Improving Credit Scoring Quality through Virtual Organization (VO) Formation

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*A*bstract: A Virtual Organization (VO) that includes a set of legally independent entities, is applied to the financial services industry with an objective to improve the quality of information products and hence the social welfare. This paper proposes a simple VO that includes participants in a financial service industry such as lenders, credit bureaus, and credit information providers. The credit information providers agree to provide accurate credit information to the credit bureau in a timely manner in exchange of a payment associated with each piece of information provided. The simple VO model developed here comprises only one lender, a credit bureau, and multiple consumers with varied default probabilities. Monte Carlo simulation results suggest that a higher price of information charged to the lender by the credit bureau leads to higher credit score quality. The simulation also shows that the lender's expected loss is a U-shape function in the price of information, the only decision variable in the simple model. Based on these results the paper provides an outline of an enhanced and more realistic VO model that would have multiple competitive lenders and other agents whose decisions mutually impact each other. A new hybrid simulation tool that combines agent-based simulation and stochastic simulation is also suggested.

Keywords: Credit Bureau; Credit score; Virtual Organization; Simulation; Price of information
JEL Classifications: C63, G240, M150, O320

1. Introduction

A virtual organization (VO), as noted by Ahuja and Carley (1999), is a geographically distributed organization, whose members have a common interest or goal. The members communicate and coordinate their activities and achieve efficiencies through information technology. The members of a VO are legally independent enterprises, institutions or individuals,

who offer their core competencies as externals to a single entity referred to as VO. The entity formed by a set of contracts among various agents, is managed primarily by using feasible information and communication technologies (Oliveira & Rocha, 2001). For instance, Dell computer Inc., which has lead formation of a virtual organization (Kraemer & Dedrick, 2001) including the Dell customer service representatives, assembly crew, supplier of various components, United Parcel Services (UPS), and credit card companies, all of which collectively offer their services to the Dell and its customers. Although the participants associated with the VO may have different geographical locations or organizational ownerships, they work together seamlessly to serve customers as a single system. A classic example of VO is a virtual call center that links 36 US social security sites across the country (Pang, 2001). Incoming calls are routed to a site where employees are available to help. This VO maximizes system-wide efficiencies by reducing busy signals waiting time in the queue, and by improving service quality. VOs are attractive for their many advantages over traditional organizations (Poorkhanjani *et al.*, 2013) as they allow members to share their resources including knowledge and information across the boundaries of organizations more efficiently. They also provide regulations and protocols for members to share their resources in a trusting and mutually beneficial relationships while sharing dynamically generated information among VO members.

The implementation of VO depends mainly on the advances made in information technology over the past decade (Camarinha-Matos & Afsarmanesh, 2005). Ubiquitous computing, mobile computing and cloud computing (Mell & Grance, 2010) provide unsurpassed computational capabilities everywhere and anywhere. Additionally, these technologies make it possible to generate data, collect information and process it for suitable end uses. Information highways including high-speed and wireless networks support instant worldwide communications. Intelligent techniques such as machine learning and data mining (Fan & Bifet, 2013) help understand and interpret complex data. Multi-agent system technologies (De la Prieta *et al.*, 2013) including automated negotiation mechanisms (Kadar & Muntean, 2014), trusting management mechanisms (Yan & Prehofer, 2011) and VO management mechanisms (Lee *et al*., 2014) realize dynamic, persistent and reliable interactions among software agents representing the best interests of their users. All these technology advancements further promote the implementation and application of VO in various information/service domains, such as home care (Priego-Roche *et al.*, 2013), hurricane risk assessment (Kijewski-Correa *et al*., 2012), grid resource management (Mashayekhy and Grosu, 2014) and resource allocation in cloud computing environment (De la Prieta *et al*., 2014).

In this proposed work, we study a new VO format that can be applied to the financial services industry. In particular, we seek to improve upon the current credit scoring process practiced by various credit bureaus. Our work is both timely and broad in its application and scope as we have gradually recovered from a financial crisis of unimagined proportions, whose roots may be traced to the use or abuse of credit scoring in the context of subprime mortgage market (Utt, 2008).

This paper also contributes in presenting a simple model of credit bureaus that incorporates a fee structure for information providers. Further, the model features consumer attributes and behavior via a stochastic process. The creditworthiness of consumers depends upon a natural drift (such as age) and a natural variation (such as habits and judgments) are modeled as a Brownian motion. A jump (such as getting new job or losing a job) is modeled as a Poisson process. Simulation on the model gives some interesting and useful insights for the VO.

2. Related Work

Virtual organizations that comprise a number of geographically dispersed and autonomous individuals and organizations are formed to achieve greater efficiencies such that all the entities involved maximize their utility. In this relatively new field of exploration, we have not come across any research pertaining to VOs that deal with credit bureaus and credit scoring. Norman *et.al.* (2004) study the agent-based models using Constraint Oriented Negotiations in an Open Information System (CONOIS) to deal with an automated formation and maintenance of a VO. The CONOIS VO, a robust and resilient system, offers decision-making of individual agents, an auction mechanism for allocation of contracts, and presentation of services. Similarly, Patel, *et.al.* (2005) also present an agent-based VO using CONOIS.

Other models such as National Industrial Information Infrastructure Protocols (NIIIP), Production Planning and Management in an Extended Enterprise (PRODNET) (Camarinha-Matos & Afsarmanesh, 1998) and Virtual Enterprise Generic Applications (VEGA) (Suter, 1999) pertain to the development of IT platforms for virtual enterprises. Specifically, the NIIIP project gears towards implementation of virtual enterprises and their life cycles. Its purpose is to establish an open, standards-based software infrastructure protocol that integrates diverse processes, data, and computing environments for the U.S. manufacturing sector. The VEGA project, smaller in its scope, offers an information infrastructure to support the technical aspects and operations of virtual enterprises by employing group-ware tools and distributed architectures. The PRODNET deals with search and selection of parties, negotiation, tenders, and awarding contracts. The VEGA focuses on development of a software system for specific use of small and medium sized enterprises. Martinez, Fouletier, Park, and Favrel (2001) study the organization, evolution, and control of virtual enterprises in the context of a self-organizing multi-agent system that offers solutions in the area of task distribution and product development management.

Agent-based systems have been used to study virtual organizations by a number of researchers. Bond (1990) has proposed a computational model for organizations of cooperative agents, which captures properties of relationships and organizations. His model introduces the "concept of commitment", which represents mutually agreed upon constraints on action, belief and world state. This concept is also applicable to the information payment agreement between credit bureaus and credit information providers in the present work. Dignum *et al*. (2002) proposes a conceptual framework for agent societies, consisting of three interrelated models that distinguish between organizational and operational aspects of the domain: contract rules, society and commitments. An auction-based virtual organization formation process is also described in Zheng and Zhang (2005). However, none of these works incorporate stochastic simulation with agent-based simulation to study the behavior of a VO that produces information products in a complex environment of financial services involving credit bureaus. We attempt to fill this gap in this article.

As far as the credit risk modeling is concerned, several approaches have been used depending upon the environment and constraints. For example, Šušteršič, Mramor, and Zupan (2009) develop credit scoring models for financial institutions with suspect data set using error back propagation artificial neural networks. Yu, Wang, and Lai (2009) propose an intelligent agent-based fuzzy decision making (GDM) model to evaluate credit risk. Their approach involves aggregation of fuzzy credit risk levels and then de-fuzzying them into tangible aggregate scores. Somers and Whittaker (2007) apply a quintile regression technique to assess the retail credit risk of financial services arms with diverse distributions of ports and losses. Andrade and Thomas (2007) propose a structural credit risk model using option pricing theory. One of the parameters for the model is the

value of a consumer's reputation. In contrast, our work differs as it focuses on improving the information flow via a virtual organization. Kammoun, and Louizi (2015) comments on the development of business models of credit rating agencies (CRA). They argue that the conflict of interest caused by issuer-pay model raises concerns on the accuracy of the ratings. Fennell and Medvedev (2011) discuss alternative business models. The VO model we proposed in this work and the initial results we have found may be useful and applicable to the CRA domain as well.

3. Analysis of Credit Scoring VO Systems

Before we construct a simple model of credit bureaus, it would be helpful to discuss the current credit scoring system, the parameters, constraints and factors pertaining to a proposed credit scoring system.

3.1 Current credit scoring system

Figure 1 shows the current credit scoring system. In the center of the figure, credit bureaus maintain a database with information contributed from credit information providers including: landlords, cell-phone companies, banks, credit card companies, car loan companies, medical service providers etc. They provide information concerning customers who have previous interactions with them. The credit information includes the amount of mortgage, the current balance on a credit card account, the default action and default amount, the payment history, and consumption habits. Based on such information, the three credit reporting companies, Experian, Equifax and TransUnion, estimate the credit score, which is used by credit information users to access the creditworthiness of a customer in their decision-making process. Credit information users pay a fee to credit reporting companies for credit scores. The credit information providers and the credit information users share common member entities. For example, a credit card company belongs to both the groups since it provides information on its current credit card users and it also uses credit score to determine whether to approve credit card applications for new users.
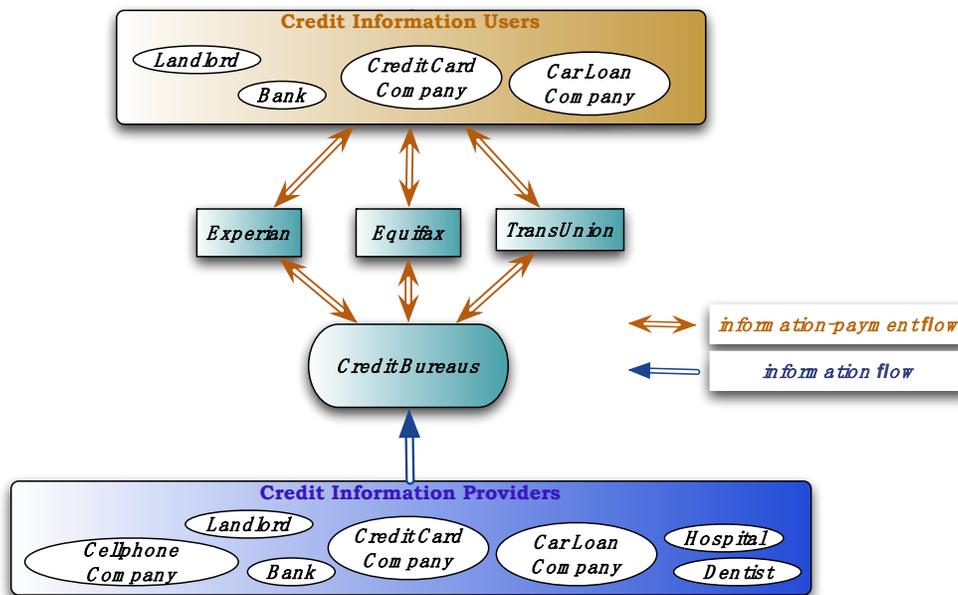
Figure 1. Current Credit Scoring System

The raw information provided by credit information providers is processed to generate a *credit score*, which is an estimate of the customer's real *creditworthiness*. The higher the quality of the credit score (implying that it is closer to the real creditworthiness of the customer), the better decision a credit information user, such as a lender can make. For instance, based on a more accurate credit score, a bank may be able to offer a lower mortgage rate to those customers who are less prone to default on future payments. This benefits both bank and the customers. In addition, an accurate credit scoring system can help modify consumer behavior and require customers to take more responsibility for their financial actions. From this perspective, an improved credit scoring system has an aggregate positive impact on the society.

The quality of the *credit score*, depends on the following two factors:

1. The quality and coverage of the credit information.

2. The process of generating credit score based on credit information.

Although there is room for improvement on both of the above factors, our primary emphasis is on improving the first one. There are problems related to missing, incomplete and inaccurate information in the existing credit scoring system, which tends to significantly distort the accuracy of the credit score. In the current system, there is not enough incentive for the information providers to supply information to the credit bureaus. As a result, not all default or corrective actions are reported to the credit bureaus. Even for those that have been reported, not all are reported in a timely manner. For example, even though a customer has made his defaulted payment to the hospital, this remedial action is often not reported although the previous default action has already been reported. This would lead to an inaccurate credit score for the customer.

There are various benefits of forming a virtual organization of credit scoring system relative to the current practices. First, the VO incentivizes information providers to supply accurate information in a timely manner in exchange for a compensation for fulfilling the obligation (the information fee proposed in Section 3). Other types of reward may also be implemented in a VO for information providers, such as exclusive membership benefits for accessing the credit score information quickly with a lower fee. Given that most information providers are also information users, a reward structure would motivate the information providers to become members of the VO. A structured set of penalties that may include higher access fee or loss of membership may be implemented to ensure that the information providers follow the VO regulations for a clean and efficient operation.

Second, a well-designed VO structure greatly facilitates the communication process among all the member participants including information providers, information users, financial agencies and credit bureaus. For instance, members can communicate using their member identification without performing cumbersome verification checks each time they need to communicate. The system can keep track of frequency and degree of their participation. If the system discovers inaccurate information or missing information, it can efficiently locate the corresponding information source and make a request for remedial actions. Without such organized channels of communication, the information reporting process could be very inefficient and inconvenient.

The third benefit of establishing a VO is to save operational cost of all participants. For example, standard communication procedure can be developed for all participants, and training can be provided for various employees of all companies who are responsible for the information communication process. In this way, the participating companies can save on their individual effort and share the resources provided by the VO.

Thus a VO facilitates communication among participants, saves their fixed and operational cost by providing resource sharing. It also provides strong motivation for participants to provide accurate information in time by positive reward and organizational policy enforcement.

3.2 Proposed VO of credit scoring system

We propose to improve the quality and increase the coverage of the credit information by forming a VO with features that ensure production of credit scores with enhanced quality. The VO structure is presented in Figure 2. This credit scoring VO includes credit bureaus, three credit reporting companies, and credit information providers. The credit bureaus agree to pay to the information providers within the VO a charge for each piece of information that they receive.

All information providers in the VO must comply with the following policies:

1. An information provider ensures the accuracy of the information it provides,

2. An information provider must provide all credit information it has in a timely manner.

There are penalties imposed on an information provider who fails to abide by the policies. In an extreme situation the provider may be deprived of the VO membership depending on the severity of the violation.
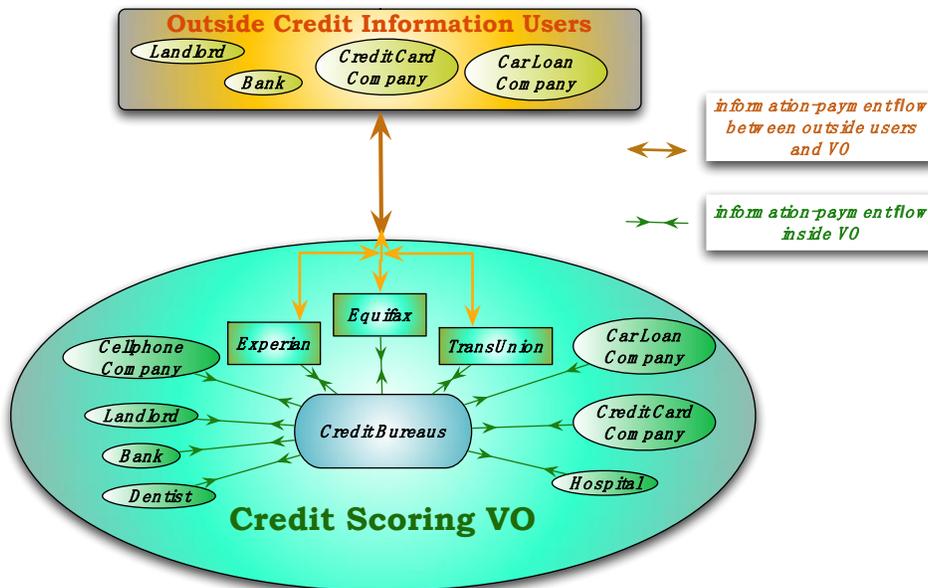
Figure 2. Credit Scoring VO

3.3 Features of the VO Model

As the first step, we build a model of the credit scoring VO, which focuses on the relationship among several key parameters including payment made to credit information provider for each piece of information, the quality (including both accuracy and coverage) of credit information received, the real creditworthiness, and the expected revenue of the users of credit scores. The model also includes the operational aspect of the VO, including the additional operational cost by following the VO policies on information accuracy, coverage and timely updating.

The next step involves implementation of a computer simulation program for the VO model in order to test, refine and adjust the simulation program to best represent the links within the VO

model preserving the autonomy of each participant in its decision making process. We pursue a hybrid approach that includes multi-agent system and stochastic processes. Each participant may assume multiple roles such as being an information provider as well as an information user. In addition, each participant, modeled as an intelligent agent, may be called for to make decisions that range from simple ones such as handling of loan applications to complex strategic ones such as joining or abandoning the VO. Other entities with large numbers and making simple decisions, such as a loan application, are modeled as part of the environment, and their behavior is described using mathematical functions.

The final step constitutes conducting simulation experiments and obtaining results and analyzing them. Based on the results, we fine-tune the model to reflect the actual circumstances. The model features the following:

- The impact of credit-scoring VO on the information quality and credit score quality.

- The effect of VO formation on the current credit score fee charged to users.

- The impact of the changes in the fee and in the quality of credit scores on the expected revenue of users for credit scores.

- The impact of credit scoring VO on the default rate, the real credit worthiness of customers, and hence the social welfare?

- Incentive to an information provider to join the VO given the additional operational cost incurred for complying with the regulations of the VO?

- Determination of the price of each piece of information to be paid to information provider.

- The effect of regulation on the information payment, on the participation in the VO, and on the quality of the credit scores.

- Best strategies for VO participants, credit information users, and customers to maximize their own utilities.

3.4 Model specifications

Consider a financial system whose participants includes one credit bureau (*bureau*), one lending institution (*lender*), a few collection agencies (*information providers*), and N consumers. A consumer seeks to draw a loan from the lender, who makes the decision to grant or deny the loan to the consumer depending on the *consumer credit score* provided by the bureau. If the consumer defaults on the loan, the information provider passes on such information to the bureau for a fee r per unit of information. The bureau processes this information to estimate the consumer credit score, which is provided to the lender at the price p. If a consumer defaults on repayment of the loan, he loses his "reputation" for credit worthiness resulting in lowering his credit score.

The bureau buys information from the information providers for a fee (*information fee*), $r(I)$, and produces the score using an internal process which is unknown to other members of the VO system. I is the information level provided by the information providers and $I \in [0,1]$, where $I = 1$ indicates all available information that the providers can provide to the bureau. More information provided by the providers helps the bureau to generate more accurate credit scores. The fee $r(I)$ is a non-decreasing function with respect to I with $r(0) = 0$ and $r(1) = r_{max}$. The information I includes current and past credit history, current and future income and assets. The bureau sells the credit score to the lender at price $p \in [0, +\infty)$, which is the only decision variable in this simplified model. Define $q(p)$ as *credit score quality*, which is a bounded and non-decreasing function with respect to p, so that $\lim_{p \to \infty} q(p) = q_{max}$, and $q(0) = q_{min}$.

Further, define $\overline{p}$ as the price such that $q(\overline{p}) \cong q_{max}$. Credit score quality captures the accuracy of information provided by the lender and measures how close the credit score estimate is to the true credit worthiness.
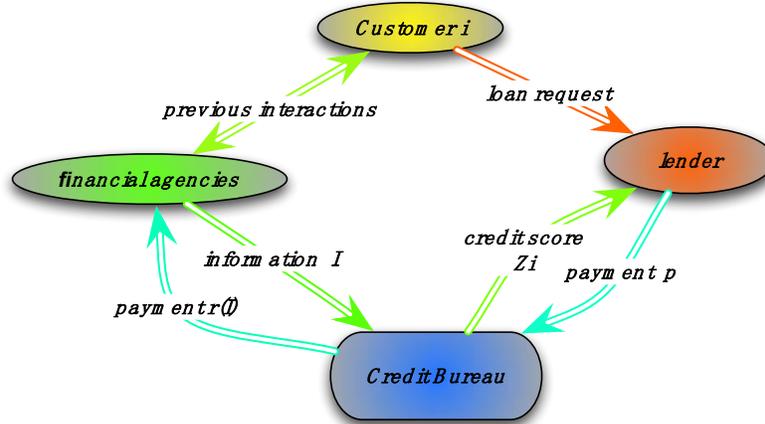
Figure 3. A Simple Model of Credit Scoring VO

There is an unobservable credit worthiness of consumer i, R_i, that comprises all the relevant information about the consumer i. The credit worthiness of the consumer i depends on some factors including a natural drift in creditworthiness (such as age), a natural variation (such as habits and judgments), modeled here by a Brownian motion, a jump (getting new job or losing a job), modeled here by a Poisson process, and credit quality.

Since the creditworthiness changes over time, we define $S_i(t)$ as the behavioral score of the consumer i at time t. Thus the creditworthiness of the consumer i at time t, $R_i(t)$ is:

$$R_i(t) = S_i(t) + e(t) \qquad (1)$$

where, $e(t)$ is the impact of exogenous factors such as economic conditions at time t on the credit-worthiness of consumer i and $S_i(t)$ satisfies the following behavioral stochastic equation:

$$dS_i(t) = \mu_i + \sigma_i dW + a_t dY_i + b\, dq(p^t) \qquad (2)$$

In the above equation, μ_i is the drift, $\sigma_i dW$ is the increment of Brownian motion, dY_i is the Poisson jump process, and $dq(p^t)$ is the quality level process. Note that $S_i(t)$ is the behavioral score of consumer i, which can vary over time regardless of the state of the system (e.g. price) and the structure of the organization. In contrast, R_i is the actual score of consumer i, which not only depends on behavior of the consumer but also depends on external factors.

Now we define $Z_i(q(p))$ as the *nominal credit score*, which is the score that is estimated by the bureau and is a function of the score quality q. The higher the information level, the closer Z_i will be to R_i. Define $\delta_i(q(p)) = |R_i(q(p)) - Z_i(q(p))|$ as the absolute value of score estimation error and note that $\delta_i(q(p))$ is a non-decreasing function in p. In addition note that at the price where the maximum score quality is reached $(p = \overline{p})$ the marginal error is zero, or $\delta_i(q(\overline{p})) = 0$, and at the lowest score quality $(p = 0)$ the marginal error of calculated score does not exceed a certain level, $\delta_i(q(0)) = \overline{\delta}$ (note that $q(0) = q_{min}$).

There are N consumer and the amount of requested loan by consumer i is L_i, $i = 1,2,...,N$, which is a random variable with a known distribution. Upon a request for a loan by

consumer i, the lender buys his credit score, Z_i, from the bureau at price p, to evaluate the consumer and to decide about granting or denying him the loan. The lender grants consumer i with probability $g(L_i, Z_i)$ where $g(L_i, Z_i)$ is a strictly decreasing function in L_i and strictly increasing in R_i. We assume that the rejected consumers will leave empty handed and will never come back. For simplicity, we assume that the lender offers the market interest rates to all consumers.

We only consider one period of time. At the beginning of the period, all consumers receive the loan and at the end of the period they are expected to repay their loan and any applicable interest. The value of a loan, say loan L_i, at the end of the lending period is xL_i, where x is a function of economic condition $e(t)$.

Now, define $K_i(L_i, R_i, q(p))$ as the *threshold level* of consumer i whose creditworthiness is R_i and requests loan L_i where the credit score quality is $q(p)$. At the end of the lending period, the consumer will default if the loan value falls below the threshold or $xL_i < K_i(L_i, R_i, q(p))$. Note that $K_i(L_i, R_i, q(p))$ is a non-decreasing in L_i and $\frac{\partial^2 K_i}{\partial L_i^2} \geq 0$, which suggests that the default rate of consumer i is higher for greater loans. In addition, $K_i(L_i, R_i, q(p))$, is strictly decreasing function with respect to the creditworthiness, R_i which suggests that the consumers with higher creditworthiness set the threshold lower and wait longer to default the loan. Finally, $K_i(L_i, R_i, q(p))$ is strictly decreasing function with respect to $q(p)$, which means that the default rate of consumers is lower in a market with higher score quality.

Now consider an option based model for the credit risk of consumer i. If the loan value of consumer i, xL_i is higher than his threshold, K_i, then the consumer will repay the debt, otherwise, if $xL_i < K_i$ then he will default.

If the credit scores are underestimated then the lender tends to reject more consumers including those who would repay the loan. In this case, the lender faces the opportunity cost yL_i, where y is the periodical interest rate. If, due to an overestimated credit score, a consumer receives a loan that is beyond his ability to repay (and defaults after the lending period), then the lender faces a default cost equal to the loan value after the lending period, xL_i. We calculate p in order to minimize the default rate or total expected loss.

4. Simulation Results

4.1 Impact of price *p* on all the customers

Based on the simple model described above, we use Monte Carlo simulation to quantify the impact of the information fee on the total expected loss of the lender. We consider one credit bureau, one lender, one information provider, and $N = 1000$ consumers in the market. The real creditworthiness of the consumers follows a uniform distribution that ranges from credit scores from 500 to 800. For each consumer, we calculated the nominal score based on $Z_i = R_i \pm \beta_i$, where $\beta_i = (1 - q(p)).log_2(R_i)$. This ensures that β_i is a non-increasing function with respect to p. In other words, in a market with a higher quality of scores (higher $q(p)$), the margin of error in calculating the credit scores is lower. Note that $log_2(R_i)$ ensures that the margin of error is a function of real creditworthiness.

Each consumer requests a loan $L_i = \log_{10}(R_i) * U[1000, 500,000]$, where $U[1000, 500,000]$ is a uniform random variable with parameters 1000 and 500,000. Consumers with higher creditworthiness request higher loans, which is captured by $\log_{10}(R_i)$. This assumption is reasonable since consumers with higher real creditworthiness most likely have stable incomes and have greater demand for larger loan amounts.

The consumer i defaults if $xL_i < K_i(L_i, R_i, q(p))$ where xL_i is the loan value of consumer i at the end of one period. If $x > 1$, this would imply that the market would be stronger with no consumer defaults. In this case, the problem is trivial. Therefore it is reasonable to set $x = 0.8 < 1$. We use function $K_i(L_i, R_i, q(p)) = L_i(\overline{R}_i - q(p)/A)$, where $\overline{R}_i = R_i/R_{max}$ is the normalized creditworthiness of consumer i and A is a constant that assures that $\overline{R}_i > q(p)/A$ ($A = 0.16$ in our simulation model). Using this formulation all properties of $K_i(L_i, R_i, q(p))$ described in previous section are satisfied. Based on this formulation the default rate is $d = j/N$, where j is the total number of default loans and N is the total number of consumers. The expected loss of the lender is then calculated as $J(p) = d \sum_{i=1}^{N} L_i + pN$.

Table 1. Expected loss for different payments- p

p	$Ei(\lvert Zi - Ri \rvert)$	$q(p)$	d	$J(p)$
0	45.90	0.50	0.31	74150.15
5	29.89	0.67	0.24	60622.16
10	23.33	0.75	0.20	57474.71
14	0.90	0.78	0.18	57002.00
20	16.97	0.82	0.17	60664.94
25	15.02	0.84	0.16	63654.01
30	13.07	0.86	0.16	67475.54
40	9.84	0.89	0.15	74441.73
50	7.82	0.92	0.14	83704.41
100	1.49	0.99	0.12	127104.95

Table 1 summarizes our simulation study and shows the impact of p on different parameters of the model. In the first column p ranges from 0 to 100. The expected value of absolute errors are listed in the second column, and as expected, as p gets higher the absolute error becomes smaller and reaches the minimum of 1.49 points. The third column shows the score quality where the higher values of p leads to higher score quality. Note that the score quality ranges from 0.5 to 0.99

For prices equal to 0 and 100, respectively. The default rates d, for different values of p are listed in the fourth column with the minimum of 12 percent of default rate that can be reached at the highest quality. The last column shows $J(p)$, the expected loss of the lender, which is a U-shape function with respect to p. The minimum expected loss is reached at a relatively low value of $p = 14$ with the default rate 18 percent.

The preliminary results obtained from the simple model described in Section 3, are contingent upon several simplifying assumptions that require validation. For example, we assume that the consumers with greater creditworthiness request larger amounts of loan with factor value as $\log_{10}(R_i)$. Although this is a reasonable assumption, we would need real data of credit scores and loan amounts to validate the relationship between them. In reality, there may be customers with different attributes of consumer behavior, such as, for instance, aggressive or conservative risk taking. Thus we need to estimate loan amounts that are optimal for each type of customer. Similarly, we also need to find the actual relationship between the *threshold level* and the real creditworthiness R_i of consumer i for loan L_i.

4.2 Impact of price *p* on various segments of customers

Another aspect of the default rate is the distribution of default among borrowers. One might be interested in learning whether charging higher prices impacts the borrowers with higher amount of loan or not. In Table 2, we examine the impact of the price, p, on different segment of the customers.

The first column is the price and the second column shows the expected value of the absolute errors between the real and observed customer creditworthiness that reduces for higher price levels. The credit score quality is reported in the third column. The fourth and fifth columns show the default rates for the overall population and the top 50th percentile of borrowers. That is, the borrowers who requested 50 percent of the maximum loan in this simulation is $500,000.

Table 2. Expected loss for various segments of customers for different values of p

p	$Ei(|Zi - Ri|)$	$q(p)$	Default	Default (50th)	Loss	Loss (50th)
1	45.901	0.50	0.31	0.35	27971.03	23209.00
5	29.89	0.67	0.24	0.34	22919.78	14428.07
10	23.33	0.75	0.20	0.37	21872.70	11748.57
14	21.326	0.78	0.18	0.37	21834.39	10433.17
18	17.763	0.81	0.19	0.35	21626.99	10700.53
20	16.969	0.82	0.17	0.32	22820.57	10555.70
25	15.015	0.84	0.16	0.34	23843.75	10439.26
30	13.068	0.86	0.16	0.36	25401.53	10728.61
40	9.837	0.89	0.15	0.33	27816.06	10868.49
50	7.822	0.92	0.14	0.33	31535.40	11969.73
100	1.491	0.99	0.12	0.32	47489.78	14617.07

The default rate in the top 50 percent of the loan amount is steady while the overall default rate has significantly dropped for higher prices. The lender approves higher amounts of loan for certain credit scores, which is independent of more information. For example, the score of a customer that is currently 780 improves negligibly as more information is received that has limited impact on the final decision of the borrower whether to grant him the loan or not. However, incremental changes in the score quality of a customer with lower credit significantly impacts the borrowers' decision. The overall and the 50th percentile expected losses are also listed in the last two columns.

4.3 Conclusion and future direction of research

Credit scores generated by the existing credit bureaus often do not reflect the true credit worthiness of consumers. This is because of lack of accurate and timely information reporting and inefficiencies in the system. In this research an incentive in the form of information fee is introduced, which allows to improve credit scoring. We present a simple mathematical model that incorporates the information fee and takes into account the dynamic stochastic behavior of consumers within the VO system. A lender buys a credit score from the bureau for a certain price, which is the only decision variable. The model aims at minimizing the expected losses of lenders in the VO system. If the credit scores are underestimated then the lender tends to reject more consumers including those who would repay the loan. In this case, the lender faces the opportunity cost. On the other hand, if the credit scores are overestimated, probability of consumer default is increased and the lender faces a default cost equal to the loan value. The simulation results show that expected loss of lenders are minimized at a relatively low value of the information price.

We also extend our simulations to study the distribution of default among different borrowers.

The default rate in the top 50 percent of the loan amount is steady while the overall default rate declines with higher prices. The lender approves higher amounts of loan for certain higher credit scores. Additional information may be of little consequence for the final lending decision. In contrast, any additional information resulting in incremental changes in the score quality of a customer with

lower credit rating may significantly impact the borrowers' decision.

The foregoing results obtained within the framework of a simplified model are important from a policy perspective as they provide guidance for regulation and decision making in the financial services industry and government agencies. Countries where credit reporting is not as advanced as in developed nations, the policies with regard to credit scoring may improve the efficiency of financial markets and consumer confidence.

The results of this multi-disciplinary research fall into three major categories. First, a set of software that implements the credit scoring VO including its download from the internet. Second, a set of experimental data to show the strength and weakness of the techniques will be available for other researchers. Third, the theory, algorithms and formalized models will generate future research on more complex virtual organizations.

4.4 Scope of an enhanced realistic VO model

The constraining assumptions of the simplified model presented in this study may be relaxed for several extensions.   An important assumption in the simple VO model is that there is only one lender in the market and that the consumer can only request loans from one lender. The assumption seriously limits the opportunity set for obtaining a loan if the single lender disallows the customer for some reason. Although this assumption has some validity in a less developed economy, or a centrally planned economy, or a monopoly, it is certainly unrealistic in a competitive and selectively regulated free market. In a competitive lending market, it can be assumed that the lenders compete in offering better interest rates in order to maximize their objective function. An enhanced VO model, therefore, includes multiple lenders in a competitive market maximizing their utility. In this framework, the loan rate offered by the lenders is a decision variable, which is based on the credit score of the customer, rather than the same market rate for all customer as in the simple model.

Another limiting factor in the simple VO model distinguishes the role of the lender (who consumes credit score information) from the role of the information providers (who provide credit information). In reality, a bank or a credit card company can act both as a lender and also as an information provider. The enhanced model allows multiple roles on the part of agents. Each agent has the choice of joining the VO. Thus the decision-making process within the system is more complex as the agents mutually influence each other's decision.

4.5 A hybrid simulation program

We performed stochastic simulation based on Monte Carlo method, however, this is not sufficient for implementing the enhanced VO model. In the VO, each participant is an independent decision-making entity, whose objective is to maximize its own utility. For example, a bank makes decision whether to join the VO given the current information fee $r(I)$, quality of credit score $q(p)$, the expected number of loan applications, and the distribution of the creditworthiness of those customers. We plan to implement a multi-agent system to model the VO, where each agent represents an independent entity, who is able to makes his own decision dynamically in his own interest. Each agent also interacts with other agents in a rational manner. For example, customers send loan requests to various banks, and these banks check the credit scores of those customers and then decide on the best rate they would like to offer for each customer. Customers may opt for the best loan offer or forego it.

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