UC San Diego
UC San Diego Previously Published Works

**Title**
The Off-Label Use of Consumer Credit Ratings

**Permalink**
https://escholarship.org/uc/item/88b6p4nc

**Journal**
HISTORICAL SOCIAL RESEARCH-HISTORISCHE SOZIALFORSCHUNG, 42(1)

**ISSN**
0172-6404

**Author**
Rona-Tas, Akos

**Publication Date**
2017

**DOI**
10.12759/hsr.42.2017.1.52-76

Peer reviewed

eScholarship.org Powered by the California Digital Library
University of California

SSOAR

Open Access Repository
www.ssoar.info

# The Off-Label Use of Consumer Credit Ratings

Rona-Tas, Akos

Veröffentlichungsversion / Published Version
Zeitschriftenartikel / journal article

**Zur Verfügung gestellt in Kooperation mit / provided in cooperation with:**
GESIS - Leibniz-Institut für Sozialwissenschaften

**Empfohlene Zitierung / Suggested Citation:**
Rona-Tas, Akos: The Off-Label Use of Consumer Credit Ratings. In: *Historical Social Research* 42 (2017), 1, pp. 52-76. DOI: http://dx.doi.org/10.12759/hsr.42.2017.1.52-76

**Nutzungsbedingungen:**
*Dieser Text wird unter einer CC BY-NC Lizenz (Namensnennung-Nicht-kommerziell) zur Verfügung gestellt. Nähere Auskünfte zu den CC-Lizenzen finden Sie hier:*
*https://creativecommons.org/licenses/by-nc/4.0/deed.de*

**Terms of use:**
*This document is made available under a CC BY-NC Licence (Attribution-NonCommercial). For more Information see:*
*https://creativecommons.org/licenses/by-nc/4.0*

gesis Leibniz-Institut für Sozialwissenschaften

Mitglied der Leibniz-Gemeinschaft

Diese Version ist zitierbar unter / This version is citable under:
http://nbn-resolving.de/urn:nbn:de:0168-ssoar-51162-9

# The Off-Label Use of Consumer Credit Ratings

*Akos Rona-Tas* *

**Abstract:** *»Zulassungsüberschreitende Anwendung von Konsumenten-Kreditwürdigkeit«*. Sovereign, corporate and consumer credit ratings are used to assess the creditworthiness of borrowers. Yet these ratings often fulfill other functions as well, serving as measures of more general qualities of countries, businesses and individuals. When ratings are used outside the context of lending, we call it 'off-label use.' This paper develops the argument in the context of consumer lending and discusses the use of credits scores in the U.S. by car insurance companies in calculating premiums, landlords in selecting tenants, and employers in hiring workers. We argue that off-label use can have harmful effects through two mechanisms: error propagation and enhanced performativity. Both amplify small initial differences, exacerbate inequalities, lock borrowers in upward or downward spirals and increase economic inequalities. Turbo performativity results when measures influenced by earlier credit scores become direct inputs for calculating new credit scores. Off-label use of consumer ratings, therefore, should be treated not just as a privacy issue but also as a factor in economic polarization.

**Keywords:** Credit scores, insurance, hiring, residential rental, performativity, inequality.

## 1. Introduction

Credit ratings recently have found a variety of new uses. Ratings developed in retail lending, called credit scores are now routinely used in fields such as auto insurance assessments, cell phone contracts, residential rentals and even hiring decisions. The proliferation of credit ratings is not limited to credit scores. Corporate ratings designed to assess companies, became deployed to evaluate local governments and structured financial instruments such as mortgage backed securities and applied not just to evaluate but also to create those instruments. It has also been alleged that unsolicited corporate ratings have been used as a "marketing device" by rating agencies to punish corporations reluctant to order the agencies' services.[1] The use of corporate ratings for regulatory

* Akos Rona-Tas, Department of Sociology, University of California, San Diego, USA; aronatas@ucsd.edu.

[1] A famous example is Jefferson County School District No.R-1 vs. Moody's Investor's Services, where Moody's famously won on First Amendment grounds, <http://caselaw.findlaw.com/

purposes is yet another example of their off-label use.[2] The use of sovereign ratings, the gauge of the reliability of government bonds and the likelihood of sovereign default has also been expanded and is now routinely employed as the measure of a country's overall economic performance and a measure of economic and political stability.

The increasing versatility of credit ratings is yet another sign of the growing role of finance in modern life (Deutschmann 2011). Financialization, the term often used to describe the way society becomes dominated by finance, spawned a large literature devoted to documenting the swelling of the relative size of the financial industry (Krippner 2011), the increasing influence of financial markets in the governance of non-finance companies (Fligstein 1990, 2008; Dobbin and Zorn 2005), and the various ways households become directly dependent on the financial world, either by means of indebtedness or by investing their savings in financial instruments (Sullivan et al. 2000; Hyman 2011; Harrington 2008; Keister 2000; Frank 2000). All of these, at different levels, testify to the expansion of finance, the pushing of its boundaries to encompass larger and larger segments of the social world. Throughout this expansion, finance lays claims to new territories by redefining old problems as those of the flow of money that then must be addressed by the logic and tools of finance. As financialization is moving forward, many of its instruments, developed in the specific context of a particular financial transaction come to be utilized for novel purposes, outside their original context. In this paper, I will focus on credit ratings, a tool developed for credit transactions. When credit ratings are used in new ways outside the context of credit granting, I call it off-label use.

Off-label use is a common form of financial innovation. An early case of off-label use was the adoption of commodities futures contracts created to smooth the lumpy production cycle in agriculture to any commodity and finally to any financial instrument (Pinzur 2016). The securitization of mortgages is another example of off-label use, as mortgages originally devised to promote home ownership were repurposed as investment vehicles (Quinn 2010). In both cases, the shift to off-label usage created new opportunities as well as problems. For the case of futures contracts, new opportunities for risk hedging were

---

us-10th-circuit/1211589.html> (Accessed February 6, 2017). A subsequent investigation by the U.S. Justice Department Antitrust Division did not result in criminal charges. The literature on this issue is split. There is general agreement that unsolicited ratings are lower, but it is hard to separate self-selection (bad companies not soliciting ratings) and agency pressure. Another way of achieving similar results is "notching." It is the practice of automatically reducing the rating given by another rating agency for a structured financial collateral such as a CDO. This too is an off label use of corporate ratings.

[2] The rating is created to serve the investor. The interest of the investor is not necessarily the same as that of the regulator. For instance, the regulator has an overriding interest in minimizing global, systemic risk, while investors want to maximize their own local profit (Partnoy 1999; Darbellay and Partnoy 2012).

coupled with the blurring between investment and gambling as the expansion of futures detached these transactions from the actual, physical commodities as collateral. The securitization of mortgages made mortgage lending less dependent on local savings, but weakened the incentives of the mortgage originator to lend prudently. In both of these examples, however, the original and the new purpose remained within the world of finance and going off-label did not stretch the instrument beyond financial markets.

This is true for some off-label use of credit ratings as well. Adapting corporate ratings to structured finance keeps ratings within financial markets, so is the rating used as a blueprint in the construction of products like Residential Mortgage-Backed Securities (RMBS) or Collateralized Debt Obligations (CDO). Their use as a coercive marketing tool stretches "the label" much further. The off-label use of credit ratings of individuals, however, moves the ratings beyond the realm of finance. There is no financial theory that would argue that coercive marketing is a necessary part of financial markets.

## 2. What is Off-Label Use?

I call 'off-label' any use of a product, which is different from what it was originally intended for. Off-label use, like employing diapers as fire-retardant, tennis balls as caps on chair legs to protect floors, or baking soda as toothpaste, is quite common. The term originates in medicine, and it designates the use of drugs for purposes unapproved by the U.S. Food and Drug Administration (Cohen 1997; Henry 1999; Dresser and Frader 2009).[3] With a few exceptions, off-label use of drugs is not illegal but raises certain questions about safety and liability. Off-label use is always a matter of degree. Using Adderall or Ritalin approved for childhood attention deficit disorder to treat adult attention problems is a smaller stretch than taking anti-seizure medication to treat migraines or anti-anxiety pills as sleeping aids, and much smaller still than using antibiotics as growth promoters in animals.[4]

There is often a narrative explaining why the unintended and novel use is related to the one originally intended for the product. The new use is justified with reference to the original purpose but changing some conditions or renegotiating certain boundaries. Where childhood ends and adult age begins for amphetamines or methylphenidates is not a simple question. Migraines and seizures can also be hard to tell apart. In some cases, such as using epilepsy medication for weight loss, there is no attempt to link the new use to the origi-

[3] To some extent I am using the term 'off-label' off-label, that is, in a way that was originally not intended. In rhetoric, this is often referred to as metaphoric extension.

[4] Off-label uses often become on-label, as it happened with aspirin that was prescribed to lower the risk of heart attack, and was approved by the FDA for that purpose in 1998.

nal indication and the justification simply rests on claims that "it works."[5] What is on- and what is off-label use when it comes to pharmaceuticals are decided by the precise language of written regulations that try to stake out clearly the conditions and boundaries of product use. In the area of credit rating, I will talk about off-label use when credit rating is not used to directly aid lenders to assess the likelihood of future good payment behavior of prospective borrowers.

In this paper, I argue that the extension of the use of credit ratings beyond this limited purpose has negative side effects, and I will focus on two types in particular. The first type is when negative effects present in the original – on label – use spread with the off-label application to new areas. If Ritalin causes abdominal pain, its extension to adults transfers this problem to a new population. For credit ratings, this means that with the proliferation of credit ratings, errors in them that used to plague only the appropriate assessment of creditworthiness now will propagate to new contexts unrelated to credit.

The second type is when off-label use has an effect on an instrument's utility in its original context. For instance, the overuse of antibiotics not just bestows its side effects such as diarrhea or nausea to new users but it also weakens its use in curing infections in humans. In the case of antibiotics, the mechanism through which off-label uses (such as its use for human sickness most likely to be caused by viral infection or for growth promotion in food animals) influence on-label use is well known. Bacteria, through natural selection, become immune to overused antibiotics, making drugs less effective over time. There is a negative feedback. Success earlier breeds failure later.

For credit rating, there is a positive feedback in the very process of credit evaluation: a poor credit record elicits a lower rating and worse payment conditions, reducing the chances of better future behavior. At the same time, good behavior earns higher rating, higher rating results in more favorable conditions which makes better future performance easier. Positive feedback can result in vicious or virtuous cycles trapping people in poverty or locking in their privileges all the while accentuating initial advantages (DiPrete and Eirich 2006; Pager and Shepherd 2008).[6] But while this positive feedback may be insidious for society at large and some individuals in particular, it actually makes credit rating, to some extent, more and not less effective as a tool of prediction. If good ratings make you a better and bad ratings a worse borrower, that will make the ratings predict more accurately. Because of this positive feedback, the efficacy of the instrument and its social utility become misaligned. Trapping people in good or bad cycles (a social bad) will make ratings more effective. In other words, ratings not just predict what will happen, but, to some extent, they

[5] See e.g. <http://scienceblogs.com/retrospectacle/2006/08/29/common-drugs-being-used-offlab> (Accessed February 7, 2017).

[6] The large literature on path dependence and increasing returns to scale also useful in understanding these processes (Arthur 1994; Rona-Tas 1997).

also help it come true. In this sense, they are "performative." Off-label use of credit rating further augments this positive feedback and we call the result "enhanced performativity."[7] By introducing additional penalties in other areas of life for a missed loan payment or a default, off-label use of ratings also acts as a powerful disciplining device in lending, provided that people understand all consequences of their bad credit behavior.

In what follows, I will explain how off-label use of credit rating of individuals creates negative side effects, through the mechanisms of error propagation and performativity. Then I will make an argument for banning the off-label use of credit ratings through stronger privacy protection.

## 3. Error Propagation

When used on-label, credit ratings, be it individual credit scores, corporate or sovereign ratings, perform two essential functions; one is passive, and the other is active. In their passive role, they are an assessment of a potential borrower's creditworthiness given some general assumptions about how the world works.[8] They are descriptions and some kind of reflections of the would-be borrowers' past and current conditions. Ratings try to capture all relevant information and organize them into a prediction of the applicant's future credit behavior, which is expected to unfold under the circumstances captured by the rating.

The most common complaint about the on-label use of ratings is that the measures used to calculate it are full of errors and those measurement errors add to the prediction error. Error of either type (measurement or prediction) can be thought of as being akin to a pill's side effect. Ratings in time t ($R_t$) are calculated as a function of a set of characteristics observed in time t ($X_t$) with some measurement ($\varepsilon_t$ ) and prediction ($e_t$) error.

$$R_t = \beta(X_t + \varepsilon_t) + e_t$$

Even if the errors are overall small and random, there is the problem of what one may call the 'asymmetry of aggregation.' The asymmetry of aggregation means that consequences affect borrowers at the individual level, while large lenders like banks and investment funds, face these errors only in the aggregate. Thus while borrowers care how ratings err in their own, individual case,

[7] MacKenzie (2006) calls positive feedback Barnesian performativity. It is also known as self-fulfilling prophecy (Merton 1948). Negative feedback is sometimes referred to as "negative performativity" or "self-frustrating prophecy." In economic sociology, performativity refers to the power of economic ideas to shape reality in line with their own predictions (Callon 1998, 2008; MacKenzie et al 2007; Rona-Tas and Guseva 2014).

[8] For instance, it is assumed that the borrowers are individually responsible for payment, that their trajectories are unrelated, that people possess a stable character, that the economy as a whole functions predictably etc.

large lenders worry only how their debtors' combined effect appears in their overall portfolio. In other words, if some debtors are overcharged for a loan because the record shows them less creditworthy than they are, it is little consolation for those borrowers that there are other debtors whose record err in the opposite direction. For the lender, however, these errors cancel out and undercharging some clients makes little difference overall, as long as others are willing to pay more than they should.

Error propagation points out that the error in credit ratings then will influence off-label calculations as well. If data on which the ratings are based have faults, ratings themselves will be biased and when they are reused in their new context they will remain faulty. The measurement error will not go away even if the off-label calculation, while using the same characteristics, calculates its own weights ($\beta'$).

$$O_t = \beta'(X_t + \varepsilon_t) + e'_t = \beta' X_t + \beta' \varepsilon_t + e'_t$$

Even if the measurement error is random and is unrelated to $X$ for a set of cases, the error for a particular case will be strongly related for the same case across various off-label calculations. In other words, if the characteristics used to evaluate a person, company or country are faulty all the evaluations based on those characteristics will be biased in the same direction for that actor (Gallagher 2006). This way, an error in a person's credit record, wrong information about a corporate issuer or sovereign will distort all assessments based on those data.

## 4. Enhanced Performativity

Ratings, however, not just describe but also shape reality. They have consequences, which is why ratings exist in the first place. Ratings guide actions of lenders and, in principle, they help avoid bad borrowers and aid in recognizing good ones. Yet ratings also have effects on the very thing they are supposed to assess; they do influence creditworthiness. Borrowers, be they individuals or corporations, receiving bad ratings will have difficulty finding new credit on favorable terms or any credit at all. Tough conditions meted out as punishment for earlier non-payments make it harder to meet payment obligations later and will make nonpayment more likely. This is why the corporate rating agencies claim they cannot give timely downgrades: they do not want to push an already troubled company further into the abyss. Bad rating is not just a consequence of poor creditworthiness but it can be its cause as well (Manso 2013). This can lead to a vicious cycle: bad borrowers can become worse and worse, even if their circumstances or intentions do not change at all.

It is equally true that a good rating can result in credit that is more favorable and thus making it easier to keep one's good rating. This virtuous cycle can be

as self-sustaining as the vicious one, although the cycles don't go on forever, and at one point will come to a stop. Performativity in virtuous cycles may mask fundamental weaknesses for some time and may result in over-borrowing and then financial troubles that stop the upward spiral. Vicious cycles too can end, as undervalued fundamentals may eventually put a break on the downward slide.

$$R_t = \beta X_t + e_t$$

$$X_t = \gamma_1 R_{t-1} + \gamma_2 \theta_{t-1} + e'_t$$

Ratings are caused by the characteristics observed, but those characteristics are a function of earlier ratings and some other factors ($\theta_{t-1}$). When used off-label, to judge (some of) those other factors, those ratings also become influenced by earlier ones.

$$\theta_{t-1} = \lambda_1 R_{t-2} + e''_{t-1}$$

And hence, ratings will be driven to a large extent by earlier ratings

$$R_t = \beta\gamma_1 R_{t-1} + \beta\gamma_2\lambda_1 R_{t-2} + (\beta\gamma_2 e''_{t-1} \quad + \beta e'_t + e_t)$$

Ratings are both descriptive and performative, and through the positive feedback, the rating helps its own accuracy as the rating turns into a self-fulfilling prophecy. Performativity may not be good for the borrower or the lender[9], but it is good for the rating, at least in the short run.

One can argue that performativity of ratings is both inevitable and unimportant, or, at least, not substantial enough to counterbalance the desirable properties of a well-constructed rating system, the same way as using antibiotics does far more good than the bad it causes by slowly building up resistance to it in common strains of bacteria. Furthermore, bad ratings are likely to have a deterrent effect. Receiving a bad rating may keep borrowers in line and once they get out of line, the penalty of bad rating protects future lenders even if it makes it harder for the offender to meet the missed obligation.

The extent to which ratings are performative depends on how important they are for the debtor, how much they influence their lives beyond credit. Does a bad rating make only credit more expensive, as intended, or does it make other things more costly as well? Is it just a penalty or a more pervasive force that influences directly the debtor's earning power, not just requiring more payment

[9] The vicious cycle may deprive the lender from the payment he is due. A non-payment on a different account that results in lower scores and higher charges on that account will drain resources away from the accounts that were paid promptly and now they may go into default. Vicious cycles also squeeze potential good customers out of the market.

for the loan but also further undercutting the debtor's ability to service the debt?[10] Off-label use makes ratings more important and influential.

## 5. Consumer Ratings

In this paper we will focus on consumer credit ratings known as credit scores. Individuals, unlike corporations, live in multiple worlds that are often sharply delineated and are evaluated by multiple criteria such as emotional, aesthetic, moral, hedonic or intellectual, not just economic ones. Off-label use, therefore, is easier to demonstrate for them than for corporations that are first and foremost economic creatures. In our conclusion, however, we will speculate what general lessons we may draw for corporate and sovereign ratings.

### 5.1 Credit Scores

Credit scores were introduced in the US during World War II, when banks lost many of their skilled credit officers to the war effort. The credit scorecard was an attempt to make do with an unskilled staff by providing clear instructions on how to decide on credit applications. Credit scoring was then developed into a statistical instrument by engineer Bill Fair and mathematician Earl Isaac, who founded the Fair, Isaac Company (FICO) in 1956. Credit scoring, however, did not become standard industry practice until the U.S. Congress passed the Equal Credit Opportunity Act (ECOA) of 1974. In the rules of its implementation, the Federal Reserve stipulated that lenders who use *empirically derived demonstrably and statistically sound* credit scores to make loan decisions would be immune to discrimination suits. Lenders initially reluctant to hand over lending decisions to computers quickly understood the benefits of this legal protection and as computer technology advanced and became more helpful and affordable, credit scoring became standard practice in consumer lending. In 1995 Fannie Mae and Freddie Mac adopted the FICO score as part of its underwriting, making credit scores indispensable in mortgage lending. By then all three large consumer credit registries (Equifax, Experian and TransUnion) used FICO to distill credit histories into a single number.

Today, the FICO credit score is based on only credit behavior entered in the registry, and is often referred to as behavior score and according to FICO, does not include any socio-demographic variable. Lenders can have their own scoring models, but ECOA and its later amendments are very specific about what information these models can and cannot include. Credit scores are calculated using a prediction function that uses a set of predictor variables to locate an

[10] The debt bondage and debtors' prisons were ways to address this very problem. Maiming or killing debtors would have left lenders without the ability to recover their losses.

individual on a scale assigning a score that expresses the likelihood that the would-be borrower will pay his debt on time. The statistical function linking the predictors to this outcome is most commonly a nonlinear probability function, such as logistic regression.[11] In all cases, the calculation of the score involves comparing the applicant to earlier applicants whose handling of their loan is already known and who were similar to the current applicant when they applied for the loan.

## 5.2 Error

Quality problems of the data on which FICO scores are based have been well documented and have a long history. Aggregate data presented in 1989 by the Associated Credit Bureaus[12] about its members showed that consumers requested some 9 million credit reports, or about two percent of the 450 million reports generated annually at that time. They disputed about 3 million of those reports and about 2 million were altered in the verification process.[13] A later study by a consumer advocate group (Cassady and Mierzwinski 2004) asked adults in 30 states to order their credit reports and complete a survey on the reports' accuracy.[14] They found that 25 percent of the credit reports surveyed contained serious errors that could result in the denial of credit, such as false delinquencies or accounts that did not belong to the consumer. A more recent study from 2005 by the Government Accounting Office (GAO 2005) found that 18 percent of those surveyed had disputed data on their records and 69 percent of those were subsequently corrected. As providing data to the credit bureaus is voluntary, lenders often ignore requests for using the standard format. Lenders can be also selective in reporting following their own interest, and because it is voluntary, credit bureaus are not in a strong position to enforce accuracy standards. With increasing concentration in lending, the largest lenders have also less and less incentive to share information with smaller lenders, who have little to offer to but much more to gain from the credit bureaus (Rona-Tas and Guseva 2014).

One serious problem, that all lenders wish did not exist, is "broken records." Data are provided to credit bureaus on transactions involving accounts with a particular lender and a borrower. The transaction then must be added to the

[11] There are many other statistical functions that one can use, including discriminant analysis, probit regression, neural networks models, genetic algorithm, as well as linear programming, recursive partitioning algorithm, support vector machine and nearest neighbor analysis.

[12] ACB is a trade association representing consumer reporting agencies. Now ACB is called the Consumer Data Industry Association (<http://www.cdiaonline.org>).

[13] Some of these changes were the result of the routine updating of files with the most current information.

[14] The study may overestimate problems for reasons of self-selection into the sample and because it accepts the person's judgment about the veracity of the information.

record of the individual borrower. Broken records are created when transactions are mismatched with persons. There are two types of broken records: the first is where information for a person is filed in two or more separate records, as if he were two or more people. The second is when pieces of information about different persons are filed as if they belonged to the same person. Matching information with people is especially challenging in the U.S. because there is no national identity card or identification number and the only unique identifier is one's Social Security Number issued for pension and tax purposes. Even though the law until the 1980s explicitly prohibited their use as personal identification, today the Social Security Number is used for identification by credit bureaus along with many other institutions. Other identifiers are especially unreliable in the U.S., as Americans move often and addresses and phone numbers change quickly. Furthermore, in a country of immigrants, names are constantly misspelled.[15] Credit bureaus use complex algorithms to match incoming information – that does not necessarily include the Social Security Number – with the proper record, but still about five to ten percent of the records are broken. The growing problem of identity theft will result in even more broken records.

In 2004, Avery, Calem, and Canner of the Federal Reserve Board conducted a study on data accuracy and its effect on access to credit using a sample of credit records of 301,000 individuals. They found among other things that 2.7 percent of the large creditors reported only negative information and failed to provide positive data. Six percent of large creditors did not report small delinquencies. Some large lenders, such as Sallie Mae, the biggest provider of student loans, withheld information altogether from two of the three credit bureaus, and credit limits, an important piece of information,[16] were missing from 19 percent of revolving accounts affecting 46 percent of individuals in the sample. Moreover, data from collection agencies were reported inconsistently (sometimes a report was filed sometimes it was not) and collection information was often duplicated when collection claims were transferred from one collection agency to another, creating multiple derogatory information for a single offense.[17] And, finally, the inquiries initiated by the subject almost never indicated the type of loan the applicant sought, therefore, in 99 percent of the cases it was impossible to distinguish "rate shopping" from rejections.[18] The Federal

[15] The credit report of the author from Experian lists nine variants of his name. His report from Experian is filed under a wrong name and his correct name is listed as "formerly known as."

[16] Calculation of credit utilization depends on knowing the credit limit. Someone who has a balance of $1000 on a credit card with a credit line of $1000 will be judged differently than someone who has the same outstanding amount with $100,000 available in credit.

[17] Records of medical collections – one of the most common type – are especially error prone.

[18] Credit records include the number of inquiries submitted for that record to the bureau. Too many inquiries relative to the number of loans extended will lower the credit score, unless the inquiries are for the same purpose within a three-week window, in which case, they are considered "rate shopping," and have no effect on the score. Many inquiries against few

Trade Commission has conducted five reports between 2004 and 2012 on the accuracy of credit histories and found various discrepancies. In its latest, 2012 study, the Federal Trade Commission found that 21 percent of consumers had identified errors that subsequently resulted in a change in their record,[19] 13 percent had a change that affected their credit score and five percent of consumers moved into a lower risk tier in a way that would make a significant difference in future borrowing (FTC 2012).[20]

Finally, the authors of the report observed that the overall effect of bad data varied for different social groups. The ones that were most hurt by bad data were the young, the poor, minorities and those with lower credit scores and thinner credit files. Thin credit files means that there are little data that can be used to predict the loan applicants' future behavior. There are various ways that credit bureaus deal with what they call "thin files," and most involve an attempt to predict the missing information. In effect, the credit bureau must guess a counterfactual: what kind of credit history this person would have had, had he had one. That introduces a new type of error, a guessing error, in the predictors.[21]

Errors are mostly not random mistakes but they are the results of the social conditions that generate the data in the registries and are driven by the fact that the registries are first and foremost there to serve lenders.

## 5.3 Performativity

Data on performativity of credit scores are much weaker. Separating the two directions of causation, one going from behavior to score and the other pointing from score to behavior, is difficult. The empirical complexity is further exacerbated by the problem of adverse selection (Akerlof 1970; Stiglitz and Weiss 1980), the tendency that worse borrowers with higher bent for not paying are more likely to take on loans offered with worse conditions, knowing well they will not pay it back anyway. There is evidence, however, that loan conditions have an effect on customers' subsequent payment behavior and since credit scores decide the terms given to borrowers, credit scores, with the intervention of credit conditions, indirectly influence credit behavior. In one study, Karlan and Zinman (2009) show that higher interest rates and faster repayment sched-

loans are thought to reflect some bad information not in the registry but that lenders found out somehow.

[19] The three companies are notoriously recalcitrant when it comes to consumer complaints. Most of their customer service is outsourced to India, Chile and the Philippines, and requests for corrections may take years. The bureaus are better off settling court cases with the most persistent complainers than committing to investigating thoroughly every complaint brought to them (Kroft 2013; Morgenson 2014).

[20] The study that relied on consumers identifying and disputing errors in their own records did not cover mistakes that benefited them.

[21] This guessing is done by statistical estimation.

ules, two common consequences of lower credit scores, when randomly assigned to borrowers, increase the likelihood of default. In another study of mortgage and car loans Edelberg (2004) finds evidence that loan terms have independent effect on payment behavior.

Literature assessing the debt trap created by payday lending also supplies some evidence. Payday lenders give short-term cash loans (typically for 30 days) at interest rates of around 400 percent but occasionally up to 1000 annual percentage rate (APR) (Ernst et al. 2004; Stegman 2007). Payday borrowers routinely fall into a debt trap where new debts must be taken out just to finance earlier ones. Payday lenders have various products designed to facilitate the rollover or churning of loans (Parrish and King 2009), and they use a special scoring system by Teletrack that emphasizes payment behavior common for subprime clients borrowing from car title lenders, rent-to-own establishments and other fringe financial institutions (Agarwal et al. 2009). Payday borrowing itself, however, is a consequence of low FICO scores as those with poor scores are locked out of the traditional sources of credit. So payday lending establishes performativity of ratings two ways. First, the high frequency of churning shows that high interest rates have consequences for indebtedness and creditworthiness, and second, it demonstrates the power of ratings to bar people from less usurious sources of borrowing such as bank loans.

## 6. Off-Label Use of Consumer Credit Ratings

The three off-label uses of consumer ratings I will discuss here are auto insurance, housing rental and hiring. These do not exhaust this topic as credit ratings are also used by utility companies to determine rates, cell phone companies to establish service, the government issuing licenses or certain benefits and insurance companies calculating homeowner insurance premiums.

### 6.1 Auto Insurance

One of the most controversial off-label uses of credit scores is in determining car insurance premiums. Since the late 1980s, insurance companies include credit bureau information in their calculations. Currently, over 90 percent of automobile insurers in the U.S. employ credit history in their decision in some way. Insurance companies use the credit registry like lenders do. They request credit histories which are then processed through a scoring mechanism, called insurance scoring that is similar to credit scoring. In the case of the Big Three credit bureaus, the technology for insurance scoring, just as for credit scores, is provided by Fair, Isaac Co. The main difference between credit and insurance scores is the outcome of interest. While for credit scores credit histories are modeled to predict delinquencies, for insurance scores, the same credit histories

are used to calculate expected future insurance claims. Because insurance claims are not recorded by the credit bureaus, insurance companies must build their own data set matching credit history from the bureaus with insurance claims in their own databases.

Why do insurance companies use credit history rather than accident histories from the Motor Vehicle Registry (MVR), crime statistics or insurance claim history (the CLUE reports)?[22] The main reason is that statistical correlation between credit history and future insurance claims appears to be higher than the correlation between accident history and future claims. This seems puzzling and the insurance industry offered a series of possible reasons.

One set of explanations speculates that the credit score captures certain personality traits that are related to insurance related behavior. They claim that people with good credit history are both more responsible and stable and as a result, they drive more cautiously and are more prudent in general. This argument is based on a speculative causal narrative, and the only empirical evidence for this narrative is the correlation it is purported to explain.

There seems to be another, more plausible explanation. One must keep in mind, that insurance claims and actual accidents are not the same. There are accidents without claim, because people don't claim all accidents for various reasons, one of which is to keep their premiums down forgoing immediate financial relief for a long-term gain. Unclaimed accidents are invisible to insurance companies. People who can afford the financial shock of paying the costs of a minor accident out of pocket, will rather do that than see their insurance premium rise. Poor people, on the other hand, will more likely use their insurance because they cannot afford even a small repair bill. This suggests that credit history is a measure of poverty; low income people are more likely to have a checkered history of debt payment and more likely to need insurance to pay for harm they caused or suffered from others who are uninsured or cannot be identified. By using credit scores, the insurance company has a proxy for income and can set higher rates for poor people anticipating more claims.

Then there are claims without accident; these are false claims. As credit scores predict claims and not actual accidents, another possible explanation for the correlation is that people who don't pay their loans are the kind of people who make false – and therefore more numerous – claims. This again is likely to be correlated with having low socio-economic status.

Another justification dispenses with the causal reasoning and simply points out the poor quality of alternative data sources. Studies show that Motor Vehi-

[22] There are a series of court cases where customers question the legality and logic of using credit information for setting prices in an area that seems completely unrelated to credit but so far with little success. In its June 4, 2007 ruling the Supreme Court in Safeco v. Burr decided that insurance companies do not even have to disclose if an applicant received a worse rate or was turned down because of his credit score.

cle Registries are inaccurate missing 10 to 20 percent of traffic violations (Hartwig and Wilikinson 2003, 8).[23] So the credit record – based on voluntary reporting of lenders – is thought to be more reliable than the records kept by the government bureaucracy. Yet we have already seen that credit histories are fraught with errors. It is hard to believe that there is strong evidence for the superiority of the quality of credit records.

What remains is the empirical correlation between scores and insurance claims. Statistical studies on the predictive power of credit scores, however, are rather unsophisticated (Kellison et al. 2003; Wu and Guszcza 2003; Tillinghast-Towers Perrin 1997; Monaghan 2000; AAA 2002). They tend to show the correlation for group aggregates not for individuals.[24] This highly inflates correlation because a large portion of individual error is erased by the averages. In other cases, studies use enormous samples of individual cases to find statistically significant relationships but say nothing about goodness of fit statistics or the net contribution of credit history to overall prediction.[25]

There are other reasons why insurance companies rely on credit scores. In many states insurance rates are strongly regulated and rate changes and rating rules must be filed for approval, while underwriting rules are not. Most insurances have three rate tiers: preferred, standard and non-standard. Credit scoring is used in the process of underwriting, that is in deciding whether to offer insurance and in which tier. While ratings and rating rules (how much one has to pay once in a tier) is strongly scrutinized by regulators, underwriting rules (in which tier one should be placed) are not. To raise insurance premiums is easier by changing underwriting guidelines and classifying people in a different category than raising premium for their category (Birnbaum 2003). Credit scores with their continuous range are easy to manipulate because the insurance company can simply raise minimum score to qualify for a better tier, and push people into a worse one, where they have to pay more. Moreover, if credit scores are measures of affluence, they also help insurance companies to find customers more likely to purchase multiple services, and people tied with several insurance products to a company are less likely to shop around for better deals. People with higher credit scores, will be richer, more likely to want several products and will be more loyal. All of this has little to do with insurance risk and a lot more with profitability.

---

[23] It is not clear how this fact was derived.

[24] For instance, they present the average loss ratios for credit score groups and correlate those averages with the midpoints of the groups.

[25] In a large enough sample, any correlation, no matter how small, can be shown to be significant.

## 6.2 Rental

If lower credit scores make people pay more for insurance, they also put them at a disadvantage when they want to rent a house or an apartment. Landlords have at their disposal a series of tenant screening services offered for a fee by several hundred companies. Reports typically include four types of information: residential history, criminal background check, civil litigation (especially eviction cases) and credit reports. Some providers offer tenant scoring creating a FICO-like single number to predict the likelihood of renting to a problem tenant.[26] Tenant screening agencies are much less regulated than credit bureaus and are even more error prone (Dunn and Grabchuk 2010, 327-31).[27]

Even landlords who do not use these services are likely to check credit records of prospective renters. They want to know if the applicant who wants to rent their house or apartment is in good financial health and if he manages his finances reliably. A large indebtedness indicates that the tenant is already in financial difficulty and therefore he is more likely to fall behind on rent payments. Thus, delinquencies in servicing loans in the past may be a sign of delinquencies in paying rent in the future. Moreover, many landlords look at credit history as a measure of character and general reliability. Credit bureaus, like TransUnion, offer their own tenant scoring based on their credit records effectively reweighting their credit score models.[28] Equifax sells additional information with credit reports to landlords as a package.[29] Experian has its own rental screening operation and claims that in addition to using credit scores to predict rental behavior, rental data are included in its credit reports.[30]

Credit reports and scores are also used to screen people for federally subsidized housing. The US Department of Housing and Urban Development (HUD) recommends for owners and managers of such housing units to use credit history information. Its guidebook HUD states that "[t]he applicant

---

[26] One provider, for instance, offers a 3-digit rental score that is scaled like the FICO score (300-850) and includes the credit score in its calculation. See <http://myrental.com/reports/tenant-score/> (Accessed February 8, 2017).

[27] For instance, suppose a tenant has a dispute with the landlord and feels that she is entitled to withhold some of her rent, but they cannot agree how much. If the case goes to court, and the final judgment lets her keep 90 percent of the rent, this will be entered in New York State as a judgment against the tenant, as she still has to pay 10 percent (Lebovits and Addonizio 2012). In many cases, eviction reports include only the fact that there was an unlawful detainer suit, but not the outcome (Dunn and Grabchuk 2010). Furthermore, unlike the large credit bureaus, of which there are three, tenant screening agencies number in the hundreds, each with its own database. For consumers to monitor the quality of the tenant data these agencies keep on them and act preemptively is impossible.

[28] <http://www.transunion.com/corporate/business/solutions/propertymgt/scoring-model.page> (Accessed May 14, 2016).

[29] <http://www.equifax.com/help/forlandlords/> (accessed May 14, 2016).

[30] <http://www.experian.com/rentbureau/renter-credit.html> (accessed May 14, 2016). This takes us to turbo performativity to be discussed later.

should have a neutral or good record for a recommendation of admission…" but also stipulates that a "lack of credit history will not have any bearing on eligibility" (HUD 2003, 56; also Brown 2005).

The use of credit ratings in rental decisions creates another avenue of error propagation and enhanced performativity. Weak credit records can result in denial of housing, higher deposit requirements and a worse rent-to-value ratio. Paying more for worse housing can exacerbate the financial difficulties that lowered the scores to begin with.

## 6.3 Hiring

Employers are also heavy users of credit registries. The Fair Credit Reporting Act stipulates that they, just as landlords but unlike insurance companies, must receive written consent from the person involved. Employers often use credit histories to decide on new hires but they can inquire about current employees for any reason (but, again, only with their consent). An employer receives the standard credit report, except with the date of birth omitted.[31] At hiring, the credit history in certain cases is only one part of a more complex background check that may include the verification of educational credentials (not included in the credit file), employment history (only the name of the employer is included but not position) and even an investigation of civil and criminal judgments against the applicant and medical history (some of which may be reflected in the credit file). The employer, therefore, often uses multiple consumer reporting agencies, not just credit bureaus.

Upsurge in using credit checks by employers in employment decisions coincided with the Employee Polygraph Protection Act of 1988, which banned the use of polygraphs in employee hiring (Jones and Terris 1991). The loss of this tool spurred employers to reach for new instruments made available by advances in information technology. The initial theory was that credit reports are useful because people in financial trouble are more likely to resort to theft at the workplace (Oppler et al. 2008). Soon, the relationship between credit and work behavior became glossed in a more generalized fashion: financial history was seen as an objective measure of a person's conscientiousness and integrity (Bernerth 2012). A 2009 study of 433 firms by the Society for Human Resource Management found that 60 percent of the companies conducted credit background checks of job candidates, and 13 percent did it for all job openings. Of those companies, who used this tool selectively, almost all vetted the financial history of prospective employees for positions with financial and fiduciary responsibilities, and almost half for any senior executive position, and about a third with responsibilities involving confidential information (SHRM 2010).

[31] This is to prevent age discrimination.

Yet evidence for the predictive power of individual credit ratings to forecast job performance is weak or non-existent (Martin 2010; Aamodt 2010; Bryan and Palmer 2012). On the other hand, there is evidence that credit scores are correlated with minority status, thus suggesting that the use of credit history is a covert form of discrimination (Fellowes 2006; Bernerth 2012; Traub 2013), a concern equally present for the other off-label uses.

The use of credit information became especially problematic after the great recession that followed the subprime mortgage crisis. As more and more people defaulted on mortgages, their FICO score got downgraded, so that before 2008 15 percent of the population had scores below 600, after 2008 25 percent did. At the same time, the economic crisis made many lose their jobs who now found themselves in a financial "death spiral: the worse their debts, the harder it is to get a job to pay them off" (Glater 2009; Schoen 2010; McNamara 2010; Miller 2010). Employers insist that they avoid this Catch-22 by using common sense as they look at the reasons of the delinquencies, and treat credit problems due to unpaid medical bills differently than those rooted in gambling. Yet their main argument, unsupported by evidence, is that financial trouble gives incentives for people to engage in mischief.

## 7. From Enhanced to Turbo Performativity: Connecting Records

What we have seen so far was a loop that was completed by the individual when applying for a job, renting an apartment or taking out insurance. For most people, these are routine and necessary decisions; employment, home and insurance are hard to avoid. Yet the feedback loop can be attenuated or broken by the discretion of the employer, who can decide to hire someone with a low credit score, or a landlord who is not obliged to hold a poor score against a prospective tenant, and even insurance companies can decide to offer a better deal for good drivers with a checkered credit record. Moreover, difficulties finding employment, housing, or higher insurance premiums do not automatically translate into lower credit scores. For instance, help from family and friends can cushion the financial hardship of people who have started on this downward spiral and may allow them to climb back up. The loop is far from ironclad.

However, the death spiral is further exacerbated if not only credit records are used off-label, but if the off-label use is then fed back directly into the data that credit ratings rely on. The feedback loop would become even tighter dispensing with the attenuating social contingencies and mechanisms. For instance, if credit ratings were used to establish the size of rental deposits and insurance premiums, and then those numbers would be used to compute credit

ratings then we would come full circle.[32] This has yet to happen, and currently higher insurance premiums or rental deposits affect credit scores only indirectly, by diverting funds from credit payments.

Yet in one area, employment, direct feedback is being constructed by adding employment records to credit history further amplifying enhanced performativity. In May 2007, Equifax, one of the three giant consumer credit bureaus purchased a little known company, named TALX for 1.4 billion dollars. TALX is the country's largest payroll outsourcing firm.[33] It claims to have payroll data of 190 million employee records, covering a third of the US workforce, from about 2,000 large employers that include the US Postal Service, the Federal and State governments, most universities and colleges, all car manufacturers, McDonald's and all the major fast food companies just to name a few.[34] Equifax justified its acquisition with the value of the proprietary data TALX possesses.[35] Equifax wanted to use payroll data to enhance its credit files. A change in pay or job title could then be reflected in one's credit score immediately. In 2008, Equifax acquired Discover Source, a company processing IRS data, and in 2009, for 124 million dollars IXI, a company that gathers wealth data on consumers. A year later Equifax rolled out Decision 360, an example of turbo performativity, a new, comprehensive rating product that includes income and wealth information along with credit history. All this is legal under the Gramm-Leach-Bliley Act of 1999. This law, among other things, allows financial companies to engage in a variety of businesses, and permits affiliated companies to share personal information on clients.

Decision 360 "combines credit, macroeconomic and customer-centric information with a vast array of exclusive data to deliver the most complete picture of consumer financial health available." As the brochure explains:

> The financial landscape is increasingly complex. As a result, traditional risk management tools may no longer provide all the insight needed to make truly informed lending decisions. How a consumer managed past credit is important, but so is their willingness, ability and capacity to pay current and future obligations. In this new normal, what you need is not just a consumer "liability statement," but a more telling "income/balance sheet" and cash flow statement – *often* driven by consumer consent. [Emphasis added.]

---

[32] Enhancing credit scores with new types of information is seen as the main way to improve scores. One example of such innovation is using social network data for predicting credit behavior. FICO announced such plans, and in August 2015, Facebook acquired a patent that would use credit information of an applicant's Facebook friends to calculate a better credit score (Patent# US 20140289815 A1). Facebook sensing popular backlash, at least for now, decided against implementation.

[33] In 2012, Equifax renamed TALX to Equifax Workforce Solutions.

[34] Details can be found at <www.theworknumber.com> (Accessed May 14, 2016).

[35] Rick Smith, CEO of Equifax, conference call for investors, on February 15, 2007, <http://www.sec.gov/Archives/edgar/data/917524/000110465907011669/0001104659-07-011669.txt> (Accessed May 14, 2016).

Equifax boasts that

> the Decision 360 practice draws from a wealth of unique data sources and insights that include:
> - Exclusive access to more than $10 trillion in investable asset data [IXI].
> - 195+ million active employment records from more than 2,000 U.S. employers [TALX].
> - Tax transcript information, delivered in 24-48 hours, verified directly from the IRS [Discover Source/TALX].
> - SSN verification based on searches of more than 15 billion public/private databases, and authenticated by the Social Security Administration.
> - An extensive credit reporting database of more than 250 million consumer records [Equifax's original credit registry].[36]

The turbo performativity of comprehensive scores also amplify error propagation. An erroneous downgrade in credit scores that then produces an adverse employment decision is counted twice by Decision 360.

## 8. Conclusion

Off-label use of consumer credit ratings results in error propagation and enhanced performativity. When different metrics are tightly coupled small events can have enormous consequences and inflate initial inequalities. In the world of consumer credit, privacy laws loosen the link between different markets. Making car insurance, rental and hiring more independent from credit ratings benefits not just those who start out with a weaker rating and find it increasingly hard to get a job, a good insurance or rental, but also those who are on the other side of these transactions. By letting insurance companies use credit ratings, lenders may see their struggling borrowers' resources diverted into higher insurance premiums and away from meeting their credit obligations. In other words, off-label use creates new competition between lenders and other users of the ratings for the resources of customers sucked in the vortex of indebtedness. Privacy protection that limits the use of credit scores to their original purpose, protects customers as well as lenders and makes these markets less bifurcated and volatile.

Economic literature interested in the welfare implications of off-label use and consumer privacy is focusing on models of single markets (Calzolari and Pavan 2004; Akçura and Srinivasan 2005; Taylor 2004 and Jentzsch 2014). My two theoretical points are at odds with this literature for three reasons. First, off-label use connects two or more markets and each market may work perfectly well but their externalities spill over to and harm other markets. It may be

[36] <http://www.equifax.com/pdfs/corp/Decision-360-Brochure_051010.pdf> (Accessed May 14, 2016).

perfectly rational even optimal to use credit scores in loan and hiring decisions, but the credit and the job market are linked and decisions in one affects conditions in the other. If low scores exclude people from jobs, that makes it harder for lenders to recover their money from their unemployed clients. Second, models optimize expected utilities, in other words, want to find the largest average gain. The processes described here, while they may be optimal with respect to the average (first statistical moment), are suboptimal in the second statistical moment: they fail to minimize variance. They create divergence in outcomes in a way that amplifies small initial differences. Errors may cancel out overall, some actors will be over- others will be underrated, but over time, the same actors will be stuck with the worse-than-deserved ratings, just as the same actors will get to keep their better-than-deserved ratings. The resulting inequalities (variation in economic outcomes) and their ill effects are invisible in models that focus on averages and ignore variances. Third, most economists are concerned with one-period models, when the real process unfolds in multiple periods over time.

The European Union, with strong laws defending personal data,[37] is currently grappling with regulating off-label use of personal information,[38] and is much more alert to its dangers than the United States. Yet, even in Europe, the problem is framed in terms of privacy. In this paper, we try to argue that there is another, equally serious issue that needs to be considered, and that is cumulative economic disadvantages, an issue which goes beyond the individual's feelings of discomfort disclosing a particular piece of information in a specific transaction for fear of ill-intentioned abuse. Our claim is that the seemingly perfectly reasonable and well-meaning use of private information, even with the consent of the individual can have adverse societal consequences.

Because the two mechanisms that we identified act for corporations and sovereign states as well, albeit in different ways, some of these findings can be extended to corporate and sovereign ratings even though they are not natural persons and have no privacy rights. Error propagation for instance, is a concern when faulty corporate ratings are used for regulatory purposes. An independent regulatory assessment of RMBSs or CDOs would have increased the chances of revealing their flaws in time (for instance, that many RMBSs were based on mortgages with no (verified) income data). For companies (as opposed to structured financial investment vehicles whose performance is directly unaffected

[37] The Data Protection Directive of 1995 issued by the European Commission (Directive 95/46/EC) states that personal data must be "collected for specified, explicit and legitimate purposes and not further processed in a way incompatible with those purposes" allowing for exceptions only for historical, statistical and scientific use with appropriate safeguards (Article 6.1(b)).

[38] The Opinion of the Article 29 Data Protection Working Party on purpose limitation, issued on April 2, 2013 available at <http://ec.europa.eu/justice/data-protection/article-29/documentation/opinion-recommendation/files/2013/wp203_en.pdf> (Accessed May 14, 2016).

by their rating) enhanced performativity emerges as good ratings beget not just new investors reacting to the rating signal but – courtesy of the regulations – more conservative investors such as pension funds, whose presence is now an additional indication that the company is doing well, that then makes their access to capital easier which helps performance, leading to even better ratings. Ratings of government bonds also become a direct measure of stability and the overall performance of a country's economy. Reacting to bad ratings investors will avoid the country's bonds or will demand a higher risk premium making governments even weaker fiscally. But if these ratings are used to assess the entire economy and polity, foreign investors will take a pass also on private companies in the country creating new weaknesses in the economy that bring worse prospects for the government and its borrowing. Again, an independent political and economic assessment may lead investors in a different direction.

Using information in new ways is one of the most common forms of intellectual creativity. Innovation in applied and academic research often turns on smart ideas of how to use existing data off-label. Yet off-label uses can have serious side effects. Ratings are designed to bring stability to credit markets. Their spread to off-label uses while in the short-run can enhance their predictive powers, in the long run, because ratings also propagate errors and reinforce and magnify economic inequalities, contribute not only to a society that is less just but also to one that is ultimately less stable.

## References


AAA. 2002. *The use of credit history for personal lines insurance: Report to the National Association of Insurance Commissioners*. New York: American Academy of Actuaries, Risk Classification Subcommittee of the Property/Casualty Products, Pricing, and Market Committee. <http://www.actuary.org/pdf/casualty/credit_dec02.pdf> (Accessed May 14, 2016).

Aamodt, Michael. 2010. *Employer use of credit history as a screening tool*. Statement at the U.S. Equal Employment Opportunity Commission, October 20, Washington, D.C. <https://www.eeoc.gov/eeoc/meetings/10-20-10/aamodt.cfm> (Accessed May 14, 2016).

Agarwal, Sumit, Paige M. Skiba, and Jeremy Tobacman. 2009. Payday loans and credit cards: New liquidity and credit scoring puzzles? *American Economic Review* 99 (2): 412-17.

Akçura, M. Tolga, and Kannan Srinivasan. 2005. Customer intimacy and cross-selling strategy. *Management Science,* 51 (6): 1007-12.

Akerlof, George A. 1970. The market for lemons: Quality, uncertainty and the market mechanism. *The Quarterly Journal of Economics*, 84 (3): 488-500.

Arthur, W. Brian. 1994. *Increasing returns and path dependence in the economy*. Ann Arbor, MI: University of Michigan Press.

Avery, Robert B., Paul S. Calem, and Glenn B. Canner. 2004. Credit report accuracy and access to credit. *Federal Reserve Bulletin*: 297-322.

Bernerth, Jeremy B. 2012. Demographic variables and credit scores: An empirical study of a controversial selection tool. *International Journal of Selection and Assessment*, 20 (2): 242-46.

Birnbaum, Birny. 2003. *Insurers' use of credit scoring for homeowners insurance in Ohio: A report to the Ohio Civil Rights Commission*. Columbus, OH: Ohio Civil Rights Commission.

Brown, Maeve Elise. 2005. A stacked deck: How credit is used to screen out those most in need of federally subsidized housing. Journal of Poverty Law and Policy, September-October: 287-301.

Bryan, Laura Koppes, and Jerry K. Palmer. 2012. Do job applicant credit histories predict performance appraisal ratings or termination decisions? The Psychologist-Manager Journal: 15: 106-27.

Callon, Michel. 1998. Introduction: the embeddedness of economic markets in economics. In *The laws of the markets*, ed. Michel Callon, 1-58. Oxford: Blackwell.

Callon, Michel. 2008. What does it mean to say that economics is performative? In *Do economists make markets? On the performativity of economics,* ed. Donald MacKenzie, Fabian Muniesa and Lucia Siu, 311-57. Princeton, N.J.: Princeton University Press.

Calzolari, Giacomo and Alessandro Pavan. 2006. On the optimality of privacy in sequential contracting. *Journal of Economic Theory* 130 (1): 168-204.

Cassady, Allison and Edwin Mierzwinski. 2004. Mistakes do happen: A look at errors in consumer credit reports. Washington, D.C.: National Association of State PIRGs.

Cohen, Peter. 1997. 'Off-label' use of prescription drugs: Legal, clinical and policy considerations. *European Journal of Anaesthesiology* 14: 231-35.

Darbellay, Aline, and Frank Partnoy. 2012. Credit rating agencies and regulatory reform. San Diego Legal Studies Paper No. 12-082. <http://ssrn.com/abstract=2042111> (Accessed May 14, 2016).

Deutschmann, Christoph. 2011. Limits of financialization. *European Journal of Sociology* 52 (3): 347-89.

DiPrete, Thomas A., and Gregory M. Eirich. 2006. Cumulative advantage as a mechanism for inequality: A review of theoretical and empirical developments. *Annual Review of Sociology* 32: 271-97.

Dobbin, Frank, and Dirk Zorn. 2005. Corporate malfeasance and the myth of shareholder value. *Political Power and Social Theory* 17: 179-98.

Dresser, Rebecca, and Joel Frader. 2009. Off-label prescribing: A call for heightened professional and government oversight. *The Journal of Law, Medicine & Ethics*, 37 (3): 476-86.

Dunn, Eric, and Marina Grabchuk. 2010. Background checks and social effects: Contemporary residential tenant-screening problems in Washington State. *Seattle Journal for Social Justice*, 9 (1): Article 13. <http://digitalcommons.law.seattleu.edu/sjsj/vol9/iss1/13> (Accessed May 14, 2016).

Edelberg, Wendy. 2004. *Testing for adverse selection and moral hazard in consumer loan markets*. Divisions of Research & Statistics and Monetary Affairs, Federal Reserve Board. <http://www.federalreserve.gov/Pubs/FEDS/2004/200409/200409pap.pdf> (Accessed May 14, 2016).

Ernst, Keith, John Farris, and Uriah King. 2004. *Quantifying the economic cost of predatory payday lending*. Center for Responsible Lending. <http://www.responsiblelending.org/payday-lending/research-analysis/CRLpaydaylendingstudy121803.pdf> (Accessed May 14, 2016).

Fellowes, Matt. 2006. Credit scores, reports, and getting ahead in America. Washington, D.C.: Brookings Institution, Survey Series. <https://www.brookings.edu/wp-content/uploads/2016/06/20060501_creditscores.pdf> (Accessed May 14, 2016).

Fligstein, Neil J. 1990. *The transformation of corporate control*. Cambridge, MA: Harvard University Press.

Fligstein, Neil J. 2008. The finance conception of the firm. In *Financialization at work,* ed. Ismail Erturk, Julie Froud, Johal Sukhdev, Adam Leaver and Karel Williams, 307-18. London: Routledge.

Frank, Thomas. 2000. *One market under God*. New York: Doubleday.

FTC. 2008. *Report to Congress under Section 319 of the Fair and Accurate Credit Transactions Act of 2003*, December, 2008. Washington, D.C: Federal Trade Commission. <https://www.ftc.gov/reports/section-319-fair-accurate-credit-transactions-act-2003-third-interim-federal-trade> (Accessed May 14, 2016).

FTC. 2012. *Report to Congress Under Section 319 of the Fair and Accurate Credit Transactions Act of 2003*, December, 2012. Washington, D.C: Federal Trade Commission. <https://www.ftc.gov/sites/default/files/documents/reports/section-319-fair-and-accurate-credit-transactions-act-2003-fifth-interim-federal-trade-commission/130211factareport.pdf> (Accessed May 14, 2016).

Gallagher, Kelley. 2006. Rethinking the Fair Credit Reporting Act: When requesting credit reports for 'employment purposes' goes too far. *Iowa Law Review* 91: 1593-621.

GAO. 2005. *Credit reporting literacy: Consumers understood the basics but could benefit from targeted educational efforts*. Report to the Congressional Committees. Government Accounting Office, March. <http://www.gao.gov/new.items/d05223.pdf> (Accessed May 14, 2016).

Glater, Jonathan D. 2009. Another hurdle for the jobless: Credit inquiries. *The New York Times*, August 6. <http://www.nytimes.com/2009/08/07/business/07credit.html?_r=0> (Accessed May 14, 2016).

Harrington, Brooke. 2008. *Pop finance. Investment clubs and the new investor populism.* Princeton, N.J.: Princeton University Press.

Hartwig, Robert P., and Claire Wilkinson. 2003. *The use of credit information in personal lines insurance underwriting*. Insurance Issues Series, 1 / 2. New York: Insurance Information Institute.

Henry, Veronica. 1999. Off-label prescribing. Legal implications. *The Journal of Legal Medicine*, 20: 365-83.

HUD. 2003. *Public housing occupancy guidebook*. Washington, D.C.: U.S. Department of Housing and Urban Development, Office of Public and Indian Housing. Office of Public Housing and Voucher Programs, Public Housing Management and Occupancy Division.

Hyman, Louis. 2011. *Debtor nation. The history of America in red ink.* Princeton, N.J.: Princeton University Press.

Jentzsch, Nicola. 2014. Secondary use of personal data: a welfare analysis. *European Journal of Law and Economics*: 1-28.

Jones, John W., and William Terris. 1991. Selection Alternatives to the Preemployment Polygraph. In *Preemployment honesty testing: Current research and future directions*, ed. John W. Jones, 39-52. Quorum: Westport CT.

Karlan, Dean, and Jonathan Zinman. 2009. Observing unobservables: Identifying information asymmetries with a consumer credit field experiment. *Econometrica*: 77 (6):1993-2008.

Kellison, Bruce, Patrick Brockett, Seon-Hi Shin, and Shihong Li 2003. *A statistical analysis of the relationship between credit history and insurance losses*. Austin, TX: Bureau of Business Research, University of Texas at Austin.

Keister, Lisa. 2000. *Wealth in America. Trends in wealth inequality*. Cambridge: Cambridge University Press.

Krippner, Greta R. 2011. *Capitalizing on crisis the political origins of the rise of finance*. Cambridge, MA.: Harvard University Press.

Kroft, Steve. 2013. 40 million mistakes: Is your credit report accurate? *CBS News*, February 10. <http://www.cbsnews.com/videos/40-million-mistakes-is-your-credit-report-accurate-50140748/> (Accessed May 14, 2016).

Lebovits, Gerald, and Jen M. Addonizio. 2012. *The use of tenant screening reports and tenant blacklisting*. LeagalEase, The New York State Bar Association. <http://www.nysba.org/tenantscreening/> (Accessed May 14, 2016).

MacKenzie, Donald, Fabian Muniesa, and Lucy Siu. 2007. *Do economists make markets? On the performativity of economics*. Princeton, N.J.: Princeton University Press.

MacKenzie, Donald. 2006. *An engine, not a camera: How financial models shape markets*. Cambridge, MA: MIT Press.

Manso, Gustavo. 2013. Feedback effects of credit ratings. *Journal of Financial Economics* 109: 535-48.

Martin, Andrew. 2010. As a hiring filter, credit checks draw questions. *The New York Times,* April 9. <http://www.nytimes.com/2010/04/10/business/10credit.html> (Accessed May 14, 2016).

McNamara, Kristen. 2010. Bad credit derails job seekers. *The Wall Street Journal*, March 16. <http://online.wsj.com/article/SB10001424052748703909804575123611107626180.html> (Accessed May 14, 2016).

Merton, Robert K. 1948. The self-fulfilling prophecy. *The Antioch Review*, 8 (2): 193-210.

Miller, Kathleen. 2010. Keeping credit checks in check. Potential employers hold financial history against applicants. Associated Press, March 7. <http://www2.ljworld.com/news/2010/mar/07/keeping-credit-checks-check/> (Accessed May 14, 2016).

Monaghan, James E. 2000. The impact of personal credit history on loss performance in personal lines. CASForum. Washington, D.C.: Casualty Actuarial Society. <http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.376.3569&rep=rep1&type=pdf#page=85> (Accessed May 14, 2016).

Morgenson, Gretchen. 2014. Held captive by flawed credit reports. *The New York Times*, June 21. <http://www.nytimes.com/2014/06/22/business/held-captive-by-flawed-credit-reports.html> (Accessed May 14, 2016).

Oppler, Edward S., Brian D. Lyons, Debora A. Ricks, and Scott H. Oppler. 2008. The relationship between financial history and counterproductive work behavior. *International Journal of Selection and Assessment* 16 (4): 416-20.

Pager, Devah, and Hana Shepherd. 2008. The sociology of discrimination: Racial discrimination in employment, housing, credit, and consumer markets. *Annual Review of Sociology* 34: 181-209.

Parrish, Leslie, and Uriah King. 2009. *Phantom demand: Short-term due date generates need for repeat payday loans, accounting for 76 percent of total volume*. Washington, D.C.: Center for Responsible Lending. <www.responsiblelending.org/payday-lending/research-analysis/phantom-demand-final.pdf> (Accessed May 14, 2016).

Partnoy, Frank. 1999. The Siskel and Ebert of financial markets: Two thumbs down for the credit rating agencies. *Washington University Law Quarterly*, 77 (3): 619-712.

Pinzur, David. 2016. *Building Futures Markets: Infrastructure and Outcome on the Chicago Board of Trade and New Orleans Cotton Exchange, 1856-1916*. Unpublished Dissertation, University of California, San Diego.

Quinn, Sarah. 2010. *Government Policy, Housing, and the Origins of Securitization, 1780-1968*. Unpublished Dissertation, University of California, Berkeley.

Rona-Tas, Akos. 1997. Path dependence and capital theory: Sociology of the post-communist economic transformation. *East European Politics and Societies* 12: 107-31.

Rona-Tas, Akos, and Alya Guseva. 2014. *Plastic money: Constructing markets for credit cards in eight postcommunist societies.* Palo Alto, CA: Stanford University Press.

Schoen, John W. 2010. Bad credit sidelines some jobless workers. *MSNBC News*, February 23. <http://www.msnbc.msn.com/id/35512038/ns/business-eye_on_the_economy> (Accessed May 14, 2016).

SHRM. 2010. Background checking: Conducting credit background checks. Alexandria, VA: Society for Human Resource Management. <https://www.shrm.org/hr-today/trends-and-forecasting/research-and-surveys/Documents/2012Background Check_Criminal_FINAL.pptx> (Accessed May 14, 2016).

Stegman, Michael A., and Robert Faris. 2003. Payday lending: A business model that encourages chronic borrowing. *Economic Development Quarterly* 17 (1): 8-32.

Stiglitz, Joseph E., and Andrew Weiss. 1981. Credit rationing in markets with imperfect information. *The American Economic Review* 71 (3): 393-410.

Sullivan, Teresa A., Elizabeth Warren, and Jay Lawrence Westbrook. 2000. *The fragile middle class: Americans in debt*. Stanford, CT: Yale University Press.

Taylor, Curtis R. 2004. Consumer privacy and the market for customer information. *RAND Journal of Economics* 35 (4): 631-50.

Tillinghast-Towers Perrin. 1997. Credit reports and insurance underwriting. *NAIC White Papers*. Kansas City, MO: National Association of Insurance Commissioners.

Traub, Amy. 2013. Discredited. How employment credit checks keep qualified workers out of a job. *Demos* 7. <http://www.demos.org/discredited-how-employment-credit-checks-keep-qualified-workers-out-job> (Accessed May 14, 2016).

Wu, Cheng-Sheng Peter, and James Guszcza. 2003. Does credit score really explain insurance losses? Multivariate analysis from a data mining point of view. CAS Forum, Casualty Actuarial Society, 113-37. <http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.376.2294&rep=rep1&type=pdf#page=117> (Accessed May 14, 2016).

Historical Social Research
Historische Sozialforschung

## Other articles published in this Special Issue:



For further information on our journal, including tables of contents, article abstracts, and our extensive online archive, please visit http://www.gesis.org/en/hsr.