

Breakout Session 2

**Fair Lending & Access to Capital: Intelligence  
and Implications**

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# Introduction

## Alternative Data Initiative Phase I

**Completed: July 2005**  
**Freely Available: [www.infopolicy.org](http://www.infopolicy.org)**

# Introduction

## Why Care About Alternative Data? (Consumer)

- 35 to 54 million Americans “unscorable”
- Primarily low income, immigrants, elderly, and ethnic minorities
- Access to credit crucial for asset formation

# Introduction: The Promise for Asset Formation

## Why Care About Alternative Data? (Commercial)

- 90% of businesses are small
- 12.5% fail within 3 years often for reasons of credit access.
- African-American and Latino owners face greater loan denial rates (SBA)

## Lower rates among minorities (2000 SBA data)

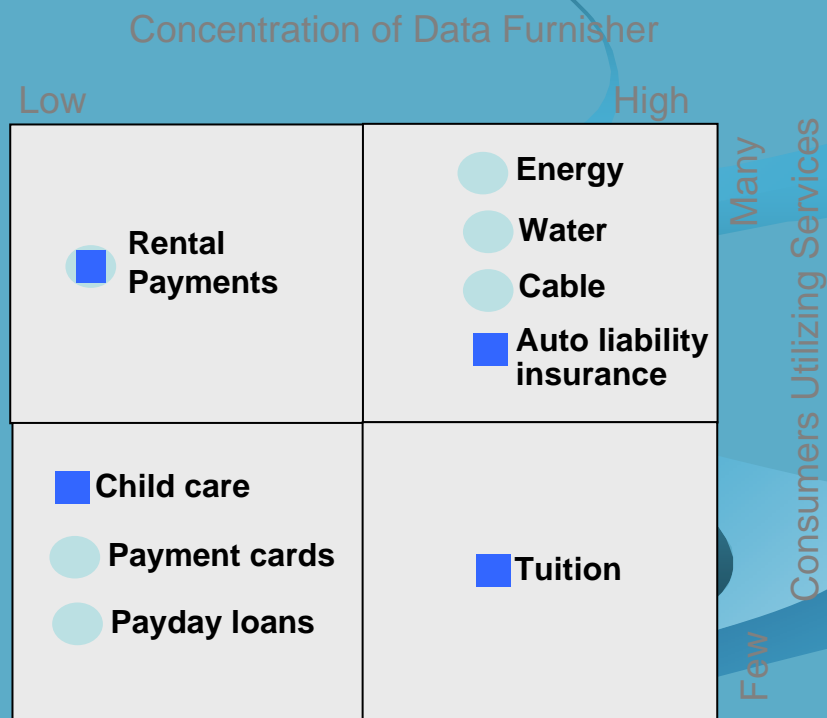
- Whites: self-employment rate 10.5%; \$53,000 average income
- African Americans: self-employment rate 4.25%; \$35,000 average income
- Non-White Latinos: self-employment rate 6.11%; average income \$28,000

African-Americans have seen great rates of growth in small business ownership: 23% between 1990 and 2000

# Methodology

## Assessed usefulness along 3 key dimensions

- “Cash-like” vs. “Credit-like” (incentive to furnish)
- Coverage (reach of data in population)
- Concentration (resources needed to reach furnishers)



● Traditional “credit-like” data

■ Non-traditional “cash-like” data

# Quantitative Research

## Alternative Data Initiative, Phase II:

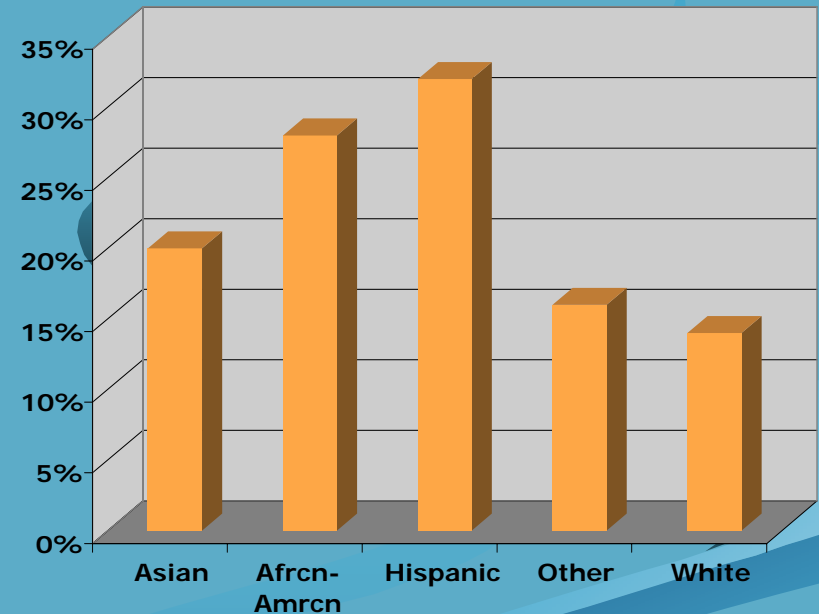
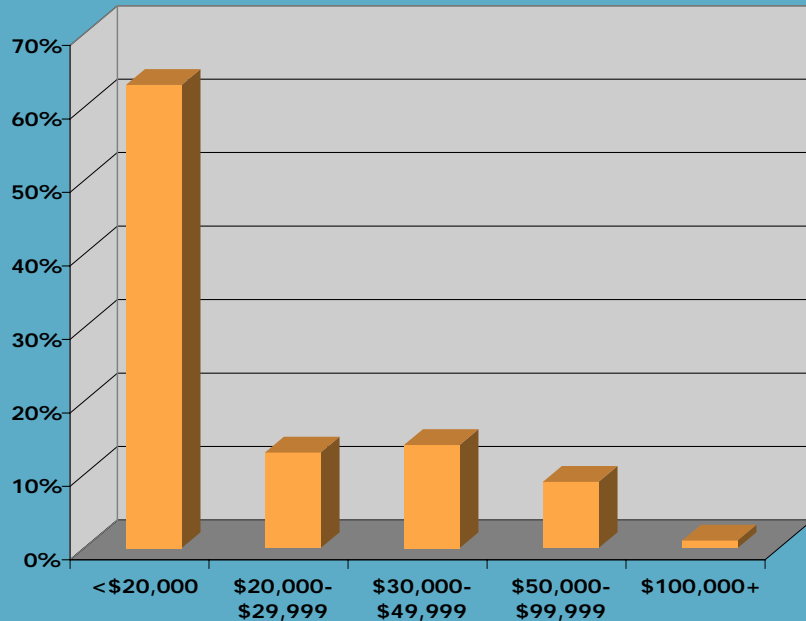
### How Much of a Difference Can the Data Make?

Released December 2006

Freely Available: [www.infopolicy.org](http://www.infopolicy.org)

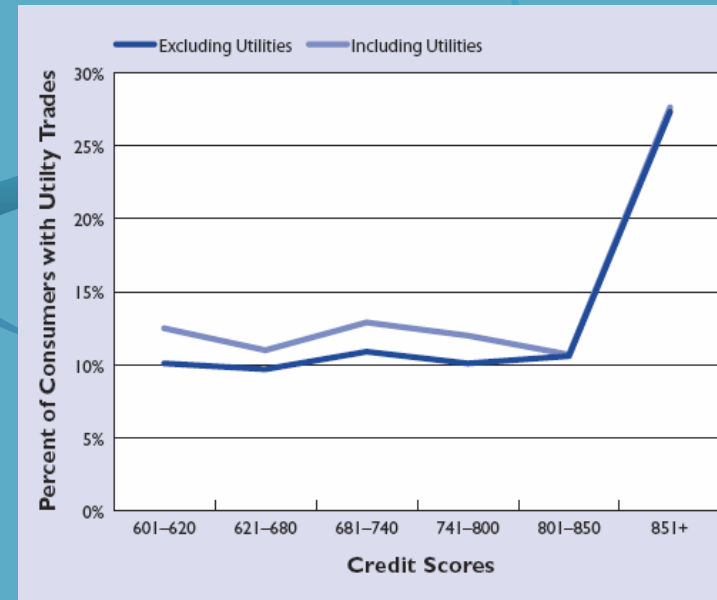
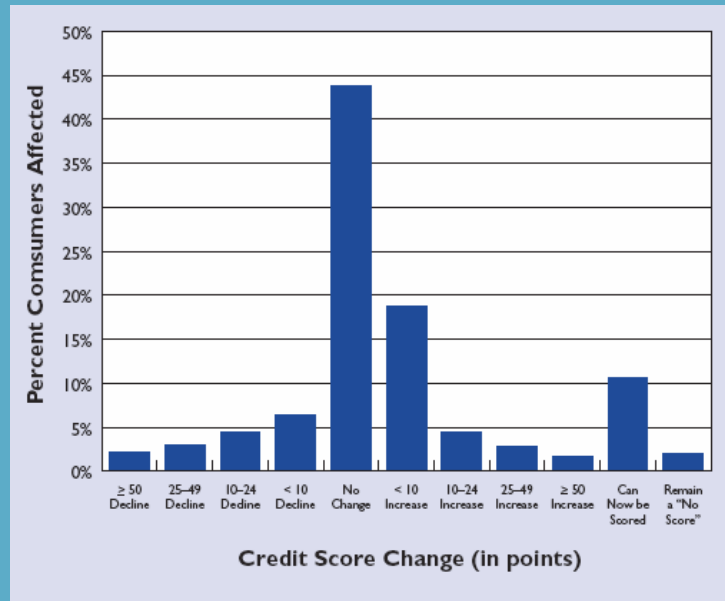
# Thin-files disproportionately low-income and ethnic

## Thin-file with Energy Utility Trade by Income & Ethnicity



# Addition of utility data has small impact on score distribution

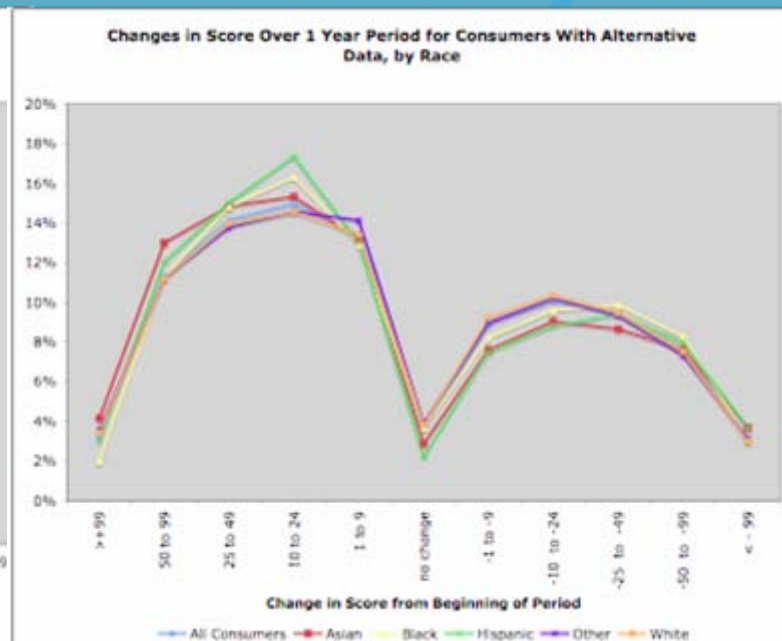
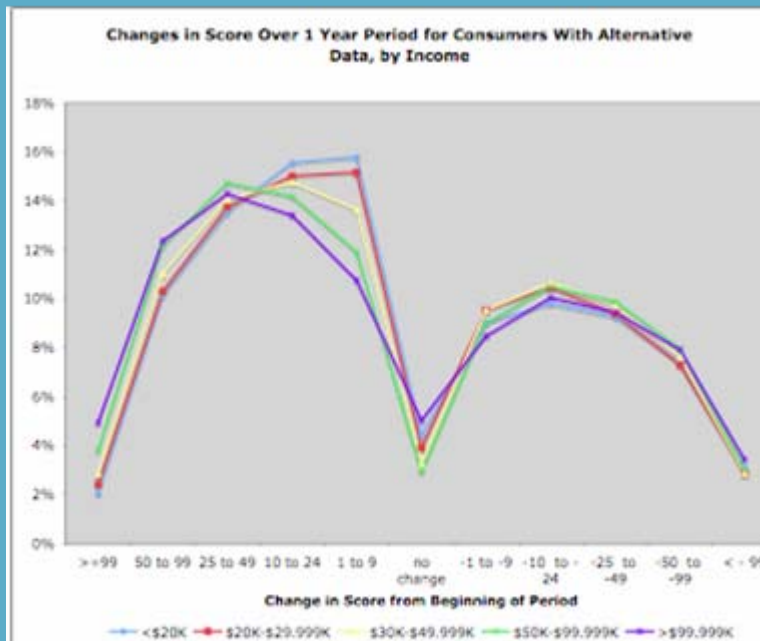
## Total sample 7.5M





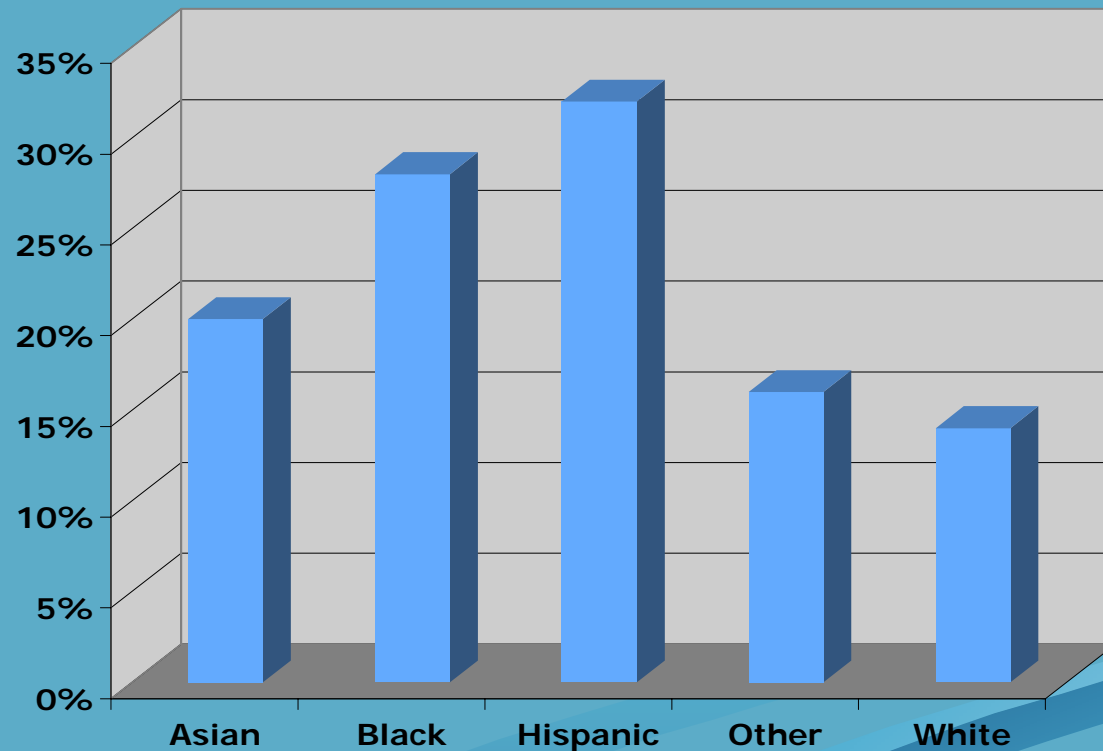
# Those with alt data added don't see worsening score over time

Change in score at end of observation period over beginning, by income and race/ethnicity



# Energy Utility Thin-file: Ethnicity

**15% African-Americans Unscoreable without Utility Trades**  
**22% Hispanics Unscoreable without Utility Trades**



# Key Finding

## Little Information Is Not High Risk

### Risk profile shows promise

- **Score distribution of thin-file sample similar to general population**
- **Nearly 40% of Black unscorable population have credits scores above 620 when energy utility and telecoms data included**
  - **1 tradeline matters**
  - **Multiple tradelines is better**

# Key Findings

## Better Predictions with Alternative Data

Using the VantageScore Model, we see the following improvements in model fit with inclusion of alternative data.

- KS rises 9.8% with utility data, 8.5% with telecom data.
- Among only those scoreable with and without alt. data, we see respective rises of 2.2% and 1.2%.

For the thin-file consumers...

- KS rises 329% with utility data, 428% with telecom data.
- Among only those scoreable with and without alt. data, we see respective rises of 7.8% and 2.1%.

# Key Findings

## Greater Access for All

Considerable increases in acceptance rates for a given performance level. For utilities, an increase of 6 percentage points for a 6% delinquency level.

### Acceptance Rates by Targeted Delinquency Rates

Delinquency Rate %	Consumers with Utility Trades	
	Including Utilities (#1)	Excluding Utilities (#2)
2	52.4	47.2
3	60.4	54.9
4	65.4	59.6
5	69.1	63.1
6	72.0	65.7

# Key Findings

## Better Loan Performance

At a 70% acceptance rate, the rate of serious delinquencies drops by a third with the inclusion of utility data.

### Delinquency Rates by Targeted Acceptance Rates

Acceptance Rate	Consumers with Utility Trades	
	Including Utilities (#1)	Excluding Utilities (#2)
30%	0.90%	1.10%
40%	1.20%	1.50%
50%	1.80%	2.30%
60%	3.00%	4.20%
70%	5.40%	8.10%
80%	9.50%	13.80%
90%	13.80%	17.70%

# Key Findings

## Greater Observed Access

Access is not merely hypothetical but seen in the share of the thin-file population for which alt data is reported.

(“Validation sample” = no alt data)

Table 4.1. New Credit Accounts Opened February 2005 to January 2006

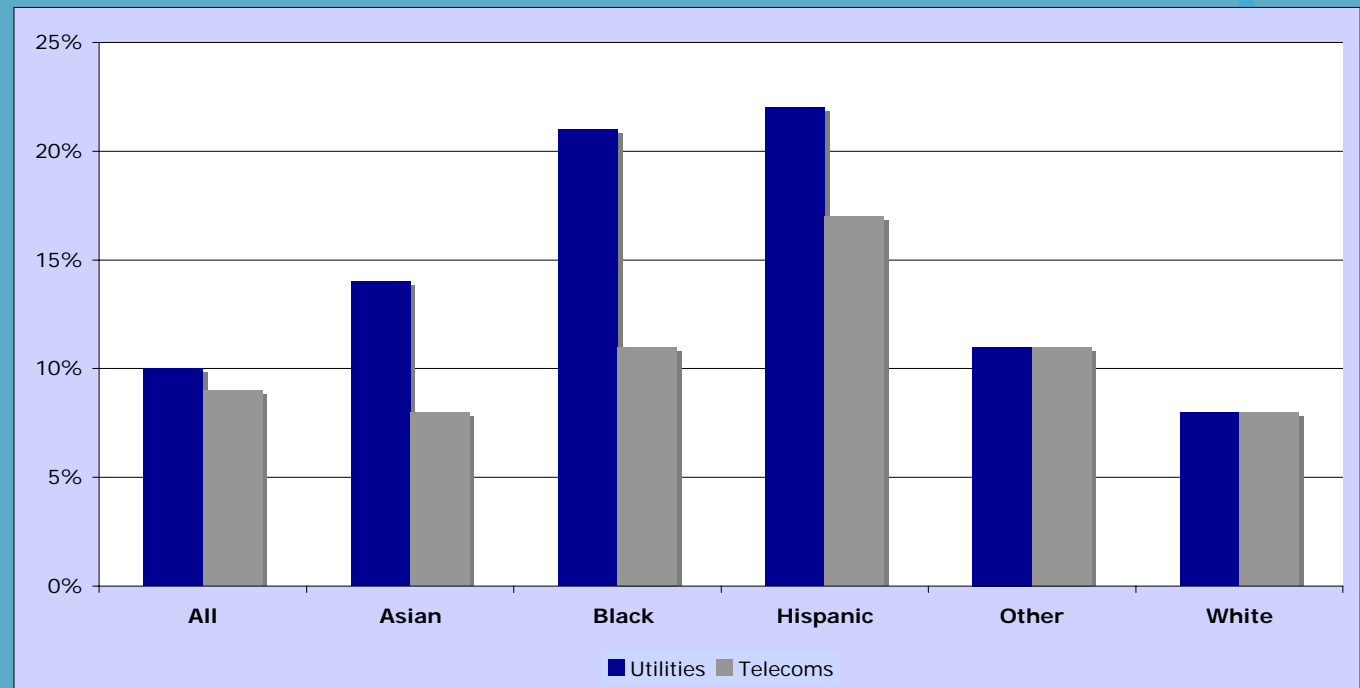
	All Borrowers			Thin-File (<3 Traditional Trades)		
	Consumers with Utility Trades (#1)	Consumers with Telecom Trades (#2)	Validation Sample (#3)	Consumers with Utility Trades (#4)	Consumers with Telecom Trades (#5)	Validation Sample (#6)
Pct with new accounts	50.92%	48.73%	42.21%	16.44%	16.42%	4.61%
Ave. no. trades opened	1.14	1.07	0.93	0.27	0.26	0.05
_ Total outstanding balance	+\$3956	+\$1466	+\$8489	+\$1972	+\$891	-\$402
_ Total available credit	+\$6973	+\$3192	+\$12309	+\$2466	+\$1094	-\$382
Sample size	6,211,323	504,481	3,785,681	1,036,396	113,240	1,030,357

# Key Findings

## Access by Race/Ethnicity

### Considerable lift for Blacks and Hispanics

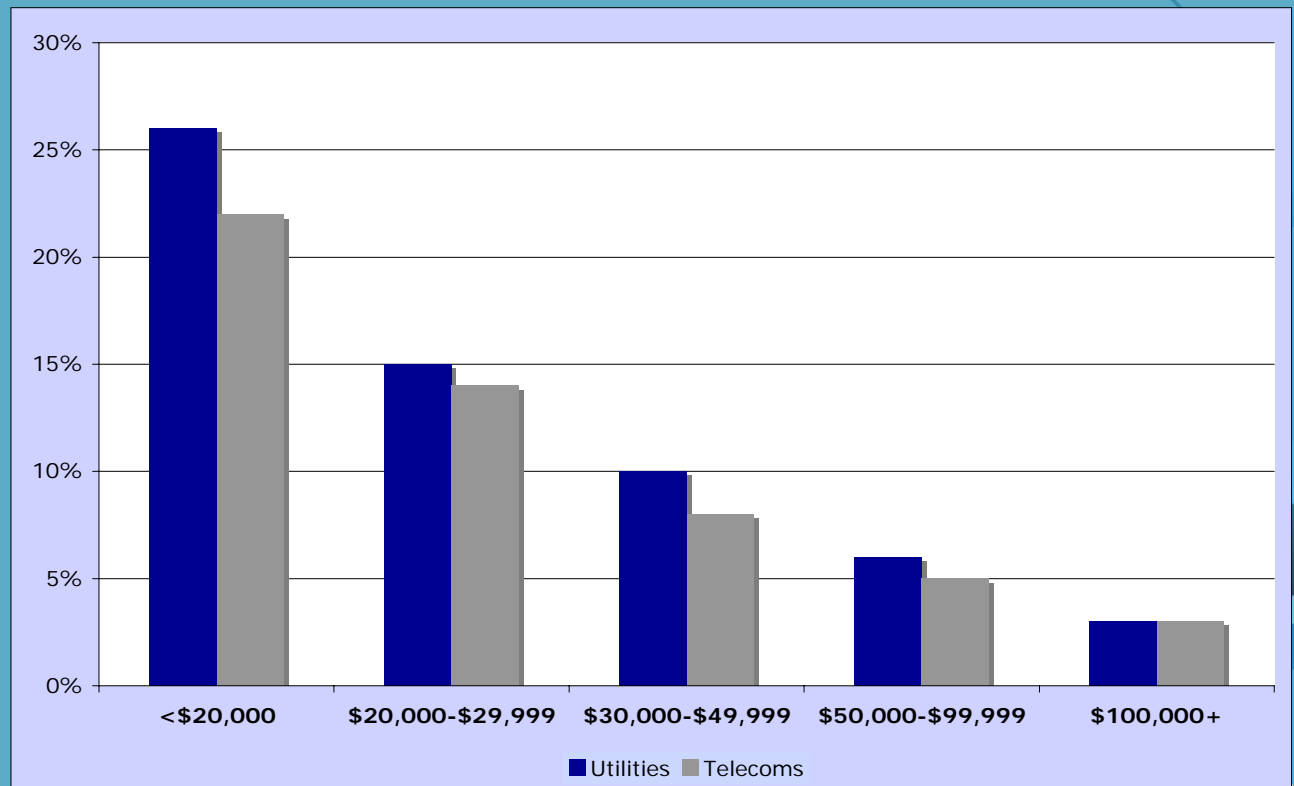
Change in Acceptance Rates by Race/Ethnicity at 3% Delinquency Target





# Key Findings Access by Income

**And a greater lift for lower income consumers**  
Change in Acceptance Rates by Income

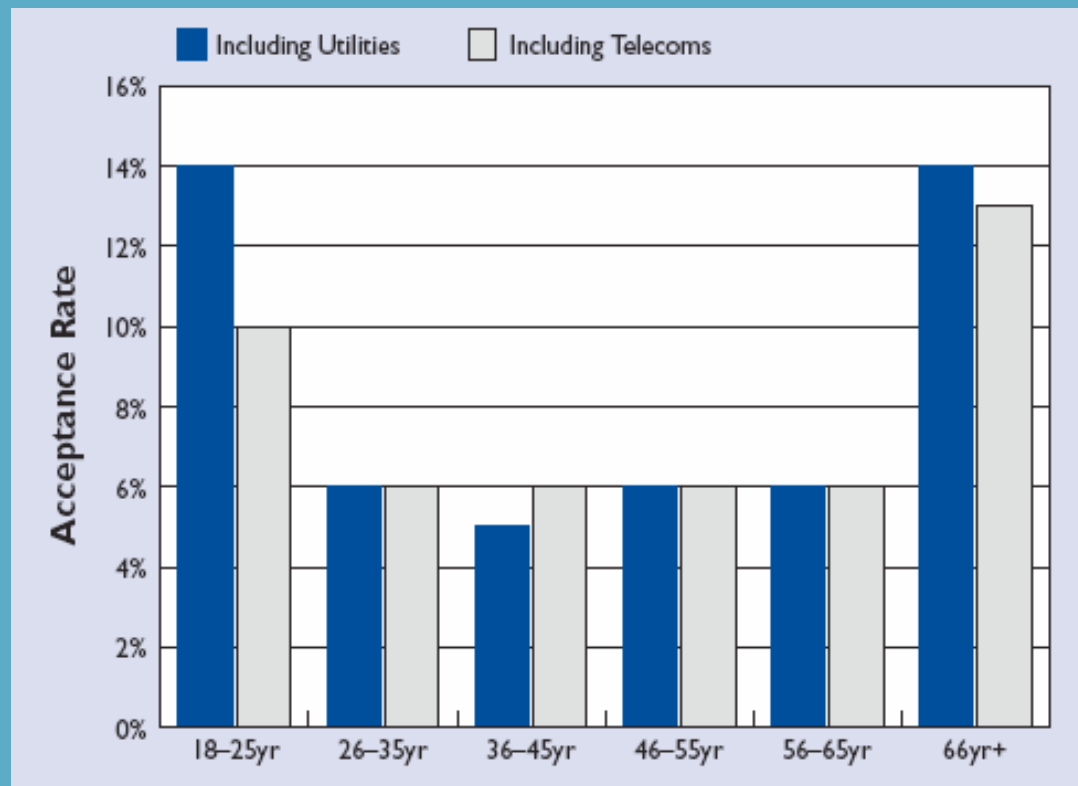


# Key Findings

## Access by Age

**A greater lift for the younger and older.**

Change in Acceptance Rates by Age

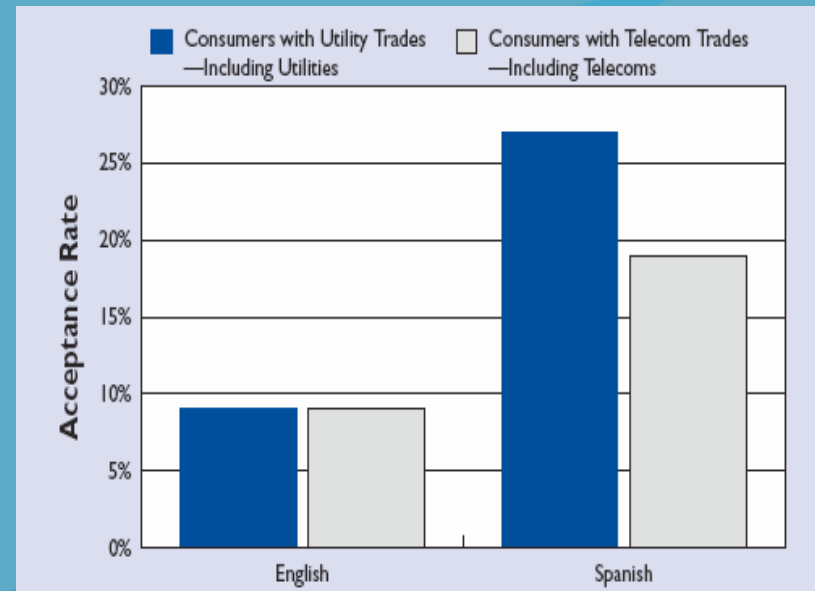
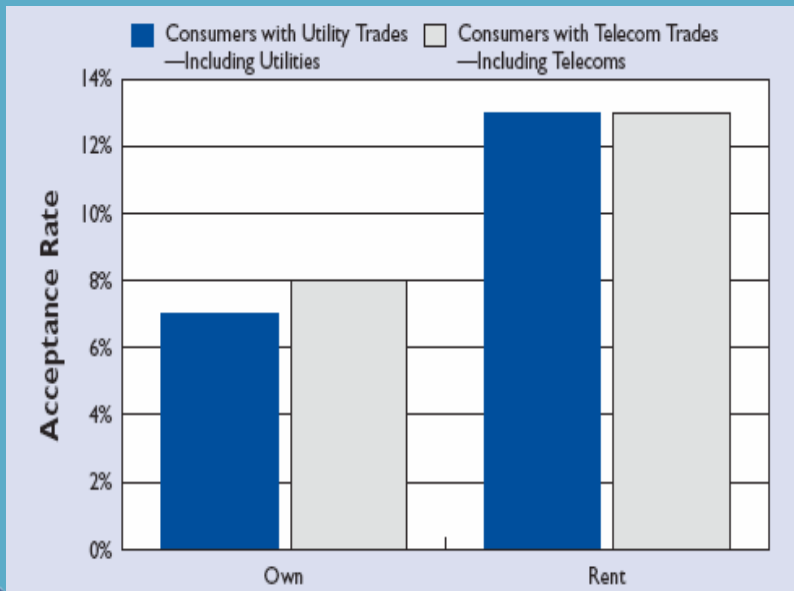


# Key Findings

## Access by Language, Home Ownership

And greater lift for renters and Spanish speakers.

### Change in Acceptance Rates



# Key Findings

## Lenders Are Interested

### Lenders are testing alternative data

- Testing across lines of business
- Results are promising (GE Money--40% thin file borrowers could be profitably booked with competitive mainstream rates using alternative data).

SYSTEMIC CHANGE--Pervasive reporting of alternative data could change the way banking is done in under-served markets.

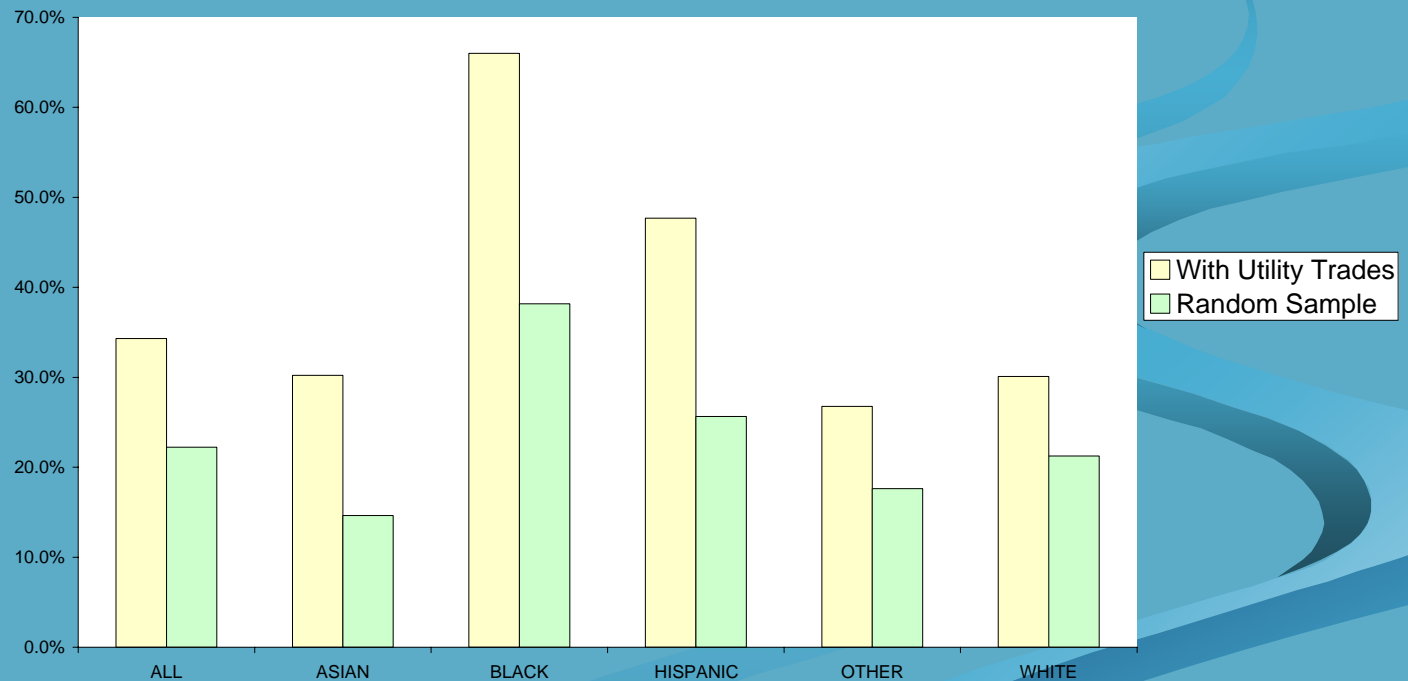
# “Alternative” Data Concerns/Myths

- The credit challenged are further penalized
- Minority and lower income borrowers are unfairly impacted
- “Alternative” data only benefits thin file and underserved markets

# Credit Challenged are Further Penalized

## Percent of Consumers with a Collection Item by Race

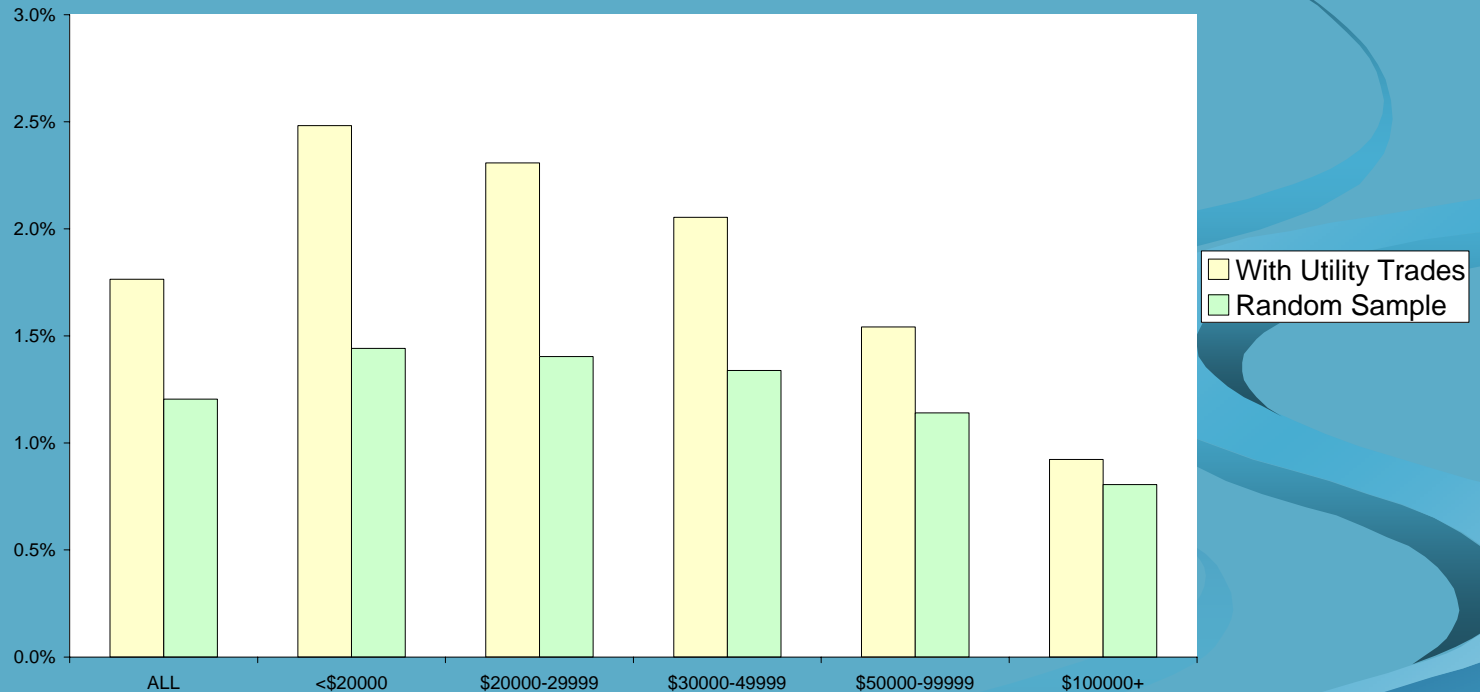
(Source: TransUnion)



# The Credit Challenged are Further Penalized

## Percent of Consumers with a Derogatory Public Record by Income

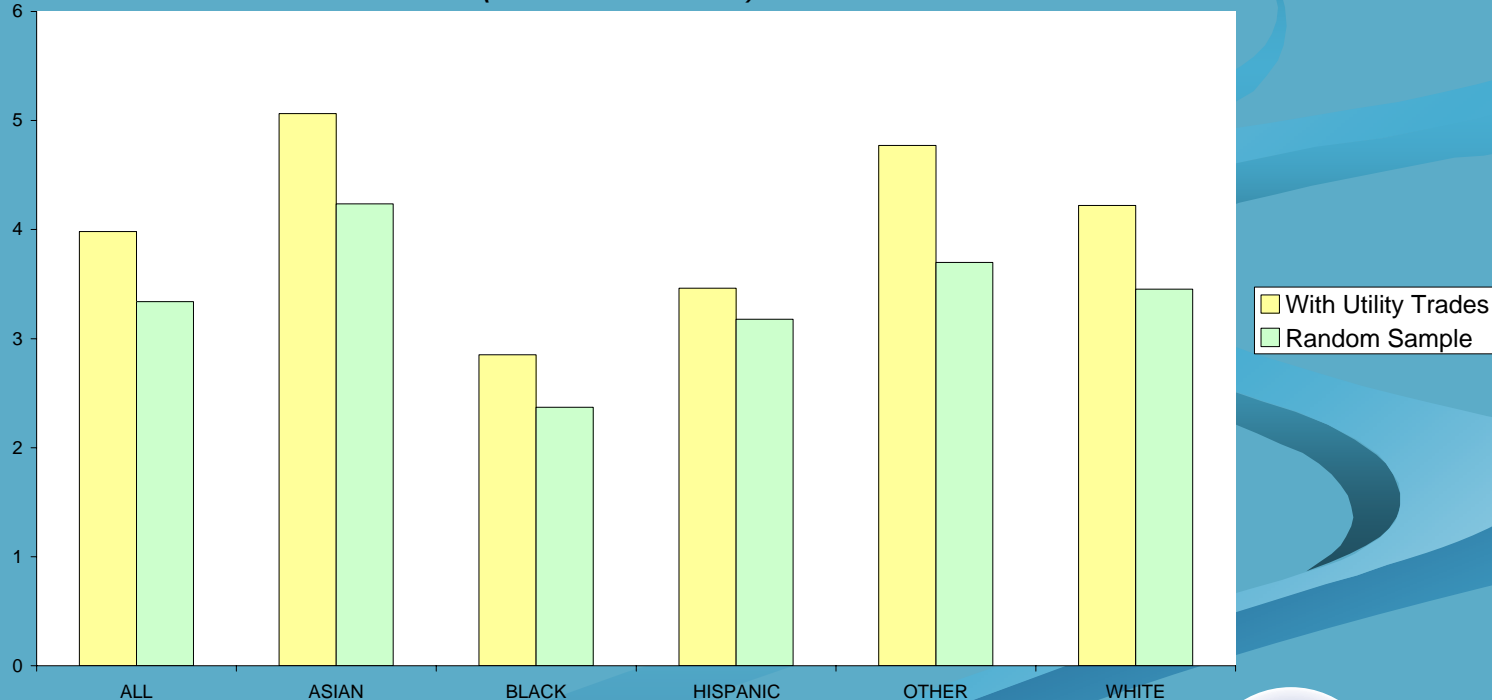
(Source: TransUnion)



# The Credit Challenged are Further Penalized

## Average Number of Satisfactory Accounts Consumers with a Collection Item by Race

(Source: TransUnion)

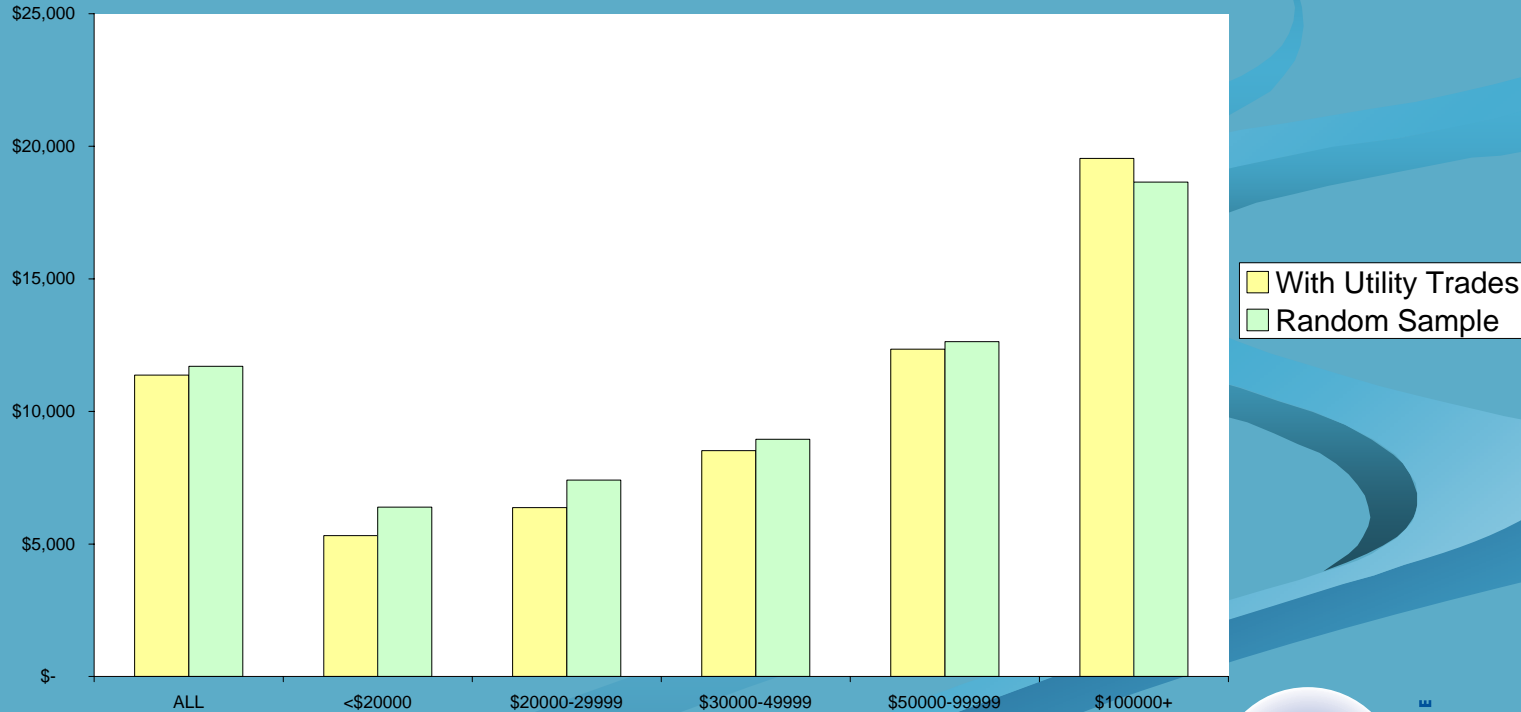




# The Credit Challenged are Further Penalized

## Average Balances by Income Consumers with a Collection Item by Income

(Source: TransUnion)



# Observations

- Alternative Data Provides Credit Challenged a Second Chance
  - Credit bureau based scoring systems perform better with “alternative” data
    - Model results on challenged consumers with alternative data are stronger
      - Better rank ordering
      - increased acceptance rates
  - The percentage of scored consumers increases significantly
    - Access to credit is facilitated
      - number of accounts increase
      - credit limits increase
  - Consumers seeking additional credit appear to perform better
    - On average more satisfactory accounts
    - Delinquency rates are lower

# Next steps

**With the benefits of alternative data now shown quantitatively, attention should be focused on getting such data reported in standardized fashion.**

## **At the time ADI II began**

- **Less than 1% of trades were alternative trades**
- **Less than 4% of consumers had an alternative trade**
- **Many credit scoring models were not optimized with respect to alternative data**

# ADI Phase 3

- **Data Furnisher Track**

- Research (PERC/UMI?CFSI)
  - Business case
  - Survey with bureaus
  - Best practices
  - Rental payment data
- Education & Outreach
  - Exhort full reporting
  - ID strategic events (TRMA, RMA, EEI, AGA, USTA, CTIA)
  - Stand alone events

- **Lender & Policymaker Track**

- Research (PERC/UMI)
  - Respond to questions and concerns from lawmakers, regulators, and media
  - State-specific reports
- Education & Outreach
  - Federal level (led by Brookings UMI)
  - State level
  - Lenders (PERC/CFSI)
  - International
    - China
    - Brazil
    - South Africa

# Key Points

- How are lenders addressing fair lending?
- How can alternative data in credit scoring improve the environment for fair lending?
- How can access to capital be improved using new models?

# Outline

<u>Topic</u>	<u>Slides</u>
Fair Lending Programs	3-7
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Mortgage Example	9-15
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# Lender Self-Evaluation

- *Advertising/marketing/sales.*
- *Underwriting*
- *Pricing.*
- *Operational*
- *Outreach*
- *Advocacy*
- *Education*

# Regulatory Testing: FFIEC Fair Lending Examination Factor Broad Categories

1. [C] Compliance Program Discrimination Factors
2. [O] Overt Indicators of Discrimination
3. [U] Indicators of Potential Disparate Treatment in Underwriting
4. [P] Indicators of Potential Disparate Treatment in Pricing
5. [S] Indicators of Potential Disparate Treatment by Steering
6. [R] Indicators of Potential Discriminatory Redlining
7. [M] Indicators of Potential Disparate Treatment in Marketing



# Analytical Approaches for Compliance Testing & Assessment

ID	Approach	ID	Approach
[L]	Qualitative approaches	[N]	Quantitative approaches
L1	Policy assessments	N1	Universal performance indicator ranking CRA/HMDA analysis
L2	Mystery shopping	N2	Statistical testing/modeling
L3	Customer advocacy	N3	Review of scorecards and overrides
L4	Operational risk control self-assessment	N4	Matched pair file reviews
		N5	Geographical information and mapping
		N6	MIS reporting
		N7	Operational risk KRIs

# Assessment Strategy Matrix

#	Qualitative (L)				Quantitative (N)						
	L1	L2	L3	L4	N1	N2	N3	N4	N5	N6	N7
R5	1				1				1		
R6	1				1				1	1	
R7		1		1							
R8			1						1		1
R9					1				1		
M1	1			1							
M2	1			1							
M3	1									1	
M4	1				1				1		
M5	1								1	1	
M6					1				1		
M7	1		1							1	1
Tot	20	8	7	20	19	9	7	9	15	16	17

# Options for Incorporating Alternative Data Into Loan Underwriting

1. Treat non-credit trades the same as credit trades for payment performance assessment and use existing scorecards
2. Develop custom scorecards that have specially designed alternative data factors
3. Adopt an alternative modeling approach for use with alternative data and credit data

# Overview

## *Hybrid Approach*

- Integrates judgmental elements into statistical process
- Can incorporate scoring models as dimensions in a more general model framework
- Robustly handles incomplete and non-traditional data
- Offers an efficient, accurate, integrated, and systematic model validation process
- Facilitates model life-cycle management

# Credit History Dimension: Ratings for Three Trade Lines Over Time

Delinquency TimeFrame/ Severity	Mortgage Trades Severity				Installment Trades Severity				Revolving Trades Severity			
	0	1	2	3+	0	1	2	3+	0	1	2	3+
Less Than 12 months												
30 days past due	G	F	F	P	G	G	F	F	G	G	F	F
60 days past due	G	P	P	P	G	F	P	P	G	F	P	P
90 days past due	G	P	P	P	G	P	P	P	G	P	P	P
12-24 months												
30 days past due	G	G	F	P	G	G	G	F	G	G	G	F
60 days past due	G	P	P	P	G	F	F	P	G	F	F	P
90 days past due	G	P	P	P	G	P	P	P	G	P	P	P
Over 24 months old												
30 days past due	G	G	G	F	G	G	G	G	G	G	G	G
60 days past due	G	F	P	P	G	G	G	G	G	G	G	G
90 days past due	G	P	P	P	G	F	F	P	G	F	F	F

# Credit History Collapsing on Time and Trade Line Categories

Case	Credit History Rating	Mortgage	Installment	Revolving
1	G	G	G	G
2	F	G	G	F
3	P	G	G	P
4	F	G	F	G
5	F	G	F	F
6	P	G	F	P
7	P	G	P	G
8	P	G	P	F
9	P	G	P	P
10	F	F	G	G
11	F	F	G	F
12	P	F	G	P
13	F	F	F	G
14	F	F	F	F
15	P	F	F	P
16	P	F	P	G
17	P	F	P	F
18	P	F	P	P
:	:	:	:	:
26	P	P	P	F
27	P	P	P	P

# Home Purchase Mortgage Loan Primary Factors

Primary Factors	Categories, Definitions & Value Assignments		
Credit Bureau Score	G- 700+	F- 621-699	P- <620
Credit Payment History for all trade lines in credit bureau report	G- detailed definition based on past due occurrence for <1r, 1-2 yrs, >2yr sep. for Rev., IL, Mtg.	F- detailed definition based on past due occurrence for <1r, 1-2 yrs, >2yr sep. for Rev., IL, Mtg.	P- detailed definition based on past due occurrence for <1r, 1-2 yrs, >2yr sep. for Rev., IL, Mtg.
DTI	L- <44%	H- 44% +	
LTV Ratio	L- 80% or less	H- 81% +	

# Handle Table

Handle	Credit Bureau Score	Credit Payment History	Debt-to-Income Ratio	Loan-to-Value Ratio
1	G	G	L	L
2	G	G	H	L
3	G	F	L	L
4	G	F	H	L
5	G	P	L	L
6	G	P	H	L
7	F	G	L	L
8	F	G	H	L
9	F	F	L	L
▪	▪	▪	▪	▪
▪	▪	▪	▪	▪
34	P	F	H	H
35	P	P	L	H
36	P	P	H	H



# Secondary Factors

<b>Months of Reserves</b>	<b>G- 6 months +</b>	<b>F- 3-5 months</b>	<b>P- 2 months or less</b>
<b>Similar Housing Expense</b>	<b>G- 120% or less of previous payment</b>	<b>F- &gt;120-135% of previous payment</b>	<b>P- &gt;135% of previous payment</b>
<b>Time in Profession</b>	<b>G- 5 yrs +</b>	<b>F- 3-4 yrs</b>	<b>P- &lt;3 yrs</b>
<b>Strong Liquid Assets</b>	<b>G- &gt;10% Loan Amt.</b>	<b>F- 5 to 9% Loan Amt.</b>	<b>P- 4% or less Ln Amt</b>
<b>History of Handling Higher Debt</b>	<b>G- 3+yrs</b>	<b>F- 1-2yrs</b>	<b>P- &lt;1yr</b>
<b>Discretionary Income</b>	<b>G- &gt; \$2M/mo.</b>	<b>F- \$1 to 2M/mo.</b>	<b>P- &lt;\$1M/mo.</b>
<b>Relationship</b>	<b>G- 2+ loan, deposit, investment accounts</b>	<b>F- 1 loan, deposit, or investment account</b>	<b>P- None</b>

□ Defined as total monthly income less total monthly debt. A minimum, say \$1M, is usually required to qualify.

# Two-Stage Action Table for Mortgage Loan Example

Credit Score	Credit History	DTI	Low LTV	High LTV	Low LTV	High LTV
Good	Good	Low	1 Accept	19 Accept	37 n/a	55 n/a
Good	Good	High	2 Accept	20 Stage 2	38 n/a	56 Denial
Good	Fair	Low	3 Accept	21 Stage 2	39 n/a	57 Denial
Good	Fair	High	4 Stage 2	22 Stage 2	40 Denial	58 Denial
Good	Poor	Low	5 Accept	23 Stage 2	41 n/a	59 Denial
Good	Poor	High	6 Stage 2	24 Denial	42 Denial	60 n/a
Fair	Good	Low	7 Accept	25 Accept	43 n/a	61 n/a
Fair	Good	High	8 Accept	26 Stage 2	44 n/a	62 Denial
Fair	Fair	Low	9 Accept	27 Stage 2	45 n/a	63 Denial
Fair	Fair	High	10 Stage 2	28 Stage 2	46 Denial	64 Denial
Fair	Poor	Low	11 Accept	29 Stage 2	47 n/a	65 Denial
Fair	Poor	High	12 Stage 2	30 Denial	48 Denial	66 n/a

# Selected Handle Cells For Secondary Factor Qualification Discussion

<b>Handle</b>	<b>Credit Payment History</b>	<b>Credit Bureau Score</b>	<b>Debt-to-Inc Ratio</b>	<b>Loan-to-Value Ratio</b>
<b>3</b>	<b>G</b>	<b>F</b>	<b>L</b>	<b>L</b>
<b>12</b>	<b>F</b>	<b>P</b>	<b>H</b>	<b>L</b>
<b>27</b>	<b>F</b>	<b>F</b>	<b>L</b>	<b>H</b>

# Hybrid Approach

## Categorizing alternative variables

- **Utility Payment History**
  - G- 0 times late      F- 1-2 late      P- 3+ times late
- **Non-Credit Payment Score**
  - G- > 720      F- 660-720      P- <660
- **Phone Payment History**
  - G- 2 yrs +      F-1-2 yrs      P- <1yr
- **Non-Credit Payment-to-Income Ratio**
  - G- < 40%      F- 41-59%      P- 60% +
- **Ratio of Non-Credit Accounts with no current or historical delinquency to total non-cash accounts**
  - G- 80% +      F- 50-79%      P- <50%
- **Mos. since most recent late non-credit payment**
  - G- 12 mos. +      F- 7-12 mos.      P- < 6 mos.

# Model Validation

- Use the *handle* to depict risk profile
- Measure population distribution shift over handle cells
- Identify changes in default risk rank ordering of handle cells

# Model Validation

Handle Number	Observed Probability of Default	Predicted Probability of Default	Risk Rank / Observed	Risk Rank / Predicted	Residual
1	0.135	0.198	1	1	-0.063
2	0.466	0.299	3	2	0.167
3	0.179	0.486	2	5	-0.307
4	0.485	0.338	4	3	0.147
5	0.564	0.594	7	6	-0.03
6	0.525	0.772	6	10	-0.247
7	0.511	0.469	5	4	0.042
8	0.704	0.662	8	8	0.042
9	0.803	0.752	10	9	0.051
10	0.772	0.62	9	7	0.152



# Summary

## Hybrid Models

**Promise to improve credit evaluation and access for the emerging markets**

More volume with equal or less credit risk

Applicable to more diverse population (e.g. unbanked)

**Afford Greater efficiency**

Easy to interpret and maintain (e.g. model updating vs. re-development)

Less resource intensive (e.g. fewer models)

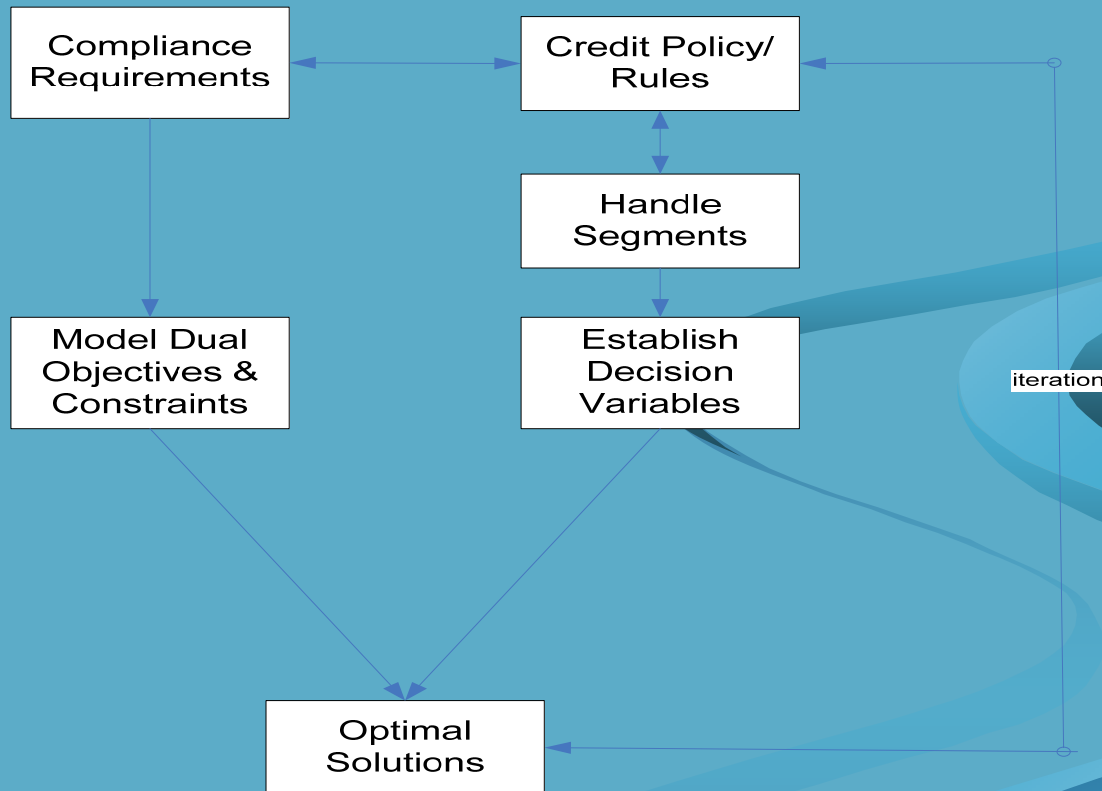
**Are More effective**

Closer fit to business reality

Adaptive to changes in risk factors



# Optimization Process



# Implications for Fair Lending

- Use of alternative data will improve market penetration in areas that have high concentrations of protected class applicants
- Use of alternative data will make credit more accessible and affordable for “thin file/no file” borrowers, many of whom fall into one or more protected classes
- Use of alternative models, such as hybrid models, may further improve credit access for protected classes and will facilitate assessment of the fair lending impact of changes in loan underwriting
- Use of both alternative data and hybrid models can have a favorable combined effect to speed credit access for qualified borrowers
- Hybrid models can help to qualify protected class borrowers where data scarcity persists, even when alternative sources are used.