An Analysis of Drug Expenditure in Portuguese Public Hospitals: Modelling and Forecasting

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December 2016

Abstract

The Portuguese National Health Service provides to its citizens health services tendentially free of cost. However, the ability to provide quality and accessible health services is an increasingly difficult global challenge. The purpose of this work is to build a model which can be used to describe and predict the total drug expenditure in Portuguese public hospitals, which can then help define a better allocation of resources. The total expenditure was grouped into the five NUTS II regions of mainland Portugal. Then, two models were built for each region: a monthly and quarterly one. The models are linear regressions with SARIMA errors and describe the expenditure with medicines in each region according to their respective demographic, economic and utilisation of health services indicators. These models adequately describe the total expenditure in Portugal and perform very satisfactory forecasts about the spending between April 2015 and March 2016. A graphical interface was also developed in order to allow interactive visualizations of the data and to facilitate the process of generating and inspecting forecasts.

Keywords: Time Series, Regression Models, Visualization, Forecasting, Pharmaceutical Market, Portuguese National Health Service

1. Introduction

One of the greatest challenges of modern societies is to be able to provide sustainable and quality health care services to the general population. As life expectancy grows, chronic diseases become more frequent. Also, the continuous and rapid technological development provide better care solutions but with great financial cost, and the global economic situation sets budget constraints on governments [1]. The Portuguese situation is no exception, and thus, it is ever more important to assure cost efficiency on all areas of the Portuguese National Health Service (SNS).

Drug expenses account for 22% to 29% of the total spending by the SNS [2]. This expenditure can be divided into two large areas: ambulatory care and in hospital use. Ambulatory care is defined as health services provided to outpatients who go to hospitals in order to be diagnosed or receive treatments, being discharged on the very same day. Medicines prescribed to these patients are collected on private pharmacies. On the other hand, in hospital use accounts for all drugs used in treatments performed on inpatients, these medicines are bought by the hospitals.

Despite there being some studies about forecasting medicine expenditure [3, 4, 5, 6], these are mostly focused on ambulatory care and largely dominated by opinions of experts and not by an historic and quantitative analysis of data. This is probably a result of a usually scarce or non existant data collection, necessary to conduct such studies.

However, Infarmed (National Authority of Medicines and Health Products I.P.), has been collecting extensive data on the consumption of medicines by Portuguese public hospitals since
2010. It was these data that allowed for the study presented in this paper to be conducted: to model and forecast the total drug expenditure in Portuguese public hospitals. The existence of this model is decisive to substantiate decisions on the budget that should be reserved for this type of expense.

1.1. State of the Art

The international literature on drug expenditure forecasting includes different prediction horizons and modelling approaches, which can be divided in two major groups: top-down and bottom-up.

The top-down approach is related with longer time-scale forecasts and uses demographic data and econometric analysis to predict expenditure. For example, the Center for Medicare and Medicaid (CMS) uses this approach for the 10-year forecasts which it regularly publishes of total drug spending on health services in the United States of America. The main indicators used are past trends and estimates of demographic variables and GDP. However, this forecast is adjusted to include the view of pharmaceutical experts on the future behaviour of the market [6].

On the other hand, the bottom-up approach is usually used for forecasts with a shorter time span. It focuses on the analysis of the impact of introducing innovative drugs, new generic medicines, as well as legislative reforms on health systems, for each therapeutic group or even for each pharmaceutical group. [3] uses this approach to produce a four-year forecast of drug spending in the UK National Healthcare System (NHS).

The authors of these articles are usually members of pharmaceutical research groups. Therefore, it is given a larger emphasis to the pharmaceutical relevance of the study. Consequently, statistical methods and procedures used to obtain the estimates are rarely described.

1.2. Contributions

In our study, in order to model and forecast the total drug expenditure in Portuguese public hospitals, we conducted a top-down data-centric analysis focused on the past behaviour of medicine consumption by the hospitals. As our data is time dependent, we performed time series analysis to describe it and time series methods to build the models and generate forecasts. To be able to achieve satisfactory results we used linear regression models with SARIMA errors. This way, we were able to use the time correlations existent in the data to predict seasonality, as well as demographic variables and indicators of use of health services in order to forecast the trend.

In order to build the models, we grouped the hospitals by NUTS II regions (North, Centre, Lisbon, Alentejo and Algarve) and modelled each group independently. This way, we were able to take advantage of the fact that most of our explanatory variables were segmented by region. Given the different frequencies of the variables used, quarterly for the explanatory variables and monthly for the drug expenditure, we applied two different modelling approaches. Thus, we achieved two models of different frequencies which fulfill our main goal of describing and predicting drug expenditure in Portuguese public hospitals in a very satisfactory way.

The R language [7] was used to analyse the data and to build the models and forecasts. The packages used were forecast [8, 9], tseries [10] and astsa [11].

A graphical interface was also developed in Shiny [12] with the purpose of allowing its users to visually explore the data and to easily forecast future expense with medicines. The simplified and interactive user experience of the interface gives Infarmed the chance to be involved in the analysis of the observed data and forecasts without having to perform the statistical modelling nor to be proficient in the R software.

Thus, in the coming years, it is expected that the work developed in this paper will contribute to support decisions on the necessary budget for medicine expenditure in Portuguese public hospitals, consequently allowing for a better allocation of resources within the SNS.
2. Sample and Models

2.1. Sample

Infarmed assigns a National Hospital Drug Code (CHNM) to all medicines with a national marketing authorisation or with a special authorisation for use in hospitals. The data on medicine expenditure provided by Infarmed for this study consist of monthly observations of the consumption of 4,795 different CHNM drugs by each of the 47 Portuguese public hospitals between January 2010 and March 2016.

In addition to the data on drug expenditure, we also used the following time series data to build our models: population; number of patients hospitalised; number of emergency calls; number of partial hospitalisations; Portuguese gross domestic product (GDP). These data sets start in January 2011, have quarterly frequency and all, with the exception of GDP, are segmented by NUTS II regions.

The data used in this study was provided by Infarmed, except for the data sets on population and GDP, which are available in the online database of the Portuguese National Statistics Institute (INE).

2.2. Methodology

A time series is a set of observations \( \{y_1, y_2, \ldots \} \), each recorded at a specific time instant: \( y_1 \) is the observed value recorded at the starting instance, \( y_2 \) is the observed value at the second instant and so on. In order to account for the unpredictable nature of future observations, we can consider each observation \( y_t \) to be the realisation of a given random variable \( Y_t \).

A time series model for the observed data \( \{y_t\} \) is a specification of the joint distributions of a sequence of random variables \( \{Y_t\} \) of which \( \{y_t\} \) is postulated to be a realisation.

We chose to model each NUTS II region separately, so that the model that describes the total drug expenditure in Portuguese public hospitals is the sum of the models obtained for each region.

Two of the most commonly used types of time series models are ARIMA and seasonal ARIMA (also known as SARIMA) models [13]. ARIMA models are applied where data show evidence of non-stationarity, where an initial differencing step can be applied to reduce the non-stationarity. The AR (autoregressive) part of ARIMA indicates that the variable of interest is regressed on its own lagged values. The MA (moving average) part indicates that the regression error is a linear combination of error terms at various times in the past. The I (integrated) indicates that the data values have been replaced with the difference between their values and the previous values. The purpose of each of these features is to make the model fit the data as well as possible.

Non-seasonal ARIMA models are generally denoted ARIMA\((p, d, q)\) where parameters \( p, d, \) and \( q \) are non-negative integers, \( p \) is the order (number of time lags) of the autoregressive model, \( d \) is the degree of differencing (the number of times the data have had past values subtracted), and \( q \) is the order of the moving-average model. Seasonal ARIMA models are usually denoted SARIMA\((p, d, q)(P, D, Q)_m\), where \( m \) refers to the number of periods in each season, and \( P, D, Q \) refer to the autoregressive, differencing, and moving average terms for the seasonal part of the ARIMA model.

At first, we tried to model the drug expenditure in each NUTS II region using only SARIMA models. Despite being able to adequately model the seasonal behaviour of each series, all models were unable to forecast correctly the positive trend recorded between 2015 and 2016.

Therefore, it was necessary to include additional information (population, GDP and indicators of use of health services) which could be used to help predict if the spending with medicines was going to increase or decrease with time.

Thus, we followed a top-down approach, focused on the different geographic regions and considering the impact of demographic, macroeconomic and also health service utilisation indicators. In order to be able to use such information we used linear regression models with SARIMA errors:

Let \( \{Y_t : t \in \mathbb{Z}\} \) be a time series,
\{X_{1t}, \ldots, X_{kt} : t \in \mathbb{Z}\} be the set of time series we want to use to describe \{Y_t\} and \{N_t\} \sim SARIMA(p,d,q)(P,D,Q)_m. Then a linear regression model with SARIMA errors of \{Y_t\} with \{X_{1t}, \ldots, X_{kt}\} is,

\[
Y_t = \beta_0 + \beta_1 X_{1t} + \ldots + \beta_k X_{kt} + N_t, \quad t \in \mathbb{Z} \quad (1)
\]

A requirement for the use of a linear regression model with SARIMA errors is that all time series involved have the same frequency. Thus, we have two different possible approaches: either we aggregate the monthly drug expenditure series in order to obtain quarterly ones, or we can estimate monthly explanatory time series to obtain monthly explanatory time series. From these two approaches, we were able to build two different models to describe and forecast the total drug expenditure in Portuguese public hospitals. These models, \{D_{Portugal,t}^1\} (quarterly) and \{D_{Portugal,t}^2\} (monthly), are as follows:

\[
\hat{D}_{Portugal,t} = D_{North,t}^F + \hat{D}_{Centre,t}^F + \hat{D}_{Lisbon,t}^F + \hat{D}_{Alentejo,t}^F + \hat{D}_{Algarve,t}^F
\]

where \(F \in \{4, 12\}\) is the frequency of the model, \(D_{Portugal,t}^F\) is the estimate of the total drug expenditure in Portugal at instance \(t\), and \(D_{R,t}^F\) is the estimate of the total drug expenditure in region \(R\), \(R \in \{\text{North}, \text{Center}, \text{Lisbon}, \text{Alentejo}, \text{Algarve}\}\), at instance \(t\). Such that,

\[
\hat{D}_{R,t}^F = \beta_0^R + \beta_1^R X_{R1,t} - F + \beta_2^R X_{R2,t} - F + \beta_3^R X_{R3,t} - F + \beta_4^R X_{R4,t} - F + \beta_5^R X_{R5,t} - F + \hat{N}_t \quad (3)
\]

where \(\{X_{R1}\}\) is the time series of the number of emergency calls in region \(R\), \(\{X_{R2}\}\) is the time series of the number of hospitalisations in region \(R\), \(\{X_{R3}\}\) is the time series of the number of partial hospitalisations in region \(R\), \(\{X_{R4}\}\) is the time series of the population of region \(R\), \(\{X_{R5}\}\) is the time series of the rate of change of the Portuguese GDP, and \(\{N_t\}\) \sim SARIMA\((p,d,q)(P,D,Q)\) are the residuals of the linear regression.

Once the parameters of the model are estimated, we move on to a control phase where we want to check its fit to the data. In order to test if the model is well adjusted, we analyse its residuals: if the model is suitable to describe the time series under study, then the residuals should be white noise. A white noise process is a random process of random variables that are uncorrelated, have mean zero, and a finite variance. We used the Ljung-Box test [14] on the time series of the residuals to test this hypothesis.

### 2.3. Performance Metrics

When we have several models that pass the control phase and correctly describe the series under study, it is necessary to have a criterion to choose which of these models is the most appropriate. We used two criteria to decide between models, the corrected Akaike information criterion (AICc) [15] and the quality of the forecasts of each model which is given by the following error metrics:

- **Mean Percentage Error (MPE):**

  \[
  \text{MPE} = \frac{1}{n} \sum_{t=1}^{n} \frac{A_t - F_t}{A_t} \times 100 \% \quad (4)
  \]

  where \(n\) is the number of observations, \(A_t\) is the observed value at time \(t\) and \(F_t\) is the forecasted value also at time \(t\).

- **Mean Absolute Percentage Error (MAPE):**

  \[
  \text{MAPE} = \frac{1}{n} \sum_{t=1}^{n} \left| \frac{A_t - F_t}{A_t} \right| \times 100 \% \quad (5)
  \]

  where \(n\) is the number of observations, \(A_t\) is the observed value at time \(t\) and \(F_t\) is the forecasted value also at time \(t\).

- **Median Absolute Percentage Error (MedianAPE).**

This metric is given by the median of the absolute percentage errors (APE) calculated at each forecasted instant \(t\).

\[
\text{APE}(t) = \left| \frac{A_t - F_t}{A_t} \right| \times 100 \% \quad (6)
\]

where \(A_t\) is the observed value at time \(t\) and \(F_t\) is the forecasted value also at time \(t\).
3. Data Analysis and Treatment

3.1. Drug Expenditure

The total drug expenditure on Portuguese public hospitals started increasing since April 2015. This drastic growth is partly explained by an increased spending in medicines prescribed for the treatment of hepatitis C.

This situation is a consequence of the decision by the Ministry of Health to subsidise 100% of the cost of Sovaldi (Sofosbuvir) and Harvoni (sofosbuvir and ledipasvir) medicines. This action was taken in February 2015, initiating a new national strategy for the treatment of hepatitis C. Since the data on spending this type of medicines is strictly confidential, it is not possible to present in this paper the original series of drug expenditure nor how much the it increased as a consequence of the new treatments.

The high cost of these medicines had a noticeable impact on recorded expenditure. However, due to the high success rate of these treatments, about 95% of all patients undergoing treatment in the year 2015 have been cured [16], the tendency is for hepatitis C patients to be cured and the demand for these drugs to consequently decrease.

In order to adequately model the spending with hepatitis C drugs, it would be necessary to use data on the number of infected, cured, and treated patients. Given the unavailability of this data and the temporary nature of this situation, the modeling of this time series was not performed and the expenditure with these drugs was removed from the analysis. The resulting time series of drug expenditure on Portuguese public hospitals is presented on Figure 1.

Following this procedure, a more detailed study of the resulting series was performed. From the analysis of the drug expenditure time series for each of the 47 hospitals, we were able to identify hospitals which reported extremely low expenses for the months of October, November and/or December.

This situation is explained by the annual agreements between the Ministry of Health and the Portuguese Association of the Pharmaceutical Industry (APIFARMA), which started in May 2012. These agreements aim to contribute to the sustainability of the SNS and establish an annual target for public drug expenses (both in hospital and ambulatory). The pharmaceutical industry agrees to make a financial contribution to the Portuguese state in order to help achieve this goal. This financial contribution takes the form of credit notes that are given by pharmaceutical companies to public hospitals, which use these credit notes when purchasing medicines.

Some hospitals (19 out of 47) reflect the value of the annual credit notes only in the expenses of the last months of the year, this leads to unrealistic low values for the spending in these months to be reported.

Algorithm 1 Treatment of anomalous credit note observations for hospital H.

1: \( \{x_t : t = 1, ..., n\} \leftarrow \text{Drug expenditure time series for hospital } H \).
2: \( \{\epsilon_t : t = 1, ..., n\} \leftarrow \text{residual time series of } \{x_t\} \).
3: \( IQR \leftarrow \text{Interquartile distance of series } \{\epsilon_t\} \).
4: \text{for } t > \text{June de 2012 do}
5: \quad \text{score } \leftarrow x_t - (Q_1 - 2 \times IQR), \text{ where } Q_1 \text{ is the first quartil of the distribution of } \{\epsilon_t\}.
6: \quad \text{if score } < 0 \text{ then}
7: \quad \quad x_t \leftarrow NA^* \text{ }
8: \quad \text{Missing values of } \{x_t : t = 1, ..., n\} \text{ are imputed using linear interpolation.}

*NA represents missing values

Since there is no accessible record of when
each hospital uses a credit note or of its respective value, we used Algorithm 1 [17] to identify and treat these observations. The algorithm uses the interquartile distance of the residuals for identification and linear interpolation for imputation. Note that, given the nature of this problem, we are looking for observations whose observed value is unrealistically low.

After both the data from hepatitis C spending and from credit note anomalous observations had been processed, we proceeded to analyse the resulting time series of the total spending with medicines in Portuguese public hospitals.

![Figure 2: Trend in total drug expenditure in the SNS hospitals from January 2010 until March 2016.](image)

There was an increase in the total drug expenditure between January 2010 and March 2011 which was followed by a decreasing period until January 2014. Between February 2014 and March 2016 this trend reverses and there is a monotonous and significant growth, the maximum value is observed in March 2016 (see Figure 2).

The Lisbon region accounts for about half of total expenditure. Thus, the correct modeling and forecasting of this region is decisive to the quality of the final forecasts that we intend to obtain for Portugal. On the other hand, the Algarve and Alentejo regions combined account for less than 10% of the total drug expenditure.

4. Forecasting and Results

For modeling purposes, we defined the training set from January 2012 to March 2015 and the testing set from April 2015 to March 2016. This choice was determined by the need to predict the annual drug expenditure and by the fact that the data collection on the indicators of the use of health services started only on the first quarter of 2011.

It should be noted that the AICc criterion depends on the cardinality of the training set used to build the model, thus it cannot be used as a criterion for comparing monthly and quarterly models. In order to compare these models we used the error metrics presented in Section 2.3.

4.1. Forecasts

The forecast of the drug expenditure in Portuguese public hospitals made by the quarterly model \( \hat{D}_{Portugal,t} \) is close to the observed data (see Figure 3). The MAPE and the MedianAPE errors of the forecasts are 1.36% and 1.32%, respectively, which confirm the quality of the predictions.

![Figure 3: Quarterly forecast by \( \hat{D}_{Portugal,t} \) between April 2015 until March 2016.](image)

The monthly model \( \hat{D}_{Portugal,t} \) also obtains satisfactory predictions, with MAPE and MedianAPE of 2.67% and 2.01%, respectively. The model is able to accurately forecast the seasonal behaviour of the time series of the total drug expenditure in Portuguese public hospitals (see Figure 4). Even though the model estimates the existent upward trend, there is still a slight underestimation of the expense, as the MPE is 1.98%.

Table 1 presents a summary of the calculated error measures and the percentage of observed values outside the prediction intervals for the models built for the different NUTS II regions and for Portugal. The North and Lisbon regions obtained the best forecasts, while the models for the other regions obtained less satisfactory results.
Table 1: Summary calculated error metrics and percentage of observed values out of prediction intervals for each of the selected NUTS II models and resulting model for Portugal. In columns M we present results for monthly models and in columns Q we present the results for quarterly models.

<table>
<thead>
<tr>
<th>Region</th>
<th>MPE</th>
<th>MAPE</th>
<th>MedianAPE</th>
<th>Out of Bounds (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>M</td>
<td>Q</td>
<td>M</td>
<td>Q</td>
</tr>
<tr>
<td>Algarve</td>
<td>4.21</td>
<td>2.81</td>
<td>5.34</td>
<td>3.10</td>
</tr>
<tr>
<td>Alentejo</td>
<td>-0.89</td>
<td>-0.47</td>
<td>6.18</td>
<td>3.64</td>
</tr>
<tr>
<td>Lisbon</td>
<td>1.70</td>
<td>0.32</td>
<td>2.98</td>
<td>1.06</td>
</tr>
<tr>
<td>Centre</td>
<td>5.50</td>
<td>5.43</td>
<td>5.50</td>
<td>5.43</td>
</tr>
<tr>
<td>North</td>
<td>-0.04</td>
<td>0.21</td>
<td>2.86</td>
<td>1.37</td>
</tr>
<tr>
<td>Portugal</td>
<td>1.98</td>
<td>1.36</td>
<td>2.66</td>
<td>1.36</td>
</tr>
</tbody>
</table>

Figure 4: Monthly forecast by $\hat{D}_{12}^{\text{Portugal},t}$ between April 2015 until March 2016.

4.2. Results

The models for the regions where drug expenditure is larger (Lisbon and North), achieved better forecasts compared to other regions (see Table 1). A possible reason for this is that the Algarve, Alentejo and Centre regions, due to their smaller size, are more susceptible to changes in the macroeconomic situation and the impact of other external factors. Both models for Portugal achieve very satisfactory results. Since the quarterly model obtains more accurate forecasts, it is indicated for long-term forecasts. However the model $\{\hat{D}_{12}^{\text{Portugal},t}\}$ is able to produce forecasts with monthly granularity, thus it is great for a more detailed view of the drug expenditure and its respective seasonal behaviour throughout the year.

It is essential that the models are also able to provide accurate total annual estimates for medicine expenditure, as it is necessary for Infarmed in order to prepare budgets and do a proper allocation of resources. Both models underestimate the observed total drug expenditure between April 2015 and March 2016: the quarterly model by 1.36% and the monthly model by 2.04%. All in all, both models were able to perform good forecasts of annual expenditure and were able to foresee the observed drastic increase in expense. In both cases the observed value of total annual drug expenditure is within the prediction intervals at 85% (see Figure 5).

The size of the training set used for the modeling process was a factor that negatively conditioned the quality of the resulting models $\{\hat{D}_{4}^{\text{Portugal},t}\}$ and $\{\hat{D}_{12}^{\text{Portugal},t}\}$. We used only 13 and 39 observations of drug expenditure to train the quarterly and monthly models, respectively (76.5% of the observations). The fact that the last observation in the training set is of March 2015 implies that the models do not have sufficient data to learn the significant positive trend.

Therefore, despite the positive results obtained by the models $\{\hat{D}_{4}^{\text{Portugal},t}\}$ and $\{\hat{D}_{12}^{\text{Portugal},t}\}$, we decided to verify the impact of increasing the size of the training set. Thus, we replicated the modeling and forecasting methodology using data from January 2012 to September 2015 as the training set, and forecasting the period from October 2015 to March 2016. As expected, there is a significant improvement in the quality of the forecasts: the forecast have an MAPE of only 0.83% and the MPE of 0.81% for the quarterly model; for the monthly model, the forecasts have MAPE and MPE of 0.99% and 0.95%, respectively.

Although the models $\{\hat{D}_{4}^{\text{Portugal},t}\}$ and $\{\hat{D}_{12}^{\text{Portugal},t}\}$ achieved quite satisfactory results, we are confident that in the future, with the possibility of using more data to update the model, the forecasts will become even closer to the observed values.
5. Graphical Interface

In order to simplify the future use of the developed model, an interactive tool was developed in Shiny [12] in order to allow its users to (i) explore and visualise all aspects of the drug expenditure data and (ii) add more recent data on the medicine expense and the on the explanatory variables to be able to generate new forecasts.

The application has great advantages since it allows a faster, adjustable and clear analysis of the data through interactive visualisations. The user of the application can use the Visualisation Dashboard to explore the data on the time series of the drug expenditure in Portugal and in each of the NUTS II regions. (see Figure 6).

The forecasting process is made easier through a simplified interface. The Forecast Dashboard allows users with little to none experience in the R language or detailed knowledge about linear regression models with SARIMA errors to forecast future expense with medicines (see Figure 7). This allows Infarmed to be involved in the interpretation and exploration of the forecasts without having to perform the statistical modeling nor to be proficient in the statistical software R.

The existence of these models and of the interactive application allow Infarmed to easily estimate future drug spending in Portuguese public hospitals. Consequently, this will lead to a better allocation of resources when setting budgets. New data will be used to updated estimations of the parameters of the proposed models and their forecasts. However, the adjustment of the updated models should be monitored as transformations in the usual behaviour of the time series of the drug expenditure will require refitting of the proposed models to the new data.

Since the application uses confidential data from Infarmed, it is not available for use by the general public. However, the concept of the application can be easily adapted to help solve similar forecasting problems, and a more general version can be distributed online.

6. Conclusions

The main goal of the study presented in this paper was the model and forecast the total drug expenditure in public hospitals in mainland Portugal. This work was proposed by Infarmed with the intention of being able to use statistical forecasts to support decision-making when setting budgets for allocation of resources. Thus, the achievements of this study will contribute to a greater cost efficiency in SNS expenditure.

A descriptive analysis of drug expenditure data in public hospitals in mainland Portugal between January 2010 and March 2016 led to the identification of two situations which required additional investigation. First, the impact on medicine expenses of new innovative treatments for the hepatitis C virus. Secondly, the consequences of the annual agreements between APIFARMA and the Ministry of Health.

After the data was carefully analysed and
treated, we used linear regression models with SARIMA errors. The data was grouped by the different NUTS II regions which were modeled separately. In the end, we obtained two different models for the total medicine expense in Portuguese public hospitals which adequately fit our data and provide very satisfactory forecasts.

In order to ease the future use of the developed models, an interactive tool was created to allow its users to explore and visualise the drug expenditure data and to generate new forecasts.

As new data on drug expenditure, health services utilisation and demographic indicators continues to be collected, it will be possible to feed the model with more information. Thus, the model will be able to fit better to the data and generate more accurate forecasts. However, if the time series change drastically, it could be necessary to re-fit the model. This way, a continuous monitoring of the data is both recommended and required.
6.1. Future Work

In the future, it would be interesting to consider modeling drug spending in SNS hospitals using a bottom-up approach, by separately modeling the different therapeutic groups and taking into account the effect of the introduction of new drugs, patent expiration and also the impact of new generic medicines. This way, by complementing the methodology developed by [3] with a careful quantitative analysis of past trends, we believe that a better and more general model can be obtained, where each partial model is better adjusted to each therapeutic area.

However, it should be emphasised that for the development of this study it would be necessary not only to collect data on the various explanatory variables for each therapeutic area, but also reports by pharmaceutical experts. These reports would allow to estimate the impact of the changes on the pharmaceutical market.

References


