# SICBL Prescribing Model – Methodology

## Overview

* This paper provides an overview of the methodology used in the SICBL Prescribing Model to forecast the monthly spend on prescriptions.
* This model relies on a simple averaging methodology and replaces the previous model which used linear regression.
* A brief overview of the model’s caveats and technical considerations are included along with a comparison to the previous model.
* A full write up of the comparisons between these models can be found in the document titled SICBLPrescribingModel\_FullWriteUp.docx.

## Introduction

1. This paper provides an overview for the SICBL prescribing model which can be used to forecast the spend on prescriptions for the remaining months of the year. From this, a cumulative profile is generated allowing SICBLs to consider how their spend looks so far and the potential spend on prescriptions for the remainder of the year.
2. The forecasting model relies on a simple averaging technique based on the month of the year and number of dispensing days which have a relationship with prescription expenditure. For example, there is often a higher spend per dispensing day in December because of patients picking up extra supplies before the Christmas public holidays. However, there is typically lower spend in February due to the low number of dispensing and calendar days in this shorter month.
3. Keeping the methodology of this model simple makes it transparent and understandable by a wide range of users.

## Model Methodology

1. The model uses data from the previous 5 years to forecast the prescription spend for the current year.
2. The average prescription spend per dispensing day is calculated by dividing the total prescription in each month by the number of dispensing days, and averaging each month over the previous 5 years. This average corrects for any policy impacts[[1]](#footnote-2) from each month and year.
3. The spend for the current year is estimated by multiplying the average prescription spend per dispensing day by the number of dispensing days in the forecast month. The policy impact is then added/deducted to give the final forecast prescription spend.
4. This methodology is described in Table 1 which shows the forecast spend at the beginning of 2021/22 based on data from 2016/17 to 2020/21.

Table : The methodology used to estimate the prescription spend in 2021/22

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Month | Average prescription spend per dispensing day |  | Number of dispensing days |  | Policy/local adjustment |  | Forecast prescription spend (adjusted) |
|  | 2016/17 to 2020/21 |  | 2021/22 |  | 2021/22 |  | 2021/22 |
|   | £ |  | days |  | £ |  | £ |
| April | 28,901,069 | x | 24 |  | + 7,766,667  |  =  |  701,392,328  |
| May | 29,017,299 | x | 24 |  | + 7,766,667  |  =  |  704,181,837  |
| June | 27,901,760 | x | 26 |  | + 7,766,667  |  =  |  733,212,426  |
| July | 27,333,786 | x | 27 |  | - 8,533,333  |  =  |  729,478,885  |
| August | 27,609,775 | x | 25 |  | - 8,533,333  |  =  |  681,711,043  |
| September | 28,406,993 | x | 26 |  | - 8,533,333  |  =  |  730,048,492  |
| October | 28,659,849 | x | 26 |  | - 17,466,667  |  =  |  727,689,398  |
| November | 28,550,630 | x | 26 |  | - 17,466,667  |  =  |  724,849,701  |
| December | 30,459,408 | x | 24 |  | - 17,466,667  |  =  |  713,559,130  |
| January | 28,246,846 | x | 24 |  | - 33,900,000  |  =  |  644,024,307  |
| February | 27,387,037 | x | 24 |  | - 33,900,000  |  =  |  623,388,890  |
| March | 28,319,183 | x | 27 |  | - 33,900,000  |  =  |  730,717,933  |
|   |   |   |   |   |   |   |   |
|  |  |  |  |  | **Total** |  | **8,444,254,369** |

1. These forecasts are then used to estimate the forecast profile each month (i.e. what percentage of the year spend is expected in each individual month) as well as the cumulative profile (the running total percentage of yearly spend in each month to date).
2. The forecast spend is fixed at the beginning of the financial year and the forecasts themselves will not change during the financial year. However, as more real data is added over the course of the year, this will replace the forecast data for any given month which will change the forecast profiles.

## Benefits and Caveats of the Model

1. This model has replaced the linear forecasting model previously used to forecast prescription spend. A full comparison between these methodologies can be seen in SICBLPrescribingModel\_FullWriteUp.docx.
2. The linear regression model is less transparent and can be harder to understand and interpret for all users. It was also found to be somewhat inaccurate at estimating the overall spend in some periods due to issues with the time variable whereby the spend is not necessarily changing with time.
3. The simple averaging model is intended to be more easily understood by most users. Due to a clear relationship between the month of the year and the number of dispensing days (the parameters used in the simpler, averaging model), the results of the simple model were comparable to those of the linear regression model.
4. There are some important caveats of this model which should be considered when interpreting the results; many of which were also the case for the linear regression model.
5. Forecasts are based on the previous 5 years’ data and hence the forecasts themselves will not change within a financial year; this means that the forecast for any month is fixed at the beginning of a financial year. However, as more data becomes available, the forecasts will be replaced with real data, meaning the overall proportions of spend will change throughout the year.
6. The proportion of spend is less accurate at the beginning of the financial year hence the outputs of the model should be used with caution for the first few months of any financial year.
7. The calculations considered in this paper rely on using National level data. However, there is likely to be a greater forecasting error when using smaller populations, for example when using the model to forecast a SICBL level total.
8. This is a simple model and does not include any factors that respond to specific risks or uncertainties that could impact prescription spend. In other words, this model will not adjust forecasts to account for: demographic changes; changes in morbidity; the emergence of new substitute or complementary technology; changes in prices; local or international market or supply chain conditions; wider national or international policy changes; local, national or global events or circumstances that interrupt business as usual; nor any new trends that are not represented in the source data for the last 5 years.
9. Data are averaged over the previous 5 years and hence the total spend estimates may be an underestimate if growth in spend has occurred over the last 5 years. This is unlikely to impact the initial proportions of spend (as it would affect all months equally) but may have an effect as estimates are replaced by real data.
10. This model is likely to be impacted by the effects of the COVID-19 pandemic on prescription spend data. However, the spend only shows a noticeable difference in March and April 2020 meaning averages are unlikely to be dramatically changed by the effects of the pandemic.

## Technical Consideration of the Model

1. This final section summarises the technical consideration of the simple averaging model and how it compares with the previous linear regression model. The reader should refer to SICBLPrescribingModel\_FullWriteUp.docx for the full comparison.
2. Both models have patterns in the residuals suggesting there are unmodelled dynamics or omitted variables, suggesting both models will have weaknesses when it comes to long-term changes. This means both models are not a complete tool for monitoring risks to spend nor are they an early warning system for any major emerging trends in prescription spend.
3. The simple averaging model was more accurate at forecasting regular month-to-month fluctuations or “seasonality”. The regression model included constraints limiting how much a month could differ from other months. For example, the simple averaging model can account for the fact that prescription spend is high in December despite low dispensing days as patients still require prescribed products during the Christmas public holidays. However, this increase is not needed in February which also has a low number of dispensing days.
4. When numerically comparing the models, the model that more accurately predicted the true values varied depending on which year was considered.
5. Both models produced few forecasts which were outside of the historical range and when it did, the difference was relatively small. For the simple model, the most that modelled spend for any month was higher than the highest actual value for that month over the previous 5 years was +2.5%. The lowest that modelled spend for any month was lower than the lowest actual value for that month over the previous 5 years was -3.7%. For the linear regression model, the most that modelled spend for any month was higher than the highest actual value for that month over the previous 5 years was +4.0%, whilst no months were forecast below the lowest actual value for that month over the previous 5 years.
6. When comparing the proportions of spend, the regression model was found to better estimate the proportions in 2018/19; the averages model better estimated the proportions in 2019/20; and there was very little difference in 2020/21.
7. When considering the cumulative proportion of spend, both models were found to have a large deviation away from the true value in the earlier months of the financial year. Improvements typically started around June, with better estimates from September onwards
1. The community pharmacy sector receives money as retained buying margin, i.e. the profit pharmacies can earn on dispensing drugs through cost-effective purchasing. The margin element is a target that DHSC aim to deliver by adjusting the reimbursement price of drugs and the delivery of margin to pharmacy is carefully monitored by DHSC. Averaging results may be very noisy without correcting for policy impacts as they may have occurred in any month of the year. [↑](#footnote-ref-2)