Estimating costs of the specialist-medical care in the Netherlands: Using known fractions

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Abstract

This study aims to estimate the total expenditures made by 'Diagnosis Treatment Combinations' (DBC) in the specialist-medical care in the Netherlands. As DBC's take time to be registered, financial information is often only known after more than a year. By investigating the DBC-duration and the registration duration, it is assessed whether data from the current year can be compared to the previous years. Data from the DBC-informationsystem as available at the NZa were used. Two models were made. The first model uses the 'known fraction' (KF), the amount of costs known after a certain number of months to predict the total costs. The second model uses the return rate, the number of patients for whom a similar DBC is opened yearly, of chronic DBC's to predict costs.

The research showed that the first model does not provide good predictions, as the KF is varying largely over time. The second model cannot be generalized from chronic diseases to the total costs as the KF's are dissimilar. The large resulting prediction errors show it is very difficult to provide a good prediction from data already known about the last year.

Introduction

Both policymakers and scholars are greatly interested in predicting health care costs. Emphasis is put on long run predictions, forecasting expenditures to be made in 10, 30 or even 50 years - a research area that is especially fueled by the for the aging populations of mainly the Western world. Less emphasis has been put on short run predictions, and even less on predicting last year's expenditures. Even though the latter research topic seems paradoxical, last year's healthcare costs are never fully known. Due to delays in registration of costs, up-to-date financial information is often missing.

Since patients, health care institutions, insurers and policy makers all require complete and up-to-date financial information, the current minister of healthcare of the Netherlands, E. Schippers, has marked the better provision of information in the health care system as one of her priorities for the coming years (Schippers, 2013).

Schippers (2013) gives several reasons for the importance of financial information. For instance, patients do not know the costs of their treatment until long after the treatment has been concluded. Furthermore, insurers and health care institution have to base their price negotiations on recent financial information and policy makers need information to present and be accountable for their results and possibly adjust the policies in place.

Schippers (2013) has installed a task force whose main focus is to speed up the provision of information and to develop a monitoring system for expenditures for the current year, by an early warning system.

The uncertainty around the healthcare expenditures in the Netherlands is strongly connected to the financing system in place. Between 2005 and 2011, the financing of specialist-medical care was organized around "Diagnosis Treatment Combinations" (abbreviated DBC, from Dutch: "Diagnose Behandel Combinatie"). DBC-onderhoud (2013) describes a DBC as "a package of healthcare with all the information concerning the treatment that a patient gets for a particular condition. A DBC comprises all the steps required to establish a particular diagnosis for a patient followed by treatment, from the first outpatient visit, up to the last check" (free translation).

Every type of DBC has a fixed price. Therefore, not every action or treatment is paid separately. Some are standardized nationally, the so-called ‘A-segment’; others are negotiable between insurers and hospitals, the so-called ‘B-segment’ (DBC-onderhoud, 2013).

When a patient arrives at the hospital, a DBC is opened. When all treatment is finished, or the maximum duration of 1 year has passed, the DBC can be closed. After a DBC is opened, the diagnosis belonging to the DBC can be changed or extra costs can be made. Therefore, Schippers (2013) states that the total costs can only be determined after closing the DBC. When the DBC is closed, the DBC has to be sent to the insurers and the government to be registered and paid. The delivery from the hospital to the insurer is allowed to take up to 5 years after which payment should happen within a month. Costs are usually determined by year of opening of the DBC’s (Schippers, 2013). However, the DBC’s are observe in the DIS database when the healthcare institution sent the DBC to the insurer. Therefore, it can take up to 6 years after opening before a DBC is registered, which results in incomplete financial information about the current year.

In 2012, the DBC system was modified into the “DBC towards transparency” system (abbreviated DOT, from Dutch: “DBC op weg naar transparantie”). The DOT system includes fewer categories. 30.000 DBC’s were replaced by 4.400 DOT products (DBC-onderhoud, 2013).

The minister of healthcare has already started several changes that should lead to improved provision of information. The maximum duration of a DBC will be limited to a maximum 120 days instead of the current maximum of 1 year. Furthermore, greater insight into the contract between insurers and healthcare institutions is requested and reported by the Dutch Healthcare Authority (abbreviated NZa, from Dutch: ’Nationale Zorg Authoriteit’). Moreover, in order to gain insight into the work-in-progress, a work-in-progress indicator has been devised. This puts a price on the DBC in case it would be closed at that point in time (Schippers, 2013).

However, even if the attempts to speed up the provision of information and creating new sources of information succeed, it is difficult to have all information available within the required time. For instance, it is almost impossible to have all DBC’s opened in December 2011 registered and paid by January 2012. Therefore, it will still be necessary to improve the estimates for total costs made.

Currently, estimates are made by all insurers separately (Schippers, 2013). Schippers (2013) wants to investigate if it is possible to create a uniform estimation method and seeks ways in which estimates can be improved. Changes have already been made to create a work-in-progress indicator that makes the DBC that are open at the time more visible. Also the use of contract information, and the changes to speed up the general provision of information are expected to help improve the estimates.

This paper explores the possibility to estimate the total expenditures made in specialist medical care using DBC data that is already available. It is hypothesized that common patterns in registration time might help to predict total expenditures, which could help patients, insurers, policy makers and health care institutions.

Methods

Data

For this research the data on specialist medical care was used from the DBC-informationsystem 'DIS' as available at the NZa. This data set includes DBC's of the specialist-medical care, opened between 1 January 2005 and 1 January 2012, when the new DOT system started. The DIS receives the DBC declarations directly from the healthcare institutions and the NZa receives monthly updates from the DIS. For this research data available at the NZa last updated halfway June 2013 was used. However, earlier research from Prismant (2010) and the NZa (2012) has shown that DIS does not contain complete or correct information for all hospitals. This is partly due to hospitals directly sending their declarations to the DIS, parallel to sending the declarations to the insurers. However, not all declarations are paid by the insurer. Therefore, the DIS data often slightly overestimates the costs made. Also, van den Berg (2010) heavily criticizes using the DIS data for research purposes. He states that the registered DBC often does not correspond to the true treatment receives by the patient. Moreover, it should be noted that the system was put in place in 2005. Therefore the first 2 years are considered relatively unreliable. DBC's starting in 2005 and 2006 are therefore excluded from the analysis.

Every DBC in the data base has a unique code. There is a code for the type of DBC, so which diagnosis and treatment was given. Furthermore, there is information on the hospital, the opening date, the closing date and the registration date. In addition, there is patient information, including the age and gender, postcode, and a pseudo-personal number.

Volume

The volume is computed by counting all DBC's. The volume in month m is given by all DBC's opened in month m. However, in 2007 there was a different policy regarding DBC's from the emergency department (abbreviated: SEH, from Dutch: 'Spoedeisende Hulp'). According to NZa (personal communication, March 14, 2011), before 2008, a DBC was opened when a patient entered the emergency department. When extra treatment was needed, a normal DBC would be opened. This leads to double registration. Following NZa (personal communication, March 14, 2011), these double SEH registrations are taken out for 2007 to make the volume better comparable to the later years.

Price

The prices used for a DBC depend on whether the DBC falls in the A-segment or the B-segment. The A-segment DBC's have nationally regulated prices, determined by the NZa. The prices of the B-segment DBC's are negotiable between insurers and hospitals. Both prices are renewed yearly.

There are several inconsistencies when looking at prices. A price can be missing or the same DBC has different prices. The price for a B-segment DBC can be different per insurer or hospital, but for A-segment DBC's they should be the same. Therefore, per year, the median national (for A-segment DBC's) and contract (B-segment DBC's) is take, as suggested by the NZa (2012). This gives a single price per DBC per year.

Costs

From the volume and price, costs per month are computed. The volume of a DBC per month is multiplied by the median price of that year of the corresponding DBC. Therefore, the costs of month m are the costs of the DBC's opened in month m. However, when computing the volume, double SEH DBC's were deleted. For price, these DBC's are left in, as costs are not counted double.

Pseudo-BSN and patient code

Identification of an individual is possible by either a pseudo-BSN or a hospital based patient code. The pseudo-BSN is an anonymization of BSN, the Dutch official personal number, as also stated on a passport. The problem with relying on pseudo-BSN is the large amount of missing values. In 2007 pseudo-BSN is almost completely missing and the amount of missing values decreases over 2008 to less than 20% at the start of 2009.

The patient code available is hospital based. It is therefore only unique when combined with hospital codes. The patient code is much more frequently available before 2009. Therefore, the patient code will be used instead of the pseudo-BSN.

Opening, closing and registering

Next to volume and costs, the most important variables are date of opening, date of closing and date of registering. The opening indicates the moment the patient first arrived at the hospital. The closing date indicates the day treatment was concluded and the registering date indicates the moment the DBC was declared by the hospital and specifically the day the DBC was observable in the DIS database. From these, it is possible to compute 2 important durations. The DBC duration is the time the DBC was open, so the $closingdate - openingdate$ and the registering duration, the time it took the DBC to become visible at the DIS after closing , so the $registeringdate - closingdate$.

Models

Model 1

This paper investigates the possibilities to predict the total costs made in year t by the end of year t. The problem is that only a part of the costs is known due to a lag in registration. On average, about 60% of the total expenditures is known about year t at the end of the year. Clearly, a larger part of the expenditures will be known about January than of November and December, as more time has past in which it was possible to register the DBC. The percentage that is known in a certain year depends on the registration speed. If this lag in registration speed is constant, it is still possible to predict the total expenditures from it. For instance, assume that it can be observed that in the previous years by December 75% of the costs made in the month July were known. The current December costs of 75 euro made in July are observed. The total costs can then be estimated as 100 euro, by putting €75 $\cdot \frac{1}{0.75}$. The general equation than becomes:

$$\hat{C}_m = C_{m,n} \cdot \frac{1}{\hat{k}_{m,n}}$$

Here $\hat{C}_m$ are the predicted costs in month m, where m is the amount of months after December 2006. So January 2007 gives $m = 1$, up to December 2011, which gives $m = 60$. $C_{m,n}$ are the costs in month m, as observed - thus already registered - in month n. $\hat{k}_{m,n}$ is the predicted 'known fraction' (KF), the costs of month m as observed in month n, divided by the true costs made in month m.

The method described would work if the KF would be constant, and if it would be possible to observe the true KF in previous months. The last part is surely violated. As it can take 6 years to register a DBC, the total expenditures are only completely known after six years. Therefore, no fraction of total expenditures can be computed for months closed than 6 years in the past. Consequently, a slightly adjusted model is needed.

Two versions of the first model will be made. The first will rely on the median and the second on exponential smoothing. The median based prediction will work best if the KF stays constant over time. If the KF is not constant over time but follows a time trend, the median will be biased. Exponential smoothing weights a few previous observations, following the time trend better.

Both the median and exponential smoothing based predictions depend on the observations of the past periods. However, as already discussed, the KF of the previous years is not yet known. The true costs are only observed after 6 years, so it therefore the true KF. It is then possible to consider the true costs C_m as equal to $C_{m,m+72}$, the costs as observed after 72 months. However, only using 6 year old observations for estimating the current KF would be inefficient as it ignores a lot of available information. In order to use as much of the available information as possible, a KF can be decomposed. For instance if the KF of what is known in the same month is of interest, which can be represented as $\frac{C_{m,m}}{C_{m,m+72}}$, it can be decomposed into 71 separate KF's.

The first is $\frac{C_{m,m}}{C_{m,m+1}}$, what is known about month m in the same month compared to what is known 1 month later. The second part of the decomposition is $\frac{C_{m,m+1}}{C_{m,m+2}}$, what is known after 1 month compared to what is known after 2 months, up to $\frac{C_{m,m+71}}{C_{m,m+72}}$. Multiplying these cancels out all but $\frac{C_{m,m}}{C_{m,m+72}}$, the true KF for what is known about the current month.

When making an estimate for month m, there are $m-1$ observations from previous months for $\frac{C_{m,m}}{C_{m,m+1}}$. There are only $m-72$ observations available for $\frac{C_{m,m+71}}{C_{m,m+72}}$, which are also all further in the past.

Median

In order to perfectly estimate the KF in month m by the median in every period, the KF should be constant over time. The median will provide a close estimate if there is at least a central point around which the KF can randomly vary. If there is a non-random time trend in the KF, the median will provide a biased estimate.

From the decomposition method, there are 72 data series. The median based prediction will take the median of all individual decomposed KF's. So

$$
\begin{aligned}
\hat{k}_{m,m+60} &= median(\frac{C_{1,1}}{C_{1,2}}, \frac{C_{2,2}}{C_{2,3}}, \ldots, \frac{C_{m-1,m-1}}{C_{m-1,m}}) \\
&\times \; median(\frac{C_{1,2}}{C_{1,3}}, \frac{C_{2,3}}{C_{2,4}}, \ldots, \frac{C_{m-2,m-1}}{C_{m-2,m}}) \\
&\ldots \\
&\times \; median(\frac{C_{1,70}}{C_{1,71}}, \frac{C_{2,719}}{C_{2,72}}, \ldots, \frac{C_{m-70,m-1}}{C_{m-70,m}}) \\
&\times \; median(\frac{C_{1,71}}{C_{1,72}}, \frac{C_{2,72}}{C_{2,73}}, \ldots, \frac{C_{m-71,m-1}}{C_{m-71,m}})
\end{aligned}
$$

If $m \leq 72$, not all steps can be computed and will be set to 1.

Exponential Smoothing

A similar method is used for the exponential smoothing based prediction. The median function is replaced by a simple exponential smoothing model. This is obtained by using the Holt-Winters function in the forecast package in R, with the gamma and beta parameter set as false. This leaves the equation:

$$s_t = \alpha \cdot x_{t-1} + (1 - \alpha) \cdot s_{t-1}$$

Here x_{t-1} is the KF in the previous month. s_t is then a weighted function of the KF in the previous months and $s_0 = x_0$, and α is the smoothing factor, the attached weights to previous months, between 0 and 1.

This method will be unbiased the KF in month m is equal to last month's KF, or at least depends on it in a similar way as previous months. This allows better for a changing KF over time, but is less robust in case of outliers. Including the decomposition then results in the following equations:

$$\hat{k}_{m,m+72} = \hat{k}_{m,m+1} \cdot \hat{k}_{m+1,m+2} \cdot \ldots \cdot \hat{k}_{m+71,m+72}$$

where

$$\hat{k}_{m+c-1,m+c} = \alpha \cdot \frac{C_{m-c,m-1}}{C_{m-c,m}} + (1 - \alpha) \cdot \hat{k}_{m+c-2,m+c-1}$$

α is optimized based on data in the previous months.

So, for each decomposed KF data series, a forecast is made for the KF of the next month. From these forecasts, the total KF is computed.

Weights

Another improvement might be the attachment of weights. The model as discussed so far estimates costs per month. However, often costs are aggregated over a year. When estimating the costs of last year, more information will be known about the early months compared to the later months, which usually results in a more precise estimate. Under the assumption that all months have equal costs - so that there would be no seasonality - putting higher weights on the more precise estimates would improve the estimate for the entire year.

The weighting method used will be population weighting. This method assigns weights to months based on the amount of observations or costs. The weight of month m in year t is equal to the costs in month m divided by the costs of the whole year. However, this decreases the total level of costs, and therefore adjustment is needed by the mean of the weights. Combined, this leads to the weights: $w_{m,t} = \frac{o_{m,t}}{\sum_{s=1}^{12} o_{s,t}} \cdot \frac{1}{\frac{1}{12}\sum_{n=1}^{12} \frac{o_{n,t}}{\sum_{s=1}^{12} o_{s,t}}}$, where $w_{t,m}$ is the weight of month m in year t and $o_{t,m}$ is the number of observations in month m of year t.

Not all months will have the same cost level, meaning the weighting introduces bias. As yearly costs are taken, all months are included once, so the bias will be smaller. It is possible to partially adjust by regressing the costs on a month dummies, which means the weights are slightly adjusted.

In general, the models now created to estimate the total costs for last year can be written as of the form:

$$C(m) = O(m)^{\top} \cdot \hat{K}(m,n) \cdot W(m)$$

where $C(m)$ is a scalar indicating the total costs from month $m-11$ to m. $O(m)$ is a 12×1 vector containing the costs of month $m-11$ to m, as observed in month m. $\hat{K}(m,n)$ is a 12×12 diagonal matrix, containing the estimates for the known fraction for month $m-11$ to m vertically, and the lag $m-n$ running from 11 to 0 horizontally. $W(m)$ is a 12×1 vector, containing the weights attached to the months.

$\hat{K}(m,n)$ depends on the estimation method chosen, but generally is a function of $O(m,n)$, $m \geq n$, a $m \times n$ lower triangular matrix containing the costs of month n as observed in month m.

Instead of considering the total costs, costs can also be aggregated by hospital or DBC type. Because the model mainly depends on registration speed, a better prediction could be possible if certain hospitals register more constant than average. However, the costs made by the subset of hospitals or DBC's taken should follow a similar pattern as the total costs in order to generalize the prediction. A similar median- and exponential smoothing based prediction will also be made for a hospital subset. This method would require extra assumptions that the subset of hospitals continues to register more constant.

Model 2

The main assumption made in model 1 is that the fraction known is either constant or that there is clear time trend. This assumption might be violated. Therefore, another model not relying on this assumption will be formed.

The second model is based upon the following idea. There are certain chronic diseases that require the patient to return to the hospital every year. So, it is expected that the patients getting treatment in year t return in year $t+1$. Assume only half of these expected patients have been observed to return in $t+1$, then the estimate for the total fraction known of all DBC's is also half.

This method would rely on 2 different assumptions:

Assumption 2.1: There is a DBC with a constant return rate. So $c\%$ of patients that opened a DBC in t open the same DBC in $t+1$ for all t.

Assumption 2.2: The known fraction of this DBC with constant return rate is equal to the known fraction of all DBC's.

If assumption 2.1 would be violated, there is no expectation to be made for the known fraction of the DBC itself. If assumption 2.2 would be violated, the result is not generalizable to all DBC's combined.

Although the percentage c in assumption 1.1 does not necessarily have to be high, but only constant, the best results are likely to be found with chronic diseases. The probability that exactly after 1 year the same DBC is opened for a different DBC is very small. Three non-lethal chronic diseases where selected, namely rheumatic arthritis (RA), multiple sclerosis (MS) and chronic obstructive pulmonary disease (COPD). The RA volume is defined by counting the DBC's with specialism code 324 and combining DBC codes 210001010111, 210001010211, 210001010311 and 210001010411. The COPD volume is defined by specialism code 322 and DBC code 210012411011 and MS volume is defined by specialism code 330 and DBC code 210005310111. The fact that all DBC codes start with 21 indicates that they are continuation DBC's. This indicates that it is not the first DBC opened for a given patient for this diagnosis. A continuation DBC has to be opened as a DBC can only be open for 1 year. The advantage of the continuation DBC's for these chronic diseases is that therefore many of these DBC's are opened exactly 1 year after the last DBC was closed.

Results

Desciptives

Between 2007 and 2011 a total of 75.702.128 DBC's where opened. Of the DBC's opened, 1241 had a duration longer than 1 year. As this should not be possible, they will be excluded. In 2007 there were 976.175 SEH DBC's. For the price calculations they are left in, whereas for comparisons using volume, they are excluded. An additional 264.499 DBC were excluded as their registration date was before their closing date, which should not be possible.

Figure 1: Costs specialist-medical care

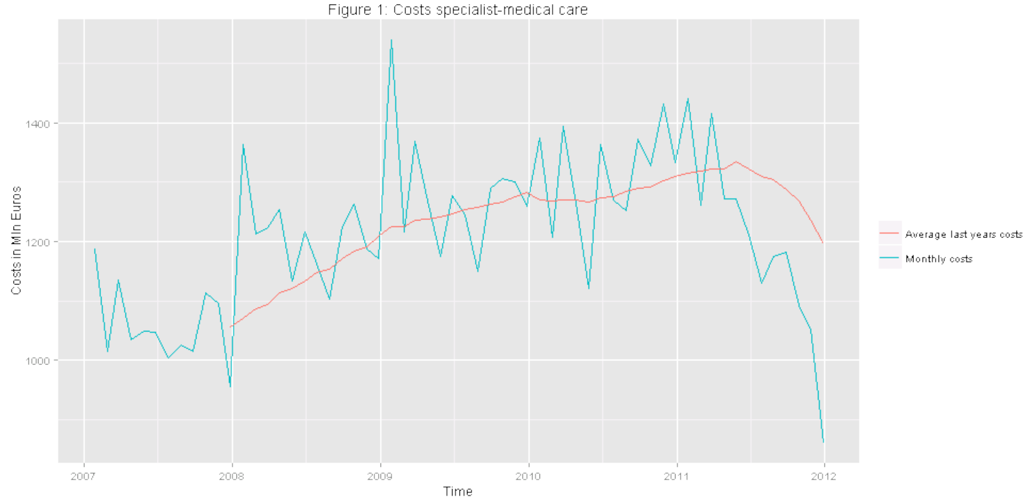


Figure 1 shows the development of the costs from the year 2005 to 2011, both monthly costs and the average costs of the last 12 months. The costs are slowly increasing over time.

The main goal is to estimate the expenditures made in the previous 12 months. As can be seen from figure 1, the average yearly costs much smoother than the monthly costs and should therefore be easier to estimate. Two large upward spikes can be observed in January 2008 and January 2009. In January 2008 the amount of B-segment DBC's, the DBC's with a negotiable price, was strongly increased. In January 2009 more A-segment DBC's were made into the B-segment DBC's. Figure 2 shows the cost development for the A- and B-segment separately. It is remarkable that the A-segment costs are still increasing in January 2008 and 2009, even though some A-segment DBC's are changes into B-segment DBC's. The most important aspect of the expansion of the B-segment, is that it is a policy change, and might therefore result in a discontinuity in other relevant and connected data series.

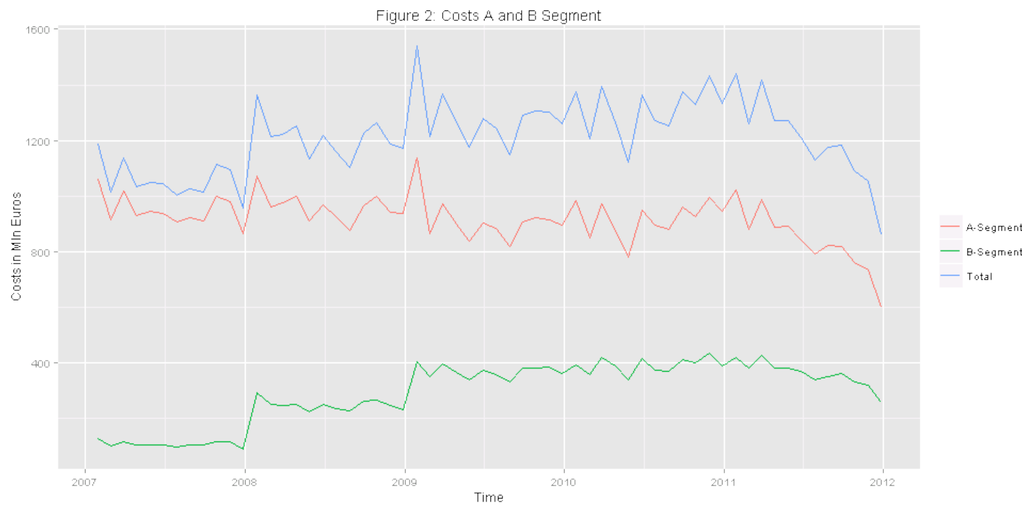


Figure 3 shows the development of monthly costs and volume indexed at January 2007. Costs are increasing faster than volume. This can be due to two effects. Firstly, it can signal price rises for the same DBC's, so inflation. Prices were not inflation adjusted. Secondly, it can signal that more expensive DBC's were chosen.

The choice for more expensive DBC's is part of the change from DBC's to DOT in 2012. The main difference when the system was changed was that there were fewer categories. In the DBC system, due to the large amount on DBC's, there was a large flexibility in choosing which DBC to claim for a patient. Hospitals then often chose the more expensive versions.

Furthermore, from figure 2, the introduction of the B-segment seems to have had a smaller impact on volume than on prices, because the increase in volume in 2008 and 2009 is lower than for costs. The cost rise compared to the volume rise is also much more than expected from regular price inflation, as there is an increase of over 10%.

Figure 3: Volume and Cost Development

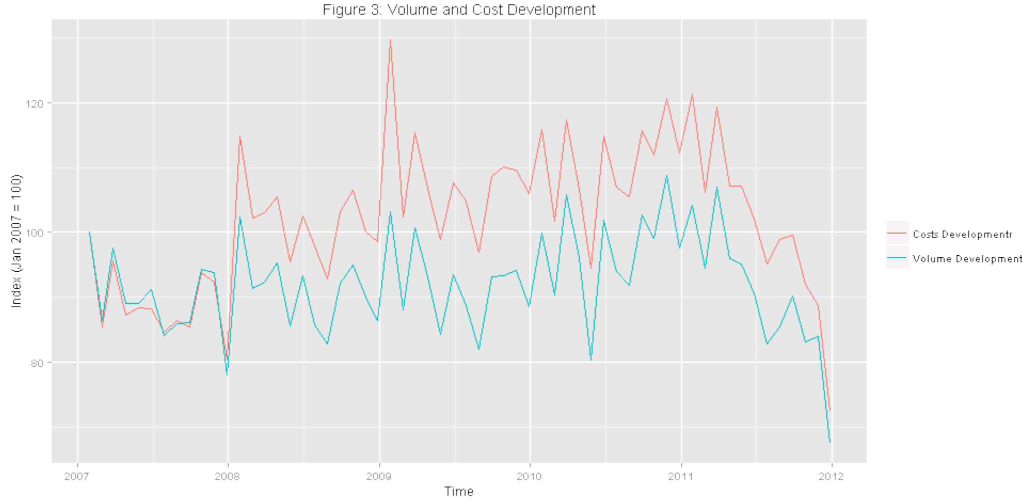


Figure 1, 2 and 3 are grouped by month of opening, according to the most used definitions of costs. This means that the costs of month m are defined as the costs of all DBC's opened in month m. Alternatively, they could be grouped by closing date or registering date, as shown in figure 4. It can be observed that costs are more variable when ordered by registering date. Furthermore, in June 2010, there were no DBC's registered at all.

Figure 4: Costs by opening, closing and registering date

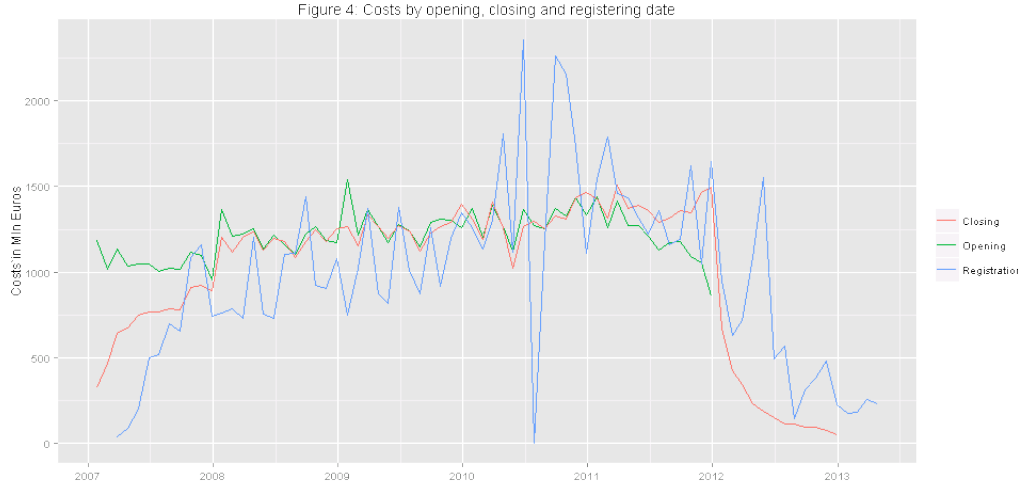
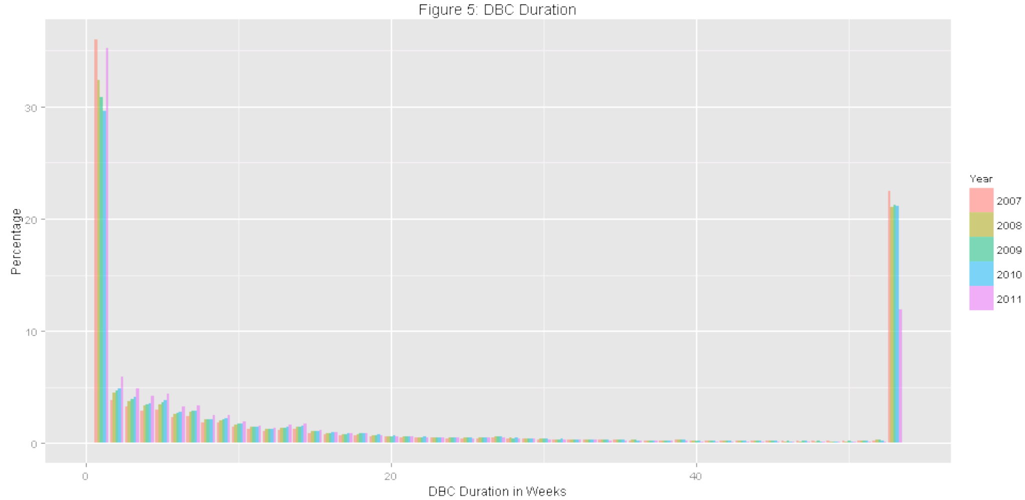


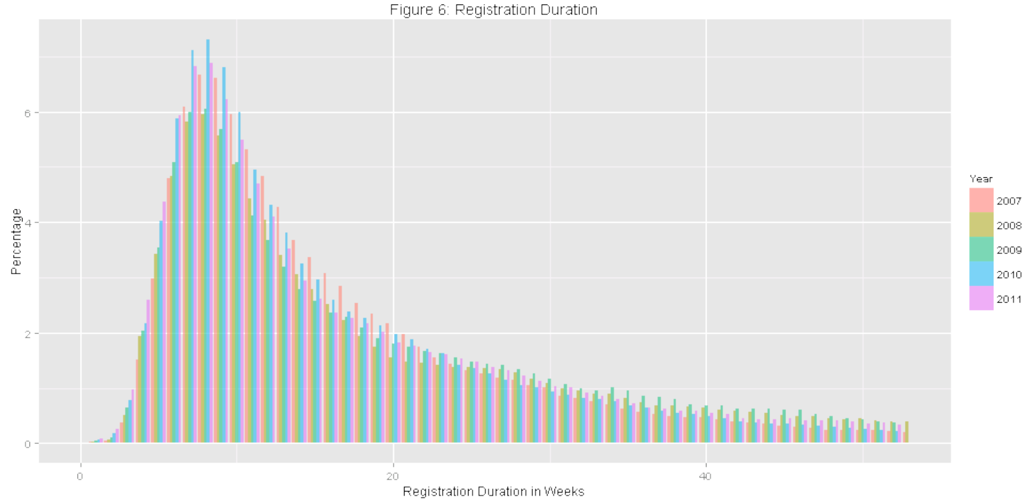
Figure 5 provides further insight in the DBC duration. The maximum DBC duration, from opening the DBC to closing the DBC, is 1 year. However, for all years, over 30% is already closed within a week. Another 20% is closed in the last week. There are differences over the years. DBC in 2011 have a shorter DBC duration, whereas a high percentage of DBC's in 2007 is either closed within a week or close to the end of the year. It is difficult to identify a general time trend, and therefore it is not possible to state that durations become shorter or longer over the years.

Figure 5: DBC Duration



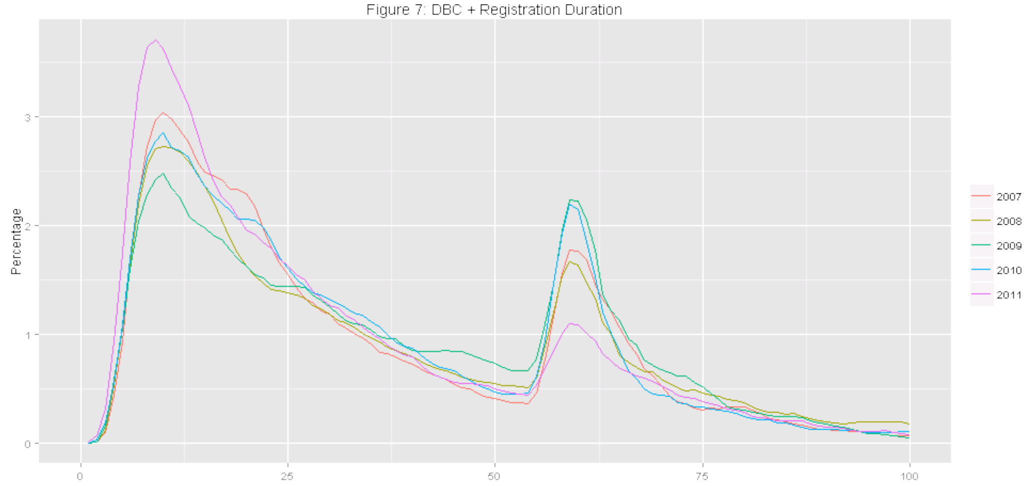
Next to the DBC duration, the registration duration is of importance. Figure 6 shows the registration duration. The mode is around 8 weeks. Registration might take up to five years, but very few DBC's are registered in the final years. Depending on the year, about 80 or 90 percent is registered within a year after closing.

Figure 6: Registration Duration



Combining the DBC duration and the registration duration results in figure 7. The DBC duration had a very bipolar nature, where most DBC's where either closed within a week or after a year of the opening date. This also leads to a bipolar graph of the combined DBC and registration duration. The DBC's opened in 2011 are now overrepresented in the earlier weeks, whereas DBC's opened in 2009 and 2010 are more often registered later after opening.

Figure 7: DBC + Registration Duration

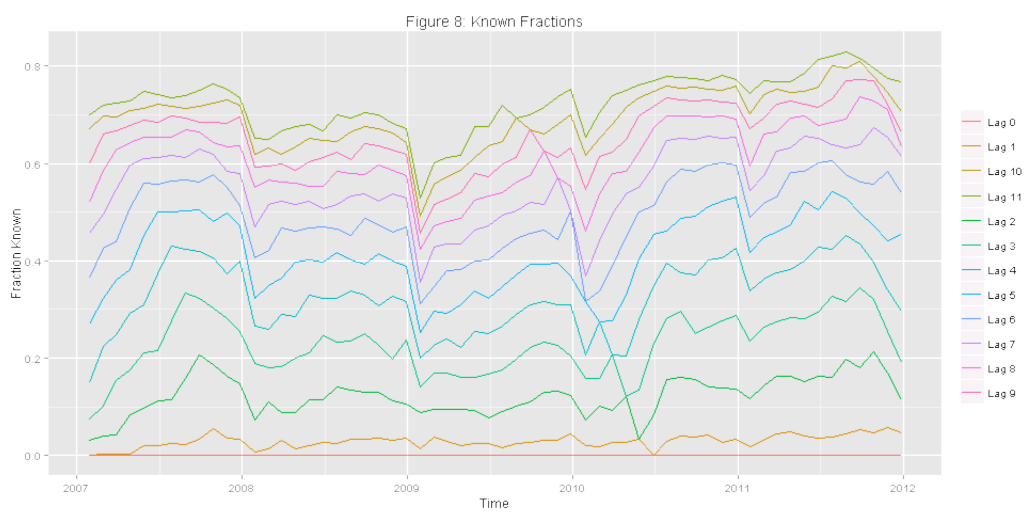


Models

Model 1

The first model involves estimating last year's costs using the known fraction (KF). If it is possible to predict the KF for the months of the current year, the total expenditures could be calculated by taking the estimated KF and multiplying this by the amount of already registered DBC's.

Figure 8 shows the KF over time and displays 12 lines. Each line indicates what fraction of the total costs was known after a certain amount of months. The line labeled as lag 0 indicates what fraction was known the same month. The line lag 11 indicates what fraction was known 11 months later. For instance, for December 2011, the value of Lag 11 indicates what fraction of the costs of January 2011 was known by the end of December 2011.



The known fraction is closely related to figure 7, the combined DBC and registration duration. However, as the highest lag displayed in figure 8 is that of 11 months back, only the part of figure 7 below 53 weeks is relevant. In figure 7, the first peak is highest for 2011 and lowest for 2009. This is also visible in figure 8, as more is known about 2011 after 1 year, about 80%. One problem here could be that 2011 is only higher as fewer years have passed since, only 1,5 years. To make the KF's better comparable, it is possible to compute the known fraction by taking what was known after 1,5 years as the total for all years. Doing this alters the graph for all periods, but only minimally. 2011 still has the highest KF.

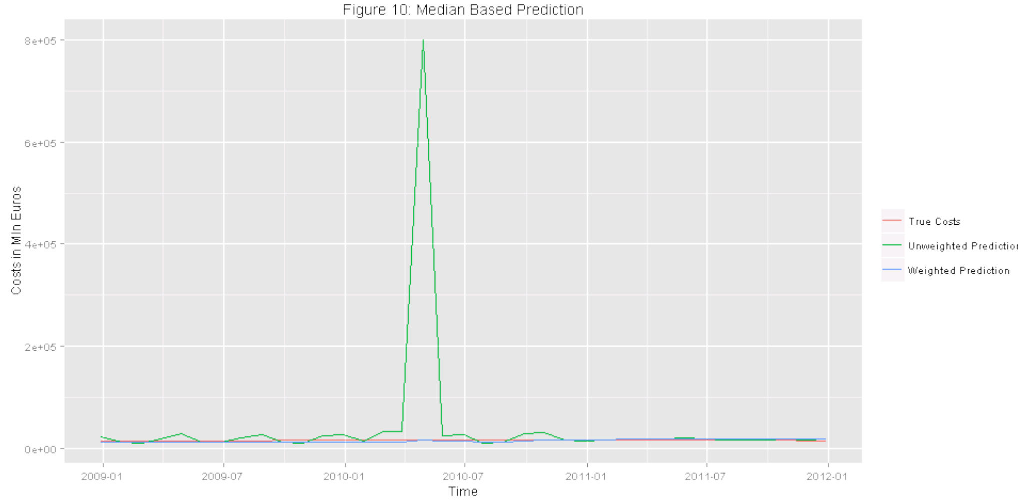
From figure 8, the main problem of model 1 can already be addresses. Is it possible to predict this year's KF's from previous years? The KF's are clearly not constant, nor is there a clear linear trend. There is however some seasonality. Drops in the KF can be found in January. The largest drops however occur in January 2008 and January 2009. These are also the months of the expansion of the B-segment, as seen in figure 2. This might give an indication that policy changes affect the registration speed, influencing prediction based on the registration speed.

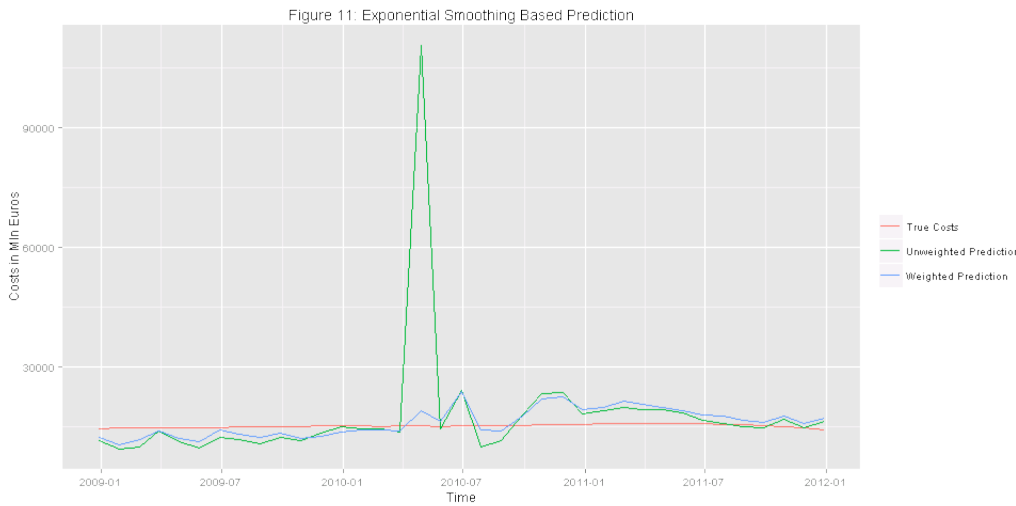
In order to observe the development of the KF's over time, the seasonality effect will be taken out. Each line as shown in figure 8 is regressed on 11 month dummies. The residuals were averaged. The result is shown in figure 9. Figure 9 indicates that there is a clear time trend. The KF at the start of 2011 is about 14% higher than halfway 2009, which is the lowest point.

Figure 10 and figure 11 display the predictions made on the basis of the median and exponential smoothing respectively. Figure 10 and 11 show three lines. The first is the true last year's costs. The second represents the unweighted prediction and the third the weighted prediction. For both figures 10 and 11, the unweighted prediction shows a spike in April 2010. In that month about 20 times more DBC's were registered in the same month as closing the

DBC (lag 0) than normal. Even though it is 20 times as large, it is still a very small percentage of the total expenditures made in that month. This shows that the volatility of the KF in early months results in volatile estimation results. Consequently, the weighted version proves superior, because the early months receive a very small weight. The superiority of the weighted functions can be represented by the root mean square error (RMSE) of the prediction compared to the real costs. The medial weighted prediction has the smallest RMSE of 2.4 billion followed by the weighted exponential smoothing model, with a RMSE of 3.4 billion. The unweighted median and exponential smoothing model have much higher RMSE's, of 129 billion and 1.6 billion respectively. The potential disadvantage of weighting is however, that in the case that there would be a true cost explosion, it would be observed much later.

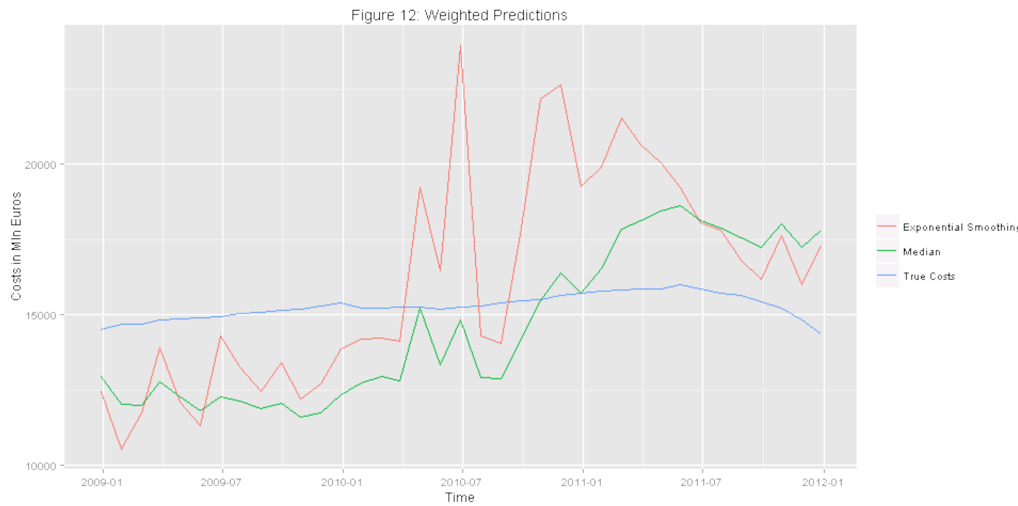
Figure 10: Median Based Prediction





Even though the weighted versions provide better estimations than the unweighted versions, the weighted predictions are not close to the true costs. Figure 12 provides a comparison of the two weighted versions.

The weighted version of exponential smoothing is even less precise than the median based version. In June 2010, the error is even 56%. The predictions are also very volatile compared to the true costs. This is completely due to the volatility of the KF's. In 2009, the predictions underestimate the true costs, whereas from halfway 2010 onwards, the predictions overestimate the true costs. A very similar pattern can be observed in figure 8, which displayed the time trend of the KF's. In 2009 the prediction underestimate the true costs as in 2009 the KF was lower than in 2007, on which the predictions were based. In 2011, the predictions overestimate the true costs as in 2011 the KF is higher than in the previous years.



Instead of looking at all hospitals or DBC's combined, it is possible to consider only at a subset of hospitals. Certain hospitals might register quicker or register at the same speed each year. It might therefore be possible to make a better prediction for this subset than for the total costs.

In total, there are 383 institutions in the data set. It is possible to create a KF matrix - with all the KF's over the months - for all institutions. It is then also possible to compute a standard deviation over the years, for every KF per institutions. The institutions with a smaller variance have a more stable KF.

There is no institution which has a smaller variance for every KF than all institutions combined. However, there 32 that have a smaller variance for the $k_{m,m-11}$, so what is known know about the period 11 months ago. This subset will be taken as an example. Many other subsets could potentially be taken, but few are likely to give a better result.

Figure 13 shows the known fractions for this hospital subset. The KF's are still not constant. However, the trend as observed in figure 8 and figure 9, with lower KF's in 2008 and 2009 is not present.

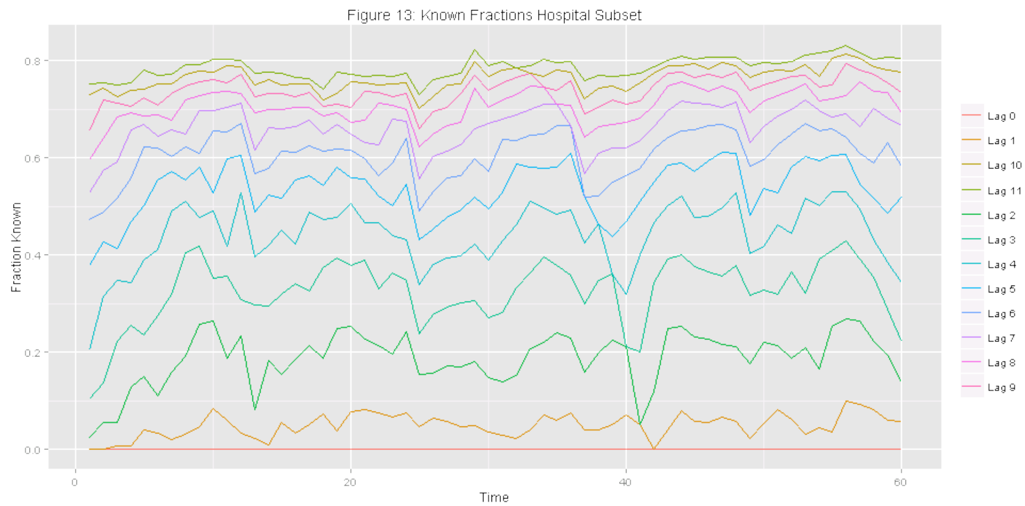


Figure 14 shows the total costs and the costs of the hospital subset. It shows that about 1/6 of the total costs are taken into account. Even if the costs of the hospital subset are predictable, it has to be possible to generalize it to the total costs. Therefore, a simple linear regression model is formed, regressing the total costs on the subset costs. The R^2 from the linear regression is 0.67, which still might be low in order to generalize. Figure 15 shows the fitted model. All peaks and drops are the same, although the magnitude is off at times. However, a good prediction of hospital costs will give a good indication of the direction of the total costs.

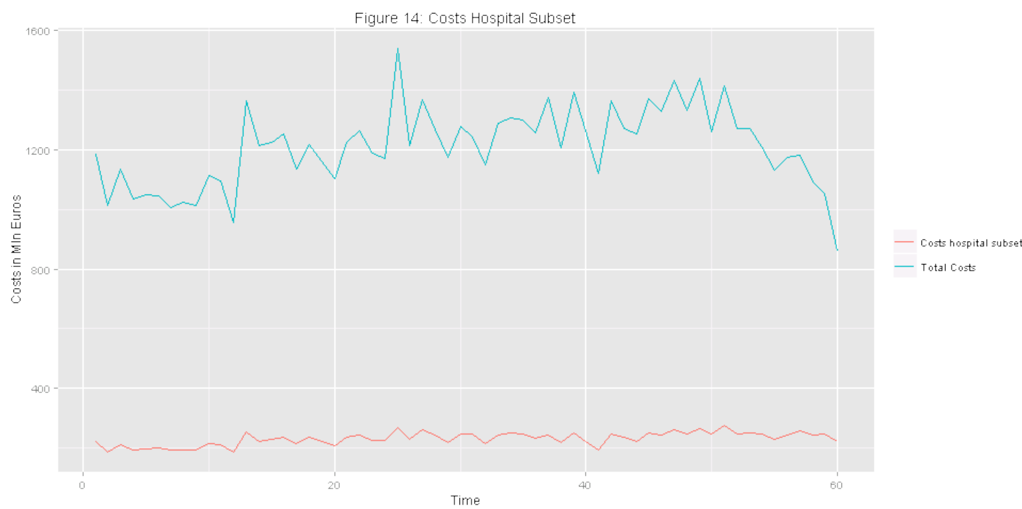


Figure 15: Costs Hospital Subset Fitted

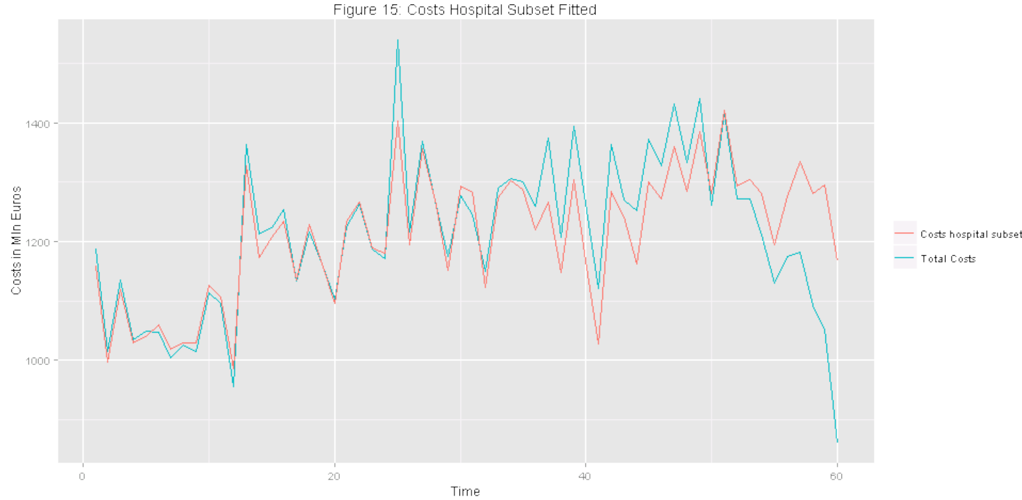
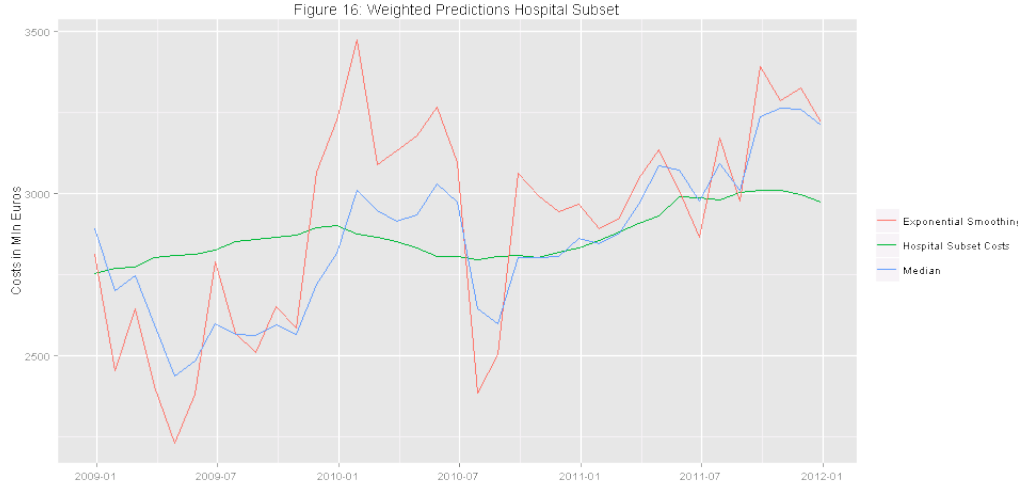


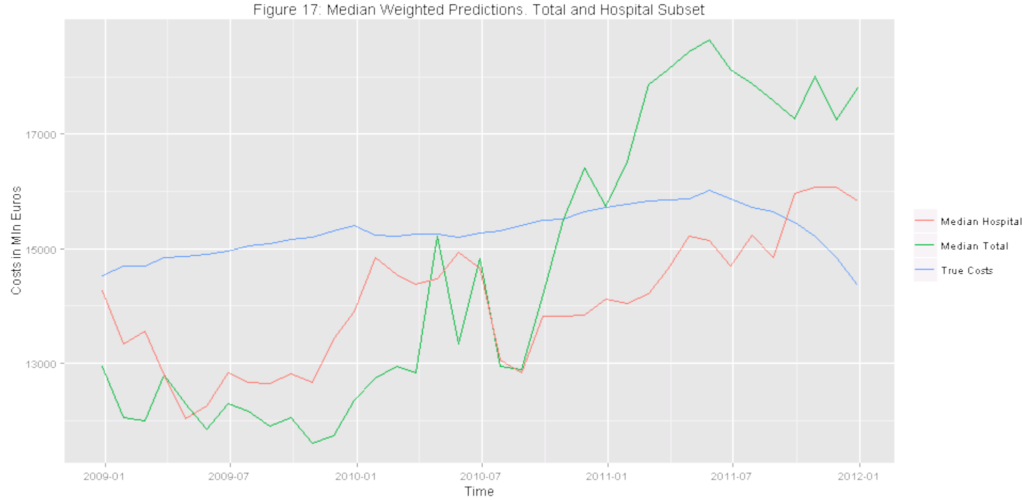
Figure 16 shows the predictions for the costs of the hospital subset. Only the weighted predictions are shown. As expected, the trend in prediction error as observed when estimating the total costs is no longer present. The median prediction is again better than the exponential smoothing prediction. The median based prediction is however still far off. The predictions are again much more volatile than the true costs. The KF's are therefore still not stable enough.

Figure 16: Weighted Predictions Hospital Subset



If the median prediction is combined with the model fit from figure 15, a prediction for the total costs can be made. This is shown in figure 17. The true costs, the median based prediction from the total costs and the median based prediction from the hospital subset are compared. The hospital prediction seems slightly better. It should be noted however, that the fit from the subset to the total is based on all time periods. So for the prediction for 2009, information only available in 2011 was also used. Therefore, basing the prediction on a hospital subset is unlikely to provide a better prediction.

Figure 17: Median Weighted Predictions. Total and Hospital Subset



Model 2

Model 2 was designed in order to circumvent the dependency on a stable registration speed. Instead, the viability of model 2 involves the following two assumptions:

Assumption 2.1: There is a DBC with a constant return rate. So c% of patients that opened a DBC in t open the same DBC in $t+1$ for all t.

Assumption 2.2: The known fraction of this DBC with constant return rate is equal to the known fraction of all DBC's.

Three types of DBC's were suggested. Rheumatic arthritis (RA), multiple sclerosis (MS) and chronic obstructive pulmonary disease (COPD). Figure 18 shows the return rate for these three diseases. The graph displays running averages over 30 days. The graph shows that for MS and COPD, for 40% of the patients that open a DBC on day x in year t, the same DBC is opened again around day x in year *t+1*. Patients were individually observed through the hospital dependent patient code. For RA, this return rate is much higher, namely over 75%. However, it is not the level that is necessarily important, but the variance. Mainly MS shows a very high variance.

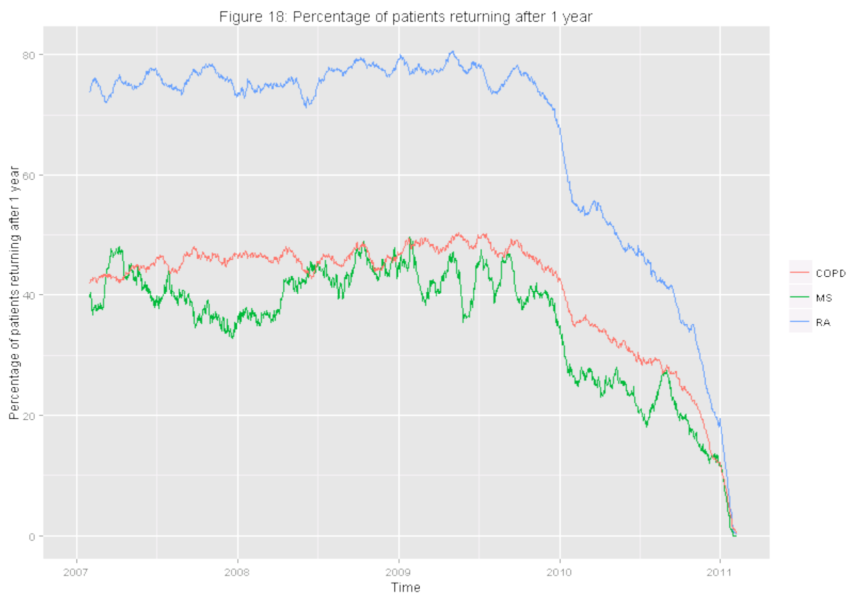
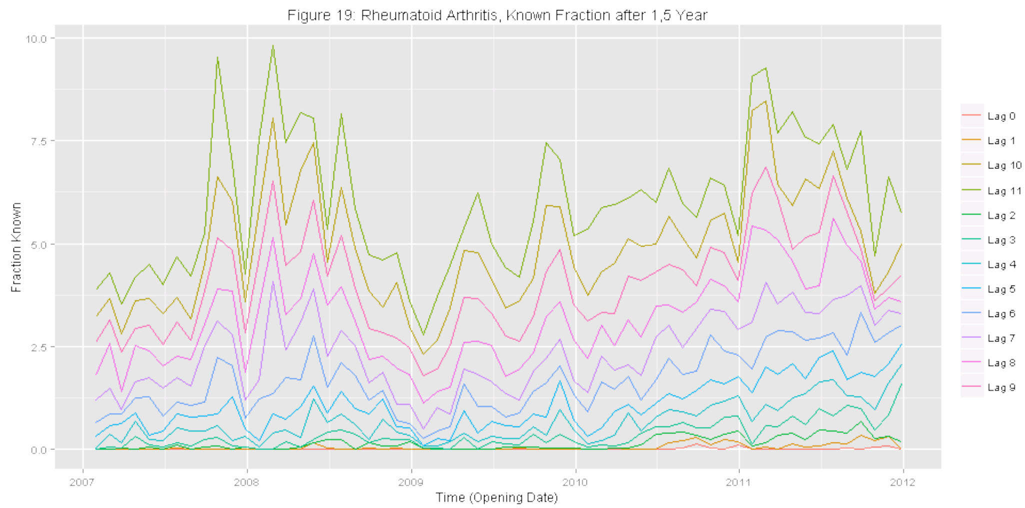


Figure 18 is connected to assumption 2.1. The approximate level of the return rate stays approximately stable, when considering the period up to 2010. After 2010, the return rates plummet. This indicates that from 2011 onwards parts of the DBC are not registered yet, if it is expected that the return rate should stay constant. There is no perfectly stable return rate however, which will add to the prediction error.

However, the slight violation of assumption 2.1 is unimportant compared to the violation of assumption 2.2. In order to generalize any prediction made from the chronic diseases, the known fraction for RA should be similar to the KF for the total costs, which was shown in figure 8. The KF's for RA are shown in figure 19, and are all very low. Less than 10% is known after a year.



The nature of these DBC's, that they all last 1 year leads to the large disadvantage of this method. Very few DBC's are known in the first year, as only the duration itself will already be a year. The registration still has to be done afterwards. This in itself is not detrimental, if enlarging the figure 19 would look similar to figure 8. As figures 8 and 19 are not comparable, the prediction for RA cannot be generalized to the total costs. For instance, if the prediction from the RA DBC's would be that 50% of the DBC's is known, however 60% of the total DBC's would be known, there is an extra bias.

This method might therefore work to predict the chronic DBC's. It will however not be possible to generalize to the total costs.

Conclusion and Discussion

This paper explored the possibility to estimate the total expenditures made in specialist medical care using DBC data that were already available. It was hypothesized that common patterns in registration time might help to predict total expenditures, which could help patients, insurers, policy makers and health care institutions.

Firstly, it was investigated whether the registration speed is constant over time, which would have resulted into a constant 'known fraction'. However, this appeared not to be the case. The KF decreased in 2008 and 2009 after which it increased to a peak in 2011. As the registration speed strongly varied over time, the models based on estimating the KF showed large prediction errors. It will therefore not be possible to use KF's for an early warning system.

Furthermore, it was explored whether it is possible to make a more precise prediction for a subset of institutions. However, this requires an extra assumption that the same hospitals stay more constant in their registration durations. Predictions from taking a subset from institutions was shown not to lead to a strongly improved prediction for the total costs.

The second model involved taking rheumatic arthritis or other chronic diseases as an indicator. This method did not rely on the assumption of a constant known fraction. It was shows that there are DBC's with a relatively constant return rate. However, as the KF's of RA is different from the KF for the total costs, the prediction is not generalizable.

It proves difficult to find clear explanations for the variation in registration over time. Possibly, it was affected by policy changes. In January 2008 and January 2009, the DBC's for which the price can be negotiated, the 'B-segment', was extended. It is plausible that the uncertainty created by these changes affected the registration speed, because in those years the registration speed showed a sharp drop.

The problem with models influenced by the registration speed is that they are likely to respond much stronger to changes in the system compared to the true expenditures made. If there is uncertainty due to policy changes or other shocks, registration might be postponed. The KF will therefore change. However, this delay does not affect the expenditures themselves. The general trend of total expenditures might therefore be more stable. Using registered DBC's as an early warning system will give many type I like errors: it would indicate costs are peaking or plummeting, even though the true costs are quite stable. Therefore, observed DBC's are unlikely to provide a good early warning system for the total costs.

Health care financing is one of the most debated topics in Dutch politics: they are taking an increasing share of public expenditures. In the years after 2011 already new significant changes have been made, and more are about to be implemented. Therefore, also in the future, policy changes will affect the predicting power of any model based on observed DBC's.

The first significant change that was introduced in 2012, was the new DOT system. The analysis performed on the DBC data from 2005 to 2011 can therefore not be generalized in any way to periods after 2012. Even if the methods proposed to estimate total expenditures would be precise, a few years of consistent health care policy would have to pass to provide a stable data set on which to base future predictions.

There are more policy changes about to be implemented. One of these shortens the maximum duration of a DBC. The maximum of 1 year will change to a maximum of 120 days (Schippers, 2013). Limiting the maximum DBC duration is one of the initiatives aimed at helping the insurers to make better estimates of costs made in the last year.

It can be expected that limiting the maximum DBC duration will also slightly improve estimates based on registration speed. A larger percentage will be known after one year of opening, especially because the second peak of the bipolar DBC + registration duration will fall within a year. Generally, KF's with a higher lag have a lower variance than KF's with a lower lag. Therefore, the total variance will decrease.

When improving the estimations based on registration speed, decreasing the maximum DBC duration is will be more effective than decreasing the maximum registration durations. Model 1 mainly uses DBC's registered within a year. By limiting the DBC duration, the second peak of the bipolar DBC + registration duration is now often shorter than a year. Limiting the registration duration of maximum five years will be less effective, as only a very small percentage take multiple years to register.

Even though the reduction of the maximum duration is likely to improve the estimation precision of model 1, it is unlikely that the method becomes viable for making a good prediction. Even the true KF of what is known after 11 months shows a large standard deviation of more than 5%. The uncertainty of predictions based on this method is therefore unlikely to approximate true expenditures. The prediction will improve if the variation becomes smaller, which is however difficult to achieve through policy.

The main advantage of using observed data from the year itself is that it can potentially serve as an early warning system. Time-series directly on costs can provide a decent prediction, however there would be no indications if costs deviate from the predicted line. As the DIS data are shown not to suffice for making an early warning system, other recent data could serve as an alternative. General practitioners might send a stable percentage of their patients to the medical-specialist care. Alternatively, data on medication use could serve as an indicator. Thirdly, the recently devised work-in-progress indicator might provide a good indicator for the KF directly.

In general, making a reliable prediction based on DIS data will be difficult. Thus, other data sources have to be involved. However, even then it seems questionable whether costs could be estimates precisely. In order to get real insight into the cost development, a real time information system - containing all open and closed DBC's - should be devised. This would result in a cost estimation superior to any prediction based on past data. However, even in this case, the costs are not fully known, as the type of DBC can change even after a DBC has been opened.

This research paper developed two models aimed at estiming health care expenditures in the Netherlands. It gave new insight into the complexities of predicting these costs and the problem with using registration speed as an estimator. More research, extra data sources and new registration systems are needed to make correct predictions. Predictions that offer important information to patients, policy makers, health care institutions and insurers.

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