# Segmentation, Probability of Default and Basel II Capital Measures for Credit Card Portfolios


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# A Model of Consumer Defaults

- Variant of the Vasicek ASRF
- Requires differentiating the portfolio into separate "homogeneous" risk buckets
- Segmentation for consumer portfolio analogous to the loan rating process for commercial loans
- VARs obtained from the ASRF model are inversely related to the degree of homogeneity of the portfolio segments

# A Model of Consumer Defaults

$$w_{j,t+1} = w_{j,t} + \mu_t + v_{j,t} \;; with\, v_{j,t} \sim N(0, \sigma^2_{vj})$$

$$w_{j,t+1} < \theta_{j,t+1}$$

$$g_{j,t+1} = \mu_t + v_{j,t} < m_{j,t+1}$$

$g_{j,t+1} = w_{j,t+1} - w_{j,t}$ and $m_{j,t+1} = \theta_{j,t+1} - w_{j,t}$

$v_{j,t} = \sqrt{\rho} Y_t + \sqrt{1-\rho}\,\varepsilon_{jt}$ *and* $Y_t \sim \mathrm{N}(0,1)$ and $\varepsilon_{jt} \sim N(0,1)$

# A Model of Consumer Defaults

$$\pi_{j,\,t+1} = \Phi(m_{j,\,t+1} - \mu_j)$$

$$\Phi^{-1}(\pi_{j,\,t+1}) = m_{j,\,t+1} - \mu_j$$

$$\varepsilon_{j,\,t} < [\Phi^{-1}(\pi_{j,\,t+1}) - \sqrt{\rho}Y_t] / \sqrt{1-\rho}$$

$$\pi_{j,t+1}(Y_t) = \Phi([\Phi^{-1}(\pi_{j,t+1}) - \sqrt{\rho}Y_t] / \sqrt{1-\rho})$$

# A Model of Consumer Defaults

$$D^{p}_{j,t+1}(Y_t) \cong \pi_{j,t+1}(Y_t) = \Phi\left[\frac{\Phi^{-1}(\pi_{j,t+1}) - \sqrt{\rho}Y_t}{\sqrt{1-\rho}}\right]$$

;

$$D^{p}_{j,t+1}(\underline{Y_t}) \cong \Phi\left[\frac{\Phi^{-1}(\pi_{j,t+1}) - \sqrt{\rho}\underline{Y_t}}{\sqrt{1-\rho}}\right] = \Phi\left[\frac{\Phi^{-1}(\pi_{j,t+1}) - \sqrt{\rho}\Phi^{-1}(\nu)}{\sqrt{1-\rho}}\right]$$

$$\sum_{j=1}^{S}\alpha_j D^{p}_{j,t+1}(\underline{Y_t}) \cong \sum_{j=1}^{S}\alpha_j \Phi\left[\frac{\Phi^{-1}(\pi_{j,t+1}) - \sqrt{\rho}\Phi^{-1}(\nu)}{\sqrt{1-\rho}}\right] \qquad \sum_{j=1}^{S}\alpha_j = 1$$

# Overview of Data Analysis

- Compared methods for estimating PD for a retail credit card portfolio
  - Origination score
  - Refreshed scores
  - Delinquency
  - Age of account
  - Balance measures
  - Combinations
- Examined seasoning effects

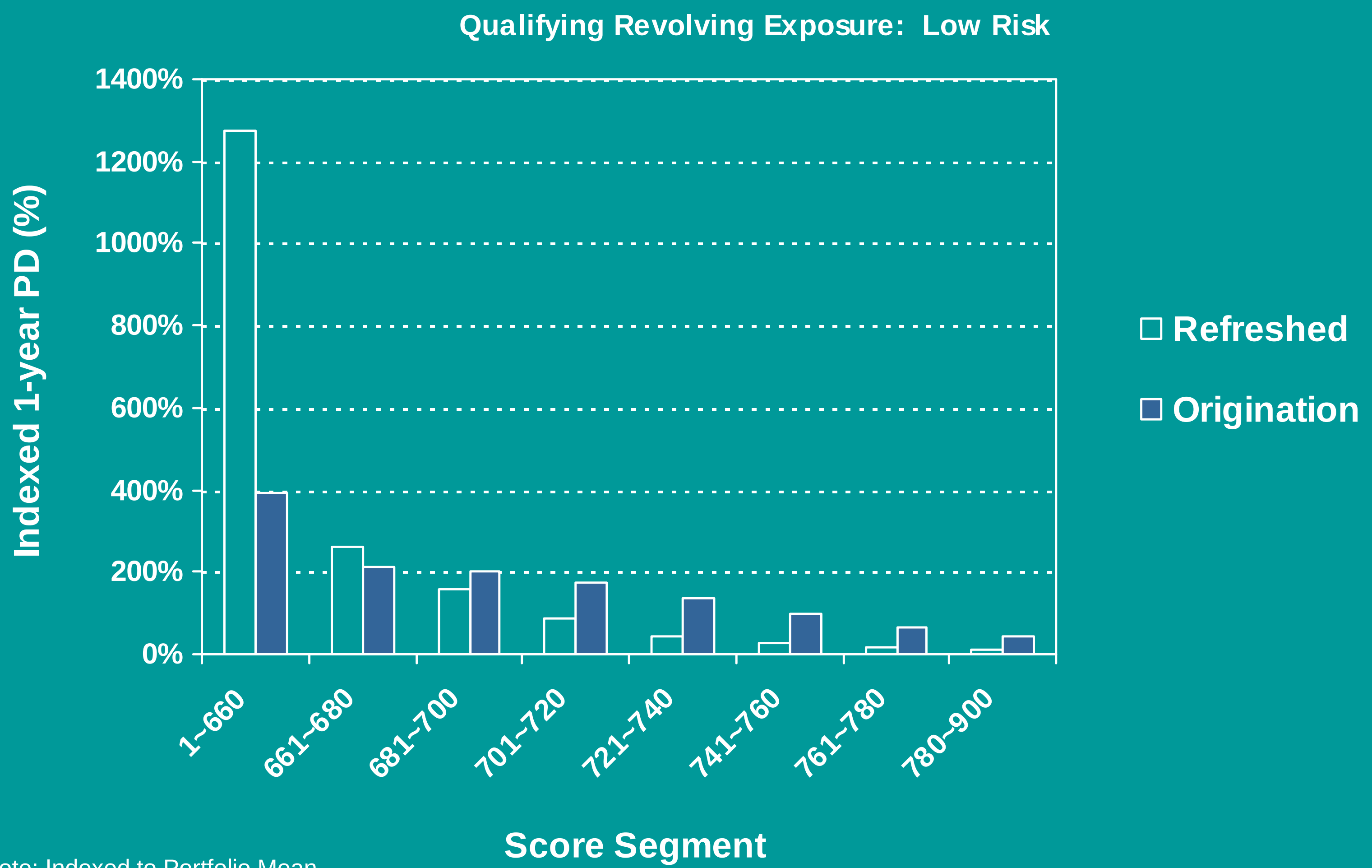
# Data

- Account level internal data from 1999-2004
  - Includes monthly Bureau Score back to origination
- Two discreet portfolios: low risk, high risk
- Origination cohorts from 1999-2000
- Performance to Sept, 2004
- 12 month outcome PD for each time point
- Default defined as charge off in outcome period

# 1. Credit scores: Refreshed vs Origination

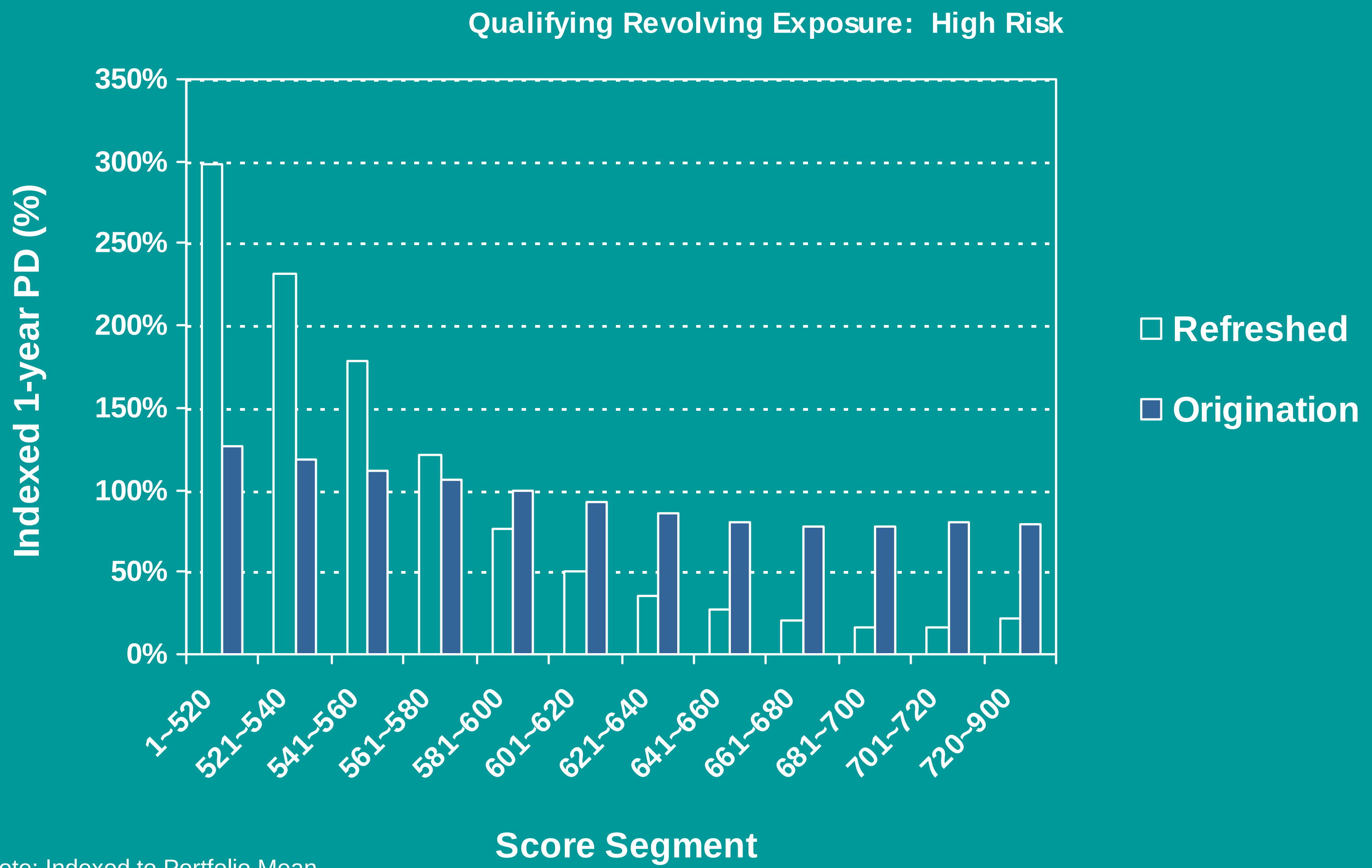
- Refreshed Bureau Score performs better than Origination Bureau Score in differentiating risk

# Low Risk Portfolio
# Indexed PD by Credit Bureau Score




Note: Indexed to Portfolio Mean

# High Risk Portfolio
# Indexed PD by Credit Bureau Score

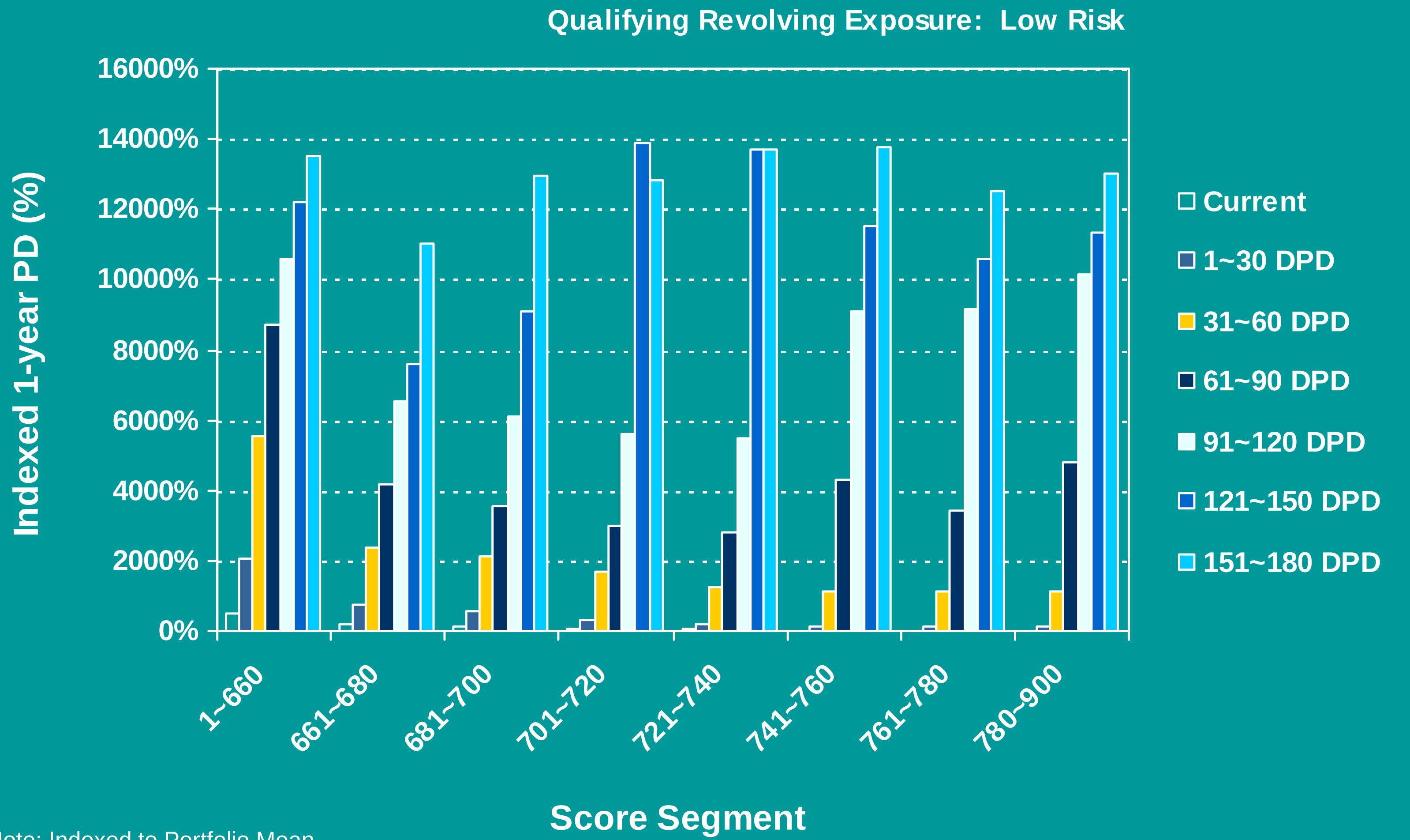



Note: Indexed to Portfolio Mean

# 2. Delinquency

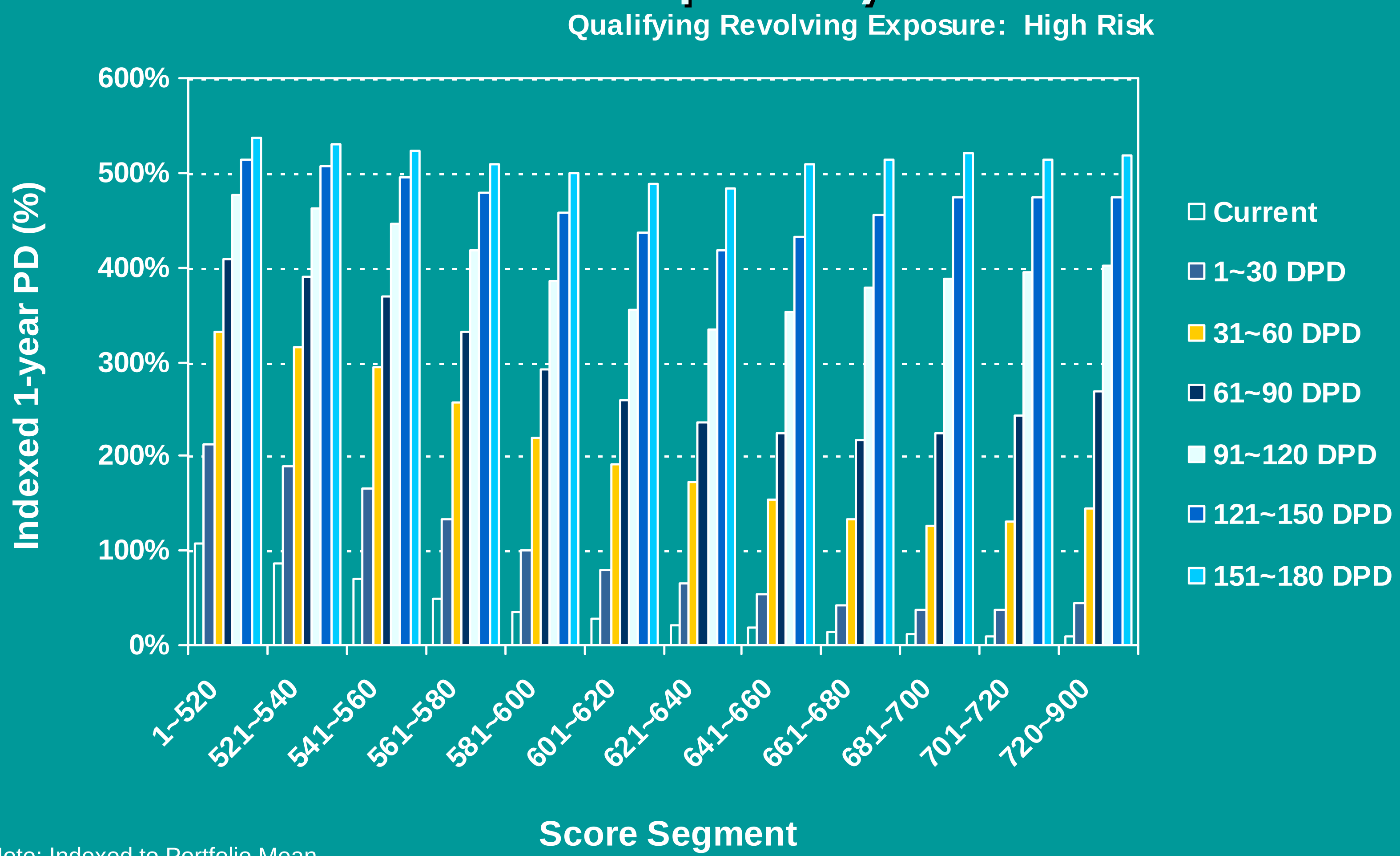
- Bureau Scores continue to differentiate risk for lower delinquency stages
- Not useful for later stages (90+ DPD)

# Low Risk Portfolio
# Indexed PD by Refreshed Score and Delinquency




Note: Indexed to Portfolio Mean

# High Risk Portfolio
# Indexed PD by Refreshed Score and Delinquency

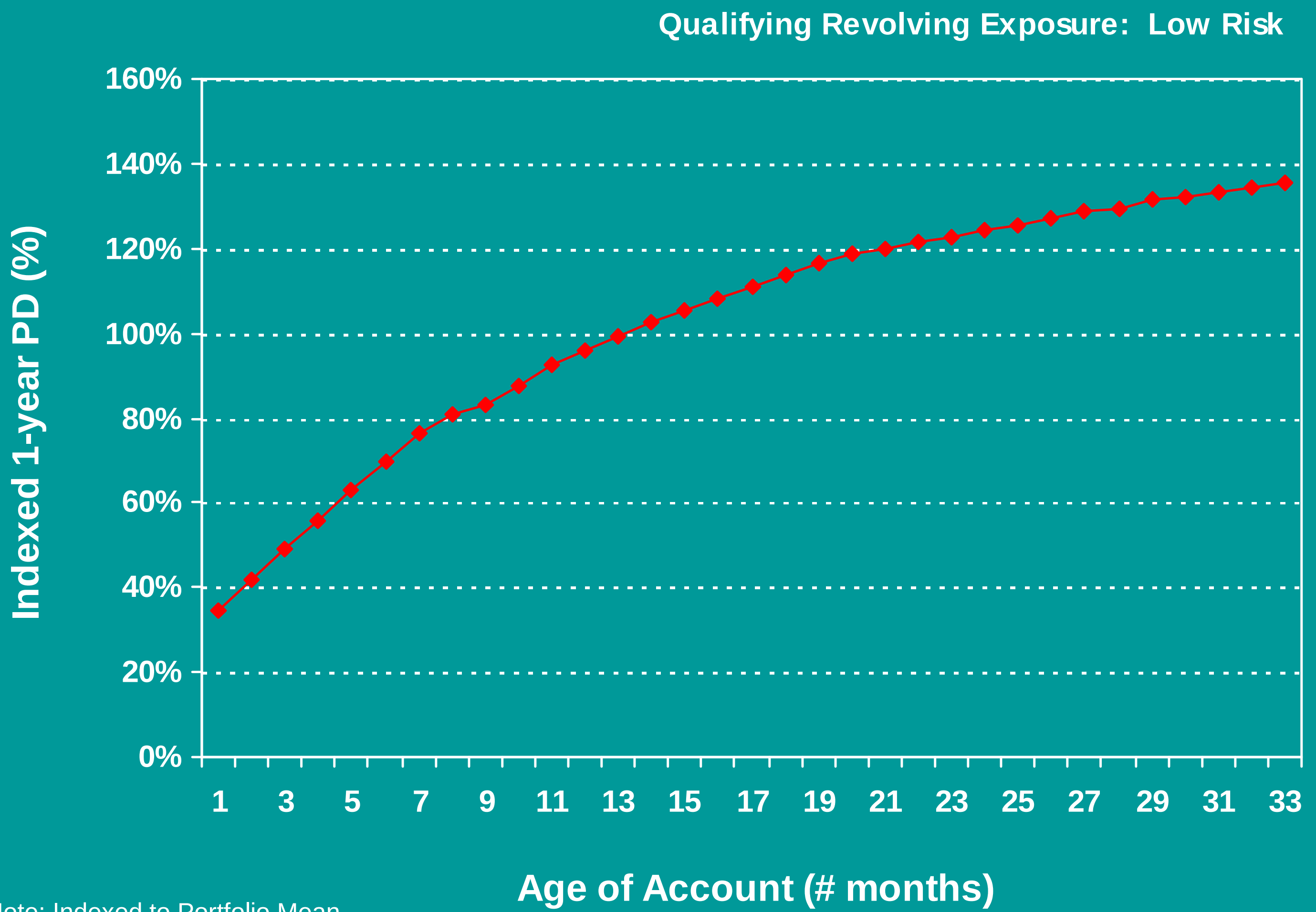



Note: Indexed to Portfolio Mean

# 3. Seasoning Effects

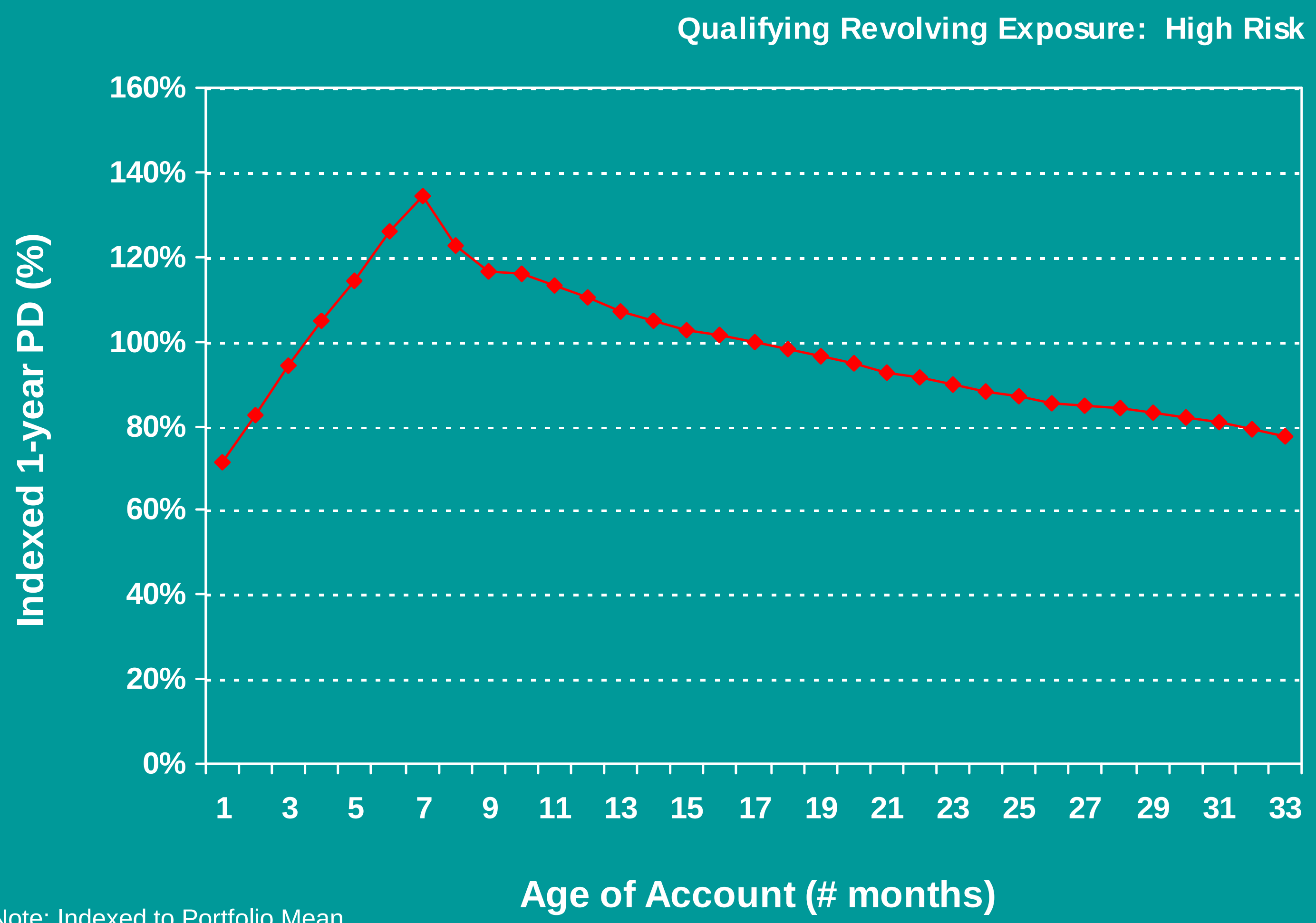
- Seasoning not much affected by Origination Bureau Score
  - Some flattening for lower score, low risk portfolio accounts
- Refreshed score reduces seasoning effect
- Delinquency has a major effect on seasoning

# Low Risk Portfolio Indexed PD by Age



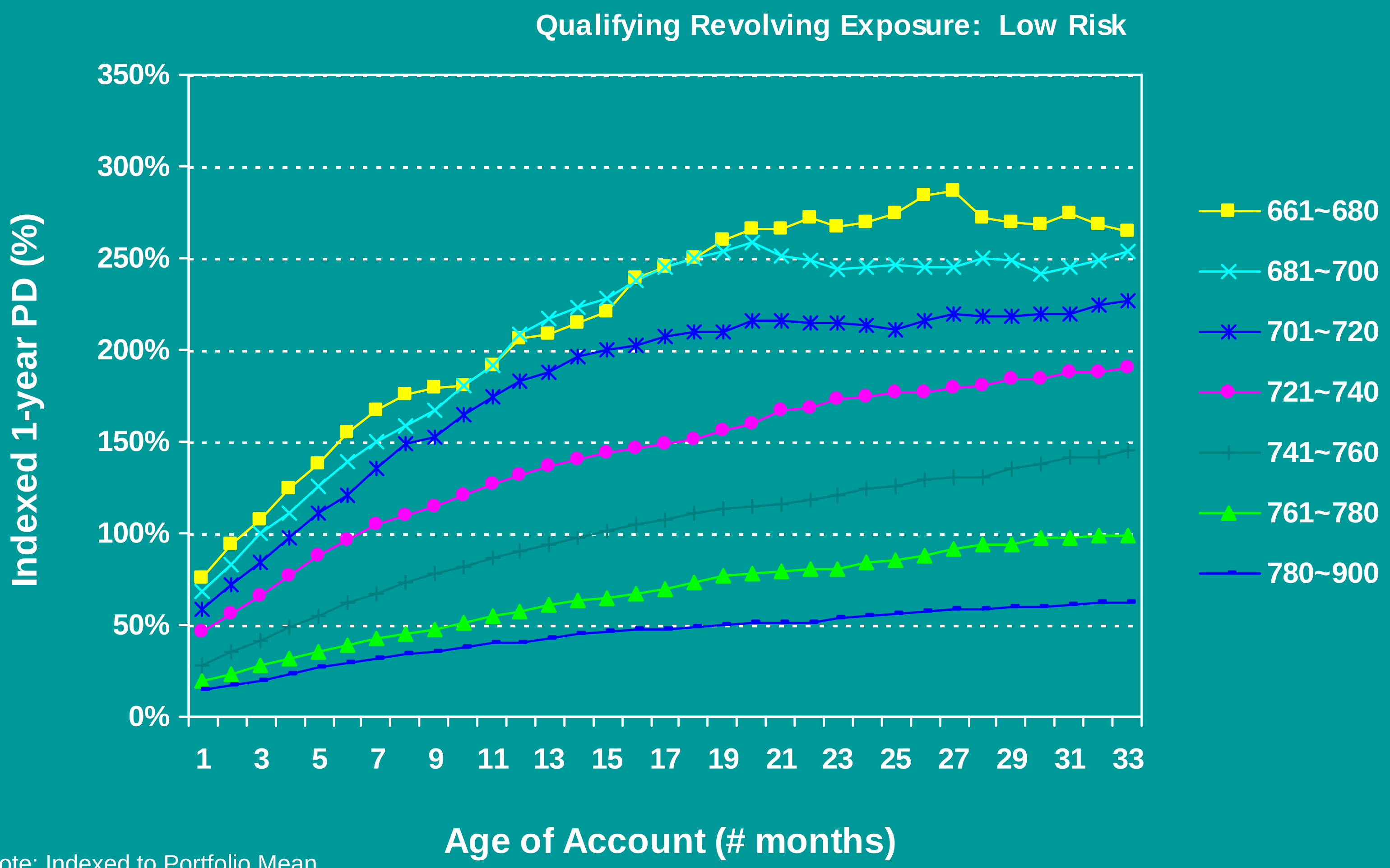

Note: Indexed to Portfolio Mean

# High Risk Portfolio Indexed PD by Age




Note: Indexed to Portfolio Mean

# Indexed PD by Origination Score and Age (Low Risk Portfolio )




Note: Indexed to Portfolio Mean

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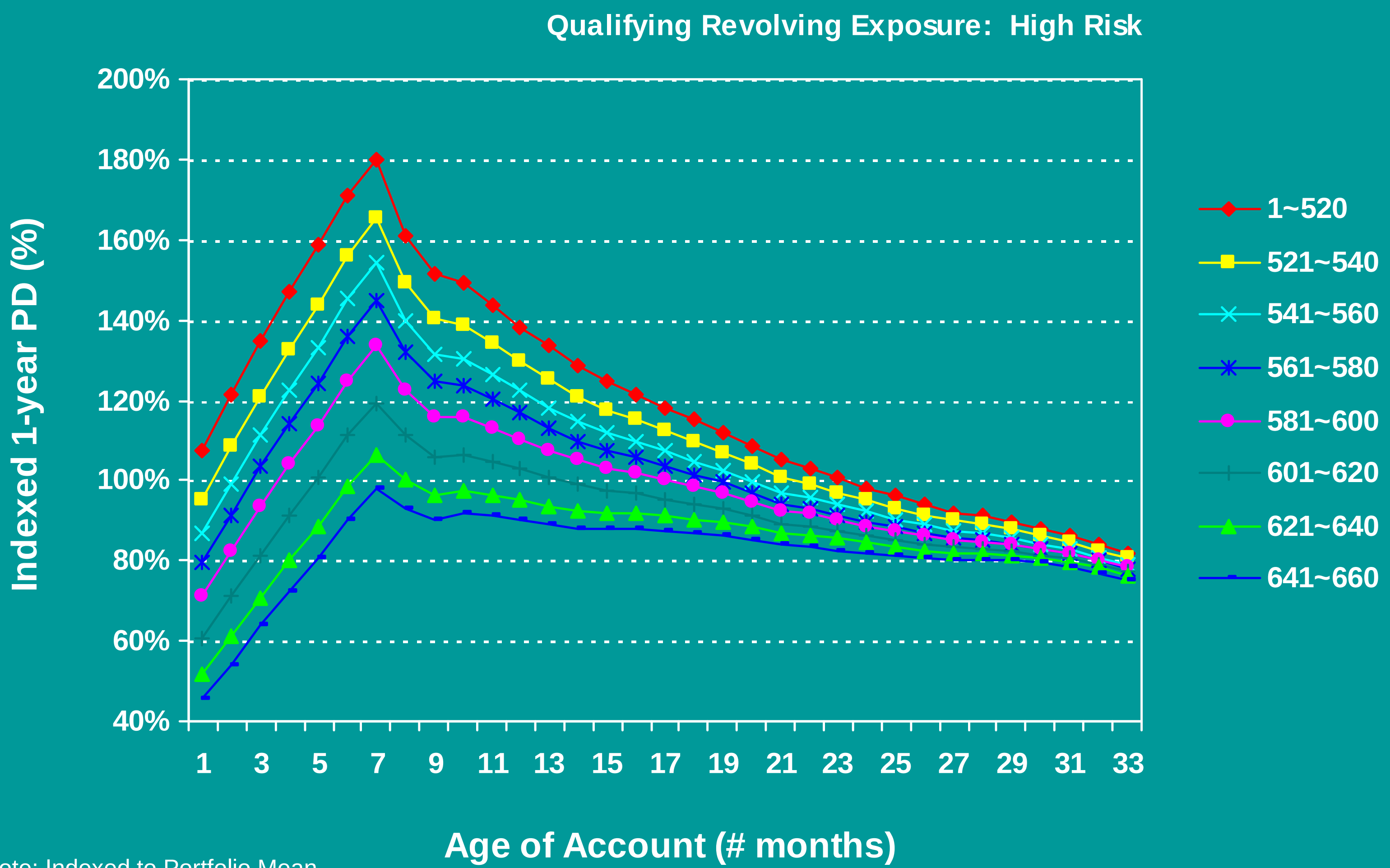
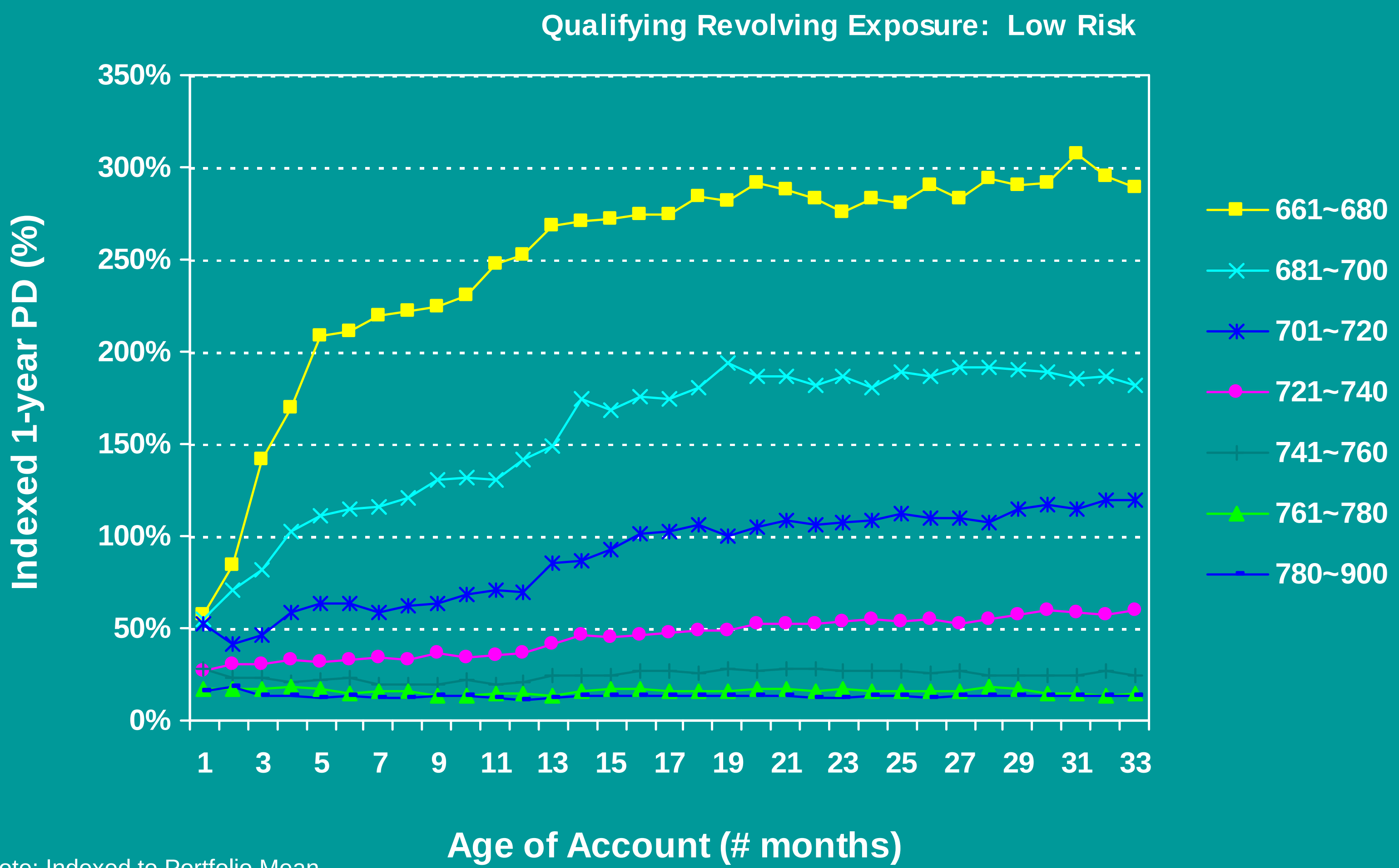


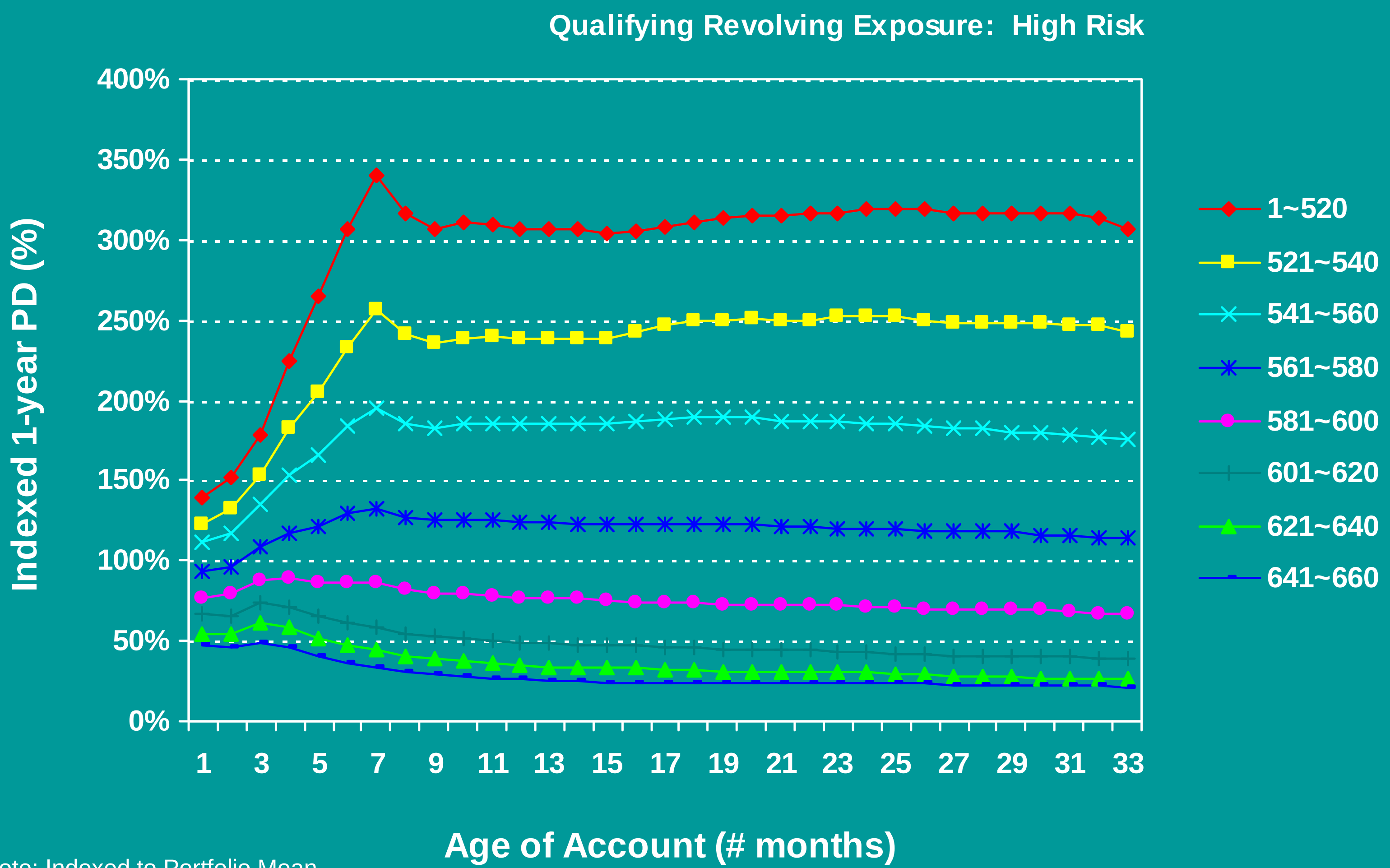

Note: Indexed to Portfolio Mean

# Indexed PD by Refreshed Score and Age (Low Risk Portfolio )



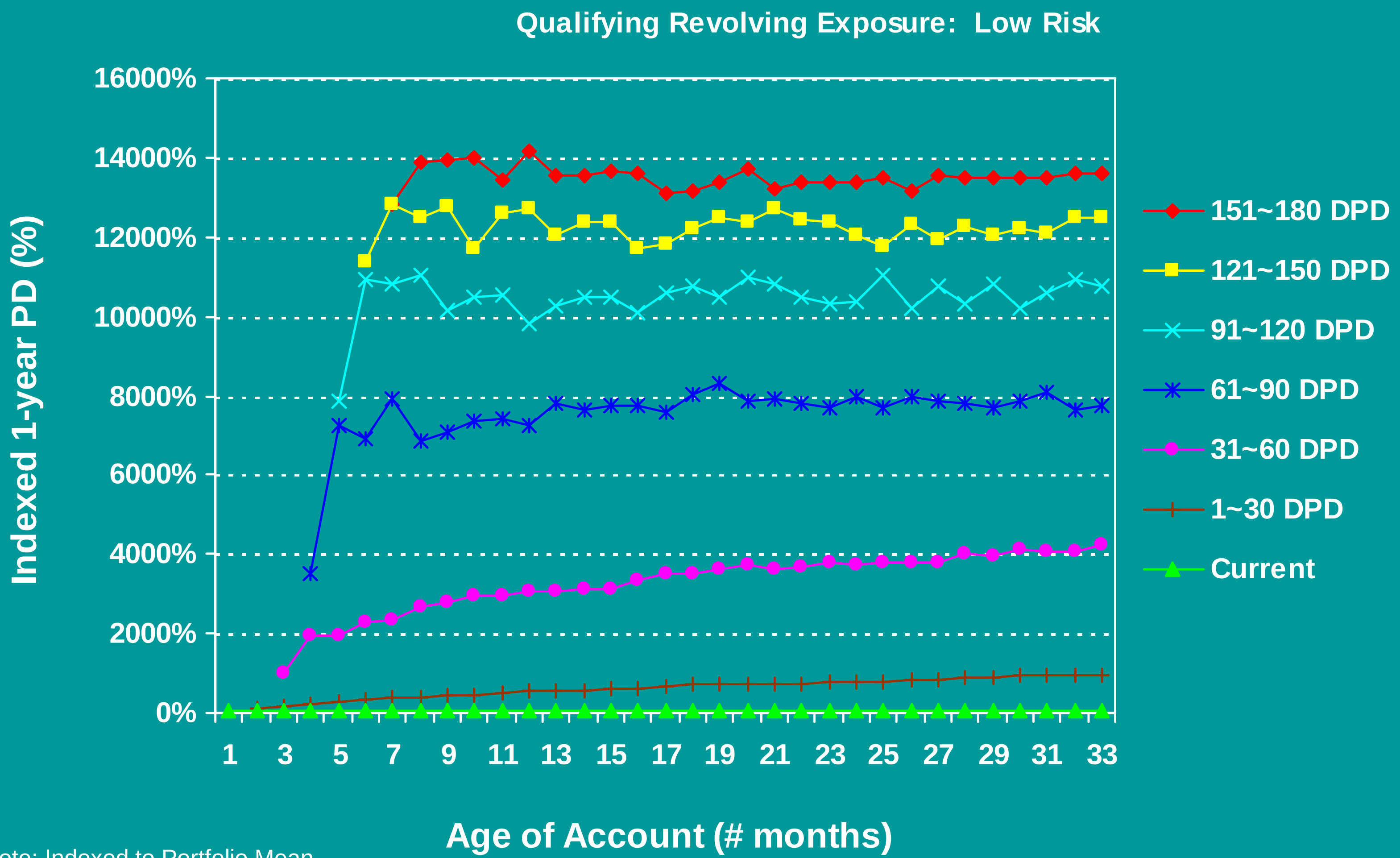

Note: Indexed to Portfolio Mean

# Indexed PD by Refreshed Score and Age (High Risk Portfolio )



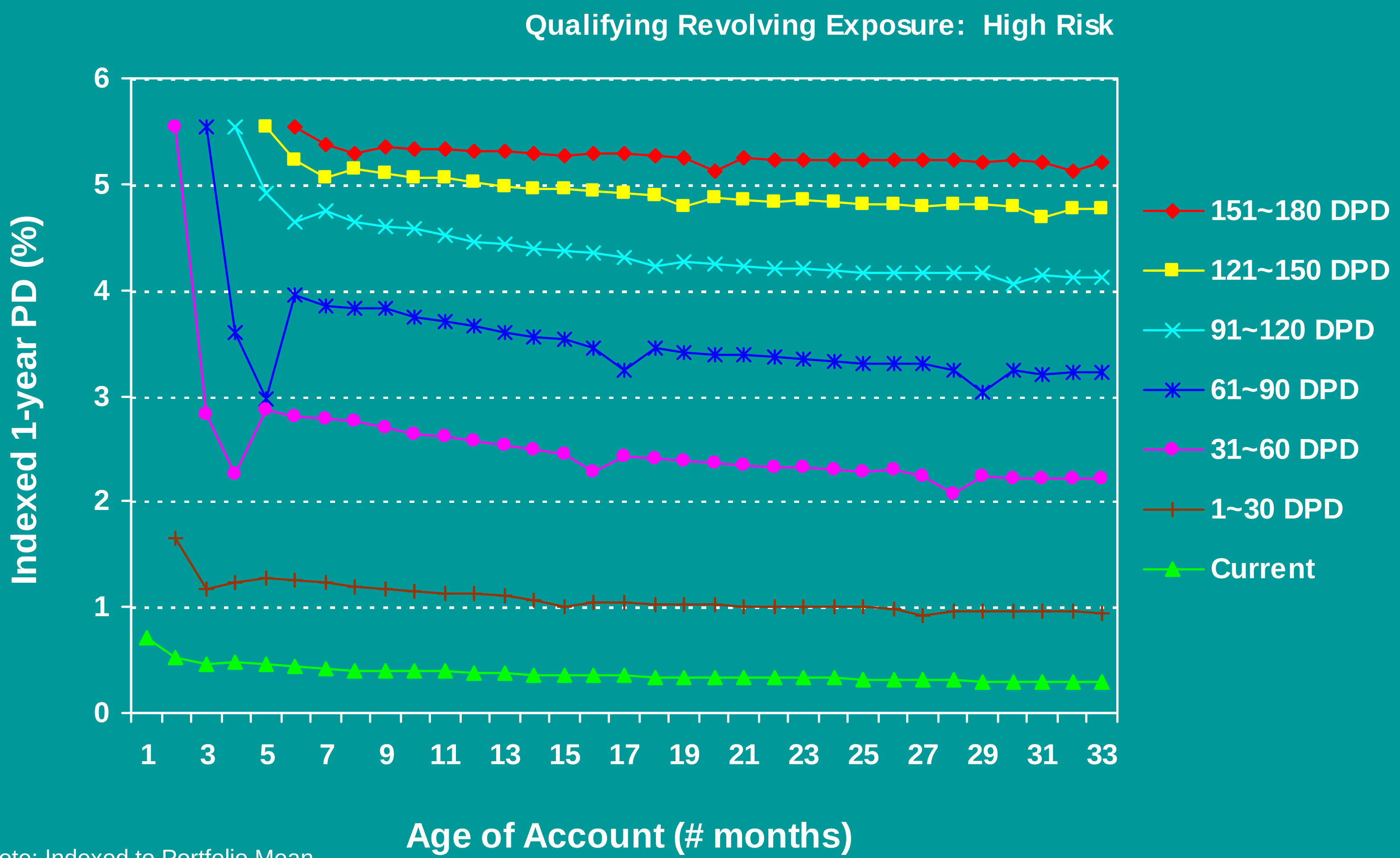

Note: Indexed to Portfolio Mean

# Indexed PD by Delinquency Status and Age (Low Risk Portfolio )




Note: Indexed to Portfolio Mean

# Indexed PD by Delinquency Status and Age (High Risk Portfolio )

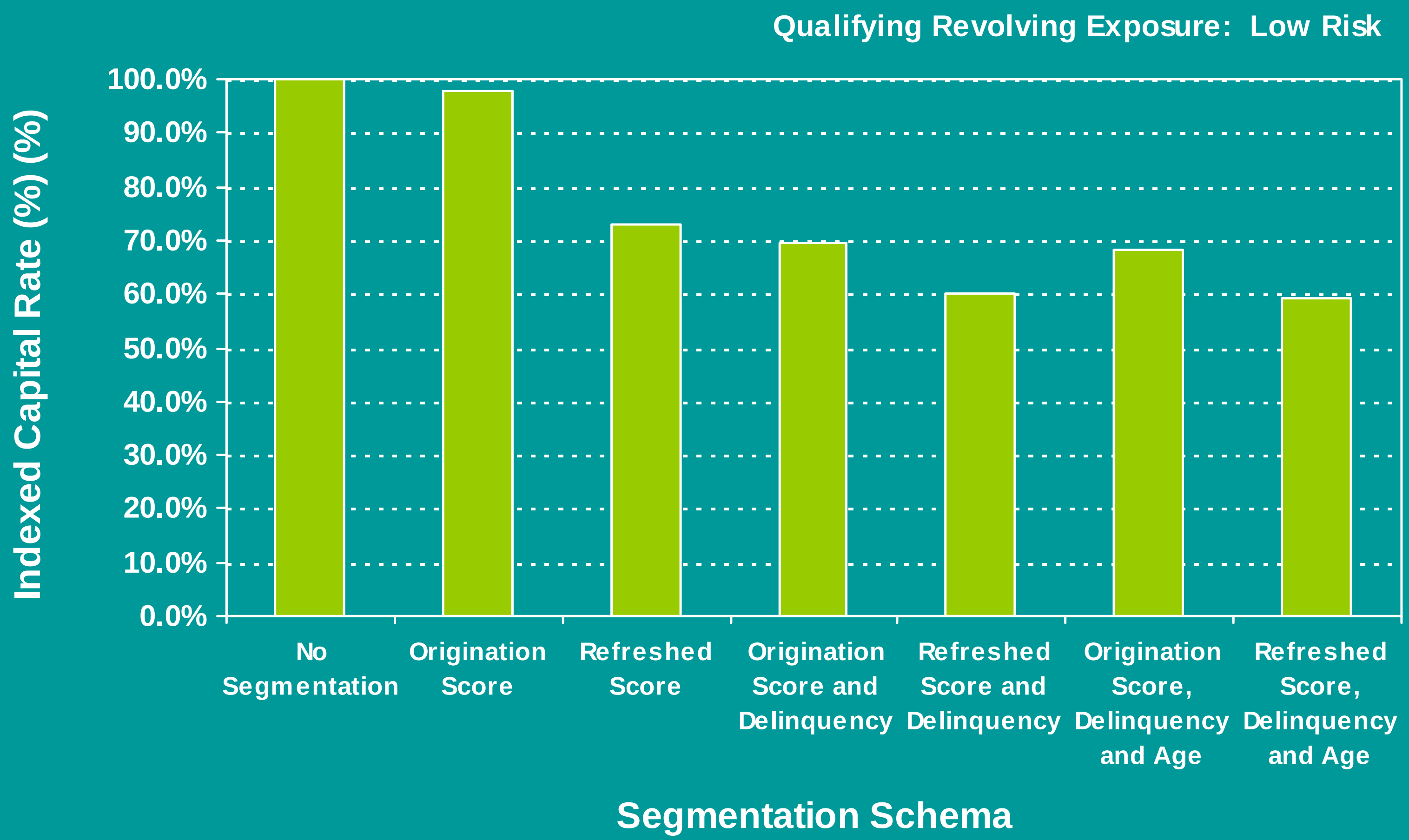



Note: Indexed to Portfolio Mean

# 5: Capital Impact

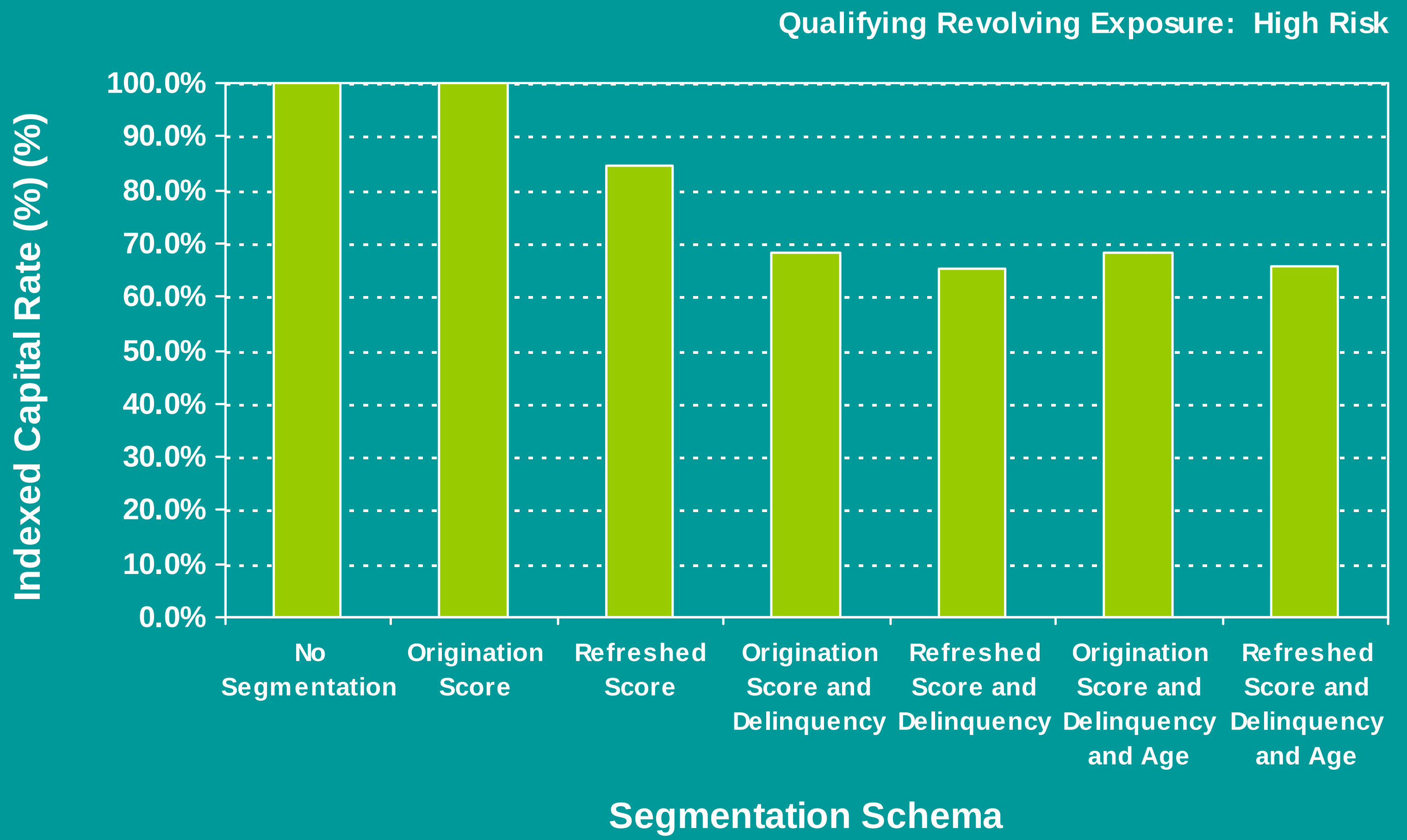
- Capital Impact (based on Long Term PD)
- Capital Seasoning Curves
- Capital seasoning curves by Origination Score
- Capital seasoning curves by Refreshed Score
- Capital seasoning curves by Delinquency

# Capital Based on Long Term PD (Low Risk Portfolio )



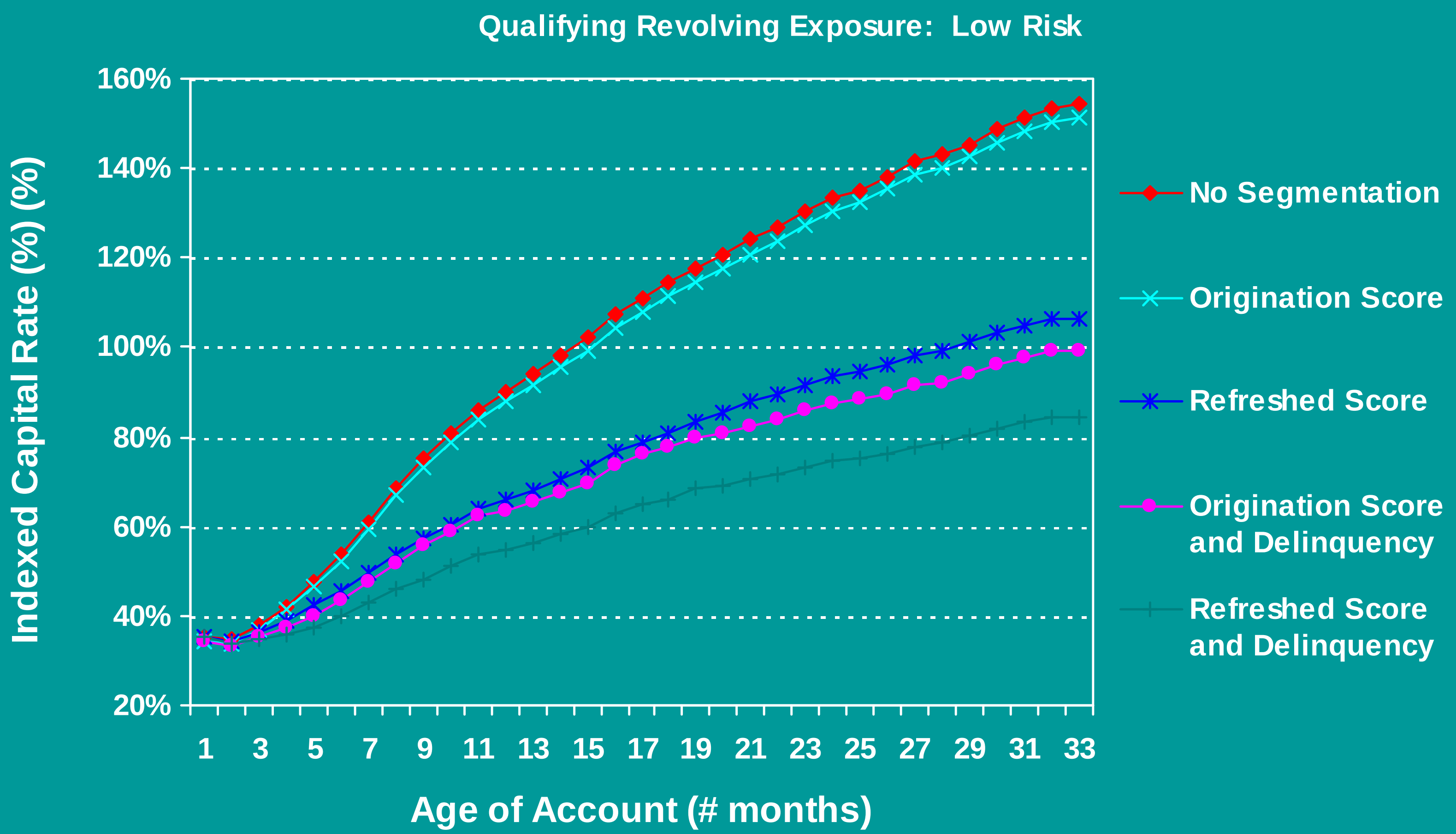

Note: Indexed to “No Segmentation”

# Capital Based on Long Term PD (High Risk Portfolio )



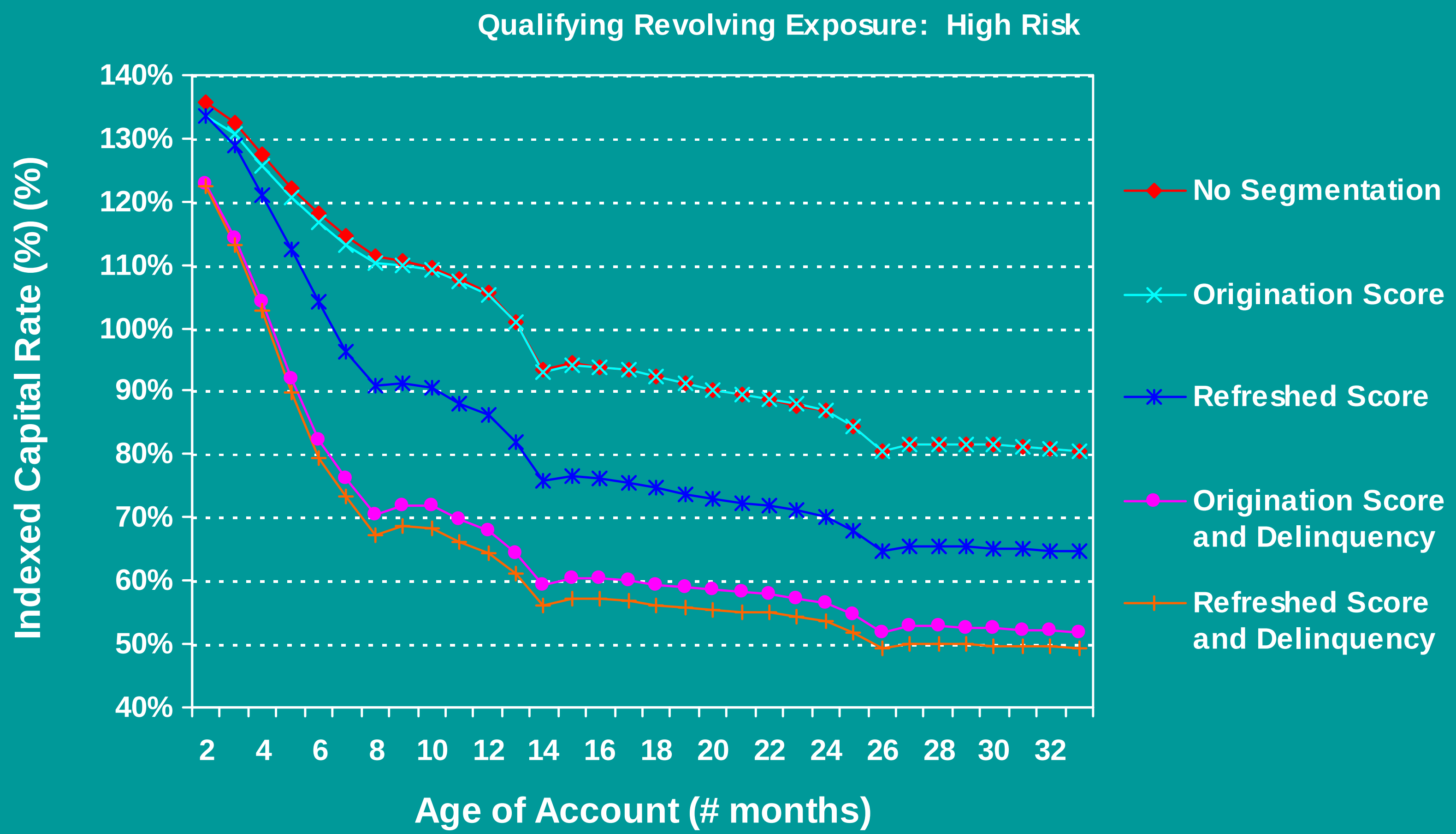

Note: Indexed to “No Segmentation”

# Capital seasoning curve (Low Risk Portfolio )




Note: Indexed to Portfolio Mean of “No Segmentation”

# Capital seasoning curve (High Risk Portfolio )




Note: Indexed to Portfolio Mean of “No Segmentation”

# Summary of Conclusions

- Credit Scores differentiate risk for lower delinquency stages only
- Seasoning effect reduced by some segmentations
- Refreshed Credit Score is most important segmenting characteristic after delinquency
- Origination Credit Score is the least important segmenting characteristic of the major risk drivers
- Refreshed Credit Score and Delinquency give most reduction in capital requirements