

Identity Theft as a Teachable Moment

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* The views expressed in this paper are those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Philadelphia or the Federal Reserve System.

Identity Theft Is Costly

- Nearly 17 million victims in 2012
 - 7 % of adults
 - 1 million had new accounts opened
- Out-of-pocket losses are uncommon
 - 85 % lose nothing; 7 % lost less than \$100
 - But over a million lost \$100+
- Increased exposure to collections, time costs, emotional distress

Why Should We Care?

- ID theft exposes sensitive consumer information
- Existing remedies (fraud alerts) provide some protection
- Alerts allow consumers to receive free credit reports
- Shock to the salience of credit files
- May induce consumers to monitor their files

Research Questions

- How do people respond to identity theft?
- How does their behavior change over time?
- What are the consequences of identity theft on credit bureau attributes?

Main Results

- Subprime consumers experience:
 - Persistent increase in risk score after alert
 - Higher % of cards satisfactory
 - Fewer accounts in collections
 - More responsible use of credit
- Prime consumers:
 - Transitory effect on scores and other credit variables

Analysis of New Data

- The PCC obtained
 - Extended fraud alerts on credit reports
 - Linked to the NY Fed Consumer Credit Panel / Equifax data
- We study likely victims of identity theft
 - We measure immediate effects and their persistence

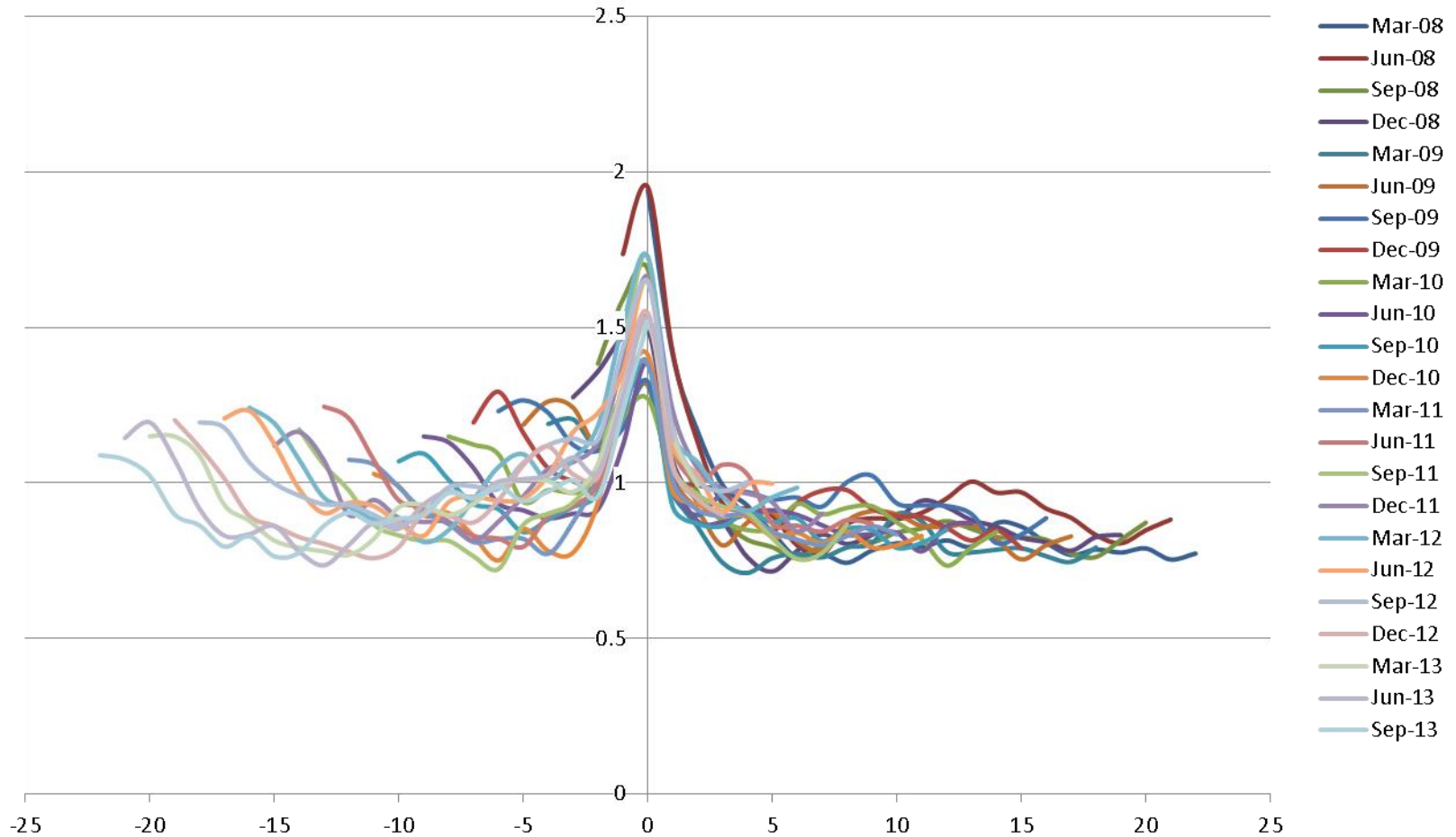
ID theft protection

- Extended alerts*
 - Last 7 years
 - 5-year opt-out of prescreened solicitations
 - No cost to the consumer
 - Require a police report alleging fraud
 - Provide free credit reports

Indications of ID theft

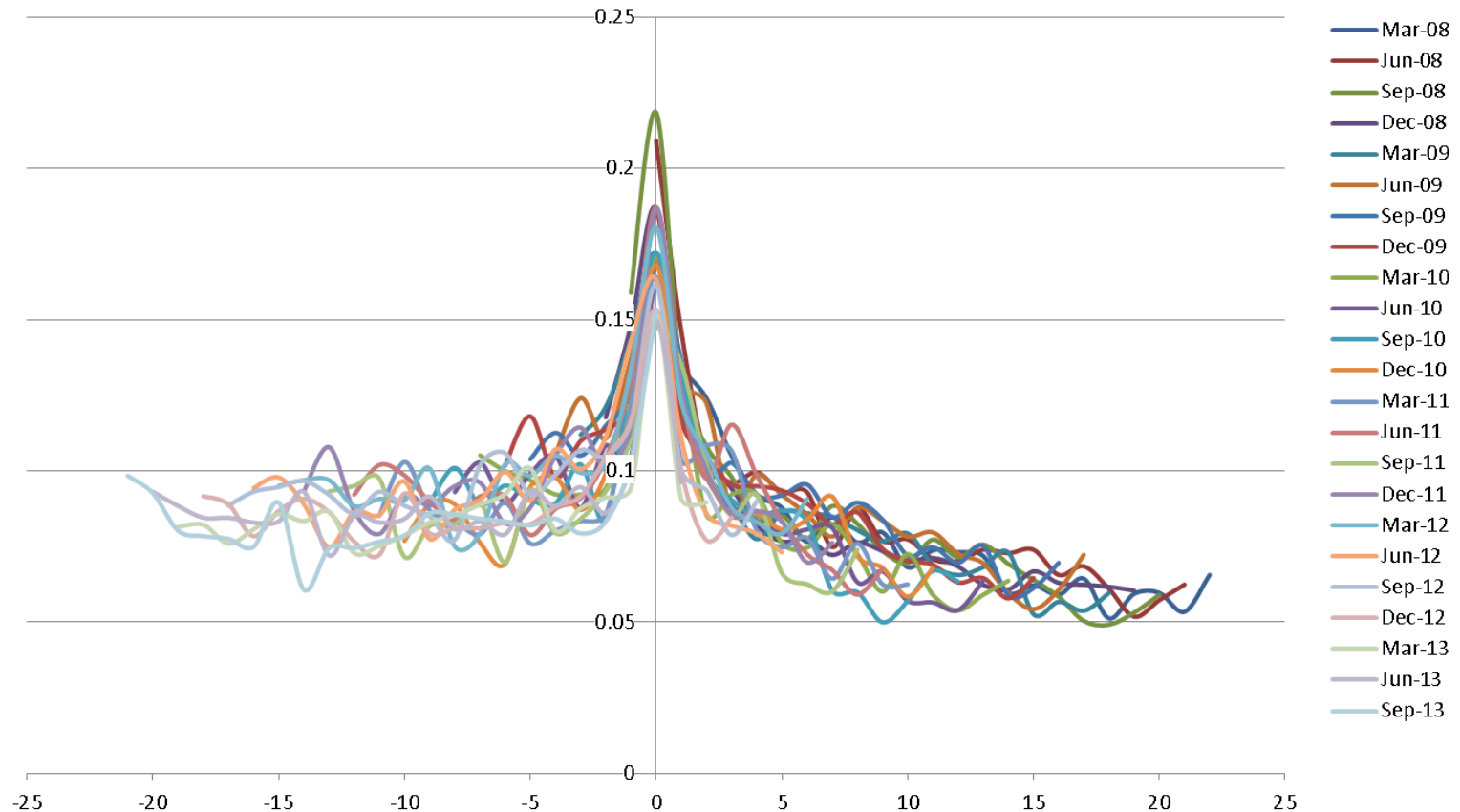
- Credit applications
- Address change
- Risk score change

Credit Applications Spike upon Filing



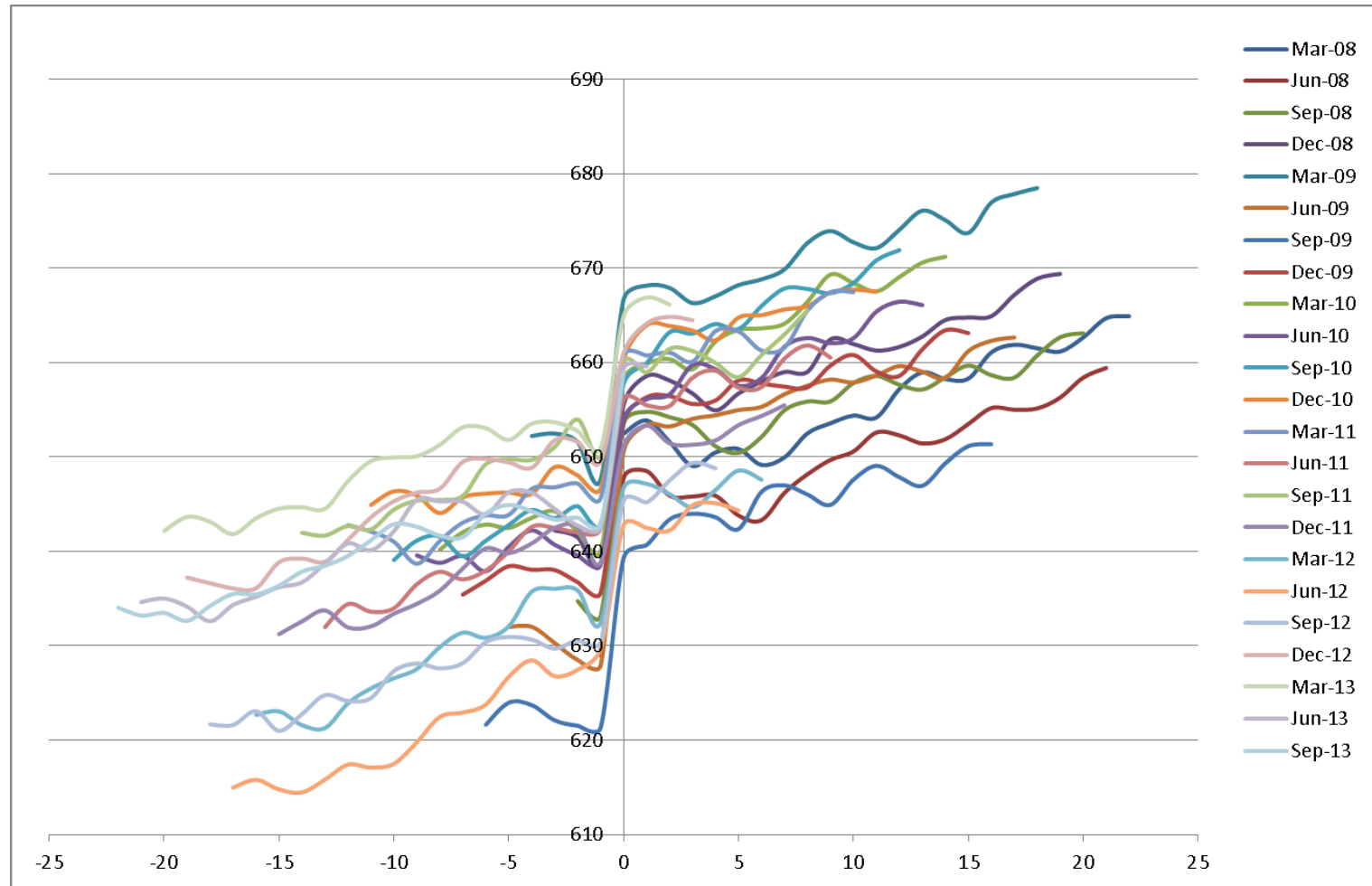
Source: Cheney et al. (2014b) using data from the FRBNY CCP, augmented with variables acquired by the Payment Cards Center

Address Changes also Spike



Source: Cheney et al. (2014b) using data from the FRBNY CCP, augmented with variables acquired by the Payment Cards Center

Risk Score Jumps at Extended Alert

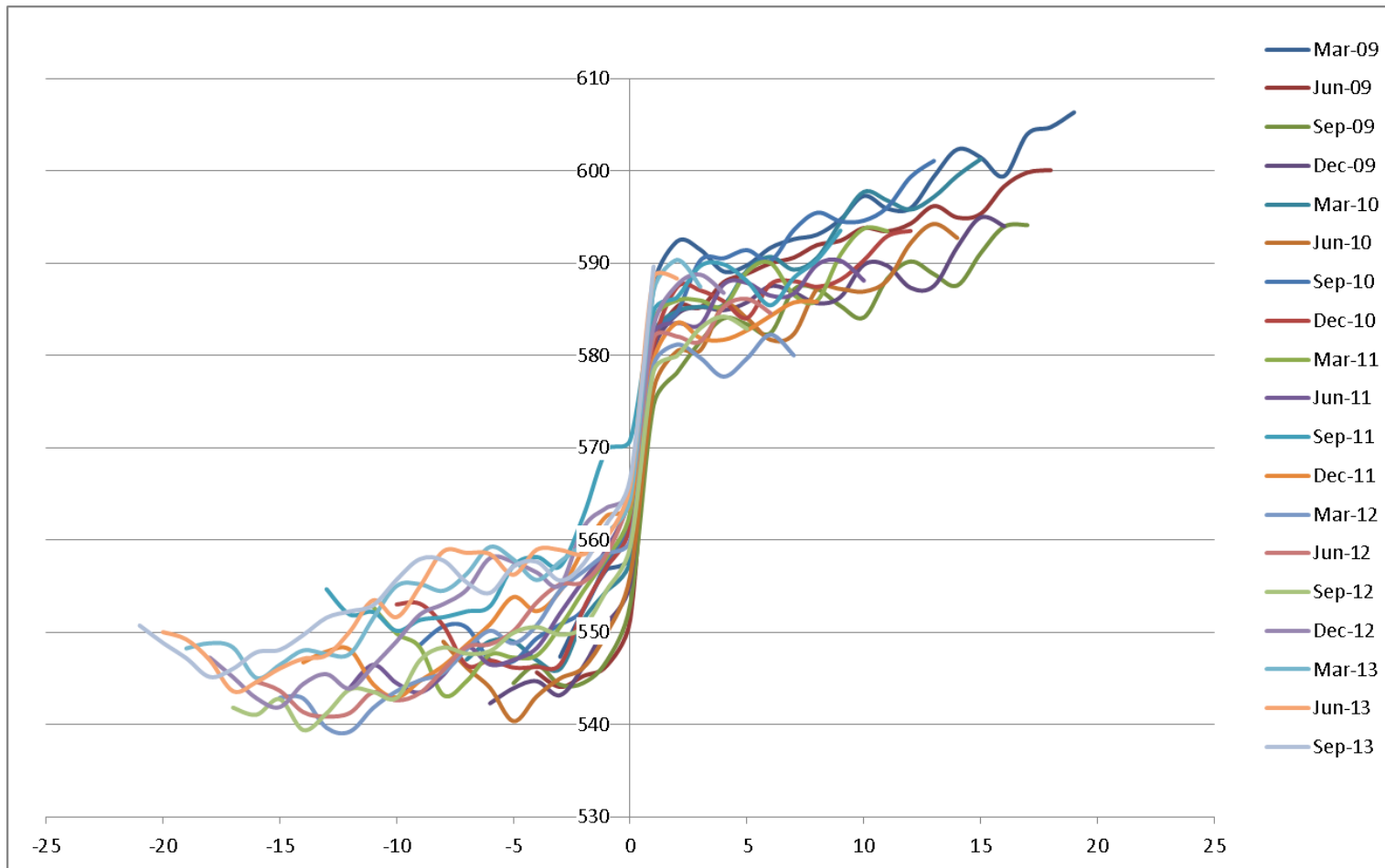


Source: Cheney et al. (2014b) using data from the FRBNY CCP, augmented with variables acquired by the Payment Cards Center

Differences by Segment

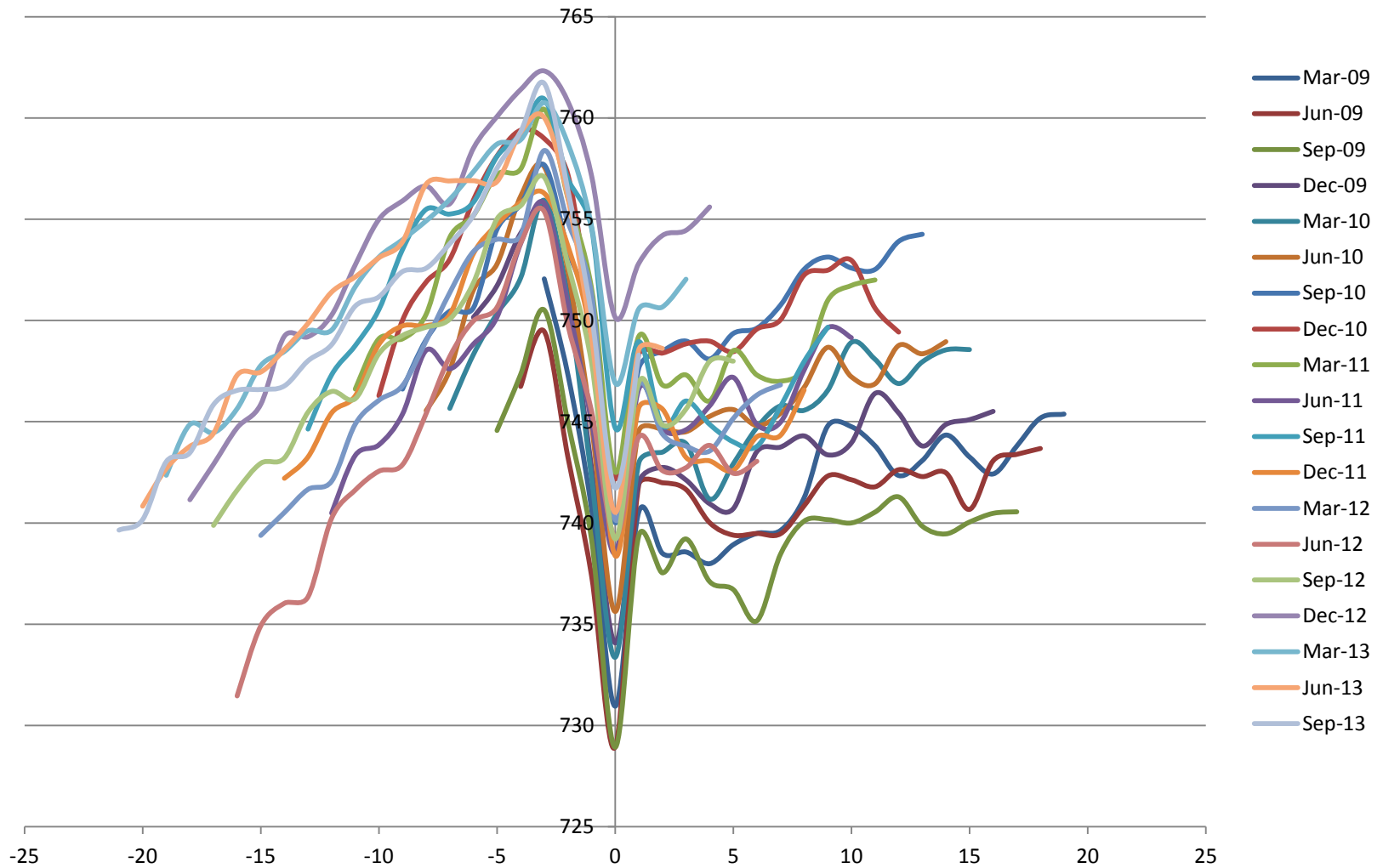
- Filers' risk scores are low
- Subprime use extended alerts more
- Look at prime and subprime separately

Risk Score for Subprime Consumers



Source: Cheney et al. (2014b) using data from the FRBNY CCP, augmented with variables acquired by the Payment Cards Center

Risk Score for Prime Consumers



Source: Cheney et al. (2014b) using data from the FRBNY CCP, augmented with variables acquired by the Payment Cards Center

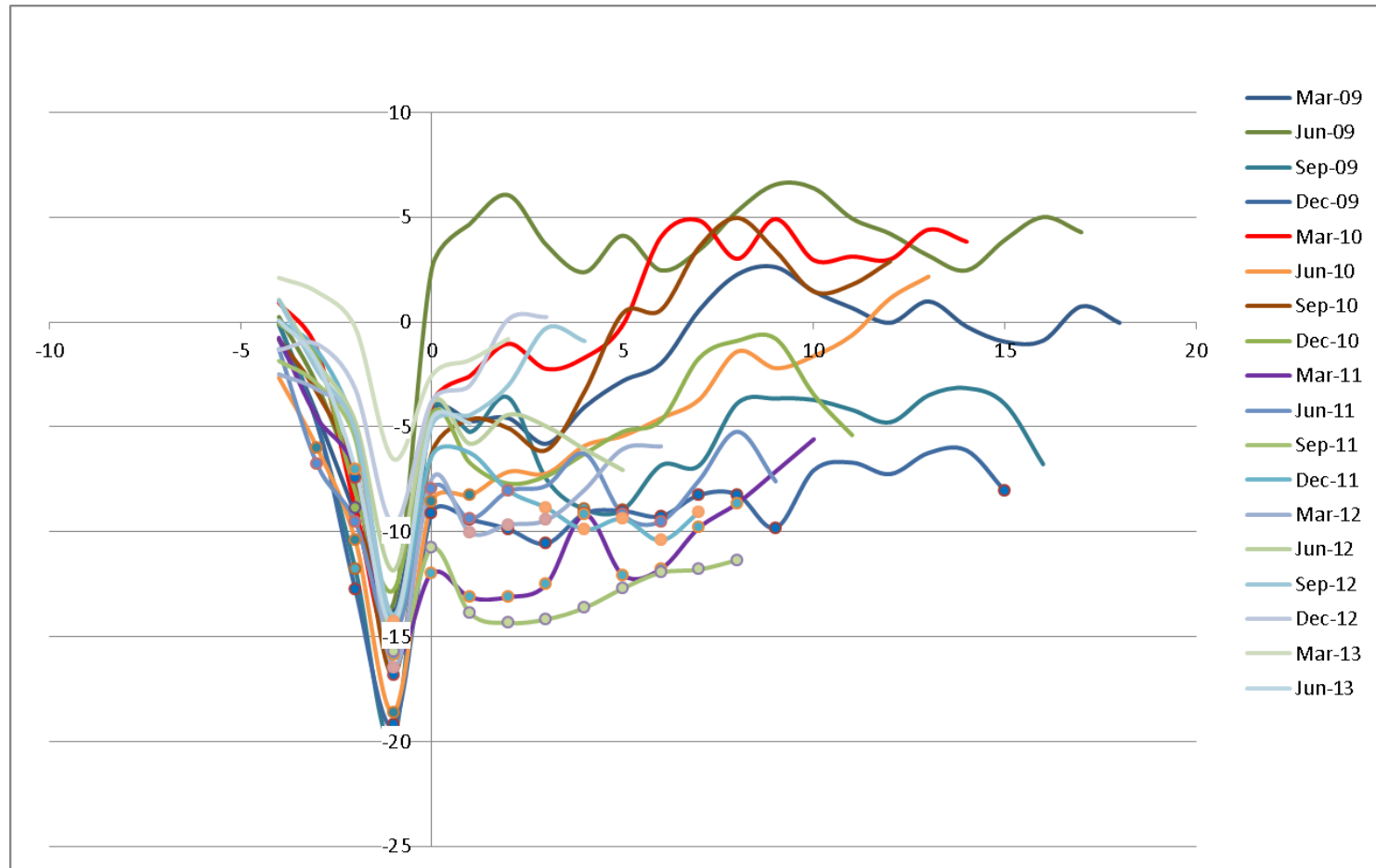
Data Issues

- Extended fraud alert filers need evidence of identity theft to file, cannot “self-select” based on worries
- Criminals may select victims based on profitability
- Not all victims file alerts:
 - Only 9 % of victims check their reports and 70 % of those file an alert or freeze (Harrell and Langton, 2013)
 - We find choice of alert is affected by lags of credit bureau variables (Cheney et al 2014)
- We use propensity score matching to select a control population
 - Sets a higher bar than simply comparing identity theft victims with population trends

Propensity Score Methodology

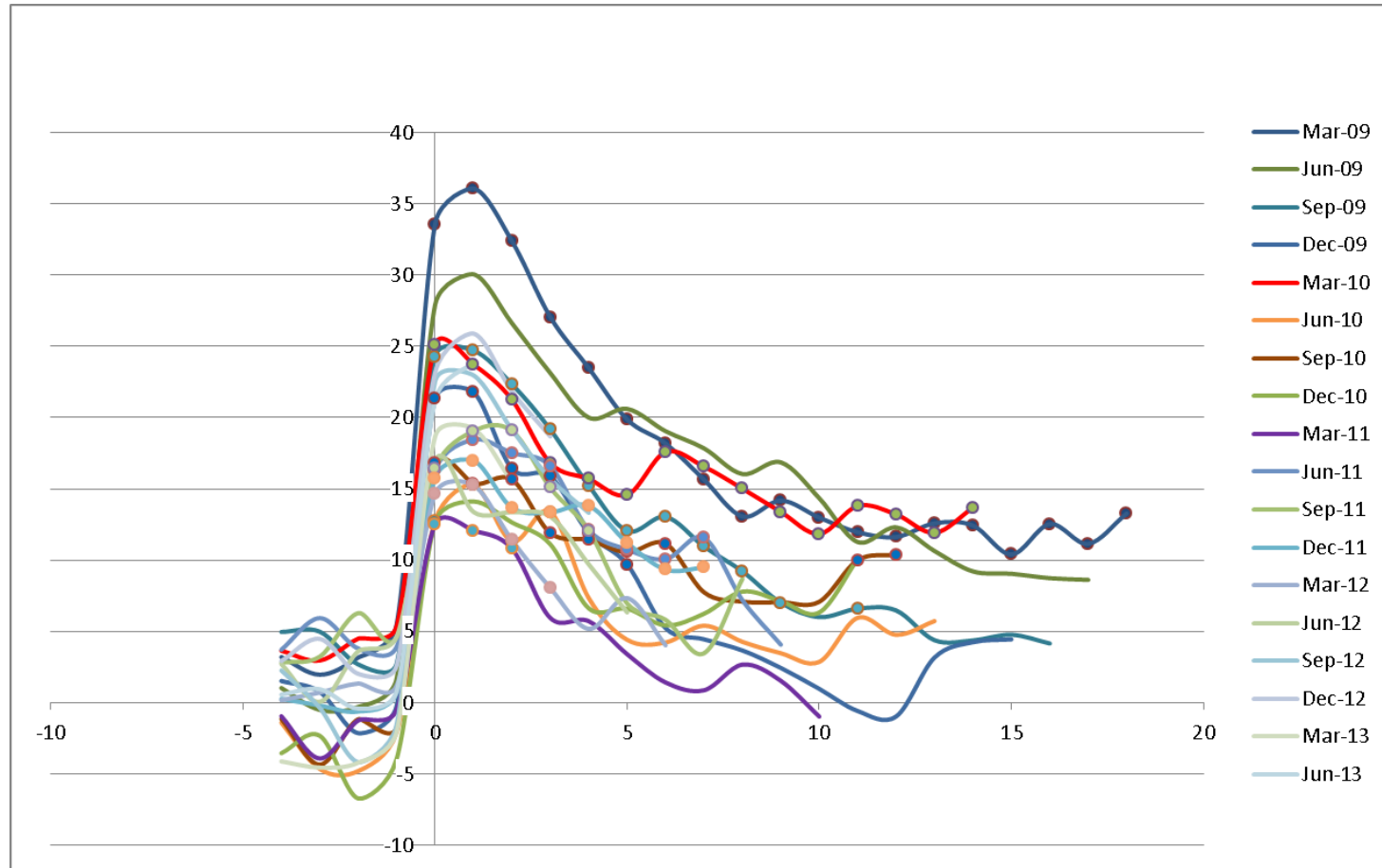
- Victims are allocated to cohorts based on the timing of their alert
 - Allows us to separate business cycle effects
 - Allows for heterogeneity in breaches
- We estimate two models for each cohort
 - One each for prime and subprime consumers
 - Models use a four quarter lag of characteristics:
 - Age, risk score, inquiries, number of accounts, utilization, etc.
- We test for differences in outcome variables

Prime Consumers: Transitory Effect on Risk Score



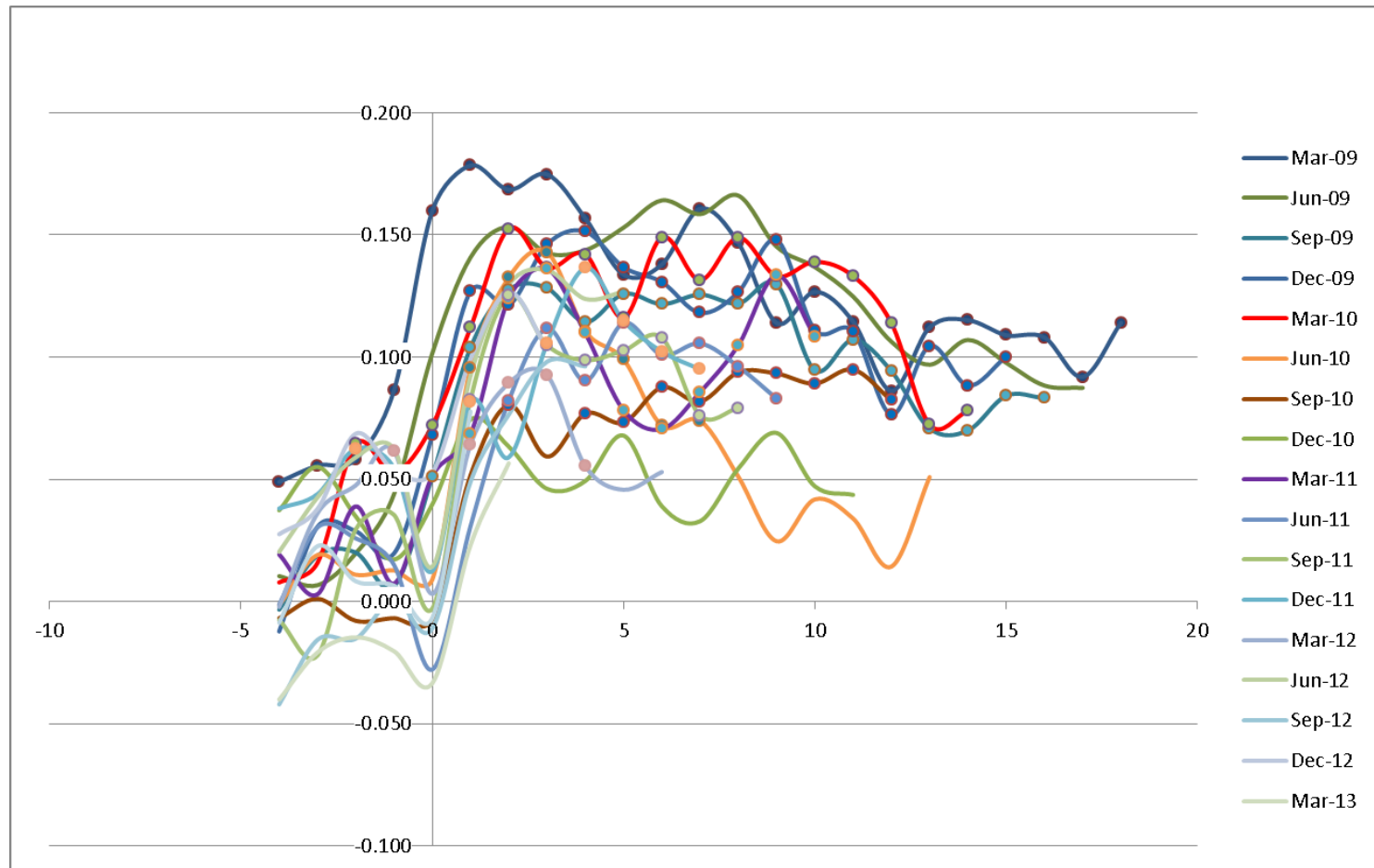
Source: Cheney et al. (2014b) using data from the FRBNY CCP, augmented with variables acquired by the Payment Cards Center

Subprime Consumers: Persistent Effect on Risk Score



Source: Cheney et al. (2014b) using data from the FRBNY CCP, augmented with variables acquired by the Payment Cards Center

More Accounts in Good Standing for Subprime Consumers



Source: Cheney et al. (2014b) using data from the FRBNY CCP, augmented with variables acquired by the Payment Cards Center

Summary

- Credit bureau outcomes for id theft victims
 - For prime consumers, the effects of identity theft are transitory
 - For subprime consumers, there are persistent, positive effects
- We believe this difference is due to consumer inattention before the event
 - A fraud event may be a “teachable moment” for some consumers

Identity Theft Has Other Costs

- Increased exposure to collections
 - Especially for new account fraud
- Time costs
 - About 30 % of new account fraud victims spent 30+ days resolving problems
- Emotional distress
 - 36 percent of identity theft victims report moderate to severe emotional distress from the incident

PSM “goodness of fit”

- Observable attributes are the same among filers and non-filers after matching
- First stage regression correctly classifies 73 % of treated and 37 % of untreated individuals
- No joint significance of explanatory variables in the matched sample after matching, $R^2 \sim 0$ (Sianesi, 2004)

Why PSM is needed

Variable name	Matched treated	Matched control	Treated minus controls	p-value
Mortgage indicator	0.20	0.21	-0.01	0.73
Inquiries within 12 months	5.82	5.88	-0.06	0.82
Inquiries within 3 months	1.73	1.74	0.00	0.97
Person's age	38.93	38.63	0.31	0.54
Age squared	1679.37	1641.72	37.66	0.40
Age of newest account	12.03	12.43	-0.39	0.47
Number of accounts with positive balance	5.27	5.13	0.14	0.38
Risk score	541.93	540.90	1.03	0.75
Number of 30 days past due	1.31	1.30	0.00	0.99
Age of oldest card	91.21	87.50	3.71	0.16
Utilization 25 - 50 %	0.12	0.12	0.00	0.81
Utilization 50 - 75 %	0.13	0.14	-0.01	0.64
Utilization 75 - 100 %	0.18	0.16	0.02	0.29
Utilization over 100 %	0.41	0.42	-0.01	0.49
Address mobility	0.14	0.12	0.02	0.19

PSM

- $\Pr(D = 1) = F(X\beta)$
- D = treatment indicator
- Probit
- 4 quarter lags of credit file variables
- Nearest neighbor matching
- No replacement
- Compare mean outcomes of the matched treated and untreated