seasonality. According to Scott (2017), the forecast errors from a local linear trend model are wider than a semilocal linear trend model for long-term forecasting. He explained that the variance of a local linear trend model continuously grew with time and he built the hybrid model, the semilocal linear trend model, which replaces the random walk with a stationary AR process. Thus, we tried both models with and without log-transformation. We set the number of MCMC iterations 1000.

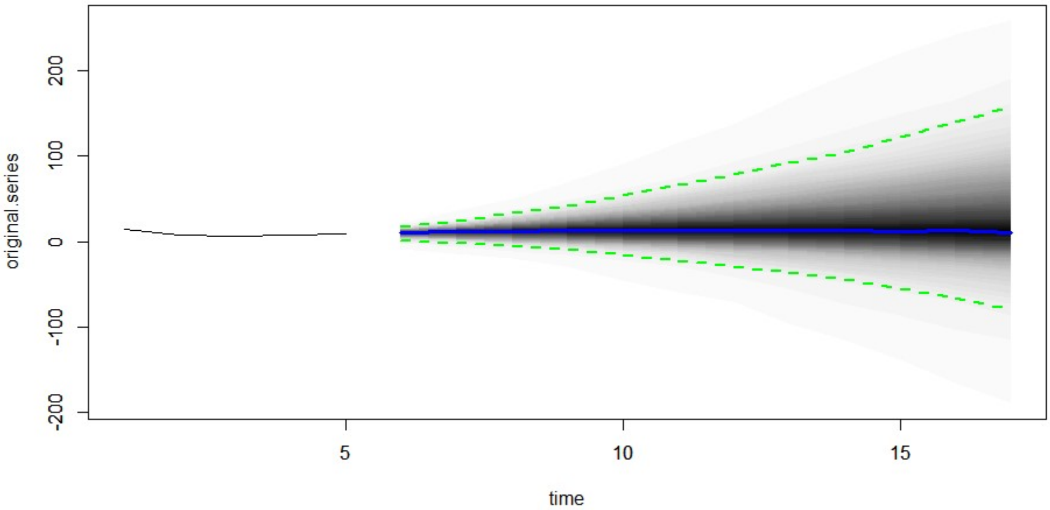


Figure 55 Model1: a local linear trend model

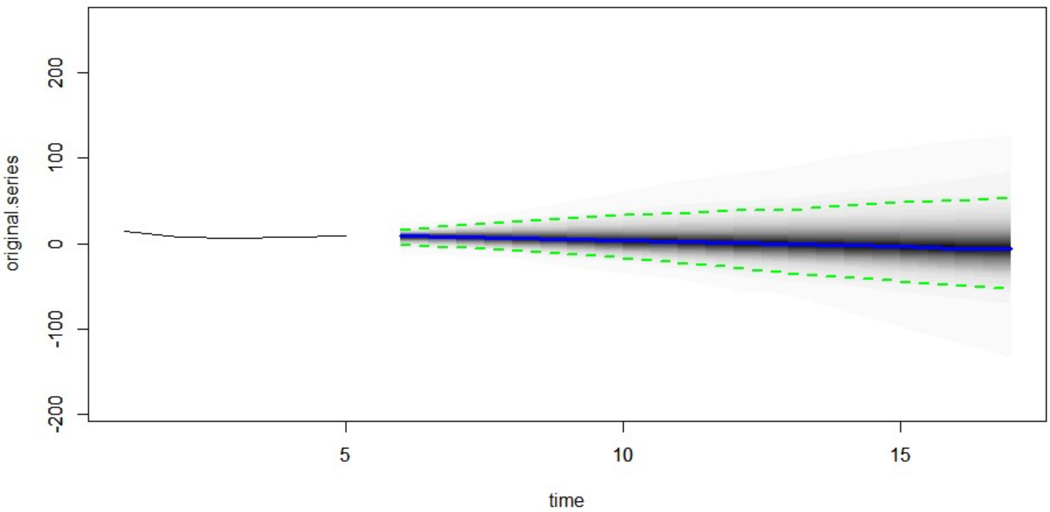


Figure 56 Model2: a semilocal linear trend model

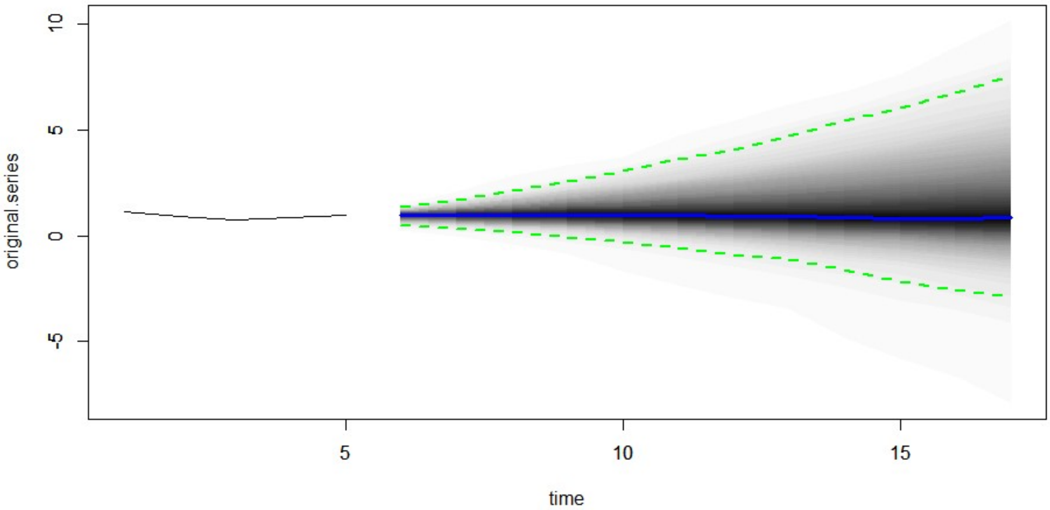


Figure 57 Model3: a local linear trend model with log transformation

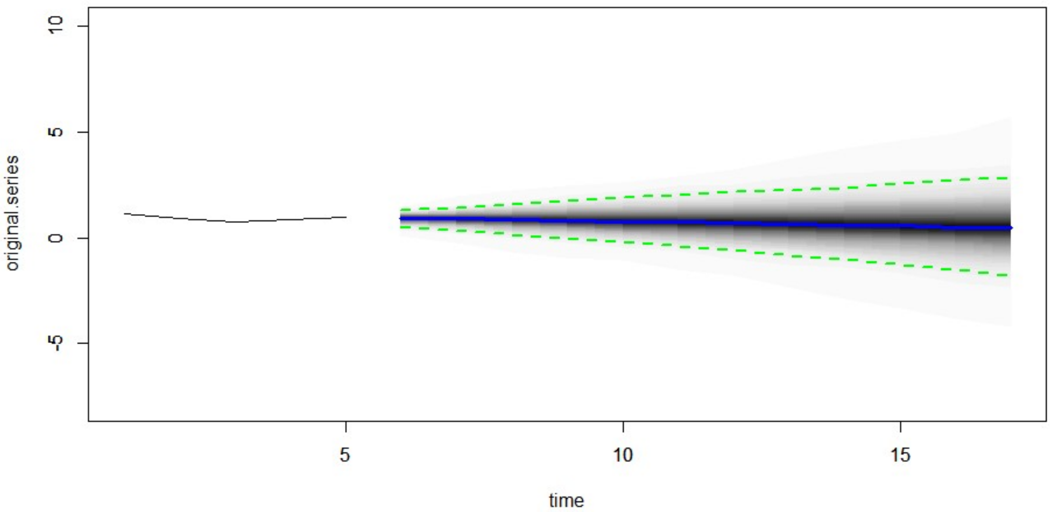


Figure 58 Model4: a semilocal linear trend model with log transformation

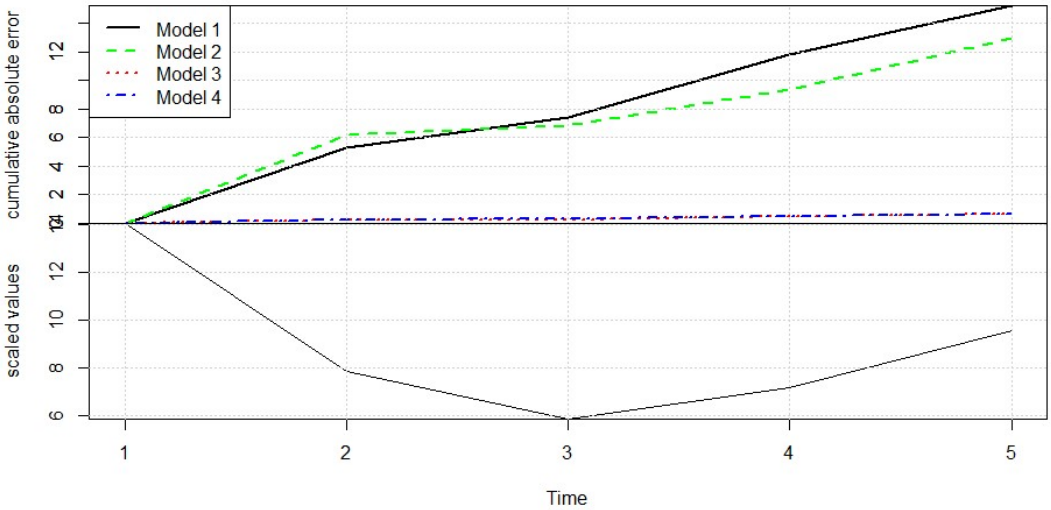


Figure 59 Comparison of cumulative absolute error

Table 8 Mean values of the forecasting period

	Model 1	Model 2	Model 3	Model 4
2019	10.019852	7.9694263	9.260309358	8.440421882
2020	11.165128	7.504902	10.09727044	7.942654701
2021	12.403347	6.5190757	11.08593049	7.421254354
2022	13.886882	5.4752395	12.40804413	6.874644437
2023	14.910548	4.1588401	13.14644037	6.187183897
2024	16.12626	3.105834	14.42436271	5.743528144
2025	17.206206	1.7651665	15.32798348	5.200214027
2026	18.462956	0.628017	16.65137286	4.741064602
2027	19.458763	-0.724578	17.77951834	4.248429844
2028	20.630173	-1.944258	19.81870317	3.853861164
2029	21.660474	-3.564338	21.14111195	3.450712088
2030	22.60162	-4.798711	22.69905402	3.153981183

The above plots (Figure 55 – Figure 58) show semilocal linear trend models had less error for the next 12 times. Comparison of cumulative absolute error among the 4 models shows Model 3 and Model 4 have less error than Model 1 and Model 2. Table 8 shows mean values of the forecasting period. Model 1 and 3 shows upward trend. Model 2 is unrealistic because the price would not be negative. In summary, we chose the value form Model 4 as the forecasting prices until 2030. However, it might not be realistic because Japan's LNG is delivered by vessels. The value forecasted for 2030 is too small. Next, we consider the contribution of regressors.

<u>Step 3 Identifying the contribution of regressors</u>

We considered to add a regression component to a semilocal linear trend model to improve the forecast with help of Google search data. The BSTS package includes a spike and slab prior. It helps to handle large number of potential variables to make a prior distribution sparsity.

As discussed in Chapter 2, 3 and 5, various factors could influence Japan's spot LNG price. Here, we considered 11 variables: Crude Oil Price (WTI), Coal Price (Australia), Natural Gas (HH), Upstream investments for Oil and Gas, Liquefaction plant investments, Japanese LNG spot market utilization rate, the global spot market utilization rate, Natural gas production, Natural gas consumption, Global LNG trade in volume, LNG imported to Japan in volume. We used each value with log transformation because each unit was different. Here, we only used 4 observations (2014-2017) of Japan's spot LNG prices to match the time dimension of the other variables.

However, before considering various factors into our models, we roughly confirmed if BSTS with a regression component would perform better. We built 9 models, from 0 regression component to 11 regression components. We checked the components of each model. Then, we compared the 9 models in terms of cumulative absolute error. The models with a regression component had smaller cumulative absolute error than the single BSTS. Therefore, the result showed the semilocal linear trend model with a regression component could perform better to forecast Japan's spot LNG prices. This confirmation results (Model descriptions, Components of each model, Regression coefficients of each model, Comparison of cumulative absolute error) are in Appendix 6.

Step 4 Estimation of the future values of each regressor

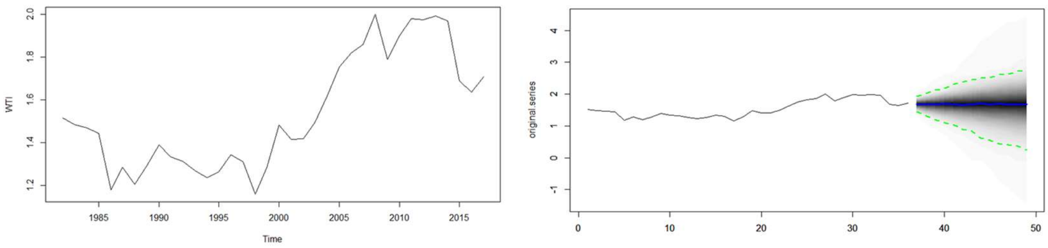
When we use a regression component, new data set with values of each regressor for the forecasting period is required. We conducted to predict the future values of the 11 variables by BSTS and made the new data set. As some potential regressors had large historical data, we assumed that the new data set is acceptable to use for the forecasting. We used a semilocal linear trend model with 1000 MCMC iterations. Table 9 shows model specification for each regressor. Figure 60 shows the original plots of each model and forecasted plots towards 2030. We collected each mean of the forecasted values and the means are highlighted in grey in Table 11. Table 11 shows the data set to be used for the long-term forecasting.

Table 9 Model specification for each regressor

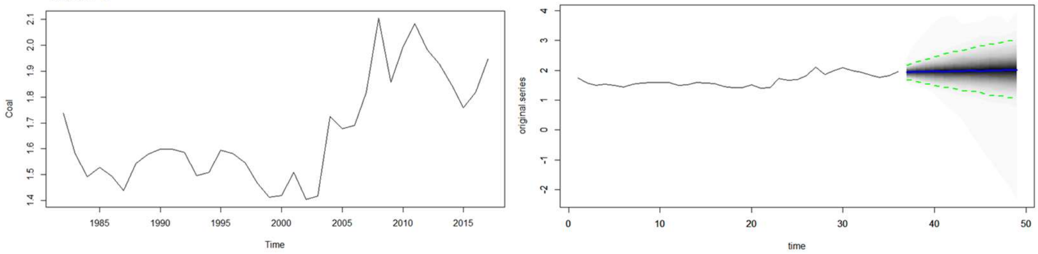
The semilocal linear trend models

	Variales	Modeling period	Number	Forecasting period	Time
Model 1	Crude_oil_WTI	1982-2017	36	2018-2030	13
Model 2	Coal_Australia_price	1982-2017	36	2018-2030	13
Model 3	Natural_gas_US_price	1982-2017	36	2018-2030	13
Model 4	Upstream_investment_oil_gas	2000-2018	19	2019-2030	12
Model 5	Liquefaction_plant_investment	2014-2018	5	2019-2030	12
Model 6	Japan_LNG_spot_market_utilization	2005-2017	13	2018-2030	13
Model 7	World_LNG_spot_market_utilization	2005-2017	13	2018-2030	13
Model 8	Natural_gas_production	1982-2017	36	2018-2030	13
Model 9	Natural_gas_consumption	1982-2017	36	2018-2030	13
Model 10	Global_LNG_trade_volume	2008-2017	10	2018-2030	13
Model 11	Japan_LNG_import_volume	1988-2017	30	2018-2030	13

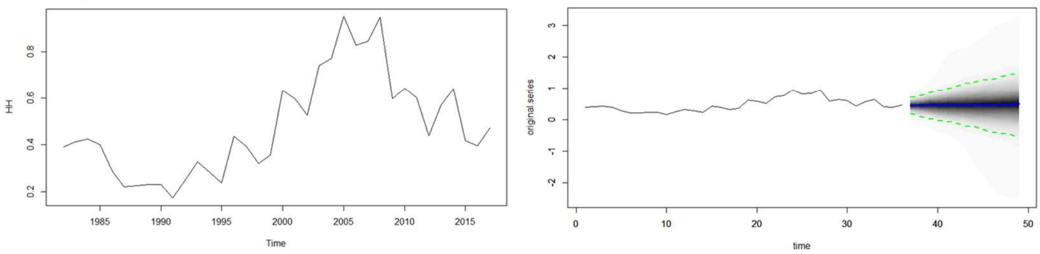
Model 1



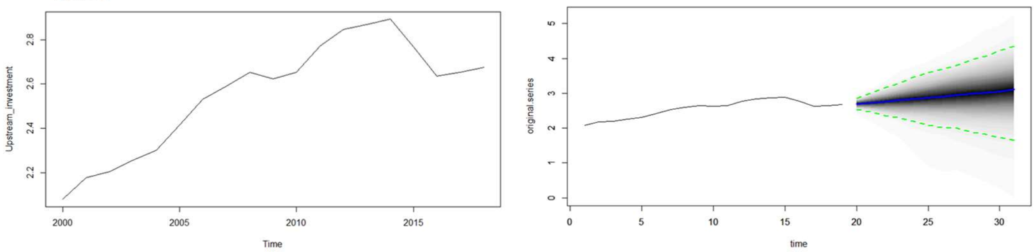
Model 2



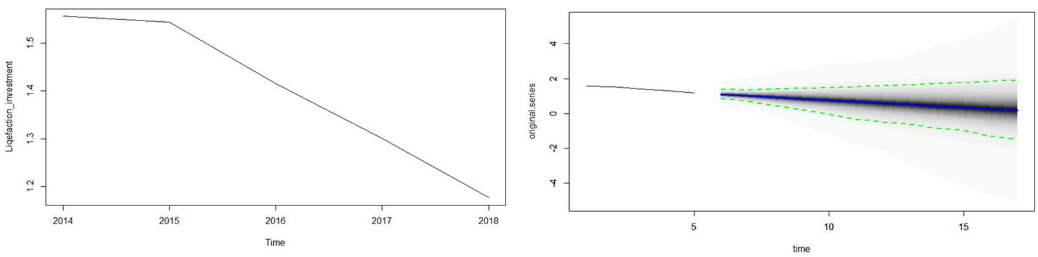
Model 3



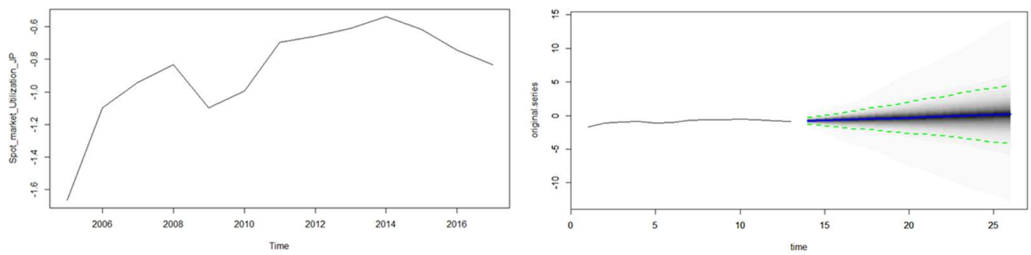
Model 4



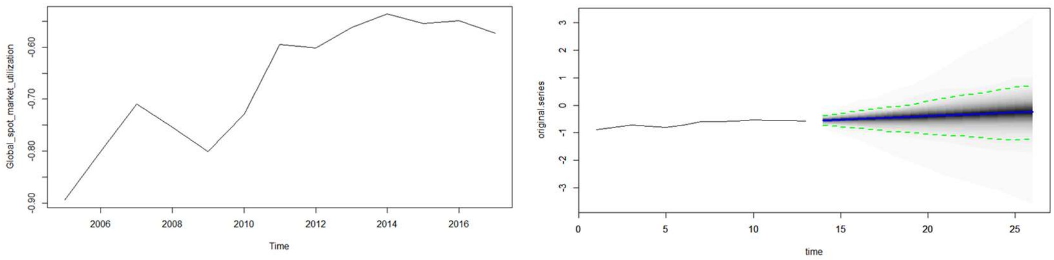
Model 5



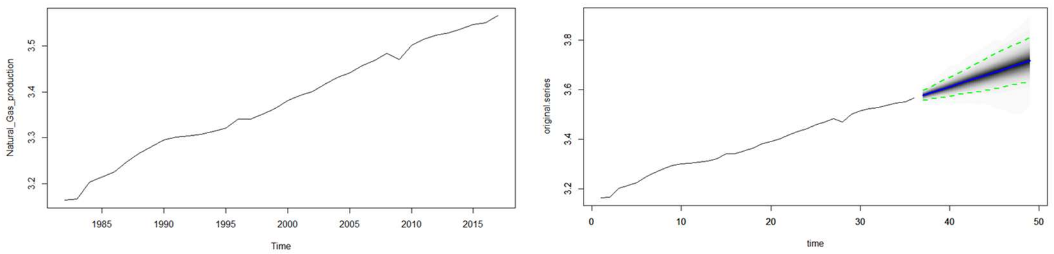
Model 6



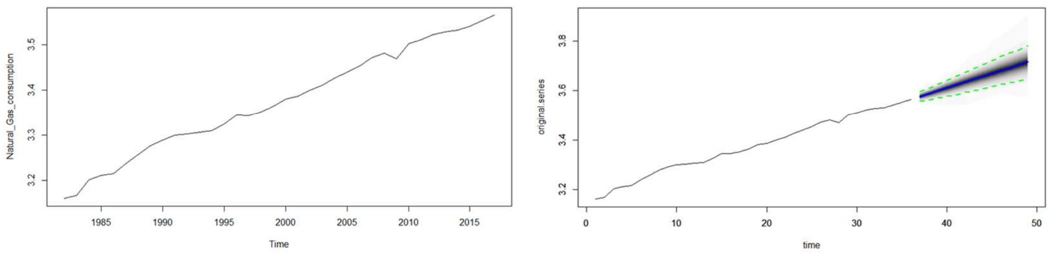
Model 7



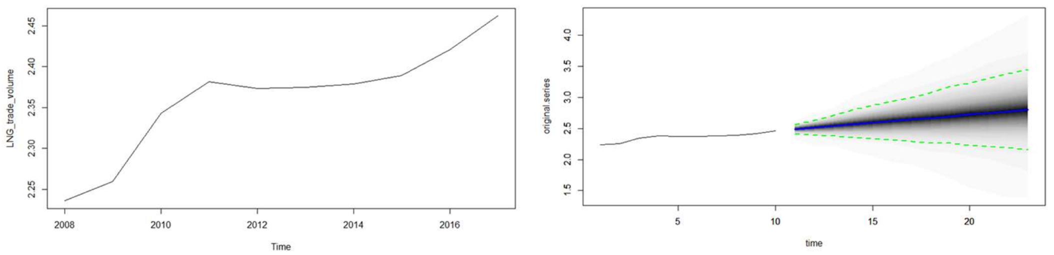
Model 8



Model 9



Model 10



Model 11

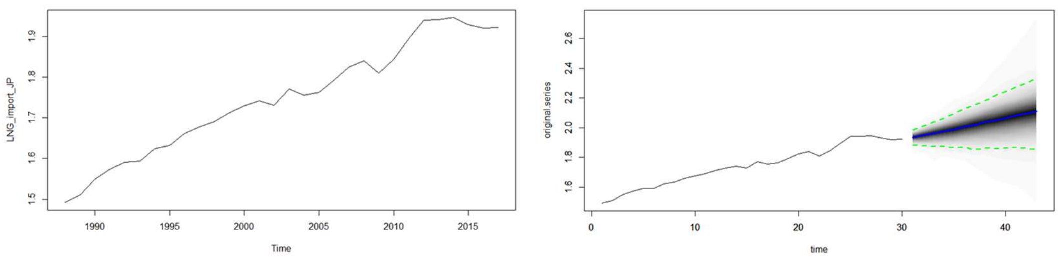


Figure 600 Original data plots and forecasts with log-transformation

Table 10 Data set to be used for the long-term forecasting

year	Spot_lng_JP	Crude_oil_WTI	Coal_Australia_price	Natural_gas_US_price	Upstream_investment_oil_gas	Liquefaction_plant_investment	Japan_LNG_spot_market_utilization	World_LNG_spot_market_utilization	Natural_gas_production	Natural_gas_consumption	Global_LNG_trade_volume	Japan_LNG_import_volume
2014	1.14799	1.969008	1.845904	0.640431	2.892095	1.556303	-0.53858	-0.5363	3.537424	3.531311	2.378725	1.946971
2015	0.89579	1.687611	1.759749	0.417257	2.767156	1.544068	-0.61792	-0.55451	3.546472	3.540853	2.389503	1.929645
2016	0.76932	1.635358	1.818631	0.396586	2.636388	1.414973	-0.74303	-0.54847	3.550206	3.553177	2.420978	1.920853
2017	0.85506	1.706775	1.946527	0.471234	2.653421	1.30103	-0.83295	-0.57253	3.565892	3.564713	2.462113	1.922372
2018	0.98098	1.685735	1.935152	0.454176	2.673942	1.176091	-0.77971	-0.54694	3.576855	3.57661	2.489939	1.935714
2019		1.676856	1.948373	0.454723	2.698488	1.101581	-0.73321	-0.52483	3.588824	3.587441	2.517191	1.947637
2020		1.674335	1.957569	0.460462	2.72931	1.013256	-0.65903	-0.50475	3.599886	3.59948	2.54491	1.960781
2021		1.672468	1.967993	0.458851	2.762059	0.929626	-0.58468	-0.48454	3.610881	3.611037	2.572154	1.974008
2022		1.673404	1.969861	0.460816	2.798278	0.843858	-0.4974	-0.45888	3.622921	3.622548	2.598597	1.987087
2023		1.66766	1.979896	0.466429	2.836373	0.757721	-0.41836	-0.432	3.634697	3.634683	2.625235	2.002083
2024		1.665968	1.986618	0.470888	2.870437	0.671962	-0.33988	-0.40044	3.646515	3.646446	2.649422	2.016389
2025		1.666782	1.995162	0.468964	2.904705	0.585422	-0.2484	-0.37349	3.657997	3.657943	2.674653	2.032754
2026		1.654492	1.996822	0.472929	2.940027	0.507732	-0.17246	-0.34648	3.669717	3.669867	2.699656	2.045932
2027		1.651163	2.006173	0.472578	2.97425	0.424779	-0.09227	-0.32056	3.681612	3.681512	2.726522	2.061383
2028		1.650581	2.000966	0.478621	3.006853	0.350465	-0.01949	-0.29112	3.693278	3.692729	2.750531	2.076834
2029		1.647673	2.00146	0.488082	3.050108	0.262175	0.068698	-0.2596	3.705114	3.704934	2.776839	2.091493
2030		1.649442	2.003987	0.486999	3.091491	0.181208	0.166488	-0.23358	3.716947	3.71661	2.803464	2.106288

Forecasted values by BSTS
To be forecasted by BSTS with regressors
* All values were log-transformed

Step 5 Forecasting the prices until 2030

Finally, we could apply the BSTS with multiple regressors. We estimated the future values of each regression component in Step 5. Based on the result of Step 3, the BSTS with estimated size 9 had the least error. However, now we have the values of the other variables in 2018. Therefore, we conducted the long-term forecasting through the following steps: Model building with the 5 values (2014-2018), Checking cumulative absolute errors of each model, and Forecasting Japan's spot LNG prices towards 2030.

Model building with the 5 values (2014-2018)

We built 12 models, whose specifications are in Table 12. The regression coefficients of each model are in Figure 61.

Table 11 Model specification

Semilocal linear trend model with regressiors (modeling period, T=5)		
Model 0	Expected model size	0
Model 1	Expected model size	1
Model 2	Expected model size	2
Model 3	Expected model size	3
Model 4	Expected model size	4
Model 5	Expected model size	5
Model 6	Expected model size	6
Model 7	Expected model size	7
Model 8	Expected model size	8
Model 9	Expected model size	9
Model 10	Expected model size	10
Model 11	Expected model size	11

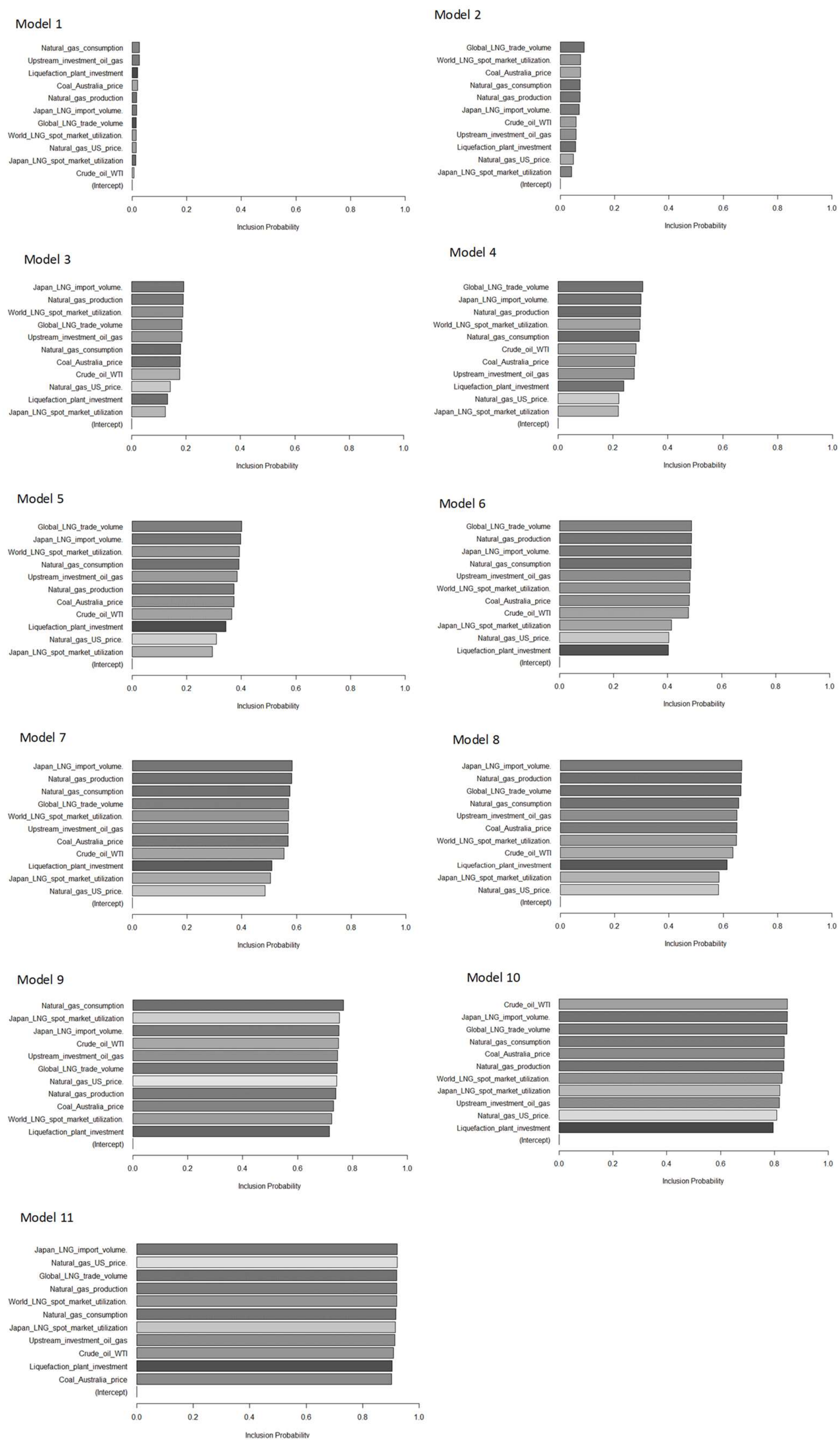


Figure 61 Regression coefficients of each model

Checking cumulative absolute error with each model

Figure 62 and Figure 63 show the cumulative absolute errors of the 12 models. As we assumed, model with regressors performed better than Model 0. The cumulative absolute errors decreased gradually from Model 0 to Model 8, although the performances of some models showed the opposite order against the number of regressors. Meanwhile, Model 9 had the least cumulative absolute error. The error of Model 11 was larger than Model 9 and the error of Model 10 was larger than Model 11. The three models (Model 9 to 11) behaved strangely. We could estimate that the number of regressors was too many to produce real results. Thus, the good performance of Model 9 might be fake.

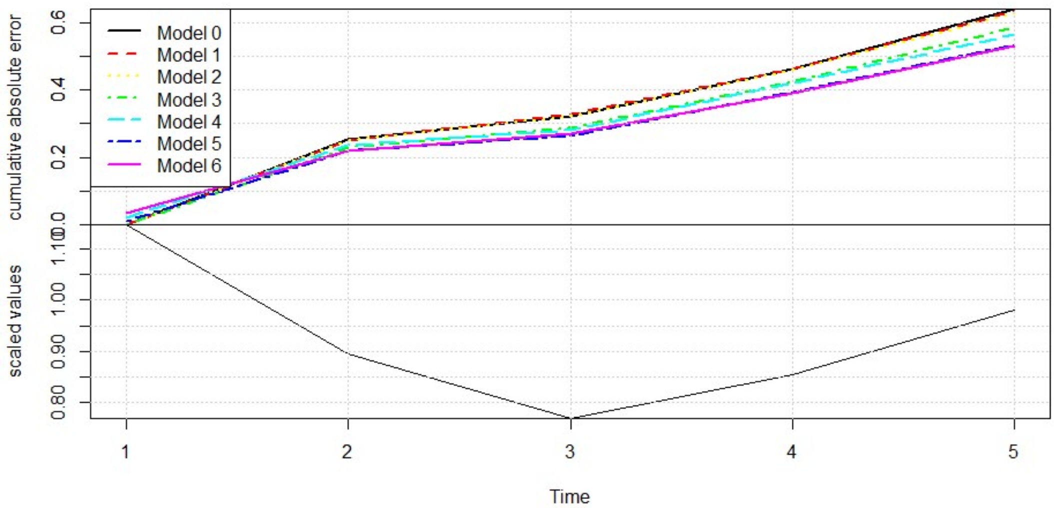


Figure 62 Comparison of cumulative absolute errors (model 0-6)

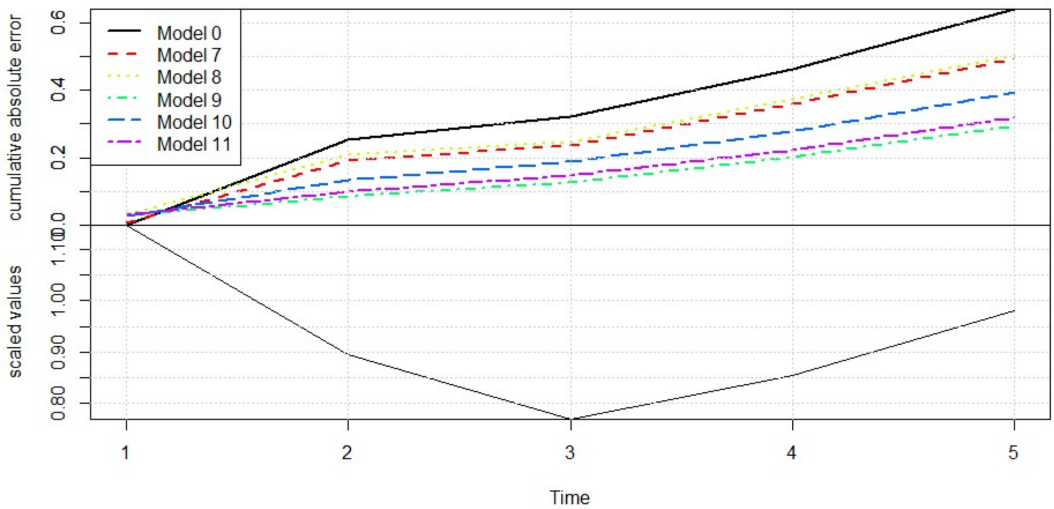


Figure 63 Comparison of cumulative absolute errors (model 0, model 7-11)

Forecasting Japan’s spot LNG prices towards 2030

Table 12 shows the results of the long-term forecasting. As mentioned in the previous part, the values of Model 9 are unrealistic. A cumulative absolute error is one of criteria to determine a model performance. However, the less error model does not always perform well as we analysed the ARIMA models for the short-term forecasting. Thus, combined with analysis of the cumulative absolute error, we selected Model 8 as our suggested model. The results of the long-term forecast would be the values from Model 8. Meanwhile, BSTS uses probability, therefore, results slightly change once we run the models. Although we already forecasted the future values from BSTS without regressors for the long-term forecasting in the previous section, we chose the values from Model 0 as our results of BSTS without regressors.

Table 12 Values produced through models

Year	Model0	Model1	Model2	Model3	Model4	Model5	Model6	Model7	Model8	Model9	Model10	Model11
2019	8.440302	8.560052	8.853938	8.776091	9.525948	9.422593	9.116566	9.653628	9.807223	10.35975	9.823792	10.56209
2020	8.306721	8.24907	8.595083	8.538375	9.723737	9.62458	9.240774	9.755027	10.18179	12.17818	10.84327	12.35313
2021	7.60951	7.614398	8.007281	8.022027	9.523381	9.536327	8.924527	9.703184	10.06208	13.39796	11.69867	13.71921
2022	7.076937	6.935679	7.449113	7.636708	9.186399	9.350153	8.78618	9.597891	10.10179	15.45918	12.45462	15.45343
2023	6.408276	6.459573	6.785506	7.175664	8.807179	9.173404	8.331032	9.400001	10.10019	17.44887	13.35171	17.22962
2024	5.852863	5.855878	6.111112	6.679089	8.55806	8.640745	8.135394	9.044177	10.00844	19.89983	14.16513	19.25738
2025	5.35479	5.241855	5.596039	6.236853	8.047148	8.32192	7.708531	8.944711	9.818568	22.6394	14.67821	21.00708
2026	4.840113	4.837728	5.056364	5.726506	7.466743	8.016867	7.55468	8.65705	9.497105	25.51978	15.43066	23.17487
2027	4.385081	4.468083	4.520316	5.357817	6.916012	7.63907	7.142297	8.170497	9.167675	28.78427	15.89082	25.07778
2028	3.939321	4.06526	4.149404	4.884035	6.550688	7.270437	6.826435	7.772437	8.786253	31.99626	16.16467	27.66945
2029	3.514761	3.597051	3.814907	4.590583	5.953148	6.883037	6.509525	7.30621	8.454537	36.99581	17.10606	30.90044
2030	3.223282	3.213498	3.442257	4.105913	5.579817	6.622307	6.14746	6.786078	7.90126	41.8803	17.99666	34.23956

Step7 Analysis of the results

Analysis of the results was discussed in 7.3.

7.6 Conclusion

Based on our theoretical analysis in Chapter 5, we set two hypotheses:
Hypothesis 1
H_0: BSTS model performs better than ARIMA model in Japan’s LNG spot market for the short-term forecasting.
Hypothesis 2
H_0: BSTS model with various variables performs better than Single BSTS model in Japan’s LNG spot market for the long-term forecasting.
After our study, we accept these two hypotheses. For the short-term forecasting, ARIMA model had the smallest error. However, we considered it as a guidance because it did not account for the forecasting results. Based on the comparison of the results from two models with the price of June 2018 and the capability of capturing patterns in the data, we conclude BSTS model outperforms. Moreover, for the long-term forecasting, BSTS model with a regression component had smaller error than Single BSTS model. We do not know what the future holds, however, we can conclude BSTS model with a regression component would be useful for extrapolating.

Chapter 8 Conclusion

8.1 Conclusion and Recommendation

The purpose of this study was to find a better method to forecast Japan's spot LNG prices and to predict the future values. This question came from the situation that the utilisation of the LNG spot market is useful for Japanese utilities to adjust their customers' LNG demand with uncertainty. In the situation, forecasting Japan's spot LNG prices would contribute to minimize their LNG procurement costs. Originally, the cause of the situation was the nuclear accident caused by the earthquake and tsunami in 2011. As the result, all nuclear power plants in Japan became offline gradually. Although some of the nuclear power plants are in the process of reactivation, the LNG demand as a fuel of thermal plants has uncertainty.

To answer the main research question, "How can we forecast Japan's spot LNG prices?", we analysed the global LNG market and Japan's LNG market. Based on the literature review and the theoretical analysis, we chose ARIMA model and BSTS model for the short-term forecasting and Single BSTS model and BSTS model with a regression component for the long-term forecasting. Since the number of our observation data is limited, we made use of the power of BSTS model.

The findings of this study suggested that BSTS model outperformed under the poor number of observations in Japan's LNG spot market. For the short-term forecasting, although ARIMA model had the smallest error, the smallest error did not account for forecasting. Since our goal was to maximize forecasting accuracy rather than to find the best model, as the overall result, BSTS captured the patterns much better in our data series. For the long-term forecasting, based on the errors, the overall results showed that BSTS improved the performance with a regression component.

We would recommend BSTS package in R studio to people who work for the estimation of LNG procurement costs in the near future as their second or third options. Because the BSTS package is a user-friendly tool and having another analytical tool would always be good.

8.2 Limitations and Further Research

Although this study showed the clear results, several limitations should be mentioned. Firstly, we chose the state specification, α_t of each model, based on our analysis such as short or long-term forecasting, seasonal effects and a regression component. However, the structure of the state could vary among analysts. Thus, there might be another choice of the state structure to produce better results. Secondly, for the long-term forecasting, we chose 11 potential regressors based on the theoretical analysis. However, any of the regressors were not shown with high probability in the figure of the regression coefficients. Thus, there might be another variable which strongly influences Japan's spot LNG prices. Thirdly, for the long-term forecasting, we chose Spike and Slab prior to select regressors with the help of Google search data. And we conducted a single BSTS analysis for each potential variable to make new data from 2018 to 2030. However, an analysist with good market knowledge could impose prior beliefs and specify a prior for a certain variable. In addition, forecasting the values of the potential variables could be predicted in another way.

As a recommendation of the future research, we suggest the following three things. Firstly, more potential variables could be chosen. Because BSTS could select useful variables even if we are not sure which variables are useful to build a better model. Secondly, prior beliefs could be set manually based on previous studies or market researches. Because Google searches reflect people's interests timely and we are not sure how it is related to the variables to forecast Japan's spot LNG prices. Thirdly, the prediction of the potential variables could be conducted in another way. However, building a better model and maximising forecasting accuracy are trials and errors. Therefore, there could be multiple ways to improve model performance.

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Appendices

1 Original data about spot LNG prices

Spot LNG Price Statistics　　　Office of Director for Commodity Market, Commerce and Service Industry Policy Group,METI

Year	Month		Contract-based	Arrival-based	（Unit：USD/MMBtu）
2014	3	Detailed	18.3	-	
	4	Detailed	16.0	18.3	
	5	Detailed	14.8	16.3	
	6	Detailed	13.8	15.0	
	7	Detailed	11.8	13.8	
	8	Detailed	11.4	12.5	
	9	Detailed	13.2	11.3	
	10	Detailed	15.3	12.4	
	11	Detailed	14.4	14.3	
	12	Detailed	11.6	15.1	
2015	1	Detailed	10.2	13.9	
	2	Detailed	7.6	10.7	
	3	Detailed	8.0	7.6	
	4	Detailed	7.6	7.9	
	5	Detailed	×	×	
	6	Detailed	7.6	7.6	
	7	Detailed	7.9	×	
	8	Detailed	8.1	7.7	
	9	Detailed	7.4	7.7	
	10	Detailed	7.6	7.9	
	11	Detailed	7.4	7.5	
	12	Detailed	7.4	7.5	
2016	1	Detailed	7.1	7.9	
	2	Detailed	6.5	6.9	
	3	Detailed	×	6.8	
	4	Detailed	4.2	5.8	
	5	Detailed	4.1	4.3	
	6	Detailed	×	4.5	
	7	Detailed	5.8	6.0	
	8	Detailed	×	5.4	
	9	Detailed	5.7	×	
	10	Detailed	6.1	5.7	
	11	Detailed	7.0	5.9	
	12	Detailed	8.0	6.8	
2017	1	Detailed	8.4	7.3	
	2	Detailed	8.5	8.8	
	3	Detailed	6.3	7.5	
	4	Detailed	5.7	5.9	
	5	Detailed	5.7	5.7	
	6	Detailed	×	5.6	
	7	Detailed	5.6	5.6	
	8	Detailed	5.8	5.6	
	9	Detailed	6.9	5.8	
	10	Detailed	8.2	6.1	
	11	Detailed	9.0	7.1	
	12	Detailed	10.2	8.1	
2018	1	Detailed	11.0	10.1	
	2	Detailed	10.6	10.9	
	3	Detailed	8.8	10.2	
	4	Detailed	9.1	8.8	
	5	Detailed	8.2	7.9	
	6	Detailed	9.3	8.9	
	7	Preliminary	10.0	10.3	

Source: http://www.meti.go.jp/english/statistics/sho/slng/index.html, 14, 8 ,2018 accessed

2 Handling missing data

Handling missing data Impute.TS package

Original	linear_interp	spline_interp	stine_interpolatic	Date
18.3	18.3	18.3	18.3	Mar-14
16	16	16	16	Apr-14
14.8	14.8	14.8	14.8	May-14
13.8	13.8	13.8	13.8	Jun-14
11.8	11.8	11.8	11.8	Jul-14
11.4	11.4	11.4	11.4	Aug-14
13.2	13.2	13.2	13.2	Sep-14
15.3	15.3	15.3	15.3	Oct-14
14.4	14.4	14.4	14.4	Nov-14
11.6	11.6	11.6	11.6	Dec-14
10.2	10.2	10.2	10.2	Jan-15
7.6	7.6	7.6	7.6	Feb-15
8	8	8	8	Mar-15
7.6	7.6	7.6	7.6	Apr-15
NA	7.6	7.3858246	7.524612106	May-15
7.6	7.6	7.6	7.6	Jun-15
7.9	7.9	7.9	7.9	Jul-15
8.1	8.1	8.1	8.1	Aug-15
7.4	7.4	7.4	7.4	Sep-15
7.6	7.6	7.6	7.6	Oct-15
7.4	7.4	7.4	7.4	Nov-15
7.4	7.4	7.4	7.4	Dec-15
7.1	7.1	7.1	7.1	Jan-16
6.5	6.5	6.5	6.5	Feb-16
NA	5.35	5.2899538	5.35	Mar-16
4.2	4.2	4.2	4.2	Apr-16
4.1	4.1	4.1	4.1	May-16
NA	4.95	4.9525452	4.95	Jun-16
5.8	5.8	5.8	5.8	Jul-16
NA	5.75	5.8486372	5.75	Aug-16
5.7	5.7	5.7	5.7	Sep-16
6.1	6.1	6.1	6.1	Oct-16
7	7	7	7	Nov-16
8	8	8	8	Dec-16
8.4	8.4	8.4	8.4	Jan-17
8.5	8.5	8.5	8.5	Feb-17
6.3	6.3	6.3	6.3	Mar-17
5.7	5.7	5.7	5.7	Apr-17
5.7	5.7	5.7	5.7	May-17
NA	5.65	5.6533298	5.65	Jun-17
5.6	5.6	5.6	5.6	Jul-17
5.8	5.8	5.8	5.8	Aug-17
6.9	6.9	6.9	6.9	Sep-17
8.2	8.2	8.2	8.2	Oct-17
9	9	9	9	Nov-17
10.2	10.2	10.2	10.2	Dec-17
11	11	11	11	Jan-18
10.6	10.6	10.6	10.6	Feb-18
8.8	8.8	8.8	8.8	Mar-18
9.1	9.1	9.1	9.1	Apr-18
8.2	8.2	8.2	8.2	May-18

3 Data observation (ARIMA short-term forecasting)

```
      Augmented Dickey-Fuller Test

data:  original
Dickey-Fuller = -1.9681, Lag order = 3, p-value = 0.5872
alternative hypothesis: stationary
```

```
      Augmented Dickey-Fuller Test

data:  lng_diff1
Dickey-Fuller = -4.4548, Lag order = 3, p-value = 0.01
alternative hypothesis: stationary
```

```
Autocorrelations of series ‘lng_diff1’, by lag

    0      1      2      3      4      5      6      7      8      9     10     11     12     13     14     15
 1.000  0.433  0.063 -0.181 -0.206 -0.152 -0.080  0.087  0.008  0.020  0.089  0.106  0.176  0.108  0.164  0.071
   16     17     18     19     20
 0.018 -0.102 -0.147 -0.126 -0.062
```

```
Partial autocorrelations of series ‘lng_diff1’, by lag

    1      2      3      4      5      6      7      8      9     10     11     12     13     14     15     16
 0.433 -0.153 -0.184 -0.048 -0.049 -0.042  0.122 -0.153  0.045  0.127  0.011  0.160  0.018  0.166  0.048  0.047
   17     18     19     20
-0.084 -0.007 -0.065  0.011
```

4 Model building (ARIMA short-term forecasting)

ARIMA 17months

```
 Best model: ARIMA(0,1,2)

> ## Check auto.arima
> lng_arima.model.estimated<-arima(A,order=c(0,1,2),seasonal=list(order=c(0,1,2), period=12))
> AIC(lng_arima.model.estimated)
[1] 78.83439
> lng_arima.model.estimated2<-arima(A,order=c(0,1,1),seasonal=list(order=c(0,1,1), period=12))
> AIC(lng_arima.model.estimated2)
[1] 75.8174
> Box.test(lng_arima.model.estimated$residuals, lag = 20, type = "Ljung-Box")

        Box-Ljung test

data:  lng_arima.model.estimated$residuals
X-squared = 14.272, df = 20, p-value = 0.8164

> Box.test(lng_arima.model.estimated2$residuals, lag = 20, type = "Ljung-Box")

        Box-Ljung test

data:  lng_arima.model.estimated2$residuals
X-squared = 14.272, df = 20, p-value = 0.8164

> summary(arima2)

Call:
arima(x = A, order = c(0, 1, 1), seasonal = list(order = c(0, 1, 1), period = 12))

Coefficients:
         ma1    sma1
      0.4247  0.0646
s.e.  0.1687  0.4046

sigma^2 estimated as 1.608:  log likelihood = -34.91,  aic = 75.82

Training set error measures:
                    ME     RMSE       MAE      MPE     MAPE      MASE         ACF1
Training set 0.2141781 0.996648 0.6053146 2.802475 9.017475 0.7058439 9.499767e-05
```

ARIMA 5 months

```
 Best model: ARIMA(1,2,1)

> ## Check auto.arima
> lng_arima.model.estimated<-arima(A,order=c(1,2,1),seasonal=list(order=c(1,2,1), period=12))
Warning message:
In log(s2) : NaNs produced
>             AIC(lng_arima.model.estimated)
[1] 83.57223
>  lng_arima.model.estimated2<-arima(A,order=c(0,1,1), seasonal=list(order=c(0,1,1), period=12))
>             AIC(lng_arima.model.estimated2)
[1] 104.6622
>
>             Box.test(lng_arima.model.estimated$residuals, lag = 20, type = "Ljung-Box")

        Box-Ljung test

data:  lng_arima.model.estimated$residuals
X-squared = 22.358, df = 20, p-value = 0.3214

>             Box.test(lng_arima.model.estimated2$residuals, lag = 20, type = "Ljung-Box")

        Box-Ljung test

data:  lng_arima.model.estimated2$residuals
X-squared = 17.579, df = 20, p-value = 0.6151

> summary(arima2)

Call:
arima(x = A, order = c(1, 2, 1), seasonal = list(order = c(1, 2, 1), period = 12))

Coefficients:
         ar1      ma1    sar1    sma1
      0.4068  -0.9890  0.0177  0.0183
s.e.  0.2375   0.1541     NaN     NaN

sigma^2 estimated as 1.837:  log likelihood = -36.79,  aic = 83.57

Training set error measures:
                   ME      RMSE       MAE      MPE    MAPE      MASE      ACF1
Training set 0.136373 0.8936741 0.4786376 2.787119 7.93386 0.5933524 0.1348707
```

```
 Best model: ARIMA(0,1,1)(0,0,1)[12]

> c1 <- arima(lng.ts, order = c(0,1,1), seasonal=list(order=c(0,1,1), period=12))
>            AIC(c1)
[1] 116.1065
>            c2 <- arima(lng.ts, order = c(0,0,1), seasonal=list(order=c(0,0,1), period=12))
>            AIC(c2)
[1] 213.9538
>
>            Box.test(c1$residuals, lag = 20, type = "Ljung-Box")

        Box-Ljung test

data:  c1$residuals
X-squared = 19.685, df = 20, p-value = 0.4778

>            Box.test(c2$residuals, lag = 20, type = "Ljung-Box")

        Box-Ljung test

data:  c2$residuals
X-squared = 69.628, df = 20, p-value = 2.095e-07

         Point Forecast    Lo 80     Hi 80    Lo 95     Hi 95
Jun 2018       7.193181 5.920227  8.466134 5.246366  9.139995
Jul 2018       6.803829 4.571606  9.036052 3.389938 10.217720
Aug 2018       7.203339 4.314527 10.092150 2.785283 11.621394

> summary(c1)

Call:
arima(x = lng.ts, order = c(0, 1, 1), seasonal = list(order = c(0, 1, 1), period = 12))

Coefficients:
         ma1    sma1
      0.4405  0.4433
s.e.  0.1380  0.2900

sigma^2 estimated as 0.9854:  log likelihood = -55.05,  aic = 116.11

Training set error measures:
                    ME      RMSE       MAE      MPE     MAPE      MASE        ACF1
Training set 0.1001928 0.8569591 0.5683499 1.171555 8.454805 0.7016666 -0.00711699
```

ARIMA 17months log-transformation

```
 Best model: ARIMA(0,1,1)(0,1,0)[12]

Series: a
ARIMA(0,1,1)(0,1,0)[12]

Coefficients:
         ma1
 0.3603
s.e.  0.1731

sigma^2 estimated as 0.003504:  log likelihood=30.01
AIC=-56.03   AICc=-55.36   BIC=-53.94
Warning message:
In value[[3L]](cond) :
 The chosen test encountered an error, so no seasonal differencing is selected. Check the time series data.
> b <- arima(a, order = c(0,1,1))
> AIC(b)
[1] -105.0988
> b2 <- arima(a, order=c(0,1,0))
> AIC(b2)
[1] -99.19313
> Box.test(arima3$residuals, lag = 20, type = "Ljung-Box")

        Box-Ljung test

data:  arima3$residuals
X-squared = 33.155, df = 20, p-value = 0.03244          (0,1,0)

> ### Fit the ARIMA model
> arima3 <-  arima(a, order=c(0,1,1), seasonal=list(order=c(0,1,1), period=12))
> Box.test(arima3$residuals, lag = 20, type = "Ljung-Box")

        Box-Ljung test

data:  arima3$residuals
X-squared = 19.792, df = 20, p-value = 0.471

> summary(arima3)

Call:
arima(x = a, order = c(0, 1, 1), seasonal = list(order = c(0, 1, 1), period = 12))

Coefficients:
         ma1    sma1
      0.3543  0.0636
s.e.  0.1790  0.4430

sigma^2 estimated as 0.003326:  log likelihood = 30.02,  aic = -54.05

Training set error measures:
                      ME       RMSE        MAE      MPE     MAPE      MASE        ACF1
Training set 0.008332449 0.04533354 0.02733488 0.924782 3.407316 0.6763462 0.004033271
> accuracy(arima3)
                      ME       RMSE        MAE      MPE     MAPE      MASE        ACF1
Training set 0.008332449 0.04533354 0.02733488 0.924782 3.407316 0.6763462 0.004033271
```

ARIMA 5months log-transformation

```
 Best model: ARIMA(2,1,0)(0,1,0)[12]

Series: a
ARIMA(2,1,0)(0,1,0)[12]

Coefficients:
         ar1      ar2
      0.3946  -0.3296
s.e.  0.1622   0.1592

sigma^2 estimated as 0.002897:  log likelihood=50.48
AIC=-94.96   AICc=-94.13   BIC=-90.47

> b <- arima(a, order = c(2,1,0))
> AIC(b)
[1] -144.6241
> b2 <- arima(a, order=c(0,1,0))
> AIC(b2)
[1] -135.0068

> Box.test(arima3$residuals, lag = 20, type = "Ljung-Box")

        Box-Ljung test

data:  arima3$residuals
X-squared = 35.227, df = 20, p-value = 0.01893

> ### Fit the ARIMA model
> arima3 <-  arima(a, order=c(2,1,0), seasonal=list(order=c(2,1,0), period=12))
> Box.test(arima3$residuals, lag = 20, type = "Ljung-Box")

        Box-Ljung test

data:  arima3$residuals
X-squared = 12.274, df = 20, p-value = 0.9063

> summary(arima3)

Call:
arima(x = a, order = c(2, 1, 0), seasonal = list(order = c(2, 1, 0), period = 12))

Coefficients:
         ar1      ar2     sar1     sar2
      0.3388  -0.2846  -0.0309  -0.5239
s.e.  0.1737   0.1852   0.3287   0.3155

sigma^2 estimated as 0.002062:  log likelihood = 51.24,  aic = -92.47

Training set error measures:
                     ME       RMSE        MAE      MPE     MAPE      MASE       ACF1
Training set 0.01006658 0.03847195 0.02510692 1.123033 3.080784 0.6270862 -0.1361554
> accuracy(arima3)
                     ME       RMSE        MAE      MPE     MAPE      MASE       ACF1
Training set 0.01006658 0.03847195 0.02510692 1.123033 3.080784 0.6270862 -0.1361554
```

ARIMA forecast log-transformation

```
 Best model: ARIMA(0,1,1)(0,1,0)[12]

> c1 <- arima(ab, order = c(0,1,1), seasonal=list(order=c(0,1,1), period=12))
> AIC(c1)
[1] -109.5619
> c2 <- arima(ab, order = c(0,1,0), seasonal=list(order=c(0,1,0), period=12))
> AIC(c2)
[1] -108.7622
> c3 <- arima(ab, order = c(2,1,0), seasonal = list(order=c(2,1,0), period=12))
> AIC(c3)
[1] -112.2445
>
> Box.test(c1$residuals, lag = 20, type = "Ljung-Box")

        Box-Ljung test

data:  c1$residuals
X-squared = 28.371, df = 20, p-value = 0.1009

> Box.test(c2$residuals, lag = 20, type = "Ljung-Box")

        Box-Ljung test

data:  c2$residuals
X-squared = 40.118, df = 20, p-value = 0.004826

> Box.test(c3$residuals, lag=20, type="Ljung-Box")

        Box-Ljung test

data:  c3$residuals
X-squared = 14.298, df = 20, p-value = 0.8151

         Point Forecast     Lo 80     Hi 80     Lo 95     Hi 95
Jun 2018      0.8395433 0.7826191 0.8964674 0.7524853 0.9266012
Jul 2018      0.8110755 0.7160191 0.9061319 0.6656993 0.9564518
Aug 2018      0.8452865 0.7303044 0.9602686 0.6694366 1.0211365
>
> plot(fore)
> accuracy(c3)
                      ME       RMSE        MAE      MPE     MAPE      MASE       ACF1
Training set 0.008416846 0.03834863 0.02483247 0.927273 3.022435 0.6235638 -0.1261651
> summary(c3)

Call:
arima(x = ab, order = c(2, 1, 0), seasonal = list(order = c(2, 1, 0), period = 12))

Coefficients:
         ar1      ar2    sar1     sar2
      0.3373  -0.3147  0.1230  -0.4781
s.e.  0.1605   0.1747  0.2277   0.2045

sigma^2 estimated as 0.001973:  log likelihood = 61.12,  aic = -112.24

Training set error measures:
                      ME       RMSE        MAE      MPE     MAPE      MASE       ACF1
Training set 0.008416846 0.03834863 0.02483247 0.927273 3.022435 0.6235638 -0.1261651
```

5 Model building (BSTS short-term forecasting)

BSTS 17months

```
> summary(bsts.model, burn = 216)
$`residual.sd`
[1] 0.4179634

$prediction.sd
[1] 1.86351

$rsquare
[1] 0.9872653

$relative.gof
[1] -1.869889


> p <- predict.bsts(bsts.model, horizon = 17, burn = 216, quantiles = c(.025, .975))
> p
$`mean`
 [1] 7.018480 6.134232 6.100676 5.395860 5.418603 5.538103 5.765362 5.899632 6.514357 7.744861 7.995478 7.764620
[13] 7.223390 6.106932 6.108074 5.172053 5.170673

$median
 [1] 7.116629 6.245789 6.090601 5.415592 5.194793 4.945197 4.866505 5.401149 5.608763 6.704595 6.407900 5.768899
[13] 5.292653 4.433113 3.828846 3.071635 2.827549

$interval
          [,1]      [,2]       [,3]       [,4]      [,5]      [,6]      [,7]      [,8]      [,9]     [,10]
2.5%   3.269765  1.407391  0.6413737 -0.6675079 -2.207368 -2.036606 -2.807205 -3.075108 -3.508825 -3.362029
97.5% 10.255588 10.766774 11.9847455 13.0128434 15.103472 16.117844 19.342304 21.092442 22.880057 25.943339
         [,11]     [,12]     [,13]     [,14]     [,15]     [,16]     [,17]
2.5%  -3.018249 -4.864642 -7.300738 -9.032895 -10.51540 -13.51832 -14.51994
97.5% 28.302967 30.171412 33.214688 34.894472  37.28785  38.40960  40.98630

$distribution
            [,1]       [,2]       [,3]         [,4]          [,5]         [,6]        [,7]        [,8]
  [1,]  6.5231497  4.1898895  2.1305019  3.514143486  5.3466644787  6.002796735  6.06644860  6.78053284
  [2,]  7.8010657  5.8867711  3.5316503  3.407004395  2.7125614020  2.461508490  0.69283065  0.06453015
  [3,]  6.5997454  5.6509169  5.4574279  6.118624022  7.2165069323  6.308907516  7.02790417  6.14489115
  [4,]  8.0392255  8.4125238  5.4661672  5.236555039  6.3093338473  6.614945307  7.72601332  8.92371358
  [5,]  6.8808805  6.9007586  6.4055963  4.151304681  5.8528925573  5.654615477  4.81442985  8.41867478
  [6,]  6.5396778  3.4278939  8.5801251  5.697288876  3.2173031213  3.306545246  3.80773925  2.90515212
  [7,]  5.6863374  4.6344430  1.9181046  1.679336000  4.3369977158  2.418566338  7.45291905  6.25938407
  [8,]  7.9991825  8.9706718  4.2684383  2.794104970  2.5818161989  1.833157457  0.49196318  0.71638913
  [9,]  3.3555726  3.2293415  2.7743159  1.839252196  2.3524478127  0.361411701 -1.71243324 -0.98721896
 [10,]  7.0855235  5.0485893  2.2149224  2.321731262  6.6107026199  6.096659118  7.28512230  8.66413395
 [11,]  9.7982968  8.9066855  7.2962429  5.489401823  2.1601259238  2.485287028  1.42639908  2.88720738
 [12,]  9.0495104  9.8041999  7.2993265  7.636220411  5.9808558151  5.680617689  7.06552017  6.10436920
 [13,]  7.2443884  3.7925283  2.5865106  1.061100094  0.1811368514  0.056559417 -1.65560822 -2.99260044
 [14,]  8.1429768  5.3943079  7.6989161  7.326588590  7.0717674713  5.584216263  6.47642053  5.55832610
 [15,]  7.4373408  7.6605537  6.3405472  6.782893905  6.7814629594  6.162736066  5.59113003  7.98617122
 [16,]  6.1268348  4.6705525  5.3235706  4.111671120  3.9646806790  3.735391754  2.73168129  1.34110312
 [17,]  8.2167801  7.3644807  4.9431274  5.719895391  5.8307227193  3.251748692  1.29758577  2.50510014
 [18,]  8.5742756  6.6653464  6.1448779  5.839982811  6.1275225839  4.192990718  4.68252648  5.97694235
 [19,]  6.8081644  7.3398052  6.0986279  3.046317703  3.9088582484  2.445077289  1.16967609 -0.36466628
 [20,]  6.2362284  2.3682868  3.6278235  2.974192107  1.7386423388  1.634021525  0.66494985 -0.75069416
 [21,]  6.3726753  5.0313027  2.6260680  2.703234840  1.8853942732  0.996140889 -1.01301493 -0.93276144
 [22,]  6.1255975  4.3753810  3.4221475 -0.535060963 -2.5269074443 -1.676570085 -1.60549567 -4.60630764
 [23,]  7.6909931  6.2545822  2.6154482 -0.515246054  2.0897345253  0.285310034  1.11637458  1.00184089
 [24,]  8.6962012  7.5168336  5.3383627  6.716925433  7.9700972246  8.793016661  8.67634875  6.36304013
 [25,]  7.2340841  9.4056746  7.1525790  6.899203355  6.1857300487  4.469004050  4.86876037  2.69242110
 [26,]  6.1935746  6.0136448  6.5547297  2.883583341  1.5435312003 -0.009568015  1.37376483  0.68285629
 [27,]  4.6357588 -0.4965881  2.8394666 -0.672365916 -0.7301607589 -1.221082050 -0.69399512 -2.67264949
 [28,]  9.7857876  8.5073240  9.4058054  7.426984542  5.4578213444  6.062991598  4.88720323  4.66234625
 [29,]  6.2391782  9.2488267 12.0598316 11.188010827  7.8826282146  6.341115381  7.72836818  9.27796882
 [30,]  6.2508928  2.5020317  4.4058541  3.921793493  2.9722300613  3.586437934  3.50027251  2.70446222
 [31,]  7.3799069  7.1843092  7.7158411  8.594916778  9.8176900129  9.261791400 10.40925379 10.15357838
 [32,]  9.2768520  7.6548382  9.4773174  8.908057787  8.0663024590  8.229569545  7.76601189  9.14841861
 [33,]  8.2233100  5.0181955  3.0591473  2.120609619  1.9269638651  1.819447583  2.51612293  2.08543991
 [34,] 10.3158688  8.6933863  9.4843904  9.642516547  9.1098602033  9.379495301  8.16107398  7.71966920
 [35,]  3.2521835  2.3716150  1.5432580  1.663282403  3.1449519734  2.885487961  3.69855609  3.50463641
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$original.series
    1     2     3     4     5     6     7     8     9    10    11    12    13    14    15    16    17    18 
18.30 16.00 14.80 13.80 11.80 11.40 13.20 15.30 14.40 11.60 10.20  7.60  8.00  7.60  7.60  7.60  7.90  8.10 
   19    20    21    22    23    24    25    26    27    28    29    30    31    32    33    34 
 7.40  7.60  7.40  7.40  7.10  6.50  5.35  4.20  4.10  4.95  5.80  5.75  5.70  6.10  7.00  8.00 
```

BSTS 5months

```
> summary(bsts.model, burn = 488)
$`residual.sd`
[1] 0.8666338

$prediction.sd
[1] 1.863066

$rsquare
[1] 0.9338453

$relative.gof
[1] -1.958937


> p <- predict.bsts(bsts.model, horizon = 5, burn = 488, quantiles = c(.025, .975))
> p
$`mean`
[1] 8.849057 8.615013 8.341591 7.344686 8.068952

$median
[1] 8.417941 8.861560 8.705780 8.807129 7.689559

$interval
           [,1]      [,2]     [,3]      [,4]     [,5]
2.5%   7.545841  6.101125  4.99997  2.486697  4.62201
97.5% 10.820995 11.255483 11.83984 10.669117 13.28231

$distribution
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[12,] 10.694513 10.062525 10.801742  9.089297  9.212548

$original.series
    1     2     3     4     5     6     7     8     9    10    11    12    13    14    15    16    17    18 
18.30 16.00 14.80 13.80 11.80 11.40 13.20 15.30 14.40 11.60 10.20  7.60  8.00  7.60  7.60  7.60  7.90  8.10 
   19    20    21    22    23    24    25    26    27    28    29    30    31    32    33    34    35    36 
 7.40  7.60  7.40  7.40  7.10  6.50  5.35  4.20  4.10  4.95  5.80  5.75  5.70  6.10  7.00  8.00  8.40  8.50 
   37    38    39    40    41    42    43    44    45    46 
 6.30  5.70  5.70  5.65  5.60  5.80  6.90  8.20  9.00 10.20 
```

BSTS Forecast

```
$`residual.sd`
[1] 0.3149379

$prediction.sd
[1] 1.601292

$rsquare
[1] 0.9904895

$relative.gof
[1] -1.289451

> pred
$`mean`
[1] 8.478255 8.507453 8.865467

$median
[1] 8.478190 8.669334 8.890329

$interval
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2.5%   5.935124  4.626469  4.686566
97.5% 10.864833 12.308254 13.065951

$distribution
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  [3,]  8.774292  9.269023  9.629053
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  [5,]  7.490872  6.156092  7.366099
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$original.series
    1     2     3     4     5     6     7     8     9    10    11    12    13    14    15    16    17    18 
18.30 16.00 14.80 13.80 11.80 11.40 13.20 15.30 14.40 11.60 10.20  7.60  8.00  7.60  7.60  7.60  7.90  8.10 
   19    20    21    22    23    24    25    26    27    28    29    30    31    32    33    34    35    36 
 7.40  7.60  7.40  7.40  7.10  6.50  5.35  4.20  4.10  4.95  5.80  5.75  5.70  6.10  7.00  8.00  8.40  8.50 
   37    38    39    40    41    42    43    44    45    46    47    48    49    50    51 
 6.30  5.70  5.70  5.65  5.60  5.80  6.90  8.20  9.00 10.20 11.00 10.60  8.80  9.10  8.20 
```

BSTS 17 months log-transformation

```
> summary(bsts.model, burn = 217)
$`residual.sd`
[1] 0.01958747

$prediction.sd
[1] 0.07259385

$rsquare
[1] 0.9866766

$relative.gof
[1] -1.069057

> p <- predict.bsts(bsts.model, horizon = 17, burn = 217, quantiles = c(.025, .975))
> p
$`mean`
 [1] 0.8565208 0.7931166 0.7749643 0.7233582 0.7185368 0.7458953 0.7620014 0.7625439 0.7761003 0.8136653
[11] 0.8275958 0.8163034 0.7854575 0.7160341 0.6989516 0.6455063 0.6432265

$median
 [1] 0.8605693 0.7963961 0.7795168 0.7144716 0.7113167 0.7318873 0.7571226 0.7464824 0.7744123 0.8031570
[11] 0.8185485 0.7972344 0.7648537 0.6882643 0.6730751 0.6091926 0.6155655

$interval
           [,1]      [,2]      [,3]      [,4]      [,5]      [,6]      [,7]     [,8]      [,9]     [,10]
2.5%  0.7038076 0.6238465 0.5657217 0.5016051 0.4509587 0.4184026 0.4156275 0.421393 0.4048312 0.4010841
97.5% 0.9950041 0.9629098 0.9802624 1.0001869 1.0285565 1.1130234 1.1625195 1.270880 1.2590857 1.4034470
          [,11]     [,12]     [,13]     [,14]     [,15]      [,16]      [,17]
2.5%  0.4665564 0.4139842 0.3012992 0.2421545 0.1460449 0.03430311 -0.0309488
97.5% 1.3340296 1.4217570 1.4690751 1.4570196 1.4960115 1.46859833  1.5399550

$distribution
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     34 
0.90309 
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BSTS 5 mnths log-transformation

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> summary(bsts.model, burn = 101)
$`residual.sd`
[1] 0.01843959

$prediction.sd
[1] 0.07163837

$rsquare
[1] 0.9860901

$relative.gof
[1] -0.8625865

> p <- predict.bsts(bsts.model, horizon = 5, burn = 101, quantiles = c(.025, .975))
> p
$`mean`
[1] 1.053037 1.061196 1.059181 1.067384 1.115474

$median
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$interval
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2.5%  0.9280929 0.8351111 0.7312337 0.5883828 0.4816109
97.5% 1.1915073 1.3066510 1.4857276 1.6474210 1.8999329

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       13        14        15        16        17        18        19        20        21        22        23        24 
0.9030900 0.8808136 0.8808136 0.8808136 0.8976271 0.9084850 0.8692317 0.8808136 0.8692317 0.8692317 0.8512583 0.8129134 
       25        26        27        28        29        30        31        32        33        34        35        36 
0.7283538 0.6232493 0.6127839 0.6946052 0.7634280 0.7596678 0.7558749 0.7853298 0.8450980 0.9030900 0.9242793 0.9294189 
       37        38        39        40        41        42        43        44        45        46 
0.7993405 0.7558749 0.7558749 0.7520484 0.7481880 0.7634280 0.8388491 0.9138139 0.9542425 1.0086002 
```

BSTS forecast log-transformation

```
> summary(model, burn = 362)
$`residual.sd`
[1] 0.01733133

$prediction.sd
[1] 0.06599464

$rsquare
[1] 0.9868003

$relative.gof
[1] -0.6608139

> pred$mean
[1] 0.9559786 0.9859648 1.0018175
> pred
$`mean`
[1] 0.9559786 0.9859648 1.0018175

$median
[1] 0.9508892 0.9920354 0.9985607

$interval
           [,1]      [,2]      [,3]
2.5%  0.8486716 0.8230763 0.7870669
97.5% 1.0880639 1.1429420 1.1857413

$distribution
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  [3,] 0.9238638 0.8882677 0.7500590
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       12        13        14        15        16        17        18        19        20        21        22 
0.8808136 0.9030900 0.8808136 0.8808136 0.8808136 0.8976271 0.9084850 0.8692317 0.8808136 0.8692317 0.8692317 
       23        24        25        26        27        28        29        30        31        32        33 
0.8512583 0.8129134 0.7283538 0.6232493 0.6127839 0.6946052 0.7634280 0.7596678 0.7558749 0.7853298 0.8450980 
       34        35        36        37        38        39        40        41        42        43        44 
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```

6 Confirmation results (BSTS long-term forecasting)

6.1 Model descriptions

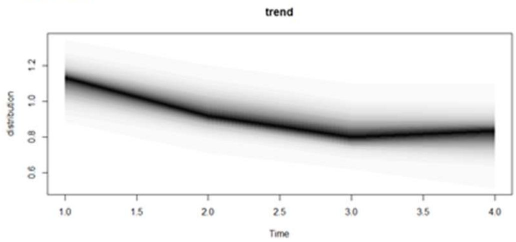
A semilocal linear trend model without a regresson conponent	
Model 4-2	
Semilocal linear trend models with a regresson conponent	
Model 5	Expected model size : 1
Model 6	Expected model size : 5
Model 7	Expected model size : 6
Model 8	Expected model size : 7
Model 9	Expected model size : 8
Model 10	Expected model size : 9
Model 11	Expected model size : 10
Model 12	Expected model size : 11

Original data

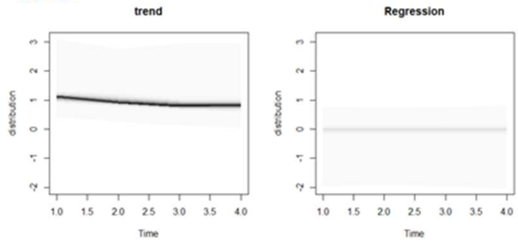
Year	Spot_JP	Crude oil, WTI	Coal, Australian	Natural gas, US	Upstream_inv	Liquefaction_inv	Uti_rate_JP	Uti_rate_W	NG_prod	NG_cons	LNG_trade	LNG_im_JP
	($/mmbtu)	($/bbl)	($/mt)	($/mmbtu)	(billion USD)	(billion USD)			(Bcm)	(Bcm)	(10^6 t)	(Million ton)
2014	14.06	93.1125	70.13	4.369491667	780	36	0.28934978	0.290868802	3446.865	3398.685	239.18	88.505727
2015	7.866666667	48.70916667	57.51070979	2.613708333	585	35	0.24103469	0.278926547	3519.429	3474.188	245.19	85.044303
2016	5.879166667	43.1875	65.86141984	2.492216667	432.9	26	0.18070554	0.282831348	3549.817	3574.183	263.62	83.33983
2017	7.1625	50.90666667	88.41521332	2.959608333	450.216	20	0.14691092	0.26758911	3680.378	3670.397	289.81	83.631844
2018	9.571428571				472	15						

6.2 Components of each model

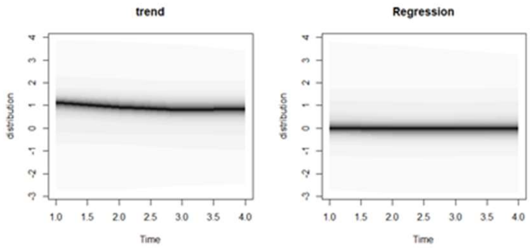
Model 4-2



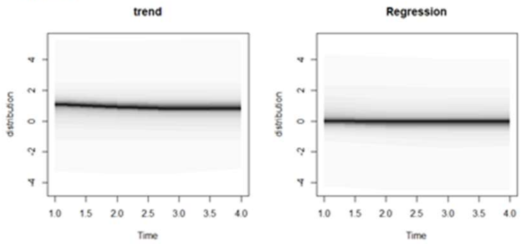
Model 5



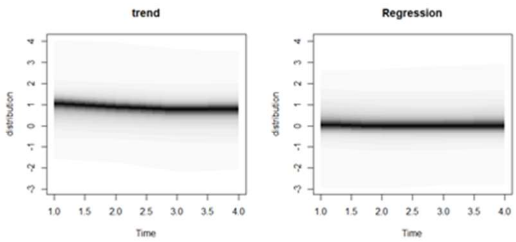
Model 6



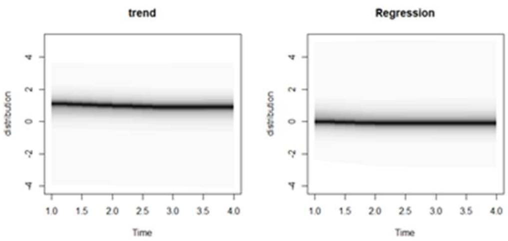
Model 7



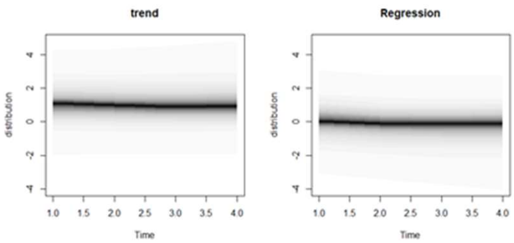
Model 8



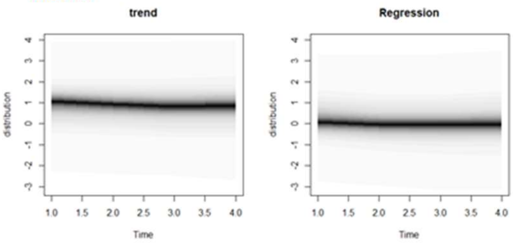
Model 9



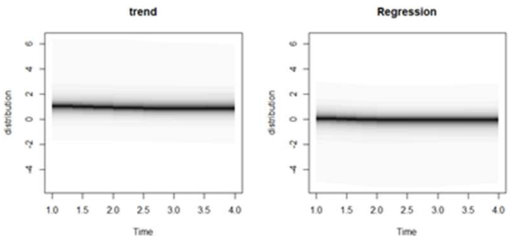
Model 10



Model 11

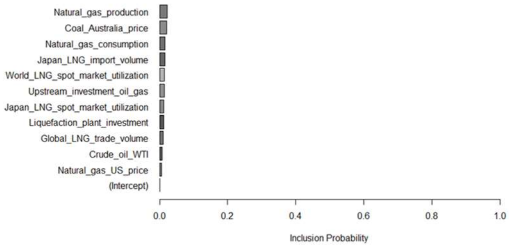


Model 12

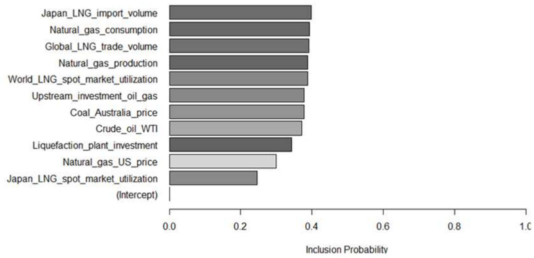


6.3 Regression coefficients of each model

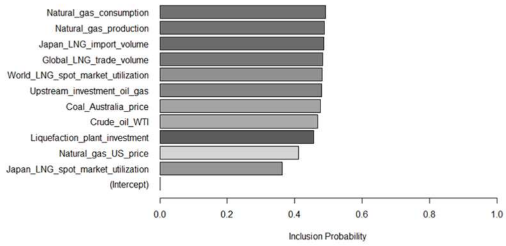
Model 5



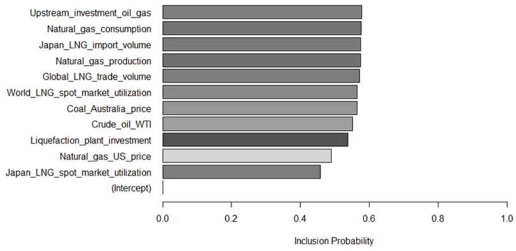
Model 6



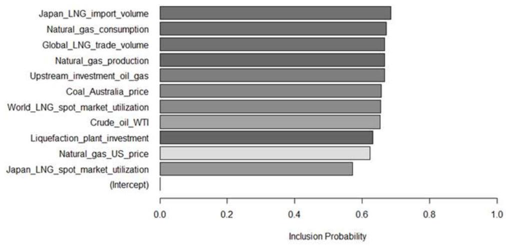
Model 7



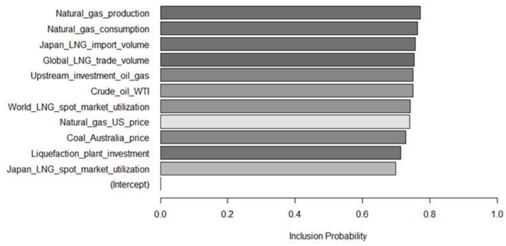
Model 8



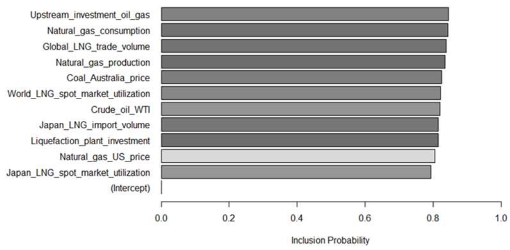
Model 9



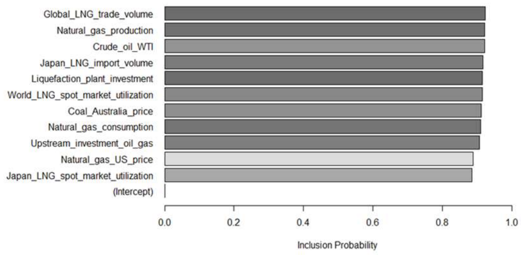
Model 10



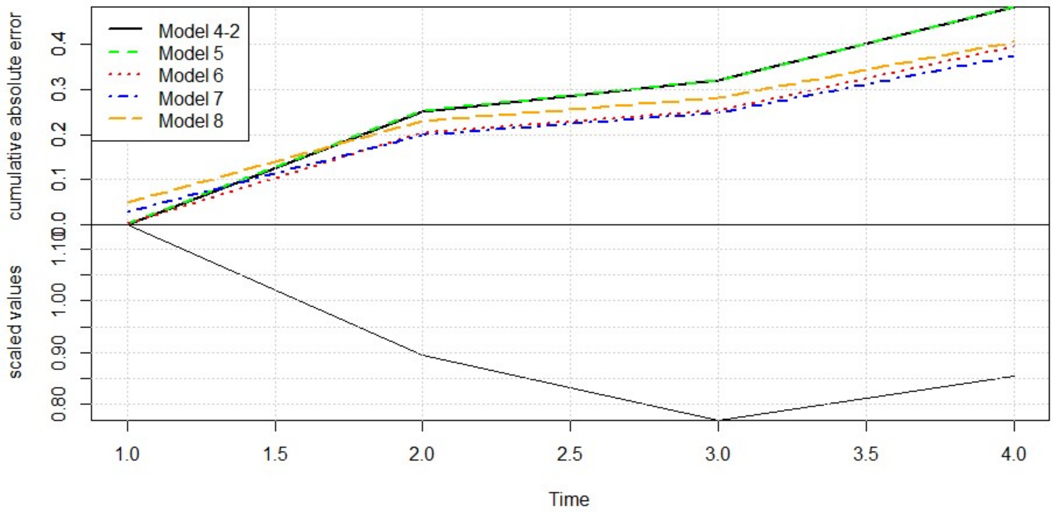
Model 11

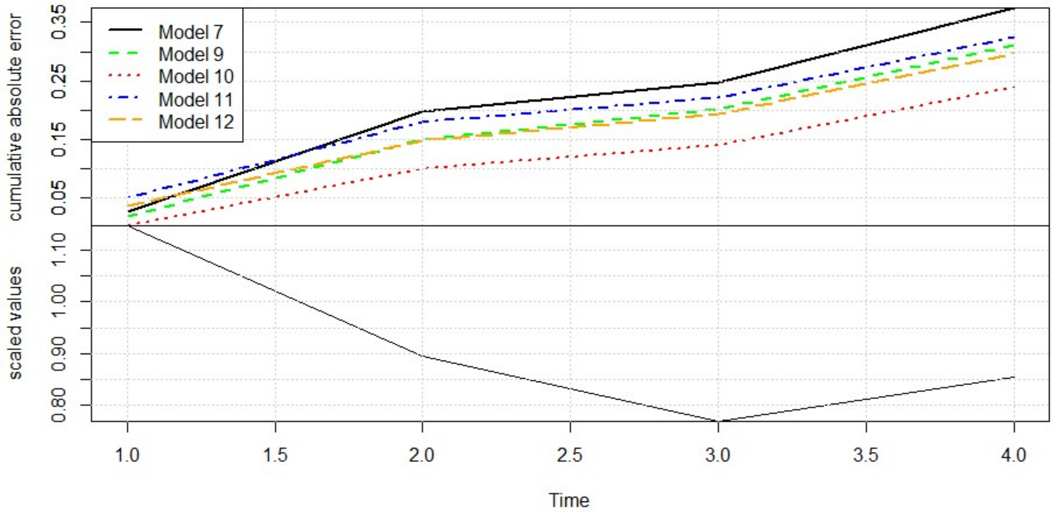


Model 12



6.4 Comparison of cumulative absolute error





7 Original data for BSTS long-term forecasting

Original data

Year	Spot_JP	Crude oil, WTI	Coal, Australian	Natural gas, US	Upstream_inv	Liquefaction_inv	Uti_rate_JP	Uti_rate_W	NG_prod	NG_cons	LNG_trade	LNG_im_JP
	($/mmbtu)	($/bbl)	($/mt)	($/mmbtu)	(billion USD)	(billion USD)			(Bcm)	(Bcm)	(10^6 t)	(Million ton)
2014	14.06	93.1125	70.13	4.369491667	780	36	0.28934978	0.290868802	3446.865	3398.685	239.18	88.505727
2015	7.866666667	48.70916667	57.51070979	2.613708333	585	35	0.24103469	0.278926547	3519.429	3474.188	245.19	85.044303
2016	5.879166667	43.1875	65.86141984	2.492216667	432.9	26	0.18070554	0.282831348	3549.817	3574.183	263.62	83.33983
2017	7.1625	50.90666667	88.41521332	2.959608333	450.216	20	0.14691092	0.26758911	3680.378	3670.397	289.81	83.631844
2018	9.571428571				472	15						

Data set for the estimation of the future variables

Year	Crude oil, WTI	Coal, Australian	Natural gas, US	Upstream_inv	Liquefaction_inv	Uti_rate_JP	Uti_rate_W	NG_prod	NG_cons	LNG_trade	LNG_im_JP
	($/bbl)	($/mt)	($/mmbtu)	(billion USD)	(billion USD)			(Bcm)	(Bcm)	(10^6 t)	(Million ton)
1982	32.76666667	54.7675	2.465					1457.759711	1447.322634		
1983	30.4149998	38.1875	2.5925					1469.878328	1470.611331		
1984	29.37750006	30.95833333	2.655					1597.005214	1591.238739		
1985	27.7625	33.75	2.510833333					1639.449801	1626.314014		
1986	15.08333333	31.125	1.935					1682.964104	1642.136448		
1987	19.15833333	27.5	1.6625					1768.219678	1728.917958		
1988	15.96666667	34.875	1.681666667					1846.320838	1808.352241		31.032076
1989	19.59583333	38	1.696666667					1909.159154	1890.285595		32.358002
1990	24.49166667	39.66666667	1.698333333					1976.277409	1948.664542		35.465422
1991	21.48333333	39.66666667	1.486666667					2003.751152	1998.458677		37.515432
1992	20.5625	38.5625	1.771666667					2012.538729	2007.692098		39.047033
1993	18.5625	31.33333333	2.120833333					2031.47281	2027.509431		39.290106
1994	17.16333333	32.3	1.92					2056.950838	2040.536342		42.078069
1995	18.36916667	39.37166667	1.7225					2093.589993	2112.178818		42.906301
1996	22.07	38.07416667	2.734166667					2191.935703	2214.341796		45.877492
1997	20.32583651	35.09916667	2.48175					2192.749234	2208.205319		47.656138
1998	14.3492	29.23083333	2.086916667					2249.683017	2248.593806		49.133038
1999	19.24083333	25.89166667	2.266666667					2314.303907	2310.757158		51.723937
2000	30.332125	26.25	4.308333333	120				2405.523898	2401.989227		53.689778
2001	25.91908289	32.3125	3.955833333	150				2464.455142	2436.711133		55.149302
2002	26.0931675	25.309375	3.355	160				2520.065774	2510.812839		53.877618
2003	31.1071782	26.090625	5.491982667	180				2613.28735	2576.917552		59.129097
2004	41.44361734	52.94791667	5.894867134	200				2699.547449	2675.216794		56.970663
2005	56.44478447	47.62090278	8.915672827	260		0.02160558	0.12760531	2764.900362	2753.709099		58.01377
2006	66.0425842	49.08958333	6.719543094	340		0.08010057	0.15807903	2866.538617	2834.757835		62.189252
2007	72.28445261	65.733125	6.981950687	390		0.11523817	0.19539786	2941.323294	2958.025097		66.816304
2008	99.55774363	127.1041667	8.857202411	450		0.14748337	0.17601987	3045.439686	3032.137836	172.086	69.262732
2009	61.65364	71.84416667	3.950291667	420		0.08010057	0.15807903	2952.762996	2947.79263	181.739	64.552348
2010	79.42553055	98.96604167	4.38525377	450		0.1009595	0.18661278	3169.316116	3175.912422	220.21	70.00781
2011	95.05432893	121.4483333	3.998578553	590		0.20164349	0.25415282	3269.017768	3241.044868	240.8	78.531629
2012	94.15887843	96.36416667	2.752041667	700		0.22014078	0.25047607	3337.132959	3327.053388	236.31	87.314285
2013	97.94276561	84.56216919	3.723983333	740		0.2465333	0.27428137	3376.188647	3371.494785	236.91	87.4911
2014	93.1125	70.13	4.369491667	780	36	0.28934978	0.2908688	3446.864552	3398.684723	239.18	88.505727
2015	48.70916667	57.51070979	2.613708333	585	35	0.24103469	0.27892655	3519.428561	3474.188349	245.19	85.044303
2016	43.1875	65.86141984	2.492216667	432.9	26	0.18070554	0.28283135	3549.817407	3574.182987	263.62	83.33983
2017	50.90666667	88.41521332	2.959608333	450.216	20	0.14691092	0.26758911	3680.377622	3670.396587	289.81	83.631844
2018				472	15						