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Rational Calculation and Trust: A Comparative Institutional Analysis of Emerging Credit Card Markets in Post-Socialist Societies

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Abstract

Economics postulates that economic actors are rational and their decisions can always be reduced to an underlying formal structure. Recently, behavioral economics has questioned these assumptions pointing to cognitive limitations. That rationality is a variable is our point of departure, but we emphasize the role of institutions rather than individual cognitive capacities. Actors make decisions in a formally rational manner turning uncertainty into calculable risk, whenever their social environment lets them do that.

We investigate how banks decide on creditworthiness of credit card applicants in nine emerging markets. Banks are super-rational actors with unusual capacities to use formal rational models. Moreover, credit cards give banks powerful incentives to utilize these models, and technology (credit scoring) is available. Yet few banks in our study rely primarily or entirely on formalized models. We investigate the reasons for this and the ways banks handle uncertainty inherent in general purpose, no collateral, consumer lending in these markets.

I. Introduction

Economics postulates that economic actors are rational and their decisions can always be reduced to an underlying formal structure. Recently, behavioral economics has questioned these assumptions pointing to cognitive limitations. That rationality is a variable is our point of departure, but we emphasize the role of institutions rather than individual cognitive capacities. Actors make decisions in a formally rational manner turning uncertainty into calculable risk, whenever their social environment lets them do that.

We investigate how banks decide on creditworthiness of credit card applicants in six emerging markets in Central and Eastern Europe.[1] Banks are super-rational actors with unusual capacities to use formal rational models. Moreover, credit cards give banks powerful incentives to utilize these models, and technology (credit scoring) is available. When do banks rely primarily or entirely on formalized models and when do they turn to some form of trust? And how do they handle uncertainty inherent in general purpose, no collateral, consumer lending in these markets?

II. Credit as a theoretical problem

Credit is central in economic life. Credit allows for transactions over time. Without it actors would not be able to spend money they don't yet have, use future income to cover their present expenses. Lending on interest, once a moral sin frowned upon by almost everyone from Plato to the Pope and banned or strictly regulated from Hammurabi to latter day usury laws, is now an essential service and as ubiquitous as the blue-white-and-gold logo of VISA or the orange-and-red balls of MasterCard. But while lending presents us with some fascinating historical questions about norms and preferences (Gelpi and Julien-Labruyère 2000, Rona-Tas forthcoming), it also presents an equally interesting puzzle about rational calculation. Lending involves uncertainty. When lending money, banks cannot be certain borrowers will be willing and able to pay the loan back. Banks face uncertainty and to stay in business they must be able to see the future and predict what their clients are going to do.

However, bank credit is an exceptionally interesting topic theoretically not just because of the problem it raises for rational calculation, but also because of the difficulties it does not pose for rationality. First of all, financial institutions are super-rational actors.[2] While individuals are known to be hampered by all forms of cognitive limitations, prone to simple errors even when they are aware of the rules rational

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[1] Our project began in 2002 and it is now in its final phase. The project included interviews in nine countries in more than 90 banks with risk managers in charge of consumer lending, as well as managers in charge of card operations. We also interviewed several bank officers in local branches. While our project also asked about consumer credit in general, it concentrated on credit cards. In this article we will present results from Russia, Ukraine, Bulgaria, Hungary, Czech Republic and Poland. More information is available on the project web site http://socsci2.ucsdd.edu/%Earonatas/project/.

[2] As Stinchcombe pointed out: unlike what economists would want us to believe, organizations are more rational than individuals (Swedberg 1990).

calculation should follow (Kahneman, Slovic and Tversky 1982; Dawes and Kagan 1988), economic organizations with their trained staffs can avoid many of the same pitfalls. Unlike ordinary people, financial institutions keep detailed records and have the capacity to calculate the most complex optimizing algorithms. Banks are also consumers of economic theory; they read and sometimes implement what economists, those tireless promoters of rational decision making, advise.

Moreover, lending money is by and large free of the other two chief cognitive scourges of rational decision-making: ambivalence and ambiguity. Ambivalence, the inability to assign clear utilities to outcomes is hardly at issue here: preferences are complete, transitive and context independent, transactions are fully monetized and financial institutions are rarely confused whether they want to earn more or less money on the transaction. Banks know what they want. Ambiguity, the inability to properly map out all the options and interpret the choice situation, is minimal. [3] The borrower either pays or does not, and once one adds to this the dimension of the timing of the payment, the decision space is fairly complete. The possibility of disagreement over what constitutes payment is quite limited. If the amount is disbursed by the borrower on time, there is no further question about the "quality" of the payment. It is clear what is what and what the options are. [4]

Because bank credit is so rationalized in all other aspects, it becomes the ideal window into the problem of uncertainty, as our focus on uncertainty is not obscured by other problems. To use the language of experimentation: most other factors of trouble are controlled for.

A. Screening and sanctioning

But how big of a problem is uncertainty in lending? Can't banks simply solve this quandary by proper sanctioning? Why can't banks punish non-payers making default too costly (after the fact)? Surely, proper sanctions are important but not sufficient. Even in countries, with effective system of credit bureaus, collection agencies, and legal enforcement, sanctioning alone is not a viable strategy, much less so in emerging markets. Even in the US, recovering damages and punishing guilty clients is quite expensive, and though appealing to credit agencies to undermine clients' future chances of obtaining credit is cheaper, it does not compensate banks for their losses. In credit card markets, the economics of sanctioning is even more daunting, given the large number of small loans lenders must manage. In the early years of the credit card, issuers tried to rely exclusively on ex-post sanctions with disastrous results. Mailing unsolicited cards to a mass of unscreened potential customers in the late 1950s and early 1960s resulted in rampant fraud and enormous financial losses for the credit card pioneers (Mandell 1990; Krumme 1987; Nocera 1994).

A natural experiment in South Korea where in the late 1990s credit card lenders issued credit cards without screening to expand the market quickly for years revealed another reason why post-hoc sanctioning alone is insufficient. Cheered on by the

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[3] The common usage of the term ambiguity in the literature (as in Fox and Tversky 1995) refers to what I call uncertainty. My concept of ambiguity is closer to the one found in Ball-Rokeach 1973

[4] One could and, maybe should, argue that the rationality of financial institutions, and the virtual absence of ambivalence and ambiguity should not be seen as natural characteristics of bank lending and that they can be just as problematic as uncertainty.

government, Korean banks and credit card companies handed out cards for the asking between 1998 and 2002 to find an alarming sudden increase in defaults. It became soon obvious that above a certain threshold of loan failures, people stop paying their debts simply because they see that many others don't pay and go unpunished. It becomes normal not to pay, and once that happens banks are powerless. The problem ceases to be the individual's fault and become a political issue where banks must share the blame for the ever rising default rate and the government will be under pressure to step in which is what happened in South Korea. Screening therefore is necessary to keep defaults within bounds; it is a precondition for the lender's ability to sanction.

B. Uncertainty in lending

As long as defaults are rare and dispersed, the nature of uncertainty in lending to consumers is simplified by the fact that the default of one borrower can be seen as independent of the default of another. Under these conditions uncertainty in credit markets take two forms.

1. Strategic uncertainty

Strategic uncertainty is traceable to information asymmetry and the bank's ignorance about the intentions and character of the borrower. The resulting adverse selection – too many applicants with no intentions of paying the loan back -- and moral hazard – the problem of deciding not to pay after the loan is given – has been discussed extensively (Akerlof 1970, Stiglitz and Weiss 1981). Both problems loom large in credit card lending (Ausubel 1991, Ausubel 1999, Evans and Schmalensee 1999). Because credit cards are issued to individuals for unspecified, general use, rather than for particular transactions or even for a specific time period, pre-existing opportunism, is not tempered by a business plan or the threat of the loss of collateral as in, for instance, mortgage markets, where the lender can foreclose on the property in case of default. And because there are fewer strings attached to credit card borrowing, the credit card for many becomes the lender of last resort and when in trouble, people pile debt on their credit cards and stop paying credit card bills first.

2. Ecological uncertainty

Ecological uncertainty emanates from the lender's lack of knowledge of exogenous circumstances beyond anyone's control. Many people default because of circumstances no one can foresee. Losing one's job, other financial emergencies, grave crises in the economy, as it happened in economies such as Argentina, Thailand, Mexico or Russia, or erratic and drastic policy changes that are frequent in emerging markets. Credit card defaults are notorious for their sensitivity to unemployment and other adverse macro-economic changes.

C. Risk and uncertainty

How do lenders solve the problem of uncertainty in credit card markets?[5] Mainstream economic theory claims that actors can always reduce uncertainty to

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[5] The following discussion is based on my earlier article with Alya Guseva (Guseva and Rona-Tas 2001).

calculable risk by forming subjective probability judgments (Hirshleifer and Shapiro 1977).[6] Once probability estimates are available, rational calculation can proceed without difficulty. This economic view of uncertainty is founded on a subjectivist notion of probability. It maintains that since any form of uncertainty is ignorance, and ignorance is a state of mind, "probability measures the confidence that a particular individual has in the truth of a particular proposition" (Savage 1954:3). Thus, with some introspection, we can always transform shapeless uncertainty into quantified risk and arrive at a likelihood estimate that expresses our uncertainty as a number between 0 and 1. There are two serious, interrelated flaws to this argument: it leads to infinite regress, and as a result, it cannot address the problem of coordination.

The first problem arises because even if we are able to come up with a probability judgment, we are often uncertain about the judgment itself. This invites a second-order probability judgment that estimates how confident we are that our probability judgment is correct. This in turn calls for a third-order probability judgment, and thus we are sliding down the chute of an infinite regress (Savage 1954:58). The psychological literature shows that the empirical relationship between the accuracy of a probability judgment and our confidence that the judgment is correct is slightly negative (Plous 1993**:**217-230; Brenner, Koehler, Liberman and Tversky 1996), suggesting that only those who are really wrong are truly confident.

The second problem emerges from the first. We may be able to express our subjective ignorance with a numeric value, but this will hardly suffice in an organizational setting where there must be some coordination of probability judgments, so that people can understand, monitor, dispute and build on others' decisions. Without a transparent and mutually agreed upon process of calculating probabilities, it is impossible to argue and defend loan decisions, train and monitor loan officers or aggregate experiences in lending.

The history of the use of probability models in credit granting in the US suggests that its success was due precisely to its perception as an "objective" method that withstands legal challenges of personal bias. Subjective probability theory may be able to reduce inconsistency of probability judgments in the case of a single person's mind, but it cannot reduce such inconsistencies across individuals (High 1990). Thus, while it may be possible as a cognitive exercise to reduce uncertainty to some calculus of risk all the time,[7] it practical value depends on certain – institutional – conditions.

The idea that institutions are the cure for bounded rationality has been the foundation of new institutional economics (NIE) (Williamson 1975; Williamson 1993). There are three ways my approach diverges from the mainstream of NIE.[8] First, I am skeptical about its functionalist belief already discarded by its historical wing (North 1990) that existing institutions necessarily minimize transaction cost. NIE deploys evolutionary theory to argue this point. It is either the blind force of natural selection or the smart, adaptive learning of actors that guarantees the economic optimality of

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[6] Note that risk carries no negative connotations. Risk here is not synonymous with danger but with quantifiable ignorance about something either good or bad.

[7] Extension of the subjectivist model to real uncertainty yields optimizing rules that are non-unique ((Wald 1950; Arrow and Hurwicz 1972; Gilboa and Schmeidler 1989). In real life, the fact that there is no single best solution further exacerbates the coordination problem.

[8] In fact I am parting here with a wider swath of literature that DiMaggio (1998) calls rational action neoinstitutionalism.

institutions. I am not disputing that evolutionary processes can exist and can produce optimal outcomes. My claim is whether they do or do not is an empirical question; it should be studied rather than assumed. I also disagree with NIE that institutions are remedies for market failure. Market success is equally based on institutions. Institutions are underpinning even the least regulated markets. At the most fundamental level, the information economic actors use to make decisions are pre-processed by institutions. Finally, I take issue with NIE on calculability. NIE starts from bounded rationality, but then it insists that problem is either solved by institutions or is placed outside the scope of economics. The central idea of transaction cost is an attempt to render calculable impediments to market transactions. Yet transaction costs are notorious for eluding precise measurement because often the very same cognitive limitations that call for the institutions, -- e.g., uncertainty over the quality of a product or over the intentions of another actor, -- prevent us from finding out how much damage we would have likely suffered had we gone through with the transaction without the help of institutions.

1. Frank Knight's theory

To specify the conditions that allow for risk calculation, I turn to Knight's classic distinction between risk and uncertainty: in situations of risk, the decision-maker is able to assign useful probabilities to future events on the basis of the known distribution of outcomes in a group of trials; in situations of uncertainty, such probabilities cannot be assigned in any meaningful way (Knight 1957[1921]; see also Keynes 1963[1921]; Beckert 1996; Langlois and Cosgel 1993; Runde 1998). To reduce uncertainty to risk the following three conditions must be present,[9] the first two pertaining to the validity of probability estimates, the third to their reliability:

a) Similarity across cases

The event to be predicted must be available in a proper classification that makes it a member of a larger class of similar events. For credit cards, this implies that other, previous clients must be classified in a way that allows the current applicant to be seen as highly comparable with members of one subset. This requires standardization, which, in turn, calls for institutions that gather and verify data, and affix and maintain standardized labels.

b) Similarity over time

The extrapolation of future behavior from past experiences requires stability—a situation when the world today and yesterday is not very much different from what it will be tomorrow. Institutions ensure stability.

c) Sufficiently large number of past observations

This ensures that individual idiosyncrasies will cancel each other out, making probability calculation not just valid but reliable. This is problematic for any new market.

In the US, banks can rely on commercial enterprises (such as other banks and credit reporting agencies) that gather and standardize information about clients. IRS and

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[9] We assume that the cases are independent. If they are not, as it happens in a portfolio of loans to related companies, the calculation of probabilities runs up against the added problem of complexity.

employer organizations can confirm the veracity of the information provided by the client. Given the American economy's stability, which allows for inferences from the past to the future, banks are able to calculate the chances they take by extending credit to new clients. Those probabilities then can be factored into their prices. Thus, to a large extent, American banks are able to turn uncertainty into calculable risk. Indeed, American banks use credit scoring (Mays 2001; Thomas 1992; Lewis 1992), a statistical calculation of the probability of default, to decide whether and with what conditions to grant credit cards.

When institutions that can homogenize past empirical observations and maintain stability over time are weak or nonexistent, economic actors (banks or clients) are not faced with risk but with radical uncertainty, a form of ignorance that does not allow for calculation. This is what one finds in many transition economies, where central institutions that could play a key role in standardization and verification of information (most importantly state agencies) are dismantled and rebuilt with varying success. Moreover, the very point of large scale economic, political and social transformations, such as the post-socialist one is to make the future radically dissimilar from the past subverting extrapolations from past to future. Finally, brand new markets such as these are also missing the last necessary condition for risk calculation—a large enough number of past observations.

D. Trust

Whenever uncertainty cannot be reduced to calculable risk, economic actors must rely on trust to sustain cooperation and economic transactions. I define trust as positive expectations in the face of uncertainty emerging from social relations. These expectations are good intent, competence (ability) and accountability (availability of the object of trust for sanctioning). This notion of trust contrasts with the usual conception of formalized rational calculation. My goal is to highlight the precise difficulty rational calculation confronts in this particular case (intractable probabilities). I do not claim that trust is blind (Simmel 1950), but it always involves a "leap of faith" (Moellering 2006 p.109). Trust is not calculative in the formal sense, but it is "studied" (Sabel 1992:318). Whether one focuses on people or institutions, especially banks, one finds that both seek good information whenever possible, and neither ignores such information if they get it. Trust is not routinized but it is far from arbitrary. It must be justifiable, but actors understand that following rigid rules to calculate risk would not lead to good results.

E. Probability calculus vs. trust

Rational probability calculus and trust based judgment proceed differently in handling uncertainty (see Figure 1). The decision-making process based on trust, gathers diagnostic information about dissimilar cases, and renders case-specific decisions in the form of individual judgments, reducing complexity only in the act of reaching the decision. The transactions resulting from trust-based decision-making are embedded and low in number, making breach of trust non-insurable and non-tradable. Rational calculation, on the other hand, relies on formal institutions. It is based on survey information about homogeneous cases, and the decision is specific to a category of cases. The actual decision-making may be much more complex than in the case of trust-based judgments, but since it takes the form of routinized calculations (e.g., complex statistical

models), the complexity is reduced at the stage of framing the decision. Decisions based on calculation are justified in terms of statistical correlation, whereas those based on trust are defended by causal narratives.

Figure 1.
Summary of Differences between Rational Calculation and Trust in Lending.

Aspect of Lending	Rational Calculation	Trust
Form of ignorance	Risk	Uncertainty
Preconditions	Formal institutions	Social networks
Decision making		
--- cases	Homogenous, classifiable	Heterogeneous, dissimilar, unique
--- information	Width, survey	Depth, diagnostic
--- reduction of complexity	In framing the problem	In solving the problem
--- process	Routinized, calculation	Judgment, discretion
--- decision	Category specific	Case specific
--- justification	Correlation	Causal narrative
Resulting transactions		
----quantity	High	Low
--- nature	Disembedded	Embedded
--- loss	Insurable	Non-insurable
--- commodification (secondary markets)	Possible	Impossible
---- loan officer	Unskilled, less supervised	Skilled, more strictly supervised
--- clientele	Lower status overall, more diversity	High status overall, less diversity

One could object that to the extent to which the two procedures are functionally equivalent, the differences are theoretically uninteresting. We know that people do not actually work out optimization problems, but they may act "as if" they did (Friedman 1964). But there are significant consequences to the manner in which the decision was made. The two are not functionally equivalent in ways that matter to actors. Rational calculation results in disembedded and numerous transactions, which can be insured and commodified: they can be bought and sold on secondary markets. Trust based decisions are embedded, and therefore are much more limited in numbers and do not allow for secondary markets. In credit markets that are based on trust, decision makers have greater latitude with respect to both borrowers and their own supervisors. Their knowledge and skills are valued more and thus they tend to have more training. Because trust based lending uses social networks and those are organized on the basis of social similarity, the clientele of trust based lenders will be more like them, and therefore they as a group will be more homogenous socially. Access to credit will be restricted not across the board,

but unevenly, following the web of social ties, and distant social groups will be excluded from lending more than closer ones.

This analytic distinction between rational calculation and trust does not deny the possibility that intermediate forms of lending can exist. In fact, there are many ways trust based decision making can be made more formalized with the help of certain rules. Yet there is a qualitative jump with the introduction of statistical models, which draws an unmistakable boundary between the two.

Thus I take a "social cognitive" approach to trust. Just as the calculation of risk, trust is solving the cognitive problem – uncertainty. However, I believe that it is institutions and social networks and not individual psychology that determine the possible solutions to this problem.

III. History of the shift from trust to rational calculation

Historically lending was trust-based, and trust, in turn, rested on the foundation of physical or social proximity as well as shared beliefs and norms of lender and borrower (Greif 1989, Muldrew 1998; Olegario 1999, Guinnane 2002, Hoffman, Postel-Vinay and Rosenthal 2000). Creditor and debtor were members of the same community. When lenders sought to expand their reach, and began to lend to strangers, they resorted to patching the holes in the connecting fabric of the social web. Their solution was to link the social networks of lenders and borrowers. For instance, Lewis Tappan's Mercantile Agency, one of the first credit reporting agency in the world, founded in 1841 in New York, used local credit reporters whose job was to investigate each applicant by interviewing them and gathering information from their friends, neighbors, grocers and postmasters, people in everyday contact with the applicant (Foulke 1941; Norris 1978; Madison 1974; Madison 1975). The reporter, who often himself had the acquaintance of the applicant then wrote a report describing in detail the applicant's character, financial situation, past and present legal problems, business acumen and everything else that could shed light on his creditworthiness. The relationship between the reporter and the community was fraught with tensions. Many regarded reporters as snitches who, by trading in trust, broke trust in the community sowing seeds of fear and suspicion.

The information from the reporters was then compiled in regular bulletins by the agency and was sold to subscribers, who initially were exempt from being reported on, and who were also networked among each other, which created the problem that they would share the information they gleaned from the bulletins reducing the number of paying customers (Norris p.26.)

A. The rise of statistical credit scoring

The kind of statistical decision making in credit transactions that replaced social networks with statistical categories was not widely used until the 1970s. Using numbers to evaluate creditworthiness is a much earlier development. R.G. Dun, the founder of Dun and Bradstreet, one of the largest business credit reporting firms today, used a rating scheme as early as the 1860s. Nevertheless, Dun's ratings were primarily a way to simplify and summarize information about individual cases.

Statistical credit scoring emerged in the United States, from operations research, a field dedicated to turn science into social technologies (Mirowski 1999; Fortun and Schweber 1993). The first attempt at credit scoring dates back to 1941, when David

Durand at the National Bureau of Economic Research devised a statistical method to investigate how good and bad loans differ on various characteristics using a chi-square test (Durand 1941). These statistical calculations required a tremendous amount of time and effort in the pre-computer age and banks showed very little interest in replacing the trained judgment of their loan officers with tedious computations based on mathematical procedures most bankers at the time found hard to comprehend. The technique was developed by the founders of the Fair, Isaac Company in California in the 1950s (Poon 2007). Originally, it produced a card that in the pre-computer age, communicated the weights or points to be assigned to each answer to every question on the application form. Later the process migrated from paper to the computer screen, but the statistical model used in credit scoring is still often referred to as the 'score card.'

Initially, banks had little interest in the method. In 1974, during the congressional hearings leading to the Equal Credit Opportunity Act (ECOA 1974), Robert Myers, an industry representative explained that credit scoring would result in the:

> "…disruption of the judgmental system's foundation. Traditionally, judgmental systems have operated under the assumption that the experienced loan officer or credit manager can use his professional instincts to screen credit risks. This flexible policy allows the managers to occasionally take a chance on a poor risk applicant if the manager has a "hunch" the applicant will repay. Similarly, if all indices of creditworthiness are positive but the manager has an intuitive feeling that the loan should be denied, the loan is denied. It is this subjective elasticity which has made judgmental systems attractive to many creditors. Several creditors who use judgmental systems consider informality and flexibility to be the system's major assets." (ECOA 1974:399.)

In other words, the technology would strip banks of the discretion to lend freely. But because the legislature's main concern was eradicating discrimination in lending, replacing the socially tainted, subjective judgment of human lenders with the "scientific and objective method" of credit scoring produced by machinery prevailed. In the US, the Equal Credit Opportunity Act (ECOA) of 1974, made it legal to judge people not on individual information but on their membership in certain statistical aggregates. To monitor the fairness of lending, the U.S. Congress demanded that decision-making in credit granting be made transparent. Statistical credit scoring was offered as a solution that could protect lenders from law suits. Regulation B, the document by the Federal Reserve outlining the details of how to implement ECOA, defined what "empirically derived and demonstrably statistically sound" (EDDSS) systems are (Federal Reserve 1985). Lenders using EDDSS credit scoring had to give up some discretion over their lending, but they gained not just legal immunity but two other benefits as well. Credit scoring, because of its transparency, allowed bank managers greater control over loan officers. And more importantly, credit scoring cut lending costs considerably. This last benefit of scoring proved to be crucial for the credit card market. Credit card lending is small potatoes compared to business lending and requires a large upfront investment. Therefore to make it profitable, it needs volume. Credit scoring allowed for lending on a mass scale. The main beneficiary was the credit card in existence since 1958, which started to grow at an enormous speed in the 1980s. The technology got a second boost in 1995, when Freddie Mac, the giant, federally chartered mortgage lender, informed its

partner institutions about the advantages of credit scoring in mortgage lending. Since then, mortgages require credit scoring.[10]

Credit scoring has been spreading fast all over the world. Fair Isaac Co. is now a large multinational, present in over sixty countries. Credit card giants Visa, MasterCard, American Express expect their partner lenders to use the technology and the soon to be introduced regulations by the Bank of International Settlement on risk management for banks (Basel 2) will make it hard for banks all over the world to avoid credit scoring (Allen et al. 2004). Today this technology is used to prognosticate not just about individual customers, but about companies and even entire countries.

There are two types of scoring models: application or generic and behavioral models. Application or generic models use socio-demographic data to estimate the risk of bad credit behavior. This is the type of model that is used almost exclusively in emerging markets where people have no extensive recorded credit history. Behavioral models use information on past credit behavior to estimate the probability of an applicant's mishandling of the loan. In the U.S., behavioral models dominate. The probability model deployed to predict the borrower's future behavior is usually a logistic regression that assigns a weight to each predictor variable.[11] Armed with these weights, the bank calculates the weighted sum of the applicant's characteristics. The resulting credit score, (in the US a number between 200 and 900 but this range varies slightly with the scoring system) is then evaluated against a cut off point (usually around 650). Scores just below the cut off point may be overridden giving some marginal discretion back to loan officers. Credit scores can also decide not just whether but under what condition the applicant will receive the loan.

All scoring systems suffer from the problem of selection bias. The people who are turned down for loans have no subsequent credit history. The analysis is always based on the probability of default given that one received the loan. Yet loan officers need to know the probability of failure to pay given that one applied for the loan. Scoring professionals are aware of this problem and they are trying to get around it, with little success.[12] There are also various modeling assumptions, such as the additivity of the independent variables or the shape of the unobserved probability distribution of payment behavior, that seem quite arbitrary and follow only statistical convenience rather than any considerations for good lending.

Credit scoring systems have created their own market. Banks can purchase their generic or customized scoring systems or they can develop their own. There are over 60 systems available on the market and most are produced by American companies. The largest is Fair and Isaac Co. and it is present in 21 countries outside the US.

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[10] While no collateral, general purpose credit card lending does require careful screening of applicants, it is not entirely clear why mortgage lending is improved by this technology. Because banks own the property until it is paid in full and can sell it if the borrower defaults, their main risk comes not from non-payment but from adverse changes in the real estate market.

[11] Discriminant analysis is also used, along with many other, more exotic methods that include neural networks, genetic algorithm, nearest neighbor analysis, linear programming and recursive partitioning algorithm. For a more on these methods see Rona-Tas 2007.

[12] The econometric literature on sample selection correction offers no silver bullet (for a review of the various problems see Stolzenberg and Relles 1997).

1. The clinical vs. actuarial prediction debate

From the outset, there was a debate whether scoring systems can be as accurate as the judgment of experienced loan officers. Clearly, if scoring were much worse in predicting who will default, its other advantages may not be sufficient to persuade lenders to implement it. A long line of literature in cognitive psychology from the 1950s (Meehl 1954) investigated the accuracy of statistical methods in various settings. (Dawes, Faust and Meehl 1989). In 2000, a meta-analysis of 136 psychological studies comparing clinical judgment with mechanical prediction found that

> "Superiority for mechanical-prediction techniques was consistent, regardless of the judgment task, type of judges, judges' experience, or the types of data being combined." (Grove et al. 2000:19.)[13]

In lending, the superior predictive power of statistical calculation has become an article of faith. The following points have been suggested to favor actuarial methods (Somerville and Taffler 1995; Chandler and Coffman 1979):

- statistical or actuarial methods are more accurate
- clinical or judgmental assessments are overly pessimistic because they focus too much on negatives
- they are unbiased, "objective", or at least can be monitored for the exclusion of certain criteria thought to be discriminating
- consistent across officers making their decisions both more defensible and allowing for accumulation of experiences across officers and correction of mistakes
- less intrusive because it requires less information
- cheaper and quicker
- loan officers need less training and they are easier to supervise
- and finally, it has been argued that statistical models do exactly what humans do, except they do it better.

Defenders of human judgment (Capon 1982; Taylor 1979) on the other hand, have pointed out that expert judgment

- judges individuals and not categories
- is more flexible and can factor in changing conditions
- judges outliers better
- results in decisions more comprehensible to clients.

This last point was made especially important by ECOA, which emphasized the protection of borrowers from lender discrimination. ECOA requires lenders to explain their negative decisions to applicants, so that the applicant can see that it was reached in a non-discriminatory fashion, and, equally importantly, to allow applicants to improve their creditworthiness. By using credit scoring, both intentions of ECOA may be thwarted (Taylor 1979). Lenders rarely divulge all the details of their credit scoring models fearing that other banks may appropriate their scoring system, but more to the point, that

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[13] Of the 136 studies, up to one half showed models to outperform humans and up to 1 in 7 found humans doing better, depending on what difference one considers large enough as evidence. The rest showed the two roughly equal. Only 5 studies included in the analysis were economic related. In four, the model did better, but only in two was there more than a marginal difference.

customers with full understanding of scoring begin to game the system to their own advantage. Borrowers must believe in the fairness of a process that they cannot understand.[14]

Empirical research on the accuracy of credit scoring compared to human judgment is not as thorough as one might surmise from literature reviews (Johnson 1992; Liu 2001; Hand and Henley 1997; Rosenberg and Gleit 1994, Chandler and Coffman 1979:2). Most evidence comes from research done by Fair, Isaac Co., the main vendor of the technology and conducting a proper comparison must surmount formidable methodological difficulties or carries high costs (see Rona-Tas 2007).

B. Alternatives to credit scoring

The claim of cognitive predictive superiority of statistical prediction over human judgment ignores the work of social institutions that prepare and collect the data and keep the future similar to the past. Indeed, experiments carefully control for these variables. In a typical experiment, data is clean and given and the process unfolds in a stable environment. But there are at least two other aspects of decision making that these experiments ignore, each can improve human judgment. These are incentives and collective decision making. If individual decision makers have high incentives to predict well and serious penalty for mistakes, they either improve rapidly or through 'natural selection' exit. By the same token, if the cognitive capacity of a single credit officer limits his or her ability to make the proper judgment consultation or collective decision making may improve the decisions. These two mechanisms point to two roads, lenders could have taken as alternatives to credit scoring.

The first is a simple commission system where loan officers can decide on loan applications whichever way they see fit and get compensated by the results. Because consumer lending involves many small transactions, no default can be large enough to deal a serious blow to a bank. If banks let officers make their own judgment calls but monitor carefully the performance of their borrowers and their loan officers, they can avoid big losses.

The second is decision by committee. Large, corporate loans are often decided by committees. In Ukraine, until recently, all loans, including consumer loans over a not very high threshold were brought in front of a loan committee and the decision was taken by vote. While this is more cumbersome, current practices of countersigning requirements where lending decisions must be made by at least two bank employees are a simplified version of the committee method.

Both the commission and the committee method would have preserved judgment and trust as a key element in lending.

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[14] American consumers until recently could not request to see their credit scores. The Fair Credit Reporting Act of 1996 amended several times by Congress, now provides consumers access to their scores. Scores must be disclosed to the consumer for a fee and without a charge if the consumer is unemployed, on public assistance or if the consumer believes the report is inaccurate or the report could lead to fraud. Customers can also request a free report if their application was turned down. When in 2000, the state of California mandated that mortgage lenders disclose credit scores regardless of how they decide on their applications, credit bureaus bowed to pressure and started to sell scores on line, with long explanations about credit scoring without explaining how exactly they calculate the final figure. See e.g., http://www.experian.com/ or http://www.equifax.com/.

IV. The institutional preconditions of credit scoring

In the following section, I will discuss four institutional conditions of credit scoring; credit bureaus, efficient tax system, solid banking system and overall stability. Each institutional condition corresponds to one or two of the Knightian theoretical conditions. Credit bureaus aggregate information to create sufficiently large numbers and allow the proper sorting of people on the dependent variable of credit behavior (similarity across cases). An efficient tax system helps in sorting people properly on one key independent variable, income. The banking system by keeping accounts contributes to both ends. Economic and political stability is necessary for extrapolating future behavior from past performance (similarity across time).

A. Cooperation in credit reporting

For credit scoring to work properly lenders must pool information. Without pooling of information, lenders can learn little about an applicant's dealings with other lenders. Having this information reduces the adverse selection problem. The sharing of credit information among banks discourages non- and late payment; borrowers know that bad behavior has consequences no matter where they go for their next loan. This cuts down on moral hazard. Finally, larger data bases allow lenders to build more complex and accurate statistical models. Without sharing information on consumer credit, credit card markets are deeply handicapped.

For competitors to share credit information is not a simple proposition (Klein 1992; Pagano and Jappelli 1993, Major and Rona-Tas 2007). Such information allows others to skim off the lender's best customers and avoid the worse ones without paying the price the bank left in the lurch had to pay.

There is also a problem of the size distribution of players. The smaller a bank's market share, the more it stands to gain from joining a credit bureau, because it gives up less information to others. In the US, banking has been very fragmented. The McFadden-Pepper Act of 1927 and the Banking Act of 1933 banned interstate banking. These stayed in effect until 1994, when the Riegle-Neal Interstate and Branching Efficiency Act eased restrictions somewhat, but barriers are still formidable. In the US, to get these midgets to cooperate was not easy but easier than to persuade big players to share information with smaller ones.[15] In financial markets, where a few big players dominate retail banking it is difficult to persuade large players to cooperate with smaller ones. In emerging Communist countries, banking was a state monopoly and retail banking was done through a single savings bank (OTP 60 per cent, Sporitelna, Sberbank 80 per cent). These banks, while losing ground are unwilling to share information.

In a few countries, such as the US, UK, Australia, Japan and Argentina, credit bureaus emerged as private enterprises. In most other countries, however, they were created by state intervention or are yet to appear. Credit bureaus are easier to create to track companies than individual consumers, because the latter have certain rights firms do not have, such as rights to privacy and to non-discrimination. Most companies must

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[15] Recently the U.S. banking system has become increasingly concentrated. As one might expect, this began to jeopardize the smooth cooperation of lenders in credit reporting. In 1999, big U.S. lenders began to withhold credit information from the credit bureaus and returned to proper reporting only after political arm twisting (Lazarony 2000).

have a bank that handles their accounts. Individuals bypass banks with most of their financial transactions. Many transition countries were not able to set up working credit bureaus for consumer loans. The three exceptions are Poland, the Czech Republic and Bulgaria. In the first two countries, the Bank Associations and state regulators played an important role to force large lenders to join in and so far in neither case have they been successful entirely. In Bulgaria, the Central Bank, worried about the rapid rise of consumer debt in the country has created a registry with force of law in 2004 and was not operational at the time we did our fieldwork.

In Hungary, the state ordered the banks to participate in a credit bureau for corporate credit, making it a precondition of a large bail-out operation that was necessary to save the banking system in 1994. At the same time, the government also succeeded in creating a black list, where banks would report non-paying individuals, although it is unclear to what extent large banks comply with reporting mandates. Attempts to establish a full-fledged credit registry were thwarted by the largest lenders and strict data privacy laws. Credit bureaus in Russia have been legislated but, for the sake of competition, bank's can in effect form their own credit bureaus, defeating the purpose of information sharing. In Ukraine, there is a black list organized by the National Bank but data enter slowly and with omissions, and retrieval is cumbersome.

B. Tax and credit

One of the key information lenders must have is the capacity of the borrower to carry the loan. Creditors, therefore, must have true and reliable data about the borrower's income. Truthfulness of reported income in developed economies is maintained by the cross-pressures of tax and credit. The two provide contradictory incentives. Tax forms elicit under-, credit applications over-reporting of incomes. If lenders can see what report the Tax Office received from prospective clients, and the clients filed those figures with anticipating that they will be borrowing, their true incomes will be easier to ascertain. But if the benefits of cheating on taxes vastly outweigh the benefits of credit, income tax figures will be useless for lenders.

The quality of income reporting for applicants who are employees depends on how the company that employs them file. In transition countries, where many companies cheat on payroll taxes, lenders will have a hard time figuring out just what the applicant earns. In Russia, many banks don't even ask for income data but either use information about the applicants' expenses, for instance their cell phone bill, or their occupation and education to estimate their income. This is why banks prefer to deal with employees of companies they work with in a corporate context and thus trust. For the self-employed, ascertaining income is even more difficult. Most banks in these countries have special procedures to verify incomes of the self employed. This often requires real detective work and ingenuity from the loan officer.

In countries without effective tax collection and with a large underground economy, mass credit encounters serious difficulties.

C. Banks as social accountants

Another set of central information lenders need comes from other banks and lenders. Banks are social accountants: they keep track of how much money their clients keep on their accounts (Stiglitz and Weiss 1988). When credit is issued, the lender

usually wants to know how much money applicants have on their various bank accounts. Most emerging markets introduced Western accounting standards early in the transition but many have weak banks that are undercapitalized, poorly run and insufficiently supervised. If the banking sector is weak and unreliable, that will have two deleterious consequences. On the one hand, lenders will not trust the accuracy and the veracity of what the banks report. On the other, most people will not trust their money to banks, but will keep it under their mattresses in cash, gold or some other form, and that will make it very difficult for the lender to assess the financial situation of applicants. Banks as lenders are also responsible for monitoring and keeping track of people's credit behavior. If banks don't do that properly, the dependent variable in the statistical model will suffer.

D. Economic stability

One of the reasons why credit markets and credit card markets, in particular, have been so successful in the United States is the extraordinary stability of the American economy. Without predictability of economic and political conditions, the development of credit markets is stunted. Agencies in the business of rating countries creditworthiness (such as Moody's or Standard and Poor) consider stability key for investment. But macro-economic and -political stability are crucial for consumer lending as well. If property rights are insecure, the judiciary is corrupt and tardy, if political coups and revolutions interrupt the flow of everyday life and if the economy is on a roller coaster ride, borrowers' past actions cease to be a good indicator of their future doings.

Many of these problems had been exacerbated in transition countries in the 1990s. The transition, by definition was a break with the – communist -- past. The restructuring of the economy re-routed career paths and restratified society.

In countries, like Russia, the banking system itself was one of the chief causes of instability. Russian banks were prone to go under bringing their depositors money with them. In some cases, the owner or top manager of the bank simply vanished with the funds of the depositors (Guseva and Rona-Tas 2001) . But not just crooked bankers but also fiscal crises, such as the one in Russia in 1994 and 1998, in Bulgaria in 1997, can erase people's life savings overnight. To operate a credit scoring system under such conditions is futile.

The introduction of deposit insurance has been a key step in creating financial stability. Bulgaria, Hungary, the Czech Republic and Poland all set up their deposit insurance system in the 1990s. Ukraine and Russia were the last ones to establish such a fund.

V. Credit cards without credit scoring

During the time of our research we found that most banks in Central Europe (Poland, Hungary and the Czech Republic) used some credit scoring, even though, as we will see, it was not only, and often not even the most important basis of their decisions. Bulgarian banks were less likely to use this method of rational calculation of risk, while Ukrainian and Russian banks rarely deployed this form of credit assessment.

If institutions are absent and rational calculation is impossible what can credit card issuing banks do? They either must cut the credit granting function of the credit card or they must issue credit on the basis of trust.

Revolving credit is still uncommon. Most credit cards are in effect debit cards or charge cards, and issuers make most of their money on fees and not on interest. Yet, even under these circumstances, extending credit is often unavoidable. "Technical overdraft" is common, because the clearing of transactions may take weeks because of the poor infrastructure in Ukraine or Russia. In the meantime, the card holder is de facto a borrower.

Here is a large Bulgarian bank describing its procedures to issue credit cards:

> Q: Let me ask you some questions about how you screen your applicants. How does your bank decide who should actually be issued a credit card?
>
> R 1/22: In the general case, if you have a [directly deposited] salary in our bank or a [security] deposit, you will receive this card. There is no restriction.
>
> Q: So if I have the security deposit or my salary is deposited, nothing else matters.
>
> R 1/22: Except that this institution [where you work must be] on a list. Then we have a second type of client who can receive this type of card with credit line. These are […] secured with mortgage.
>
> Q: So in fact, you have security deposit secured cards, then you have the special institutions and government ministries where the salary is the security, and then the mortgage security.
>
> R 1/22 and R2/22: Yes.
>
> Q: Any other way?
>
> R 1/22: Oh yes, simple salary without institution.
>
> Q: Then I have to ask one more question about the security deposit. If I have a credit line of say 10,000 levas then how much security deposit do I have to put down?
>
> R 2/22: 12,500.
>
> Q: That's a lot of money to put down. But if I have 12,500 to put in my account then I may not need credit from you.
>
> R 2/22: This is the world of our clients! (Laughter.) (Bank #22)

This bank uses three strategies. Two of them -- requiring real estate collateral and demanding a security deposit, -- cut the credit function of the credit card. In the case of the security deposit larger than the available credit line, it is the client who, in effect, lends the money to the bank and not the other way around.

The third uses a special kind of trust extended to people who work for government ministries and other trusted institutions. This is a form of what we call elsewhere anchoring (Guseva and Rona-Tas 2001). Banks establish cardholders' accountability by anchoring applicants in a set of social networks that serve as channels of communication that banks can use to negotiate and exchange information with, apply pressure to or threaten ill-behaved cardholders. The groups or organizations that function as anchors do not have to be legally liable for the potential misdeeds of the borrower. Nor do the anchors themselves have to sanction offenders. Simply making individuals available for sanctions is enough to increase the bank's trust.[16]

When banks issue credit cards that extend credit they often make individual judgments about applicants. They have to come to trust them to issue a card. To achieve this they use existing trust, stretch it and build new trust. Banks use existing personal

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[16] Similar credit-granting approaches have been used in China, another developing market with great potential but similar problems, including the absence of credit reporting and banks' limited credit assessment (Perkins 2003). For example, American Express made cards available only to employees who were approved by their enterprises ('That'll Do Nicely, Comrade', The Economist, August 13, 1998, p.67).

trust their managers built in the past with others. Bank managers give cards to worthy friends, clients and people they know.

Another Bulgarian bank, that started in corporate finance and then moved into the retail market, used a common strategy. It issued credit cards to the managers and top employees of its corporate clients. In fact, the bank did not offer credit cards to the general public. On its web site it advertised only debit cards, because:

R 1/24: … credit cards are only for select individuals. We usually know everything about them and it's not somebody who [applies for the] card[..]. Usually the bank says, we suggest you the card. This service is not included in the [usual] service of the bank. That's why here we don't have some software product with scoring.
Q So how does one get a credit card?
R 1/24: The bank says we are ready to offer you.
Q The center says?
R 1/24: No, no, the local office. We are ready to offer you this service. (Bank #24)

It is the local branch that offers the card because the local branch managers are the ones who know the person. There are three ways the card is offered reflecting different levels of personal trust. The first requires the client who was approached to put down a collateral equal to the credit line. The second, these are mostly credit cards used for company business, requests the company where this client is usually a manager to provide the security deposit. In neither case, does the bank take on much risk.

R 1/24: And of course we have [credit cards] without any cash collateral. In this case, we have a credit committee in the bank and they have to vote. All these people go through them. And we have limit for these kinds of cards.
[…].
Q Who is the credit committee?
R 1/24: The senior managers of the bank. For example, managers of the risk management department, corporate manager.
Q: But a branch presents it?
R 1/24: Yes a branch presents it [..]
Q: The credit committee decides by vote or by consensus?
R 1/24: I can't [tell] because I've never been included in this committee. But, for example, sometimes I can present an application form. I have to send a message by email and to explain [the case]. "This is the manager of this company, the company has this and so on." And […] the members of the committee they are prepared, they are aware about the applicant. And I'm not sure how the decision is usually made but there is [rarely] a problem. Because if I email and some of the managers do not like it, they say no, it's not suitable, and I will not present the application to all the members of the committee. (Bank #24)

The credit committee, the one that decides on larger loans and special requests, makes an individual decision on the recommendation of the branch office. This individual assessment is not limited to people working for corporate clients. The bank issues cards without scoring to other important persons.

R 1/24:… for some politicians we have cards.
Q: So for important people?
R 1/23: Yes.
Q: What kind of important people?
R 1/24: Difficult question! […] The important people […] [who are important] for now.
Q: Say, also famous artists, or pop singers or TV personalities?.
R 1/24: Yes.

[..]
Q: Is there personal contact between this manager or this important person and say you or the person who is putting forward the application? Do you see these people in person?
R 1/24: Of course, absolutely. (Bank #24)

Famous people are recruited on the basis of their individual reputation. This elite segment can be serviced on the basis of trust, without any form of credit scoring, but there has to be a personal connection between the "important" person and the some high-level bank official. Even when banks begin to use scoring techniques for regular applicants, elite customers retain their exemption from the indignities of being reduced to numbers. VIPs are almost never scored even when most of everyone else is. With the exception of a few banks owned by very large multinationals, there is a formal or informal and always classified VIP list in every bank. The VIP list includes high value customers with large accounts but also other important people known to the bank's leadership as trustworthy.

The VIP always has some personal contact with the bank's bosses. As the foreign risk manager of a Czech bank, whose job was to introduce scoring to the bank on behalf of its foreign owner, put it:

Q: Are there rules to consider personal recommendations [for credit cards]?
R 1/63: Yes. Of course.
Q: How does that work?
[…]
R 1/63: If a board member comes and says this is somebody important to us then, of course we would do that. (Bank #63)

Most of the VIPs are highly placed either in business, politics or the media. Who gets on the VIP list is completely the discretion of the top managers, although banks often allow local branch chiefs to have their own VIP list of local notables. VIPs get special terms and special services that include the credit card. If the VIP loses his important position, he rarely loses his VIP status and is kept on the VIP list on the strength of his personal ties to the bank.

Elite clients comprise a different market from the mass public. In this market, trust remains important even when rational calculation is applied to other, ordinary customers. The perception is that VIP customers are unique, they cannot be statistically classified on the basis of a few variables and they are too small in number to yield meaningful probabilities.

To get special treatment one does not have to be famous. The trust of an employee can be sufficient, but authorization is still issued at the top. A Polish banker explained:

Q: Is personal acquaintance with bank management or employees considered?
R 1/41:. They try sometimes to convince the president of the bank, for sure it is one factor, for instance if there is a long term relationship with one of the employees. (Bank #41)

Finally, banks also build new trust through an iterated game. They lock their clients in by insisting that they do not provide credit card unless they become their client's principal money manager. Clients then must deposit their incomes directly with the bank, and keep their savings accounts there. While this is a form of demanding

security deposit and provides the bank with collateral, it also allows the bank to monitor its clients' behavior closely over time. Banks begin with a small credit line, and they slowly up the credit as their trust in the client increases. In the absence of credit bureaus, creditworthiness is very hard to transport from one bank to another.

There are a series of techniques that allow banks to issue credit cards without credit scoring. As institutional conditions make it more feasible to deploy rational calculation of risk, banks retain these trust based techniques to judge customers who they can through trust.

VI. Credit cards with some credit scoring

When banks have a scoring system in place in the emerging markets we studied, it is never the only thing that decides creditworthiness. Most banks that use scoring, employ it as one piece of evidence to be weighed together with other information by the lending officer. In one Polish bank, this is how the decision is made:

Q: Is there information that comes from this personal contact? In some banks, you fill out this questionnaire but then the salesperson or the officer fills out another questionnaire about this interaction […]
R 1/49: Of course the customers have direct contact with the credit officer and in our scoring system there is a special group of fields where he can move this information you are talking about. So he can give this information to us, to headquarters, that this customer was drunk as he came in to fill out his application. […] He can put [down] this information. "The customer is known in our branch," that "he got three or four loans and all are [being] paid in time."
Q: Is this something that enters in the formal scoring system or is this something that is considered before you start the scoring?
R 1/49: No, no. It is not entered in the formal scoring system. This information is something that is used. So … in my bureau, credit scoring bureau, we have some credit analysts who verify the applications. So first, the application gets scored […] So this information is used by the credit analyst [at the headquarters, but it is] not used by formal scoring.
Q: So the credit analyst looks at the score and looks at this extra information …
R 1/49: Yes and looks for information from BIK [the credit bureau] and from the application and makes a recommendation. […] in Poland, [the phrase] is often used: a 'grey zone' for these customers. We call this the 'grey zone,' when we divide from good and bad, there is this grey zone […]. So this is a problem and these loans are verified by credit analysis.
Q: The credit analyst considers the score, considers the additional information and considers the BIK data and then makes a recommendation to the branch manager, right?
R 1/49: Yes. […] (Bank #49)

In this bank, the officer in the branch who has contact with the applicant sends the applicant's file to the credit analyst in central office. The credit analyst calculates the score from the file, then makes a judgment based not just on the score, but also on the credit bureau report (that is available in Poland) and the branch's written comments. In most cases, his judgment is not final, it is just a recommendation to the branch. The analyst's judgment is aided by certain rules. The rules give clear guidance on the low and high end of the scoring scale: the best and the worst customers are easily sorted. The middle group is the 'grey zone' where the analyst must use her judgment.

R 1/49: Let me make it clear. [He draws on a piece of paper.] This is the population. This is the good, this is the bad. In this area, the branch cannot make decision. [He points to the extreme area representing the worst customers.] In this area, for now, to validate our scorecard, it can make the decision, positive

decision. So in this area we say that this client is bad but for now of course [the branch] can make a positive decision.
[..]
Q: Ok, so then there is [recommended to] accept, decline and automatic decline. What percent of the applications are, roughly, automatic decline?
R 1/49: About three percent or five percent of all applications. It is a very small number. (Bank #49)

In this bank, the percentage of those automatically declined is only 3 to 5 percent. But there are no automatic accepts. The rest of the cases, together with the recommendation, are handed over to the branch which can now make its own decision. In this bank, about 70 percent of the cases come with a positive recommendation, but 90 percent gets accepted. Thus for 20 percent of the applicants, the local branch overrode the decision of the credit analyst in the center whose judgment was already influenced by the branch's comments.

The reason for this high acceptance rate is explained as follows:

R 1/49: [At the] branch the credit officers make interviews with the customers before the application fee paid. So the customer goes to the branch, says that he has this salary, this education levels and so on, and the credit officers say, yes, you can apply for the credit. So, the really worst customers are rejected in this first interview before they fill out the application. This is I think a common situation in every bank. (#49)

There is a pre-selection based on the local branch officer's judgment. Those that pass this screening are rarely turned down in this bank. In fact, this is where the real decision is made. It is true that the branch officers do try to second guess the center. Sending up too many automatic rejects will not reflect well on the branch. But the branch officers are not given the score and the actual model weights are top secret, known only to a select few in the risk management department. The risk managers do not want the local officers, interested in selling cards, to help applicants to get a higher score by tailoring and shaping their answers according to the model to maximize their scores. A large part of the information provided by the applicant, including some that are weighted heavily, such as education, are not verified.

The risk managers in the head office, whose job is to worry about bad loans are wary of the local officers whose job is to push the product, but they let them make the decision for several reasons. First there is a sense that the local people know their customers better than people sitting at the headquarters. Second, if it is the scoring that decides all cases, the scoring model cannot be properly validated because one will never find out about false negatives: the people rejected by the model but would, nevertheless, have done well. Because this is a new product and the banks must gain new customers, false negatives are a serious concern.

It is common practice to allow the scoring system to decide for the lowest and highest scores and use human judgment in the "grey zone." Another Polish bank gave the following estimate for its grey zone:

R 1/46: [With] Our scorecards at the moment, we would get an automation of about fifty percent of the applications. In round figures, about twenty percent would be automatically declined, thirty percent would be automatically sanctioned, and the other fifty percent would hit one or more of the rules. And they're sent for lender review. We have a number of credit analysts who literally review them using the prompts that are built into our review rules. (Bank #46)

One bank, in Poland, that has gone the furthest in our sample in mechanizing the entire lending process centralized credit assessment in a single office in the bank's headquarters. The heart of the system is the "decision engine" attended by three female officers. The "engine" is a computer algorithm that includes all the considerations the bank could formalize. The algorithm is quite complex. For people who are already clients of the bank and apply for a credit card, the engine has a simplified process, sorting them into five groups on the basis of the financial services they received from the bank (1. mortgage holders, 2. those with credit older than 6 moths, 3. those with multiple accounts, 4. those with a direct deposit account and 5. the rest. The first four are all clients in good standing). The "engine' includes scoring only for new customers, but existing customers, for instance those with a short history with the bank and with no substantial blemish on their record, can be scored as well, if scoring data are available and the score leads to a more favorable decision than the other method. The engine uses about 10 variables to construct the credit score.

The credit score, however, is only one of four factors programmed into the decision model. The model also includes the credit bureau (BIK) information as a separate consideration. As a third criterion, the engine takes into account whether the person is in any of the desirable "target groups" devised by the marketing department. This creates difficulties, because the categories useful for the marketing department are not always readily available in the system. Finally, there is a set of conditions included by the risk department picking out groups considered either high risk or especially reliable by its experts. A series of logical rules adjudicate these four criteria and the system hands down a final decision in 65 percent of the cases. The rest is given over to the credit analysts who then must decide "manually." When asked why they need these additional rules and then the manual adjustments, and why the bank cannot just simply include all these factors in a single scoring model, the answer was a series of examples involving special circumstances, where the scoring model would be in error.

R 2/43: For example, the scoring system usually assesses higher level of risk for young customers, for males, for people who rent a flat and not own a flat, people who work only for a short time, and usually, all these characteristics, separately, considered as predictors of bad behavior. But it could happen that we have an applicant who rents a house, has worked only for a short time, he is a consultant, he is usually very, very good customer, reliable customer, but it is not possible to asses him a risk, a score, in this particular case the score is simply not a good way to assess the risk.
Q: But, in principle, you could add this as another variable or variables in the model.
R 2/43: In fact, we could build a model which would have only cases, not characteristics but cases. We could consider all the possible cases and this would be best model. For example, if we had 10 characteristics and each of these characteristics had 5 possible arguments, we will have five….. such a huge number of observations [would be] needed that it is not possible to calculate it in a statistical way. It would be the best model but it is not possible to do. So we have to have a simplified score cards and then [we need to add] little changes to perform better. (Bank #43)

In fact, the best model would assess each person individually with a unique combination of the values of the predictors.

Conclusion

Consumer lending in the U.S. has undergone a revolutionary change in the two decades following the mid 1970s. Local and trust based lending has been replaced by a system of formalized credit assessment relying on probability calculations. This revolution made possible the spread of new forms of retail lending including credit card loans. In post-communist countries, modern retail banking has a short history. Consumer credit did not begin to take off until the late 1990s, when these economies started to grow and conquered inflation. In the last five years, there has been a fast expansion of consumer credit of all kinds and the credit card market in all these countries grew at a rapid pace. Most credit cards issued by banks in the region belong to one of the few international brands. The card multinationals sell their brands to banks with advice on credit assessment that advocates the use of credit scoring. Fair, Isaac and Co., Experian and countless multinational companies specialized in decision analytics, offer off-the-shelf credit scoring systems. A large portion of banks were sold to Western financial institutions that bring their own risk managers and scoring systems to their newly purchased organizations. The Basel 2 agreement recommends the use of sophisticated risk modeling for lending institutions.

Even if banks in the region were to ignore the wisdom of economic theory that rational formalization of decision making is both the proper way to describe decisions and the prescription for improving efficiency, they would still be under enormous institutional pressures to formalize their credit screening.

Banks are exceptionally rational but they know that formalization under certain circumstances has little utility. In fact, the rigidities of formalization make decisions worse. Under certain conditions, they shun formalization and when they use formal probability calculation to assess lending risk for credit card customers, they complement it with trust based judgment.

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