UK Credit Card Loss Forecasting Using Markov Chain Models

Credit Scoring and Credit Control XII conference

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Capital One is a successful global bank, specialising in credit cards

Globally

- Top 10 US bank
- 40 million customers
- Offices in US, UK & Canada

UK

- 800 employees
- Top 10 credit card issuer
- Nottingham & London offices

In our short history, we have expanded from a small regional credit card provider to a fully diversified international bank

1988 – Book first customers

1994 – Capital One IPO

1996 – Expand into Canada and UK

1998 – Acquire auto-lending business

2005 – Acquire Hibernia Bank

2006 – Acquire North Fork Bank

2009 – Acquire Chevy Chase Bank

Today – 40m customers worldwide; top ten US Bank

Importance of accurate loss forecasting

- **Loss forecasts are of fundamental importance to lending businesses.**

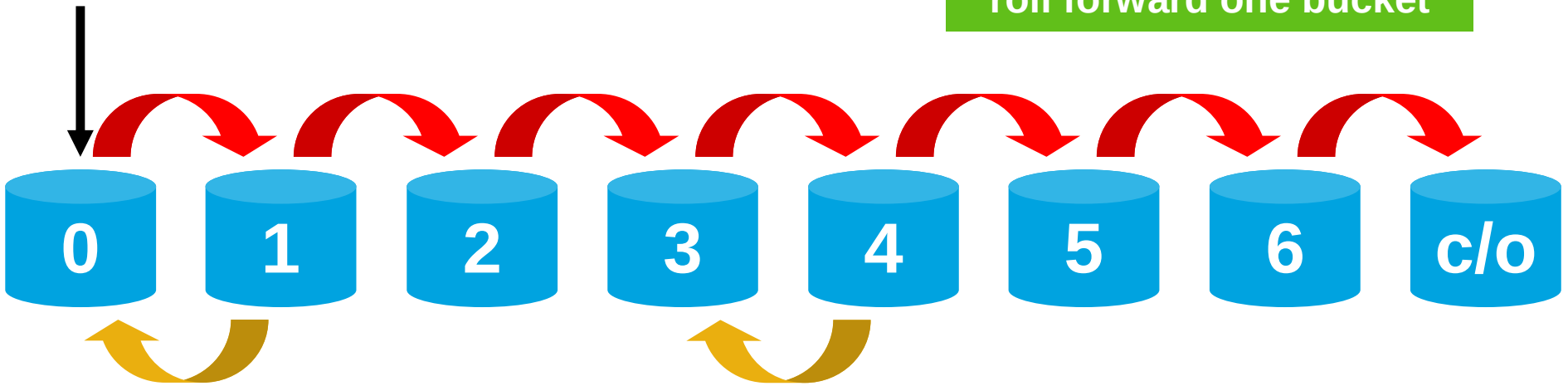
- **Assessments of future losses are used to ensure current strategies are profitable and resilient to changes in the economic environment.**

- **Adequate provision of capital is contingent on accurate forecasting of losses.**

Once a customer misses a payment they roll through a series of delinquency buckets until they are considered a ‘charge-off’

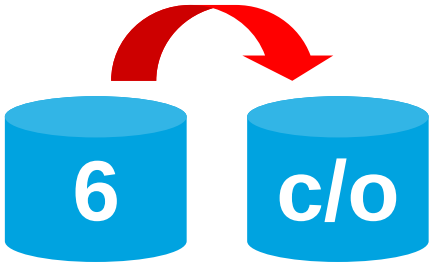
Customer ‘up-to-date’

Every month a customer misses a payment they roll forward one bucket



By making payments a customer may move back out of delinquency

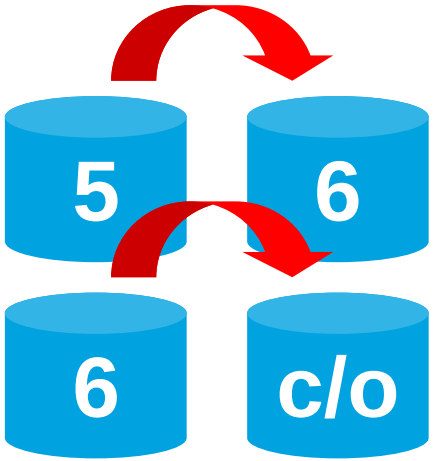
Our current approach to loss forecasting is to use ‘roll-rates’ between delinquency buckets to predict 6 month losses



Month 1 Losses = y.x/100

Last month x% of accounts in bucket 6 moved to c/o

This month we have y accounts in bucket 6



Month 2 Losses = w.z.x/10000

Last month x% of accounts in bucket 6 moved to c/o

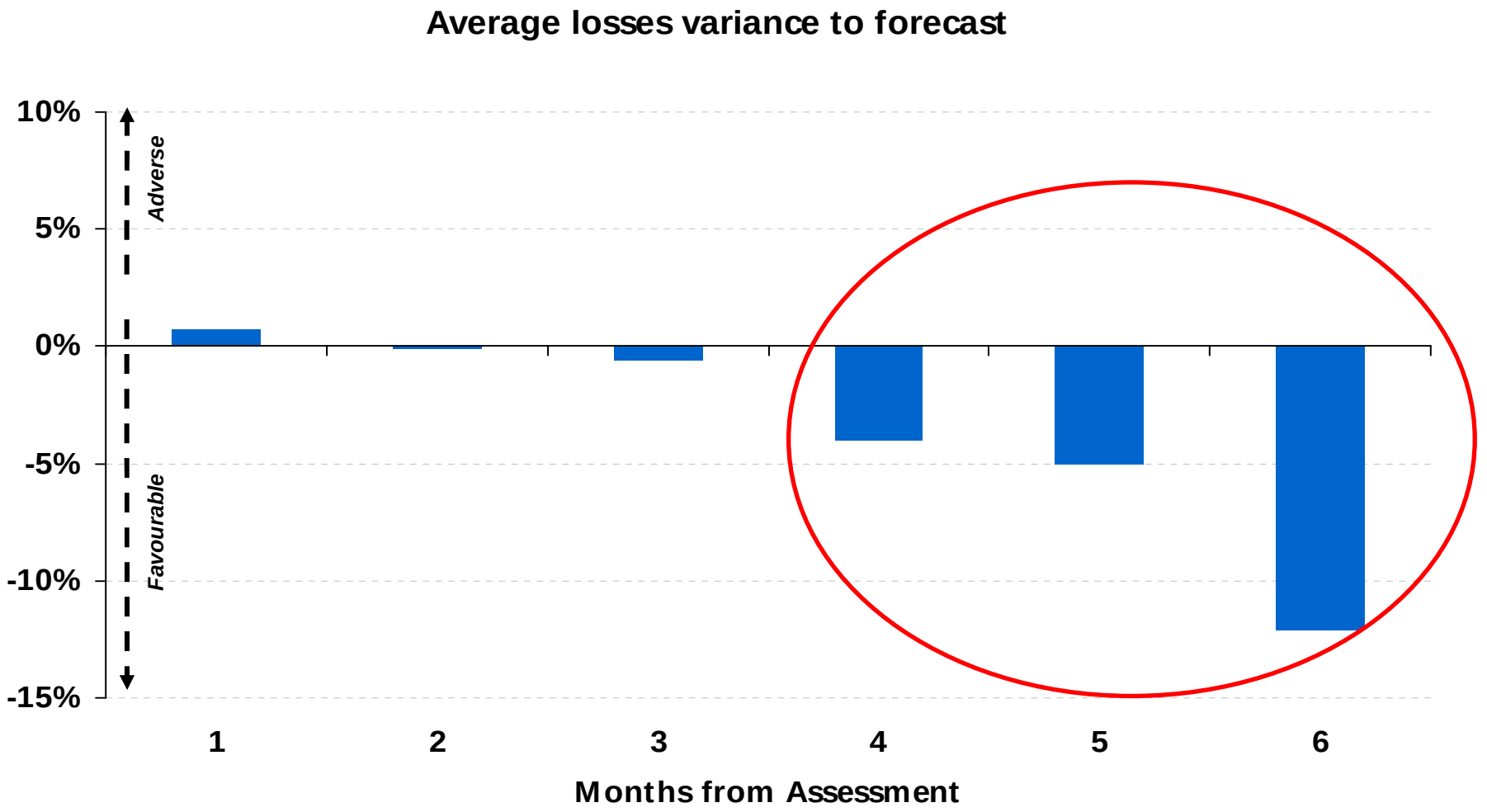
Last month z% of accounts in bucket 5 moved to 6

This month we have w accounts in bucket 5

. . .

This approach is generalised to predict losses for the next 6 months

Charge-offs variance to forecast suggests we are systematically favourable to forecast by month 4 onwards



The big drawback of this approach is that it assumes likelihood of rolling is homogenous within a delinquency bucket

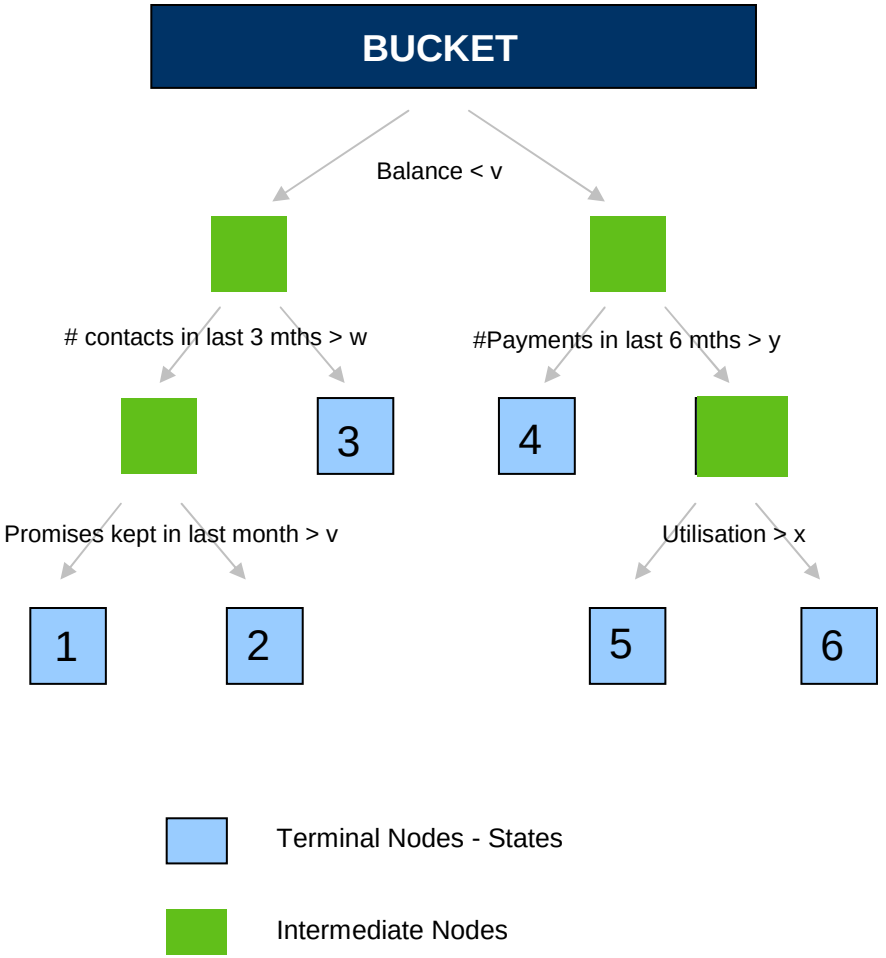
We have used Decision Tree Analysis to segment delinquent accounts in each bucket into homogenous states

• We have used account attributes, bureau and collections data to split the delinquent accounts into homogenous states.

• The event of charging off in the next six months is used as the target variable for splitting.

• Rules that define each of the states are kept fixed and for every monthly iteration delinquent accounts are scored using them.

• Six decision trees were built, one for each delinquency bucket



A transition matrix is created which describes the probability to charge off from each of these states

- Accounts from last two months are scored using the decision tree rules which segments the population into states.

- Cross-tabulation of states from the two months gives the transition matrix of actual movement of accounts from one state to another which could be expressed as percentage.

- This transition matrix serves as the probability matrix for future predictions.

States in Month 1

States in Month 0	1	2	…	N	CO
1	10%	40%	…	25%	5%
2	15%	25%	…	15%	15%
…	…	…	…	…	…
N	10%	10%	…	40%	10%
CO	0%	0%	0%	0%	0%

We then invoke the Markov Property to create charge off predictions for the next six months

- Markov property states that the probability distribution of future states of a process depends only upon the present state or a fixed number of past states.

- So to get probability to charge of two months from now, we could simply square the transition matrix.

States in Month 1 X States in Month 1 = **States in Month 2**

States in Month 0

	1	2	..	N	CO
1	.1	.3	..	.2	.1
2	.2	.4	..	.1	.2
.	..	..	..	..	..
N	.1	.1	..	.2	.4
co	0	0	0	0	0

States in Month 0

	1	2	..	N	C
1	.1	.3	..	.2	.1
2	.2	.4	..	.1	.2
.	..	..	..	..	..
N	.1	.1	..	.2	.4
co	0	0	0	0	0

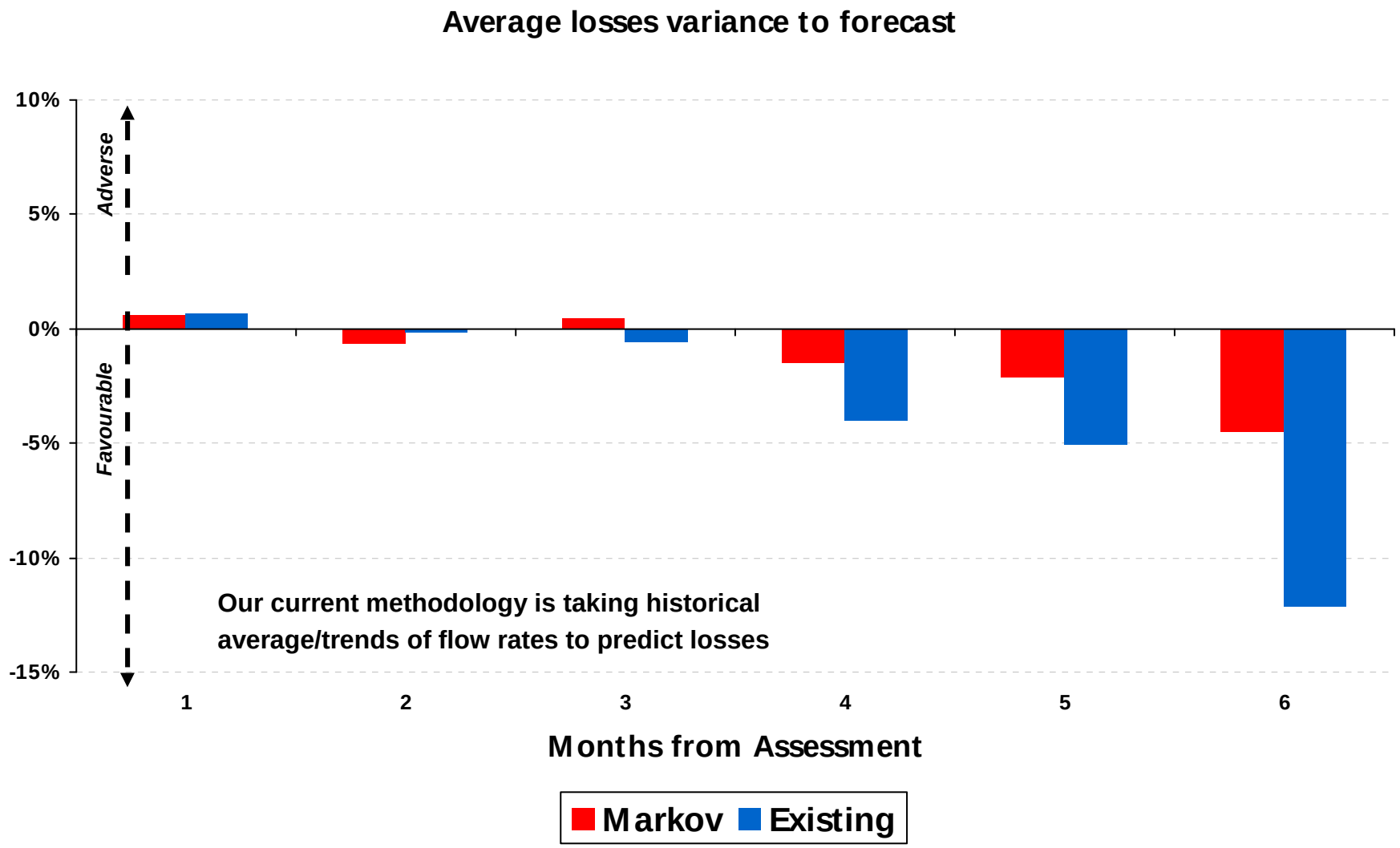
States in Month 0

	1	2	..	N	CO
1	.12	.32	..	.09	.21
2	.12	.28	..	.1	.16
.	..	..	..	..	..
N	.07	.19	..	.07	.15
co	0	0	0	0	0

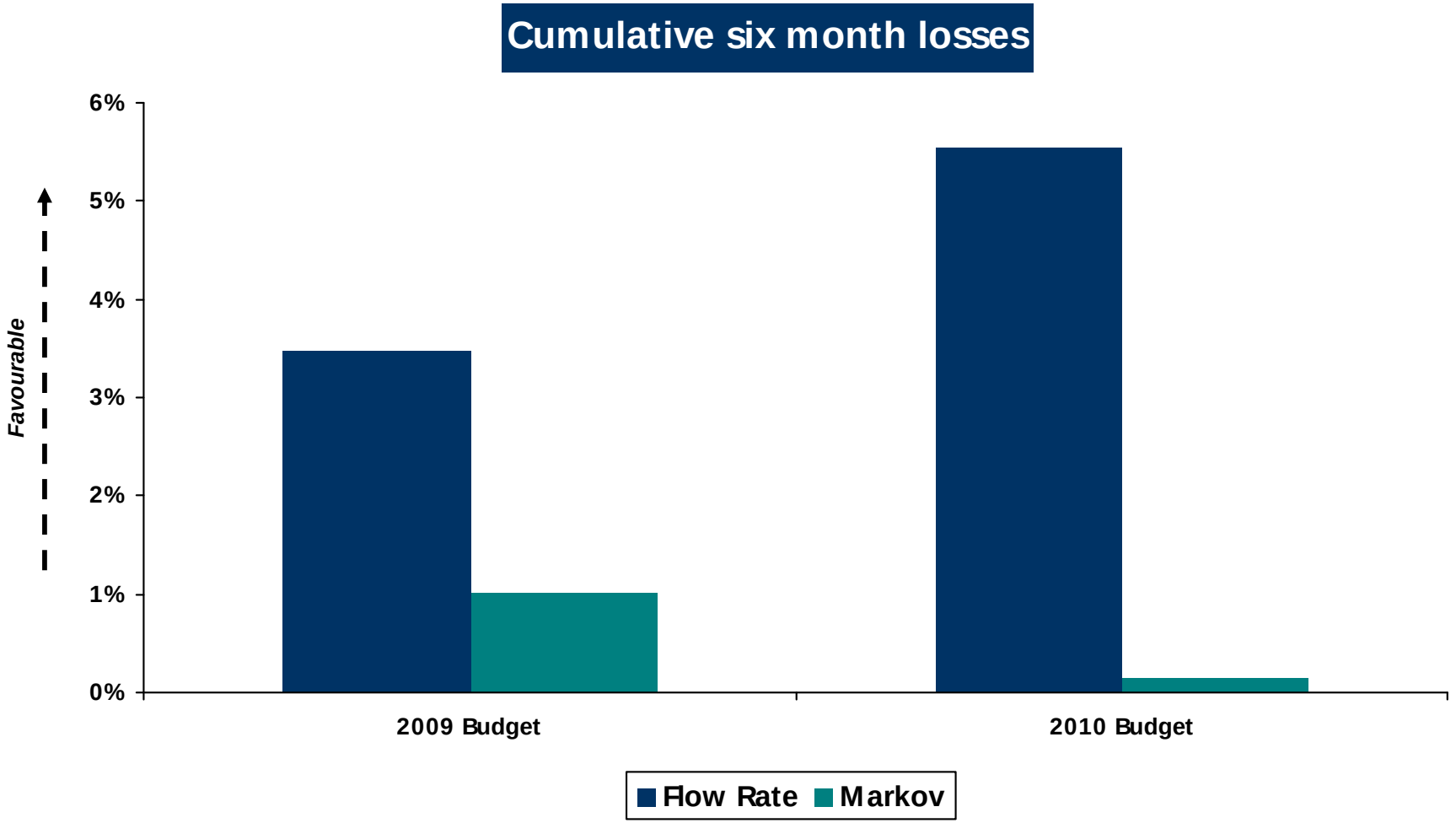
Transition matrix to the power n multiplied by the number of accounts in each state in month 0 gives the total number of charge offs in month n.

Del Accts in each State-Month 0			Transition Matrix to the power n							Charge offs in month n	
States	Accounts			1	2	..	N	CO	n	States	Accounts
1	120	X	1	.1	.3	..	.2	.1	=	1	50
2	250		2	.2	.4	..	.1	.2		2	150
.	…		.	..	..	..	..	..		.	…
N	600		N	.1	.1	..	.2	.4		N	200
co	0		co	0	0	0	0	0		co	500

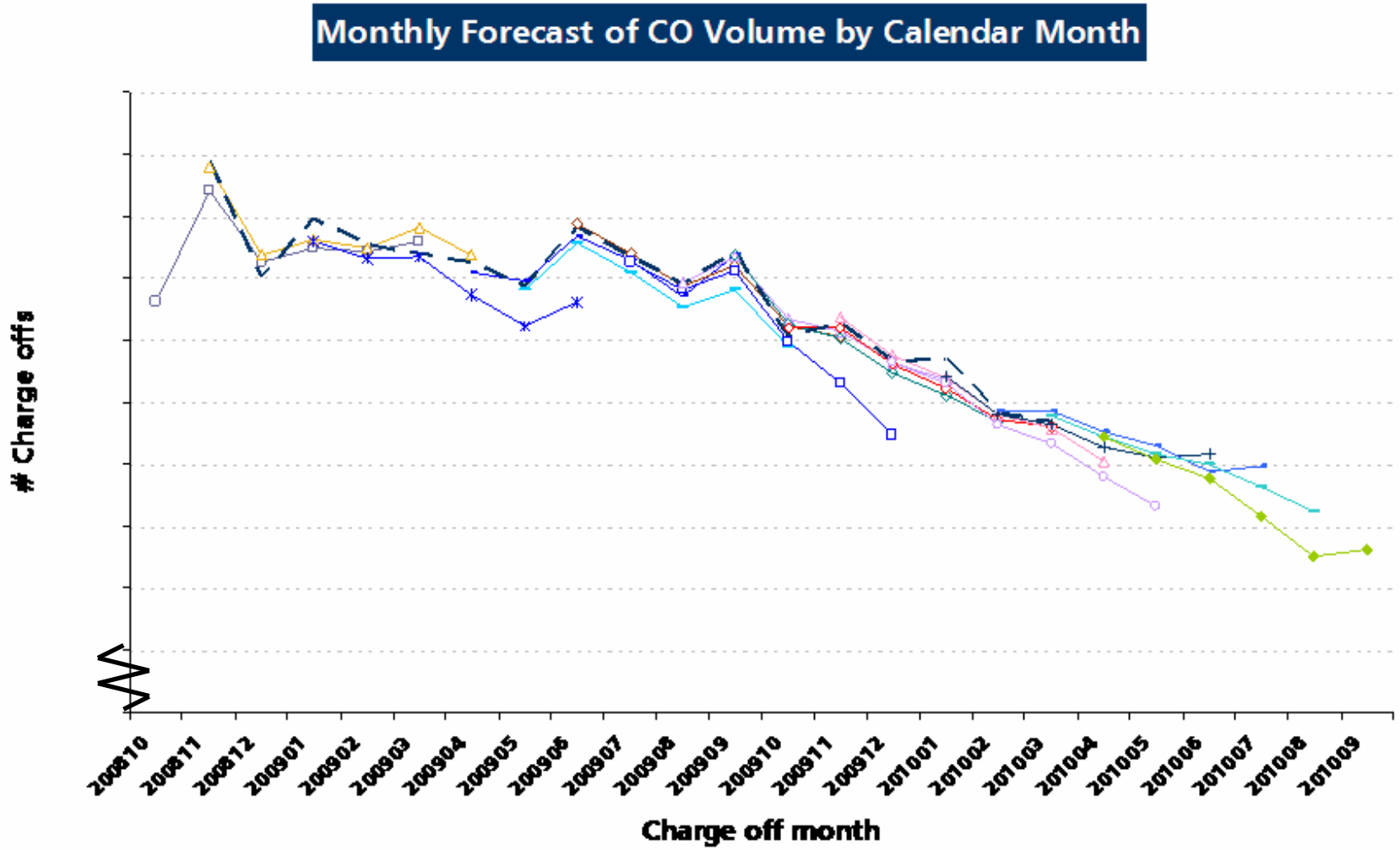
Model validates well over time with charge off prediction within +/-5% in each of next six months



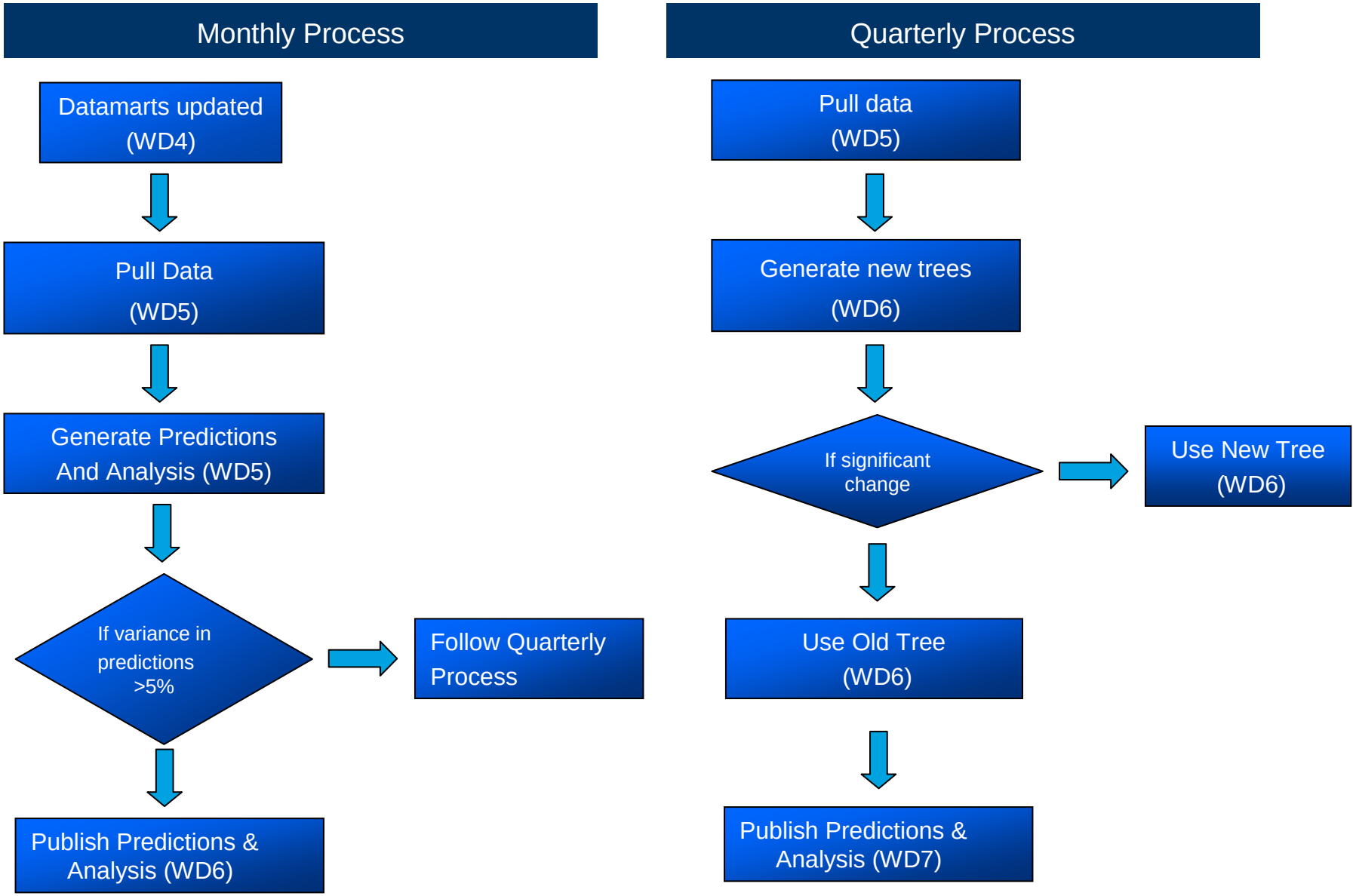
The approach has shown itself to be consistently better than the flow rate approach in predicting short term losses



Forecasted charge off volumes are similar month on month giving confidence around the stability of the approach



We have completely automated the model to get the output by weekday 6 of each month



Summary

- **Accurate loss forecasting is critical to Capital One to ensure we make the right decisions in the future around strategy & loss provisioning**

- **Our new approach has provided greater accuracy:**
  - We have used decision trees to help segment our portfolio into homogenous populations
  - These segments are used to construct a transition matrix
  - Matrix multiplication gives estimated losses for the next 6 months

- **This approach has proven to be stable, accurate & is now our standard approach to future loss forecasting**