Discussion of "On the Rise of FinTechs-Credit Scoring using Digital Footprints" by Berg, Burg, Gombović, and Puri

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Summary

- The paper analyzes the information content of the digital footprint for predicting consumer default
 - Digital footprints match the information content of credit bureau scores
 - Complements rather than substitutes for credit bureau information
 - Broad implications for financial intermediaries and financial inclusion

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Overview

- Very interesting and well-written paper
- Convincing evidence
- Minor issues on sample selection and the implications for other long-term loan markets

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What are Digital Footprints?

- A digital footprint is a trail of data you create while using the Internet. It includes the websites you visit, emails you send, and information you submit to online services.
- We are living in a digital world
 - Mobile payments (Alipay, Google Pay, etc.)
 - ► E-commence (Amazon, Taobao, etc.)
 - Social networks (Facebook, Twitter, WeChat, etc.)
 - Sharing economy (Uber, Airbnb, Filecoin, etc)
 - Peer-to-peer lending and insurance

Use Cases of Digital Footprints

Alternative credit Scoring

- For the unbanked
- Enables instant Point of Sale (PoS) financing
- Peer-to-peer lending platform
- CredoLab (Singapore)—developed a credit scoring mobile app, CredoApp, which evaluates over 50,000 data points from a client's phone and produces a credit score in under two minutes

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Insurance pricing

- i.e. Are you often on your phone between 12 midnight 6:00 a.m.?
- Could increase your car and health insurance premium

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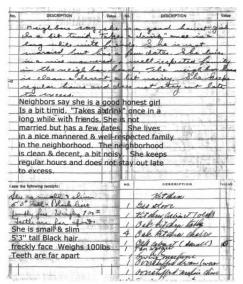
Insurance pricing

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Dynamic pricing

- Anecdotal evidence: Orbitz shows higher prices to Mac users
- Ride-hailing surcharge

Credit Evaluations from the 1930s



"teeth are far apart"
"takes a drink" once a
while
Not married, but has a
few dates
Neighbors say she is a
good-hearted girl

source: Eric Falkenstein, Finding Alpha: The Search for Alpha When Risk and Return Break Down

The Paper in a Nutshell

- Analyze the default prediction using approximately 250,000 purchases from an E-Commerce company selling furniture in Germany
- Customers with good creditworthiness have deferred payment option—pay after shipment
- The company started to use ten digital footprints (DF) variables for predicting default in Oct. 2015
- Main findings:
 - After using DF, the company's default rates decreased
 - DF Complements for credit bureau information
 - ▶ DF matters for other loan products such as consumer or mortgage loans

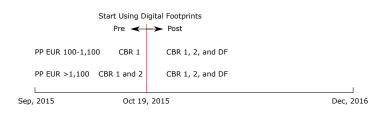
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Which DF variables matter?

Variable	Standalone AUC	Marginal AUC
Computer & Operating system	59.03%	+1.71PP***
Email Host	59.78%	+2.44PP***
Email Host: paid versus non-paid dummy	53.80%	+0.98PP***
Email Host: Variation within non-paid email hosts	57.82%	+1.79PP***
Channel	54.95%	+0.70PP***
Check-Out Time	53.56%	+0.63PP***
Do not track setting	50.40%	+0.00PP
Name In Email	54.61%	+0.30PP**
Number In Email	54.15%	+0.19PP**
Is Lower Case	54.91%	+1.15PP***
Email Error	53.08%	+1.79PP***

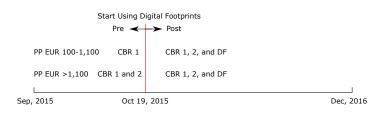
- Only "do not track" not significant
- Non-income proxies more important than income proxies

Evidence of Decreased Default Rates



Purchases	Sample	Creditworthiness	Invoice	Default
Amount	Period	Judging Source	Offered Rate	Rates
EUR 100-1,100	Pre	CBR 1	96.65%	2.54%
	Post	CBR 1, 2 and DF	90.05%	1.19%
> EUR 1,100	Pre	CBR 1, 2	39.00%	3.62%
	Post	CBR 1, 2 and DF	40.11%	2.33%

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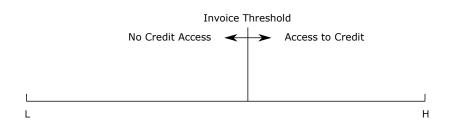
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Results are solely driving by digital footprints.



How do Digital Footprints Improve Default Prediction?

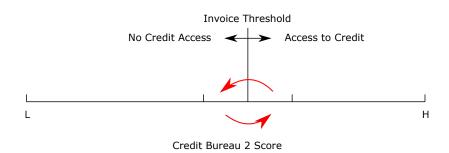
For the case of purchases amount > EUR 1,100 and before Oct 19, 2015:



Credit Bureau 2 Score

Using Digital Footprints (DF)

- Some above the threshold but with poor DF score get rejected
- Some below the threshold but with good DF score get the credit



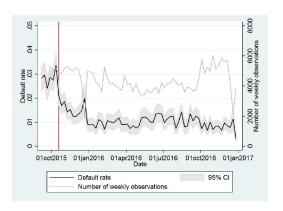
My Comments

The paper is forthcoming at the *Review of Financial Studies*!

Only minor comments on:

- The correlation between invoice offered and default rates
- Sample selection
- Representativeness of other loans

Comment 1: Correlation between the Number of Invoice Offered and Default Rates



- Expect a positive correlation
- Positive pre-DF period, and seems to have a clear negative correlation post DF period. Why? Show more results in the pre-DF period?

Comment 2: Minor Issues on Sample Selection

- The main sample includes all purchases with access to credit after the company using digital footprints from Oct 19, 2015 to Dec 31, 2016
- Estimate default probability in a linear logistic regression
- How did the company use digital footprints to judge a customer's creditworthiness? Non-linear functional form?
- Can predictions be different for those customers rejected for credit access?

Comment 3: Are the Results Representative of long-term loan?

My prior is not. Because:

- It's a one-time short term loan with an average amount of USD 350
- Hard to think customers default because of financially constraint
- Moreover, default probability is negatively correlated with the loan amount (footnote 23)

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But the authors show that digital footprints today can forecast future changes in the credit bureau score. I think there is still room for future research:

- How do digital footprints proxy for soft information in lending?
- For different loans, borrowers have various reasons and cost of default
- Still interesting to see how digital footprints work in a long-term loan like mortgage loans

Conclusions

- The first paper on analyzing the information content of digital footprints
- Interesting and intuitive results
- Providing evidence that digital footprints have important implications for the unbanked

Possible future research:

- Digital footprints vs. soft information
- The role of screening vs. monitoring of digital footprints
- The impacts of digital footprints on insurance and dynamic pricing