

The Use of Credit Information as an Underwriting Tool in Personal Lines Insurance

Analysis of Evidence and Benefits

Michigan House Insurance Committee on
Credit Scoring Discounts



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Presentation Outline

Insurance Scoring & Personal Lines Insurance

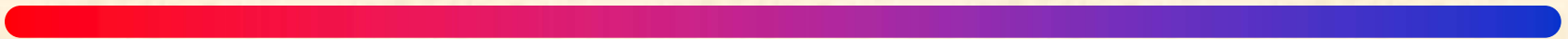
- **What is “Insurance Scoring?”**
- **Why Do Insurers Use Credit Info?**
- **The Science Behind Scoring**
- **Information Used by Insurers**
- **Actual Example of Consumer Savings**
- **Review of the Evidence**
- **Search for Adverse Impact**



Insurance Scoring

- What is “Insurance Scoring”?
 - Insurance scores are HIGHLY accurate predictors of future loss in auto and homeowners insurance
 - Insurance scores provide an objective, accurate and consistent tool that insurers use with *other* applicant information to better anticipate claims
 - Insurers use credit information as a way of determining individual’s responsibility and performance under the terms of an insurance contract, allowing insurer to offer a price that is more fair and equitable

Why Do Insurers Use Credit Information?



Why Insurers Use Credit Information in Insurance Underwriting

1. There is a **strong correlation** between **credit standing** and **loss ratios** in both auto and homeowners insurance.
2. There is a **distinct** and **consistent decline** in relative **loss ratios** (which are a function of both claim frequency and cost) as **credit** standing **improves**.
3. The relationship between credit standing and relative loss ratios is statistically **irrefutable**.
4. The odds that such a relationship does not exist in a given random sample of policyholders are usually between 500, 1,000 or even 10,000 to one.

What You Might Not



Know About Insurance Scoring

1. Insurers have been using credit since early 1990s
 - Credit has been used in commercial insurance for decades
2. Insurance scores do **not** use the following information:
 - *Ethnicity* *Nationality* *Religion* *Age*
 - *Gender* *Marital Status* *Familial Status* *Income*
 - *Address* *Handicap*
3. Insurance scoring is revenue neutral
4. Increased use of credit information is a fact of life in the 21st century (*Why?*: Works for trust-based relationships)
 - *Loans* *Leases* *Rentals* *Insurance*
 - *Utilities* *Background Checks* *Empl. Screening*



*Intuition Behind Insurance Scoring**

1. Personal Responsibility

- Responsibility is a personality trait that carries over into many aspects of a person's life
- It is intuitive and reasonable to believe that the responsibility required to prudently manage one's finances is associated with other types of responsible and prudent behaviors, for example:
 - Proper maintenance of homes and automobiles
 - Safe operation of cars

2. Stability

- It is intuitive and reasonable to believe that financially stable individuals are likely to exhibit stability in many other aspects of their lives.

3. Stress/Distractation

- Financial stress could lead to stress, distractions or other behaviors that produce more losses (e.g., deferral of car/home maintenance).

*This list is neither exhaustive nor is it intended to characterize the behavior of any specific individual.



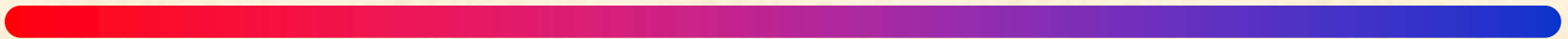
Consequences of Banning Use of Credit in Insurance Underwriting

Banning the use of credit information will:

- Force good drivers and responsible homeowners to subsidize those with poor loss histories by hundreds of millions of dollars each year.
- Decrease incentives to drive safely
- Decrease incentives to properly maintain cars and homes
- Force insurers to rely on less accurate types of information, such as DMV records.
- Make non-standard risks more difficult to place
- Increase size of residual market pools/plans

Risk & Loss

*Accounting for Differences in Losses
by Risk Characteristics Makes
Insurance Pricing More Equitable*



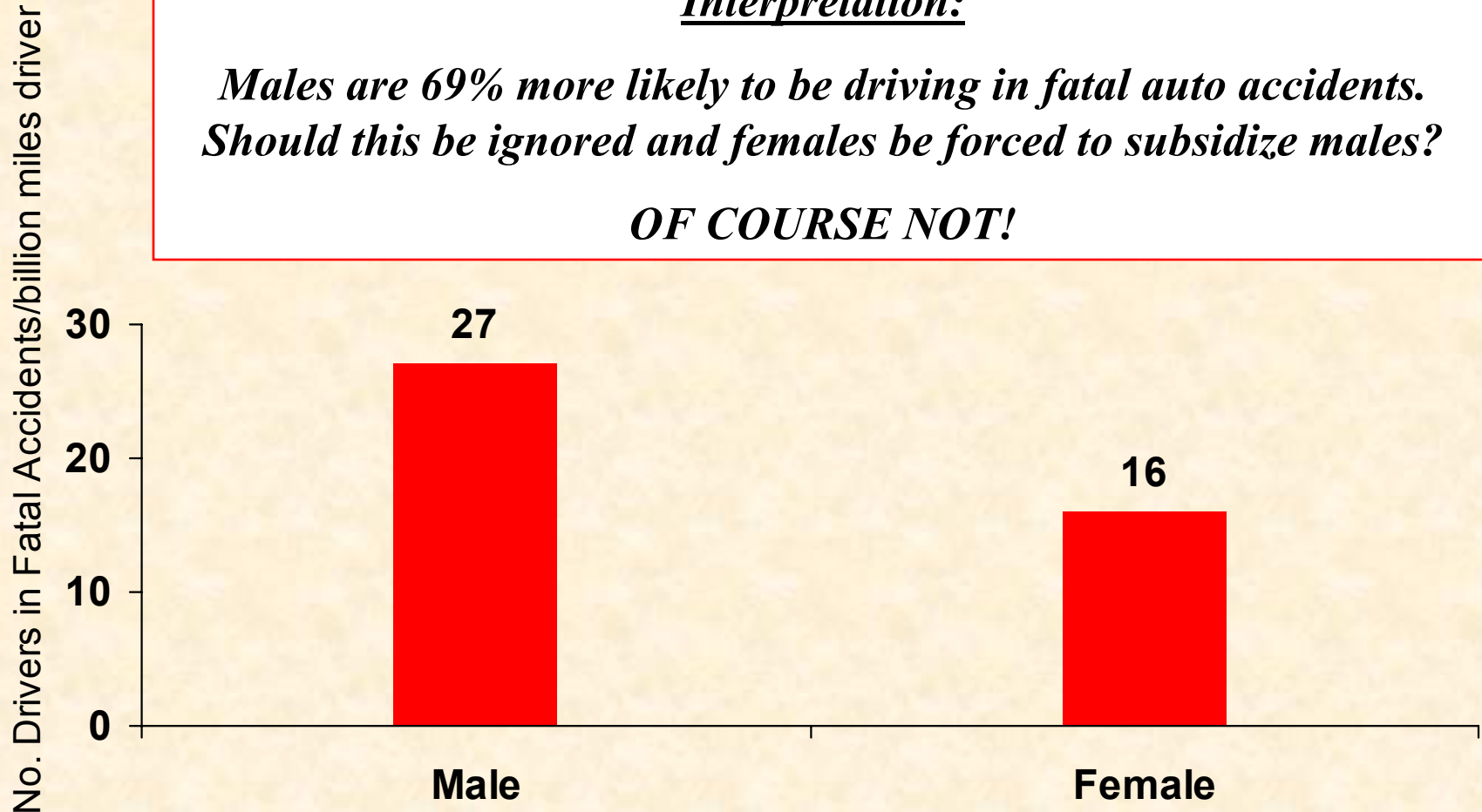


Gender of Drivers Involved in Fatal Auto Accidents, 2000

Interpretation:

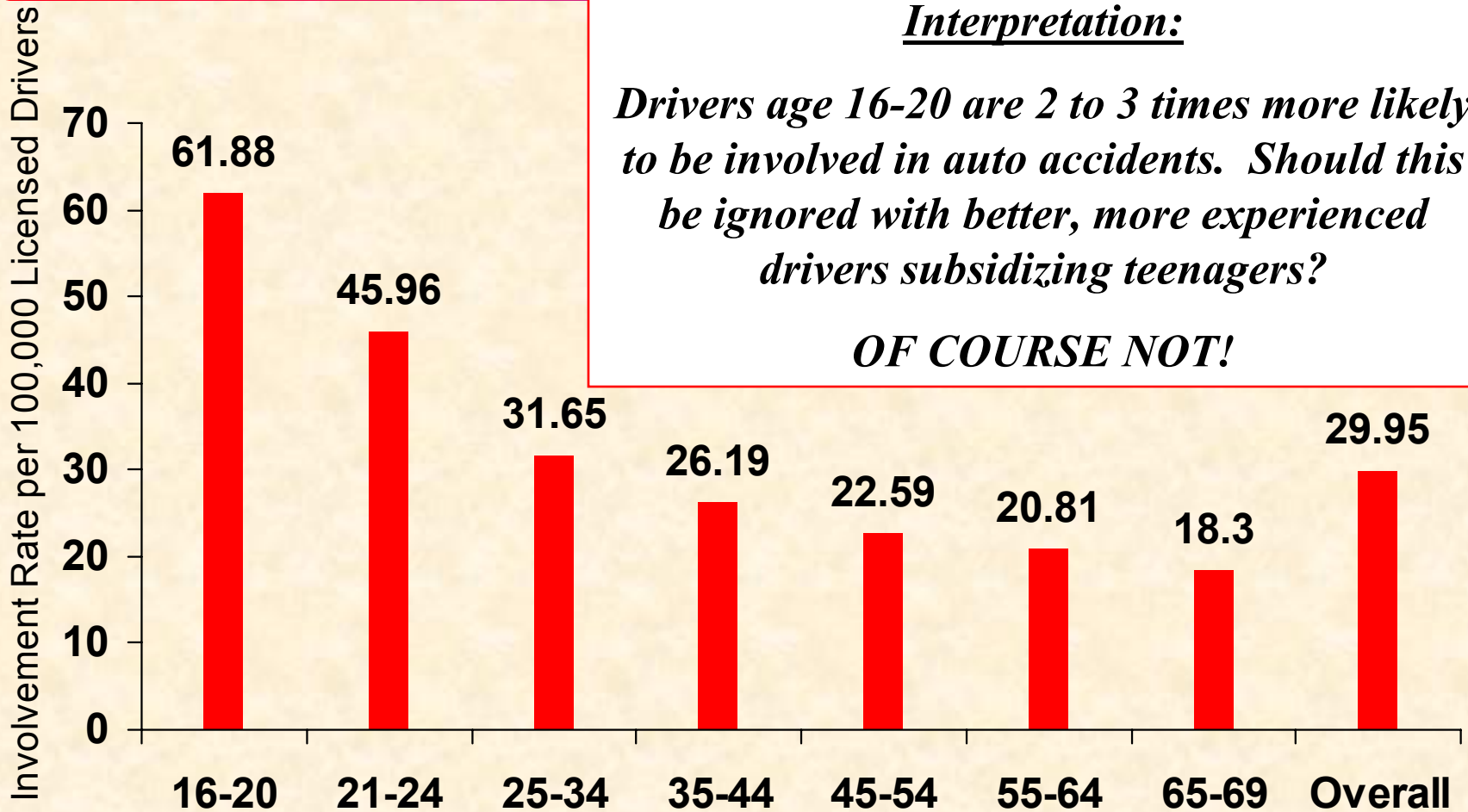
Males are 69% more likely to be driving in fatal auto accidents. Should this be ignored and females be forced to subsidize males?

OF COURSE NOT!





Age of Drivers Involved in Auto Accidents, 2000



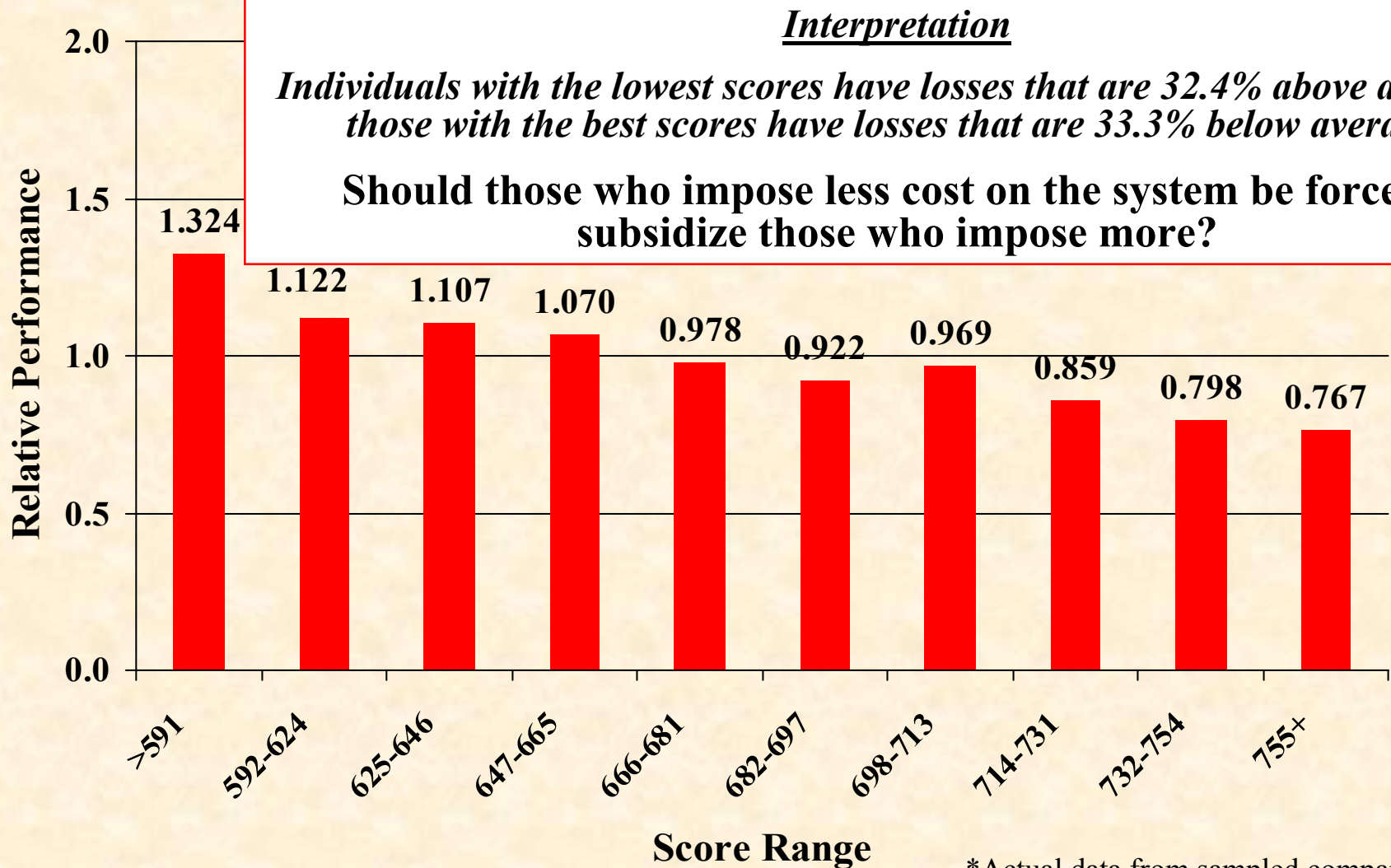
Interpretation:

Drivers age 16-20 are 2 to 3 times more likely to be involved in auto accidents. Should this be ignored with better, more experienced drivers subsidizing teenagers?

OF COURSE NOT!



Credit Quality & Auto Insurance*

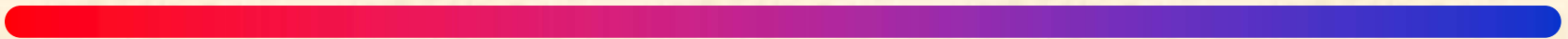


Source: Tillinghast Towers-Perrin

*Actual data from sampled company. More examples are given later in this presentation.

Actual Example:

*How Insurer Use of Credit
Benefits Consumers &
What Consumers Stand to Lose*





Example: Insurance Savings from Use of Credit Information

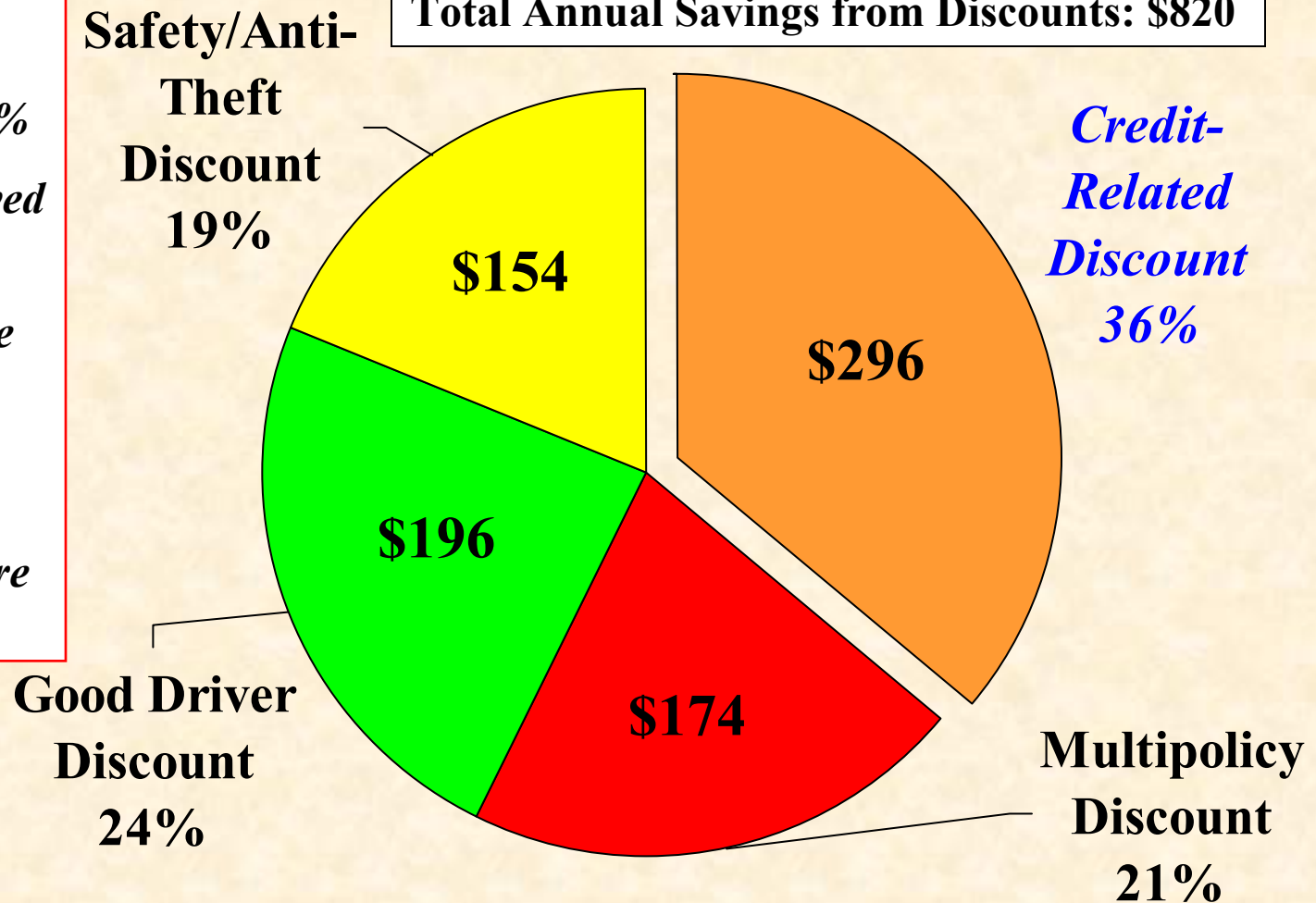
- Insured lives in Westchester County, NY (NYC suburb)
- 2 fully insured vehicles (\$250K/\$500K liability, \$1000 deductible)
 - 2000 Nissan Xterra & 1994 Honda Civic
- Insured's biannual premium was \$862 (March 2003 renewal)
 - No accidents or moving violations on record
- Insured's credit-related discount for the 6-month period was \$148 out of \$410 in total discounts.
 - Credit-related discount saves consumer nearly \$300/year
 - Effectively lowers premium by 14.7%
 - Should this (and millions of other) consumers be denied this discount? Some regulators and consumer groups want you to pay more unnecessarily and subsidize bad drivers.
- August 2002 FICO Score = 777 (out of 850) (= 72nd percentile)
 - i.e., 28% have better (higher) scores, 72% have lower (worse) scores



Example (cont'd): Credit Discount Can Save \$100s per Year*

- *Credit discount lowered annual premium by 14.7%*
- *Policyholder saved nearly \$300*
- *Credit was single largest discount*
- *Opponents of credit will force people to pay more for coverage*

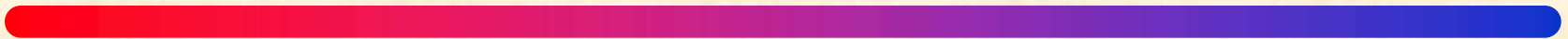
Total Annual Savings from Discounts: \$820



*Annualized savings based on semi-annual data from example

Review of the Evidence:

History, Studies,
Data & Analyses





Casualty Actuarial Society

Credit Study

Personal Automobile Loss Ratio by Credit Category

Category	Earned Premium	Incurred Loss	Loss Ratio	Loss Ratio Relativity
A	\$74,279	\$75,333	101.4%	133
B	158,922	124,723	78.5%	103
C	69,043	47,681	69.1%	91
D	91,746	52,688	57.4%	75
Total	\$393,990	\$300,425	76.3%	

Category A – Unacceptable Credit Rating

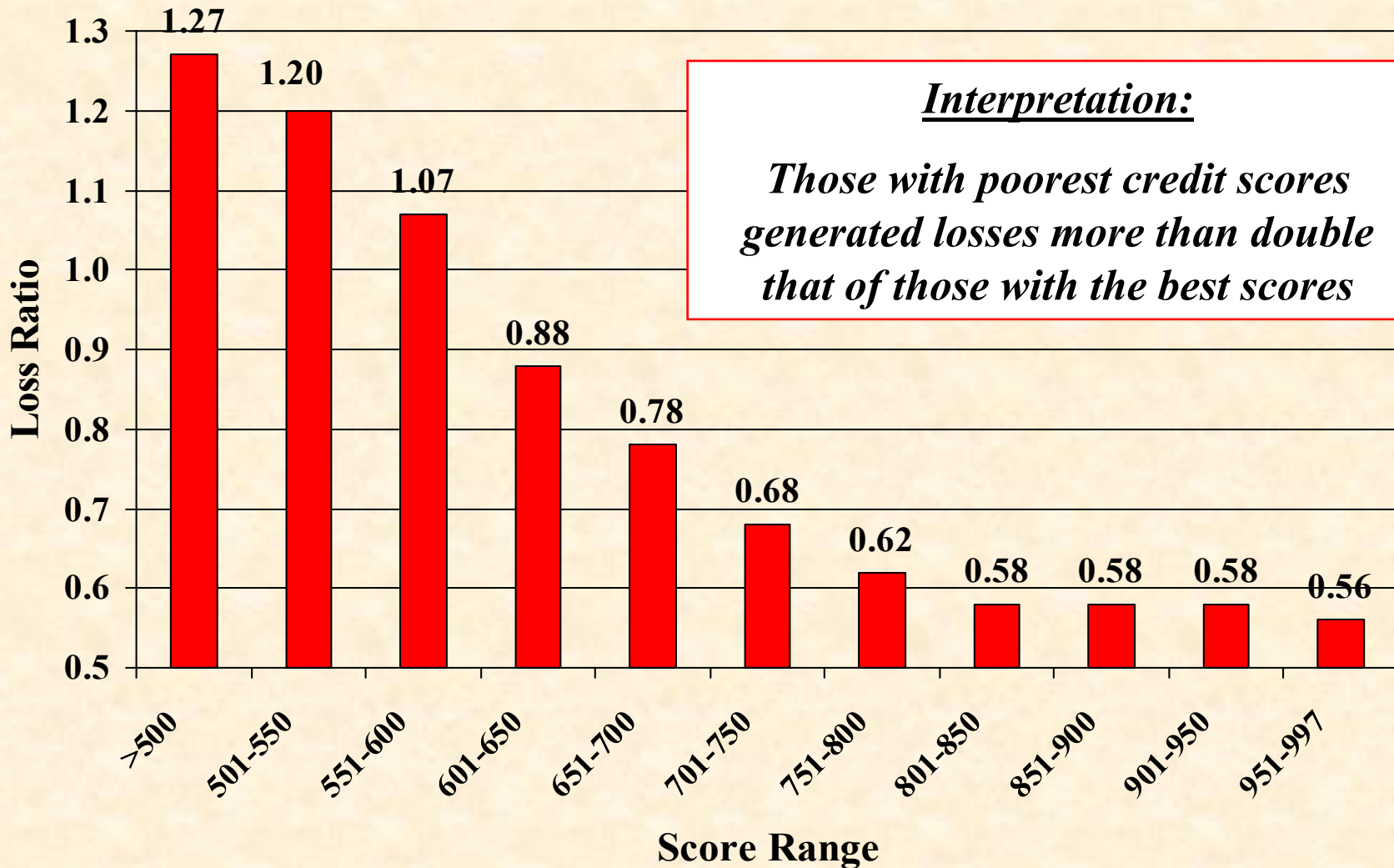
Category B – No established credit history (or does not meet the definition of A, C or D)

Category C – Good Credit Rating

Category D – Excellent Credit Rating



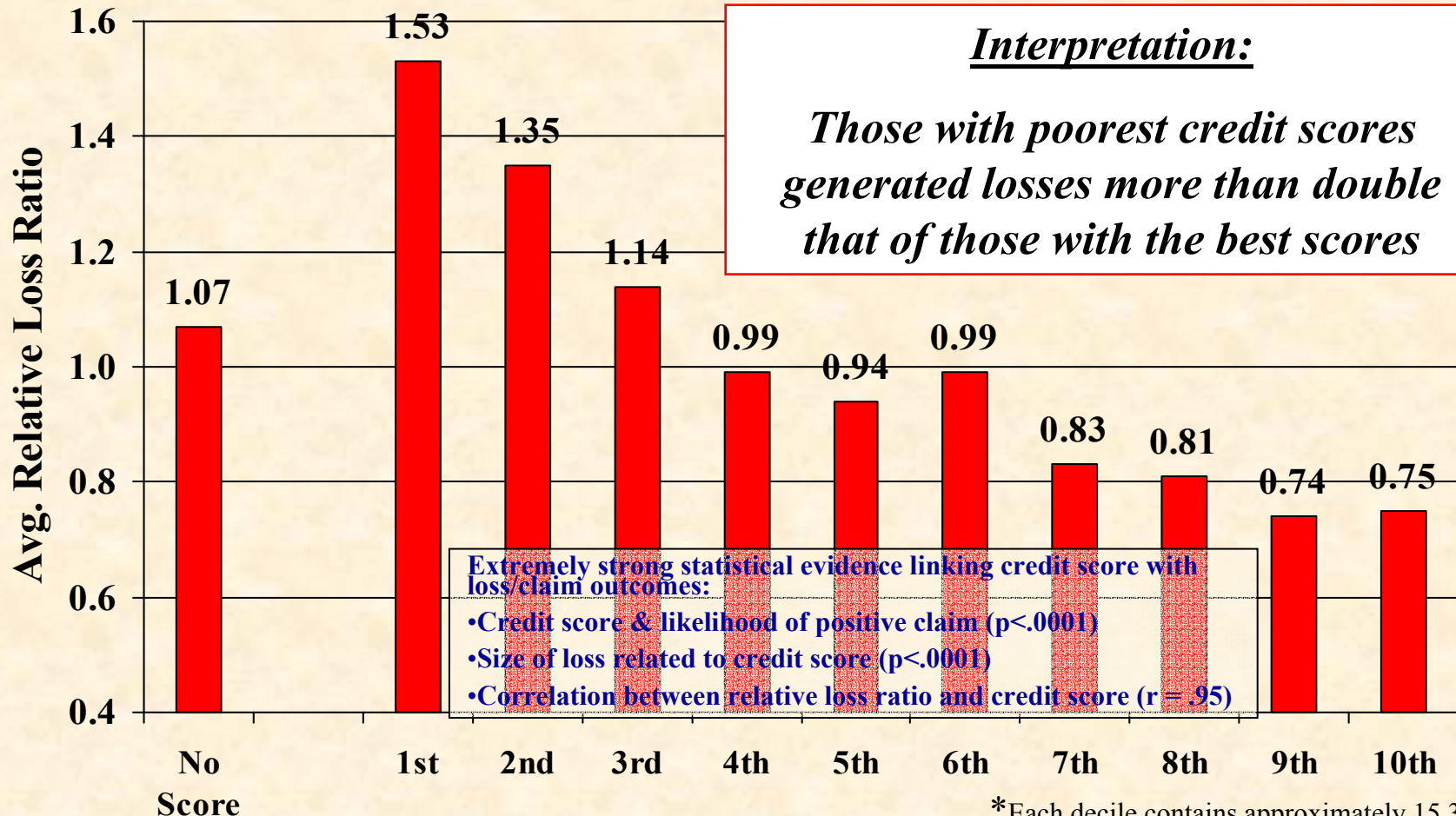
Major Auto Company Analysis of Credit and Loss Ratio*



*Average loss ratios for new auto policies written over a 3-year period.



Texas Auto: Relative Loss Ratio (by Credit Score Decile, Total Market)*



Interpretation:
Those with poorest credit scores generated losses more than double that of those with the best scores

Extremely strong statistical evidence linking credit score with loss/claim outcomes:

- Credit score & likelihood of positive claim (p<.0001)
- Size of loss related to credit score (p<.0001)
- Correlation between relative loss ratio and credit score (r = .95)

1st Decile = Lowest Credit Scores
10th Decile = Highest Credit Scores.

Score Range

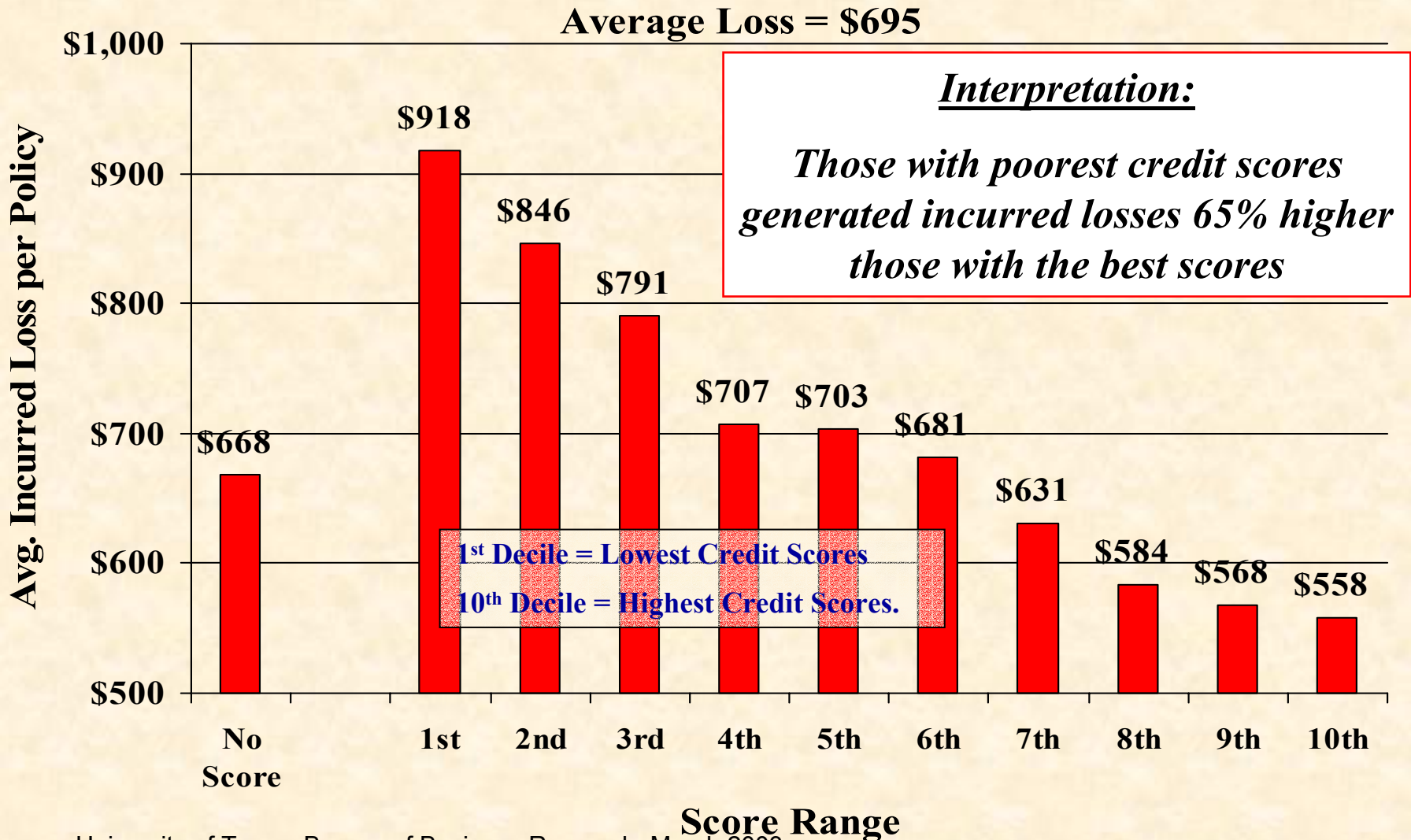
*Each decile contains approximately 15,300 policies.
Includes standard and non-standard policyholders.

Source: University of Texas, Bureau of Business Research, March 2003.



Texas Auto: Average Loss per Policy

(by Credit Score Decile, Total Market)





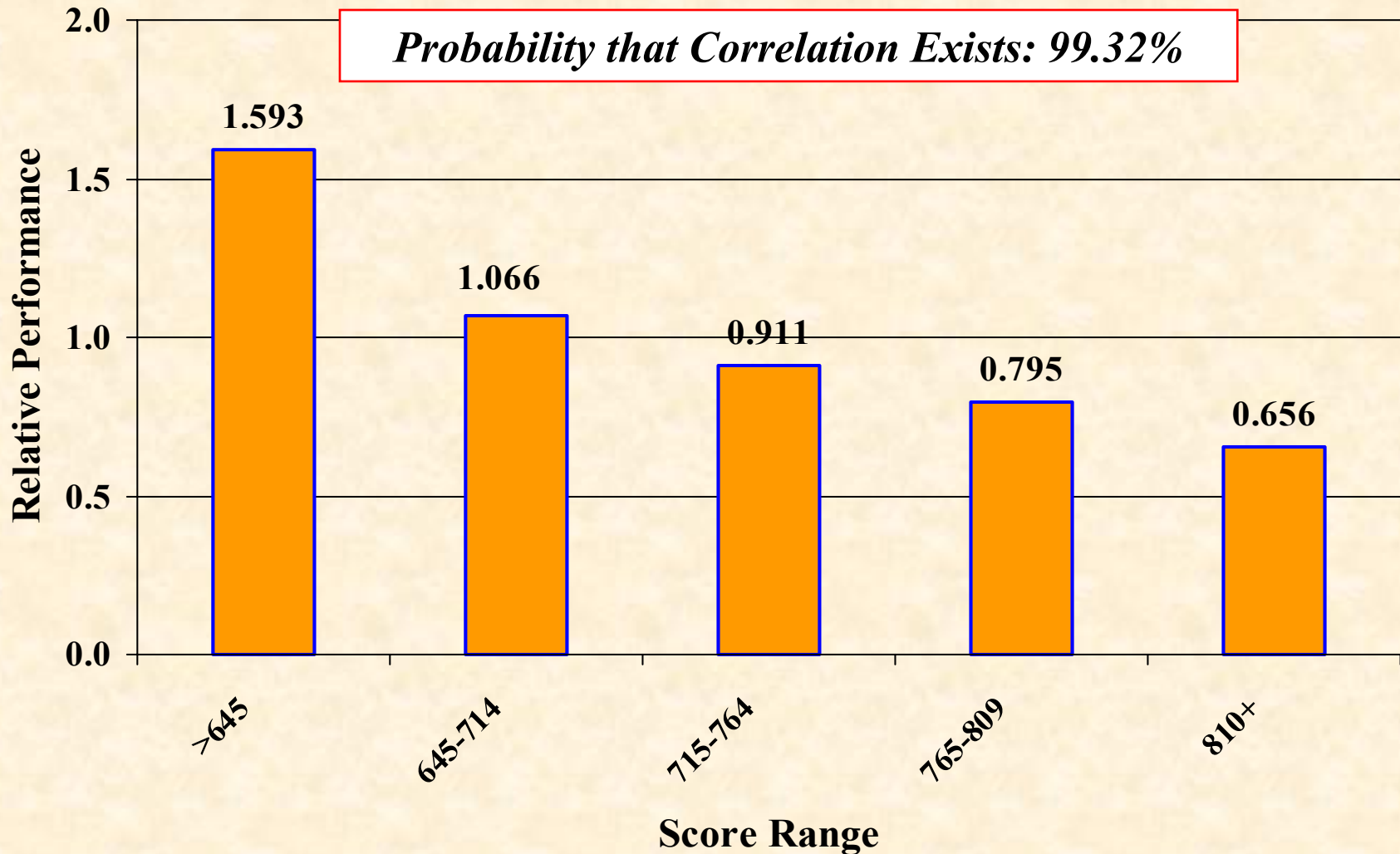
Tillinghast Towers-Perrin Study

- Studied 9 Samples of Data from 8 Companies*
 - Looked at loss ratio relativity in relation to insurance score
 - Studied both auto/home
- Analyzed probability that a correlation exists between insurance score and loss ratio relativity
 - In 8 of 9 samples, probability that a statistically significant correlation exists exceeded 99% (in one case the probability was approximately 92%)

*One company supplied both auto and homeowners data. The submissions are counted as separate companies for the purposes of this analysis.

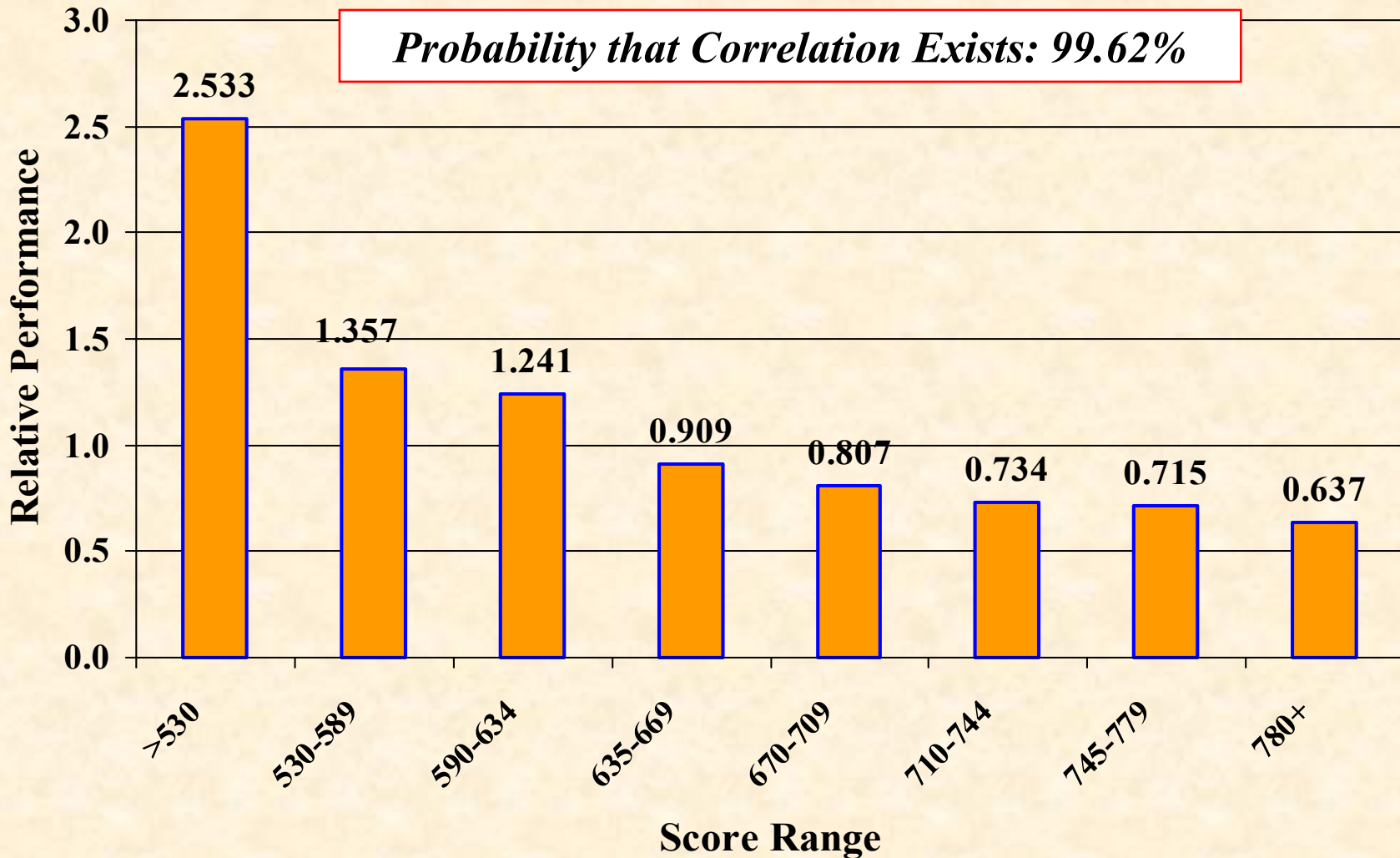


Homeowners Company A





Homeowners Company C





Homeowners Insurance: Statistical Correlation

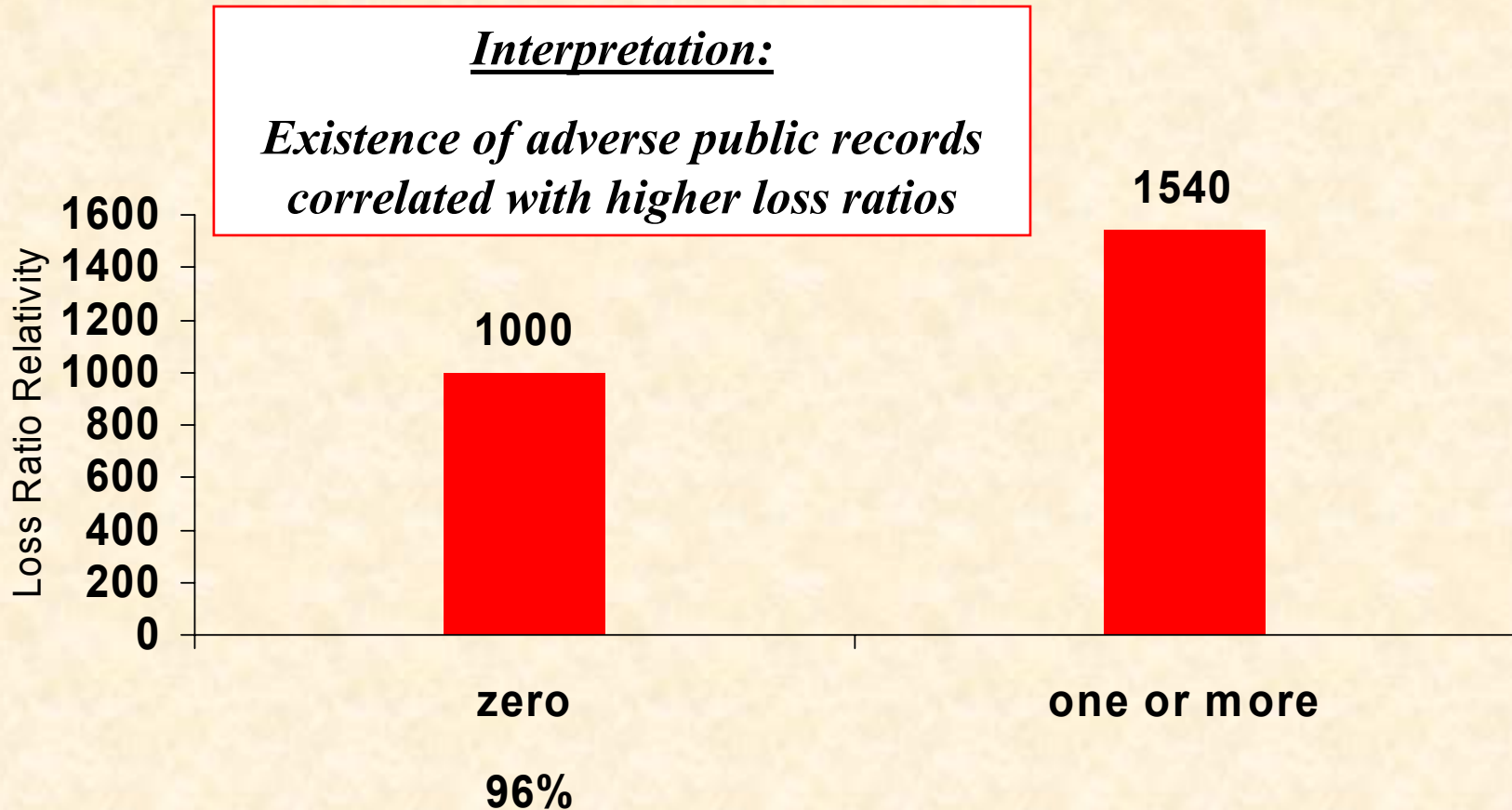
- Homeowners univariate analyses
 - Number of adverse public records
 - Months since most recent adverse public record
 - Number of trade lines 60+ days delinquent in last 24 months
 - Number of collections
 - Number of trade lines opened in the last 12 months
- Data Used in Fair, Isaac Homeowners Analysis
 - 1.23 Million policies in data base
 - 1,000,000 policies without claims
 - 230,000 with claims
 - 11 Archives



Statistical Correlation

Homeowners HO - 3

Number of Adverse Public Records





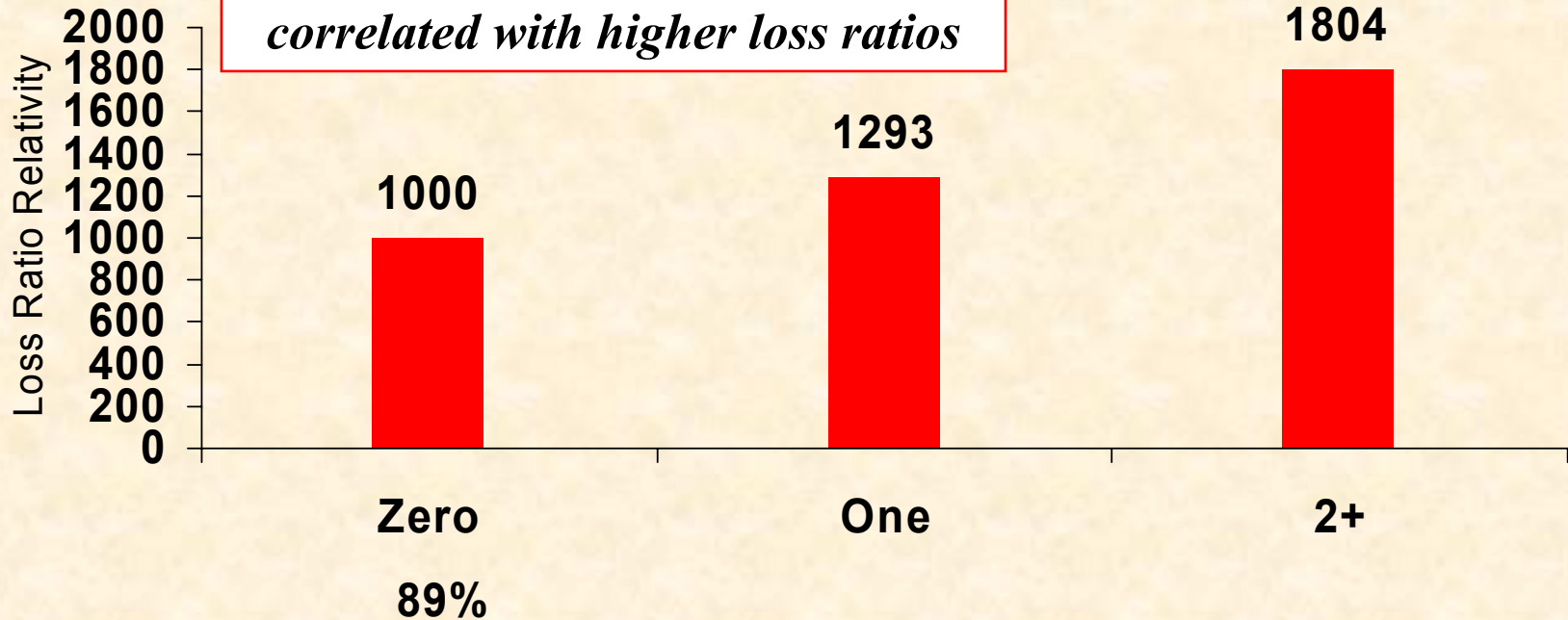
Statistical Correlation

Homeowners HO - 3

Number of Trade Lines 60+ Days Delinquent in
Last 24 Months

Interpretation:

***Higher number of delinquencies
correlated with higher loss ratios***





Personal Auto Insurance: Statistical Correlation

- Personal Auto Univariate Analyses
 - Number of adverse public records
 - Months since most recent adverse public record
 - Number of trade lines 60+ days delinquent in last 24 months
 - Number of collections
 - Number of trade lines opened in the last 12 months
- Data Used in Fair, Isaac Personal Auto Analysis
 - 1.35 Million policies in data base
 - 1,000,000 policies without claims
 - 350,000 with claims
 - 6 Archives



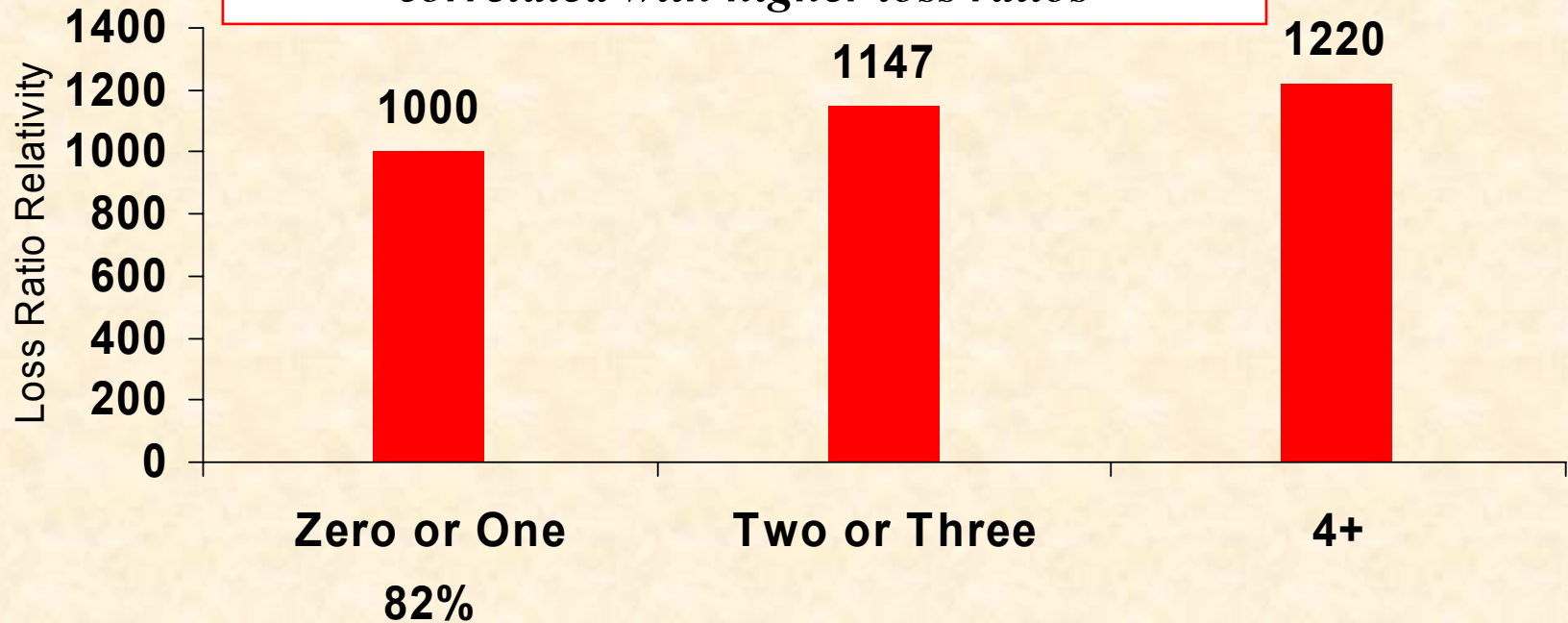
Statistical Correlation

Personal Auto

Number of Trade Lines Open in Last 12 Months

Interpretation:

*Higher number of trade credit lines opened
correlated with higher loss ratios*





NAIC (EPIC) Study (June 2003)

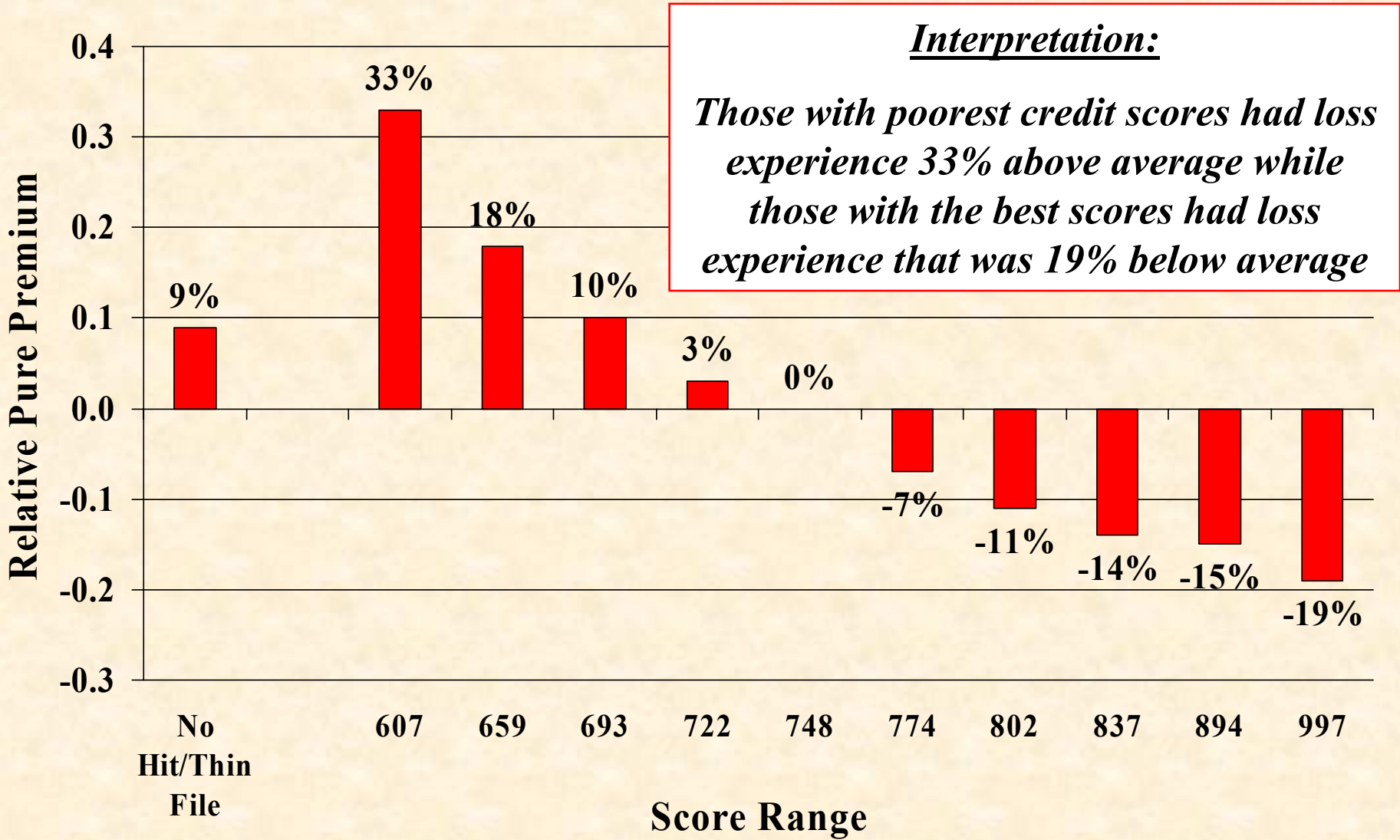
- Analyzed random sample of claim records totaling 2.7 million earned car years from all 50 states for period from 7/1/00 through 6/30/01

4 MAJOR FINDINGS:

1. Insurance scores were found to be *correlated* with the propensity of loss (primarily due to frequency)
2. Insurance scores *significantly* increase accuracy of the risk assessment process, even after fully accounting for interrelationships with other variables.
3. Insurance scores are among the 3 *most important* risk factors for each of the 6 coverage types studied
4. Study results apply generally to *all* states and regions



Indicated Relative Pure Premium by Insurance Score (PD Liability)*





Importance of Rating Factors by Coverage Type

Coverage	Factor 1	Factor 2	Factor 3
BI Liability	Age/Gender	Ins. Score	Geography
PD Liability	Age/Gender	Ins. Score	Geography
PIP	Ins. Score	Geography	Yrs. Insured
Med Pay	Ins. Score	Limit	Age/Gender
Comprehensive	Model Year	Age/Gender	Ins. Score
Collision	Model Year	Age/Gender	Ins. Score

Source: *The Relationship of Credit-Based Insurance Scores to Private Passenger Automobile Insurance Loss Propensity* Michael Miller, FCAS and Richard Smith, FCAS (EPIC Actuaries), June 2003 (Presented at June 2003 NAIC meeting).



Washington State Study on Credit Scoring in Auto UW & Pricing

STUDY DESIGN

- WA State study released in January 2003 required under ESHB 2544, which also restricted the use of scoring
- Conducted by Washington State University (WSU)
- Objective was to determine who benefits/is “harmed” by scoring, impact of scoring on rates, disparate impacts on “the poor” or “people of color”
- Sampled about 1,000 auto policyholders from each of 3 insurers: age, gender, zip, inception date, score/rate class.
- Study’s models typically explain only 5% - 15% of variation (very low R-square in regression analyses)
- WSU contacted policyholders asked: ethnicity, marital status, income, details of experience if cancelled



Washington State Study on Credit Scoring in Auto UW & Pricing

SUMMARY OF FINDINGS

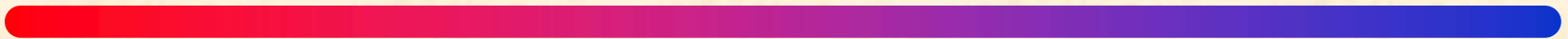
- Statistically the findings are extremely weak, leading even the study's author to conclude: *“The ...models only explain a fraction of the variance in score or discount found in the sample population”* and that *“...while there are statistically detectable patterns in the demographics of credit scoring, most of the variation among individual scores is to due to random chance or other facts not in this data.”*
- Study's models typically explain only 5% - 15% of variation (very low R-square in regression analyses).
- Strongest and most consistent finding is that credit score is positively associated with ***age***
 - Implication: banning on scoring creates disparate impact on older, more experienced drivers



Problems With Such Studies

- Already statistically irrefutable evidence that scoring works. This fact is ignored in WA study.
- Ignores fact that scoring is 100% blind to ethnicity, color, gender, marital status, income, location, etc.
- Introduces the divisive issue of race into an issue where it does not belong (and doesn't exist today)
- *Perpetuates false stereotype that minorities and the poor are incapable of managing their finances responsibly*
- Puts regulators in awkward position of determining who is a minority, who is poor
- Lead to disparate impacts on groups such as older drivers, people who file few claims, and millions of minorities and low income people who benefit today
- Leads to poor public policy decisions that produce perverse economic incentives (e.g., subsidies to drivers who have higher relative losses)

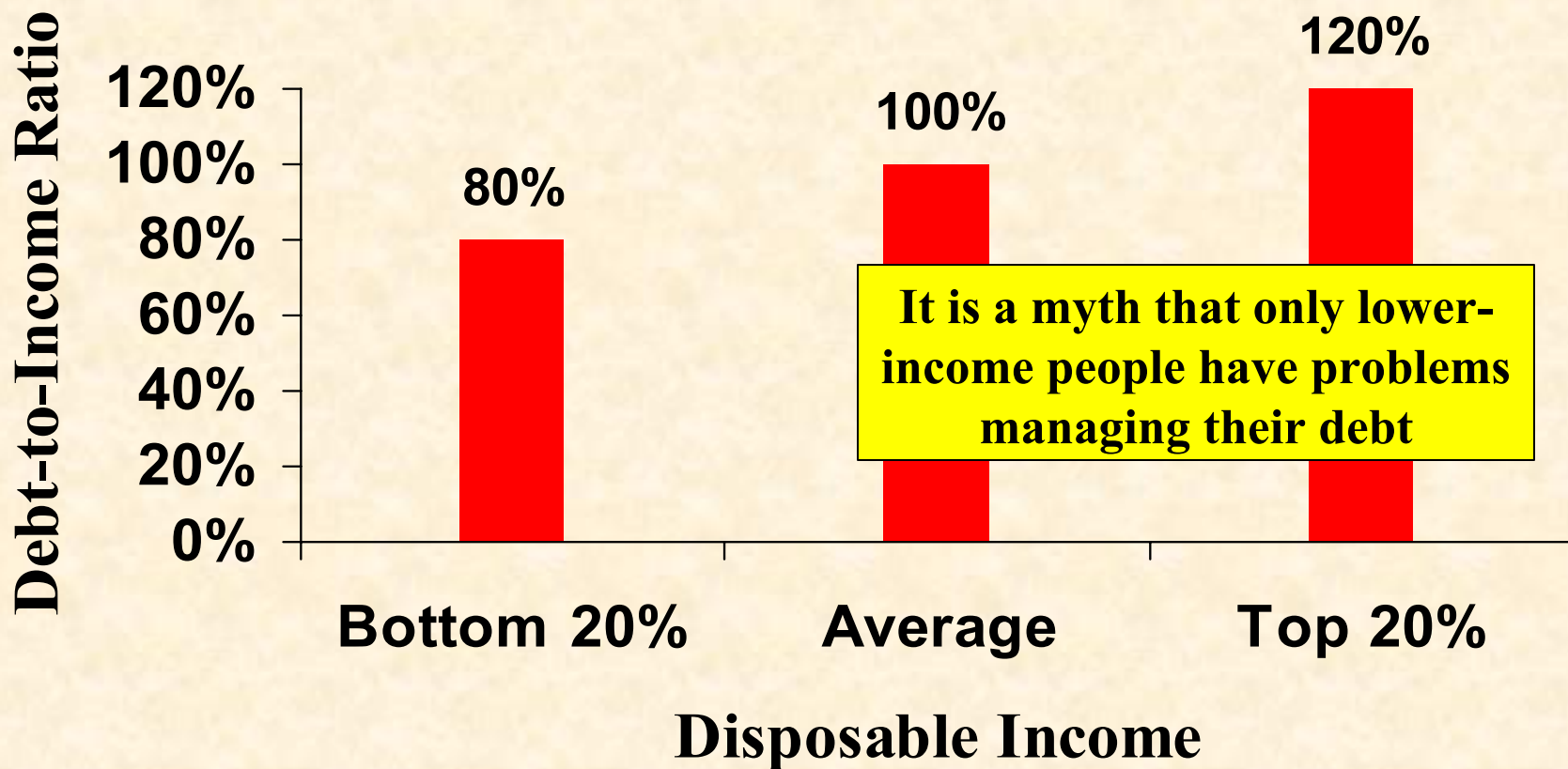
The Relationship Between Income and Credit Score





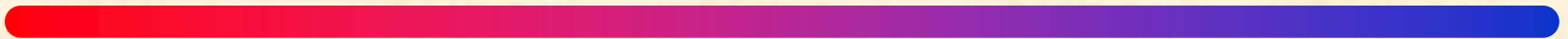
Wealthy Americans Have the Highest Debt as a % of Disposable Income

Debt-to-Income Ratios



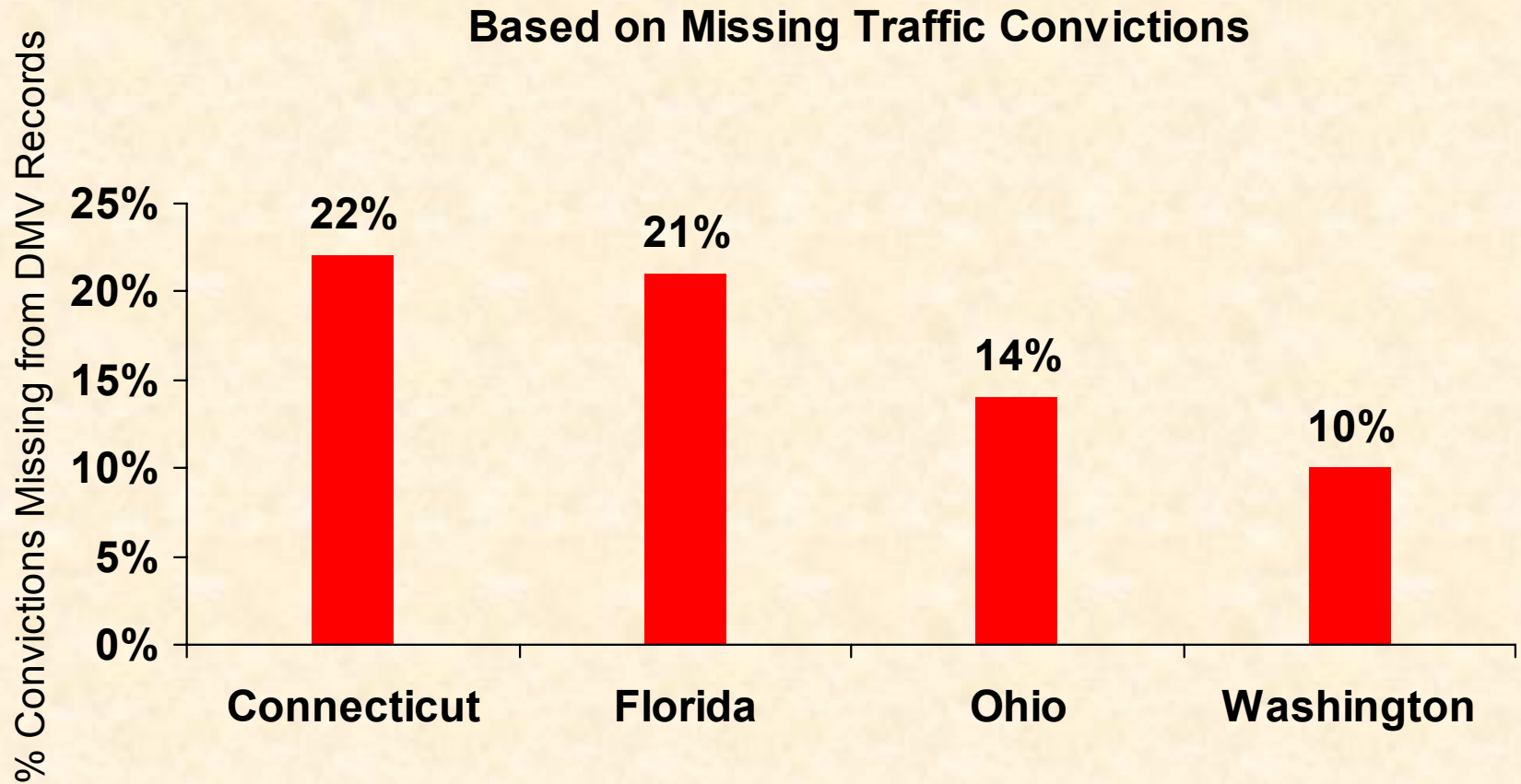
Why Not Just Rely on Motor Vehicle Records?

→ Too Inaccurate!





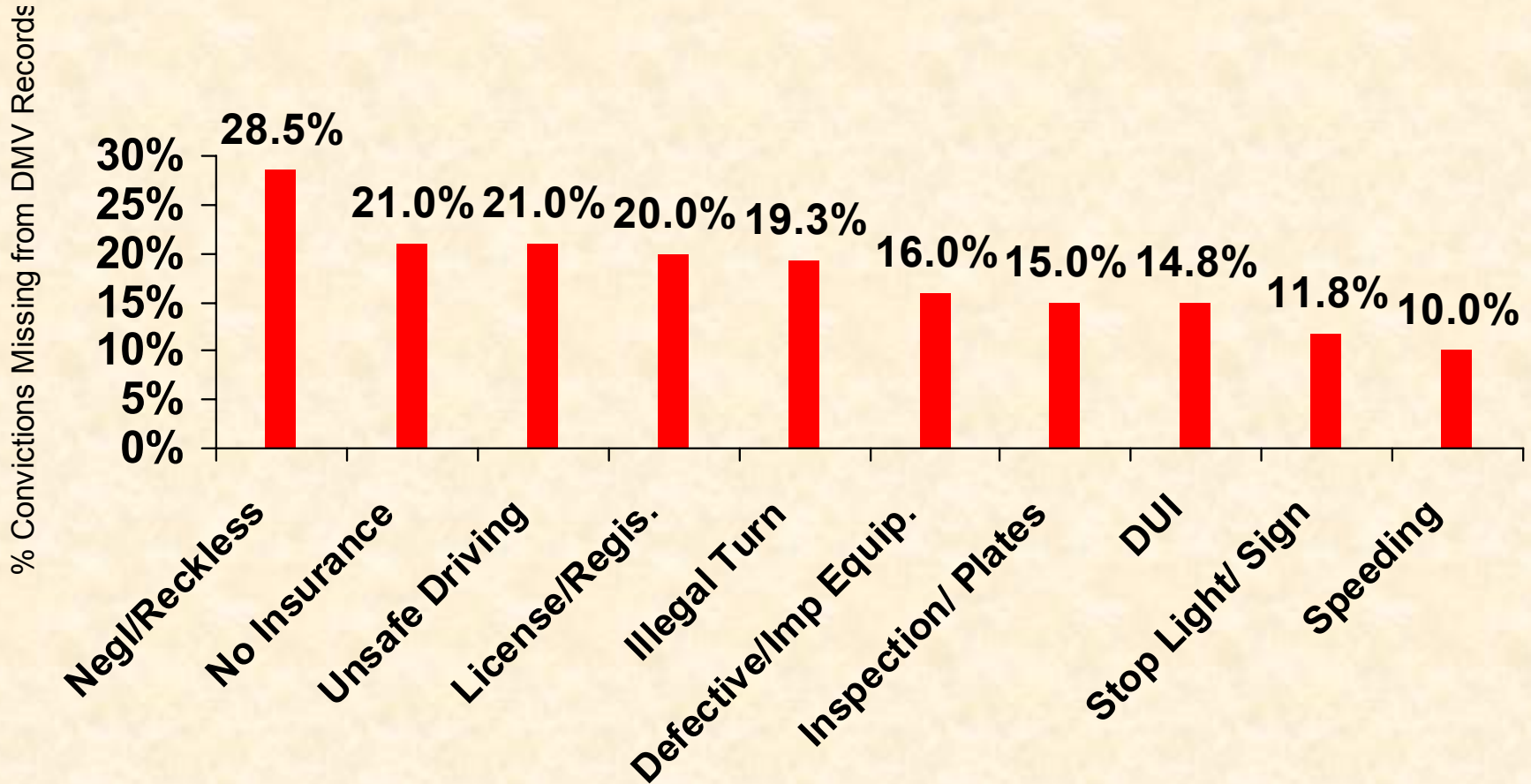
Overall Inaccuracy of State Motor Vehicle Records



Source: Insurance Research Council, *Accuracy of Motor Vehicle Records* (2002).

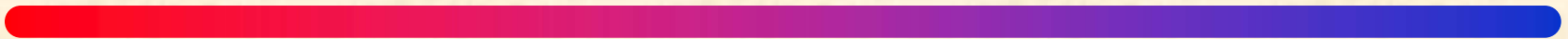


Average Omission Rate for Selected Convictions



Source: Insurance Research Council, *Accuracy of Motor Vehicle Records* (2002).

*Has the Use of Credit
Information Adversely
Impacted Homeownership in
America?*





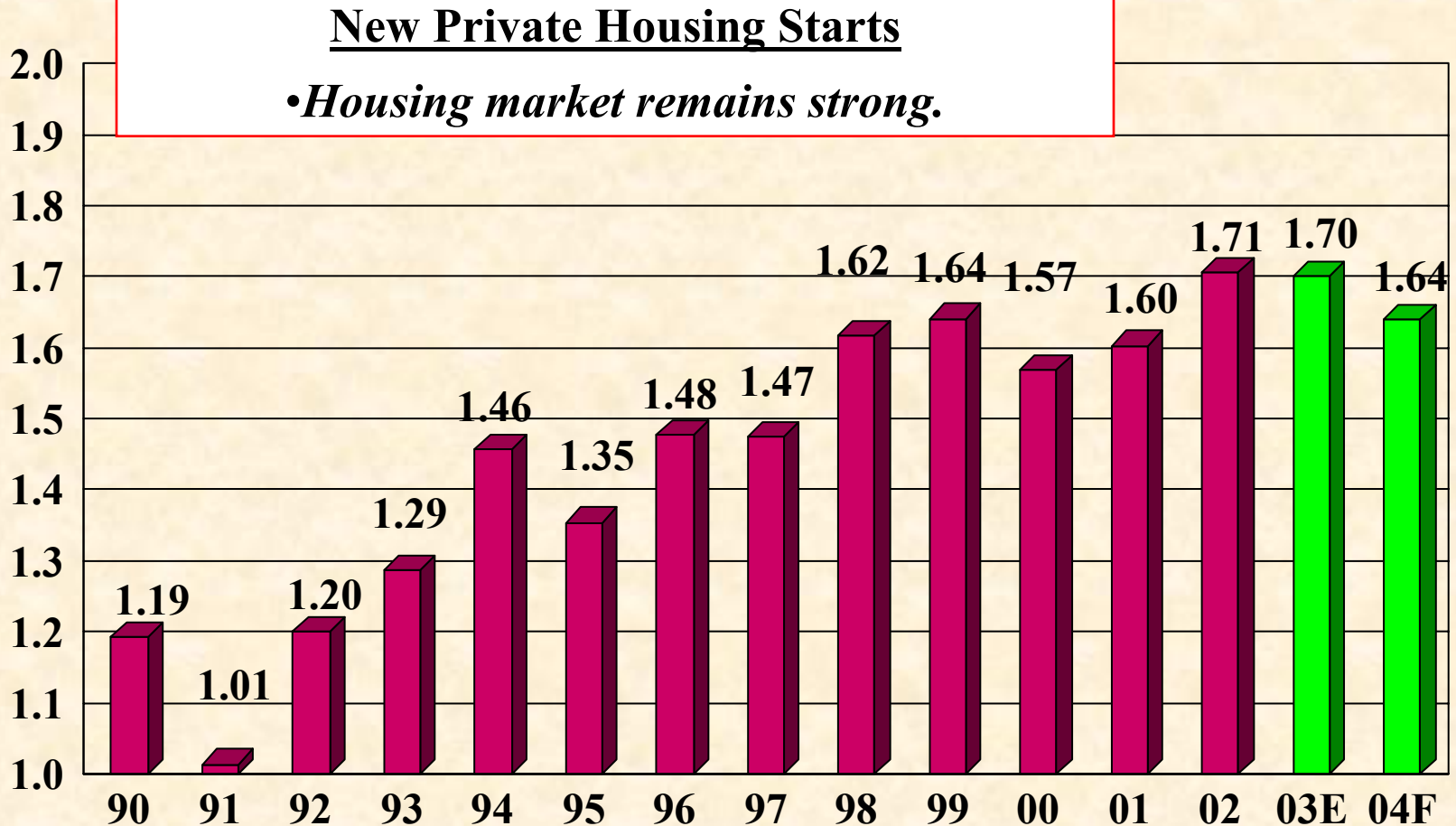
Difficult to See Where Insurance

Scoring/CLUE Hurting Real Estate Buyers

- **“Record for Home Sales Likely in 2003”**
 - *“Record low mortgage interest rates, a growing number of households, rising consumer confidence and an improving economy mean probably will set a **third consecutive record for both existing- and new-home sales this year.**”*
 - David Lereah, NAR Chief Economist, June 3, 2003
- **“Existing Home Sales Still on a Roll in April”**
 - *“Sales of existing homes single-family homes rose in April 2003 and are at the **fifth highest level of activity ever recorded.**”*
 - As reported on www.realtor.org on June 13, 2003
- **“Most Metro Area Home Prices Rising Above Norms”**
 - *“...short supply is continuing to put pressure on home prices in many areas, with more buyers than sellers...”*
 - David Lereah, NAR Chief Economist, February 12, 2002



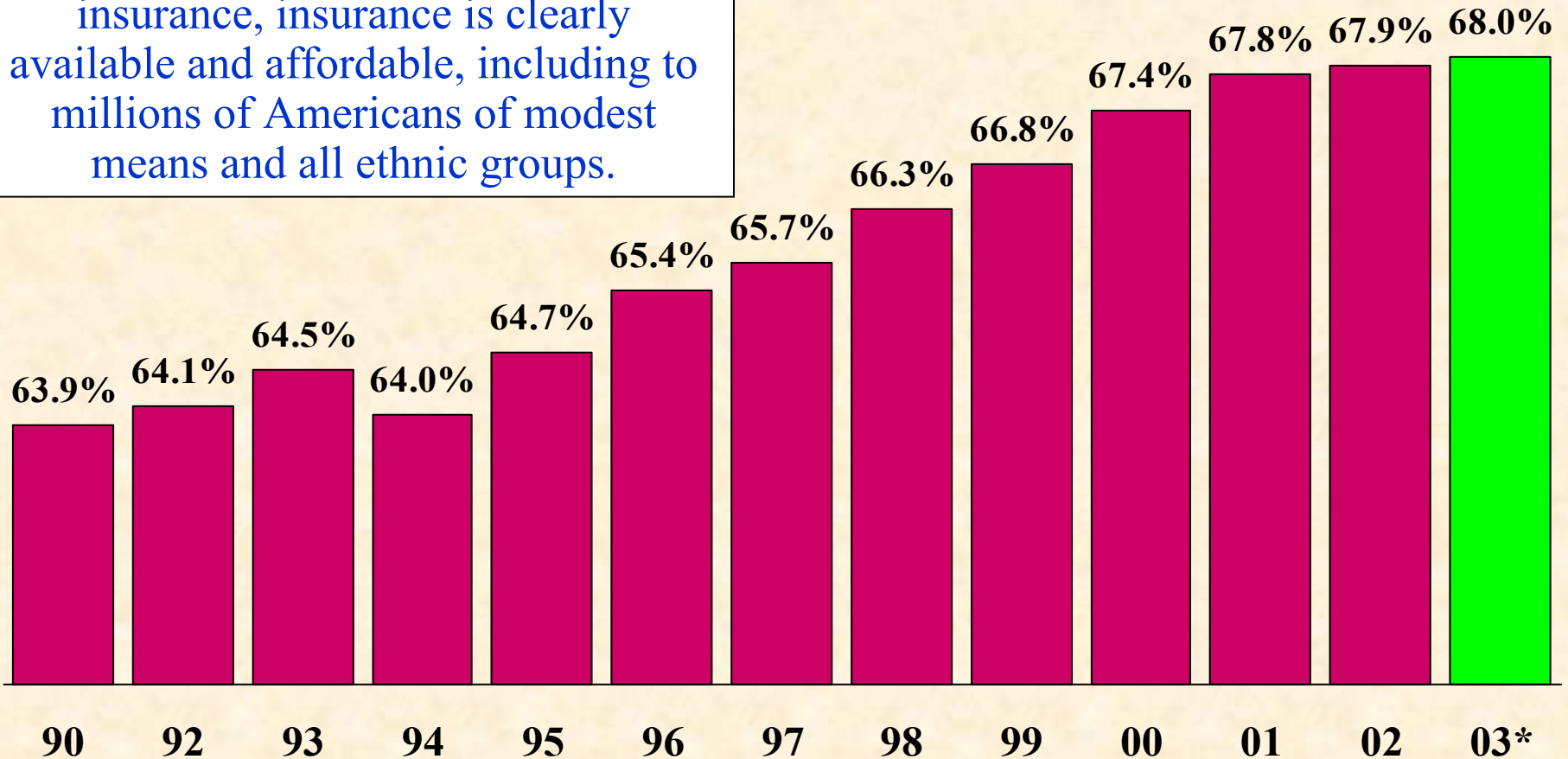
New Private Housing Starts *(Millions of Units)*





Homeownership Rates, 1990 to 2003*

Homeownership is at a record high. Because you can't buy a home without insurance, insurance is clearly available and affordable, including to millions of Americans of modest means and all ethnic groups.

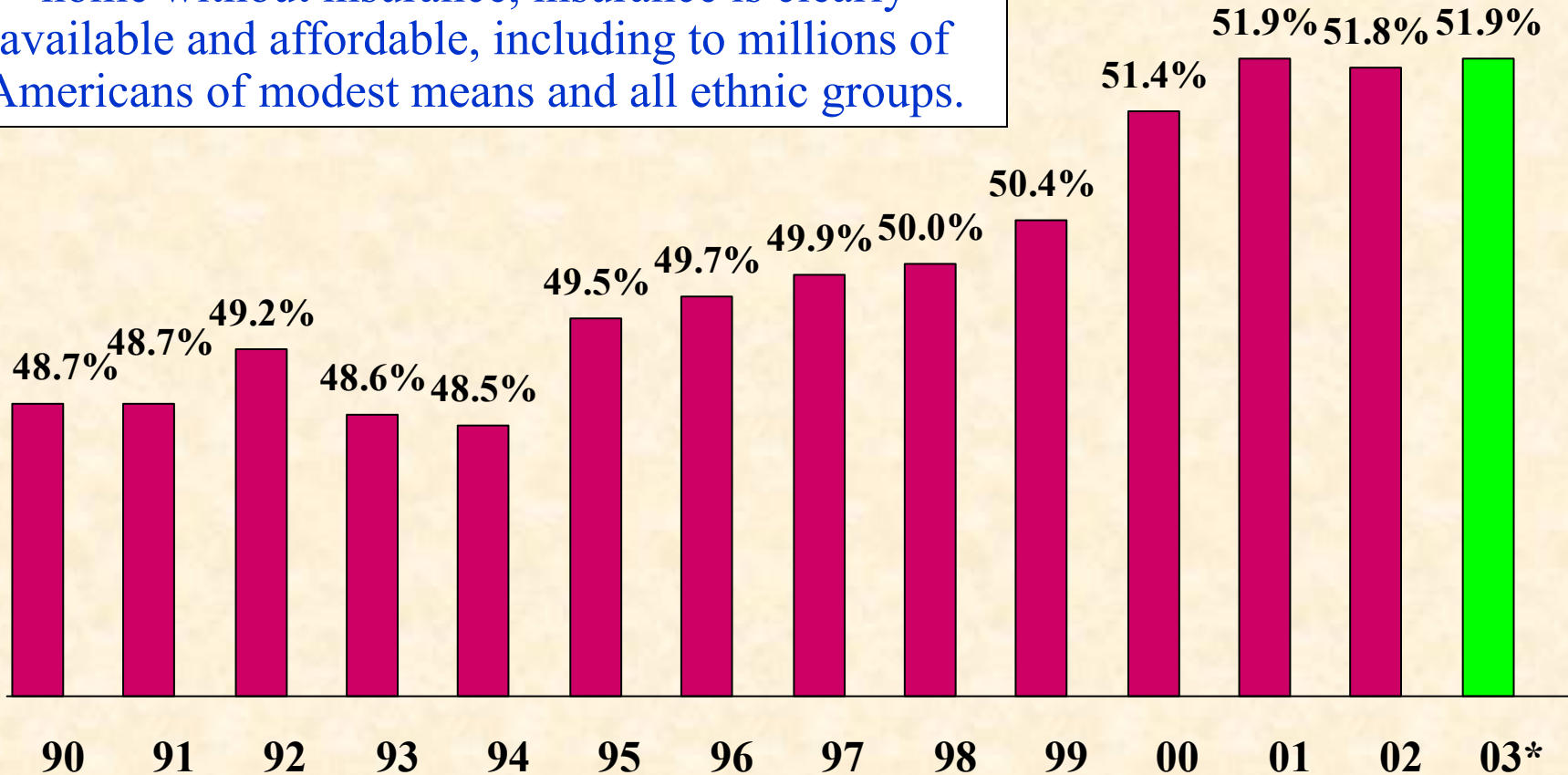


* First Quarter
Source: U.S. Census Bureau



Homeownership Rates in Central Cities, 1990 to 2003*

Homeownership rates in central cities is rising to record/near record levels. Because you can't buy a home without insurance, insurance is clearly available and affordable, including to millions of Americans of modest means and all ethnic groups.



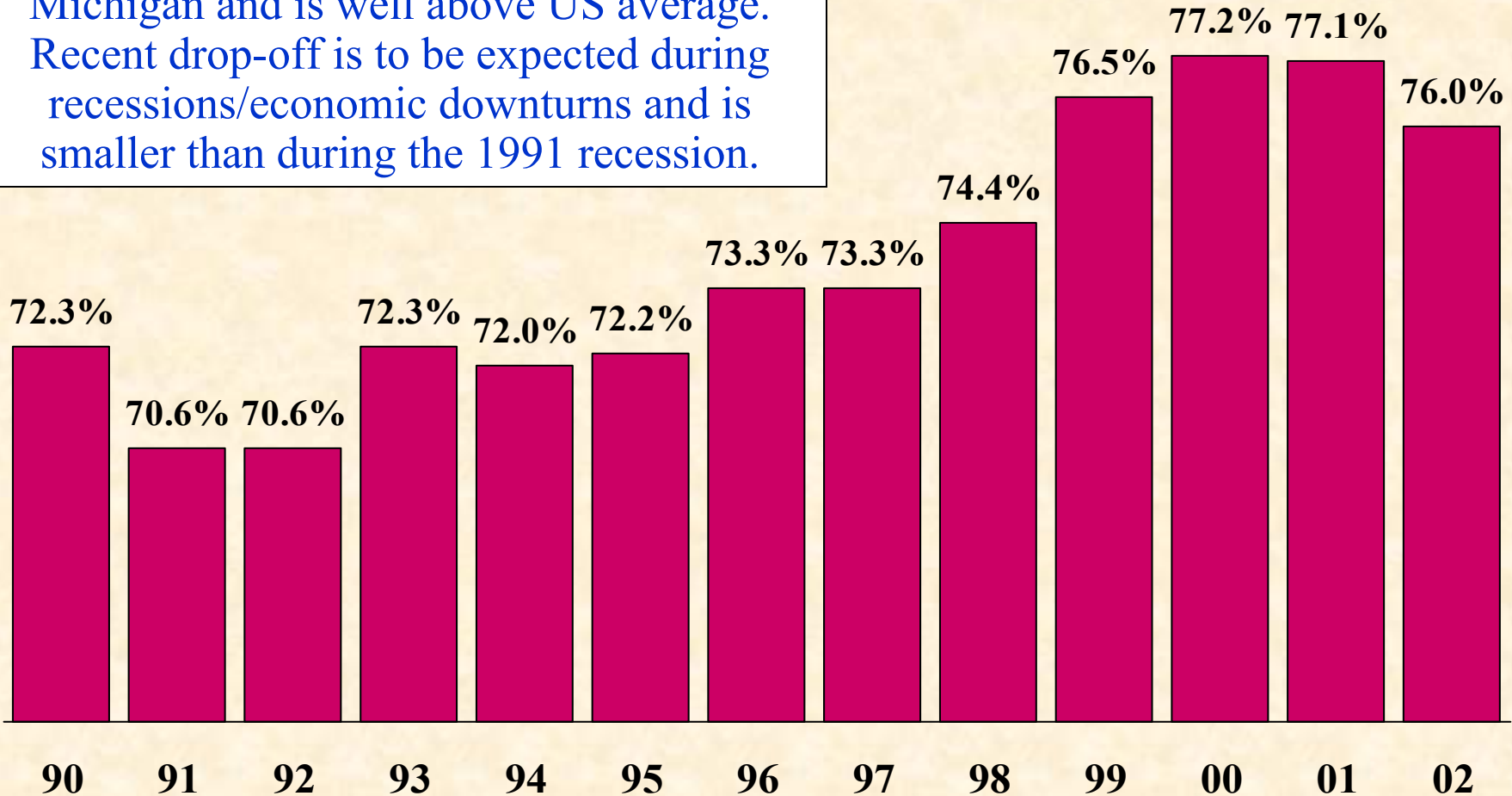
*First quarter 2003.

Source: U.S. Census Bureau



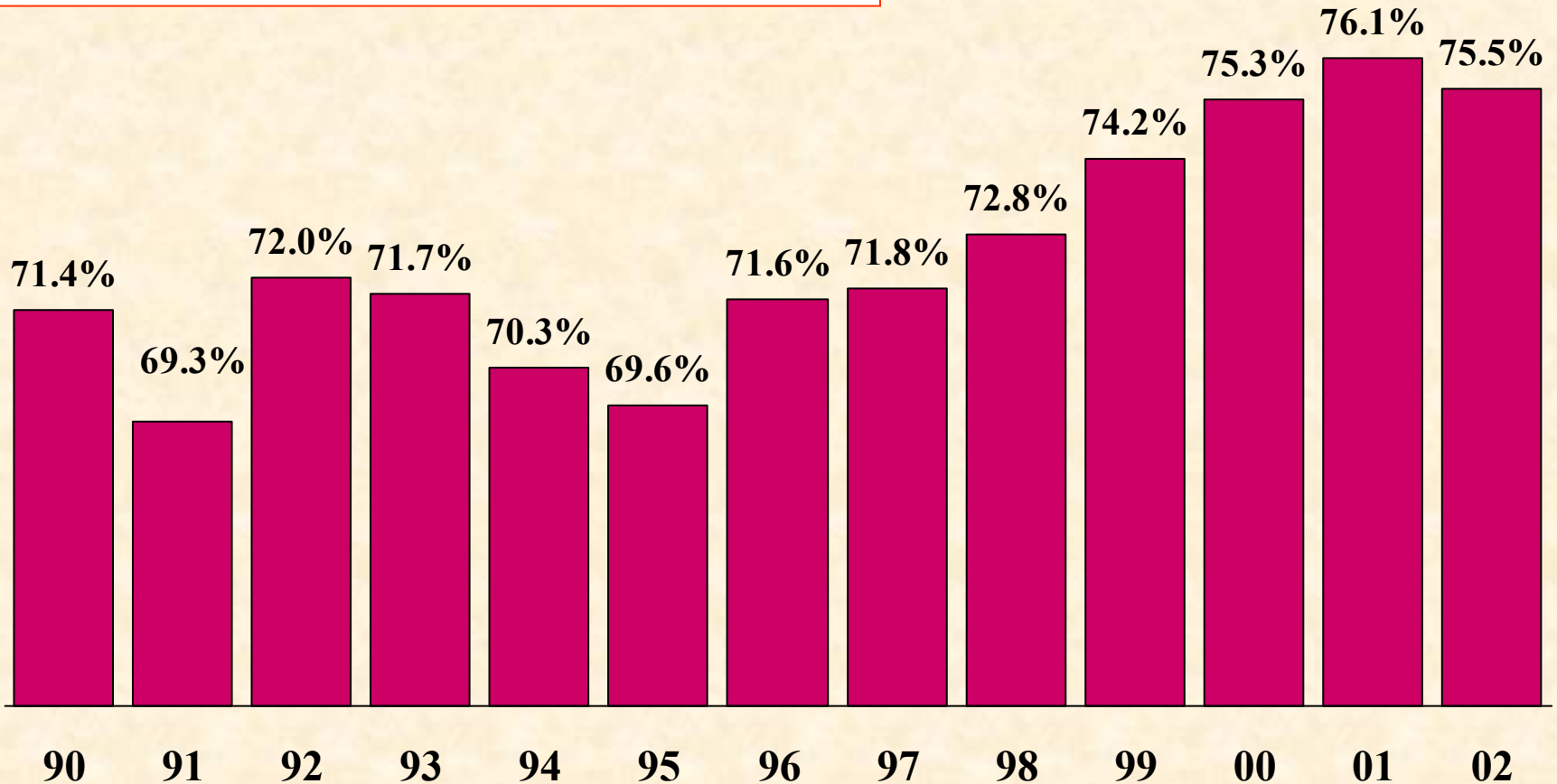
Homeownership Rates in Michigan, 1990 to 2002

Homeownership is near a record high in Michigan and is well above US average. Recent drop-off is to be expected during recessions/economic downturns and is smaller than during the 1991 recession.



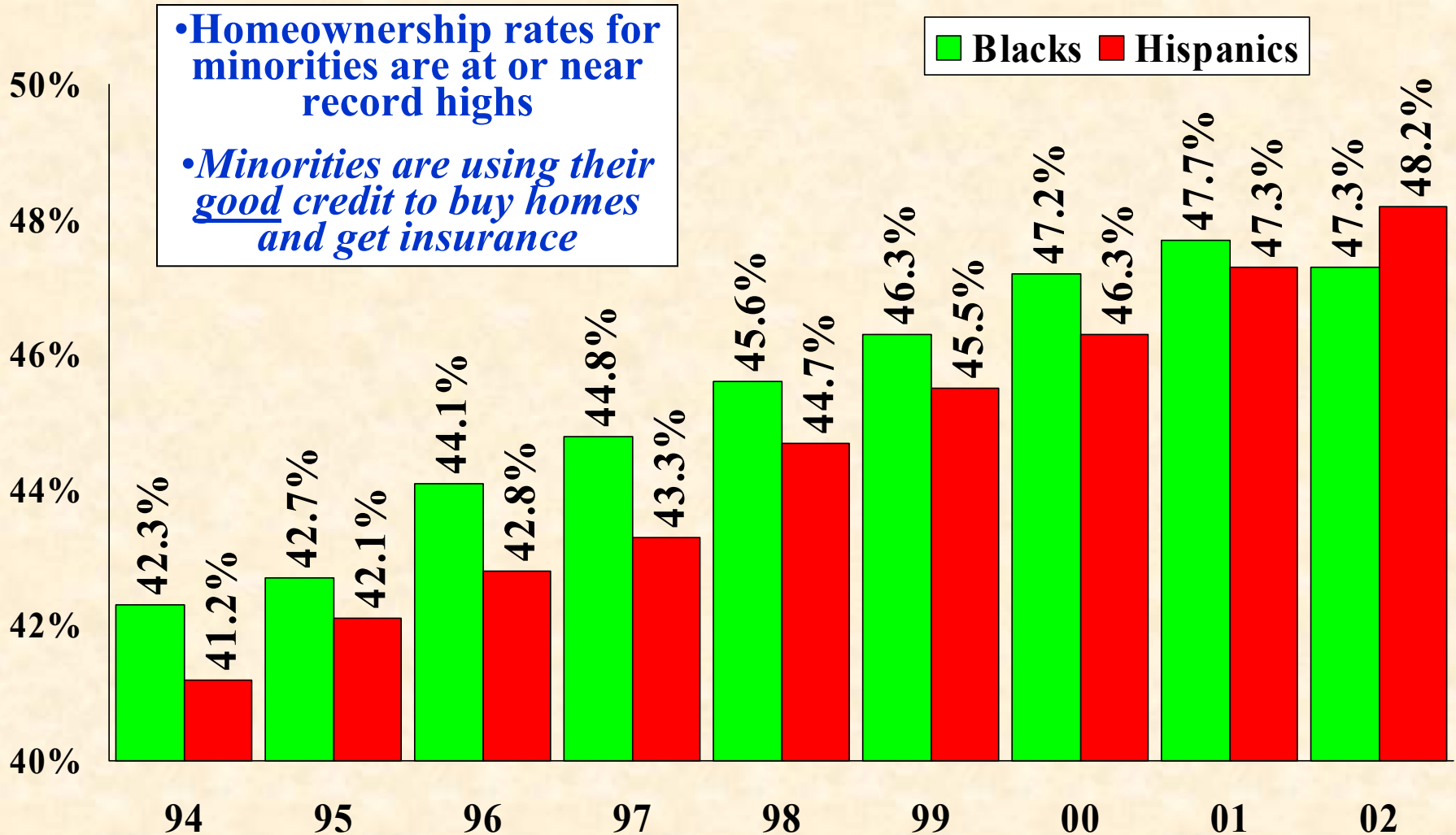
Homeownership Rates in Detroit Metro Area, 1990 to 2002

Homeownership rates in Detroit metro area are near record highs





Homeownership Rates Among Minorities is Rising, 1994 to 2002





Insurance Information Institute On-Line

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