

CREDIT-BASED INSURANCE SCORES: IMPACTS ON CONSUMERS OF AUTOMOBILE INSURANCE



Jesse Leary

Federal Trade Commission

Any views expressed are not those of the Federal Trade Commission or any individual Commissioner.

FACT Act of 2003 – Required Study

- Background on credit scores and credit-based insurance scores (“state of the world”)
 - Study of effects of credit scores and credit-based insurance scores on:
 - Price and availability of credit and insurance products
 - Negative or differential treatment of protected classes under the ECOA (and other defined groups)
 - FTC Study on automobile insurance released in July 2007
 - Federal Reserve Board study on credit scores and credit markets released in August 2007
 - Still to come: FTC study of homeowners insurance
-
-

Negative or Differential Treatment (A)

Sec 215 (a)(2): a study of: “the statistical relationship, utilizing a multivariate analysis that controls for prohibited factors under the (ECOA) and other known risk factors, between ... credit based insurance scores and the quantifiable risks and actual losses experienced by businesses;”

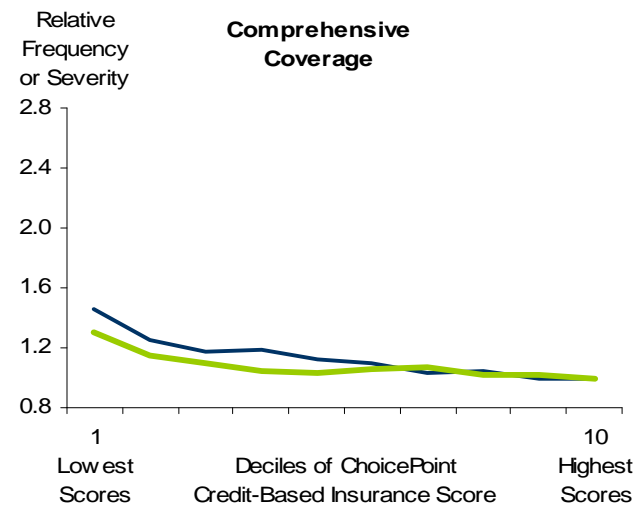
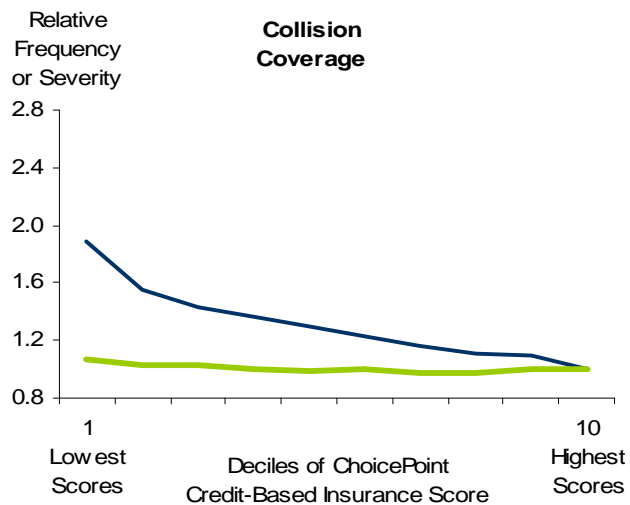
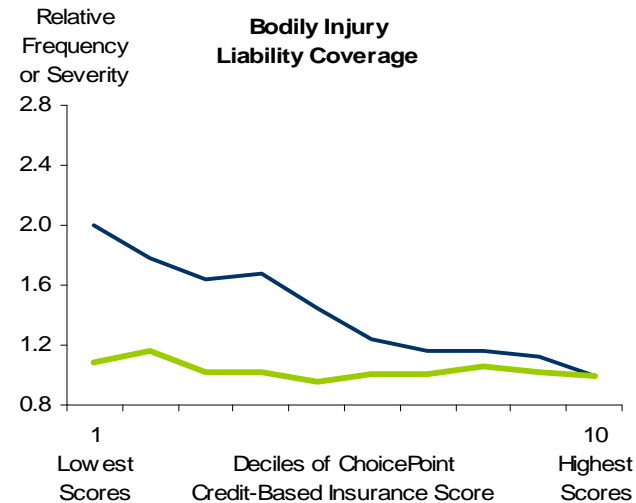
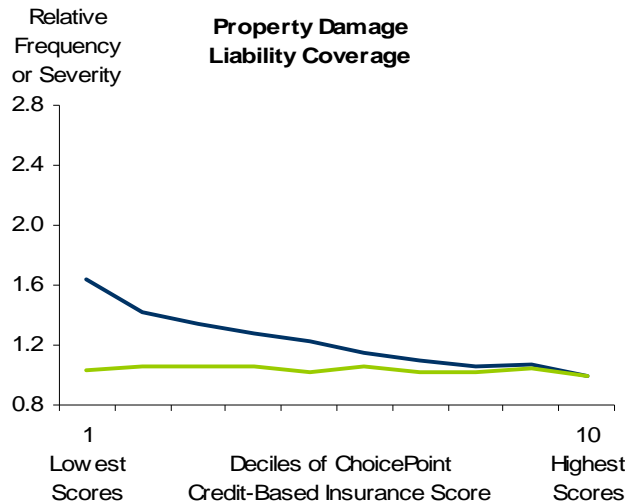
Negative or Differential Treatment (B)

Sec. 215 (a)(3): a study of “the extent to which, if any, the use of ... credit-based insurance scores impact on the availability and affordability of ... insurance to the extent information is currently available or is available through proxies, by geography, income, ethnicity, race, color, religion, national origin, age, sex, marital status, and creed, including the extent to which the consideration or lack of consideration of certain factors by credit scoring systems could result in negative or differential treatment of protected classes under the (ECOA), and the extent to which, if any, the use of underwriting systems relying on these models could achieve comparable results through the use of factors with less negative impact;”

Data

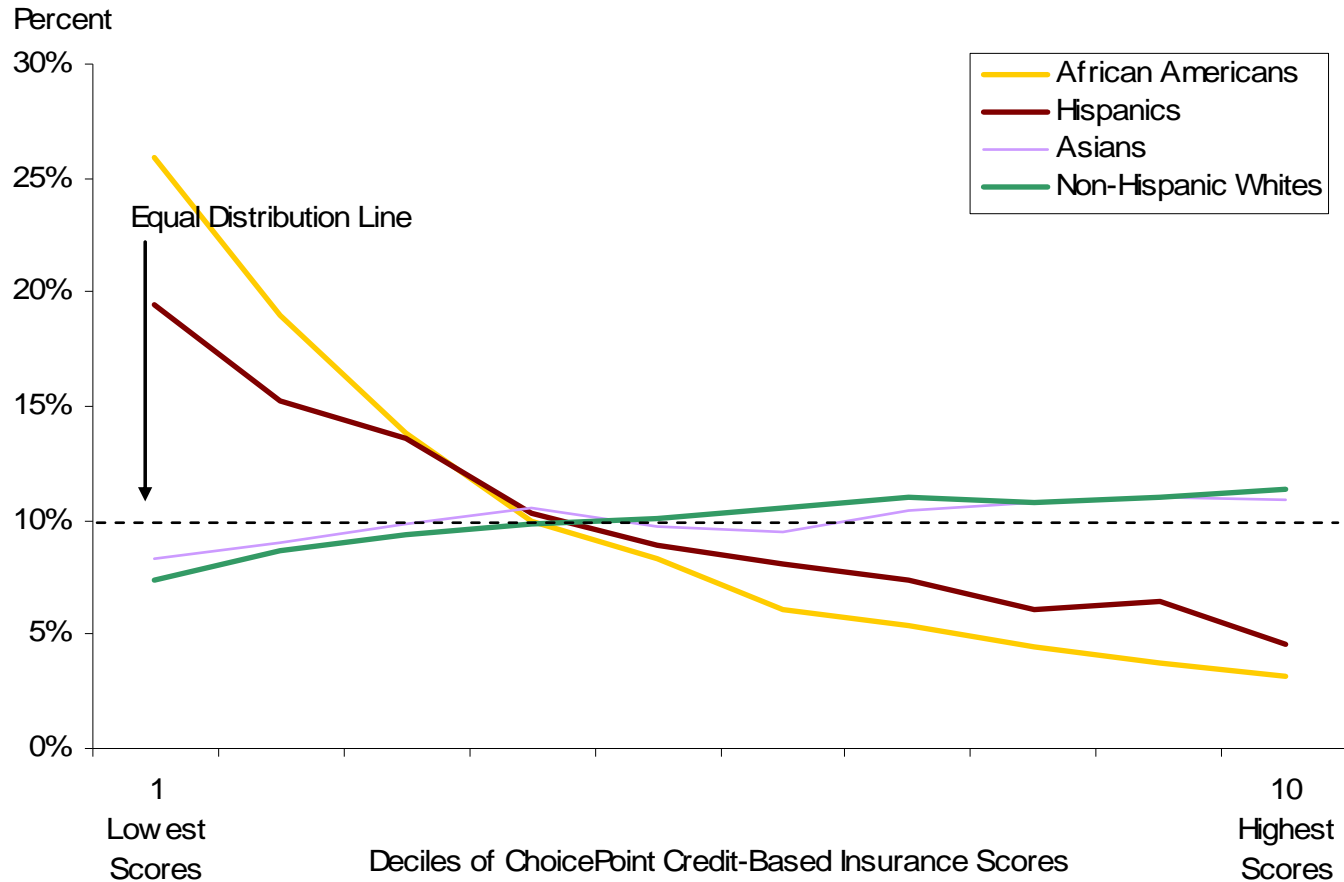
- Policy data – Subset of the “EPIC Database”
 - 5 firms, ~27% of the market
 - 1.4MM policies, 1.8MM earned car years
 - Analysis subset: 275K policies, 400K earned car years
 - Policy data
 - Claims
 - Underwriting and rating variables
 - ChoicePoint Attract credit score
 - Race and Ethnicity Data – 3 Sources
 - Social Security Administration
 - Pre-1981: Black/White/Other
 - Census (block level)
 - Hispanic surname match
-
-

Frequency and Severity of Claims by Credit-Based Insurance Score

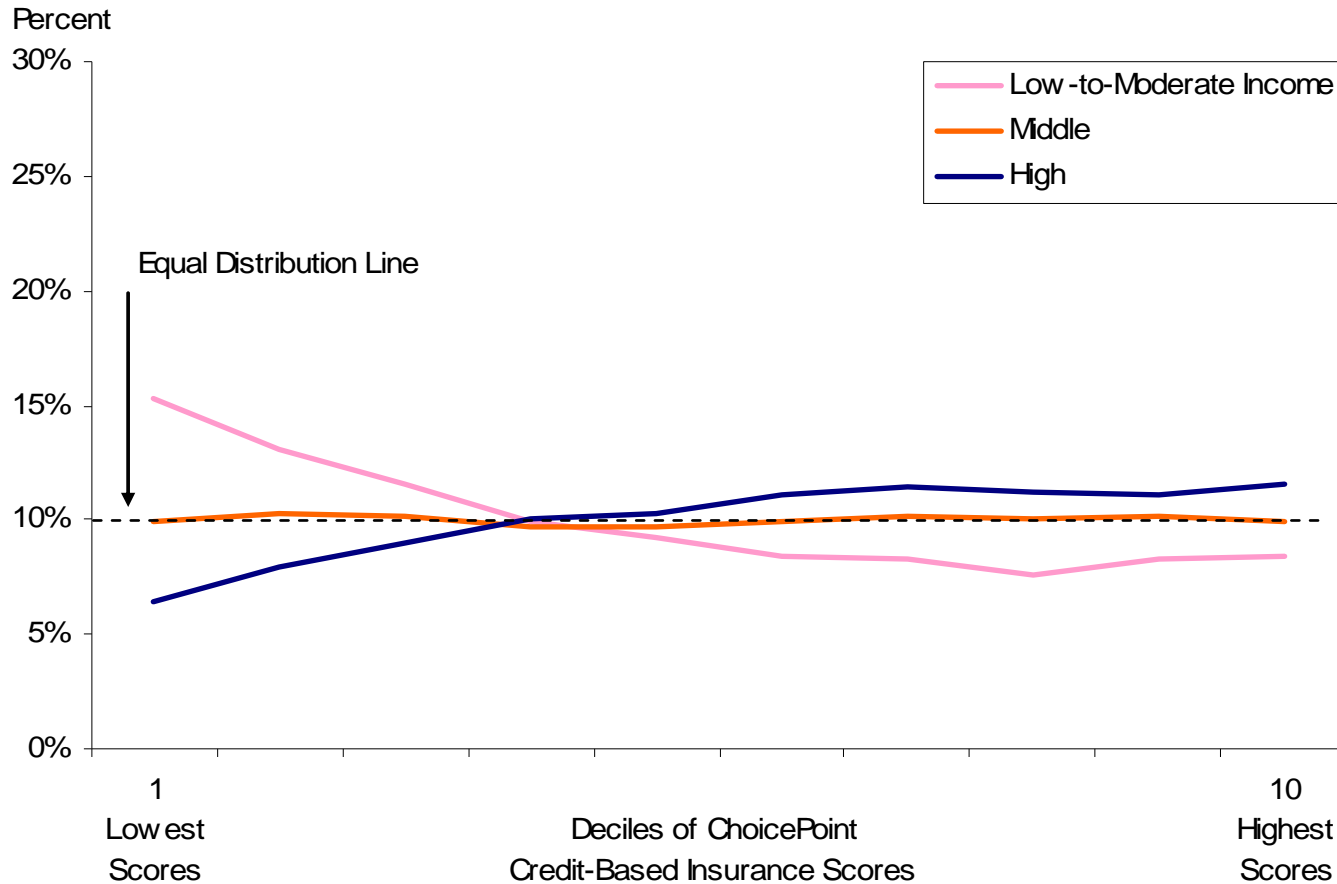


— Frequency of Claims
— Average Severity of Claims

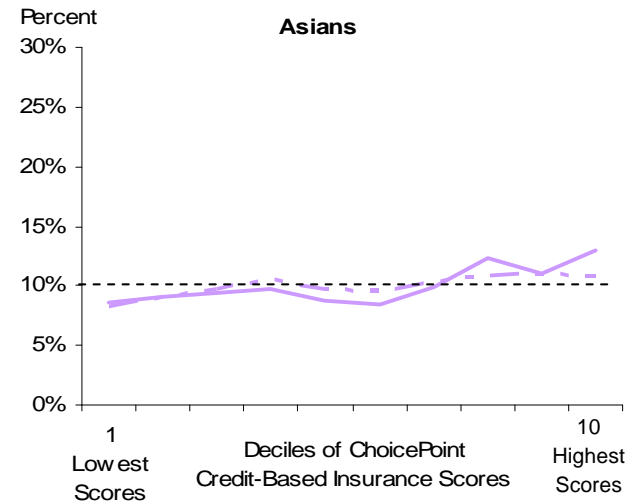
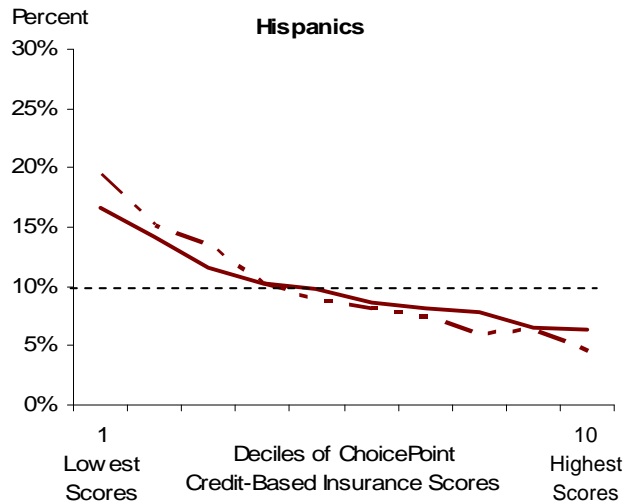
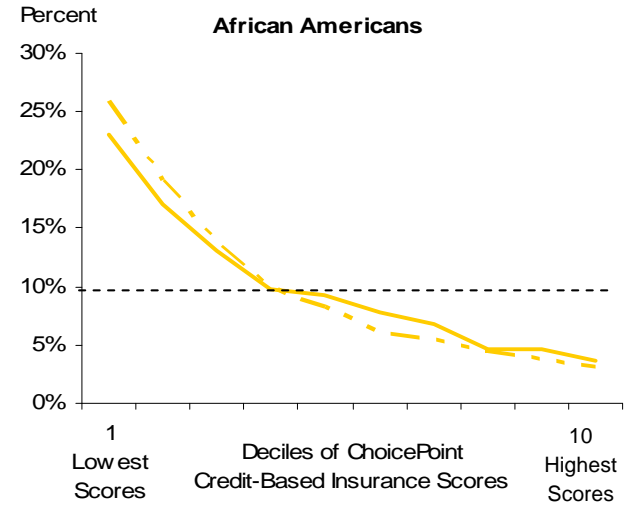
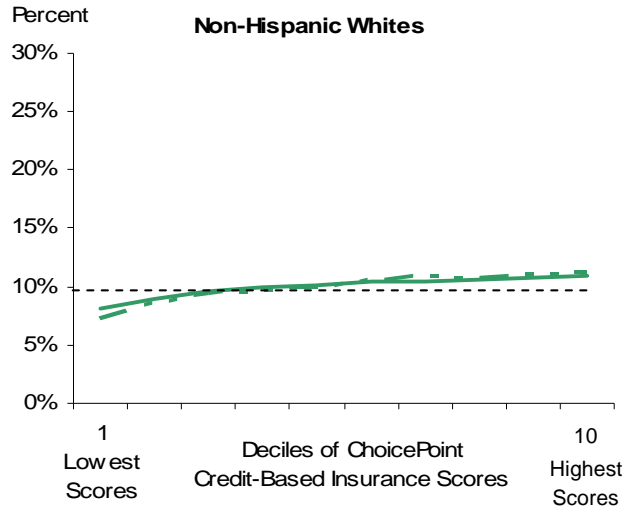
Distribution of Scores by Race and Ethnicity



Distribution of Scores by Income

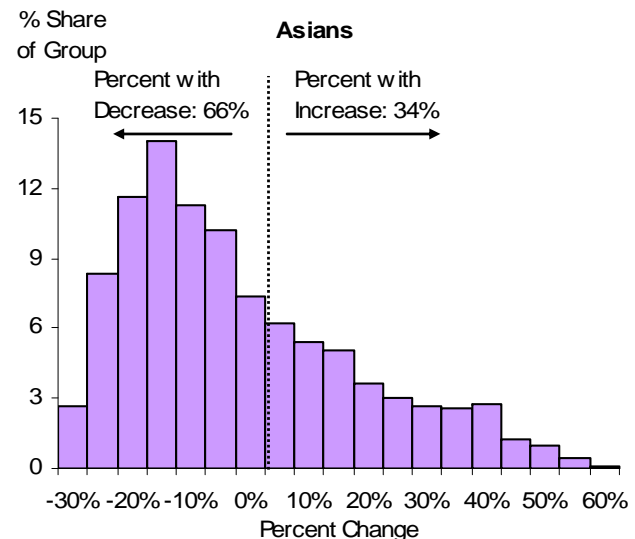
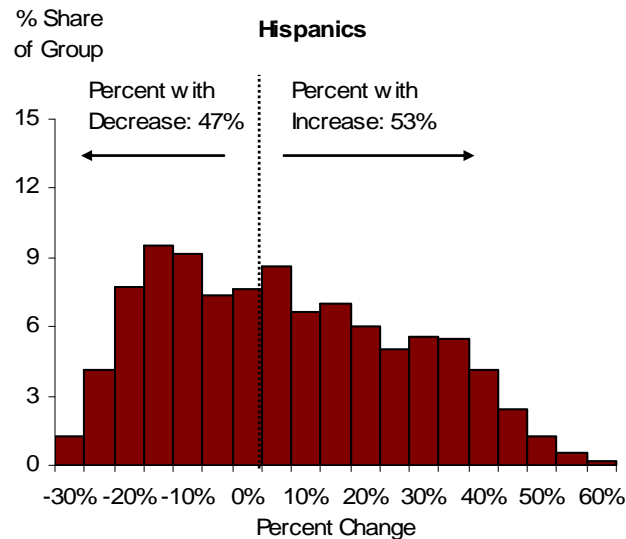
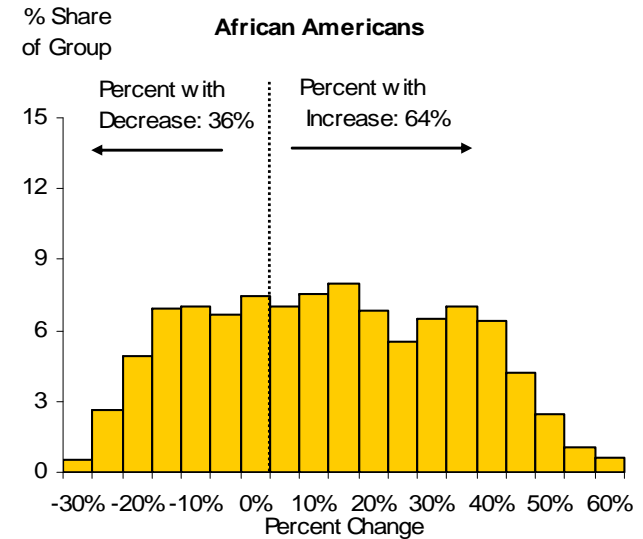
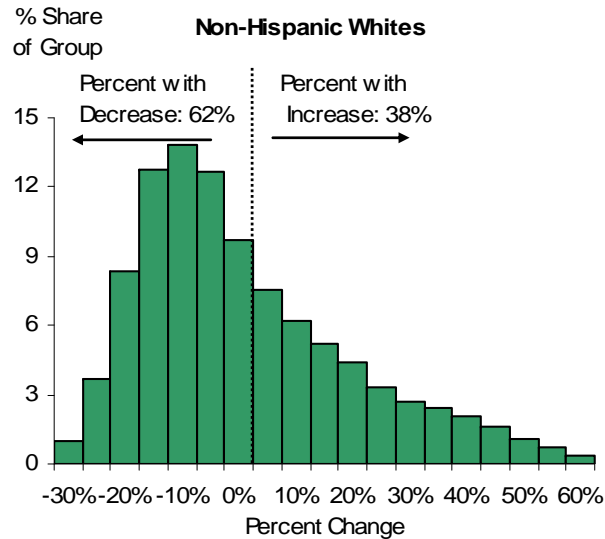


Distribution of Scores by Race and Ethnicity Controlling for Age, Gender, and Neighborhood Income

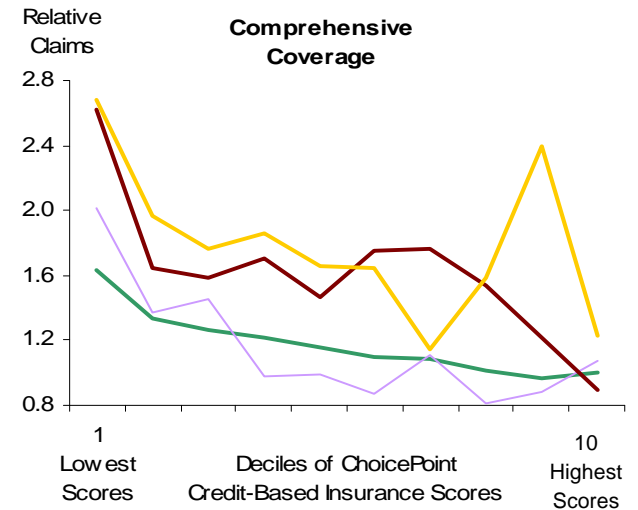
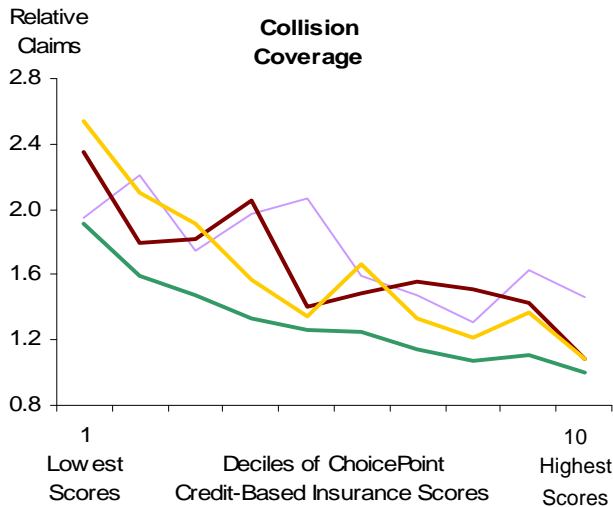
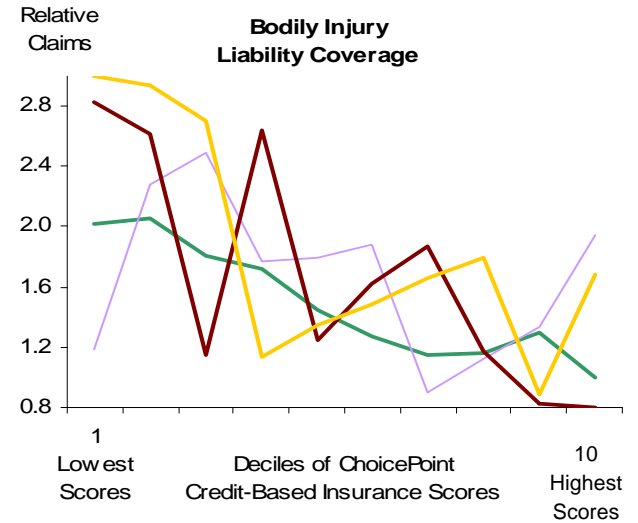
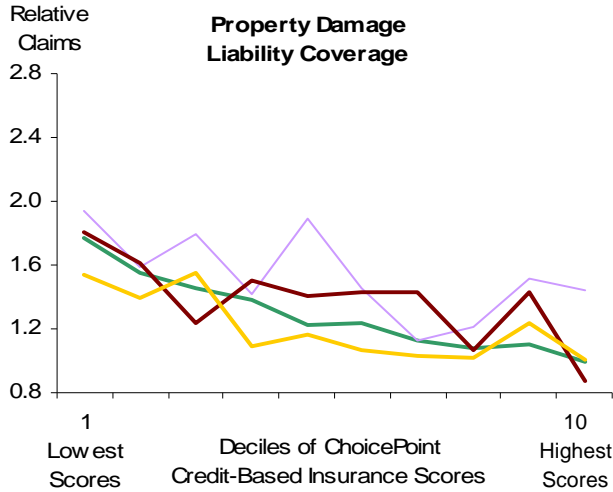


With Controls
 Without Controls

Effect of Scores on Predicted Pure Premium By Race and Ethnicity

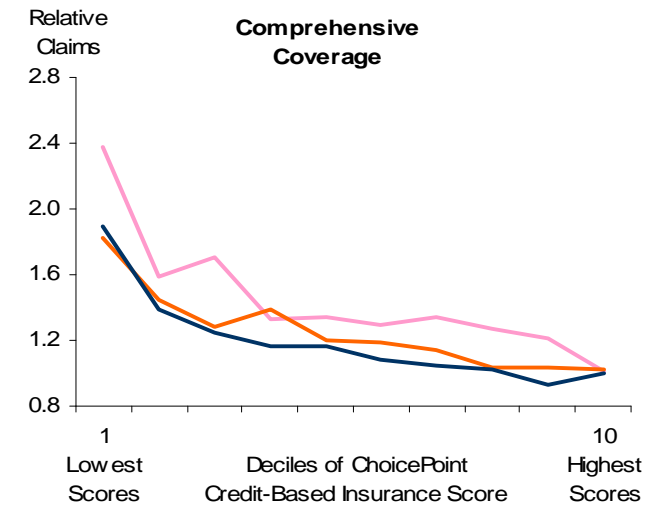
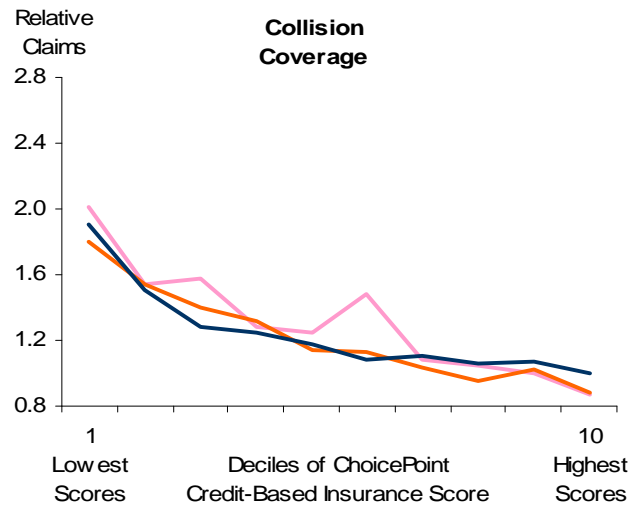
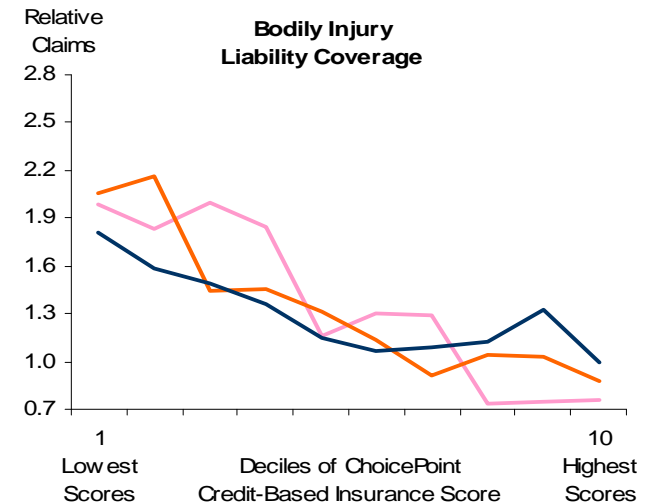
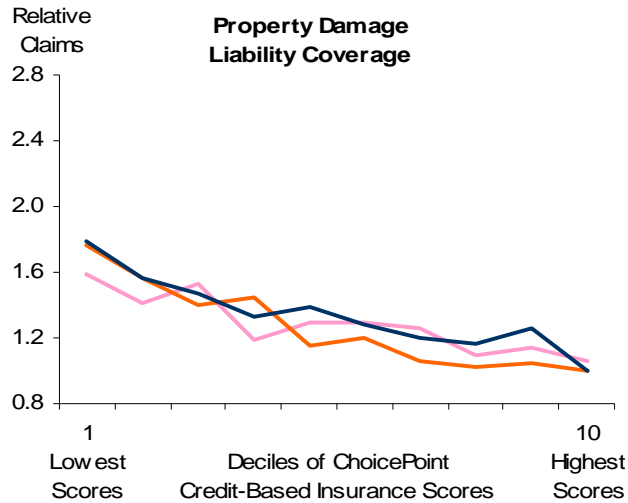


Estimated Relative Pure Premium by Race and Ethnicity



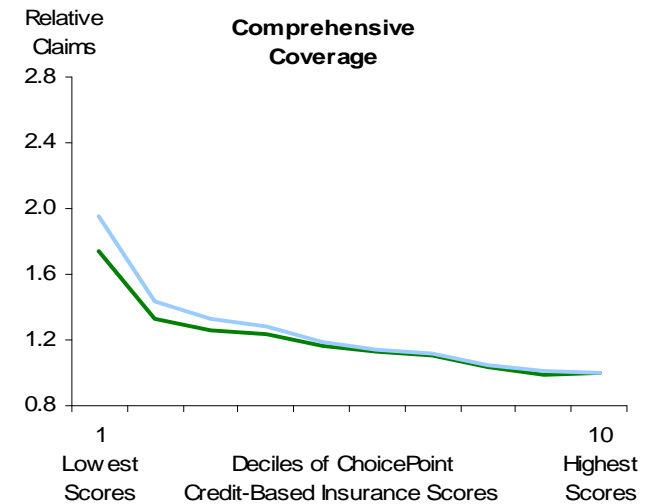
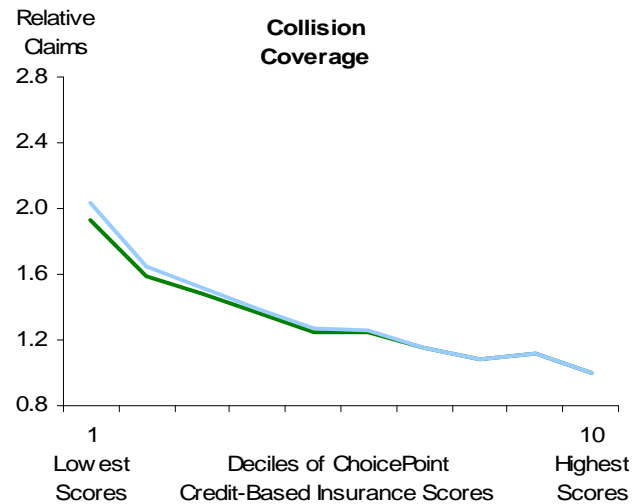
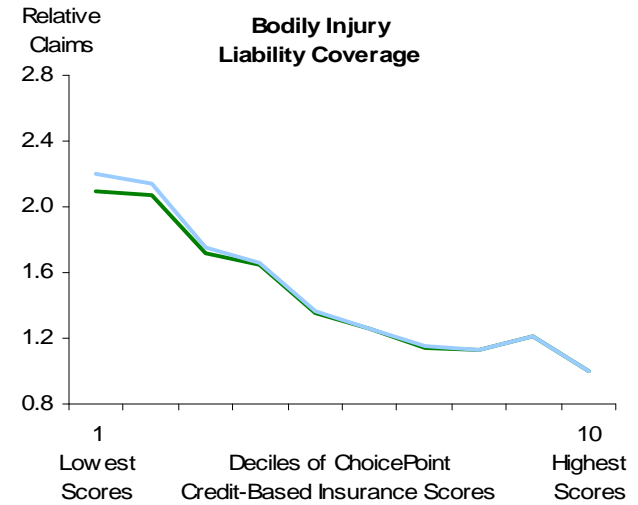
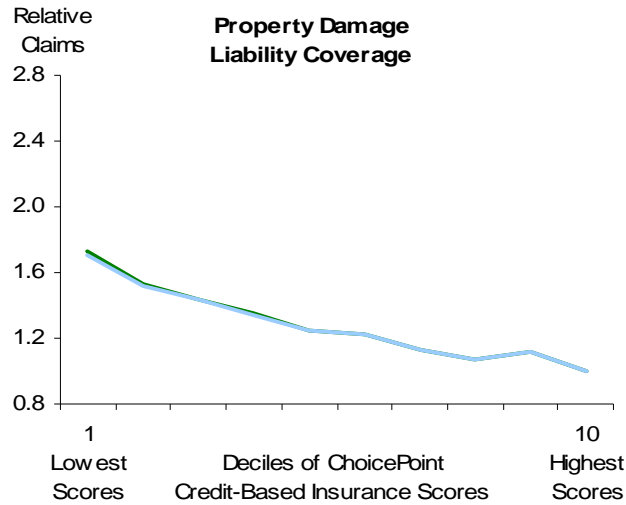
- Non-Hispanic Whites
- African Americans
- Hispanics
- Asians

Estimated Relative Pure Premium by Neighborhood Income



— Low-to-Moderate Income
— Middle Income
— High Income

Estimated Relative Pure Premium With Controls for Race, Ethnicity, and Income



— Without Race, Ethnicity and Neighborhood Income Controls
 — With Race, Ethnicity and Neighborhood Income Controls

Effects of Scores on Predicted Pure Premium With Controls for Race, Ethnicity, and Income



	Average Score Effect From Model Without Race, Ethnicity, and Income Controls	Average Score Effect from Model With Race, Ethnicity, and Income Controls
	(a)	(b)
African Americans	10.0%	8.9%
Hispanics	4.2%	3.5%
Asians	- 4.9%	-4.8%
Non-Hispanic Whites	- 1.6%	-1.4%

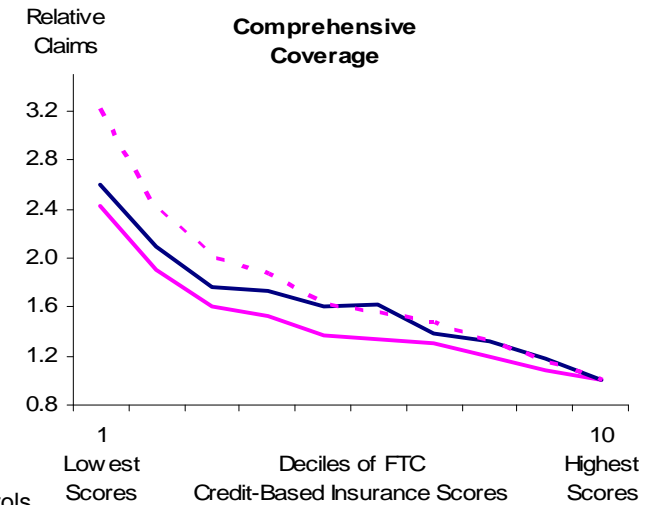
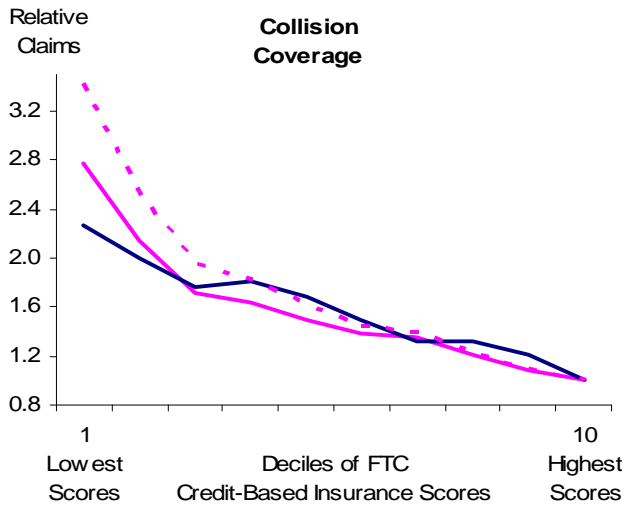
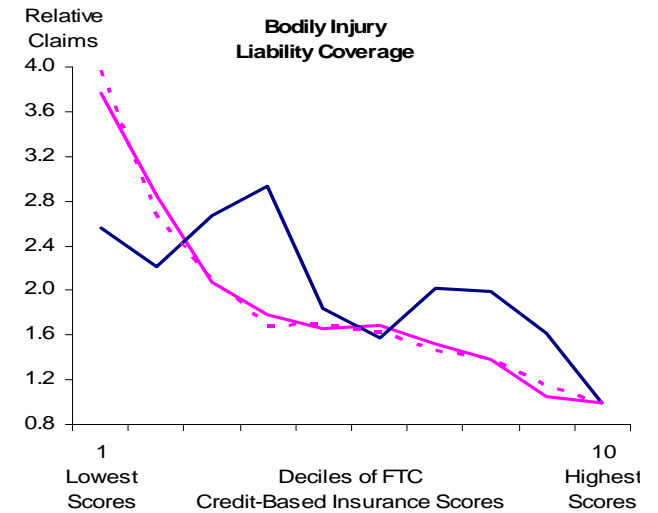
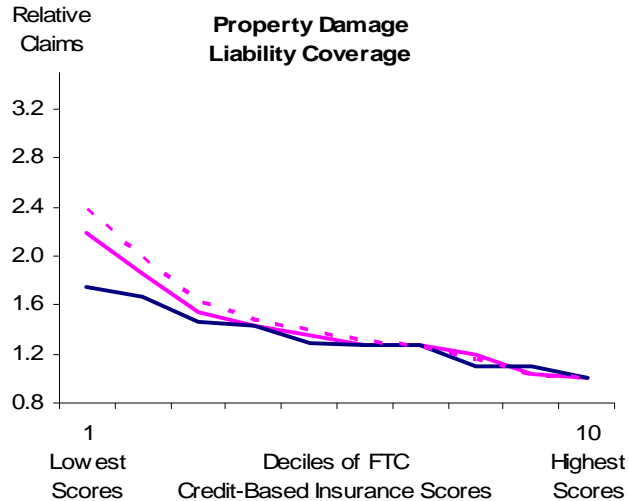
FTC Score-Building - Data

- Policy database with race, ethnicity, income
 - ChoicePoint credit-history variables
 - Have for all records except “no-hits”
 - 180 variables designed to capture information in consumer credit reports
 - Various delinquency measures
 - Public records
 - Inquiries
 - Length of history
 - etc.
 - Used by ChoicePoint in their model building
 - Not all variables appear in a ChoicePoint model
 - Proprietary
-
-

FTC Score-Building

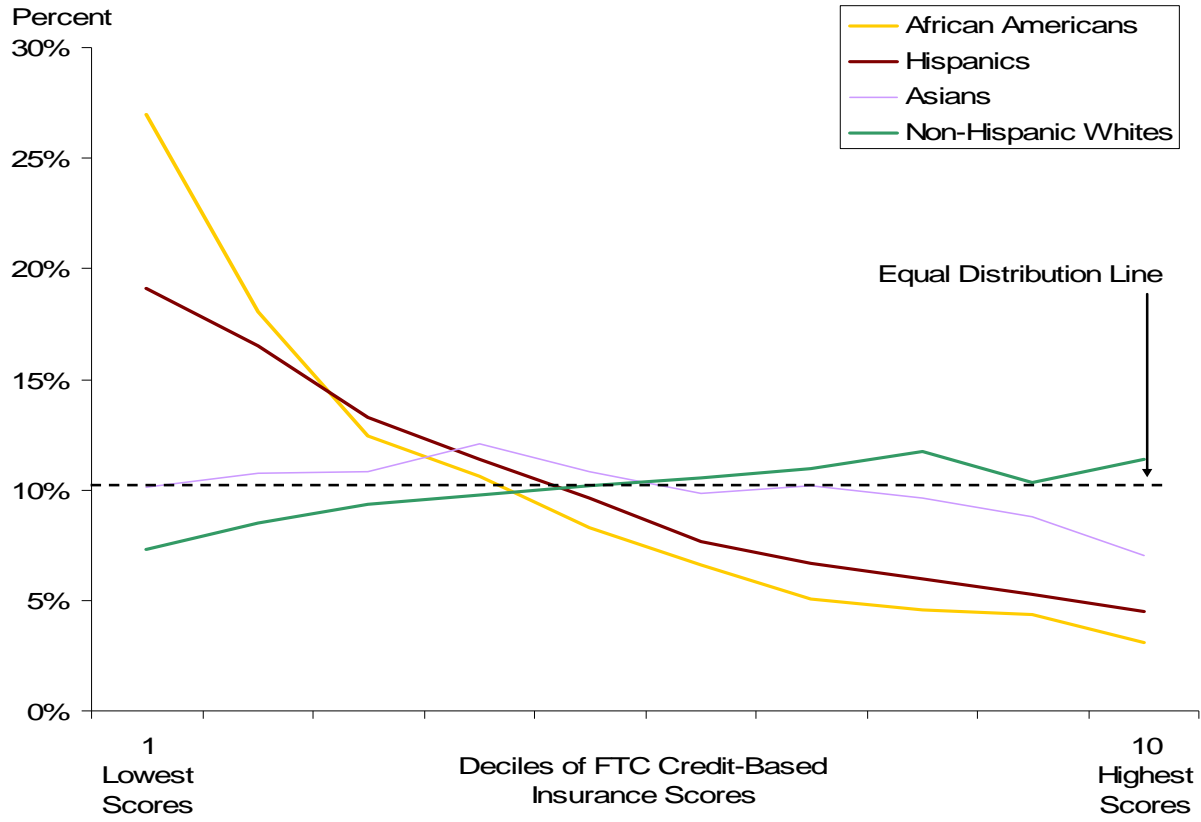
- Step 1: Tweedie GLM of pure premium on “usual suspects” risk variables. Use predicted pure premium to create adjusted pure premium.
 - Step 2: Bin credit history variables using a mechanical (non-judgmental) procedure.
 - Step 3: Forward-selection OLS with adjusted total claims as dependent variable and 180 binned credit history variables as candidate explanatory variables.
 - Step 4: Tweedie GLM of pure premiums on “usual suspects” risk variables and “winning” credit history variables. Use estimated parameters on credit history variables to create FTC scorecard.
-
-

FTC Baseline Scoring Model



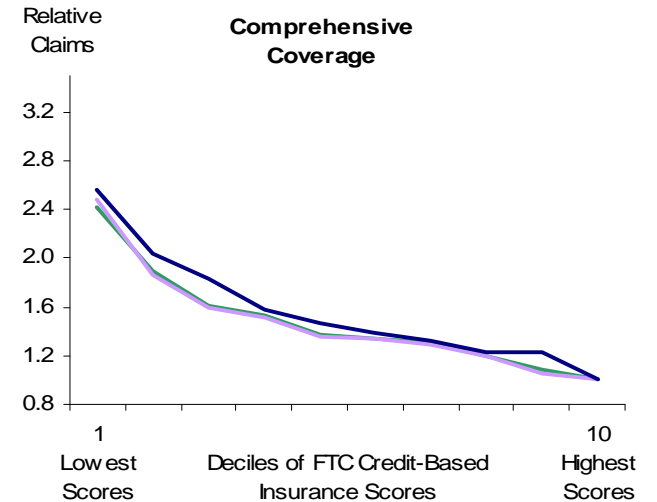
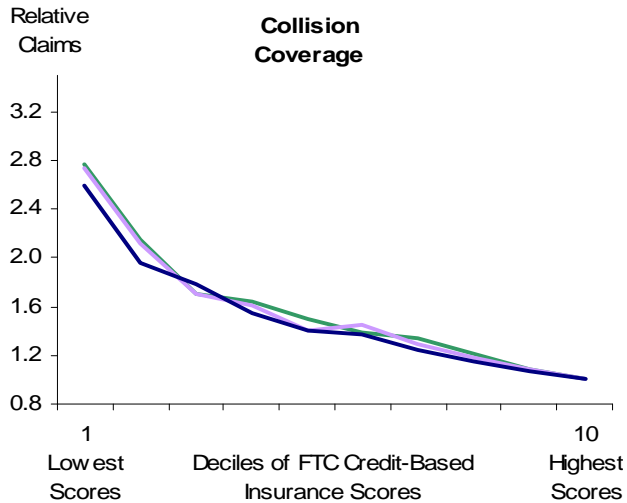
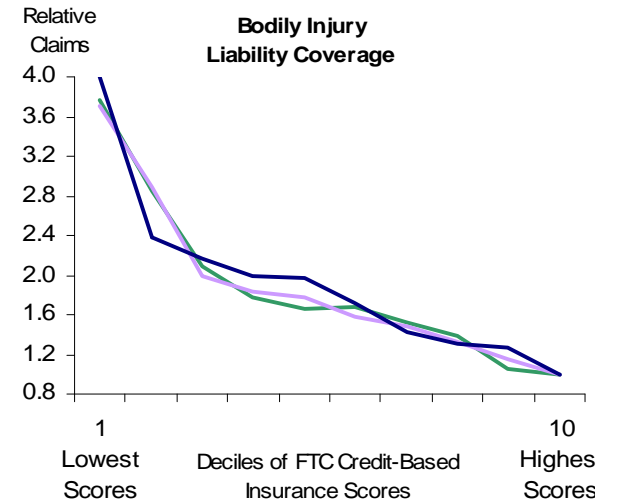
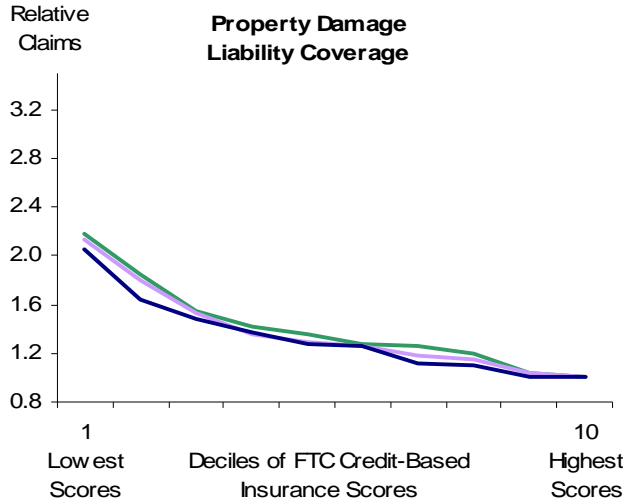
—— Within Sample with Controls
- - - - Within Sample without Controls
—— Out of Sample without Controls

Distribution of FTC Baseline-Model Scores by Race and Ethnicity



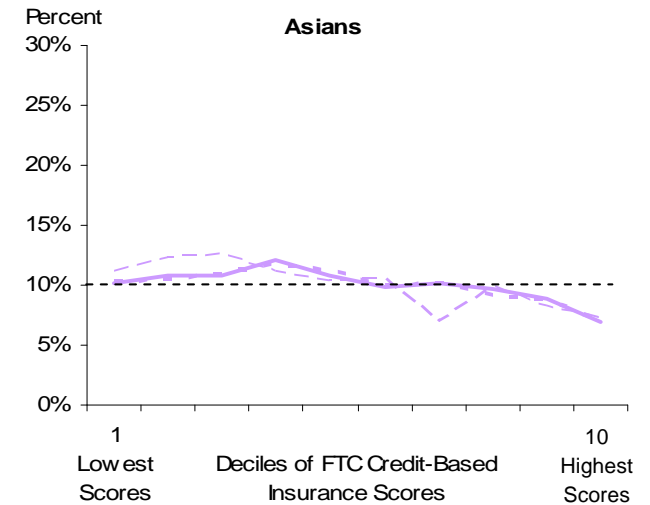
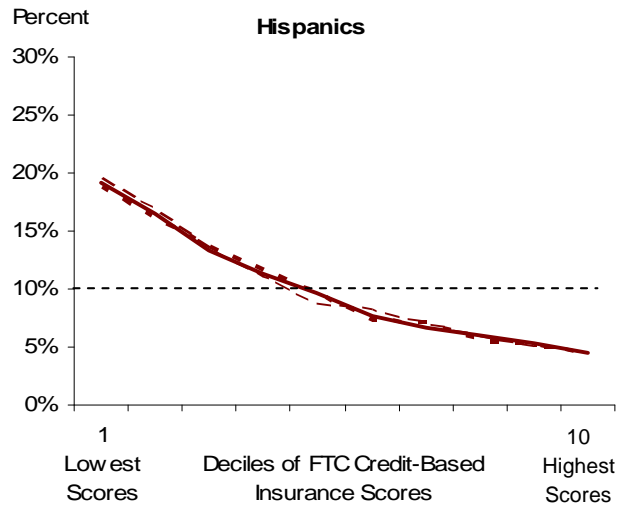
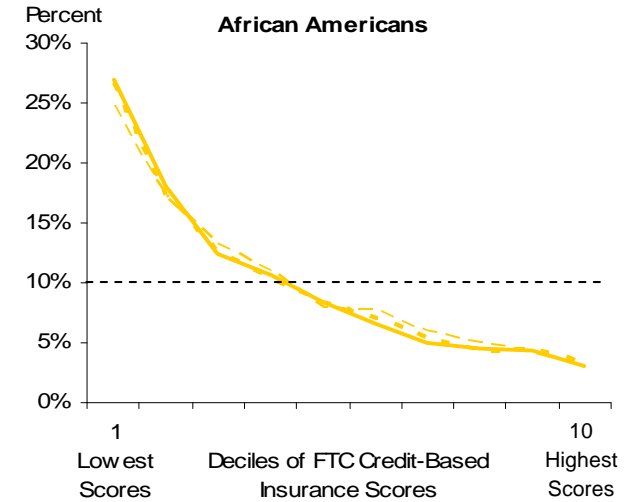
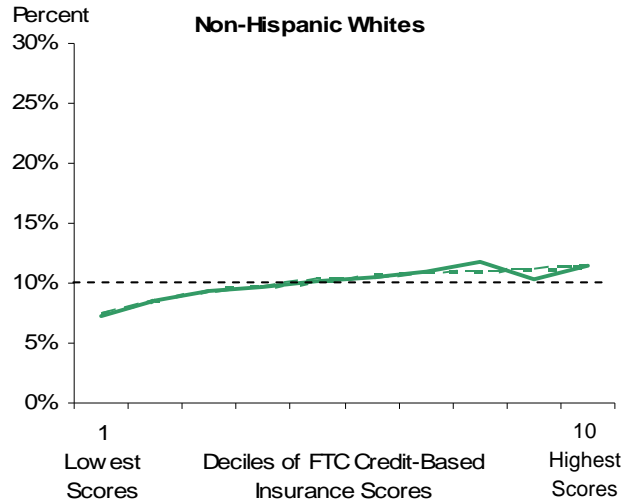
FTC Scoring Models

Built Controlling for Race, Ethnicity, and Income



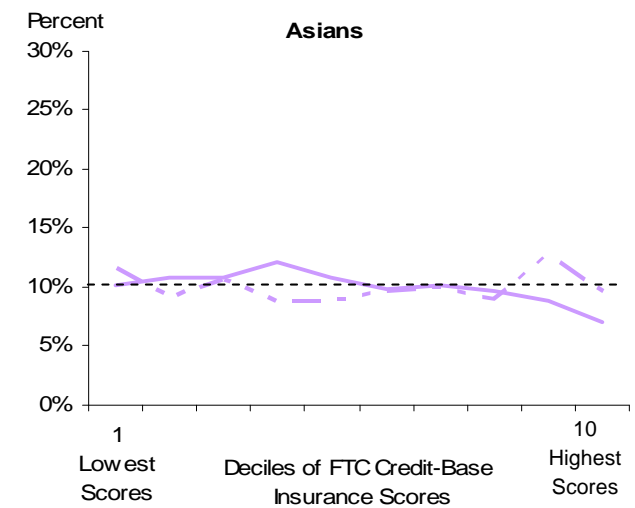
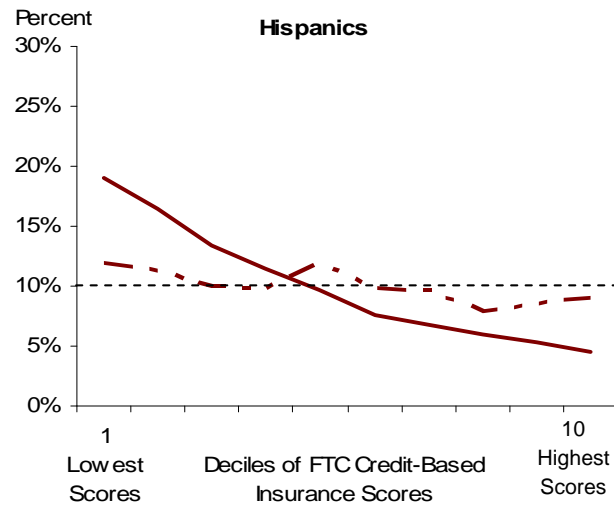
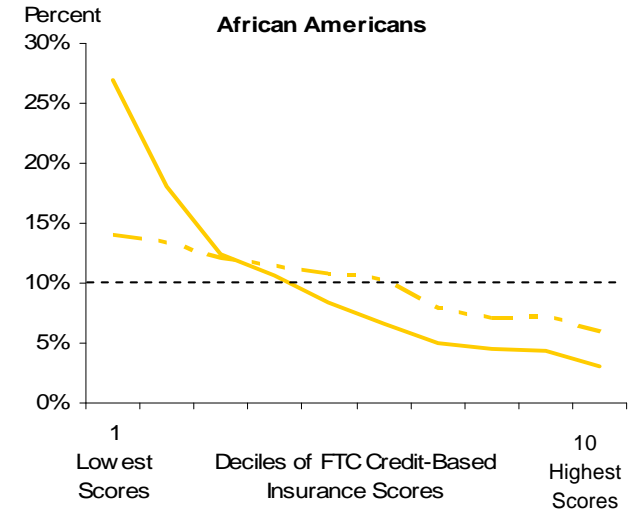
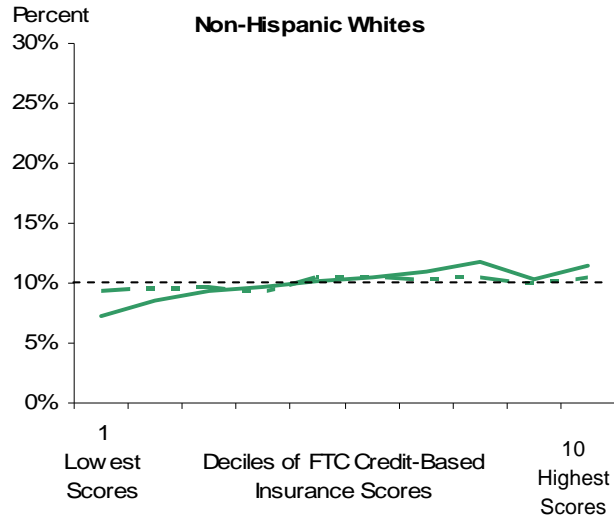
— FTC Baseline Model
— Model Built with Controls
— Model Built with Non-Hispanic Whites Only

Distribution of FTC Scores by Race and Ethnicity (A)



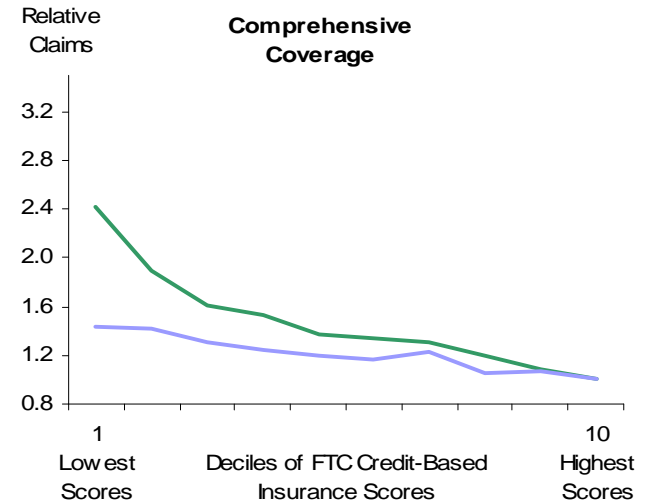
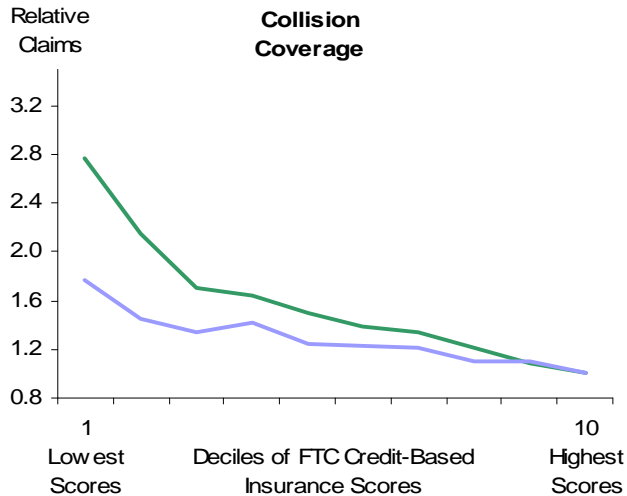
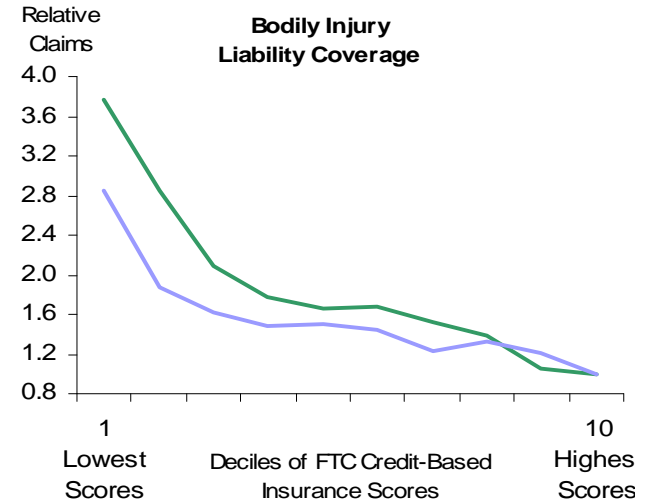
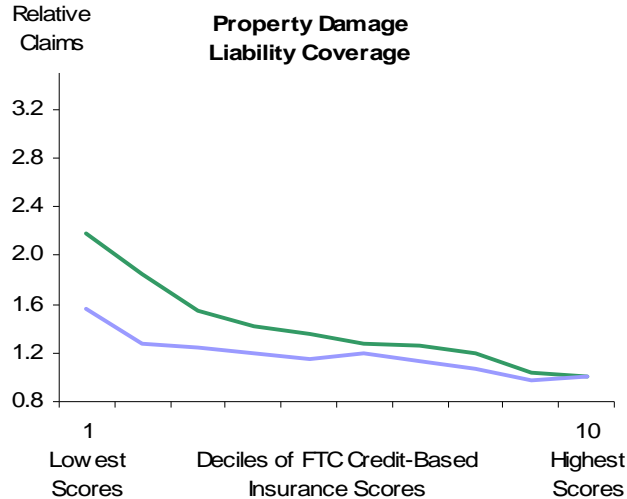
———— FTC Baseline Model
 Model Built with Controls
 - - - - - Model Built with Non-Hispanic Whites Only

Distribution of FTC Scores by Race and Ethnicity (B)



FTC Baseline Model
 "Discounted Predictiveness" Model

FTC "Discounted Predictiveness" Model



— FTC Baseline Model
— "Discounted Predictiveness" Model

Conclusions and Next Steps

- Scores predict risk
 - Lowest decile 1.7 to over 2 times riskier than highest
 - Scores differ across racial and ethnic groups
 - Using scores raises average predicted pure premiums of African Americans by 10% and Hispanics by 4.2%.
 - Little of the relationship between scores and claims comes from the relationship between scores and race/ethnicity (the “proxy effect”).
 - We could not develop an effective scoring model with smaller differences across groups.
 - Up next: Homeowners!
-
-