Natural Gas Development in the Brazilian Industry: A Short-term Projection

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Abstract

The aim of this study is to estimate the demand for natural gas of the Brazilian industrial sector. Industry is responsible for more than half of the national consumption of this type of energy in Brazil. Therefore, being able to precisely predict the natural gas consumption of the industrial sector is crucial for policy makers. Planning and managing natural gas supply operations are essentials. However, only a limited number of studies specifically address the gas consumption of the industrial sector, both at the national and global level. The existing literature has mostly addressed the composite demand for natural gas and households’ consumption. This paper aims at filling this gap in the literature. We applied the Kalman filter, a bayesian structural state-space model, to a comprehensive dataset of the energy consumption in Brazil and its industrial sector obtained from the Brazilian Association of Piped Gas Distributors. The Kalman Filter is a simple econometric dynamic model, it acts as an efficient recursive filter, which allows the adaptation of its parameters to each period, thus allowing a better accuracy in demand projections. We based our estimations on an extended version of the model. The proposed framework is innovative in the frame of natural gas consumption projections. We evaluated the robustness of the proposed framework comparing it with two routinely adopted methods. The results of this work proved that the Kalman filter delivers a more accurate projection of the industrial natural gas consumption in the short term compared to the proposed benchmarks. The methodology suggested in this work allows the analysis of time-varying parameters and may be readily employed to obtain demand projections for several other products and energy sectors.

Keywords: Natural Gas; Industry; Forecasting; Kalman Filter; Brazil

JEL: P28, E17
1. Introduction

In the recent years, natural gas has gained a significant role in the Brazilian energy matrix. The primary consumer of gas is the industrial sector, accounting for about 54% of the total natural gas consumed in the country.\footnote{BEN, 2016.} The use of natural gas in various industries has boosted the expansion of this source of energy.

The inauguration of the Brazil-Bolivia gas pipeline (GASBOL), in July 1999, has been a fundamental driver of the natural gas expansion in the last 15 years. The large availability of gas allowed the replacement of other energy sources with natural gas. Brazil aims at diversifying the provision of energy and reducing its dependence on oil to isolate from the impact of rising oil prices on the Brazilian economy (Figure 1).

![Figure 1: Market Share Evolution of Natural Gas in the Brazilian Energy Matrix](image)


In the past, natural gas was almost often reinjected, burnt, or used on platforms and land fields due to the massive infrastructure investment needed to exploit it (Almeida and Colomer, 2013). The discovery of the Campos Basin in the '80s opened up a new horizon for the development of the natural gas industry, generating new incentives for the commercialization of this source of energy.

Natural gas is characterized by a high calorific value, good energy efficiency, and low levels of pollutant emissions compared to other energy sources. However, its primary disadvantage is the low caloric density or large volume: the same amount of energy occupies a volume about 1,000 times higher in the form of natural gas than in the form of petroleum (Pinto Jr. et al., 2016).

Natural gas accounted for 4.2% of the total energy consumption in Brazil in the year 2000.\footnote{Ibidem.} With the advent of GASBOL and the development programs implemented by the federal and local governments, the share of natural gas increased to 7.2% of the total energy consumption in 2015.\footnote{Ibid.} In the period between 2000 and 2015, the national consumption of natural gas grew by 6.7% per annum, well above the increase in the energy matrix as a whole, which was 2.8% per annum (Figures 2 and 3).
The primary energy consumer in Brazil is the industrial sector. This segment has been decreasing its consumption share in the last 15 years, but it still leads in the use of energy, being responsible for more than 32% of the total national consumption (Figures 4 and 5).
The industrial sector is also the largest natural gas consumer in Brazil, with a share of more than 50%\textsuperscript{4} of the overall national consumption (Figures 6 and 7). This segment plays a key role in the development of natural gas. Its stable demand, the almost absent variations in energy consumption, and large volumes consumed allow the investment in infrastructures for the production and transportation of natural gas (Almeida and Colomer, 2013), such as pipeline networks, transport through Liquefied Natural

\textsuperscript{4} Ibid.
Gas (LNG) vessels, and distribution through Compressed Natural Gas (CNG) trucks. The large volume of natural gas consumed in this segment enables and boosts other consumption sectors, like the automotive and residential sectors, supplied by the gas pipeline network developed for the industrial sector. The energy consumption of the industry also allows an increased energy consumption in other sectors, which guarantee greater margins to the natural gas distributors.

Figure 6: Natural Gas Consumption by Segment in the year 2000 (%)

[Image: Pie chart showing gas consumption by segment in 2000.]


Figure 7: Natural Gas Consumption by Segment in the year 2015 (%)

[Image: Pie chart showing gas consumption by segment in 2015.]

[Image 108x62 to 539x321]
The breakdown of the industry sector by energy source shows the increased relevance of natural gas between 2000 and 2015 (Figures 8 and 9). Its share grew from 6.4% to 11.8%², replacing firewood, fuel oil, and coal among other traditional energy sources. This development is linked to several factors, such as the strengthening of environmental restrictions at the national and local level, and competitive pricing policies against potential energy substitutes. In addition, local legislations have begun to encourage fuel exchange, partially addressing the cost of converting the existing equipment to natural gas (Pinto Jr. et al., 2016).

Figure 8: Industrial Energetic Consumption in the year 2000 (%)


Figure 9: Industrial Energetic Consumption in the year 2015 (%)


² Ibid.
The consumption of natural gas in the Brazilian industry has also experienced a slowdown in recent years (Figure 10). The weak evolution of the Brazilian industrial sector, influenced by local and global issues, has significantly affected the use of natural gas (Figure 11).

**Figure 10: Natural Gas Consumption – Industrial Segment (Thousand m³/day)**


**Figure 11: Brazilian Industrial Production – General Index**

Source: Abegas (Brazilian Association of Piped Gas Distributors).
Natural gas is a more environmentally friendly energy source compared to traditional fuels (fuel oil, diesel oil, and coal, for example). Assessing the evolution of the demand for natural gas in the Brazilian industry has become increasingly important both for operational aspects and for the evaluation of sustainable investments in logistics. Due to both economic and environmental reasons, the supply system capacity in Brazil is designed to be close to peak demand. Besides, due to limitations in the gas infrastructure, a great disequilibrium between demand and supply may not be compensated by short-term operations. As a result, demand and supply have to be matched by the system operator in advance. Thus, energy demand is one of the key variables for projecting the capacity required to ensure an appropriate energy supply.

An analysis based on the projection of the short-term set-up, which also recognizes the relevance of long-term scenarios, and a constant market monitoring are needed to stimulate public policies in support of natural gas consumption. The remainder of this paper is organized as follows. In Section 2, we introduce some commonly used forecasting models, and we develop our prediction model proposition. In Section 3, we describe the key variables, test our model, and discuss the main results comparing the proposed model’s performance with two other traditional frameworks. Our concluding remarks and policy suggestions are presented in Section 4.

2. Methodology

2.1. Background

A large body of literature has focused on forecasting models for natural gas demand. Soldo (2012) classified the existing literature based on the following criteria:

- Years.
- Applied area:
  - World level;
- National level;
- Regional level;
- Gas distribution system level;
- Individual customer level.

- Forecasting horizon:
  - Hourly;
  - Daily;
  - Monthly;
  - Annual;
  - Combined.

- Gas consumption data:
  - Hourly;
  - Daily;
  - Monthly;
  - Annual.

- Forecasting tools:
  - Hubbert model;
  - Grey model;
  - Statistical models;
  - Econometric models;
  - Neural network model;
  - Mathematical models;
  - Combination model.

The present work investigates the most appropriate tools for the projection of the natural gas demand in the industrial sector. We examined the related literature starting from the studies reviewed by Soldo (2012).

We found that Grey’s model can deal with incomplete information, but its estimation accuracy is low for random data sequences, and the model often needs to be combined with the Markov chain.

Ma and Wu (2009) used Grey’s model to forecast the production and consumption of natural gas in China from 2008 to 2015. The authors combined the model with the Markov chain to address randomness in the Chinese natural gas data. The effectiveness of the proposed framework decreased with the increase of the time horizon. Bo and Li (2016) employed Grey’s model to forecast Chinese gas demand from 2011 to 2020, using an improved Self-adapting Intelligent Grey Prediction Model (SIGM), and achieved a better deviation measure than other papers.

Several predicting frameworks have been developed since the '60s. As discussed by Soldo (2012), Herbert et al. (1982) proposed a regression model to assess the effects of some explanatory variables on the natural gas demand of the industrial sector. The sign on the coefficients was consistent with economic theory: a higher temperature is associated with higher sales by sector and a higher industrial natural gas consumption, while a higher oil price implies a larger demand for natural gas by the industry. Besides, a higher natural gas price suggests a lower demand for natural gas, as confirmed by the negative sign on this coefficient.

Sánchez and Berzosa (2007) presented a model to estimate the medium-run industrial demand for natural gas in Spain (1-3 years) with daily precision. The proposed framework can deal with time series characterized by both annual and weekly seasonality. The forecast was obtained by the combination of three different components: one that captures the trend of the time series, a seasonal component based on the Linear Hinges Model, and a transitory component to estimate daily variations using explanatory variables.

Artificial Neural Network (ANN) is a tool developed to mimic neural biological systems (such as the human brain) and is composed of several interconnected elements, called nodules. Suykens et al. (1996) used ANN to estimate industrial and residential natural gas consumption in Belgium. The authors compared an OLS model with the ANN model and showed the better deviation obtained by the latter.
We also examine various econometric and mathematical models for forecasting purposes. Nagy (1996) estimated the natural gas consumption in Kuwait using a partial adjustment econometric model estimated by OLS. All coefficient parameters had coherent signs and were statistically significant at the 5% level. The adjusted $R^2$ was high (0.996). The natural gas price coefficient was negative, but its low value indicates that the demand for natural gas was inelastic in the short term, as for the income variable. Khan (2015) also compared an OLS and VAR analysis of the natural gas demand in Pakistan and showed that both short-run and long-run price elasticities are relatively low. Prices are inelastic for the residential, transportation, commercial, and industrial sectors, while the elasticity of the power sector is relatively high.

In Brazil, Braga (2014) proposed a set of models for analyzing natural gas monetization studies and long-term regional planning. The first one is GEE-Matrix Model estimates the industrial natural gas potential under different price scenarios and substitution conditions, taking into account the energy performance. This model can be applied both at the national and local level. The second one is industrial register cadastre model allows assessing the potential energy demand at the individual level in industries that require natural gas and the results can be aggregated by industry, municipality, state, or region.

2.2. Proposed Methodology

In this article, we introduce a state-space model based on the Kalman filter procedure (Kalman, 1960) with a variation of the parameters over time (Carlos, 2009). This methodology was developed by Gomez and Legey (2015). One of our objectives with the development of this work is to verify whether the proposed model can outperform others in terms of forecast deviation.

The Kalman filter produces an estimate of the state of the system that corresponds to an average of the system’s predicted state and the new measure using a weighted average. The weights are calculated using the covariance, a measure of the estimated uncertainty of the prediction of the system’s state and are introduced in the model because a low uncertainty produces more reliable estimates (Harvey, 1990).

The result of the weighted average is a new state estimate that lies between the predicted and the measured state, and has a better-estimated uncertainty than either alone. This process is repeated at every step, with the new estimate and its covariance informing the prediction used in the following iteration. The Kalman filter works recursively and requires only the last estimate, rather than the entire history of a system’s states, to calculate a new state (Harvey, 1990).

The Kalman filter is a Bayesian method, similar to a hidden Markov model where the latent variables belong to a continuous space and have Gaussian distributions. It is a simple econometric tool that will help us analyze and forecast the demand projection (Hamilton, 1994).

We applied the procedure suggested by Johansen (1988), in line with the guidelines set out by Enders (2004). The proposed methodology also enabled us to test restricted versions of the cointegrating vectors and establish the causality between the model’s variables using the Granger’s causality test (Granger, 1980) (Wooldridge, 2002).

Five equations are estimated simultaneously by the Kalman filter state-space algorithm: an observation/correction equation, and four state/prediction equations that demonstrate the evolution over time of the parameters of the first equation.

The recursive estimation of the unknown parameter vector from the updated information available at each point in time, $t$, is obtained through the Kalman filter equations. The state-space representation allows unobserved variables to be included in the model and estimated along with the observable variables (Durbin and Koopman, 2001).

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7 GEE: Grupo de Economia da Energia (Energy Economics Group) from UFRJ.
The estimation of the model (presented in the next section) has been adapted to the step-by-step procedure suggested by Carlos et al. (2009) and to the analysis performed by Gomez and Legey (2015), as described below:

1) Check whether the time series are stationary using unit-root tests;
2) If the series are non-stationary, use the Johansen cointegration approach, as follows:
   a) Specify the VAR model with the chosen variables, defining the optimal number of lags with the help of an information criterion, such as the Max-Eigenvalue Test or Trace Test;
   b) Using these lags, test for cointegration;
   c) If the integrated variables of order 1 show a cointegration relationship, then, their respective parameters correspond to their long-run elasticity;
3) To test for the existence of predictive causality between the independent variables and the dependent variable, use the Granger causality test. These first three steps are developed to ensure that the variables are relevant, are related to each other and the analysis is following a correct procedure;
4) Specify the state-space model with the Kalman Filter procedure (Harvey, 1960) and forecast a short-term scenario;
5) To test the accuracy of the model projections, use the Mean Absolute Percentage Error (MAPE) metric to measure out-of-sample deviations between predictions and actual values from the proposed model and alternative forecast models.

3. Results and Discussion

In this work, we analyze the Brazilian industry using variables characterized by the following attributes: reasonable, comprehensive, transparent, from different origins, open to the public, and timely. Two factors emerged as key drivers of the industrial natural gas consumption in Brazil: Expedition of Corrugated Paperboard (Papelão), as presented in Figure 12, and ONS Power Load (CargaONS), as shown in Figure 13. Both indexes affect the industrial production and were used by the Institute of Applied Economic Research (IPEA) to prepare its Monthly Industrial Production Indicator. The first indicator is related to the need for packaging of various industrial products and the second is linked to the pace of the industrial activity. Both indexes are released about a month before the production indicator of the Brazilian industry, published by Brazilian Institute of Geography and Statistics (IBGE).

The use of these indexes helps us deal with the time gap before the announcement of the Brazilian Industrial Production. Without these indicators, our projections would suffer from an extreme delay.

Figure 12: Monthly Expedition of Boxes, Accessories, and Plates (thousand tons)

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8 Source: ABPO – Cardboard Brazilian Association of Corrugated Paperboard.
9 Source: ONS - National Electric System Operator.
Source: ABPO (Cardboard Brazilian Association of Corrugated Paperboard).

Figure 13: Average Electric Power Load, Brazil (MW Med)

Source: ONS (National Electric System Operator).
Figure 14 reports the dollar quotation, which provides a partial representation of the evolution of the natural gas prices. We use it as a proxy for natural gas price due to the lack of data on natural gas consumer prices (Cotadolar)\(^{10}\).

![Figure 14: Dollar Quotation (R$/US$)](image)

Source: BACEN (Brazilian Central Bank).

Tables 1 and 2 report the results of the unit root tests (ADF Test, Step 1) for the analyzed variables and the results of the cointegration tests (trace and maximum eigenvalue tests, Step 2) with a significance level of 5%. All the tests were performed by the EViews software.

Table 1: Unit root tests for the independent variables (logarithmic transformation) – ADF Test

<table>
<thead>
<tr>
<th>Variable</th>
<th>Optimal Lag Length</th>
<th>t-stat (Critical Values: 5%: -2.867123 1%: -3.463749)</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>LPapelao</td>
<td>12</td>
<td>-1.141941</td>
<td>0.6977</td>
</tr>
<tr>
<td>LCargaONS</td>
<td>3</td>
<td>-1.303167</td>
<td>0.6281</td>
</tr>
<tr>
<td>LCotadolar</td>
<td>1</td>
<td>-1.730290</td>
<td>0.4144</td>
</tr>
<tr>
<td>LGNIndustrial</td>
<td>0</td>
<td>-2.991435**</td>
<td>0.0374</td>
</tr>
</tbody>
</table>

Source: Author’s calculation executed with Eviews (Model Analysis).

\(^{10}\) Source: BACEN (Brazilian Central Bank).
*, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 2: Results of the Johansen cointegration procedure (Equation 1)
Trace Test and Maximum Eigenvalue Test

<table>
<thead>
<tr>
<th>Hypothesised No. of CE(s)</th>
<th>Eigenvalue</th>
<th>Trace Statistic</th>
<th>0.05 Critical Value</th>
<th>Prob.**</th>
</tr>
</thead>
<tbody>
<tr>
<td>None *</td>
<td>0.228073</td>
<td>58.60826</td>
<td>47.85613</td>
<td>0.0036</td>
</tr>
<tr>
<td>At most 1</td>
<td>0.099408</td>
<td>26.50905</td>
<td>29.79707</td>
<td>0.1142</td>
</tr>
<tr>
<td>At most 2</td>
<td>0.078702</td>
<td>13.52587</td>
<td>15.49471</td>
<td>0.0969</td>
</tr>
</tbody>
</table>

Trace test indicates 1 co-integrating eqn(s) at the 0.05 level

<table>
<thead>
<tr>
<th>Hypothesised No. of CE(s)</th>
<th>Eigenvalue</th>
<th>Max-Eigen Statistic</th>
<th>0.05 Critical Value</th>
<th>Prob.**</th>
</tr>
</thead>
<tbody>
<tr>
<td>None *</td>
<td>0.228073</td>
<td>32.09922</td>
<td>27.58434</td>
<td>0.0122</td>
</tr>
<tr>
<td>At most 1</td>
<td>0.099408</td>
<td>12.98317</td>
<td>21.13162</td>
<td>0.4538</td>
</tr>
<tr>
<td>At most 2</td>
<td>0.078702</td>
<td>10.16446</td>
<td>14.26460</td>
<td>0.2014</td>
</tr>
</tbody>
</table>

Max-eigenvalue test indicates 1 co-integrating eqn(s) at the 0.05 level

Source: Author’s calculation executed with Eviews (Model Analysis).
*, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 1 shows the impossibility to reject the hypothesis of a unit root in all series, except the natural gas series. Table 2 indicates the presence of one cointegration vector between the model variables, both for the Trace test and for the maximum eigenvalue test, suggesting a long-term equilibrium between the log variables Papelao (Expedition of Corrugated Paperboard), CargaONS (Power Load), Cotadolar (dollar quotation) and GIndustrial (Industrial Natural Gas Consumption). Therefore, the parameters of the five equations can be estimated through OLS.

Based on the unit root and cointegration tests, we try to evaluate the Granger's causality between the model's variables (Step 3). Granger's causality is a type of "predictive causality." Variable X is said to Granger-cause variable Y if past values of X help predict the present value of Y. The concept of Granger's causality does not account for any contemporary effects of one variable on another. Table 3 shows that the Granger’s causality between the dollar and the industrial consumption of natural gas runs in both directions. And we can also conclude that all variables, jointly, affect industrial natural gas variable.

Table 3: Granger’s causality test results

<table>
<thead>
<tr>
<th>Dependent Variable: D (LGNIndustrial)</th>
<th>Excluded</th>
<th>Chi-sq</th>
<th>df</th>
<th>Prob.</th>
</tr>
</thead>
</table>

15
The baseline model proposed in this article (state-space model with the Kalman filter procedure) can be expressed as follows with a logarithmic transformation (Step 4):

\[
\text{@signal lgnindustrial} = sv0 + sv1*lcotadolar + sv2*lpapelao + sv3*lcargaons + \text{[var} = \exp(c(1))\text{]}; \quad \text{eq.1}
\]

\[
\text{@state sv0} = sv0(-1); \quad \text{eq.2}
\]
\[
\text{@state sv1} = sv1(-1); \quad \text{eq.3}
\]
\[
\text{@state sv2} = sv2(-1); \quad \text{eq.4}
\]
\[
\text{@state sv3} = sv3(-1). \quad \text{eq.5}
\]

The behavior of the parameters over time is shown in Figure 15. The analysis of the variation of the parameters allows us to account for several events that may have affected the behavior of the variables. ONS power load is associated with the highest volatility parameter among the three analyzed
in this study, probably due to the substantial reduction in the industrial production between 2008 and 2009, as a result of the subprime crisis in the United States.

Figure 15: Behavior of the parameters of interest over time

Source: Author’s calculation executed with Eviews (Model Analysis).

The data used for the analysis cover the period from January 2005 to June 2015, since Expedition of Corrugated Paperboard data were not available before.

Table 4 reports the final parameters for Equations 1 to 5 and their statistical significance. All parameters are significant at the 1% level and the signs are as expected. The \( \text{lcotadolar} \) parameter (sv1) is negative as expected, since it reflects the price response. The other parameters (sv2, \( \text{lpapelao} \), and sv3, \( \text{lcargaons} \)) are positive and reflect the impact of income and activity on natural gas consumption.

Table 4: Final Parameter Estimates for Equations 1 to 5

| State space: SSKFEQ_VEC_C_LPAP_LONS |
| Method: Maximum likelihood (BHHH) |
| Sample: 2005M01 2015M06 |
| Included observations: 126 |

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C(1)</td>
<td>-5.517162</td>
<td>-50.41460</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Final State</th>
<th>Root MSE</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>SV0</td>
<td>4.283451 ***</td>
<td>7.043293</td>
<td>0.0000</td>
</tr>
</tbody>
</table>
To assess the validity of the proposed model, we compared its performance with the results of two commonly used models over the same forecasting period (July 2015 to June 2016). The first benchmark is a naïve AR (1) model and the second is a cointegration analysis with an Error Correction Model with no time-varying parameters, as suggested by Johansen (1988) and in line with the guidelines by Enders (2004).

The Mean Absolute Percentage Error (MAPE) measures out-of-sample deviations between predictions and actual values for the proposed model and alternative forecast models. The greater the value of the MAPE, the worse the accuracy of the forecasting values. The results are as follows:

- Naïve AR (1) Model: 4.4%;
- Cointegration with Error Correction Model with no time-varying parameters: 5.1%;
- State-space model with Kalman Filter (time-varying parameters): 3.3%.

Therefore, we can conclude that the model proposed in this paper delivers better results compared to traditional models of analysis and demand forecasting.

Table 5: MAPE - AR (1)

<table>
<thead>
<tr>
<th>AR (1)</th>
<th>Forecast (thousand m³/day)</th>
<th>Real (thousand m³/day)</th>
<th>R-F (thousand m³/day)</th>
<th>R-F/R</th>
<th>ABS(R-F/R)</th>
<th>MAPE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jul-15</td>
<td>27,683.73</td>
<td>27,638.09</td>
<td>-45.64</td>
<td>-0.2%</td>
<td>0.2%</td>
<td>0.2%</td>
</tr>
<tr>
<td>Aug-15</td>
<td>27,625.65</td>
<td>27,465.34</td>
<td>-160.31</td>
<td>-0.6%</td>
<td>0.6%</td>
<td>0.4%</td>
</tr>
<tr>
<td>Sep-15</td>
<td>27,569.90</td>
<td>27,615.98</td>
<td>46.08</td>
<td>0.2%</td>
<td>0.2%</td>
<td>0.3%</td>
</tr>
<tr>
<td>Oct-15</td>
<td>27,515.92</td>
<td>27,463.69</td>
<td>-52.23</td>
<td>-0.2%</td>
<td>0.2%</td>
<td>0.3%</td>
</tr>
<tr>
<td>Nov-15</td>
<td>27,463.96</td>
<td>27,980.41</td>
<td>516.45</td>
<td>1.8%</td>
<td>1.8%</td>
<td>0.6%</td>
</tr>
<tr>
<td>Dec-15</td>
<td>27,413.75</td>
<td>23,933.15</td>
<td>-3,480.60</td>
<td>-14.5%</td>
<td>14.5%</td>
<td>2.9%</td>
</tr>
<tr>
<td>Jan-16</td>
<td>27,365.54</td>
<td>25,025.49</td>
<td>-2,340.06</td>
<td>-9.4%</td>
<td>9.4%</td>
<td>3.8%</td>
</tr>
<tr>
<td>Feb-16</td>
<td>27,318.79</td>
<td>25,660.80</td>
<td>-1,657.98</td>
<td>-6.5%</td>
<td>6.5%</td>
<td>4.2%</td>
</tr>
<tr>
<td>Mar-16</td>
<td>27,273.75</td>
<td>25,316.46</td>
<td>-1,957.29</td>
<td>-7.7%</td>
<td>7.7%</td>
<td>4.6%</td>
</tr>
<tr>
<td>Apr-16</td>
<td>27,230.42</td>
<td>25,848.30</td>
<td>-1,382.12</td>
<td>-5.3%</td>
<td>5.3%</td>
<td>4.6%</td>
</tr>
<tr>
<td>May-16</td>
<td>27,188.79</td>
<td>26,730.22</td>
<td>-458.57</td>
<td>-1.7%</td>
<td>1.7%</td>
<td>4.4%</td>
</tr>
<tr>
<td>Jun-16</td>
<td>27,148.31</td>
<td>28,558.22</td>
<td>1,409.91</td>
<td>4.9%</td>
<td>4.9%</td>
<td>4.4%</td>
</tr>
</tbody>
</table>

Source: Author’s calculation executed with Eviews (Model Analysis).
Table 6: MAPE – VEC

<table>
<thead>
<tr>
<th></th>
<th>Forecast (thousand m³/day)</th>
<th>Real (thousand m³/day)</th>
<th>R-F (thousand m³/day)</th>
<th>R-F/R</th>
<th>ABS(R-F/R)</th>
<th>MAPE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jul-15</td>
<td>27,667.67</td>
<td>27,638.09</td>
<td>-29.59</td>
<td>-0.1%</td>
<td>0.1%</td>
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<tr>
<td>Aug-15</td>
<td>27,701.17</td>
<td>27,465.34</td>
<td>-235.84</td>
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<td>0.5%</td>
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<td>27,705.88</td>
<td>27,615.98</td>
<td>-89.90</td>
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<td>0.4%</td>
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<td>Oct-15</td>
<td>27,701.45</td>
<td>27,463.69</td>
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<td>0.9%</td>
<td>0.5%</td>
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<tr>
<td>Nov-15</td>
<td>27,791.35</td>
<td>27,980.41</td>
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<td>0.7%</td>
<td>0.6%</td>
</tr>
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<td>Dec-15</td>
<td>27,726.67</td>
<td>23,933.15</td>
<td>-3,793.51</td>
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<td>15.9%</td>
<td>3.1%</td>
</tr>
<tr>
<td>Jan-16</td>
<td>27,697.85</td>
<td>25,025.49</td>
<td>-2,672.36</td>
<td>-10.7%</td>
<td>10.7%</td>
<td>4.2%</td>
</tr>
<tr>
<td>Feb-16</td>
<td>27,729.16</td>
<td>25,660.80</td>
<td>-2,068.36</td>
<td>-8.1%</td>
<td>8.1%</td>
<td>4.7%</td>
</tr>
<tr>
<td>Mar-16</td>
<td>27,776.07</td>
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<td>9.7%</td>
<td>5.2%</td>
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<tr>
<td>Apr-16</td>
<td>27,798.85</td>
<td>25,848.30</td>
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<td>5.5%</td>
</tr>
<tr>
<td>May-16</td>
<td>27,834.74</td>
<td>26,730.22</td>
<td>-1,104.52</td>
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<td>5.3%</td>
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<tr>
<td>Jun-16</td>
<td>27,800.80</td>
<td>28,558.22</td>
<td>757.42</td>
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<td>2.7%</td>
<td>5.1%</td>
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</table>

Source: Author’s calculation executed with Eviews (Model Analysis).

Table 7: MAPE - State-space model with the Kalman Filter Procedure

<table>
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<tr>
<th></th>
<th>Forecast (thousand m³/day)</th>
<th>Real (thousand m³/day)</th>
<th>R-F (thousand m³/day)</th>
<th>R-F/R</th>
<th>ABS(R-F/R)</th>
<th>MAPE</th>
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<td>27,537.11</td>
<td>27,638.09</td>
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<tr>
<td>Aug-15</td>
<td>27,379.50</td>
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<td>27,287.12</td>
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<td>328.87</td>
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<td>1.2%</td>
<td>0.6%</td>
</tr>
<tr>
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<td>27,764.96</td>
<td>27,463.69</td>
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<td>0.7%</td>
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<tr>
<td>Nov-15</td>
<td>27,396.21</td>
<td>27,980.41</td>
<td>584.20</td>
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<td>2.1%</td>
<td>1.0%</td>
</tr>
<tr>
<td>Dec-15</td>
<td>27,538.22</td>
<td>23,933.15</td>
<td>-3,605.06</td>
<td>-15.1%</td>
<td>15.1%</td>
<td>3.4%</td>
</tr>
<tr>
<td>Jan-16</td>
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<td>25,025.49</td>
<td>915.53</td>
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<td>3.7%</td>
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</tr>
<tr>
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<td>25,660.80</td>
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<td>25,316.46</td>
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<tr>
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<td>25,848.30</td>
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<td>0.7%</td>
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<td>May-16</td>
<td>25,864.07</td>
<td>26,730.22</td>
<td>866.15</td>
<td>3.2%</td>
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<td>Jun-16</td>
<td>26,646.95</td>
<td>28,558.22</td>
<td>1,911.27</td>
<td>6.7%</td>
<td>6.7%</td>
<td>3.3%</td>
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</table>

Source: Author’s calculation executed with Eviews (Model Analysis).

4. Conclusions

The main contribution of this paper is applying a relatively straightforward methodology, originally developed to answer a different research question, project space rocket trajectory, to obtain reliable short-run projections of the natural gas demand of the industrial sector. The present analysis recognizes the leading role of the industrial sector in the determination of the national gas demand in
Brazil. Therefore, we tried to disentangle the industrial demand for natural gas, thus filling a gap in the existing literature.

This study shows that the demand for natural gas is affected by three variables representing the fundamental elements of the demand equations (“price” and “income”): Papelao (Expedition of Corrugated Paperboard), CargaONS (Power Load), and Cotadolar (dollar quotation). We assessed the role of these variables in the evolution of natural gas consumption in the Brazilian industry.

The projections obtained through the proposed model allow us to reduce the forecasting errors compared to the standard methodologies and, therefore, avoid incurring unnecessary costs. Additionally, in this work, all parameters from the equation are not fixed. They change along the periods. This characteristic allows a fast adaptation of the model to market dynamics.

The time-varying values of the parameters and their volatilities analyzed through the Kalman filter quantify the impact of changes in the evolution of the explanatory factors on the natural gas consumption of the Brazilian industrial sector. At different periods, the parameters have different values, what implies that they have different impacts at different periods. A variable can impact more or lesser at different periods. And the Kalman Filter allows us to analyze this changing pattern along the time period.

The econometric model discussed in this paper is simple and flexible and allows fitting the dynamic context of energy supply in a rapidly changing environment. The results allow us to provide meaningful insights for policy makers at different levels of the federation for the energy development, reducing the possibility of errors in the energy system planning.

Due to data limitations, our analysis only focuses on the Brazilian context. In addition, the variables used in the proposed model cannot capture all market dynamics. The proposed methodology could be extended to different countries, using specific variables that influence the natural gas consumption of their industrial sector or other segments. Finally, this work proposes an econometric framework that can be easily applied to the analysis of other energy sources.
References