Antidepressant Prescribing and Cost Analysis in England (2021–2024)

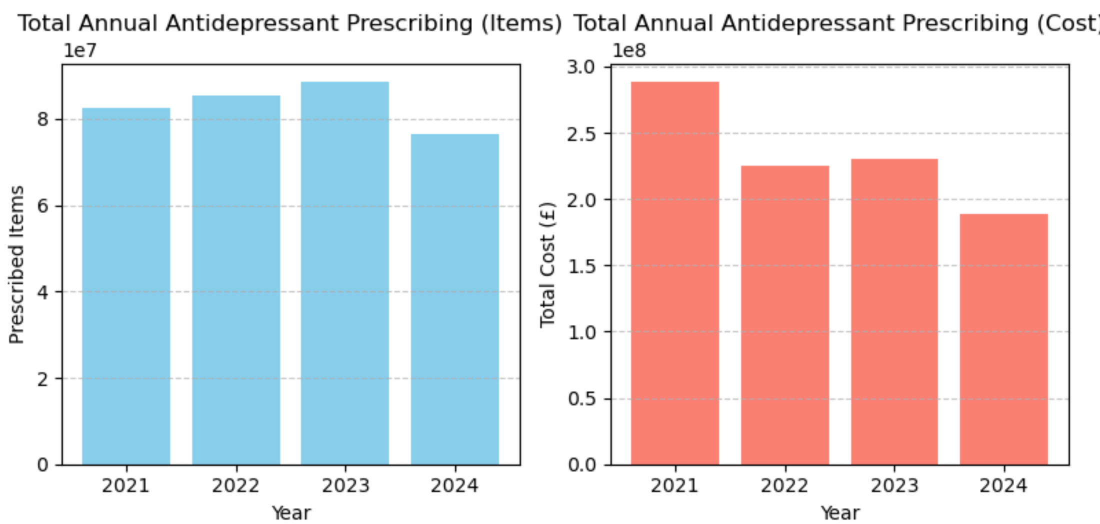
March 14, 2025

1 Introduction

The purpose of this report is to examine antidepressant prescribing across England over a four-year period, using detailed monthly data from the NHSBSA Open Data Portal. Specifically, we focus on how prescribing volumes (i.e., the number of items) and costs for various antidepressant drugs differ nationally and regionally. By analyzing these trends, we gain insights into overall prescribing patterns, spotlight the most frequently prescribed antidepressants, and identify areas with notably high or low prescribing levels.

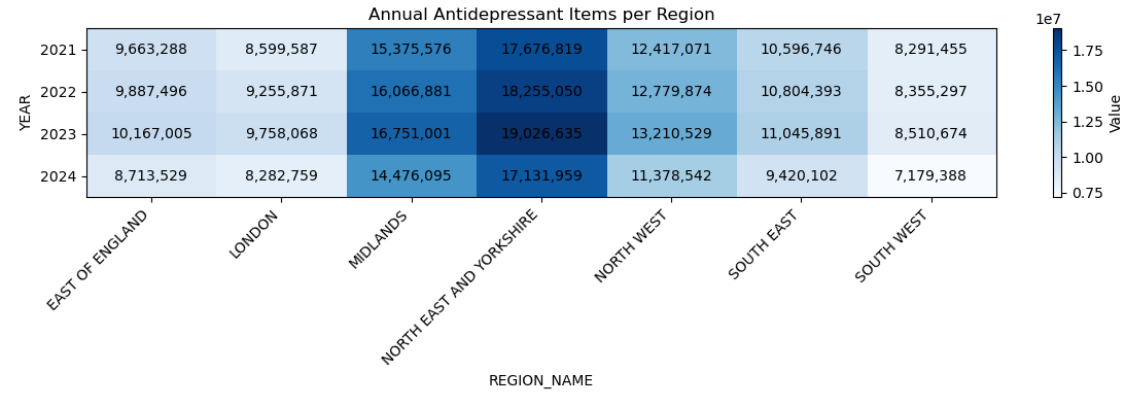
2 Prescribing Patterns & Costs

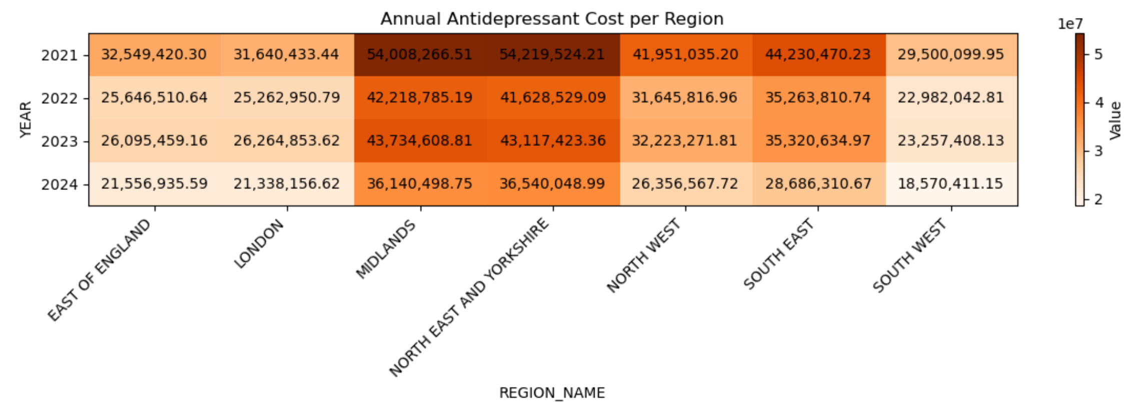
[1]:
```
%run part_one_plots_a.py
```



From 2021 to 2023, the total number of antidepressant items goes up each year, before dipping in 2024. Meanwhile, the total cost starts out high in 2021, drops in 2022, goes up slightly in 2023, and then falls to its lowest point in 2024. As a result, the number of items and the cost do not move in step with each other, showing that increases in prescriptions do not always lead to higher spending.

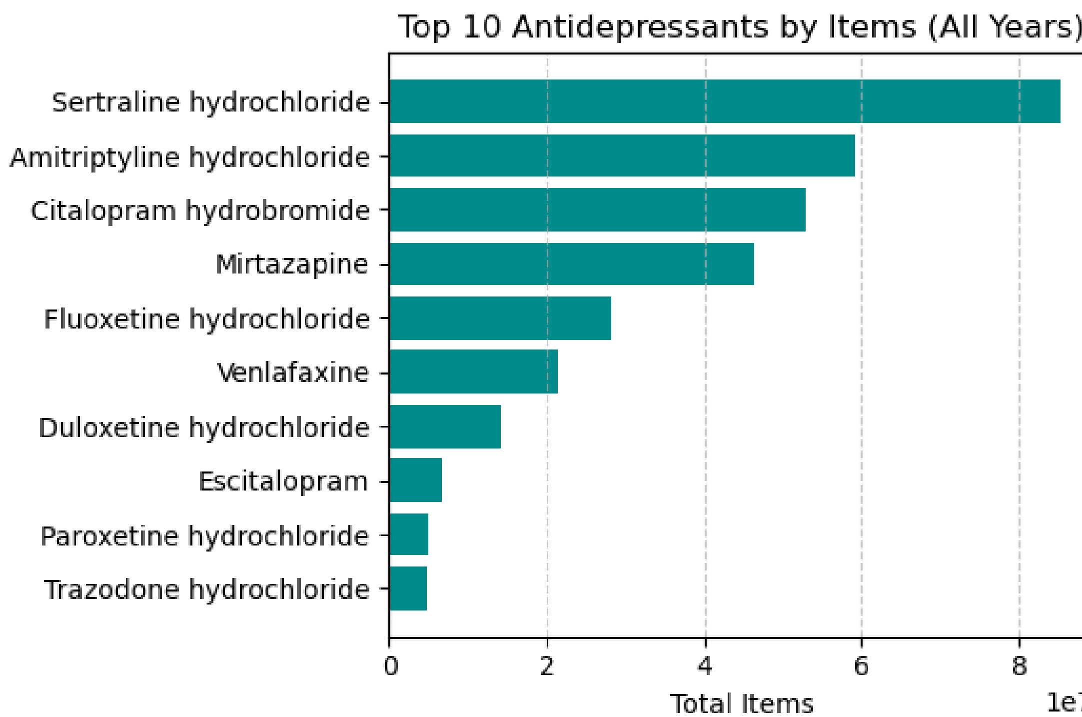
[2]:
```
%run part_one_table.py
```

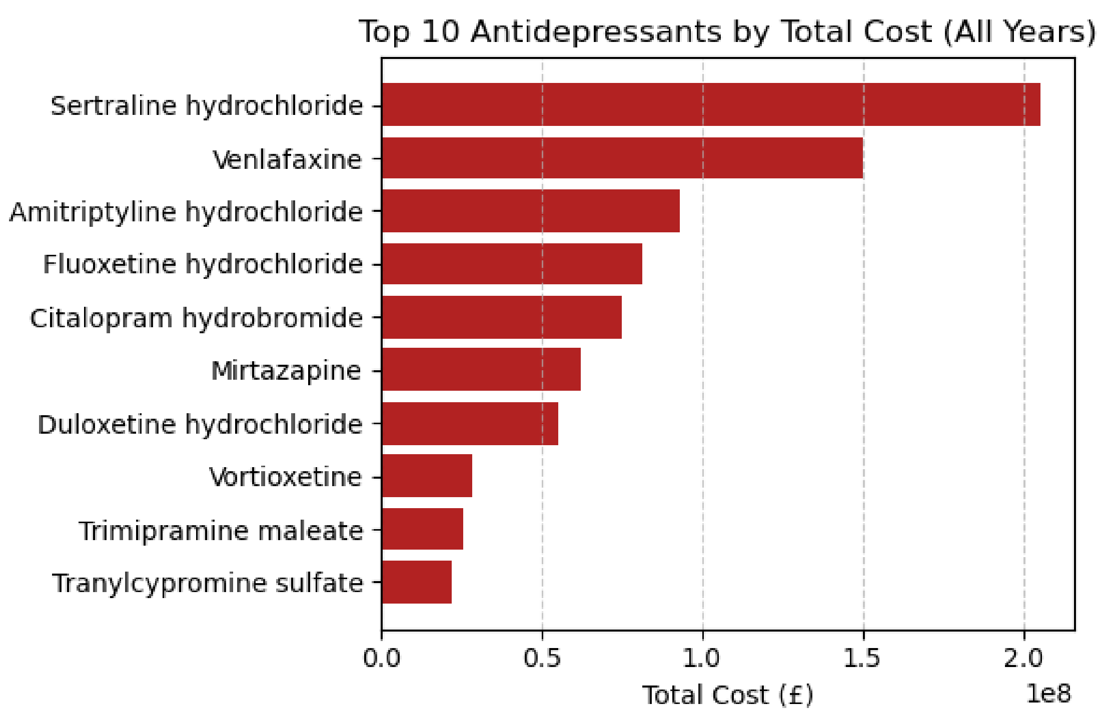




Across all regions, the total number of antidepressant items goes up from 2021 to 2023, then drops in 2024 to below 2021 levels. The East of England, London, and the South West have lower volumes overall, while the Midlands and North East & Yorkshire stand out with the highest item counts each year. For costs, every region shows a big decrease from 2021 to 2022, a modest rise in 2023, and then another drop in 2024—ending up well below 2021 levels. Regions with higher item counts (such as the Midlands and North East & Yorkshire) also tend to have higher total costs. In contrast, London and the South West generally stay at the lower end for both items and cost. The main shifts between 2021 and 2024 are therefore the steady rise then fall in prescription volumes across all regions, coupled with an overall decline in spending, despite a small rebound in 2023.

[3]:
```
%run part_one_plots_b.py
```



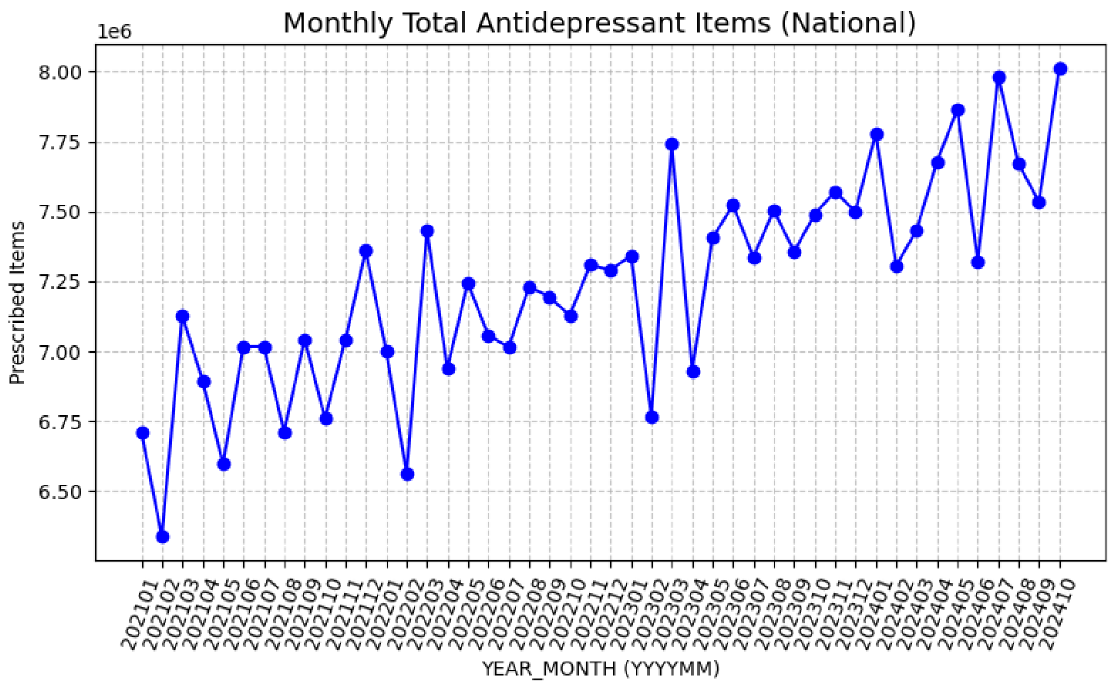


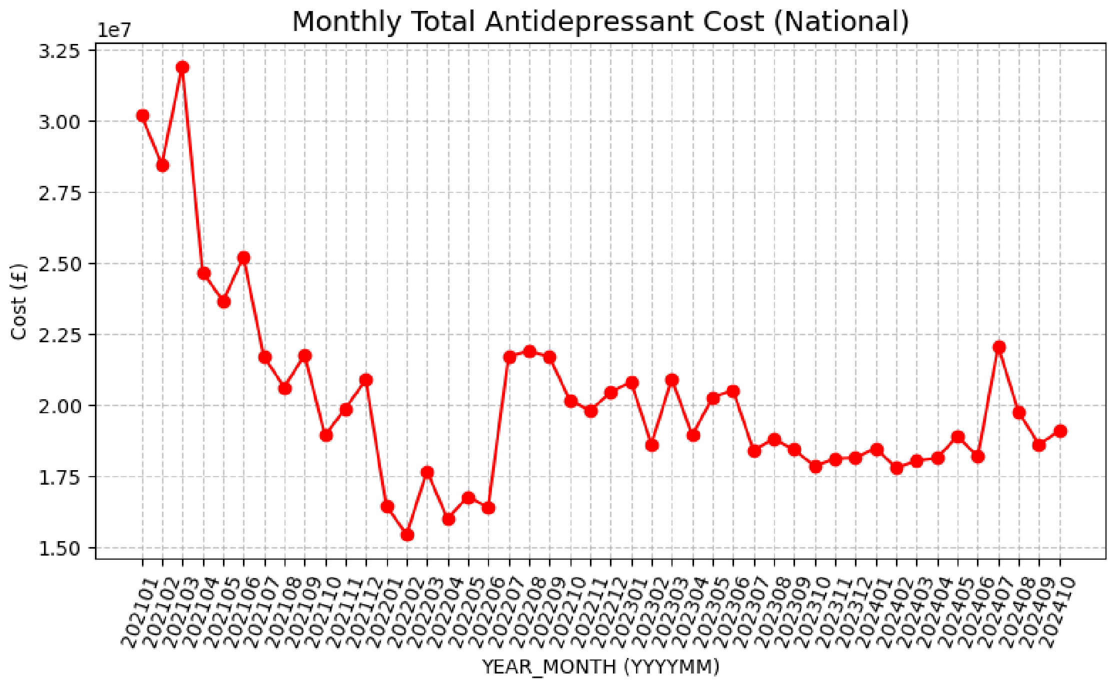
Comparing these two lists reveals that Sertraline sits comfortably at the top for both total cost and total items, whereas several other drugs shift positions. For example, Venlafaxine is second-highest by cost but only sixth by volume. Amitriptyline, on the other hand, is second by items yet third by cost. Similarly, Citalopram ranks higher by items (third) than by cost (fifth). Meanwhile, Vortioxetine makes it into the top 10 for cost but doesn't appear in the top 10 for items, indicating a higher cost per prescription. Conversely, some medications—such as Trazodone and Paroxetine—make the top 10 in items yet not in cost. Overall, the ranking differences suggest that certain antidepressants carry a greater cost per unit, whereas others are prescribed more frequently but at a lower cost per unit.

3 Part Two

3.1 Monthly Trends in Items & Costs

[4]:
```
%run part_two_a.py
```



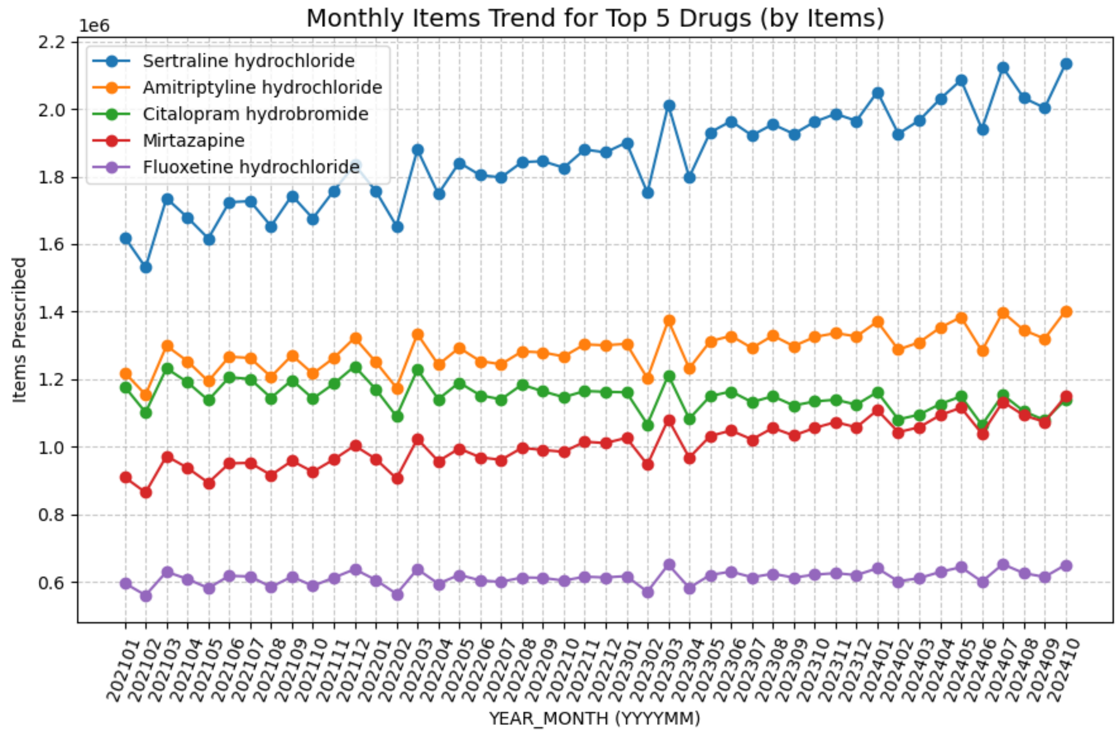


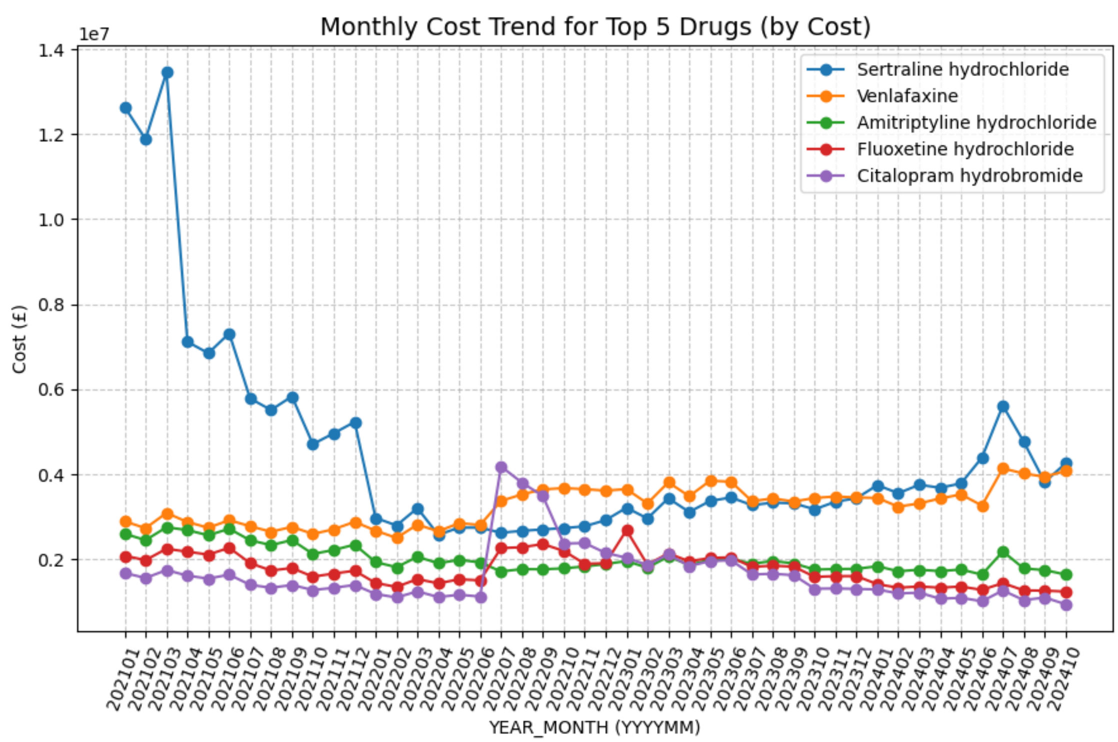
A quick look at the national line charts shows that monthly antidepressant items have been steadily rising since early 2021. Although the number of items fluctuates a bit month to month, the overall path is clearly upward—from about 6.5 million items per month at the start of 2021 to nearly 8 million by late 2024.

By contrast, monthly antidepressant cost starts very high in early 2021 (well above £30 million in January), then drops sharply across the first half of the year. After hitting its lowest point in mid-2021 (roughly £15–17 million), total monthly spending remains lower than it was initially, bouncing between £17–22 million. A few spikes occur—for example, a noticeable peak around mid-2024—but overall costs do not return to their early-2021 levels.

[5]:
```
%run part_two_b.py
```

```
Top 5 Drugs by Total Items: ['Sertraline hydrochloride', 'Amitriptyline
hydrochloride', 'Citalopram hydrobromide', 'Mirtazapine', 'Fluoxetine
hydrochloride']
Top 5 Drugs by Total Cost: ['Sertraline hydrochloride', 'Venlafaxine',
'Amitriptyline hydrochloride', 'Fluoxetine hydrochloride', 'Citalopram
hydrobromide']
```


Monthly Items Trend for Top 5 Drugs (by Items)
1e6
Sertraline hydrochloride
Amitriptyline hydrochloride
Citalopram hydrobromide
Mirtazapine
Fluoxetine hydrochloride
Items Prescribed
YEAR_MONTH (YYYYMM)


Monthly Cost Trend for Top 5 Drugs (by Cost)
1e7
Sertraline hydrochloride
Venlafaxine
Amitriptyline hydrochloride
Fluoxetine hydrochloride
Citalopram hydrobromide
Cost (£)
YEAR_MONTH (YYYYMM)

3.2 Top Five Drugs Trends

Looking at the monthly cost trend for the top five drugs (Sertraline, Venlafaxine, Amitriptyline, Fluoxetine, and Citalopram) reveals that Sertraline had by far the largest share of total cost at the beginning of 2021, but then its cost fell dramatically by mid-2021. Even so, it remains at or near the top of the list. Venlafaxine and Amitriptyline each maintain significant portions of the total cost, though at substantially lower levels than early-2021 Sertraline. Meanwhile, Fluoxetine and Citalopram also contribute notable shares of total cost, though at smaller magnitudes. Short-term cost spikes for Citalopram (mid-2022) and Sertraline (around mid-2024) stand out as key drivers of month-to-month variation.

From the monthly items perspective, Sertraline is again the leading drug, consistently occupying the highest position throughout the 2021–2024 period. Amitriptyline and Citalopram follow next, each gradually trending upward over time. Mirtazapine and Fluoxetine also show smaller but steady rises. Overall, Sertraline's dominance in prescribing volume helps explain its influence on cost patterns, especially during months when its cost per prescription is higher.

In summary, the monthly data underscores a widening gap between rising prescription volumes and more moderate (or even declining) overall spending. Although the number of items has climbed steadily, total costs dropped sharply in early-to-mid-2021 and stabilized at a lower level, with occasional spikes. Among individual drugs, Sertraline remains the single biggest factor, driving both volume and cost trends—though its sharp cost drop in 2021 hints that pricing and reimbursement changes may have been a key influence. Venlafaxine, Amitriptyline, Citalopram, and Fluoxetine also contribute meaningfully to national costs and prescribing volumes, but each at lower levels than Sertraline. Going forward, focusing on both cost dynamics and prescription volume for these top-prescribed medications will help clarify any further shifts or anomalies that might arise.

4 Forecast

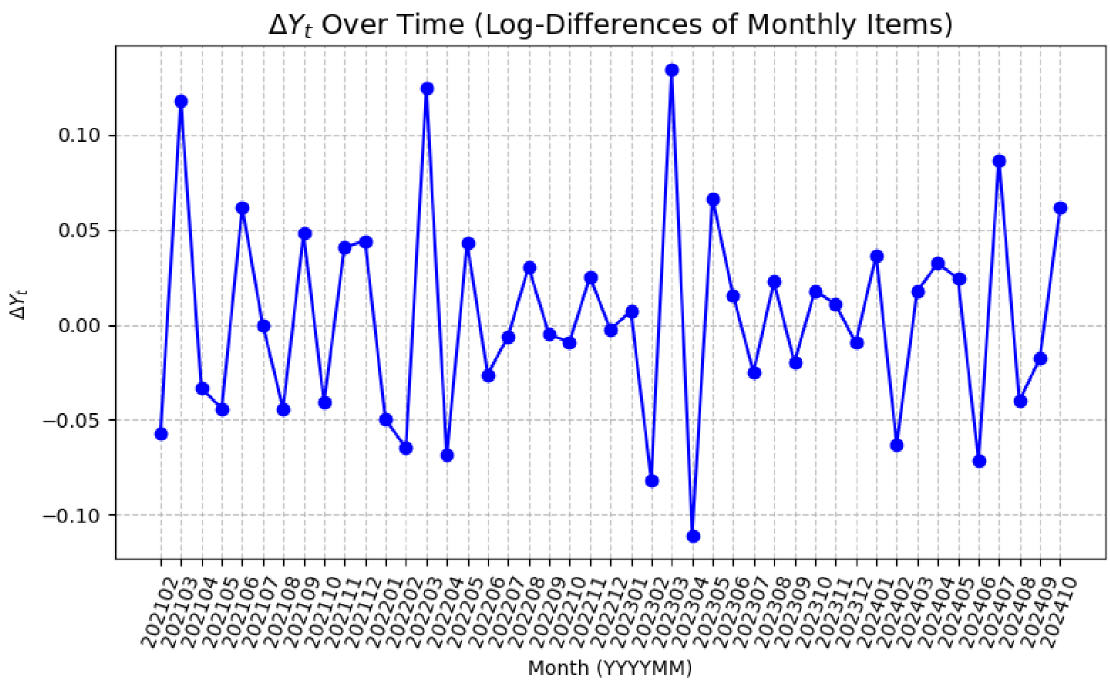
4.1 Checking Normality and Independence

The next python script examines whether the monthly log-differences of our antidepressant prescribing data behave like an independent and identically distributed (i.i.d.) normal sequence. It begins by aggregating monthly totals and applying a log transform to stabilize variance, then computes the first difference ΔY, where

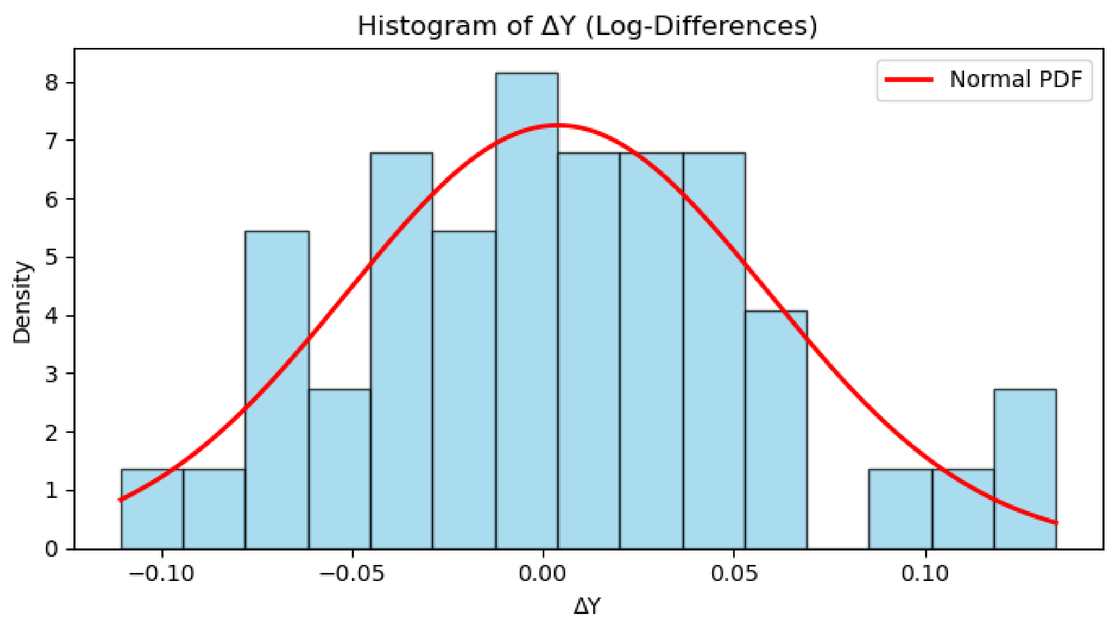
$$\Delta Y_t = Y_{t+1} - Y_t = \ln(\text{Items}_{t+1}) - \ \ln(\text{Items}_t)$$

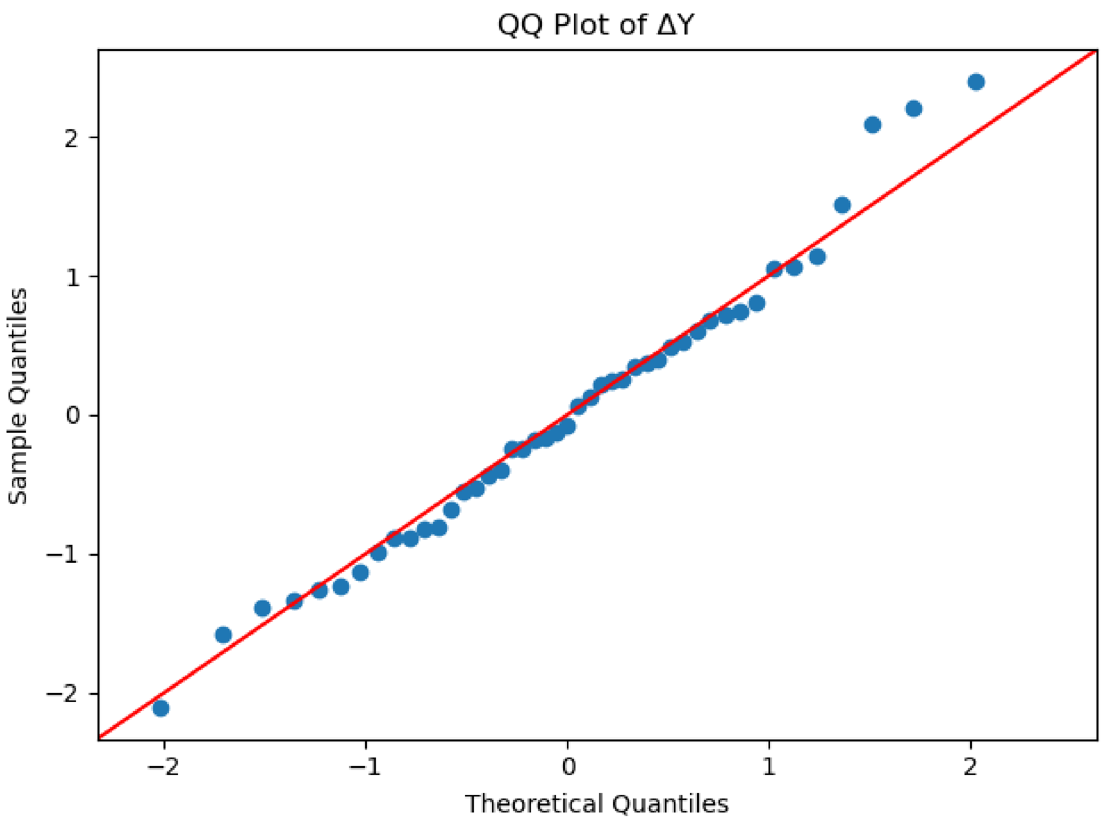
to remove trends. Next, it visualizes these differences with a histogram/KDE and a QQ plot to gauge the shape against a normal curve, and runs a Shapiro–Wilk test for formal normality assessment. Finally, the script plots the ACF and PACF to detect autocorrelation and applies a Ljung–Box test at lag 20. If the differences appear normal and show no significant autocorrelation, the log-differenced data can be considered approximately i.i.d. noise—an important assumption for many forecasting or model-fitting procedures.

[6]:
```
%run delta_Y.py
```

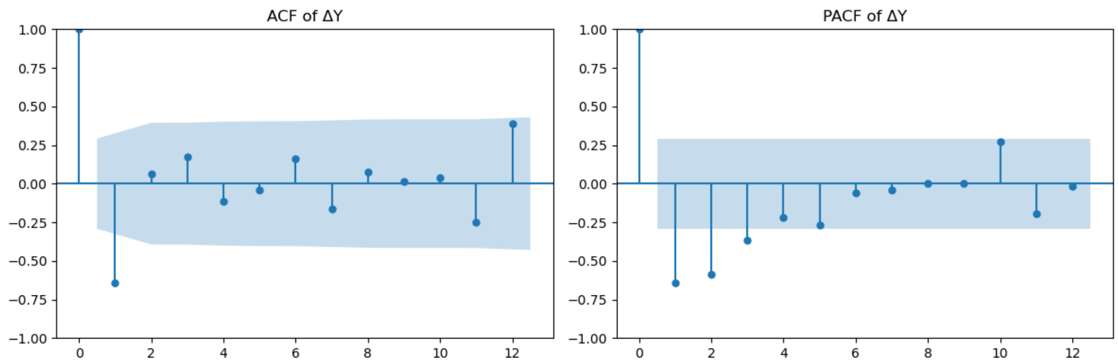


[7]:
```
%run check_normal.py
```






```
Shapiro-Wilk Test for dY: W=0.9818, p-value=0.6948
=> We cannot reject normality at 5% level.
```




```
Ljung-Box Test (lag=20):
      lb_stat  lb_pvalue
20  55.717187   0.000032
```

Shapiro–Wilk Normality Test The first figure, $W = 0.9818$ with p 0.6948, comes from the Shapiro–

Wilk test, which evaluates whether the monthly log-differences ΔY behave like a normal (bell-shaped) distribution. A p-value substantially above 0.05 indicates you cannot reject normality—in other words, you see no significant departure from a normal distribution. This suggests that, purely in terms of shape, the data does not exhibit skewness or heavy tails inconsistent with a Gaussian profile.

Ljung–Box Test (Lag = 20) Next, the Ljung–Box statistic yields a p-value 0.000032 when testing for autocorrelation up to lag 20. This very low p-value strongly suggests the series is not composed of independent random draws; there remains a time-based structure in the data. While the log-differences look Gaussian overall, they are not i.i.d., as one month's change influences subsequent months. This means even if ΔY follows a roughly normal distribution, it still exhibits significant autocorrelation—requiring further modeling (e.g., AR terms) to capture that dependency.

4.2 Proposed Model

Turning to the monthly antidepressant item counts, two key characteristics emerge: (1) long-term growth in overall prescribing, and (2) negative autocorrelation at lag 1 in the log-differences ΔY. A simple random walk with drift would handle ongoing growth plus random variability but fail to capture the "bounce-back" effect—when one month's increase is large, the next month's tends to drop.

By selecting an ARIMA(1,1,0) specification, we incorporate an AR(1) term on the once-differenced series, precisely reflecting that bounce-back phenomenon. Formally:

$$\Delta Y_{t+1} = \mu + a \Delta Y_t + \varepsilon_{t+1},$$

where $\Delta Y_t = Y_t - Y_{t-1}$. Here, a negative a signifies mean reversion: a large spike in one month is partially offset the next. This setup effectively balances a random walk with drift—suitable for series that trend upward over time—with a short-term stabilizing mechanism on month-to-month changes.

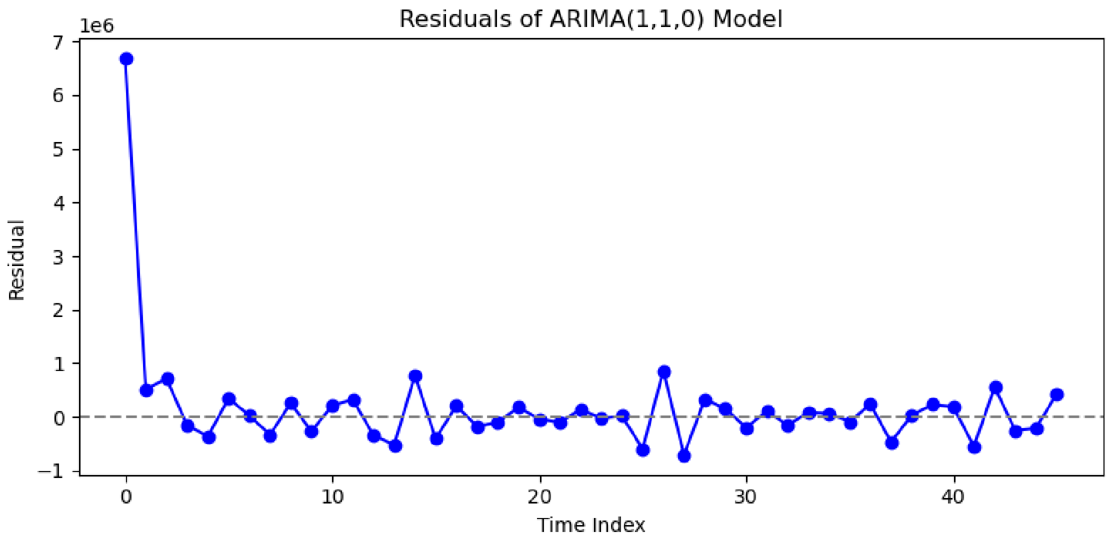
To validate the model, we can check diagnostic criteria such as the residual autocorrelation and Ljung–Box test outcomes. If additional patterns persist, we might include an MA component or investigate seasonal adjustments. Still, ARIMA(1,1,0) already captures the fundamental behavior of negative lag-1 dependence, ensuring that unusually large monthly increases tend to be followed by some degree of correction in the subsequent month.

[8]:
```
%run residual_diagnostics.py
```

```
                               SARIMAX Results
==============================================================================
Dep. Variable:                  ITEMS   No. Observations:                   46
Model:                 ARIMA(1, 1, 0)   Log Likelihood                -641.920
Date:                Fri, 14 Mar 2025   AIC                           1289.841
Time:                        10:57:59   BIC                           1295.261
Sample:                             0   HQIC                          1291.861
                                 - 46
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
```

```
------------------------------------------------------------------------------
x1          2.892e+04   3.14e+04      0.921      0.357   -3.26e+04    9.05e+04
ar.L1         -0.1379      0.024     -5.849      0.000      -0.184      -0.092
sigma2      8.564e+10      0.021   4.08e+12      0.000    8.56e+10    8.56e+10
================================================================================
===
Ljung-Box (L1) (Q):                  11.35   Jarque-Bera (JB):
0.50
Prob(Q):                              0.00   Prob(JB):
0.78
Heteroskedasticity (H):               0.51   Skew:
0.22
Prob(H) (two-sided):                  0.20   Kurtosis:
2.71
================================================================================
===

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-
step).
[2] Covariance matrix is singular or near-singular, with condition number
2.9e+28. Standard errors may be unstable.
```




```
Ljung-Box Test Results (lags=12,20):
     lb_stat  lb_pvalue
12  1.116892   0.999974
20  3.297731   0.999991
```

```
Partial Autocorrelation Function (PACF) values up to lag=12:
  Lag 0: 1.0000
  Lag 1: 0.0110
  Lag 2: 0.0959
  Lag 3: -0.0069
  Lag 4: -0.0724
  Lag 5: 0.0482
  Lag 6: 0.0275
  Lag 7: -0.0831
  Lag 8: 0.0340
  Lag 9: -0.0205
  Lag 10: 0.0327
  Lag 11: 0.0008
  Lag 12: -0.0233
```

4.3 Interpreting the Model Parameters and Diagnostics

Looking at the values of $x1$, ar.L1, and σ^2 in the result table, we get

$$\Delta Y_{t+1} = 28{,}920 \;-\; 0.1379\,\Delta Y_t \;+\; \varepsilon_{t+1},$$

which is our best guess of the ARIMA(1,1,0) model. Selection criteria AIC = 1289.841, BIC = 1295.261, HQIC = 1291.861 indicate that this relatively simple specification fits the data reasonably well. Diagnostic checks confirm this: the Jarque–Bera test JB = 0.50, $p = 0.78$ shows no evidence of obvious non-normality in the residuals, and the Heteroskedasticity test $H = 0.51$, $p = 0.20$ suggests no major shifts in variance over time. Although the Ljung–Box statistic at lag 1 $Q = 11.35$, $p = 0.00$ flags some short-horizon autocorrelation, tests extended to lags 12 and 20 yield high $p - values \approx 1.00$, indicating no sustained correlation.

Moreover, the partial autocorrelation function (PACF) values through lag 12 are all small (ranging roughly from –0.08 to 0.10), reinforcing that the main time-dependent structure is adequately modeled. Notably, the residuals stay within ± 1, implying the ARIMA(1,1,0) configuration makes predictions very close to the actual data points on the observed scale. Taken together, these outcomes strengthen the conclusion that ARIMA(1,1,0) successfully captures both the long-term growth trend and the mean-reverting "bounce-back" behavior in monthly antidepressant prescribing.

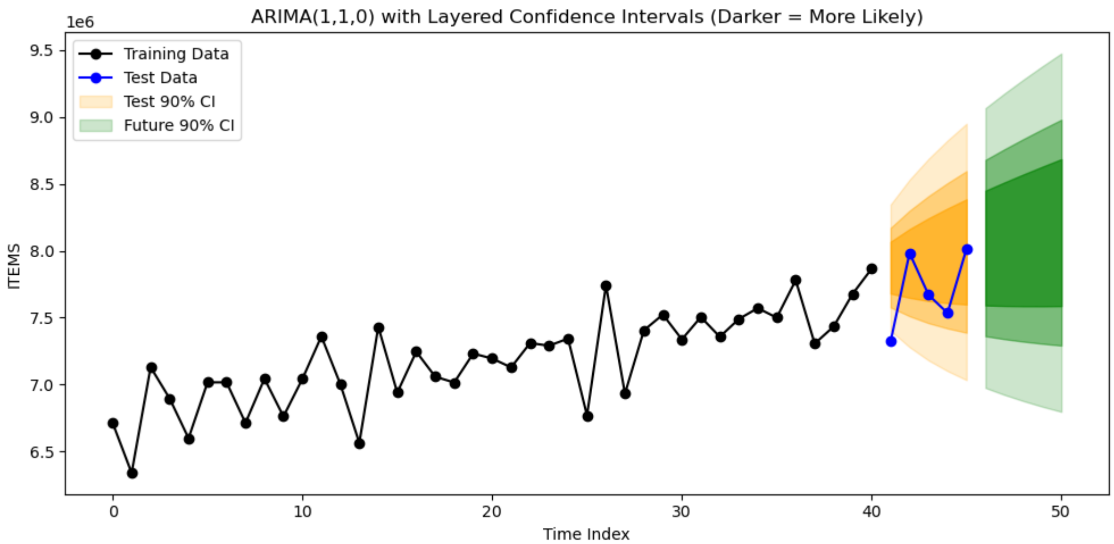
4.4 Prediction

We apply the same ARIMA(1,1,0) model but now split the original dataset into a training set of 41 points and a test set of 5 points. This approach allows us to estimate the model parameters on the training portion and then evaluate how the model—complete with its 90% confidence intervals—performs on the test segment. After validating the model against the test data, we extend the forecast into the future, again displaying the 90% CI around those predictions.

For the confidence interval (CI) shading, darker portions indicate narrower intervals (i.e., higher probability regions closer to the model's best estimate), whereas lighter portions represent wider intervals (i.e., covering more uncertainty). By layering these intervals from wide to narrow, viewers can quickly discern both the most likely range and the broader uncertainty bounds around each forecasted point.

[9]:
```
%run prediction.py
```

```
Parameter estimates (90% CI):
  x1       = 28843.6250 (90% CI: -25580.2136, 83267.4636)
  ar.L1    = -0.1267 (90% CI: -0.1696, -0.0838)
  sigma    = 286816.3748 (90% CI: 286816.3748, 286816.3748)
```



5 Limitations

The proposed ARIMA(1,1,0) specification is kept simple, capturing just a linear trend plus short-term autocorrelation in the differenced series. This means it may miss more complex structures such as seasonal fluctuations or non-linear effects that could influence antidepressant prescribing patterns. Another constraint is the relatively small number of data points—just four years of monthly observations—limiting the reliability of estimates and the robustness of any conclusions drawn. Longer historical data would help stabilize parameter estimates and better uncover multi-year trends. Finally, the dataset itself consists primarily of prescribing volumes and costs, providing minimal context for deeper predictive analytics. More advanced machine learning methods typically rely on a larger set of explanatory features (e.g., demographic or clinical variables). Without those, the potential gains from sophisticated algorithms might be limited.

6 Summary

This analysis looks at antidepressant prescribing across England over a four-year period, focusing on both monthly prescription volumes and costs. By examining the national and regional data, we can identify where and how much antidepressants are being prescribed, as well as the financial implications. The goal is to highlight overall patterns, highlight frequently prescribed medications, and pinpoint areas with notably high or low prescribing levels.

In addition, we evaluate a predictive ARIMA(1,1,0) model by splitting the dataset into a training set of 41 observations and a test set of 5. Estimating parameters on the training data, we then forecast the test period and extend the predictions further, plotting 90% confidence intervals with darker shading near the model's most likely estimates and lighter intervals reflecting greater uncertainty. This layered approach aids in visualizing not only the primary forecast path but also the broader uncertainty around each prediction. The parameter estimates sample from the fitted model show a negative AR(1) coefficient, hinting at a small "bounce-back" effect, and the confidence intervals help confirm the model's stability.