Credit Rationing and Internal Ratings in the face of Innovation and Uncertainty

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Abstract

Some empirical investigations are pointing to the fact that high-tech firms are subject to credit rationing to a higher extent than the average. This excess of credit rationing may not be due to information asymmetries, but rather to the inability of credit institutions to screen projects in novel fields. This article provides a model of this phenomenon and explores its implications in the light of recent changes in the screening procedures of major banks. In particular, the changes to be made in order to comply with the "Basel II" accord emphasize the impact of screening procedures on credit rationing.

Keywords: Credit Rationing, High-Tech Firms, Internal Rating Systems, Basel II.

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 repaied. Essentially, credit is rationed because by increasing the interest rate banks would screen for riskier, less profitable projects [30] [31] [43] [8]. 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 [40].

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 [33]. 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.

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

Indeed, credit rationing has been found to be strongest when innovative technologies are involved [28] [3]. 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 and their classification criteria are so unflexible that the most innovative firms are forced to hide their

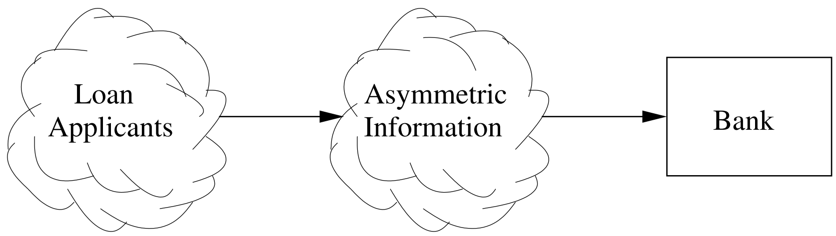

Figure 1: Information asymmetries make it difficult to establish one-to-one relationships between classes of risk and interest rates. Moreover, uncertainty makes it difficult to define classes of risk.

features in order to be positively valued [47]. 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 pointed to this additional reason for credit rationing [16] [17] [38] [46] [7], though this issue has remained quite marginal hitherto. However, it may become very relevant since the *Bank of International Settlements* is purporting a link between liquidity requirements and the riskiness of loans, and this link should be based on internal rating systems [5]. In fact, the initiative of the *Bank of International Settlements* 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 reality. 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 projects which they decide to finance (the so-called "pass-grades") as well as for projects which they decide not to finance (the so-called "fail-grades"). Categories for projects that are not financed are rare and 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 judgment 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* [4] 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" [26]. Indeed, a guide for practitioners recommends to focus on the "previous few years" [14].

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 [10] [21]. In 1997, Treacy and Carey carried out a reasearch 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 [44]. In 1998 Weber, Krahnen and Voßman interviewed the four largest German banks found out numbers of risk categories ranging from 5 to 8 [45]. Similarly, De Laurentis found out that the five largest Italian banks in the years 1996-98 were using 6-7 classes of risk [34]. In 1999, the *Bank of International Settlements* on a sample of over thirty banks, generally large and interanationally diversified [4]. Finally, by interviewing three specialized German banks in 2001 Norden found that the number of risk categories was 6, 9 and 14, respectively [37].

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 [44]. They remarked that the number of risk categories increased both with

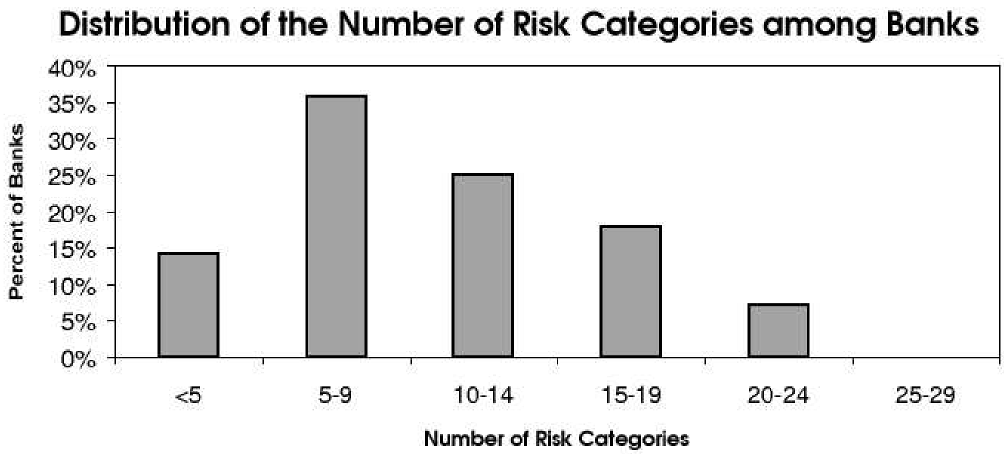

Figure 2: The distribution of the number of risk categories among thirty large international banks. By courtesy of the *Bank of International Settlements* [4]

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 judgment 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 [44].

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 [11] [4] [27]. A possible list of the aspects involved may be the following:

1. Loan specification in terms of collaterals and terms of payment [9] [34] [4].

In particular, securities are a condition for evaluating other aspects [14].

2. Financial indicators [45] [34] [4], eventually used by automatized procedures such as the *Z-score* [2] or neural networks [32].

3. The technology employed by the project, to be evaluated with respect to the industries on which it is expected to impact [35] [45]. In particular, marginal firms in mature sectors are often sources of financial distress [14].

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 [6] [39] [35] [45] [4]. Management quality may be inferred by the absence of litigations, suppliers satisfaction and managers succession plans [14].

5. Reliability of the information provided by the applicant. It is increased by a lasting acquaintance [20] [34] but may eventually be disrupted by signals of increasing information asymmetries such as changes of accounting procedures or a growing reluctance to provide information [15].

6. Information provided by the stock market and its rating agencies, or by customers and suppliers of the applicant [9] [34] [4]. For firms with over 25% of operations abroad, the country risk evaluated by rating agencies may be included [14].

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) [44] [4] [34]. 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 [45]. By having different bank officials specialized 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 [34].

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

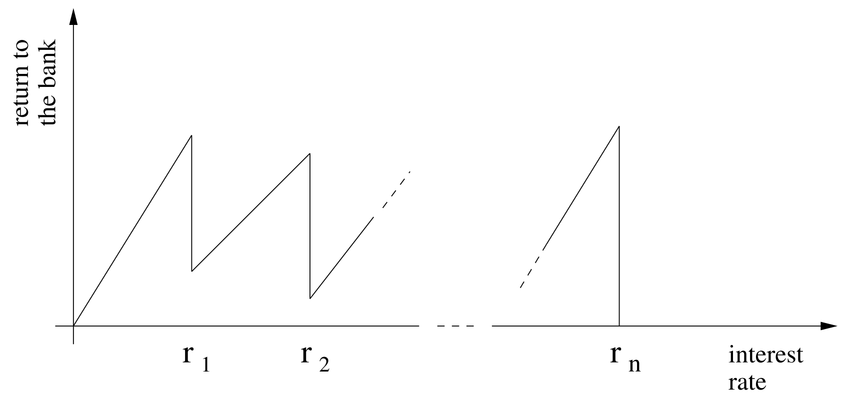

Figure 3: The return on lending as a function of the interest rate. If projects belong to n classes of risk, this function is not monotonic.

impair the evaluation of innovative projects that cut across the borders of existing categories.

More on this in § 4. In the ensuing § 3, credit rationing is examined with reference to one single set of risk categories. In this simpler setting, which is still a realistic description of the functioning of many banks, each category refers to a different class of risk but each category encompasses all of the above aspects.

3 Credit Rationing

Stiglitz and Weiss [43] pointed out that by increasing the interest rate the least risky loans drop out a bank's portfolio. Thus, it is not convenient for banks to select loan 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 [43], 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

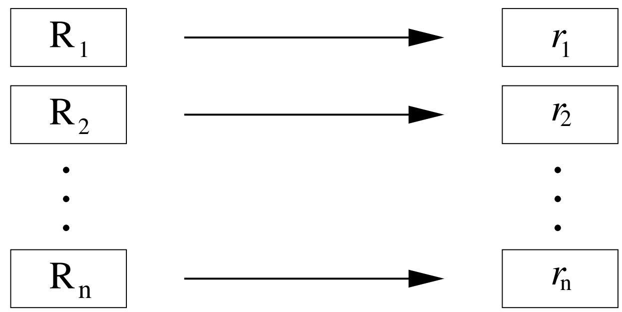

Figure 4: When risk categories work properly, to each risk category corresponds a different interest rate.

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 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 novel 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.

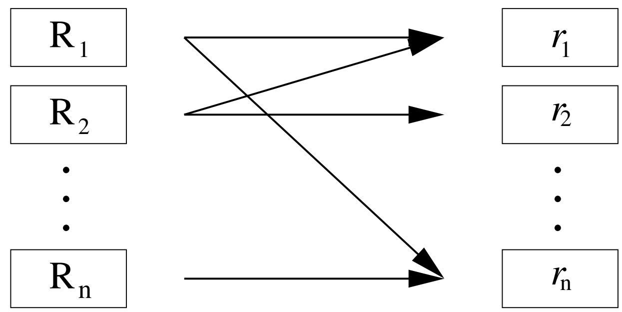

Figure 5: If innovations are such that some projects obtain very different returns from those expected, then the causal relationships from classes of risk to interest rates become one-to-many.

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 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. Provided that the cababilities 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 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 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 occurrencies.

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 [24]. The following account is an excerpt of more technical publications [13], [22], [23].

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* $\mathbf{s}$ 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 $\mathbf{s}$ 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, $\{\mathrm{R}_1, \mathrm{R}_2\}$ is a class of simplices connected at $q = 2$ and $\{\mathrm{R}_1, \mathrm{R}_2, \mathrm{R}_3\}$ is a class of simplices connected at $q = 1$. However, $\{\mathrm{R}_1, \mathrm{R}_2\}$ 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 [13] and improved by Fioretti [22], [23]:

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

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/his 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

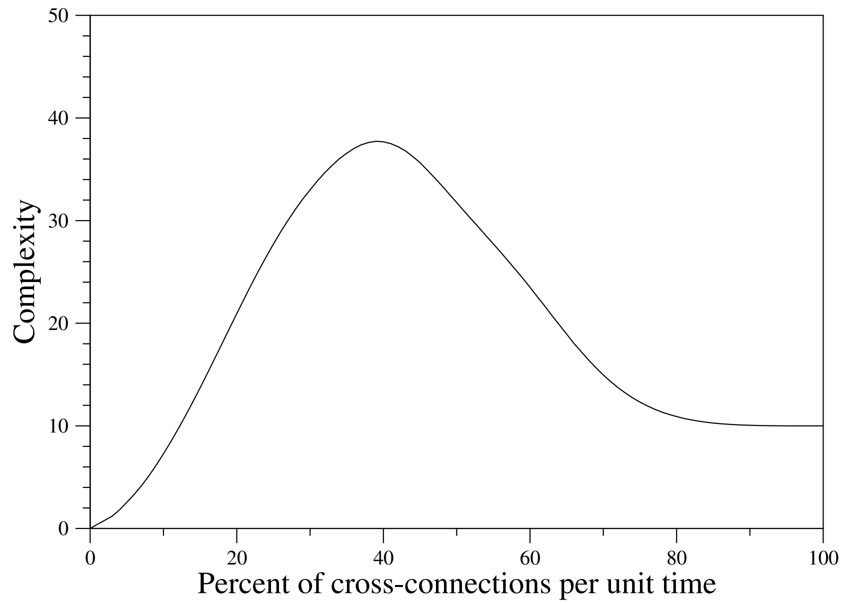

Figure 6: Complexity as a function of f, with $m = 3$, $n = 10$. All values have been averaged over 1,000,000 steps.

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 adifferent 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. More precisely, complexity approachs to n for very high values of f.

However, things change if cross-connections do not extend very far. Let us assum 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 localized in a spot of radius ρ around each R_i.

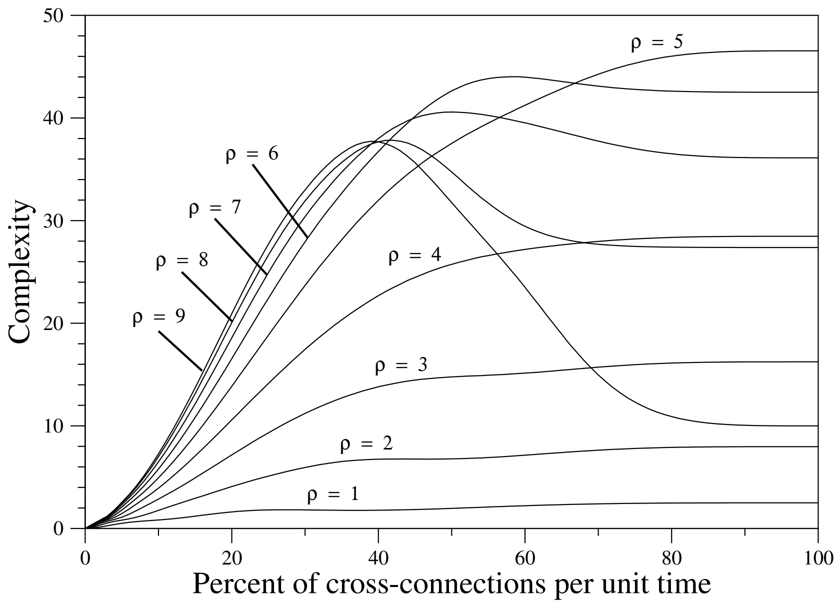

Figure 7: Complexity as a function of f, with $m = 3$, $n = 10$, for $\rho = 1,2,\ldots 9$. With $\rho = 9$, the case of figure 6 obtains. All values have been averaged over 1,000,000 steps.

Figure 7 illustrates simulations with $\rho = 1,2,\ldots 9$, all 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 localized, 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.

Since 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 $C > 0$. However, it is conceivable that some banks start to revise classification criteria when $C > \delta$, where $\delta > 0$ is a bank-specific threshold, or when $\partial C/\partial t > 0$.

While the exact formulation is an open empirical question, the proposed measure of complexity constitutes a theoretically grounded indicator of the point in time when classification criteria are revised. So long this revision is on-going, loans may not be conceded.

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 $C^i > 0$ 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 other that are no longer so.

This problem is akin to solving puzzles such as Chess or the Rubik Cube. The final state to be reached is known — each face of the cube of one single colour, all C^is at zero — and a set of possible moves — rotating the faces of the cube, adding or expunging issues of collaterals, technology, management quality etc.

If humans had the time and the computational resources to explore all possible combinations, the set of optimal solutions to any puzzle would be known [18]

[19]. Indeed, puzzles are such because the number of possible states — e.g. the number of configurations of the tiles of the rubik cube, the number of technological features to be combined with management features, terms of contracts etc. — exceeds human bounded rationality.

Boundedly rational decision-makers may make mistakes when possibilities are too many. Thus, they may find it convenient to ignore some information [29], for instance by compacting it into coarse categories. However, to the extent that these categories generalise certain moves to states to which they do not apply, decision-makers may be trapped far away from the solution [18] [19].

Obviously, boundedly rational decision-makers attempt to decompose difficult problems into simpler ones [41]. The difficulty lies precisely in the fact that many problems are not decomposable [19]. For instance, by rotating the slices of the Rubik Cube until one obtains that all tiles on a face have the same colour may not help to reach the solution. The problem of finding a set of risk categories such that complexity is zero is plagued by the same sort of difficulty. For instance, the evaluation of the prospects of a technology may not be independent of the evaluation of management quality.

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. No empirical evidence is available concerning the number of these sub-aspects, though the qualitative descriptions reported in § 2 may suggest numbers in the order of a few units. A possible exception may be the number of technological features, which may conceivably be very many.

Let A be the number of aspects, denoted by an index $a = 1, 2, \ldots A$. Let N_a denote the number of sub-aspects within aspect a. The total number of sub-aspects is $N = \sum_{a=1}^{A} N_a$, denoted by $i = 1, 2, \ldots N$. For $\forall a$ it is $N_a \geq 0$, but since there must $\exists a$ such that $N_a \geq 1$ it is also $N \geq 1$. Thus, a rating system employs N sets of categories $\{R^i_1, R^i_2, \ldots R^i_n\}$.

If $A \leq 6$ and $N_a \leq 10$, a reasonable interval for N may be $1 \leq N \leq 60$. Even with a low estimate of $N = 10$, the number of configurations where for each i it is either $C^i = 0$ or $C^i > 0$ is 2^{10}. The number of non-cyclical paths from any such configuration is $(2^{10} - 1)!$, which is very likely to exceed the human computational abilities.

However, the six aspects identified in § 2 are rather independent from one another. On the contrary, the sub-aspects within each aspect depend strongly of one another. For instance, the evaluation of collaterals is likely to be totally indepen-

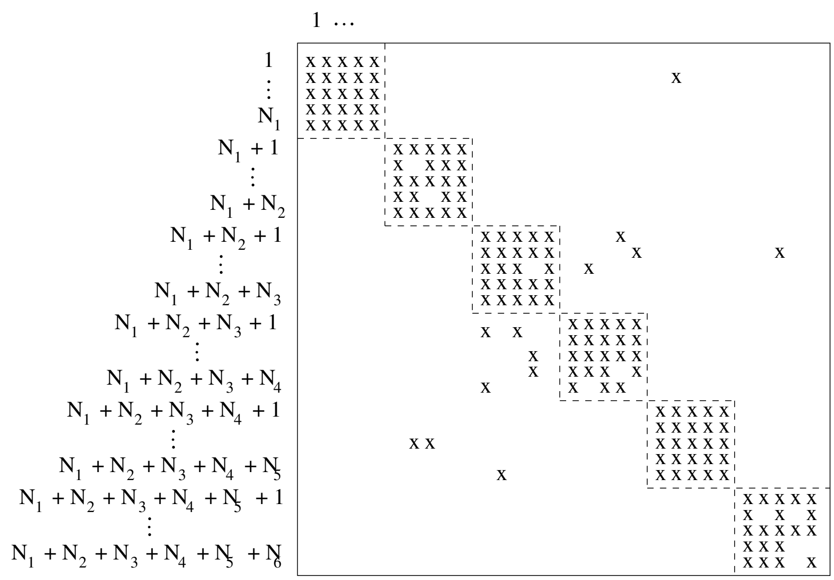

Figure 8: A plausible form of the decomposability matrix for the six aspects mentioned in § 2. The six aspects have been supposed to entail N_1, N_2, N_3, N_4, N_5 and N_6 sub-aspects each. Columns are denoted by the same indices as rows.

dent from the evaluation of management quality, whereas the financial indicators that enter the *Z-score* to some extent overlap one another.

The *transition matrix* is a $N \times N$ binary matrix where the element at row i and column j specifies whether C^i depends on C^j. By permutation of its rows and columns one obtains a *decomposability matrix* where the non-zero elements are arrange as close as possible to the diagonal. If sub-aspects are strongly dependent of one another whereas the main aspects are relatively independent of one another, the decomposability matrix is likely to take the form depicted in figure 8.

The diagonal squares entail most interdependencies between sub-aspects, represented by an "x". A few dependencies are outside the diagonal squares because e.g. the prospects of a technology may not be totally independent from the abilities of managers. On the whole, the problem of difining categories such that $C^i = 0$ for $\forall\, i$ is *nearly-decomposable* along the six aspects [42]. On the contrary, the sub-aspects within each aspect are very much dependent on one another.

To the extent that these six aspects of the loan classification problem are independent of one another, it is convenient to decompose the problem into subproblems. On the contrary, an integrated approach is best suited for interdependent

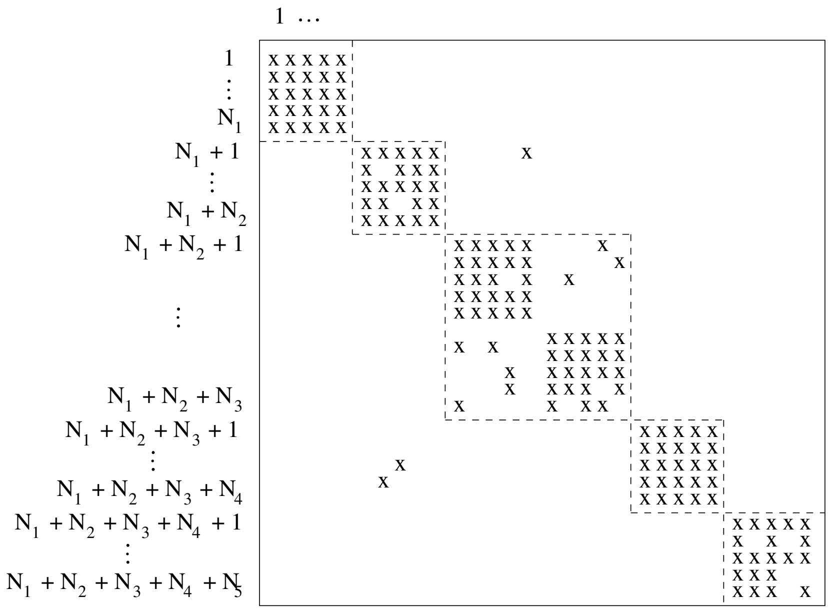

Figure 9: Another plausible form of the decomposability matrix for the six aspects mentioned in § 2, provided that aspects 3 and 4 are compounded in a single one. The six aspects have been supposed to entail N_1, N_2, N_3, N_4, and N_5 sub-aspects each. Columns are denoted by the same indices as rows.

aspects. Thus, in the case of figure 8 it seems sensible to carry out independent evaluations of the six aspects, whereas all sub-aspects within each aspect should be considered in a single evaluation. In fact, parallel exploration of highly interdependent sub-aspects may keep the decision-maker on a local optimum (most C^is are zero, but not all of them) that may be far away from the global solution (all C^is at zero).

The six aspects of § 2 were extracted out of several independent information sources regarding various money-lenders. In reality, many banks do not decompose the loan classification problem so finely. For instance, some banks may compound the evaluation of management quality with the evaluation of the prospects of technologies, as in figure 9.

One may sensibly ask whether such structures of problem-solving are remainders of the past, doomed to extinction. The previous considerations suggest that there are strong incentives to decompose the loan classification problem as finely as possible. However, this may not be the case for all banks.

Simulations show that, because parallel exploration is fast, in an ecology of decision-makers those who (wrongly) apply parallel search to interdependent problems are likely to crowd out those who (correctly) search an integrated solution. this is coherent with the idea that there are strong incentives to decompose, perhaps even more finely than along the six main aspects [25] [12] [36].

However, the same simulations show that there is exception to this pattern, namely, when the environment is so variable that an integrated approach is absolutely necessary in order to escape from local optima. Thus, one may expect that money lenders willing to discover exploit market niches — such as venture capitalists or local banks — will keep problem decomposition at a minimum. This makes the loan classification problem very difficult and prone to mistakes, but solutions may be found, that those banks who follow more standardised procedures will never reach.

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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