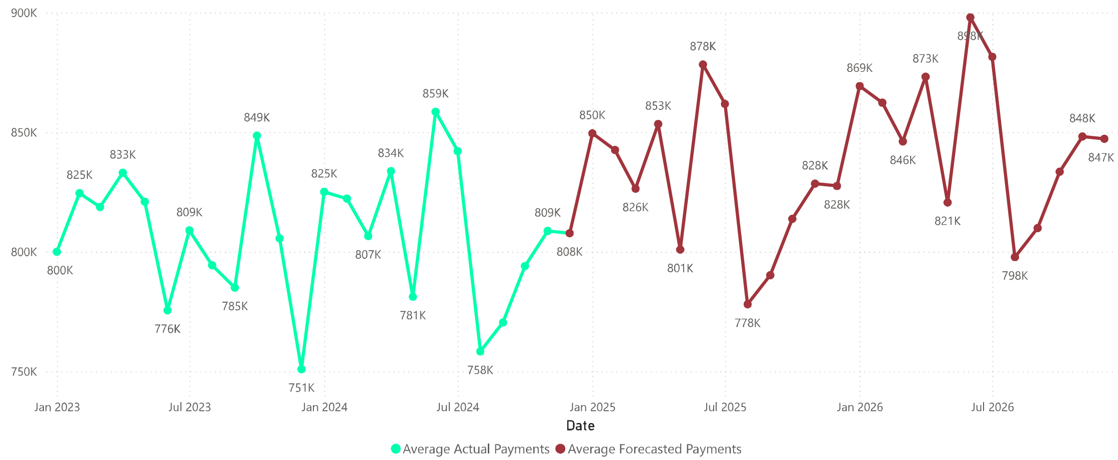
Retail Banking Forecast Suite

Aziz Akhtar

Average Payment Volume	Average Loan Apps	Average Deposit Balance	Average Churn Rate	Average App Logins	Average Loss Rate
$807K	300	5M	17.43%	1.20K	9.57%

Average Monthly Payment per Account – 24-Month Actual & 24-Month SARIMA Forecast



SARIMA FORECASTINC CHART

- **The first trio** (1, 1, 1) are the **non-seasonal** parts of the model, often written as ARIMA(p,d,q):
  - **p = 1** → "AR(1)" means we include last month's value in predicting this month.
  - **d = 1** → "I(1)" means we difference the series once (we look at month-to-month changes rather than raw levels).
  - **q = 1** → "MA(1)" means we include last month's forecast error (the amount we missed by) to correct this month's prediction.
- **The second quartet** (0, 1, 1, 12) are the **seasonal** parts, written as (P,D,Q,s):
  - **P = 0** → no seasonal autoregressive term (we're not leaning on the value from 12 months ago).
  - **D = 1** → one seasonal difference (we compare this month to the same month last year).
  - **Q = 1** → one seasonal moving-average term (we correct based on the forecast error from the same month last year).
  - **s = 12** → the season length is 12 months (i.e. yearly seasonality).

So altogether **SARIMAX(1,1,1)x(0,1,1,12)** means:
"Forecast using last month's level (AR1), last month's error (MA1), after removing month-to-month change (I1), and also remove yearly change (seasonal D1) plus correct by last year's error (seasonal MA1), with a 12-month seasonal cycle."

Dep. Variable: Forecasted_Payment_Volume
No. Observations: 24
Model: SARIMAX(1, 1, 1)x(0, 1, 1, 12)
Log Likelihood: 0.000
AIC: 8.000
BIC: nan

ar.L1 = 0.13
0.1273
"We lean about 13% on last month's actual average."
ma.L1 = –0.60
–0.6008
"We subtract 60% of last month's error to correct us."
seasonal MA = 0
0
"Skipping the 'same month last year' check."
sigma² ≈ 3.65 × 10⁹
3.65 billion
"size of the noise, how often data spikes"

Log Likelihood = 0: Just a technical score of fit; here with tiny data it doesn't mean much.
AIC = 8: A cheat-score that says "low number means simple yet OK fit."
BIC = NaN: We didn't have enough data for this test, so ignore it.

Fit Metrics simplified:

1. **I told the model**: "Use last month's average, plus fix 60% of last month's mistake. Don't bother with last year's same month."
2. **The model found** that leaning a bit on last month and correcting for most of last month's error gave the best simple forecast.
3. **Due to small sample data set (2 years)** some of the usual check-ups (like BIC or confidence tests) aren't reliable—so you'll see weird "NaN" or infinite values in those spots.

Bottom line: Our forecast line (the red one) is just you + 13% of last month – 60% of last error, month after month. It's simple but works OK for short runs when you don't have tons of data.

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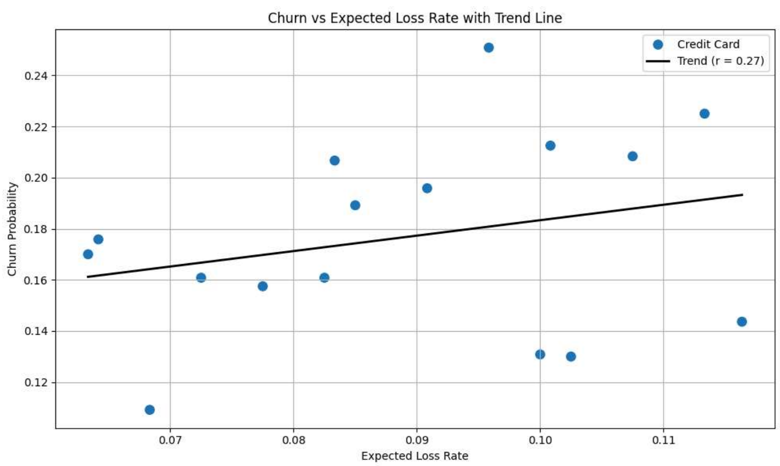

Product Filter - Graph Only

Multiple selections

```
# from your linregress call
slope     ≈ 0.25    # how steep the line is
intercept ≈ 0.135   # where the line crosses the Y-axis
r_value   ≈ 0.21    # correlation coefficient
p_value   ≈ 0.08    # probability this slope could be zero
stderr    ≈ 0.10    # uncertainty on the slope
n_points  = len(grouped)
r_squared = r_value**2  # ≈ 0.044
```

slope
0.25
For every extra 1% in loss rate, churn goes up by 0.25%.

intercept
0.135 (13.5%)
If loss rate were 0%, you'd still lose 13.5% of customers.

r_value
0.21
Loss rate & churn have a small, positive link

r^2
0.044 (4.4%)
Only 4.4% of churn swings are explained by loss rate changes.

p_value
0.08 (8%)
There's an 8% chance this slope happened by random luck.

stderr
0.10
slope (0.25) could plausibly be off by ±0.10 in either dir.

n_points
~64
You ran this on all quarter×product dots (e.g. 16 quarters × 4 products).

TLDR
- **Slope 0.25**: If you bump expected loss from, say, 10 % to 11 %, expect churn up by 0.25 %.
- **Intercept 13.5 %**: Even at zero loss rate, you'd still bleed ~13.5 % of customers.
- **r = 0.21**: There's a tiny positive vibe between loss and churn—but it's weak.
- **r^2 = 4.4 %**: Loss rate barely explains churn (95.6 % of churn is about other stuff).
- **p = 0.08**: It's not "statistically significant" at the usual 5 % cutoff—so maybe the link is just noise.
- **stderr 0.10**: Our slope estimate isn't super-precise; it could be as low as 0.15 or as high as 0.35.

riskier loans see slightly more churn, but only a tiny bit—and most churn has nothing to do with loss rate.