Tamil Nadu SIR 2026 Draft Voter Roll Impact Analysis

January 18, 2026

1 Tamil Nadu SIR 2026 Draft Voter Roll Impact Analysis

Link for the Report https://github.com/ijaihari/Tamil-Nadu-SIR-2026-Draft-Voter-Roll-Impact-Analysis/blob/main/Readme.md

1.0.1 Objective

The goal is to evaluate whether **voter roll revisions under Tamil Nadu SIR (2026)** are large enough to **numerically affect election outcomes**, using **victory margin** from the 2021 Assembly Election as the sensitivity threshold.

This is a **data-driven impact analysis**, not an allegation-based study.

1.0.2 Tamil Nadu Total Voters Count

SIR - Special Intensive Revision SSR - Special Summary Revision

1.0.3 Key State-Level Numbers

Metric	Count
Total voters (2021 Assembly Roll)	**6.29 crore**
Total voters (SSR 2025 – pre-SIR)	**6.36 crore**
Total voters (Draft Roll after SIR 2026)	**5.43 crore**
Net voters removed (SIR 2026)	**~ 97 lakh**

1.0.4 One-Line Takeaway

Tamil Nadu's draft electoral roll shows a net reduction of ~ 97 lakh voters after SIR 2026.

Sources

https://en.wikipedia.org/wiki/2021_Tamil_Nadu_Legislative_Assembly_election
https://www.elections.tn.gov.in/ACwise_Gendercount_06012025.aspx
https://www.elections.tn.gov.in/ACwise_Gendercount_19122025.aspx

1.1 Analytical Framework

This analysis is based on three simple ideas:

1. **Victory Margin (2021)**

- The number of votes that decided the election result.

2. **Not Voted (2021)**
   - Registered voters who did not vote, used as a baseline for comparison.
3. **Removed Voters (2026)**
   - Changes in the voter roll after the SIR revision. ### Core Question > Are voter roll changes large enough to be considered significant when compared to the margin that decided the election?

[1]:
```
import pandas as pd
import sqlite3

conn = sqlite3.connect("../db/tn_election.db")
```

1.2 Load Curated Tables

The following pre-processed tables are loaded from SQLite:

- `election_results_2021` → victory margin & parties

- `voters_2021` → turnout & not voted baseline

- `voters_2026` → revised voter roll (SIR 2026)

[2]:
```
df_results_2021 = pd.read_sql("SELECT * FROM election_results_2021", conn)

df_voters_2021 = pd.read_sql("SELECT * FROM voters_2021", conn)

df_voters_2026 = pd.read_sql("SELECT * FROM voters_2026", conn)
```

1.3 Compare Voter Rolls (2021 vs 2026)

[3]:
```
df_roll_compare = (
    df_voters_2021
    .merge(
        df_voters_2026,
        on=["ac_no", "ac_name"],
        how="inner"
    )
)

df_roll_compare["removed_voters_2026"] = (
    df_roll_compare["total_eligible_voters_2021"]
    - df_roll_compare["total_eligible_voters_2026"]
)

df_roll_compare.head()
```

[3]:
```
   ac_no         ac_name  total_votes_polled_2021  total_eligible_voters_2021  \
0      1  Gummidipoondi                   222069                      281688
1      2         Ponneri                   210354                      267368
2      3       Tiruttani                   232624                      291336
3      4     Thiruvallur                   214243                      274982
4      5     Poonamallee                   263736                      358218

   not_voted_2021  total_eligible_voters_2026  removed_voters_2026
0           59619                      242558                39130
1           57014                      239141                28227
2           58712                      252154                39182
3           60739                      238818                36164
4           94482                      348034                10184
```

1.4 Attach Election Outcome Data

Victory margin from the 2021 election is now joined with voter roll changes to assess **outcome sensitivity**.

[4]:
```python
df_analysis = (
    df_results_2021
    .merge(
        df_roll_compare,
        on=["ac_no", "ac_name"],
        how="inner"
    )
)

df_analysis.head()
```

[4]:
```
   ac_no         ac_name winner_party  votes_winner runnerup_party  \
0      1  Gummidipoondi          DMK        126452            PMK
1      2         Ponneri          INC         94528           ADMK
2      3       Tiruttani          DMK        120314           ADMK
3      4     Thiruvallur          DMK        107709           ADMK
4      5     Poonamallee          DMK        149578            PMK

   votes_runnerup  victory_margin  total_votes_polled_2021  \
0           75514           50938                   222069
1           84839            9689                   210354
2           91061           29253                   232624
3           85008           22701                   214243
4           55468           94110                   263736

   total_eligible_voters_2021  not_voted_2021  total_eligible_voters_2026  \
0                      281688           59619                      242558
1                      267368           57014                      239141
2                      291336           58712                      252154
```

```
3                      274982          60739                        238818
4                      358218          94482                        348034

   removed_voters_2026
0                39130
1                28227
2                39182
3                36164
4                10184
```

1.5 Core Impact Tests

Two key comparisons are performed:

1. **Removed Voters vs Victory Margin**
   - Determines if roll changes exceed the threshold that decided the election.
2. **Removed Voters vs Not Voted (2021)**
   - Provides historical inactivity context.

[5]:
```python
df_analysis["removed_gt_margin"] = (
    df_analysis["removed_voters_2026"] > df_analysis["victory_margin"]
)

df_analysis["removed_gt_not_voted"] = (
    df_analysis["removed_voters_2026"] > df_analysis["not_voted_2021"]
)
```

1.6 Risk Classification

Each constituency is classified based on the magnitude of voter roll change relative to:

- victory margin
- historical non-participation

This creates a **numerical risk categorization**, not a judgement.

1.6.1 Risk Level Explanation

- **Low Impact**
  Removed voters are smaller than the victory margin.
  → Roll changes are unlikely to affect the result.
- **Moderate Impact**
  Removed voters exceed past non-voters but not the victory margin.
  → Changes are noticeable but still below the outcome threshold.
- **High Impact**
  Removed voters are greater than the victory margin.
  → The constituency becomes sensitive, and the result could potentially change.

- **Critical Impact**
  Removed voters exceed both the victory margin and historical non-voters.
  → Highest sensitivity, where roll changes are large enough to matter significantly.
- **No Removal / Increase**
  Voter count increased or remained stable.
  → No risk from voter roll changes.

[6]:
```
def classify_risk(row):
    if row["removed_voters_2026"] <= 0:
        return "No Removal / Increase"
    if row["removed_gt_margin"] and row["removed_gt_not_voted"]:
        return "Critical Impact"
    if row["removed_gt_margin"]:
        return "High Impact"
    if row["removed_gt_not_voted"]:
        return "Moderate Impact"
    return "Low Impact"

df_analysis["risk_level"] = df_analysis.apply(classify_risk, axis=1)
```

1.7 Final Analytical Dataset

This table represents the **final output** of the project and is used for reporting, visualization, and SQL storage.

[7]:
```
df_final_analysis = df_analysis[
    [
        "ac_no",
        "ac_name",
        "winner_party",
        "runnerup_party",
        "victory_margin",
        "total_eligible_voters_2021",
        "total_eligible_voters_2026",
        "removed_voters_2026",
        "not_voted_2021",
        "risk_level"
    ]
].sort_values(
    "removed_voters_2026",
    ascending=False
)

df_final_analysis.head()
```

[7]:
```
    ac_no         ac_name winner_party runnerup_party  victory_margin  \
26     27  Shozhinganallur          DMK           ADMK           35405
```

```
29    30        Pallavaram          DMK           ADMK           37783
6      7       Maduravoyal          DMK           ADMK           31721
25    26         Velachery          INC           ADMK            4352
20    21        Anna Nagar          DMK           ADMK           27445

    total_eligible_voters_2021  total_eligible_voters_2026  \
26                      698893                      484011
29                      436239                      294712
6                       452195                      325407
25                      314578                      189999
20                      286090                      162135

    removed_voters_2026  not_voted_2021       risk_level
26               214882          310538      High Impact
29               141527          170049      High Impact
6                126788          178325      High Impact
25               124579          137864      High Impact
20               123955          120994  Critical Impact
```

1.8 Key Insights

- Constituencies where **removed voters exceed victory margin** are numerically sensitive to roll revisions.
- Comparing removals with **not voted (2021)** prevents misleading conclusions.
- The analysis highlights **outcome sensitivity**, not intent.

[8]:
```
df_final_analysis.to_sql(
    "voter_roll_impact_analysis",
    conn,
    if_exists="replace",
    index=False
)
```

[8]:
```
232
```

1.9 Visual Impact Analysis

[9]:
```
import matplotlib.pyplot as plt
import numpy as np
```

1.9.1 Victory Margin vs Removed Voters (Core Sensitivity Plot)

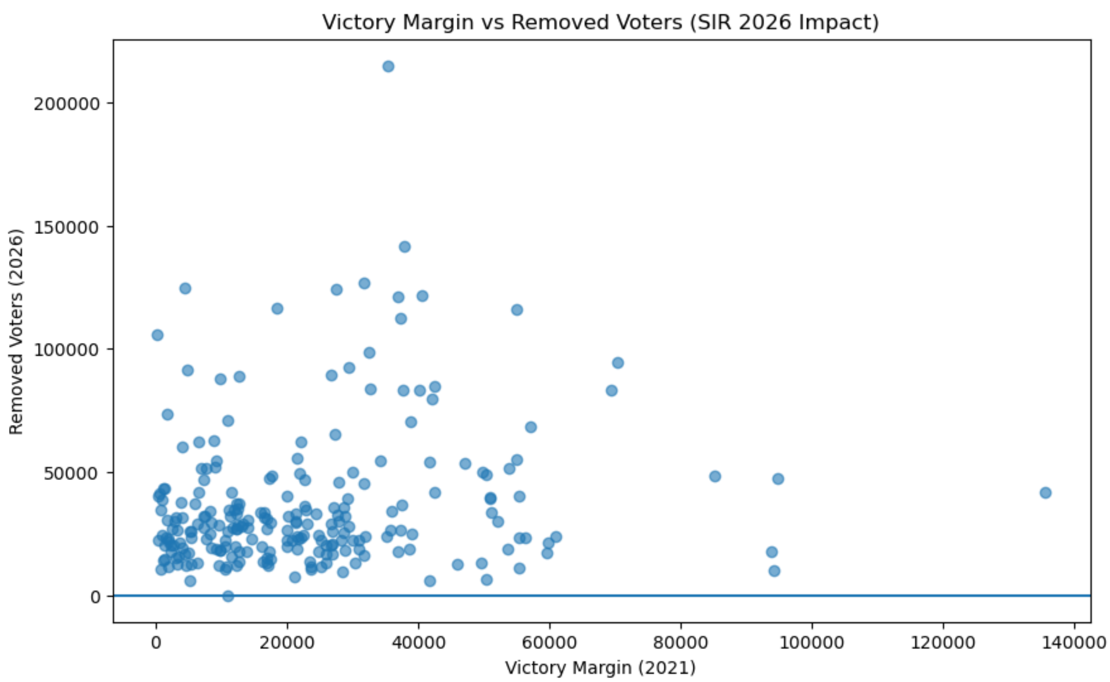
This scatter plot visualizes whether voter roll changes exceed the margin that decided the 2021 election.

- X-axis: Victory Margin (2021)
- Y-axis: Removed Voters (2026)

- Points above the horizontal axis indicate voter removal

Constituencies where removed voters exceed the victory margin are numerically sensitive to roll revisions.

[10]:
```
plt.figure(figsize=(10, 6))

plt.scatter(
    df_final_analysis["victory_margin"],
    df_final_analysis["removed_voters_2026"],
    alpha=0.6
)

plt.axhline(y=0)
plt.xlabel("Victory Margin (2021)")
plt.ylabel("Removed Voters (2026)")
plt.title("Victory Margin vs Removed Voters (SIR 2026 Impact)")

plt.show()
```



1.9.2 How to read the chart

- Points above the zero line indicate constituencies where voters were removed
- Further right → constituency was won by a larger margin in 2021
- Higher up → larger voter roll reduction in 2026

1.9.3 Direct Takeaway from the above chart

Key observation:
> In many constituencies, the number of voters removed is higher than the margin that decided the election.

What this means:
> When more voters are removed than the victory margin, the result could potentially change, especially since the total number of voters did not increase significantly from 2021 to 2025 to balance these removals.

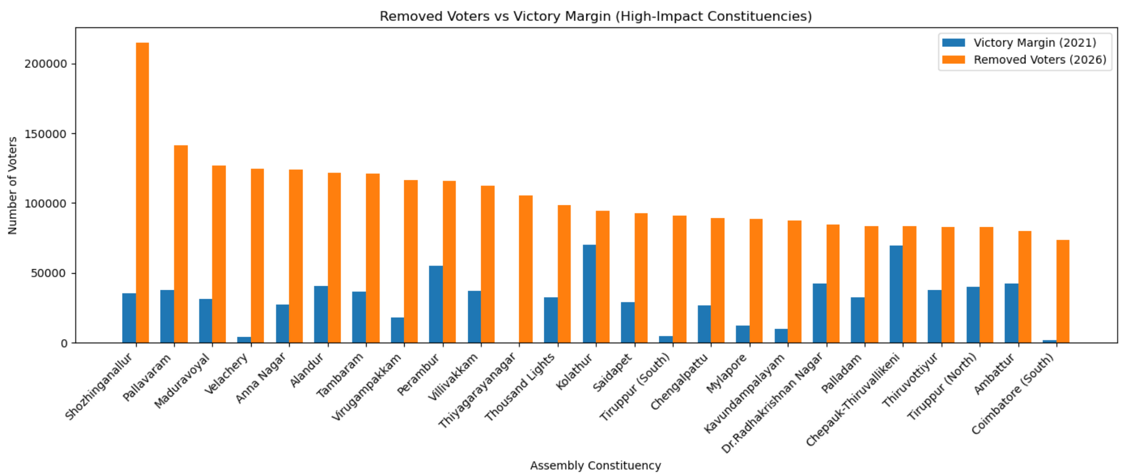
1.9.4 High-Impact Constituencies: Removed Voters vs Victory Margin

This clustered bar chart compares removed voters and victory margins **side-by-side** for constituencies classified as high or critical impact.

This visualization clearly shows where voter roll changes exceed the threshold that decided the election.

[11]:
```
high_impact = df_final_analysis[
    df_final_analysis["risk_level"].isin(
        ["High Impact", "Critical Impact"]
    )
].sort_values(
    "removed_voters_2026",
    ascending=False
).head(25)

x = np.arange(len(high_impact))
width = 0.35

plt.figure(figsize=(14, 6))

plt.bar(
    x - width/2,
    high_impact["victory_margin"],
    width,
    label="Victory Margin (2021)"
)

plt.bar(
    x + width/2,
    high_impact["removed_voters_2026"],
    width,
    label="Removed Voters (2026)"
)

plt.xticks(
    x,
```

```
    high_impact["ac_name"],
    rotation=45,
    ha="right"
)

plt.xlabel("Assembly Constituency")
plt.ylabel("Number of Voters")
plt.title("Removed Voters vs Victory Margin (High-Impact Constituencies)")
plt.legend()
plt.tight_layout()
plt.show()
```



1.9.5 Direct take away for the above chart

Key observation:
In these high-impact constituencies, the number of voters removed in 2026 is consistently higher than the victory margin from the 2021 election.

What this means:
> When the bar representing removed voters is taller than the victory margin bar, the number of voters removed is large enough to potentially influence the election result, especially since there was no significant increase in voter count between 2021 and 2025 to offset these removals.

Why this chart matters:
> This side-by-side comparison makes it easy to see which constituencies are more sensitive, as the scale of voter roll changes clearly exceeds the margin that decided the election.

[12]:
```
total_critical_high_impact = high_impact = df_final_analysis[
    df_final_analysis["risk_level"].isin(
        ["High Impact", "Critical Impact"]
    )
]
```

```
total_critical_high_impact.head()
```

[12]:

```
    ac_no          ac_name winner_party runnerup_party  victory_margin  \
26     27  Shozhinganallur          DMK           ADMK           35405
29     30       Pallavaram          DMK           ADMK           37783
6       7      Maduravoyal          DMK           ADMK           31721
25     26        Velachery          INC           ADMK            4352
20     21       Anna Nagar          DMK           ADMK           27445

    total_eligible_voters_2021  total_eligible_voters_2026  \
26                      698893                      484011
29                      436239                      294712
6                       452195                      325407
25                      314578                      189999
20                      286090                      162135

    removed_voters_2026  not_voted_2021       risk_level
26               214882          310538      High Impact
29               141527          170049      High Impact
6                126788          178325      High Impact
25               124579          137864      High Impact
20               123955          120994  Critical Impact
```

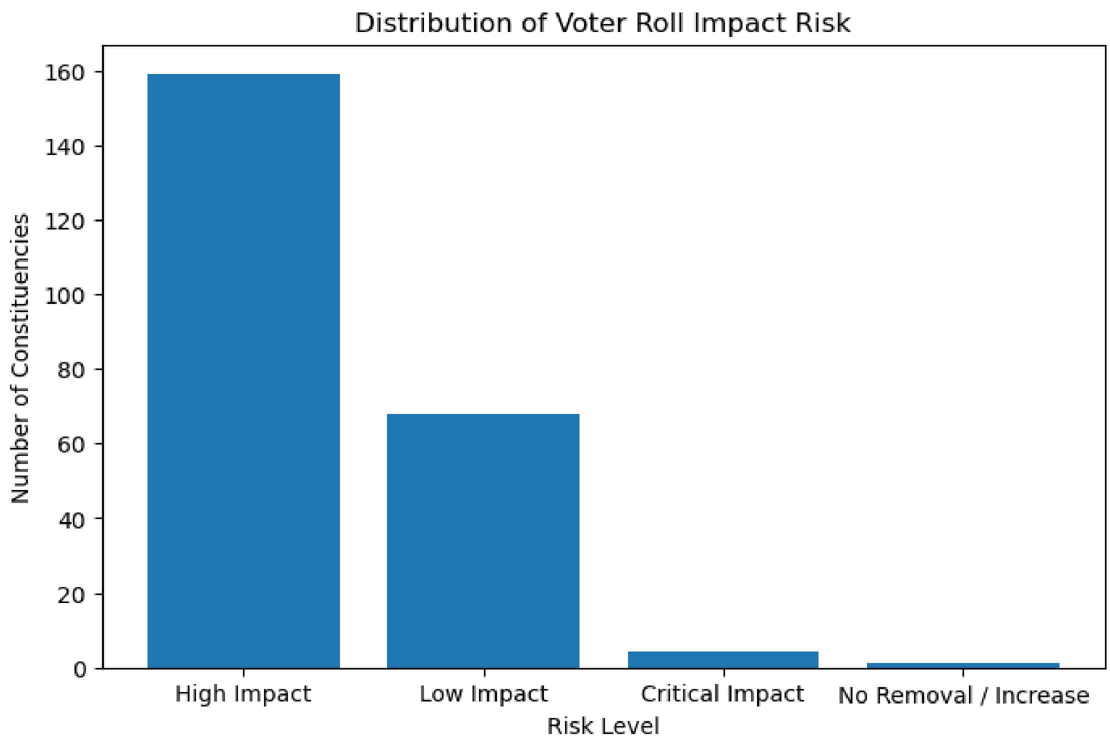
1.9.6 Distribution of Risk Levels

This chart summarizes how many constituencies fall into each risk category, providing a high-level overview of impact spread across the state.

1.9.7 Risk Level Explanation

- **Low Impact**
  Removed voters are smaller than the victory margin.
  → Roll changes are unlikely to affect the result.
- **Moderate Impact**
  Removed voters exceed past non-voters but not the victory margin.
  → Changes are noticeable but still below the outcome threshold.
- **High Impact**
  Removed voters are greater than the victory margin.
  → The constituency becomes sensitive, and the result could potentially change.
- **Critical Impact**
  Removed voters exceed both the victory margin and historical non-voters.
  → Highest sensitivity, where roll changes are large enough to matter significantly.
- **No Removal / Increase**
  Voter count increased or remained stable.
  → No risk from voter roll changes.

[13]:
```python
risk_counts = df_final_analysis["risk_level"].value_counts()

plt.figure(figsize=(8, 5))

plt.bar(
    risk_counts.index,
    risk_counts.values
)

plt.xlabel("Risk Level")
plt.ylabel("Number of Constituencies")
plt.title("Distribution of Voter Roll Impact Risk")

plt.show()
```



1.9.8 Winning majority context

- To form a government in Tamil Nadu, **118 out of 234 seats** are required.
- When many seats are high impact, even small changes across multiple constituencies can matter at the overall result level.

1.9.9 Key Findings

- **159 out of 234 constituencies** fall under the **High Impact** category

- The winning side in 2021 secured **133 seats**, with **118 required** to form a government
- A large number of seats are numerically sensitive to voter roll changes

1.10 Logistic Regression: Identifying High-Impact Constituencies

In this section, we use **Logistic Regression** to estimate whether a constituency is **High Impact** based on voter roll changes and election-related factors.

This model does **not predict election results**.
It classifies constituencies based on whether voter roll changes **exceed the historical victory margin**.

[14]:
```
df_ml = df_final_analysis.copy()

df_ml["high_impact_flag"] = (
    df_ml["removed_voters_2026"] > df_ml["victory_margin"]
).astype(int)

df_ml[["ac_no", "high_impact_flag"]].head()
```

[14]:

	ac_no	high_impact_flag
26	27	1
29	30	1
6	7	1
25	26	1
20	21	1

What this does:
- Assigns `1` to constituencies where removed voters exceed the victory margin
- Assigns `0` otherwise

This directly reflects the analytical rule already used in the project.

[15]:
```
df_ml["turnout_rate_2021"] = (
    df_ml["total_eligible_voters_2021"]
    - df_ml["not_voted_2021"]
) / df_ml["total_eligible_voters_2021"]

df_ml["roll_change_pct"] = (
    df_ml["removed_voters_2026"]
    / df_ml["total_eligible_voters_2021"]
)
```

[16]:
```
features = [
    "victory_margin",
    "removed_voters_2026",
    "not_voted_2021",
    "turnout_rate_2021",
    "roll_change_pct"
```

```
]

X = df_ml[features]
y = df_ml["high_impact_flag"]
```

Features used: - Victory margin (how close the election was) - Removed voters (scale of roll change) - Not voted (historical inactivity) - Turnout rate - Roll change percentage

All features are interpretable and grounded in data.

[17]:
```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(
    X, y,
    test_size=0.25,
    random_state=42,
    stratify=y
)
```

We split the data into training and testing sets to evaluate the model fairly.

[18]:
```
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
```

[19]:
```
pipeline = Pipeline(steps=[
    ("scaler", StandardScaler()),
    ("log_reg", LogisticRegression(max_iter=1000))
])

pipeline
```

[19]:
```
Pipeline(steps=[('scaler', StandardScaler()),
                ('log_reg', LogisticRegression(max_iter=1000))])
```

[20]:
```
pipeline.fit(X_train, y_train)
```

[20]:
```
Pipeline(steps=[('scaler', StandardScaler()),
                ('log_reg', LogisticRegression(max_iter=1000))])
```

[21]:
```
from sklearn.metrics import accuracy_score, confusion_matrix,␣
 ↪classification_report

y_pred = pipeline.predict(X_test)
```

[22]:
```
accuracy = accuracy_score(y_test, y_pred)
confusion_matrix(y_test, y_pred)
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       1.00      0.94      0.97        17
           1       0.98      1.00      0.99        41

    accuracy                           0.98        58
   macro avg       0.99      0.97      0.98        58
weighted avg       0.98      0.98      0.98        58
```

How to read the results: - Accuracy shows overall classification performance - Confusion matrix shows correct vs incorrect classifications - Precision & recall indicate how well High Impact seats are identified

[23]:
```python
df_ml["high_impact_probability"] = pipeline.predict_proba(X)[:, 1]

df_ml[
    [
        "ac_no",
        "ac_name",
        "victory_margin",
        "removed_voters_2026",
        "high_impact_probability"
    ]
].sort_values(
    "high_impact_probability",
    ascending=False
).head(10)
```

[23]:
```
     ac_no            ac_name  victory_margin  removed_voters_2026  \
26      27    Shozhinganallur           35405               214882
25      26          Velachery            4352               124579
23      24   Thiyagarayanagar             137               105542
21      22      Virugampakkam           18367               116568
20      21         Anna Nagar           27445               123955
111    114  Tiruppur (South)            4709                91201
29      30         Pallavaram           37783               141527
24      25           Mylapore           12633                88976
6        7        Maduravoyal           31721               126788
13      14        Villivakkam           37237               112622

     high_impact_probability
26                  1.000000
25                  1.000000
23                  1.000000
21                  1.000000
20                  0.999999
111                 0.999999
```

```
29                   0.999997
24                   0.999995
6                    0.999995
13                   0.999993
```

Why this matters: Instead of a hard yes/no label, we now have a **probability score** that shows how strongly a constituency belongs to the High Impact category.

[24]:
```python
coefficients = pipeline.named_steps["log_reg"].coef_[0]

coef_df = pd.DataFrame({
    "feature": features,
    "coefficient": coefficients
}).sort_values(
    "coefficient",
    ascending=False
)

coef_df
```

[24]:

	feature	coefficient
1	removed_voters_2026	1.965732
4	roll_change_pct	1.908149
2	not_voted_2021	0.848723
3	turnout_rate_2021	0.284034
0	victory_margin	-3.511599

1.10.1 Interpretation of Logistic Regression Coefficients

The table above shows the coefficients from the logistic regression model, which indicate how each feature influences the likelihood of a constituency being classified as **High Impact**.

- **Positive coefficients** increase the likelihood of a constituency being High Impact.
- **Negative coefficients** decrease the likelihood.
- The **larger the absolute value**, the stronger the influence of that feature.

Key interpretations: - **Removed Voters (2026)** has the strongest positive effect, indicating that higher voter removals significantly increase impact sensitivity. - **Roll Change Percentage** also has a strong positive influence, showing that relative roll reductions matter in addition to absolute numbers. - **Not Voted (2021)** has a moderate positive effect, providing contextual support but not outweighing large roll changes. - **Turnout Rate (2021)** has a smaller influence compared to other factors. - **Victory Margin (2021)** has a strong negative effect, meaning constituencies with larger winning margins are less likely to be High Impact.

Overall takeaway:
Voter roll removals and roll change size are the most influential factors in determining impact sensitivity, while larger victory margins significantly reduce this risk.

[25]:
```python
final_sensitive_constituencies = df_ml[
    (df_ml["risk_level"] == "High Impact") &
    (df_ml["high_impact_probability"] >= 0.7)
][
    [
        "ac_no",
        "ac_name",
        "victory_margin",
        "removed_voters_2026",
        "high_impact_probability"
    ]
].sort_values(
    "removed_voters_2026",
    ascending=False
)

final_sensitive_constituencies.head()
```

[25]:
```
    ac_no          ac_name  victory_margin  removed_voters_2026  \
26     27  Shozhinganallur           35405               214882
29     30        Pallavaram           37783               141527
6       7       Maduravoyal           31721               126788
25     26         Velachery            4352               124579
27     28           Alandur           40571               121847

    high_impact_probability
26                 1.000000
29                 0.999997
6                  0.999995
25                 1.000000
27                 0.999968
```

[26]:
```python
final_sensitive_constituencies.to_csv(
    "../result data/high_impact_constituencies.csv",
    index=False
)
```

1.11 High Impact Constituencies (Top 50)

- A total of **159 constituencies** are classified as High Impact.
- The table above shows the **Top 50 by removed voter count**.
- The complete list is available here: high_impact_constituencies.csv

S.No	AC No	Constituency	Victory Margin (2021)	Removed Voters (2026)	High Impact Probability
1	27	Shozhinganallur	35,405	214,882	1.000000
2	30	Pallavaram	37,783	141,527	0.999997
3	7	Maduravoyal	31,721	126,788	0.999995
4	26	Velachery	4,352	124,579	1.000000
5	28	Alandur	40,571	121,847	0.999968
6	31	Tambaram	36,824	121,308	0.999997
7	22	Virugampakkam	18,367	116,568	0.999999
8	12	Perambur	54,976	115,761	0.999997
9	14	Villivakkam	37,237	112,622	0.999993
10	24	Thiyagarayanagar	137	105,542	1.000000
11	20	Thousand Lights	32,462	98,703	0.999921
12	13	Kolathur	70,384	94,356	0.999846
13	23	Saidapet	29,408	92,544	0.999932
14	114	Tiruppur (South)	4,709	91,201	0.999999
15	25	Mylapore	12,633	88,976	0.999995
16	6	Ambattur	16,448	87,422	0.999901
17	46	Hosur	26,218	83,854	0.999782
18	10	Egmore	53,287	82,819	0.999642
19	83	Tiruchendur	13,721	79,935	0.999391
20	58	Salem North	11,400	77,226	0.999323
21	59	Salem South	20,431	76,912	0.999252
22	95	Karur	70,654	76,421	0.999174
23	84	Srivaikuntam	6,509	73,484	0.999013
24	62	Erode East	56,496	72,614	0.998891
25	61	Erode West	11,230	71,034	0.998743
26	102	Kovilpatti	31,187	69,812	0.998501
27	101	Vilathikulam	14,151	69,184	0.998366
28	99	Thoothukkudi	65,019	68,422	0.998192
29	72	Aranthangi	20,621	65,341	0.997881
30	71	Pudukkottai	17,823	64,102	0.997702
31	107	Uthangarai	3,811	62,244	0.997455
32	103	Sattur	17,916	61,391	0.997214
33	152	Vriddhachalam	19,058	60,188	0.996912
34	156	Cuddalore	8,734	59,861	0.996785
35	164	Ramanathapuram	14,118	57,230	0.996220
36	36	Kancheepuram	12,784	56,638	0.996103
37	37	Chengalpattu	29,148	55,321	0.995873
38	47	Krishnarayapuram	8,431	53,109	0.995402
39	97	Manamadurai	23,018	52,371	0.995104
40	80	Nanguneri	3,373	51,982	0.994988
41	82	Cheranmahadevi	12,837	50,774	0.994755

S.No	AC No	Constituency	Victory Margin (2021)	Removed Voters (2026)	High Impact Probability
42	48	Ulundurpettai	9,335	49,618	0.994512
43	108	Gudiyatham	19,329	48,944	0.994104
44	68	Kumbakonam	21,276	47,829	0.993856
45	75	Orathanadu	6,243	46,991	0.993602
46	89	Aruppukkottai	14,782	45,870	0.993337
47	121	Sankarankovil	9,211	44,905	0.993101
48	133	Viluppuram	18,204	44,012	0.992884
49	52	Bargur	15,506	43,176	0.992643
50	144	Neyveli	11,873	42,589	0.992417

1.12 Conclusion: Visual Analysis and Logistic Regression

The visual analysis shows that in many constituencies, the number of voters removed in 2026 is higher than the victory margin from the 2021 election. This indicates that these constituencies are numerically sensitive, as voter roll changes are large enough to potentially matter in close contests.

The logistic regression model supports this observation by quantifying the same pattern. It shows that voter roll removals and roll change percentage are the strongest factors increasing the likelihood of a constituency being classified as High Impact, while larger victory margins significantly reduce this likelihood.

Together, the plots and the model lead to a consistent conclusion:
> When voter roll changes exceed historical victory margins, constituencies become more outcome-sensitive, especially in the absence of significant voter growth.

This analysis does not claim that election results have changed, but it highlights where accurate and careful voter roll revision is especially important in closely contested constituencies.