Credit Rationing with Symmetric Information

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Abstract

Without denying the importance of asymmetric information, this article purports the view that credit rationing may also originate from a lender's inability to classify loan applicants in proper risk categories. This effect is particularly strong when novel technologies are involved. Furthermore, its relevance may increase with the importance assigned to internal rating systems by the Basel accord.

This article presents a measure of the inadequacy of a lender's classification criteria to the qualitative features of prospective borrowers. Even without information asymmetries, credit rationing may occur if this quantity reaches too high a value. Furthermore, some general principles are outlined, that may be used by lenders in order to change their classification criteria.

Keywords: Credit Rationing, Risk Categories, Internal Rating Systems, Deciding not to Decide, Problem Decomposition.

1 Introduction

It is well known that credit is not conceded to those applicants who offer the highest interest rate. Rather, it is conceded to those who offer the most reliable prospects that the debt will be repaid. Essentially, credit is rationed because by increasing the interest rate banks would screen for riskier, less profitable projects [35] [36] [58] [10]. Thus, economic theory sees credit rationing as an instance of asymmetric information.

Interestingly, practitioners tend to stress another aspect. Giving for granted that loan applicants typically hide some information, they are rather concerned with the content of the information that they provide. Specifically, they are concerned about the soundness of the projects that they should finance and the ability of their proponents to carry them out. In the limit, one may mention a popular guide for venture capitalists listing such things as a deprived childhood, an absent father, a strong mother and a sense of guilt for having not lived up to parents' expectations as the hallmarks of successful entrepreneurs [55].

Be these features relevant or not, the crucial issue is that practitioners want to know whether potential borrowers know what they are doing. After discounting for the fact that loan applicants portray a rosy picture of their enterprise, they want to focus on the details of the projects they are asked to finance.

These details may be quite easy to specify if the project is presented by a well-acquainted firm that is expanding on a stable technology. On the contrary, it may be a very difficult task when money is demanded for an enterprise of a novel kind, one that has never been undertaken before.

Investments often involve novel technologies, and possibly the creation of novel institutions and consumption habits [39]. Being novel, no objective probability distribution of their success can be measured. Thus, even if information asymmetries would not exist, banks officials would still have a hard time trying to understand whether a potential borrower is a visionary business man or a mad man.

Figure 1 illustrates my point with respect to the received theory. Information asymmetries make for a cloud between loan applicants and the bank. The presence of this cloud is a sufficient reason for screening applicants and rationing credit rather than increasing the interest rate until demand equals supply. Thus, the received theory makes credit rationing depend on the cloud in the middle of the figure.

However, I am claiming that if technological or institutional innovations make for uncertainty, the very information available to loan applicants is cloudy as well.

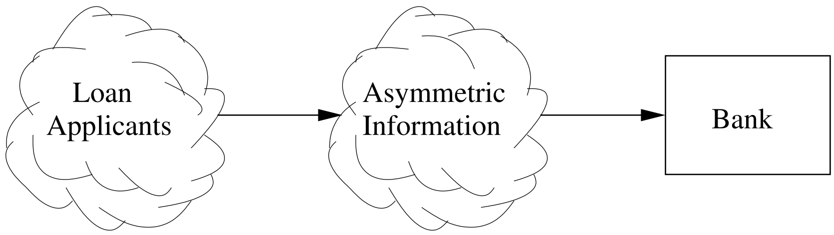

Figure 1: Information asymmetries make it difficult to establish one-to-one relationships between classes of risk and interest rates (cloud in the middle of the figure). Moreover, uncertainty makes it difficult to define classes of risk (cloud in the left of the figure).

Even a bank disposing of the same information as the loan applicant may nevertheless feel unable to classify the proposed project in a class of risk. Consequently, it may decide not to make any offer, for no value of the interest rate. Thus, precisely the most innovative firms may experience credit rationing to a larger extent than the average. Without denying the importance of the cloud in the middle, the cloud on the left of figure 1 plays a role as well.

Indeed, credit rationing has been found to be strongest when innovative technologies are involved [32] [3] [4]. In principle, it is the stock market with its variety of investors that should be able to finance the most innovative enterprises [1]. In practice, stock markets are oriented by rating agencies whose classification criteria are so stiff that the most innovative firms are forced to hide their features in order to be positively valued [64]. The problem is that both banks and financial markets need some form of classification of investment projects, and since classification rests on past experience, innovative projects that do not fit conventional wisdom have a hard time. Simply, bank officials do not lend money for projects that they do not understand, and rating agencies do not do better.

Several economists have stressed that the inability to classify qualitatively novel project is at least as important for credit rationing as information asymmetries [19] [20] [52] [62] [9]. This issue has remained quite marginal hitherto, but it may become paramount in a near future. In fact, the *Bank of International Settlements* (BIS) is purporting a link between liquidity requirements and the riskiness of loans, and this link should be based on internal rating systems [7]. Thus, the BIS is prompting banks to improve their rating systems and to compete for the best classification procedures.

This article is a first attempt to model these processes and their possible dynamics. Section 2 reports on qualitative and quantitative empirical evidence on internal ratings. Section 3 presents a model of credit rationing that combines information asymmetries with lack of confidence in the rating system when innovations appear. Section 4 explores the processes by which internal rating systems may be adapted to a changing environment. Finally, section 5 concludes.

2 Empirical Evidence

The process of classifying loan applications into risk categories is the very core of banking. Traditionally, it has been hidden by strict secrecy. However, since a few years the *Bank of International Settlements* is searching ways for adapting liquidity requirements to the riskiness of loan portfolios. Consequently, a certain amount of empirical research has been carried out and some results have been published.

According to these investigations, banks make use of categories for the projects which they decide to finance (the so-called "pass-grades") as well as for the projects which they decide not to finance (the so-called "fail-grades"). Categories for projects that are not financed are few in number. Categories for projects that are financed are many more.

In this study, only categories for projects that are financed will be considered. Several features of these categories are important in order to understand the impact of innovation on credit rationing.

First, one may ask how far in the past the judgement is stretched. It is obvious that classification is made depending on past performance, but in order to run a model we may need to know whether it is a matter of months or decades.

A study by the *Bank of International Settlements* [6] collected the answer "three years or more", but only from a fraction of the thirty banks that were interviewed. In a public declaration, an official of a large Italian bank spoke of "three years" [30]. Indeed, a guide for practitioners recommends to focus on the "previous few years" [17].

Secondly, one may want to know the number of risk categories employed by banks. Several studies have shed light on this issue.

In 1995, English and Nelson collected data from 114 U.S. banks. They found that 85% of them had a rating system and that the average number of risk categories ranged from 3.4 for smaller banks to 4.8 for larger banks [12] [24]. In 1997, Treacy and Carey carried out a research among the 50 largest U.S. banks, finding a number of risk categories ranging from 2 to the low 20s and an average of 3-4

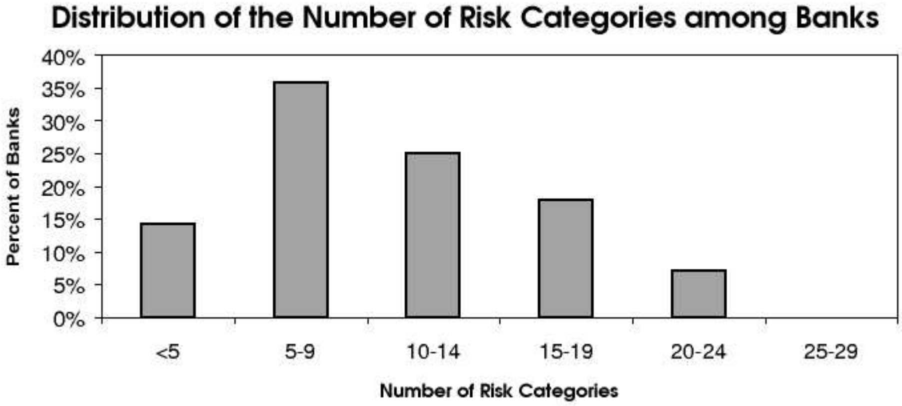

Figure 2: The distribution of the number of risk categories among thirty large international banks. By courtesy of the ©*Bank of International Settlements* [6]

[59]. In 1998 Weber, Krahnen and Voßman interviewed the four largest German banks found out numbers of risk categories ranging from 5 to 8 [61]. Similarly, De Laurentis found out that the five largest Italian banks in the years 1996-98 were using 6-7 classes of risk [40]. In 1999, the *Bank of International Settlements* on a sample of over thirty banks, generally large and internationally diversified [6]. Finally, by interviewing three specialised German banks in 2001 Norden found that the number of risk categories was 6, 9 and 14, respectively [47].

Figure 2 reports the distribution of the number of risk categories found by the *Bank of International Settlements*. The number of risk categories ranges between 2 and 20. This, this range includes the numbers found by other studies.

In their empirical study of 1997, Treacy and Carey revisited older investigations as well. They came to the conclusion that a decade earlier the number of risk categories might have been smaller, in the order of three if they were in place at all [59]. They remarked that the number of risk categories increased both with time and with the size of banks, but not indefinetly. According to their suggested interpretation, this is due to a trade-off between the advantages of a large number of categories for running automatized systems for detecting problem loans on the one hand, and the difficulties posed by large number of categories to boundedly rational decision-makers on the other hand.

Notably, banks that are using a very large number of categories generally derived them by adding a “+” or “-” to a smaller set of categories. For instance, a system with 6 categories can be easily turned into a system of 12 categories by requiring bank officials to qualify their judgement specifying whether the loan is in the upper end of the category (with a "+") or in the lower one (with a "-"). By doing so, human operators can approach the classification problem in two steps [59].

Finally, it is very important to know the criteria by which loan applications are classified. In particular, this is important in order to formulate guidelines along which the classification criteria may be changed with time.

According to several empirical studies, it appears that both "hard" and "soft" aspects are considered by banks, though this distinction is blurred by the fact that even "soft" aspects are translated into numerical values [13] [6] [31]. A possible list of the aspects involved may be the following:

1. Loan specification in terms of collaterals and terms of payment [11] [40] [6] [48]. In particular, securities are a condition for evaluating other aspects [17].

2. Financial indicators [61] [40] [6], eventually used by automatized procedures such as the *Z-score* [2] or neural networks [37]. For venture capitalists, the liquidity of assets is also important [45].

3. The technology employed by the project, to be evaluated with respect to the industries on which it is expected to impact [43] [61]. In particular, marginal firms in mature sectors are often sources of financial distress [17]. In contrast, proprietary or otherwise protected technologies and products are positively valued [45].

4. Psychological features of the applying entrepreneur and quality of the management team, to be considered in conjunction with the structure of the industry where the applicant operates [8] [53] [43] [61] [6]. Management quality may be inferred by the absence of litigations, suppliers satisfaction and managers succession plans [17]. In high-tech start-ups, the willingness of scientists to give up managing positions to professional managers is highly valued [5].

5. Reliability of the information provided by the applicant. Reliability is increased by a lasting acquaintance [23] [40] but may eventually be disrupted by signals of increasing information asymmetries such as changes of accounting procedures or a growing reluctance to provide information [18]. Long-term relations have been found to integrate, not to substitute for collaterals [48].

6. Information provided by the stock market and its rating agencies, or by customers and suppliers of the applicant [11] [40] [6]. For firms with over 25% of operations abroad, the country risk evaluated by rating agencies may be included [17].

It has been observed that several banks are shifting from rating systems based on one single set of categories to rating systems based on several sets of categories, each for a different aspect of a loan application. The most common distinction is between aspects that pertain to the applicant (issues 2, 4 and 5 above) and aspects that pertain to the particular project for which a loan is requested (issues 1, 3 and 6 above) [59] [6] [40]. However, it appears that some banks are moving even further, evaluating several or all of the above aspects separately or, in some cases, even subdividing them further according to their components [61]. By having different bank officials specialised in one or a few aspects of rating, a bank is better able to detect warning signs that involve only one aspect. Subsequently, a thorough examination of all the aspects of a loan may be started [40].

This suggests that the number of aspects that are considered separately has a huge impact on lending decisions. The more aspects are considered separately, the easier it is for a bank to detect problem loans. However, too subtle categories may impair the evaluation of innovative projects that cut across the borders of existing categories.

In § 4 we shall examine the consequences of having multiple aspects to be considered in separate sets of categories. In the ensuing § 3, credit rationing is examined in the simple case of one single set of risk categories, ordered from "low risk" to "high risk". In this simple setting, which is still a realistic description of the functioning of many banks, each category refers to a different class of risk though each category encompasses all of the above aspects.

3 Classification Failure

This section illustrates a procedure for modelling credit rationing due to a bank's inability to classify the qualitative features of loan applications in proper categories. Since credit rationing due to classification failure will be espoused in conjunction with credit rationing due to asymmetric information, the basic formalisation by Stiglitz and Weiss [58] will be briefly recalled.

Their starting point is that, by increasing the interest rate, the least risky loans drop out of a bank's portfolio. Thus, it is not convenient for banks to select loan

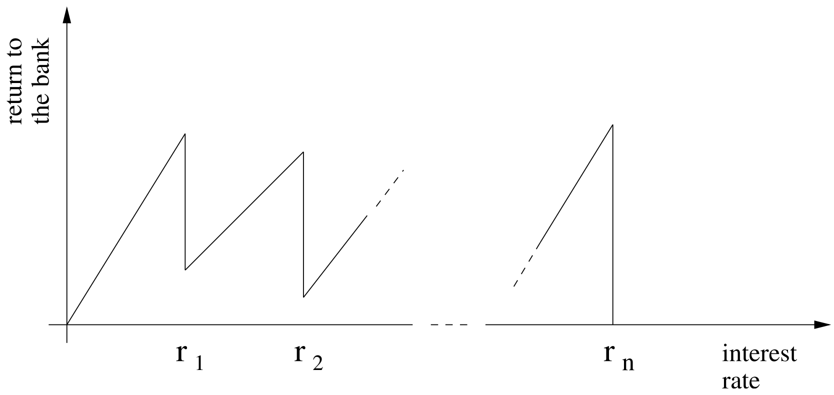

Figure 3: The return on lending as a function of the interest rate. If projects belong to n classes of risk, this function is not monotonic.

applications by means of the interest rate. Rather, they should segment the market classifying loan applications in a discrete number of classes of risk. To each class of risk, a different interest rate applies. Figure 3, freely adapted from [58], explains this concept.

For interest rates $r < r_1$, all projects are proposed to the bank. Thus, by increasing $r \in (0, r_1)$ the bank makes higher profits. However, for $r \geq r_1$ the least risky projects are no longer proposed. Thus, at $r = r_1$ the expected return to the bank drops. It increases again with r for $r_1 \leq r < r_2$, to drop again at $r = r_2$ and so on up to r_n. Thus, it is convenient for the bank to segment the market by classifying loan applicants into n classes of risk applying a different interest rate each.

The highest interest rate, r_n, does not necessarily coincide with the interest rate that would obtain by equating demand and supply. In fact, if the bank fears that the market equilibrium interest rate would only attract swindlers, it may not concede any loan at that rate. Thus in general it is $r_n \leq r^*$, where r^* is the interest rate that obtains at market equilibrium.

Since $r_1 < r_2 < \ldots < r_n$, for $\forall i < n$ it is $r_i < r^*$. Thus, at least to the applicants borrowing at $r_i < r_n$ credit is rationed.

Credit is allocated by classifying the projects waiting for a loan into n categories $\mathrm{R}_1, \mathrm{R}_2, \ldots \mathrm{R}_n$ ordered by increasing risk. To each risk category corresponds a different interest rate $r_1, r_2, \ldots r_n$, where $r_1 < r_2 < \ldots < r_n$. Thus, a decision about the interest rates is made at the same time a loan applicant is classified in a risk category.

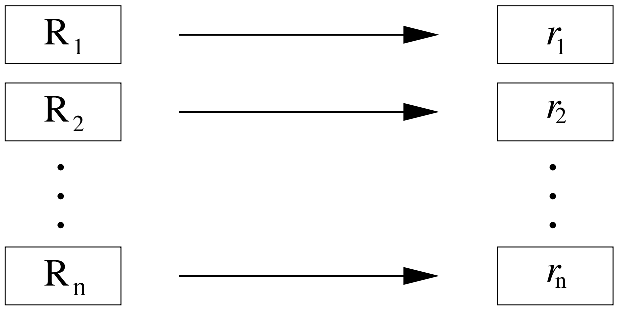

Figure 4: When risk categories work properly, to each risk category corresponds a different interest rate.

Figure 4 illustrates these one-to-one correspondences between classes of risk and interest rates. The arrows indicate that being classified in a particular class of risk implies that the loan applicant is offered the corresponding interest rate.

My point is that, if technological innovations change the features of projects in ways that are not well understood by a bank, classification in a class of risk may be impossible. Thus, a bank may suspend credit until the risks and prospects of the proposed investment projects have become clear.

Innovations may be such that investment projects financed with great confidence end up with failures. For instance, investments by the industry of photographic films may be ruined by digital cameras, or investments in oil extraction may be ruined by wars and revolutions. Such occurrences call for refinements of the classification criteria. For instance, one may want narrow the scope of low-risk projects to exclude the construction of plants for the production of photographic films.

Likewise, projects of novel kinds may become very profitable so the category of low-risk projects should be redesigned. For instance, the category of low-risk projects may be adjusted to include investments in the production of digital cameras.

If innovations decrease the profitability of projects that used to be safe, than the bank observes a causal link from a class of (previously) low risk to a high interest rate. Conversely, to the extent that innovations opened up new fields the bank observes a causal link from a class of (previously) high risk to a low interest rate. In both cases, the one-to-one connections of figure 4 becomes the one-to-many connections of figure 5.

In other words, the bank expected a certain probability of default but observes

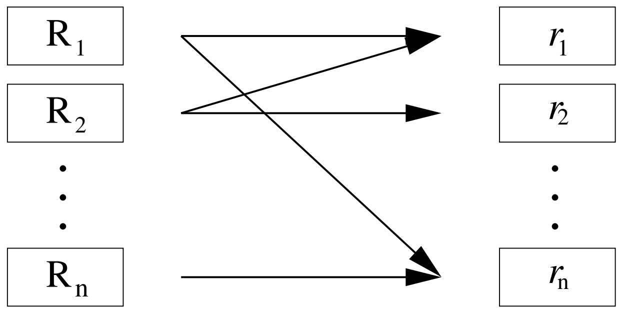

Figure 5: If innovations are such that some projects obtain very different returns from those expected, then the causal relationships from classes of risk to interest rates become one-to-many.

another one. For instance, it may observe that defaults on investments related to photographic films are occurring more often than expected.

The cross-connections of figure 5 warn that projects have been classified in the wrong risk categories. If the capabilities of bank officials did not change with time, this is a signal that the features of the projects did. Thus, the criteria by which projects are classified should be changed as well.

The classification criteria should be adapted to the innovations that have taken place by including technological and institutional details that had been ignored hitherto. For instance, the class of low-risk projects may now include those based on digital cameras whereas projects based on photosensitive film technology may be downgraded to very risky, though the producers of X-ray photosensitive films may need to be included in still another risk category.

Eventually, the revised classification criteria may achieve the goal of turning back the connections between the R_is and the r_is into a one-to-one mapping as in figure 4. Subsequently, other innovations may turn it again into a one-to-many mapping as in figure 5, and so on with every new innovation.

During the time periods when there are one-to-many connections between classes of risk and interest rates, a bank is unable to assign a project to a class of risk. Therefore, it may not concede credit altogether.

Since in our case this decision depends on detecting novelties, it must be based on a restricted number of very recent observations. Let $m \in \mathcal{N}$ denote the number of past time intervals upon which bank officers evaluate the appropriateness of their causal map. For brevity, m will be called the *memory* of bank officers. It is obviously $m \geq 0$, with $m = 0$ in the special case when bank officers look only at present-day occurrences.

Let us define the *complexity* of the decision-making problem as a measure of the extent to which the connections that occurred in the last m time intervals are intertwined [27]. The ensuing account is an excerpt of more technical publications [15], [25], [26].

The structure of connections between classes of risk and interest rates can be usefully subsumed by means of a *simplicial complex.* This is composed by connected simplices, each for each class of risk. The vertices of each simplex are the interest rates to which a particular class of risk is connected.

If the connections between classes of risk and interest rates are one-to-one as in figure 4, simplices are isolated points so no simplicial complex exists. In this case, complexity is zero.

On the contrary, if at least two simplices have at least one vertex in common, a simplicial complex exists and complexity is greater than zero. For instance, the connections of figure 5 corresponds to a simplicial complex made of n simplices $\mathrm{R}_1, \mathrm{R}_2, \ldots \mathrm{R}_n$. The simplex R_1 is a segment whose vertices are r_1 and r_n. The simplex R_2 is a segment whose vertices are r_1 and r_2. More intertwined connections may be represented by simplicial complexes composed by many more simplices, possibly of higher dimension.

Two simplices are connected if they have at least one common vertex. Two simplices that have no common vertex may nonetheless be connected by a chain of simplices having common vertices with one another. Let us say that simplices $\mathrm{R}_{i'}$ and $\mathrm{R}_{i''}$ are $q-connected$ if there exists a chain of simplices $\{\mathrm{R}_u, \mathrm{R}_v, \ldots \mathrm{R}_w\}$ such that $q := \min\{l_{i'u}, l_{uv}, \ldots l_{wi''}\} \geq 0$, where l_{xy} is the dimension of the common face between R_x and R_y. In particular, two contiguous simplices are connected at level q if they have a common face of dimension q.

Let us consider the common faces between simplices and let us focus on the face of largest dimension and let Q denote the dimension of this face. It is $Q \leq n-1$, where $Q = n-1$ means that there are at least two overlapping simplices that include all possible vertices.

Let us partition the set of simplices that compose the simplicial complex according to their connection level q. In general, for $\forall\, q$ there exist several classes of simplices such that the simplices belonging to a class are connected at q. Let us introduce a *structure vector* **s** whose q-th component s_q denotes the number of disjoint classes of simplices that are connected at level q. Since $q = 0, 1, \ldots Q$, vector **s** has $Q+1$ rows.

In order to avoid repetitions in the calculus of complexity, a class of simplices connected at level q is not considered to be connected at levels $q-1$, $q-2$, $\ldots$ 0 as well. For instance, let simplices R_1 and R_2 be connected at level $q = 2$, and let simplex R_3 be connected with R_2 at level $q = 1$. Then, $\{R_1, R_2\}$ is a class of simplices connected at $q = 2$ and $\{R_1, R_2, R_3\}$ is a class of simplices connected at $q = 1$. However, $\{R_1, R_2\}$ is *not* a class of simplices connected at level $q = 0$.

The following measure for the complexity of a simplicial complex has been proposed by Casti [15] and improved by Fioretti [25], [26]:

$$\mathcal{C}(\mathcal{F}\,; m,n) = \begin{cases} 0 & \text{if all connections are one-to-one} \\ \sum_{q=0}^{Q} \frac{q+1}{s_q} & \text{otherwise} \end{cases} \tag{1}$$

where the sum extends only to the terms such that $s_q \neq 0$. Finally, it is stipulated that the complexity of two or more disconnected simplicial complexes is the sum of their complexities.

The complexity seen by a bank official who is evaluating the reliability of an attribution of classes of risk depends on the observed connections between classes of risk and interest rates, which realise out of an unknown stochastic distribution $\mathcal{F}$. It also depends on m, the memory length, as well as on n, the number of classes of risk. While $\mathcal{F}$ is unknown by the bank official, m and n are parameters under her control.

Expression 1 takes account of two opposite effects. On the one hand, the numerator increases with the number of connections between classes of risk and interest rates. Thus, it simply measures the extent to which novel connections confuse the causal map. On the other hand, the denominator of 1 makes complexity decrease if cross-connections are separated in distinct groups.

Complexity 1 increases monotonically with both m and n. On the contrary, its dependence on $\mathcal{F}$ is more interesting.

Let us consider the simple case where cross connections occur stochastically as a fraction f of all connections. Thus, $C(\mathcal{F}\,; m,n)$ becomes $C(f; m,n)$. Considering the empirical evidence of § 2, $m = 3$ and $n = 10$ appears an appropriate choice. Figure 6 illustrates the ensuing values of complexity with f increasing from 0 to 100% of total connections.

Figure 6 makes clear that complexity is different from "randomness", "disorder" or any other property of the environment. Rather, it is a subjective evaluation. Up to a fraction of cross-connections of about 35-40%, a bank official may judge that the more disordered the connections, the more "complex" the environment. Beyond this threshold, cross-connections are so many that the bank official may judge that it is not worth to distinguish among projects whose returns are totally unpredictable. Consequently, the business environment is less "complex" for her.

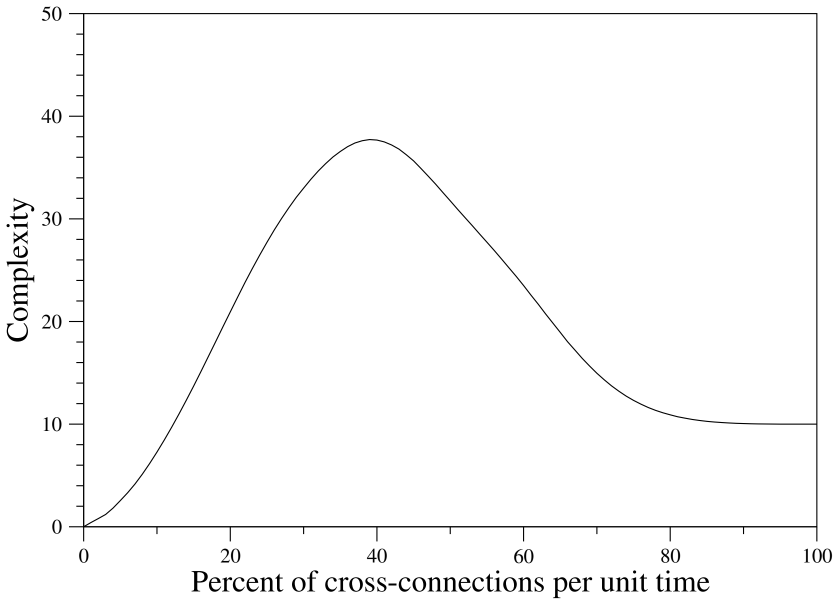

Figure 6: Complexity as a function of f, with $m = 3$, $n = 10$. All values have been averaged over 1,000,000 steps.

More precisely, complexity approaches n for very high values of f.

However, things change if cross-connections do not extend very far. Let us assume that projects in a class of risk R_i may turn out to be appropriate to an interest rate $r_{i-\rho} \leq r_i \leq r_{i+\rho}$ ($r_1 \leq r_i \leq r_{i+\rho}$ if $i < \rho$, $r_{i-\rho} \leq r_i \leq r_n$ if $i > n-\rho$). The previous case obtains if $\rho = n-1$. If $\rho = 0$ no cross-connections occur, so complexity is zero. In all intermediate cases some cross-connections do occur, but they are localised in a spot of radius ρ around each R_i.

Figure 7 illustrates simulations with $\rho = 1, 2, \ldots 9$, all other parameters as in figure 6. Cross-connections occur with increasing probability, but only within an interval specified by the parameter ρ.

In figure 7 we see that if cross-connections are sufficiently localised, confusion between causal attributions of interest rates to classes of risk never grows so large that a decision-maker may give up the hope to improve classification criteria — i.e. complexity never decreases. It reaches plateaus, however. These may suggest bank officials to accept as unavoidable a certain level of imperfection of their classification criteria.

Following Simon [57], let us think of bank officials as satisfycing decision-makers who make a decision if a relevant variable exceeds a threshold. Since

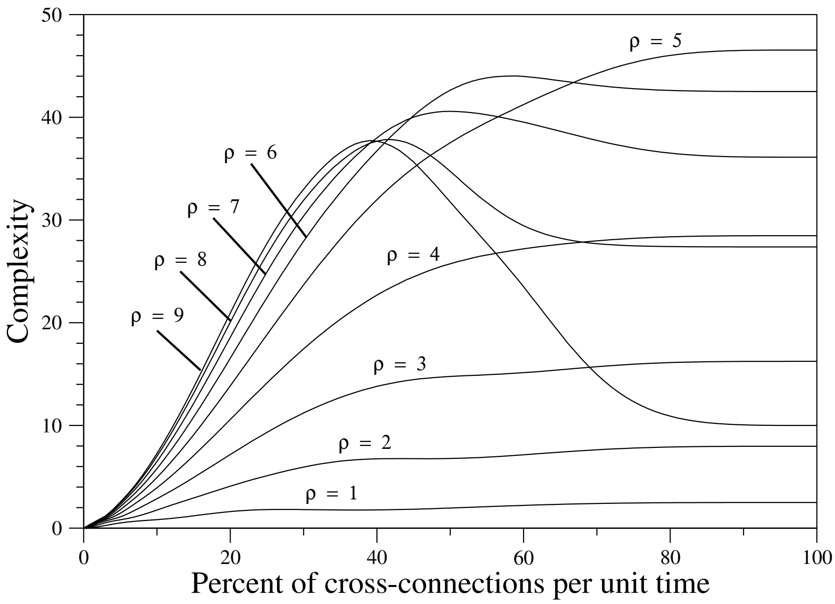

Figure 7: Complexity as a function of f, with $m = 3$, $n = 10$, for $\rho = 1, 2, \ldots 9$. With $\rho = 9$, the case of figure 6 obtains. All results have been averaged over 1,000,000 steps.

complexity measures the unreliability of classification criteria as it is subjectively evaluated by bank officials, it is sensible to assume that they may decide to revise these criteria whenever $C > \overline{C}$, where $\overline{C}$ is a proper threshold. So long C remains greater than $\overline{C}$, loans are not conceded, no matter which interest rate the applicant is willing to pay.

The threshold $\overline{C}$ may depend on past experiences, market specificities and institutional arrangements. It may change with time, though at a lower time scale than C.

Eventually, the above description may be duplicated across markets or geographical area. For instance, a bank may carry out separate classifications of loan applications in different industries or regions.

4 Revising the Classification Criteria

If complexity is greater than zero, bank officials set out to revise the criteria by which they classify loan applications. If bank officials employ one single set of risk categories $\mathrm{R}_1, \mathrm{R}_2, \ldots \mathrm{R}_n$, the process of revising the classification criteria is largely carried out informally in their minds. Little can be said about it, either because it is tacit knowledge or because explicit rules are eventually covered by secrecy.

However, the empirical investigations reported in § 2 revealed that banks are moving towards an arrangement of the classification process where different aspects are considered separately (financial indicators, management quality etc.). Allegedly, the reason is that if one single aspect becomes problematic, a thorough evaluation of all aspects of a loan is carried out.

Suppose that N aspects are considered, denoted by an index $i = 1, 2, \ldots N$. The model expounded in § 3 can be applied to each separate aspect yielding N complexity values $C^1, C^2, \ldots C^N$.

So long all C^is are zero (or below a pre-defined threshold), the classification criteria are not doubted. A loan application may be classified in different classes of risk for each different aspect, and the overall class of risk may result out of a weighted average of the classes of risk in each aspect.

On the contrary, if $\exists i$ such that $C^i > 0$ (or above a pre-defined threshold) the criteria of classification are doubted. Bank officials must make sense of the observed empirical evidence by re-defining the classification criteria in such a way that all mappings between classes of risk and interest rates are one-to-one, i.e. all C^is are zero. Essentially, it is a matter of including issues that have become relevant while excluding others that are no longer so.

The collection of empirical testimonies reported in § 2 identified a maximum of six broad aspects, depending in their turn on finer sub-aspects. For instance, the aspect “financial indicators” may be broken down in a number of accounting variables, and the same holds for technologies, management features and so on. We shall say that each aspect can be broken down in several sub-aspects. If complexity is greater than zero (or above a pre-defined threshold), bank officials may need to re-distributed sub-aspects in order to change the content of the aspects that generated too high a complexity.

An example is in order. No empirical evidence is available concerning the sub-aspects employed by banks, but a good deal of information is available regarding the classification criteria employed by venture capitalists. Although this is a very particular case of money lending institution, its logic is not different from that of a bank.

Let us consider the aspect that, in § 2, was labelled “The technology employed by the project, to be evaluated with respect to the industries on which it is expected to impact”. From the main studies of the classification criteria employed by venture capitalists [60] [41] [42] [38] [33] [29] [50] [46] [49] [16] [45], one can excerpt that venture capitalists declare that the above aspect is composed by the following sub-aspects:

1. The product is protected from imitation by the law or by its technical features;
2. Uniqueness of product (the product has very imperfect substitutes);
3. The product has been developed up to the stage of a functioning prototype;
4. The product has a demonstrated market acceptance;
5. Availability of raw materials and stability of their price;
6. Easiness of procurement of specialised labour;
7. Availability of specialised equipment;
8. The venture will stimulate an existing market or create a new market;
9. This market has a high expected growth rate;
10. There is a well-developed distribution system;

11. Favourable geographical location and good export potential.

There is quite a clear distinction between aspects 1 to 7, which pertain to the product, and the aspects 8 to 11, pertain to its market. Thus, venture capitalists generally decompose the aspect “The technology employed by the project, to be evaluated with respect to the industries on which it is expected to impact” into two aspects: “characteristics of product”, entailing sub-aspects 1 to 7, and ”characteristics of market”, entailing sub-aspects 8 to 11. In other words, venture capitalists have remarked that, in their fields of activity, technological considerations can be safely decoupled from market considerations. In the terms of our model this means that, in this case, by subdividing this aspect in two, the correspondence between risk categories and interest rates in closer to be one-to-one in at least one of the two derived aspects. Other money-lending institutions, in other contexts, may find it useful to group aspects together; others still, may find it useful to re-distribute sub-aspects among existing aspects.

The issue is that of arranging sub-aspects into aspects such that, while sub-aspects are strongly related to one another within the aspect in which they are included, aspects are largely independent of one another. Only if this can be done, the aspects can be considered independently of one another when deciding whether a loan can be conceded. It is an instance of problem decomposition [56] [21] [22], where the problem of classifying loan applicants into proper classes of risk can be eased if the features of the applicant can be considered separately along nearly-independent aspects.

The properties of problem decomposition have been studied by means of simulations where a “problem”, consisting of a string of variables whose numerical values had to be guessed, could be “solved” by mutating blocks of variables of different lengths. While the string was such that it admitted an optimal decomposition into blocks of a certain length, both shorter and longer lengths were tried [28] [14] [44]. In the terms of our problem, this corresponds to having sub-aspects that admit an optimal grouping into a certain number of aspects. Simulations allow give us a hint of what happens when the number of aspects is either smaller or larger than the optimal one.

The results of these simulations may be summarised as follows:

- If the decomposition is coarser than the optimal decomposition, the optimal solution is found later.
- If the decomposition is finer than the optimal decomposition, a sub-optimal solution is found. However, during the initial trials the sub-optimal solution

performs better than the optimal solution. Thus, the optimal solution may be crowded out by sub-optimal solutions that perform better in the short run.

These results suggest that all attempts to discriminate among "aspects" in the decision to grant a loan, as banks are doing since the last ten years (see § 2), do not really aim at improving the quality of decision-making. Rather, the aim is to be able to make a decision before rivals do. By distinguishing "aspects" and considering them separately, a decision can be more easily made. If it is just sufficiently good to ensure a positive profit, and sufficiently fast to be made before the loan applicant applies to a competitor, then it is good to make it.

Other simulations on problem-solving were tried, where the optimal solution was allowed to change with time [28] [14] [44]. In this setting, the problem-solver must chase an optimal solution that escapes any attempt to be reached. In this case, the simulations suggested that coarse decompositions perform better since, by allowing for longer jumps in the space of solutions, they enable the problem-solver to approach the optimal solution from time to time, albeit she may remain far from it most of the times.

This result suggests that those credit institutions that are most often concerned with financing innovative projects should not subdivide their judgement into a large number of "aspects" and "sub-aspects". However, we have seen in this section that venture capitalists seem to do the opposite, i.e., they consider several aspects, subdivide them into a large number of sub-aspects and are keen of explaining their classification criteria to researchers.

A possible explanation might be that what venture capitalists actually do, is not what they think they do. Indeed, a stream of literature questions the results obtained by simply asking venture capitalists what their classification criteria are. Although the main aspects considered by venture capitalists are really those that best indicate the future evolution of a business venture [51], too many aspects decrease the judgement efficiency of venture capitalists [63] so in general they actually employ just a few of the many aspects that they mention [54]. Indeed, theoretical considerations suggest that it may be rational for a decision-maker to ignore some information if this increases her likelihood to make mistakes [34].

In general, it appears that the processes actually used in order to change classification criteria are much more difficult to understand than the mere decision not to grant a loan as soon as the categories in use prove not to be effective (see § 3).

5 Conclusion

Credit rationing is one of those issues where the neoclassical model of competitive markets does not apply. Similarly to other market failures, asymmetric information has been suggested as an explanation.

Since asymmetric information is sufficient to justify the existence of credit rationing, little effort has been devoted to alternative, or additional explanations. Though a few economists voiced that uncertainty does play a role in credit rationing, this argument has not been pursued in either empirical or analytical terms.

The empirical evidence on credit rationing to high-tech firms is questioning this approach, since there is no reason why information asymmetries should be higher if sophisticated technologies are involved. Furthermore, the new accord on capital requirements (Basel II) is emphasising the importance of bank internal rating systems, a circumstance that triggered many interesting empirical investigations. Both streams of enquiry point to the cognitive difficulties posed by difficult classification problems.

The modelling approach presented in this article is innovative, but admittedly tentative and incomplete. Nevertheless, the author deems that it is worth to be presented and discussed in the hope that more information will be disclosed to researchers. The diffusion of computer-based procedures for evaluating loan applications is likely to increase both the need and the feasibility of scientific studies on banks's internal rating systems and the extent to which they influence credit rationing.

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