



Case Study

Multiple Model Generations in a Sub-Prime Lending Environment; the benefits of new variables, splits, and data sources

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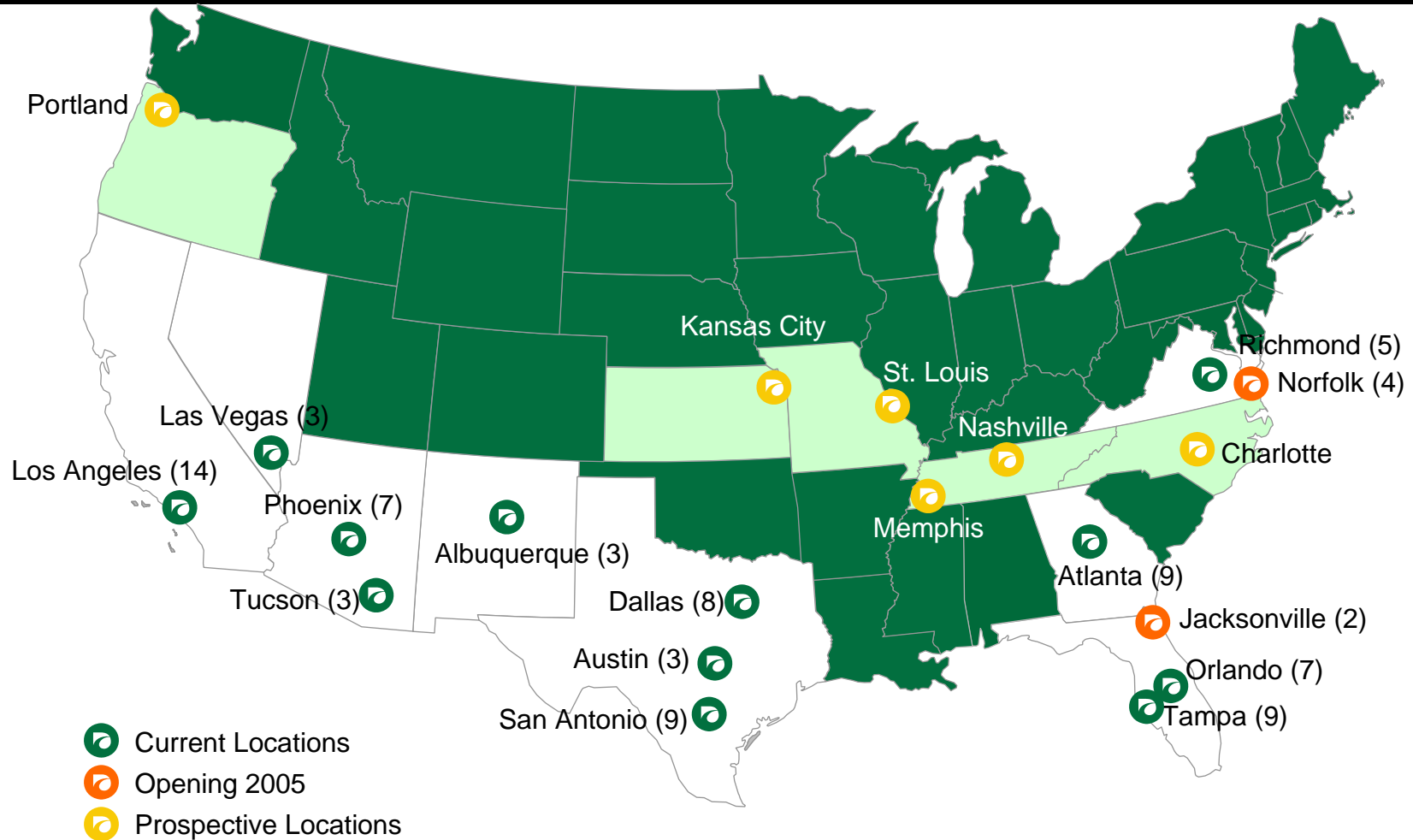


The Company

- Large regional (SW and SE) used car sales and financing company
- 81 stores in 13 markets
- “Deep” Sub-Prime client base
 - Over 50% of applicants and loans are below 500 FICO score (includes no scores)

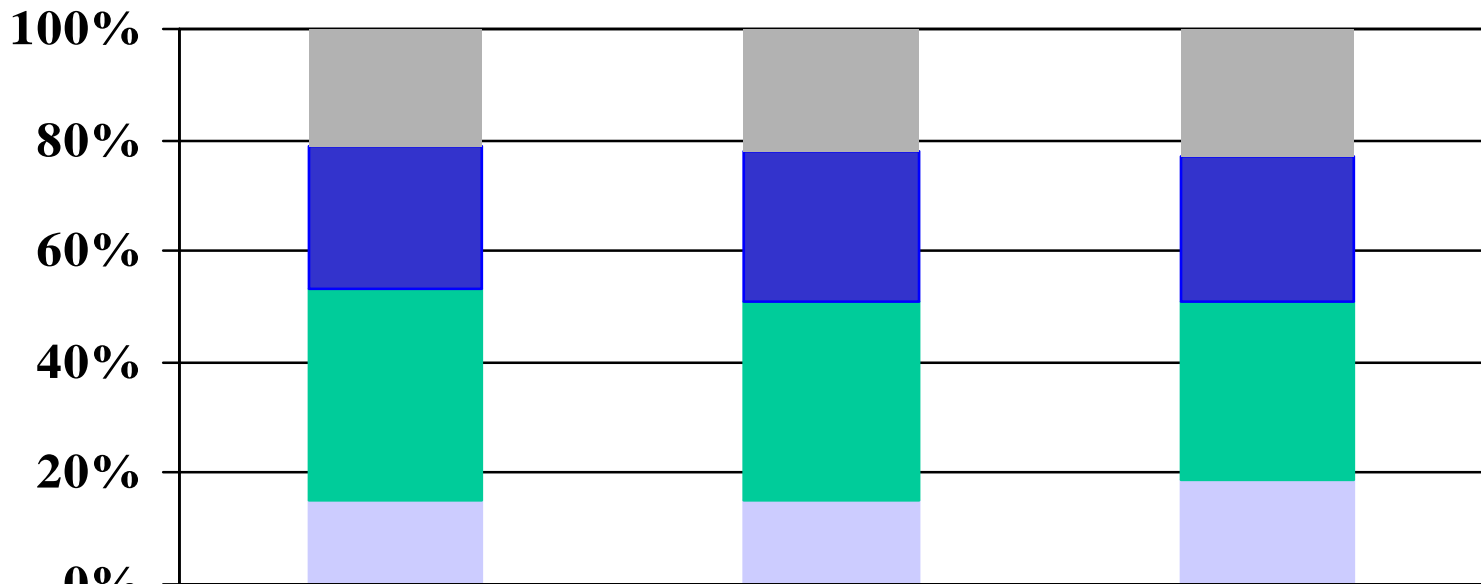


Dealerships and Expansion Markets





Loan Mix: FICO



	FY 2003	FY 2004	YTD 2005
■ 550+	21%	22%	23%
■ 500-549	26%	27%	26%
■ <500	38%	36%	32%
■ No Score	15%	15%	19%



Situation: Late 2000 - 2001

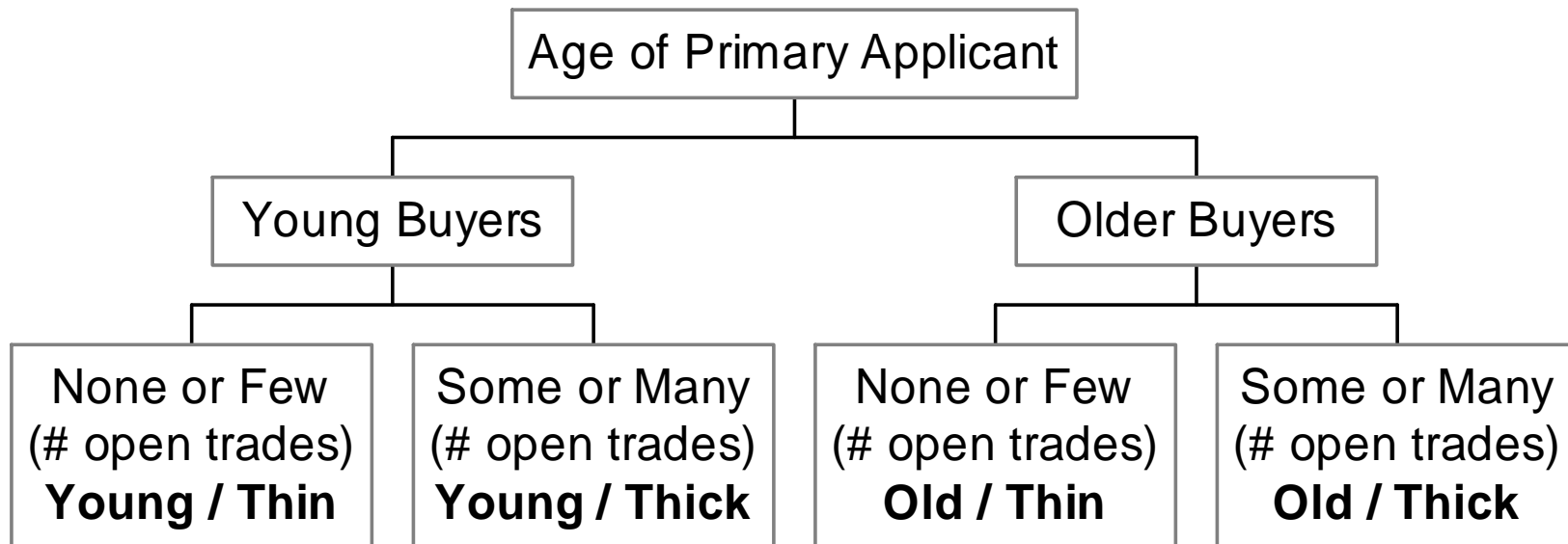
- “Sales driven”, but there were ‘underwriting’ guidelines
 - \$600 down payment, proof of income, telephone, residence, DL
 - 25/50 PTI/DTI thresholds (focus was on cheap, older cars)
 - The “interview” was used to control credit quality
 - “Scoring won’t work in our business” attitude
- Lifetime unit charge-off rate on booked accounts over 60% (over 40% by 18 months on book)
- Score-based policies in place by 3Q 2001, but high losses from 2000 business hit hard in the second half of 2001
- By the end of 2001, survival of company was in question
 - higher than expected loss rates, hitting triggers, trapping cash, losing money, substantial increase in loss reserves, sinking stock price, withdrawal of funding sources, 9/11 shock, and recession



First Generation

- Needed a rapid development and quick implementation
 - Began in Mar01, implemented in Jun01
- *Bureau Variables*: Basic
- *Application Variables*: Minimal
- *Segmentation*: Limited, but easy to implement
- *Data Sample*: Around 20,000 loans primarily from 2Q 2000 (average aging of around 11 months)
- *Performance Definitions*: Simple (Bad = Charge-off)
- Auto specific bureau scores incorporated to enhance scoring system (matrix approach, Jul01)
- Overall, simple system, but it worked during a turbulent time (poor financial results, Sept. 11, recession)

Segmentation Tree



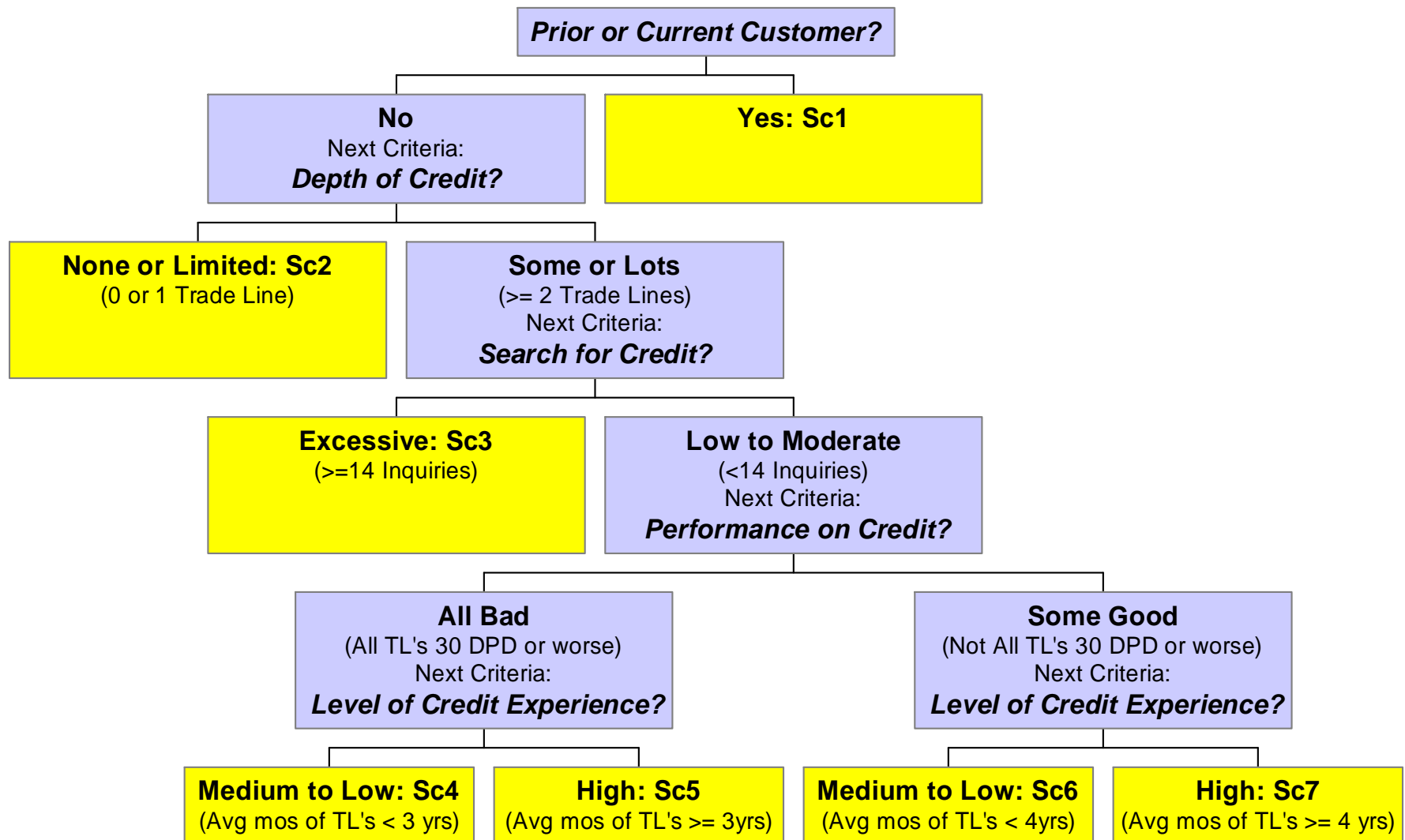


Second Generation

- Strong desire to replace 1st Gen as quickly as possible
- *Bureau Variables*: While waiting for ‘aging’, major effort undertaken to design, code and test a set of sub-prime focused CB variables (~ 150 variables)
- *Segmentation*: More complicated than 1st Gen
- *Data Sample*: Around 20,000 loans primarily from 2Q 2001 (average aging of around 14 months)
- *Performance Definitions*: More data available
 - Distinctions made between Goods-Bads-Indeterminates
- After reaching sufficient aging, PD developed 7 models in 8 weeks, live 45 days later (late 2002)
- Auto specific bureau scores incorporated as adjustors



Segmentation Tree





Sub-Prime Focused Variables

- There were 55 characteristics used in the 7 models
- There were 32 unique characteristics distributed as follows:
 - Application Information (5)
 - Performance of Credit (10)
 - Level of Credit Experience (4)
 - Composition of Credit (9)
 - Search for Credit (4)
- 22 of the 27 unique *bureau* characteristics were totally or partially created from variables developed in the “Custom Variable” Project



Second Generation: 2.1

- Aside from custom model developments, we had been conducting various research studies to explore new data sources
- In 2004, we began using the RiskWise scores (matrix approach) while work began on the next generation of custom models
- This improved our ability to classify more applications as low risk and less as high risk



Third Generation

- No rush to development (time dedicated to “exploring” the data)
- *Bureau Variables*: Continued creating new variables
- *Application Variables*: Inclusion of time-based variables
- *Segmentation*: Sophisticated, based on improved understanding of the business and data
- *New Data Source*: Debit bureau data from eFunds (included thru development of custom bureau models)
- Summary of models (development a little slower – 90 days)
 - 8 models, 66 variables, 41 unique variables
 - Complex adjustor technique used to integrate the custom bureau score that included the eFunds data
- Implementation issues encountered due to new data source (60 days from model delivery to live date, Jan-05)



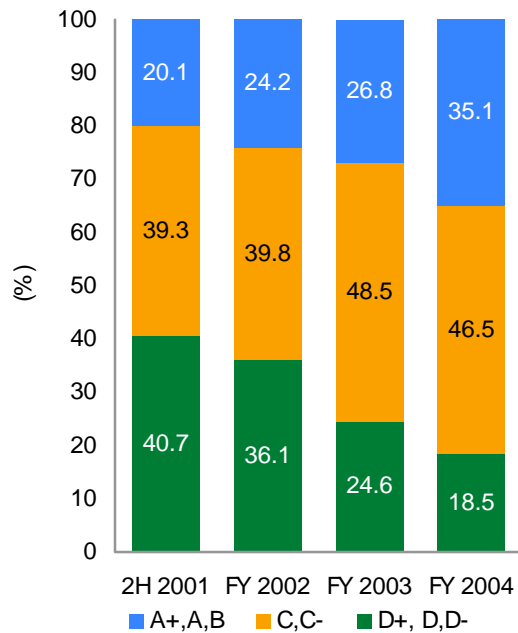
Implementation

- Implementation speed & accuracy: Excellent
 - ‘Live’ implementation has been accomplished within 90 to 150 days from delivery of development dataset to Portfolio Defense
- Cultural change
 - Operations staff are now “believers” in scoring (judgmental approach, ‘hard’ interview discarded)
 - Emphasis is on changing the brand image and customer experience from the ‘inside-out’
- Integration into operational credit policies is unusual
 - Deal structure variables kept out of the models, but used to control overall credit quality, risk-based pricing, vehicle selection, maximum monthly payments and terms
 - Origination ‘grade’ mix & actual loan performance links to store-based profit metrics system (BLM)

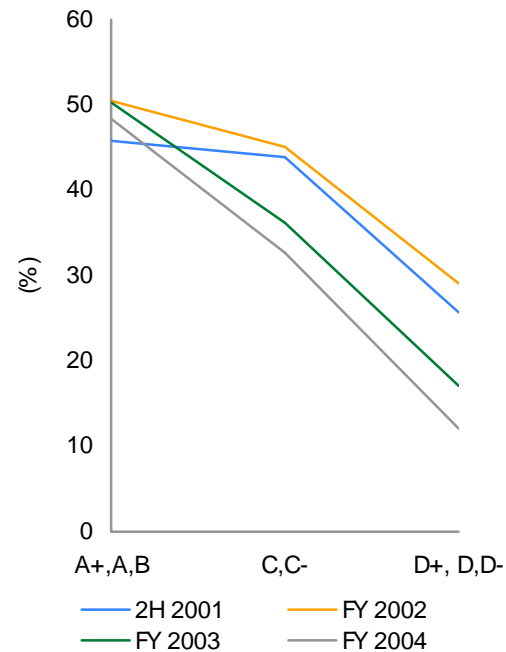


Approach Used to Manage Overall Credit Quality

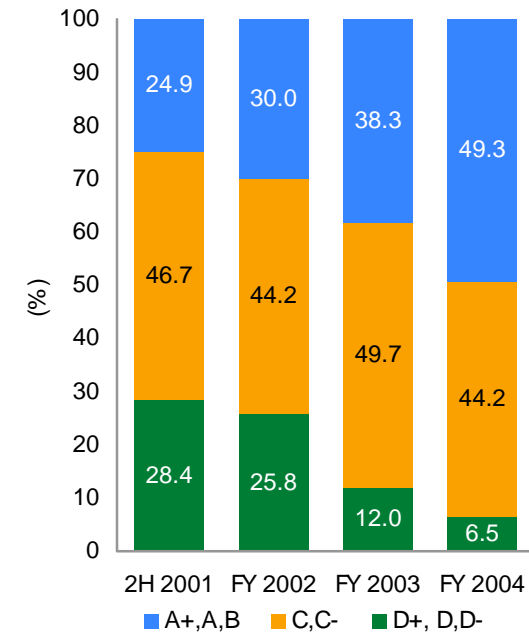
Application Grade Mix



Effects of DPs on Close Rates



Loan Grade Mix



Note: Close Rates = Net Sales/Applications



Performance Improvement

- Scoring models and policies have worked well in ‘deep’ sub-prime environment
 - Very good rank-ordering of losses by ‘grades’
- Reduction in losses
 - Controlling origination credit quality thru down payment policies has led to a 25% to 30% reduction in vintage unit loss rates (*2003 & 2004 vs 2000*)
- Financial turnaround has been outstanding
 - Company quickly returned to profitability
 - Huge increases in net interest revenues from lower unit loss rates and better quality vehicles (larger loan balances)
 - Stable results & stable financing sources has led to implementation of growth strategy



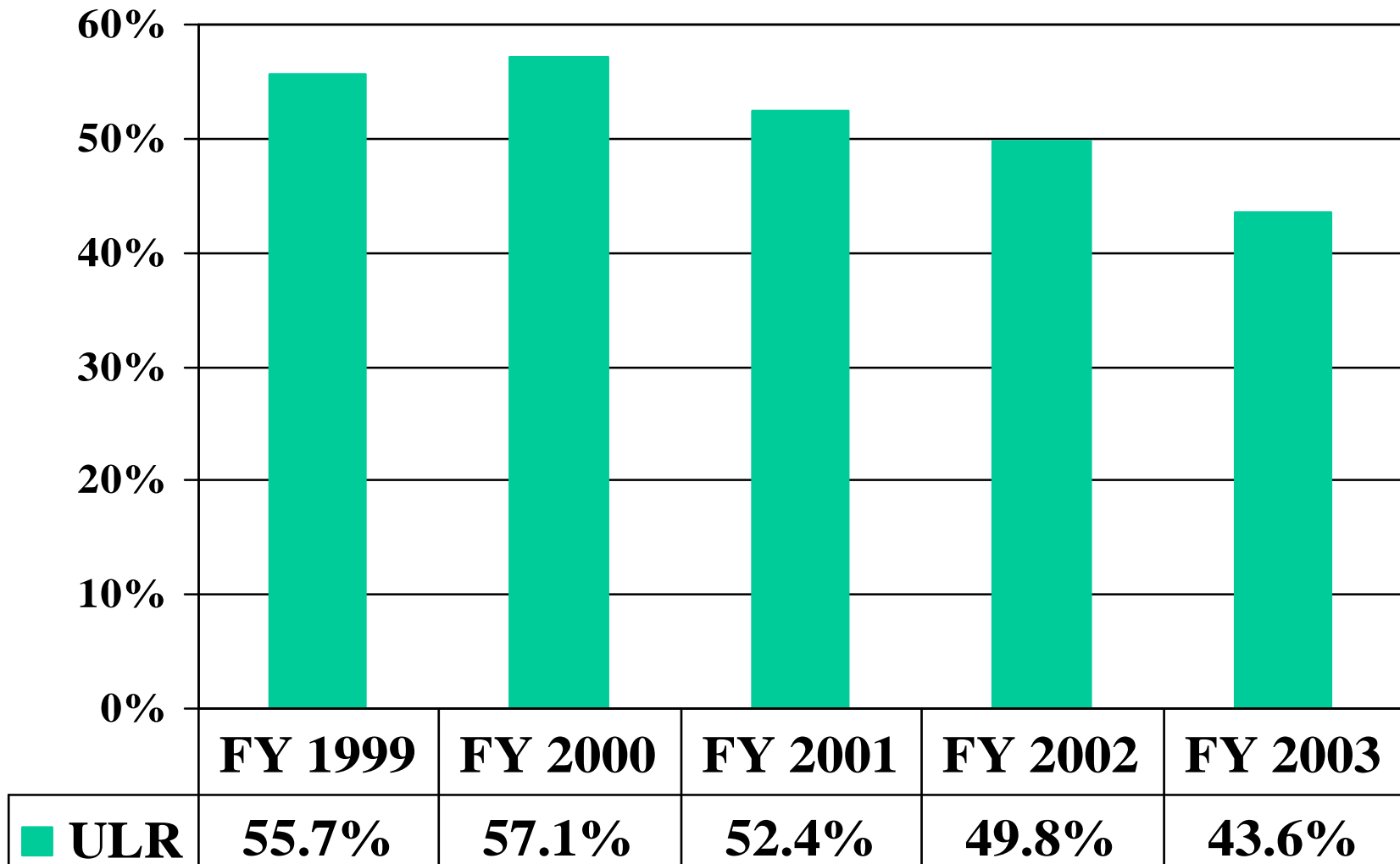
Historical Financial Performance

	Year End				
	2000	2001	2002	2003	2004
# of used cars sold	56,870	47,718	49,264	50,614	49,686
Avg # of dealerships	77	76	76	75	74
Earnings (loss) before income taxes	\$15,268	(\$12,546)	\$15,262	\$42,672	\$80,207
Accounts outstanding @ year-end	84,869	82,255	82,991	87,333	93,683
Principal outstanding @ year-end	\$514,946	\$514,699	\$586,845	\$709,689	\$815,814
Net charge-off as % of avg. principal	26.2%	28.0%	26.6%	21.7%	18.3%



Cumul Unit Loss Rates by Yr of Orig

(Controlled for aging: avg age = 26 months)

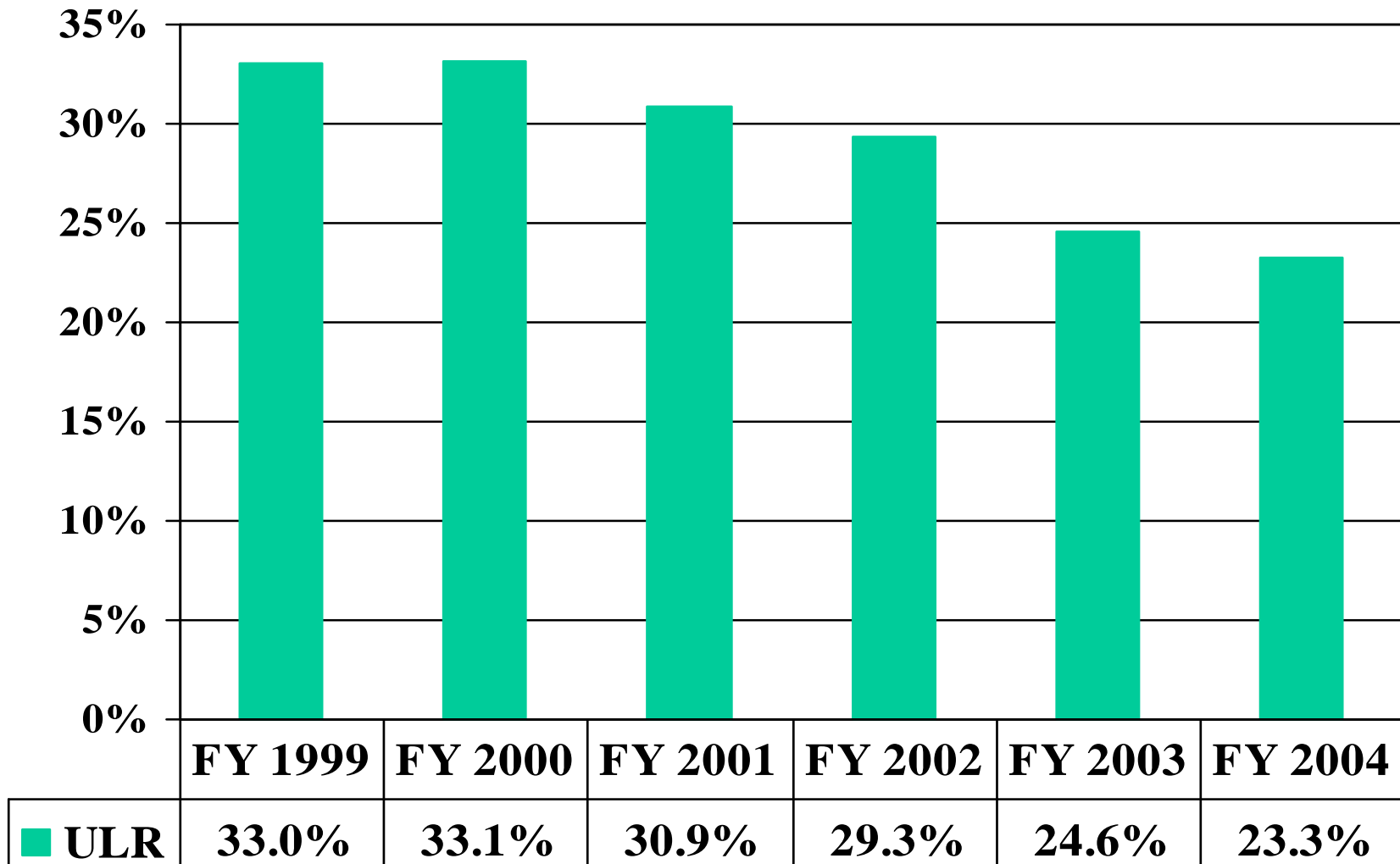


(Ex of aging method, Jan03 has 31 months of aging while Dec03 has 20 months of aging)



Cumul Unit Loss Rates by Yr of Orig

(Controlled for aging: avg age = 14 months)

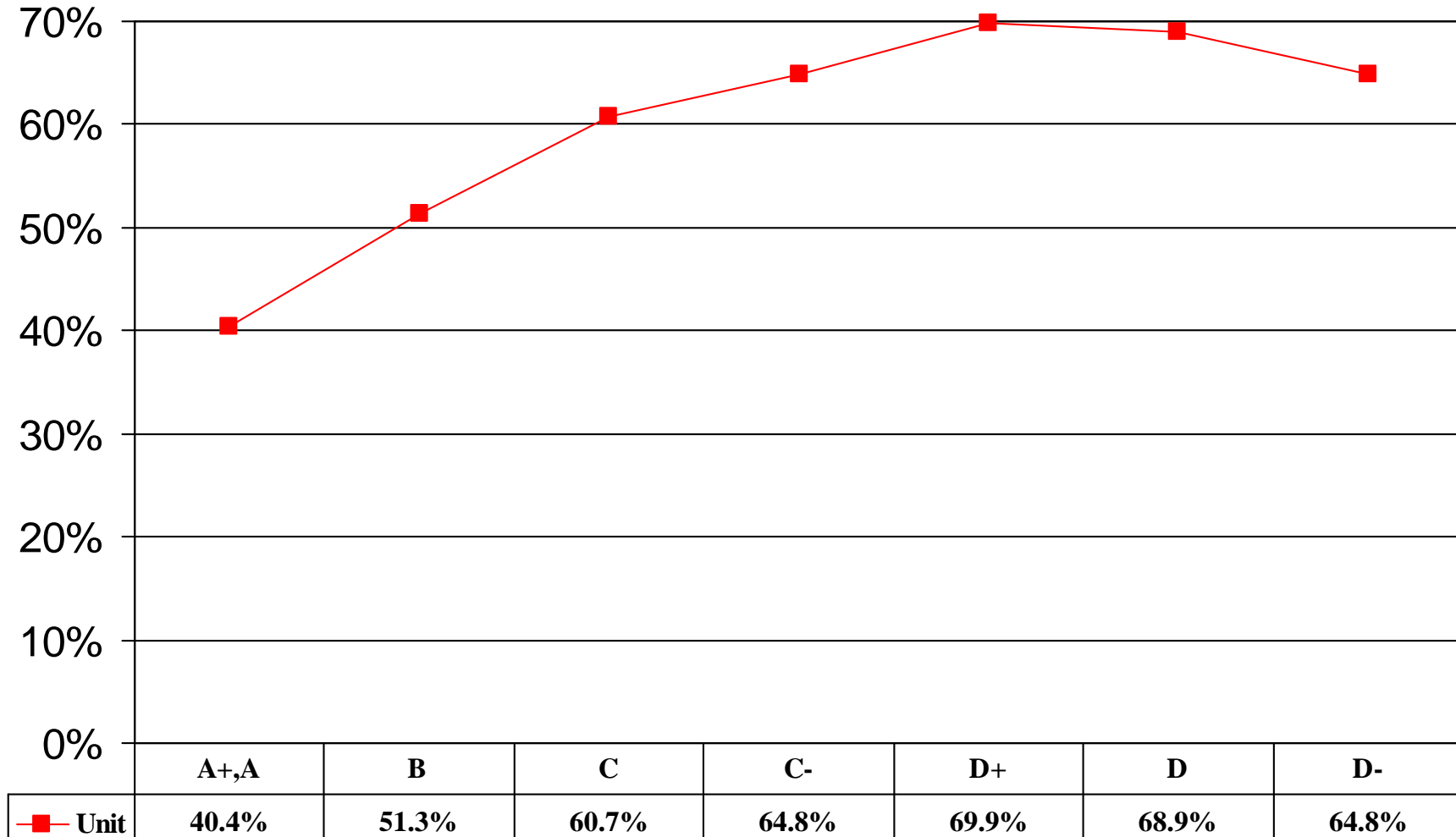


(Ex of aging method, Jan04 has 19 months of aging while Dec04 has 8 months of aging)



Cumulative Loss Rates by Credit Grade

(1st Gen Origs: Jul01 – Sep02, Losses as of Aug05)

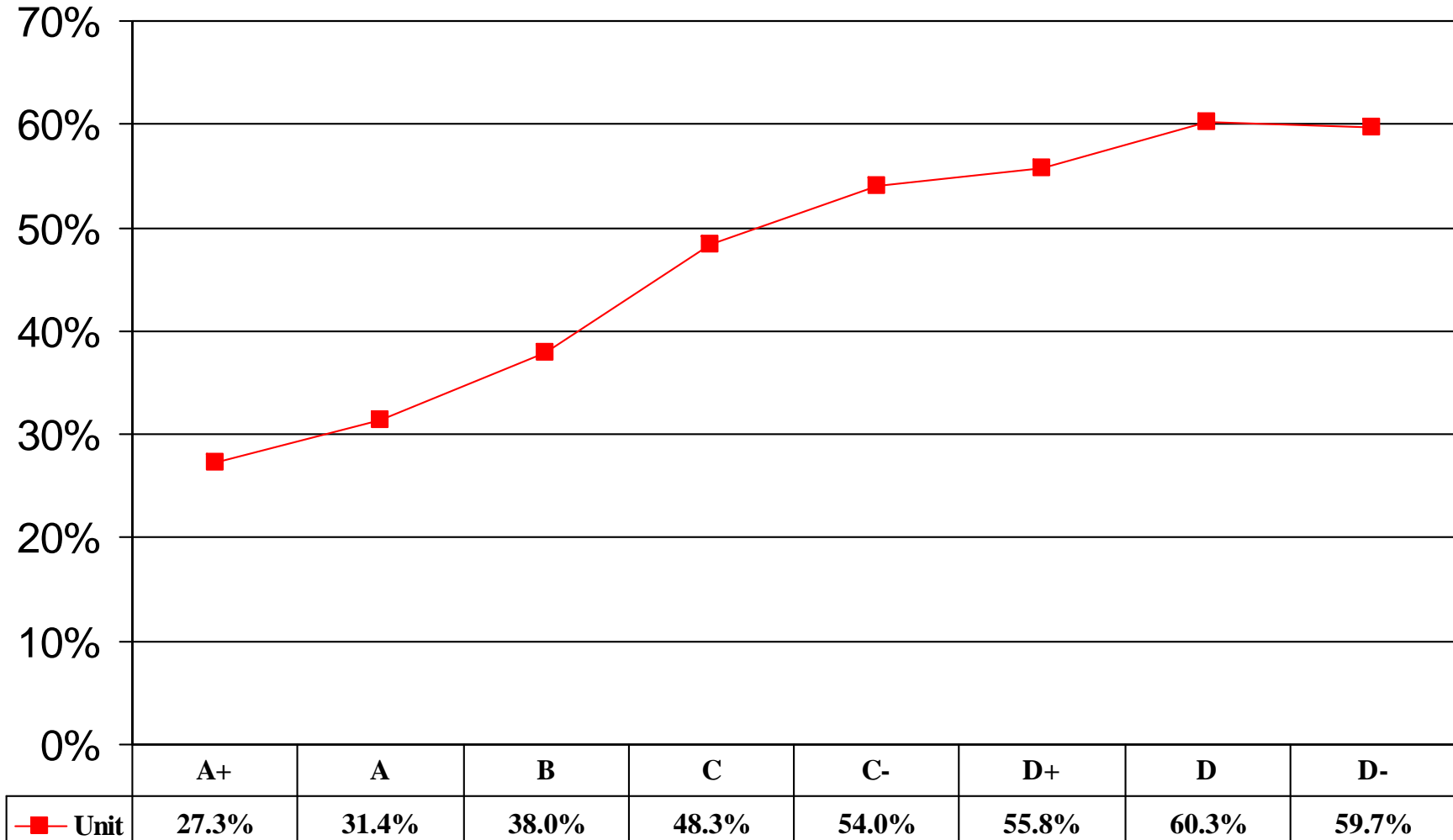


(Average portfolio age of 42 months)



Cumulative Loss Rates by Credit Grade

(2nd Gen Origs: Oct02 – Dec03, Losses as of Aug05)

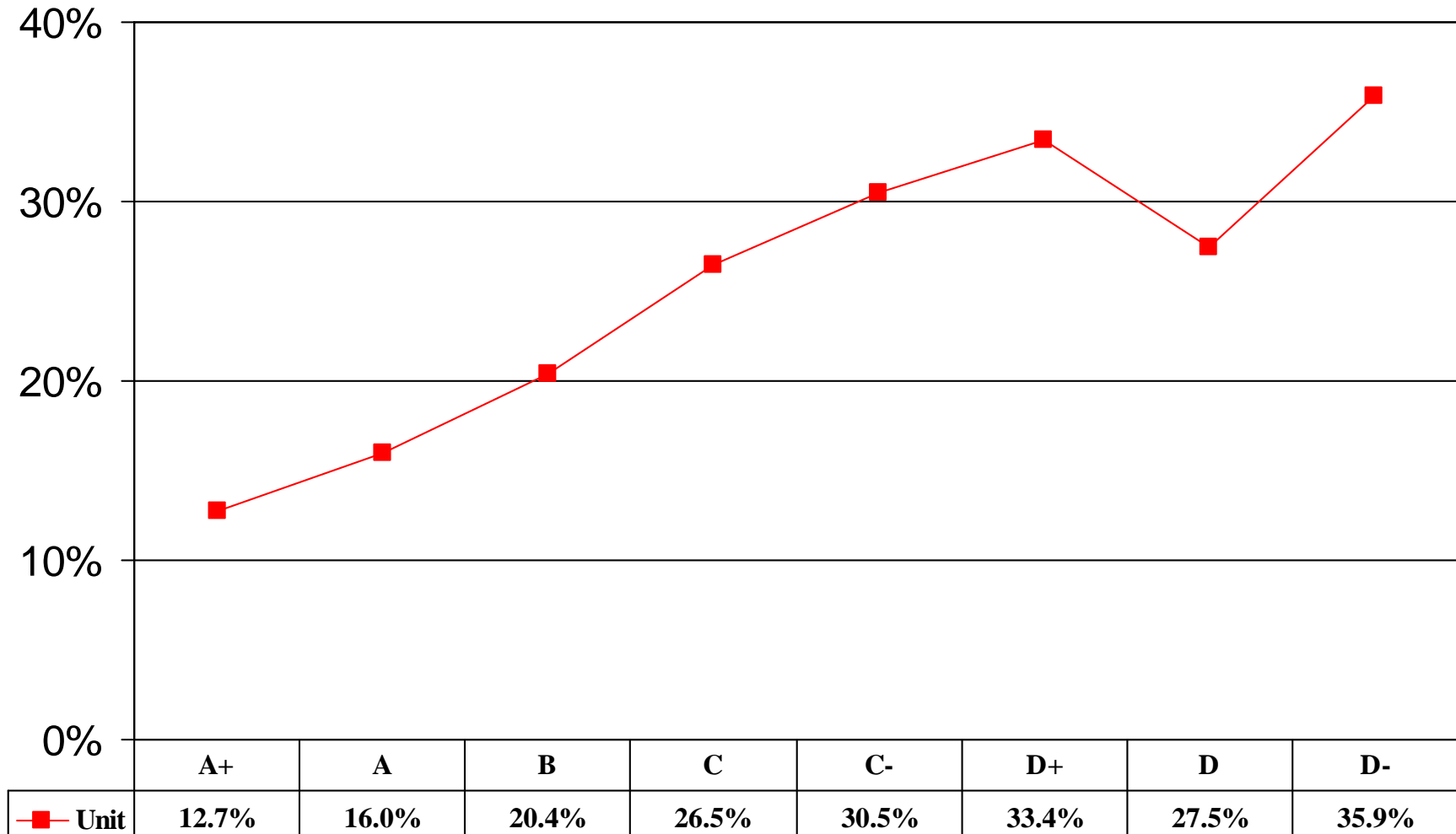


(Average portfolio age of 27 months)



Cumulative Loss Rates by Credit Grade

(2.1 Gen Origs: Jan04 – Dec04, Losses as of Aug05)

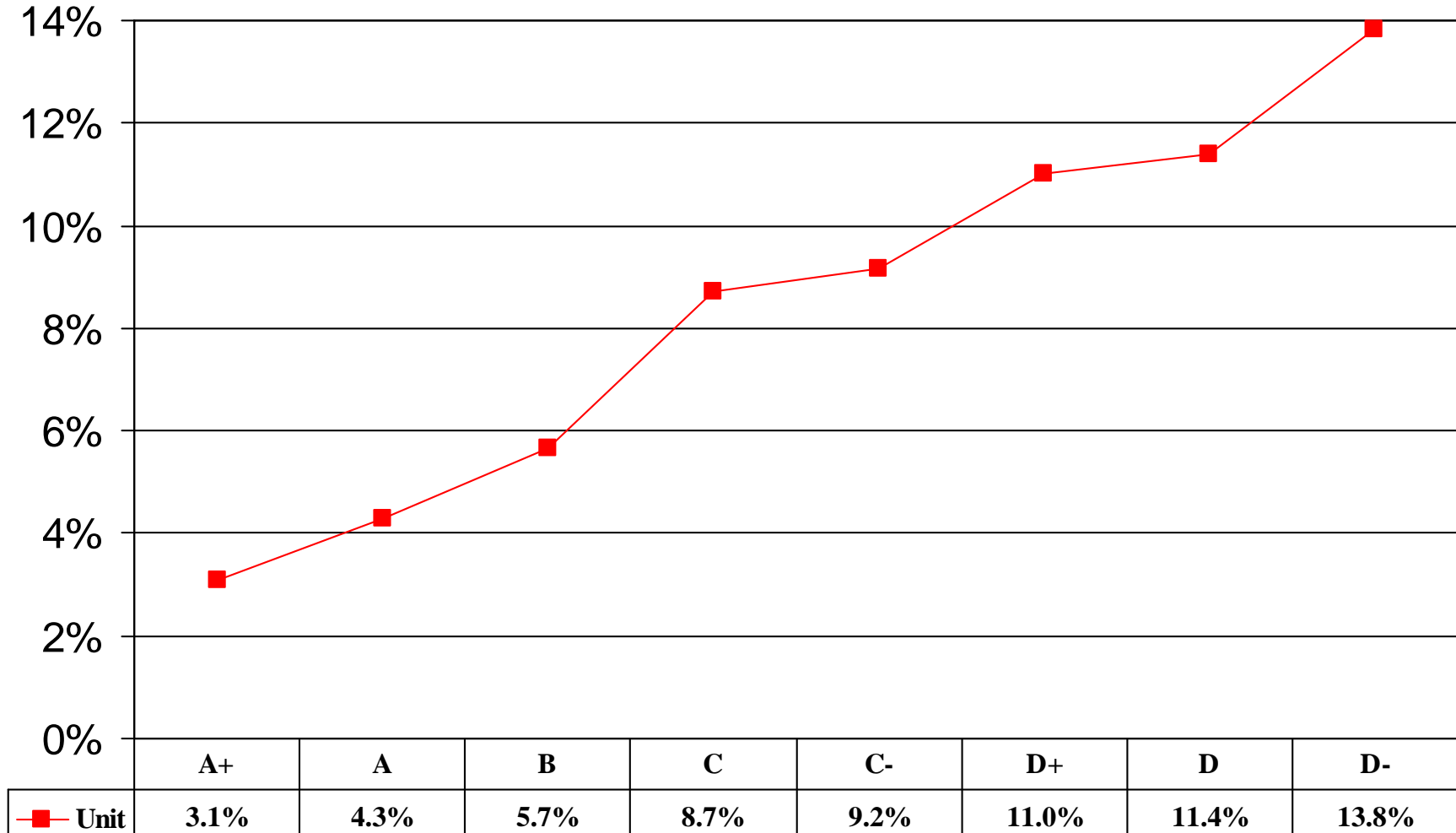


(Average portfolio age of 14 months)



Cumulative Loss Rates by Credit Grade

(3rd Gen Origs: Jan05 – Mar05, Losses as of Aug05)



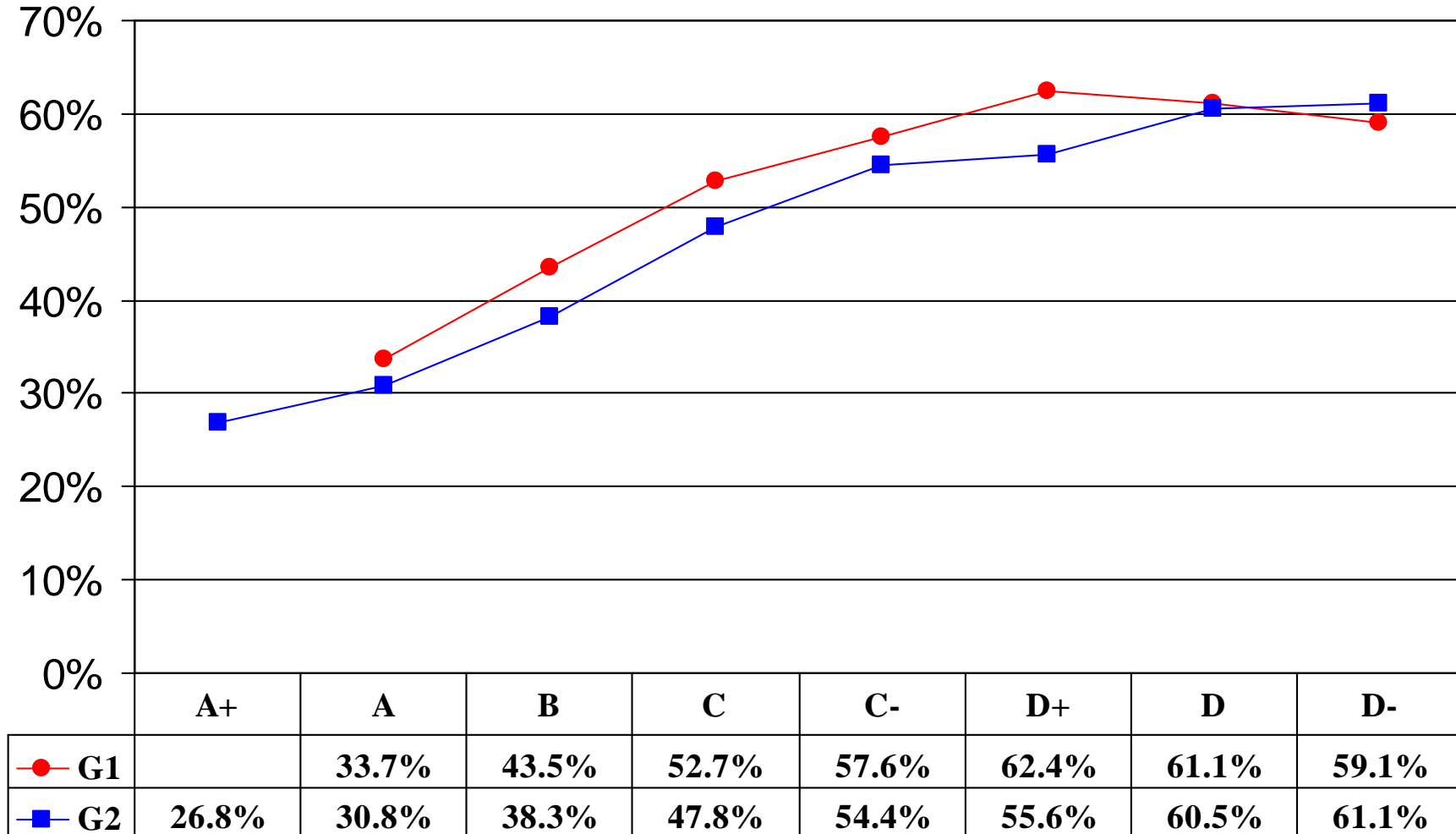
(Average portfolio age of 6 months)

Consistency of Results?

- Movement from one generation to another was calibrated prior to implementation to deliver consistent results for each “grade”
- As changes were made in the distribution mix of applications among risk levels (grades), there were a lot of questions as to whether the performance would actually remain the same between different generations of models and methods
 - Would an “A” still perform like an “A”?



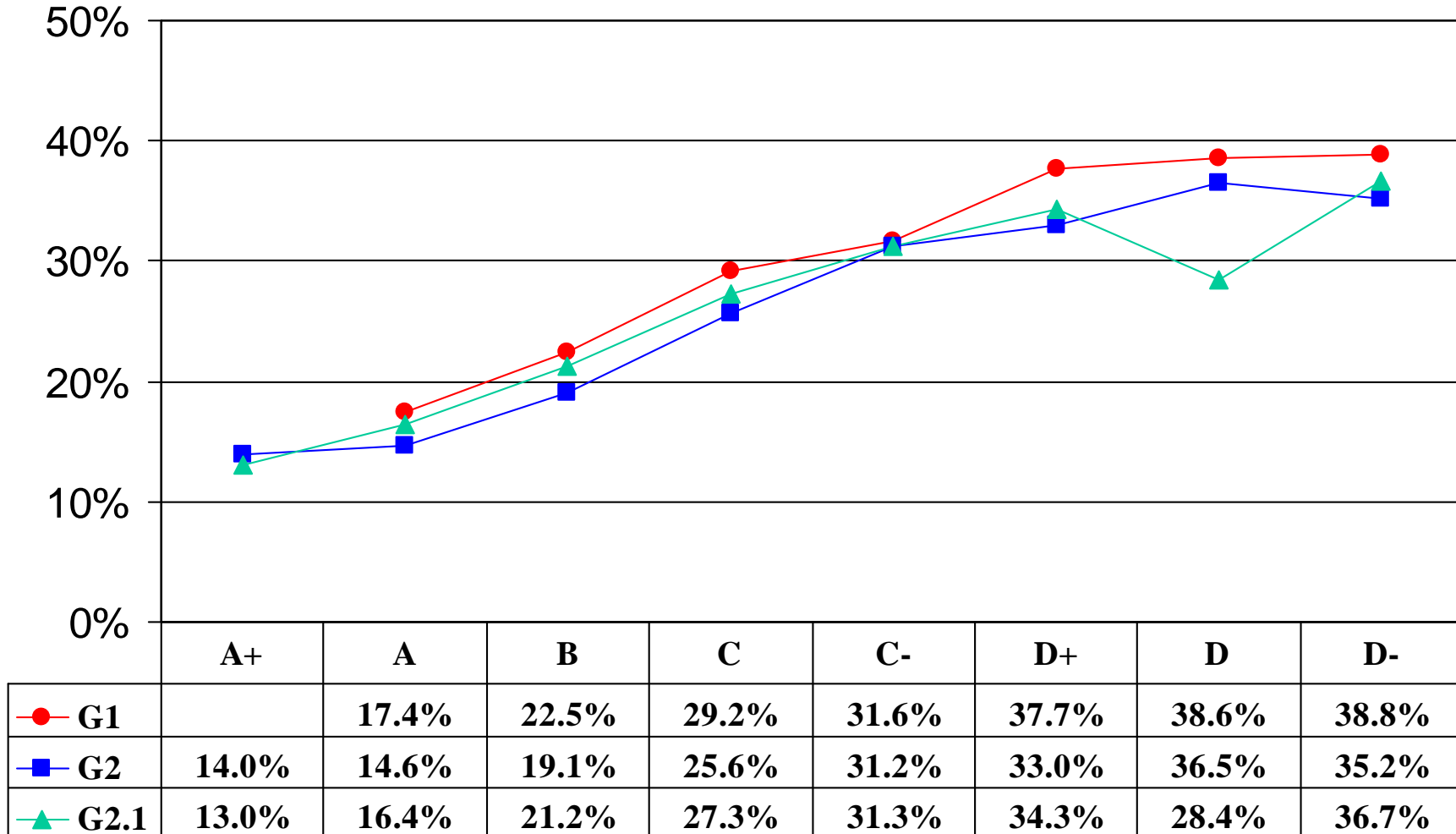
Cumulative Unit Loss Rates: Results by Generation of Grading System



(Avg Aging = 27 months: Origination periods are as follows: G1: Jan02-Sep02, G2: Jan03-Sep03)



Cumulative Unit Loss Rates: Results by Generation of Grading System



(Avg aging = 14 months, Origination periods as follows: G1: Jan02-Dec02, G2: Jan03-Dec03, G3: Jan04-Dec04)



Summary: Model Generations

- *First Generation*: Simple models
 - Basic bureau variables, segmentation
- *Second Generation*: Standard models
 - Custom designed bureau variables, some application variables, bureau-based segmentation
- *Third Generation*: Sophisticated models
 - Full suite of application and bureau variables, complex bureau-based segmentation, inclusion of new data source (eFunds); complex adjustor technique to integrate custom bureau score