Human Computation-Enabled Network Analysis for a Systemic Credit Risk Rating

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Abstract This chapter proposes a novel approach to credit risk rating based upon Network Analysis and enabled by Human Computation. Credit risk rating, which is essential on financial markets, has become difficult with the advent of financial instruments called derivatives and structured notes and of credit management techniques called securitization. The consequences have been dramatic: A wide-spread improper credit risk rating in the presence of these instruments and techniques has been recognized as a major cause of the financial crisis of 2007-2009 which sparked worldwide recessions. This chapter first proposes to collect risk estimates from debtors and derivatives' parties and to aggregate these estimates into eigenvector centralities expressing a systemic rating of the credit risk faced by the market's agents. This rating is shown to hold the promise of overcoming many deficiencies of current credit risk rating. Then, practical and theoretical implications of the proposed approach are discussed. Finally, observing that Human Computation systems and markets are related, it is argued that both Human Computation systems and markets are promising applications for approaches of the kind proposed here.

1 Introduction

This chapter proposes a novel approach to credit risk rating on financial markets based upon Network Analysis and Human Computation and consisting in a dual-purpose participatory mechanism [79].

Credit risk rating is an important activity for participants in financial markets which has become difficult with the advent of financial contracts called derivatives and structured notes and of credit risk management techniques called securitization. A wide-spread improper rating of credit risk, especially of the risk associated with

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derivative and securitization instruments, has been recognized as a major cause of the financial crisis of 2007-2009 [95, 22, 84, 38, 89, 90, 69, 41, 46, 91, 3] which sparked a great recession, the European Sovereign-Debt Crisis [40] and recessions which, after half a decade, are still going on in many countries.

An improper credit risk rating could wide-spread because derivatives, structured notes, and securitization challenge the methods used in current credit risk rating. The disregard of counter-party risk, which is absent in conventional contracts but inherent to derivatives, undoubtedly played a role in the financial crisis of 2007-2009 [38] (but has been largely irrelevant to the Subprime Mortgage Crisis which led to that crisis [46]). Therefore, deficiencies of current credit risk rating methods, or of the current credit risk rating practice, can be seen as core reasons for the improper credit risk rating which has been a major cause of the financial crisis of 2007-2009.

The approach to credit risk rating proposed in this chapter radically departs from current credit risk rating in four aspects. First, it collects credit risks assessments from the debtors and not, as usual, from the creditors. Second, it propagates debtors' risk estimates through the risk dependency graph induced by credit contracts, derivative contracts, and currencies by aggregating as eigenvector centralities the agents' contributions in the global market's risk. Third, it is not based upon stochastic methods and statistical data. As a consequence, it keeps its relevance in exceptional situations such as rare crises or bubbles. Fourth, its principle promises much earlier warnings of an increasing credit risk than possible with current credit risk ranking methods.

Since it combines human computed credit risk assessments and a machine computed eigenvector in which these human inputs are aggregated, the proposed method is a Human Computation algorithm [61, Chapter 2, p. 15]. An essential part of this Human Computation algorithm is an incentive, the "Grace Period Reward" (GPR), for an actual or potential debtor to compute, constantly actualize, and disclose to a system running the proposed Human Computation algorithm estimates of the risk that, in the future, she will fail to honor her debts. The approach to credit risk rating proposed in this chapter is a dual-purpose system [79]: On the one hand, the GPR gives actual or potential debtors a reason to assess and to disclose to the system the risk of their own defaulting; on the other hand the system provides the market participants with a systemic credit risk rating. Since the reason for an agent to contribute to the Human Computation system, namely her use of the GPR, is not the primary purpose of the system, one can call it a passive Human Computation system.[1]

The novel credit risk rating proposed in this chapter is systemic because of its global assessment of credit risk by Network Analysis as eigenvector centralities. This distinguishes it from current credit risk rating performed locally by financial agents for themselves, or by credit rating agencies (such as Standard & Poor's, Moody's Investor Service, and Fitch Ratings) for financial agents, and which do not at all, or only to a very limited extent, propagate credit risk estimates between agents bound by financial contracts.

[1] This denomination has been suggested by Pietro Michelucci.

Implementing the approach proposed would require and induce changes on financial markets that are briefly discussed in this chapter.

Human Computation systems (whether they are Crowdsourcing marketplaces such as Amazon Turk, online job marketplaces such as oDesk, prediction markets [75, 86, 33, 106, 44, 94, 8, 4], decision markets [62], or games with a purpose [103]) on the one hand and markets on the other hand have much in common. These commonalities are finally investigated. This chapter argues that markets can be seen as Human Computation systems *avant la lettre.* This chapter also argues that, as markets become global and transactions get faster, markets' good functioning will require Human Computation-enabled network analyses of the kind proposed in this chapter for financial markets.

This chapter is based upon the research report [19] which it extends.

The contributions of this chapter are as follows:

- A Human Computation algorithm for a systemic credit risk rating.
- A discussion of the practicability of this Human Computation algorithm and of implications of its deployment.
- The thesis that the good functioning of many markets and Human Computation systems will, in the future, benefit from Human Computation-enabled network analyses of the kind proposed in this chapter.

This chapter is structured as follows. Section 1 is this introduction. Section 2 briefly introduces into credit risk rating, derivatives, structured notes, and securitization explaining why these financial instruments and techniques challenge current credit risk rating. Section 3 proposes an incentive, the "Grace Period Reward" or GPR, for debtors to determine, constantly actualize, and disclose estimates of the risk that they fail to honor their debts. Section 4 proposes a systemic credit risk rating as eigenvector centralities. Section 5 discusses the practicability of the Human Computation algorithm proposed and a few perspectives its deployment on financial markets would open. Section 6 compares Human Computation systems and markets. Section 7 is a conclusion.

2 Credit Risk Rating Challenged by Derivatives, Structured Notes, and Securitization

2.1 Importance of Credit Risk Rating

Credit risk is the name given to the risk that a financial agent (like a bank) will not recover the money it is owed according to financial contracts (like mortgages).

Credit risk is essential on financial markets for several reasons. First the values of financial assets depend on the risks associated with these assets. Second, taking too much risk can lead to bankruptcy. Third, financial institutions are expected to reduce credit risk, that is, to convey to their creditors less credit risk than they themselves face [9]. For this reason, depository financial institutions (like banks) have to enforce risk-based capital guidelines or "capital requirements" (such as those issued by the Board of Governors of the U.S. Federal Reserve System and the Basel Accords commonly referred to as Basel I, BaseI II and Basel III) that specify a "capital adequacy" ensuring that a depositary financial institution holds enough capital to both, sustain possible losses and honor withdrawals [45]. The minimum of capital required by risk-based capital guidelines is called "regulatory capital" [9, 45].

Derivatives, structured notes, securitization and a considerable speed differential between financial transactions and credit risk rating, as it is currently performed, have been challenging credit risk rating since at least four decades [21]. This challenge, which so far has not been met, is one of the acknowledged causes of the financial crisis of 2007-2009 [95, 22, 84, 38, 89, 69, 90, 41, 46, 91, 3] which sparked worldwide recessions. In [90, page 1], Michael Simkovic stresses as follows the role of an improper credit risk rating in igniting the financial crisis of 2007-2009:

> "One of the most important contributors to the financial crisis of 2008 was the proliferation of opaque and complex financial instruments that effectively withheld key information from market participants. Without detailed, reliable information about debtors' off-balance-sheet debts and conditional liabilities such as derivatives exposures, creditors cannot accurately evaluate the creditworthiness of debtors and the markets cannot appropriately price risk."

2.2 Current Credit Risk Rating

On financial markets, not only credit contracts of various kinds (loans, mortgages, bills, and bonds) are traded with but also derivative contracts of many kinds (futures, forwards, options, warrants, swaps among others credit default swaps (CDS) and contingent credit default swaps (CCDS)), structured notes and securitization instruments) [24, 46].

Technically, with a derivative there are no creditors and no debtors because, when the derivative contract is entered and during most of the contract's lifetime the direction of money flow between contract parties is left unspecified.This is a fundamental difference between credit and derivative contracts: A credit contract fully specifies the flows of money between the contract parties, a derivative doesn't.

The payments specified in derivatives, like those specified in credits, may not be honored. Thus, while with a credit only the creditor assumes a risk, with a derivative both parties in the derivative assume a risk [24, 27, 38, 46, 3]. The risk induced by both, derivatives and credits, is called credit risk. The credit risk associated with derivatives is often called counterparty risk [38, 3] reflecting that both parties in a derivative assume a risk. Counterparty risk as well as the credit risk assumed by holders of structured notes and securitized instruments is difficult to assess and, so far, is often improperly assessed [24, 38, 3, 46].

Abusing the terms, we shall call debtor (creditor, respectively) a party in a credit or derivative contract which has, or may have, to perform (receive, respectively) a payment. We shall use the phrase "actual or potential debtor" for stressing this abuse of terminology.

The credit risk faced by an agent *i* is measured as a weighted sum [101, 17, 27, 38, 3]: It is the sum over all debtors of *i* of the likelihood that this debtor fails to serve and/or reimburse her debt weighted by the loss this failure would entail for *i*. If, for example, an agent *i* is creditor of three agents *a*, *b*, and *c* for the following sums *a*: 10 \$, *b*, 20 \$, and *c*: 60 \$ and if the risks that these agents will fail to reimburse their debts to *i* are *a*: 25%, *b*: 5%, and *c*: 90%, then the credit risk faced by *i* is $(10 \times 25\%) + (20 \times 5\%) + (60 \times 90\%)$.

Creditor and parties in derivatives use sophisticated stochastic models and statistical methods for assessing the credit risk induced by credits and derivatives [101, 1, 17, 66, 12, 59, 38, 56, 3, 56]. This is called credit risk rating or credit risk assessment. Some of these methods are codified in national and international regulations such as Basel I, II and III. In spite of a large number of models, mathematical methods, procedures and regulations, credit risk rating remains awkward and is far from being reliable [48, 6, 38, 41, 69, 3].

2.3 Derivatives, Structured Notes, and Securitization

This subsection is a brief introduction into derivatives, structured notes, and securitization. See [24, 46] for detailed presentations. This Section can be skipped by readers familiar with derivatives, structured notes, securitization, and current credit risk rating and who are aware of the limitations, and criticisms, of current credit risk rating.

2.3.1 Motivating Example

The following example may help to understand derivatives and, indirectly, structured notes and securitization that, though different from derivatives, are used for similar reasons.

Assume that a family lets a small apartment in Vienna and that a child of this family goes to study to Heidelberg. Finding affordable accommodations at predictable costs is a major challenge for students in Europe in general and in Heidelberg in particular. The family could enter a contract over the duration of its child's studies granting the owner of an apartment in Heidelberg the Vienna appartment's rent for the use of her apartment. With such a contract, the family would make a loss if housing rents raise more in Vienna than in Heidelberg and a gain if the rent differential evolves in the opposite direction. However, with such a contract, the family does not need to concern itself any longer with its child's accommodation and entering such a contract is much cheaper, especially as taxes are concerned, than selling the Vienna apartment for buying an apartment in Heidelberg. For the owner of the Heidelberg apartment, the contract may have advantages as well like low-cost, especially low-taxes, income diversification, and securing a tenant for several years. A derivative is, basically, such a contract. Reasons for parties to enter derivatives, structured note, and securitized instruments are, basically, like in this example.

2.3.2 Derivatives

A derivative contract, short derivative, is a contract between two parties whose value derives from the value of an underlying asset, reference rate, or index. A derivative serves to transfer at low costs the risk associated with its underlying financial instrument or asset from one party to another. Since the end of the 70s of the 20th century, the use of derivatives has grown considerably. Economics' "law of comparative advantages" [80, 50], that is, the ability of an agent to produce a good or service at a lower marginal and opportunity cost than another, explain why a transfer of risk between parties may make sense.

There are different types of derivatives: futures, forwards, options (among others swaptions), warrants, swaps (among others credit default swaps (CDS) and contingent credit default swaps (CCDS)).

A *future* is contract to buy or sell an asset on, or before, a future date at a price specified at contract entering time. Futures have no entering costs, are exchange-traded and standardized. Futures are written (that is, guaranteed) by a clearing house: The clearing house becomes the buyer to a future's seller, and the seller to a future's buyer, so that if a party defaults, then the clearing house assumes the loss. To reduce the credit risk incurred by the clearing house, each party in a future must post a margin (that is, provide an initial amount of cash or a performance bond), usually 5% to 15% of the future's price. The margin is adjusted daily in a process called "marking to market".

Forwards are like a future except that they are not traded on an exchange (they are "off-exchange" or "traded over-the-counter (OTC)"), they induce no interim payments (they require no "marking to market"), and they are not standardized.

An *option* is a contract giving its owner the right, but not the obligation, to buy or sell an asset (commonly a stock, a bond, a currency or a future) at some future time. Options can be both, "exchange-traded" or "traded over-the-counter". Exchange-traded options are, like futures, standardized. A *swaption* or *swapion* is an option on a swap –see below.

A *warrant* is a long-dated option, that is, a contract similar to an option but having a maturity period of more than one year. Warrants are mostly, but not only, "traded over-the-counter" and not standardized.

A *swap* is a contract to exchange over a period of time, usually up to fifteen years, the cash flows of one party's financial instrument for those of the other party's financial instrument. Most swaps are "traded over-the-counter" and not standardized.

With *credit default swaps (CDS)* and *contingent credit default swaps (CDS)* the exchange of cash flows depend on "credit events" (such as capital restructuring, bankruptcy, if an agent's credit rating is downgraded) independent of the two financial instruments the swap is based upon. A CDS is comparable to an insurance because in return for a premium the buyer receives from the seller a sum of money if one of the credit events specified in the contract occur. Unlike an insurance, however, a CDS may, and usually does, cover an asset not owned by its buyer. Not being called "insurances", CDSs escape the (state and federal) regulations insurances are subject to in the USA. A *contingent credit default swap (CCDS)* is like a CDS except that the notional amount of protection is also referenced to an additional "credit event", usually a change in a market or another variable. Thus, the credit risk induced by a CDS to each of its parties depends upon a third party, the party responsible of the credit event the CDS refers to. The credit risk induced by a CCDS to each of its parties depends in addition on a further party, the party which is responsible of the contingent credit event the CCDS refers to.

Finally, derivatives may be squared, that is, a derivative may be derived from ... a derivative.

Except futures, that are guaranteed by a clearing house, all derivatives induce a counterparty risk (that is, a risk for both parties in a derivative) making their credit risk rating more complex than that of credits. Rating the credit risk of CDSs and CCDSs is especially challenging because of CDSs' and CCDSs' "credit events" referring to assets usually not owned by a party in the CDSs or CCDSs.

Derivatives that are guaranteed by a clearing house or exchange-traded are usually standardized, other derivatives are usually not standardized. The reason is that standardization makes possible current credit risk rating, which is based on statistics. The need for standardization, which restricts derivatives, is often mentioned against proposals to regulate the derivative market by requiring all derivatives to be guaranteed by clearing houses and/or to be traded on exchanges.

The approach to credit risk rating proposed in the following requires an institution keeping track of, or "list", trades in credits, derivatives and securitization instruments. It does not require, however, credits, derivatives or securitization instruments to be standardized.

2.3.3 Structured Notes

Structured notes are debt securities (like mortgages, government and corporate bonds) and therefore no derivatives. Like derivatives, however, the interest on a structured note depends on another security, or on price moves, or on a rate (like the London Interbank Offered Rate known as LIBOR). The formula specifying this dependency may be complex.

Thus, like a derivative, a structured note induces a credit risk for both of its parties which depend on the structured note's security of reference. The credit risk assumed by a structured note's creditor, depends on the note's security of reference as well as on the debtor of the structured note. The formula specifying how a structured note's interest refers to its security of reference complicates, often significantly, the rating of the credit risk incurred by the structured notes' parties [24].

2.3.4 Securitization

Securitization consists in building portfolios of debt securities (like mortgages and government or corporate bonds) called securitized instruments or securitized assets and in issuing new securities with claims on the portfolio called "tranches". The payments of interest and principal by the debtors in the debt securities underlying a securitized instrument are allocated to the tranches. The tranches are served by decreasing seniority, the tranche with smallest seniority, called equity tranche, receiving what remains. Thus, for investors, with decreasing tranches' seniorities the credit risk increases.

Securitized instruments are often built from debt securities like home or loan mortgages for which prepayments are possible. As a consequence, the credit risk of all tranches, including the most senior one, of a securitized instrument also depend on the prepayment risk, that is, the risk that debtors in the debt securities underlying the securitized instrument prepay all or part of their debts prior to their debts' maturity. Prepayments happen when interest rates on the credit market fall sufficiently what makes the credit risk assumed by the holders of some securitized instruments dependent on the interest rates. Prepayment risk is often underestimated, or even ignored, by investor estimating the credit risk of securitized instruments [46]. Since a contractual prepayment is no defaulting, technically, prepayment risk is no credit risk. However, the aim of credit risk rating –that is, assessing the likelihood that contractual flows of payments may stop in the future– makes it appropriate to consider prepayment risk as credit risk.

There are several types of securitized instruments: Mortgage-backed securities (MBS) among other Agency MBS, collateralized mortgage obligations (CMO), and collateralized debt obligations (CDO). How and when their tranches are served is specified in the instrument's contract which may be several hundred pages long and quite complicated what, in turn, may make credit risk rating difficult.

Agency MBS are MBS, the principal and interest of their underlying mortgages are guaranteed by US government entities or government-sponsored enterprises (like the Government National Mortgage Association, GNMA, also known as Ginnie Mae, the Federal Home Loan Mortgage Corporation, FHLMC also known as known as Freddie Mac, and the home Loans Banks). Holders of Agency MBS nonetheless assume a risk because of the afore-mentioned prepayment risk. In the past, most holders of Agency MBS have ignored this risk. This was one of the causes of the Subprime Mortgage Crisis [46].

With a CMO, the various tranches assume different prepayment risk and other credit risk. With some simple CMOs, some tranches receive only interest and therefore assume only prepayment risk, while other tranches receive only principal payments and therefore only assume the credit risk of the debt securities underlying the CMO. Thus, the credit risk assumed by holders of CMOs depends on the tranches and in turn on the CMO contract which may be complicated. Furthermore, CMOs are issued as follows by financial entities, the financial health of which is in general difficult to assess. A financial institution creates a legal entity called in the USA special purpose entities (SPE), outside the USA special purpose vehicle (SPV), and transfer mortgages, the "collateral", to this SPE which use them for issuing mortgage-backed securities. SPE isolate the financial institution which create them from the risk of the CMOs the SPE has been created to issue.

Securitized instruments are also built from debt securities such as commercial mortgages, car loans and credit card debt obligations. Such securitzed instruments are called collateralized debt obligations (CDO). The credit risk induced by CDO depend on many debtors, and therefore on many economical variables, what makes it difficult to assess.

Finally, securitized instruments can, like derivatives, be squared, that is, securitized instruments can be built from ... securitized instruments. With such constructions, the credit risk even of the most senior tranches of a squared securitized instrument can increase considerably and the credit risk can become, even for large financial institutions, extremely difficult to assess. One of the acknowledged causes of the Subprime Mortgage Crisis is that credit rating agencies and investors have under-estimated the credit risk induced by such constructions [69, 90, 46].

2.4 Limitations of Current Credit Risk Rating

Credit risk rating, as it is currently performed, has been criticized for empirical and methodological reasons.

As of empirical criticisms, it is acknowledged that an inaccurate assessment of credit risk has been instrumental in the Subprime Mortgage Crisis and the Financial Crisis of 2007–2009 [95, 22, 38, 89, 69, 41, 46, 91] and that the wide-spread disregard, or under-estimation, of the credit risk induced by derivatives, structured notes, and securitization has been one of the major causes of the Financial Crisis of 2007-2009 [69, 38, 91]. Assessing the credit risk derivatives induce is considered rather complex [17, 21, 38, 89, 22, 41].

A further empirical criticism of current credit risk rating is that it mostly fails when applied to securitization instruments. Securitization limits an investor's ability to assess the risk associated with mortgage-backed securities and CMOs. An improper credit risk rating of securitization instruments is seen as a cause of the US Subprime Mortgage Crisis [46, Chapter 8 "Securitization and the Crisis of 2007"] which sparked the Financial Crisis of 2007-2009. Off balance sheet securitization, which is based on a transfer of unqualified risk, is believed to have played a significant role in the high leverage level of US financial institutions before the financial crisis, and the need for bailouts after the outbreak of the financial crisis of 2007-2009 [91]. No credit rating agencies, for example, downgraded the investment bank Bear Stearn, which had issued large amounts of asset-backed securities, before its collapse in 2008.

As of methodological criticisms of current credit risk rating, some, prominently Benoit Mandelbrot and Nassim Nicholas Taleb, have argued that, since current credit risk rating is based on stochastic methods and statistical data, it is inherently inaccurate in exceptional situations such as market crises and bubbles [64, 63, 99].

Current credit risk rating is necessarily inaccurate during market bubbles because current credit risk rating is performed by the parties assuming the risk, not by those causing it, and because bubbles, from the Tulip Mania Bubble in 17th century Holland to the Dot-com Bubble in 21st century USA, always result from a loss of sense of assumed risk [11]: As a bubble booms, that is, some prices keep raising more and over longer periods of time than usual, more and more traders get seduced by the perspective of unexpected gains, loose their sense of risk and join in the frenzy, buying because they expect to later sell at higher prices, thus contributing to keep the price raising up until enough traders come to reason, what causes the bust.

A further wide-spread methodological criticism of current credit risk rating concerns biases. As mentioned in [101, page 921] biased views, whatever their causes, often result in an inaccurate credit risk rating.

A further wide-spread methodological criticism of current credit risk rating is that, being performed mostly by banks to display evidence of their financial health and by credit rating agencies on behalf, and often at the expenses, of debtors that need good ratings for being granted credits at good conditions, current credit risk rating is not free from moral hazard. The charts of [101, page 917] for example report on much more optimistic credit risk ratings at banks than at credit rating agencies long before the Subprime Mortgage Crisis and the Financial Crisis of 2007-2008. The article [18] cautiously states that

> "the way the current rating market is organized may provide [rating] agencies with intrinsic disincentives to accurately report credit risk of securities they rate."

A further problem with current credit risk rating, which, admitedly, is rarely mentioned, is the considerable speed differential between financial transactions and credit risk rating. Algorithmic trading [51, 35], in particular "high-frequency trading", automatically reacts to index variations in fractions of seconds, much faster than humans can react to observations they make. In contrast, credit risk rating is computed by humans working mostly in committees delivering their updates at best weekly (for example for the home mortgages of a region), usually every couple of weeks, at worst every quarter of a year (for example for government bonds) [101, 1, 66, 12].

The Human Computation-enabled network analysis for credit risk rating described in the following addresses the afore mentioned limitations of current credit risk rating: It is affected neither by the nature nor by the complexity of financial instruments traded with on a market, it is not based on stochastic methods and statistical data what makes it reliable also in exceptional situations, the rating it delivers is neither impaired by investors loosing their sense of risk, nor by financial institutions eager to demonstrate a good financial health, and it significantly reduces the speed differential between transactions and credit risk rating. And, importantly, it does not require a standardization of financial instruments.

3 Human Computation: Potential Debtors Assess Their own Risk of Defaulting

We propose to collect from the market's agents assessments of the risk that, in the future, they fail to honor their debts. Collecting such assessments from actual or potential debtors has three advantages:

- It provides earlier estimates than current credit risk rating performed by creditors or credit rating agencies. Indeed, debtors suspect their possible defaulting earlier, usually much earlier, than their creditors.
- It complements current credit risk rating performed by creditors and credit rating agencies.
- It is not subject to the moral hazard of current credit risk rating (mentioned above in Section 2.2).

3.1 The Incentive: The Grace Period Reward (GPR)

For an agent facing its possible defaulting, time is extremely precious. Time makes it possible to recover outstanding debts or to take a credit and thus, in some cases, to prevent one's defaulting and, possibly, bankruptcy. We exploit this in devising an incentive, the "Grace Period Reward" (GPR), for an actual or potential debtor to compute, constantly actualize, and disclose its own estimates of the risk of defaulting.

The GPR functions like a credit default insurance but, importantly, only for a limited period of time of a few weeks to a few months, the "grace period" and at costs that are the same for all agents on the financial market. As a consequence, the GPR is not a credit default insurance and does not yield moral hazard as do credit default insurances.

The GPR can be activated by (actual or potential) debtors at any time t so as to begin at any future time $t_1 \geq t$ and for any coverage (that is, percentage) of actual or possible outstanding payments. Once activated by an agent for an actual or potential debt, the GPR can be deactivated at any time by this agent.

An activation by an agent of the GPR at time t beginning at a later time t_1 for $x\%$ of an actual and possible debt expresses the opinion at time t of this agent that, at time t_1 or later, it may default to pay the principal or the interest of this debt. Increasing (decreasing, respectively) values of x reflect an increase (a decrease, respectively) of the agent's belief in its own defaulting. An activated GPR comes at a cost for the agents, what incites them only to activate the GPR when they see a need. The costs of an activated GPR are proportional to both, the outstanding payments and the activation duration, making GPR activations reliable estimates of how likely debtors' hold their own defaulting.

The costs of an activated GPR are covered from a compulsory GPR deposit to be made by actual or potential debtors when entering a credit or derivative contract. The hight of this compulsory deposit depends on the credit or derivative contract. The GPR deposit is lost (to the creditor or the agency running the GPR) by the debtor if it defaults while the GPR is not activated and otherwise refunded at the end of the credit or derivative contract up to the costs resulting from, possibly temporary, activations of the GPR. The possible loss of the GPR deposit incites debtors to activate the GPR accordingly to the risk of defaulting they perceive.

Furthermore, it would make sense not to grant the GPR's grace period, or to grant it only to a limited extent, to defaulting agents that have activated the GPR much later than when they acquired knowledge of events motivating their activating the GPR.

Whether a debtor activates the GPR or not is not disclosed within the agent's community. This ensures that no moral hazard impairs the risk assessments deduced from GPR activations.

Finally, the GPR could come at a low cost so as to cover its management costs as well as the costs of the network analysis described in the next section.

3.2 Calibrating the GPR

The GPR requires calibration. The costs of an activated GPR must be set according to insurances' good practices, the duration of the grace period must be defined (most likely depending on the type of agents), the types of credits, and types of derivatives, and the value of the GPR deposit must be appropriately set (most likely depending on the types of agents and contracts), etc.

Part of the GPR's calibration might consist in "socio-cultural adjustments" of the following kind: If a social and/or economical group G of agents is known to overestimate (or underestimate) their own credit risk, than this could be accounted for with adjustment factors reducing (or enhancing) the credit risk estimates they express through the GPR. Furthermore, such socio-cultural adjustments could be democratically agreed upon in the community of all agents, possibly using ad hoc Human Computation systems.

Calibrating the GPR requires further investigations and is out of the scope of this chapter.

3.3 Assessing Prepayment Risk

As mentioned in Section 2.3.4, it is appropriate to consider prepayment risk as credit risk. The question therefore arises, whether the GPR could contribute to an early assessment of prepayment risk.

This seems to be the case. The GPR would incite creditors to inform early of possible prepayment if, while activating the GPR, a creditor could limit the activation duration to the date of an expected prepayment and if the GPR costs would be reduced by early activations.

Like calibrating the GPR, tuning the GPR towards assessing prepayment risk requires further investigations and is out of the scope of this chapter.

3.4 Social Control

The GPR gives room to social control. If some agents, say some banks, feel that other agents, say home mortgage debtors, over-estimate, or under-estimate the likelihood of their defaulting, then the first agents can trigger a debate on the issue what, eventually, can lead to the other agents changing their assessments of their risk of defaulting.

3.5 The GPR and Traditional Credit Risk Rating

The GPR complements traditional credit risk rating. It neither replaces it nor conflicts with it. Indeed, in deciding whether or not to activate the GPR, agents are well advised to make use of all information and all risk rating methods at their disposal.

The estimates the GPR would collect differ from those obtained with current credit risk rating in several essential aspects. First, the GPR returns estimates by actual or potential debtors of the likelihood of their own defaulting while current risk rating is performed by the actual or potential creditors. Arguably, estimates collected by the GPR from debtors are less biased than current credit risk rating. Second, the estimates collected with the GPR can be expected to be updated at least daily and, in case of algorithmic trading, much more often. Indeed, algorithmic trading calls for algorithmic GPR activations. Third, in contrast to traditional credit risk rating, the GPR promises estimates differentiated after different time points in the future. Fourth, estimates collected by the GPR are not based on stochastic methods and statistical data. This makes GPR-based estimates reliable in crisis times (such as bubbles) and when new financial instruments are introduced for which no statistics are available.

3.6 The GPR and Moral Hazard

Since the grace period is limited to a short period of time, the GPR is not subject to the moral hazard of a credit default insurance which may induce debtors to take risks that, without insurance, they would not take.

3.7 The GPR as a Transaction Tax

The GPR can be expected to act like a financial transaction tax, or Tobin tax, the objective of which is to hinder short-term speculative financial "round-trip transactions" [100]. Indeed, adequately activating the GPR requires human work and come at a cost while not activating it may result in losses. Algorithmic GPR activations would not reduce the value of the credit risk rating based on the GPR activations because of both, the costs of activating the GPR and the time-limited safety the PPR provides to both, the GPR activators and the market as a whole.

A fundamental difference, however, is that in contrast to a financial transaction tax, the GPR collects information which, as described in the next section, is used for a systemic credit risk rating. Thus, the GPR can be called an "informationally productive" financial transaction tax, while the standard financial transaction tax, or Tobin tax, how effective it might be, can be seen as "informationally unproductive".

4 Network Analysis: Aggregating Human Estimates into a Systemic Credit Risk Rating

This section describes how the estimates collected by the GPR –see above Section 3– can be aggregated as eigenvectors expressing a systemic credit risk rating.

Eigenvectors are solutions of systems of linear equations. They are commonly used for expressing the stability of physical systems and the relative importance, so-called centralities, of the nodes of a network [14]. It is this second usage which is relevant here.

4.1 Formalizing an Agent's Credit Risk

Using the estimates of defaulting likelihood provided by the GPR, the credit risk $\mathrm{CR}^t(i)$ of an agent i at any future time t can be estimated as follows:

$$\mathrm{CR}^t(i) = \sum_j (w^t_{ji} \times c^t_{ji}) \tag{1}$$

where:

- $w^t_{ji} \in [0,1]$ is the estimate collected by the GPR of the likelihood that agent j defaults to agent i at time t
- c^t_{ji} is the payment surely or possibly due by agent j to agent i at time t

Variations of $\mathrm{CR}^t(i)$, or of a conveniently chosen aggregation $\Phi_{i\in G}\mathrm{CR}^t(i)$ for a group G of agents like, for example, the home mortgage debtors of a region, are useful indicators of agent i's, or of the group's, financial health. A constant increase of $\mathrm{CR}^t(i)$, or of $\Phi_{i\in G}\mathrm{CR}^t(i)$, over a period of time can help in restoring early enough agent i's, or group G's, credit strength so as to prevent cascading defaulting.

If agent i has a large number of debtors, for example, if i is a sufficiently large financial institution, then an appropriate aggregation $\Phi_{i\in D(i)}\mathrm{CR}^t(i)$ over the set $D(i)$ of (actual or potential) debtors of agent i can be disclosed to this agent without disclosing the estimates w^t_{ji} what, as discussed in Section 3 would compromise the good working of the GPR as a collector of reliable estimates of defaulting likelihood. The variations over time of conveniently chosen aggregates would be valuable credit risk indicators for a financial institution that would complement its own credit risk rating.

4.2 Credit Risk Flow

Considering how credit risk flows from agent to agent on a financial market suggests a systemic credit risk rating, that is, a rating reflecting the flows of credit risk on the financial market. Credit risk flows are first discussed.

A first observation is that nowadays on financial markets creditors are also debtors. Indeed, cash (that is, assets that can be realized immediately or almost immediately) is marginal in backing the credits that financial institutions (be they depositary institution, investment institutions, or insurances or pension funds) grant. Indeed, it would not make much sense to take a credit and to back it with cash! For the same reason, cash is also marginal in backing future payments a company may face due to a derivative contract.

A second observation is that, as of credit risk, governments are like other agents on financial markets both debtors and creditors. They are creditors, since taxpayers owe governments taxes, and debtors, since governments issue securities, government bonds, and bills.

A further observation is that some financial institutions borrow and lend money from central banks, that is, are debtor and creditor of central banks. Furthermore, central banks differ from other financial institutions inasmuch that they are not expected to reduce credit risk. While reducing credit risk (that is, to convey to their creditors less credit risk than they receive from their debtors) belongs to the *raisons d'être* of depositary banks, investment institutes, insurances and pension funds [9], the *raison d'être* of a central bank is to control the monetary base (that is, to create money and control its quantity), to control the interest rates, and to be lenders of last resort [16].

A last observation is that money and more generally a currency, too, conveys credit risk [67, 37]. Indeed, money is a "claim upon society" [92]. Credit risk, flowing from debtors to creditors, reaches central banks from which it flows back to all agents of the financial market. The European Sovereign-Debt Crisis since 2009 gives ample evidence of this backflow through a currency of real, as well as perceived, credit risk [40].

4.3 A Central Bank's Contribution to Credit Risk

What, in Equation (1) of Section 4.1 above defining the credit risk $\mathrm{CR}^t(i)$ of agent i (at time t), should be the contribution of the central bank b to the credit risk of i (at time t)? Since, as observed above, a central bank b does not reduce credit risk, we propose to define this contribution as the amount of credit as well as cash or cash equivalents (that is, assets readily convertible into cash) owned by agent i (at time t). Thus, Equation (1) is refined as follows so as to take the central bank into account:

$$\mathrm{CR}^t(i) = C_i^t + \sum_j c_{ji}^t + \sum_j (w_{ji}^t \times c_{ji}^t) \tag{2}$$

where C_i^t denotes the cash and cash equivalents owned by agent i at time t.

For financial institutions i subject to risk-based capital guidelines, the so-called capital requirements, C_i^t can easily be known. Indeed, it is disclosed by i to the agencies controlling the enforcement of capital requirements. For other agents i on the financial market, C_i^t can either be neglected as very small in comparison to $\sum_j c_{ji}^t$ or estimated from statistics.

All agents i should disclose c_{ji}^t when entering the corresponding credit or derivative contract. Knowledge of c_{ji}^t contract could be given by agents i and j to the GPR (or any other agency) upon entering a credit or derivative contract even if the GPR is not immediately activated, what, most likely, should be the most frequent case.

Thus, $\mathrm{CR}^t(i)$, as defined in Equation 2, can be considered a known value for all agents i.

4.4 Credit Risk Graph

Call Credit Risk Graph (CRG) of a financial market the directed graph the nodes of which are the market agents (including government(s) and the central bank) and the labelled edges of which are defined as follows:

- There is an edge
$$j \xrightarrow[w_{ji}^t \times c_{ji}^t]{t} i$$
from each agent j which is not the central bank and which is an actual or potential debtor of an agent i expressing the contribution of agent j to the credit risk $\mathrm{CR}^t(i)$ of agent i.
- There is an edge
$$b \xrightarrow[C_i^t + \sum_k c_{ki}^t]{t} i$$
from the central bank b to each agent i.

The CRG of a financial market is strongly connected. Indeed, as observed above, every agent is a debtor of a financial institution. Every financial institution is directly or indirectly connected by a directed path, or "debtor path", to a central bank. Indeed, this is because of such paths that central banks can control the monetary base. Thus, in the CRG, there is a directed path from every agent j to a central bank. Since there is a directed edge from a central bank to every agent i, there is, in the CRG, a directed path from every agent j to every other agent j, that is, the CRG is strongly connected.

4.5 Credit Risk Rating as Eigenvector Centralities

The facts that credit risk is defined as a weighted sum, that is, as a linear combination, and that the CRG of a financial market is strongly connected suggests that eigenvector centralities [85, 52, 36, 13, 14, 15, 55, 102] are appropriate as credit risk ratings. The following elaborates on this intuition and shows that it is adequate.

Let $A^t = (a^t_{ji})$ denote the adjacency matrix of the labelled graph CRG at time t. Beware that the superscript t denotes time, not matrix transposition. Matrix transposition is denoted, as usual, by the superscript T).

$A^t = (a^t_{ji})$ is defined by

$$a^t_{ji} = \begin{cases} w^t_{ji} \times c^t_{ji} & \text{if } j \text{ is not the central bank and is an actual or potential} \\ & \text{debtor of } i \text{ at time } t \\ C^t_i + \sum_k c^t_{ki} & \text{if } j \text{ is the central bank} \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

Note that matrix A^t is real and non-negative and the diagonal elements of A are all 0. If I is the identity matrix of same size $n \times n$ as A^t, $A^t + I$ is a real and non-negative matrix the diagonal elements of which are all 1, that is, non-negative. Considering $A^t + I$ instead of A^t is needed for the Perron vector considered below to exist.

Let $B^t = (b_{ji})$ be the column-stochastic normalization of the transposed $(A^t + I)^T$ of $A^t + I$ defined as follows:

$$b^t_{ji} = \begin{cases} \frac{a^t_{ij}}{\sum_j a^t_{ij}} & \text{if } j \neq i \\ \frac{1}{\sum_j a^t_{ij}} & \text{if } j = i \end{cases} \tag{4}$$

Like matrix A^t, matrix B^t is real and non-negative and its diagonal elements b^t_{ii} are all positive. Matrix B^t is, by definition, column-stochastic. The CRG being, as observed above, at any time t strongly connected, B^t is irreducible.

While the entry a^t_{ji} of A^t expresses the *absolute* contribution of agent j to the credit risk of i (at time t), the entry b^t_{ji} with $j \neq i$ of B^t expresses the *relative* contribution of agent i to the credit risk of j (at time t).

Equation (2) can be re-expressed as follows:

$$(\overrightarrow{cr^t})^T = \overrightarrow{1}^T A \tag{5}$$

where:

- $\overrightarrow{cr^t}$ is the credit risk (column) vector at time t, the ith element of which is $\mathrm{CR}^t(i)$
- $\overrightarrow{1}$ is the unity (column) vector of dimension n (n being the number of agents on the financial market), all components of which are 1

Disregarding the diagonal elements of B, a relative version of (5) and therefore of (2) is:

$$\overrightarrow{cr^t} = B\overrightarrow{1} \tag{6}$$

Equation (6) suggests to define a systemic risk rating as follows. Assume $\mathrm{CRR}^t(i)$ is a rating, or index, expressing the "credit risk strength" of agent i at time t. The credit risk strength of i (at time t) should surely be seen as proportional to the average of the credit risk strengths of its debtors j (at time t) weighted by the proportions b^t_{ji} to which debtors j contribute to the credit risk of i (at time t):

$$\mathrm{CRR}^t(i) = \frac{1}{\lambda} \times \sum_j (b^t_{ij} \times \mathrm{CRR}^t(j)) \tag{7}$$

where λ is a positive real scalar. Equation 7 can be expressed as:

$$\lambda\overrightarrow{crr^t} = B^t\overrightarrow{crr^t} \tag{8}$$

where $\overrightarrow{crr^t}$ is the credit risk rating vector (at time t) the ith component of which is $\mathrm{CRR}^t(i)$, the credit risk rating of agent i (at time t).

Equation 8 specifies a credit risk rating as eigenvector centrality. The rest of this section, which shows that Equation 8 is an acceptable definition, is common knowledge [85, 52, 36, 13, 14, 15, 55, 102]. It is included here for the sake of completeness.

B^t being, as observed above, irreducible, real, non-negative, column-stochastic and each diagonal element of B^t being positive, it follows from celebrated theorems by Perron and Frobenius [76, 31, 105, 60] that $\lambda = 1$ is a simple and strictly dominant eigenvalue of B^t the eigenvector associated with is called Perron vector of B^t.

Since $\lambda = 1$ is a simple eigenvalue of B^t, the Perron vector of B^t is, up to a scalar, the unique real non-zero solution of Equation 8. This makes the Perron vector B^t with norm 1 an acceptable credit risk rating vector. Indeed, if Equation 8 had several real solutions with norm 1, then there would be no reasons to choose the one instead of another as a credit risk rating vector.

Finally, if a vector $\overrightarrow{u}$ is not orthogonal to the Perron vector of B^t, then normalized power sequences of B^t and $\overrightarrow{u}$ converge to the Perron vector of B^t [104, 60]. This makes it possible to apply the power iterations [104, 60] to compute the Perron vector of B^t expressing a credit risk rating. If, by chance, a vector $\vec{u}$ normalized power sequences would start with would be orthogonal to the Perron vector of B^t, then rounding errors would nonetheless ensure convergence to the Perron vector of B^t.

5 Discussion

This section first questions the model underlying the systemic credit risk rating proposed in the former section. Then, it discusses the technical practicability of running the Human Computation algorithm consisting of the Grace Period Reward (GPR) of Section 3 and the computation of the Perron vector defined by Equation (8) of Section 4. It also discusses whether financial markets could accept the constraints imposed by the GPR. Finally, it stresses that the Human Computation algorithm proposed in this chapter would provide the information necessary for more accurate, dynamic, settings of the regulatory capital [9, 45].

5.1 Questioning the Model

Even though there are good arguments for assuming that all agents on a financial market are debtors, the reality is sometimes more complex than one expects.

If some agents are, at some time t no debtors, then the Credit Risk Graph (CRG) of Section 4 would not always be strongly connected and the matrix B^t (obtained from the adjacency matrix A^t of the CRG) would not fulfill the conditions ensuring the existence of the Perron vector. In such a case, the matrix A^t could be modified so as to express that an agent, who in reality is no debtor, being in equal proportions the debtor of all other agents on the financial market. PageRank [73, 60] is based upon a similar transformation of the Hyperlink matrix. This transformation does not impair PageRank's adequacy as a ranking.

In Section 4, a single central bank is considered. The CRG, and therefore the systemic credit risk rating specified in that section, can easily be extended to several central banks. Such an extension requires to consider different currencies. To this aim, instead of the matrices A^t (B^t, respectively), 3-rank tensors need being considered each consisting, for each currency of a matrix A^t (B^t, respectively). Exchange rates between the currencies also need to be considered, if, as one may expect, some agents are parties in credit or derivative contracts in different currencies.

The model is based upon the view that a currency in general, and money in particular, conveys credit risk. This view implies that the value of a currency (and of money) is two dimensional, one dimension reflecting the prosperity of, the other the systemic credit risk in, the area where the currency is a unit of account. The European Sovereign-Debt Crisis since 2009 gives ample evidence that this interpretation is appropriate [40].

5.2 Practicability

Could, from a computing viewpoint, the GPR of Section 3 be deployed and repeated computations of the Perron vector defined by Equation (8) of Section 4 be performed?

The GPR requires a transaction for each new financial contract and each time a contract party activates, de-activate, or modifies an activation of the GPR. Except in crisis times, most contracts can be expected to result in no or a very small number of activations of the GPR. Hence, the IT support of the GPR would, in normal times, be no challenge for the IT infrastructure of a financial market. If in crisis times the GPR requires too high an IT support, then this would be a sufficient reason to slow down the market activity and, as a consequence, the GPR usage. Indeed, a "GPR frenzy" would be a clear sign of a market getting out of control.

Repeated computations of the Perron vector of Equation (8) is a real challenge which would require a significant extension of the IT infrastructure of a financial market and which deserves more investigations. Since it refers to time, Equation (8) in fact refers to a 3-rank tensor A, one of the ranks of which is the time line. The time considered is, of course, discrete (the time unit being the (bank) day) and finite (the latest time point being the latest credit event referred to in an activation of the GPR). This tensor is likely to be very sparse, because only a few different degrees of activations of the GPR for a same contract by a same agent can be expected. This sparsity provides a hook for efficient power iterations which, admittedly, remain to be fully worked out. This tensor is also sparse because,

- at each time t, the matrix A^t, and therefore the matrix B^t, are sparse. Indeed, most agents are no financial institutions and therefore enter financial contracts with a limited number of agents,
- there are only a few financial institutions, that at any time are bound by contracts with large numbers of agents.

Repeated updates of the Perron vector defined by (8) could be performed, like the Google search engine does, by considering only those parts of the matrices B^t that have been updated since the last computation.

Thus, computing the Perron vector defined by (8) would be rather similar, in the techniques and computing effort needed, to computing the structure ranking of a Web search engine.

5.3 Acceptance

Deploying on a financial market the systemic credit risk rating proposed in this chapter would require significant changes on this market. First, all financial transactions would have to be registered. Second, computations similar to that of a Web search engine would have to be performed.

In [90] Michael Simkovic makes a plea for "recordation", that is, for creditors to make

> "a full and complete disclosure [of creditor-debtors-liens] in return for payment priority"

in case of a debtor's defaulting. Disclosure of creditor-debtors-liens to the system running the GPR and computing the systemic credit ranking is all the systemic credit risk rating proposed in this chapter requires, that is, less than Michael Simkovic considers necessary for other reasons.

One might expect that the inertia natural to individuals and organizations will prevent such changes. The promise of a financial market better and earlier foreseeing a wide-spreading of credit risk should be sufficient an incentive to changes, if not for the financial markets themselves, for the executives and legislatives responsible for the bailouts of financial institutions deemed "to big to fail" that, as the financial crisis of 2007-2009 has shown, may result from today's credit risk rating.

The GPR should be appealing to financial markets, regulators of these markets, and the society because its functioning can be seen for three reasons as "bailouts in the small": First, the GPR makes it possible to bail out debtors before too high a credit risk has been concentrated in financial institutions deemed "too big to fail". Second, the GPR is limited in time and, in contrast to a credit risk insurance, does not bail out defaulting debtors but instead only give them, and the society, time to financially recover. Third, the GPR's costs are covered from the markets' agents, the GPR fee acting like a transaction tax.

5.4 Feedback Loop: Dynamic Regulatory Capital

Currently, the regulatory capital [9, 45] a depository financial institution must hold depends on the credits it has given but not on its credit risk. This is consistent with the fact that, so far, there is no systemic credit risk ranking and that assessing credit risk is, in spite of regulations, to a large extent "one's own affair".

The systemic credit risk ranking proposed in this chapter would make it possible to specify for each depository institution an amount of regulatory capital depending on the systemic credit risk rating of this institution.

The systemic credit risk ranking proposed in this chapter would also make it possible to foresee changes in the regulatory capital of a depositary financial institution implied by changes of the institution's systemic credit risk ranking.

5.5 Systemic Risk

The rating of credit risk proposed in this article is "systemic" because it is computed as an equilibrium property of the credit risk graph induced by credit contracts, derivative contracts, and currencies. Can this systemic rating of credit risk also serve as a rating of systemic risk?

There is an abundant research literature on systemic risk, a large part of which has been published after, and because of, the Asian Crisis of 1997-1998. Following the Financial Crisis of 2007-2009 and the European Sovereign-Debt Crisis going on since 2009, the Board of Governors of the Federal Reserve System in the US, the boards of banks in the US and in Europe, and public agencies such as the European Securities and Markets Authority (ESMA) have launched research groups commissioned to propose systemic risk measurements. This triggered many more publications on the subjet. The recent survey [10] the authors of which state (on page 4) "we do not attempt to be exhaustive in our breadth" lists no less than thirty-one proposals for measuring systemic risk! In spite, or because, of this intense research activity, systemic risk remains a concept without widely accepted definition [26, 10, 42] as the article [10] stresses in its introduction:

> "The truism that 'one cannot manage what one does not measure' is especially compelling for financial stability since policymakers, regulators, academics, and practitioners have yet to reach a consensus on how to define 'systemic risk'. While regulators sometimes apply Justice Potter Stewarts definition of pornography, i.e., systemic risk may be hard to define but they know it when they see it, such a vague and subjective approach is not particularly useful for measurement and analysis, a pre-requisite for addressing threats to financial stability."

Informally, "systemic risk" refers to the risk of breakdown of a financial market as a consequence of cascading insolvabilities of market agents bound to each other by financial contracts. The article [42, Section 2.1] points to three different acceptations of "systemic risk" in the research literature: (1) "a modern-day counterpart to a bank run triggered by liquidity concerns", (2) "the vulnerability of a financial network in which adverse consequences of internal shocks can spread and even magnify within the network", and (3) one of the former senses extended so as to "include the potential insolvency of a major player in or component of the financial system."

The purpose of the systemic credit risk rating proposed in this article is an early detection of systemic risk in the first of the above mentioned senses. Most likely, it would also help in detecting some "vulnerabilities in a financial network". There are no reasons to believe, though, that it could help in detecting all of them. It should also be useful for an early detection of potential insolvencies of components of a financial market. Indeed, its principle, an eigenvector computation, makes it easily adaptable to compute the centralities of groups of market agents. It would provide with an estimate of the systemic risk assumed by a currency, that is, by the community of the currency area. The matrices A and B of Section 4.5 would be useful for many kinds of systemic risk investigations.

In contrast to most systemic risk measures proposed so far (see [10] for a survey) the rating proposed in this article is neither based on the assumption that systemic risk arises endogenously within a financial market nor does it rely on stochastic methods and statistical data. This makes it a plausible risk indicator in times of exogenous shocks and of crises that rarely happen.

The articles [65, 41, 58] deserve a special mention here because, like the present proposal and unlike most of the credit risk and systemic risk literature, they propose approaches based on Network Analysis and eigenvector computations. The article [41] develops models of financial networks inspired from ecological food webs and from networks within which infectious diseases spread. The article [58] which reports on an empirical time series analysis of the financial transactions over one year between the major financial agents in Austria uses eigenvalue spectra.

6 Human Computation and Markets

In conceiving well-working Human Computation systems (such as Crowdsourcing marketplaces [61, Section 5.1 page 45], prediction markets [44, 106, 75, 86, 33, 94, 8, 4], decision markets [62], immediate response Crowdsourcing systems [68, 97], or games with a purpose (GWAPs) [103, 98, 20, 54]), the following issues are worth considering: The incentives provided for humans to contribute to the systems [74, 43, 30, 107]; whether the systems are capable of growing (in the sense of attracting more human participation) [53, 78, 77, 71, 57]; whether the systems are self-sufficient (inasmuch that they generate all data needed for their proper working);[2] and whether they are efficient (in the sense of achieving maximum productivity with minimum wasted human and machine effort or expense) [47, 2, 32, 23].

It is striking that these issues are economical characteristics. This is not by chance. The amount of human computation a Human Computation system makes possible can be seen as the "wealth" it generates and economics is the field concerned with the production, consumption, and transfer of wealth [49]. Furthermore, markets can be seen as Human Computation systems *avant la lettre,* that is, before the term had been coined. Indeed, on markets traders perform the following "computations" (even though in the past without computer support): Interpreting information on the goods traded with and adjusting the trading prices. On markets so-called "market-makers" also perfom "computations" (in the past without computer support) when they ensure the markets' liquidity by selling (purchasing, respectively) at prices lower (higher, respectively) than the current sale (purchase, respectively) prices and possibly speculating on the prices' evolution for making a profit [39].

The Efficient Market Hypothesis [83, 28, 72] according to which prices on financial markets reflect all information[3] on the assets traded with makes sense because of these "computations" performed by humans, that is, the human activity necessary for the timely wide-spreading of the information the traders and market-makers rely on for their price adjustments. Thus, Adam Smith's "invisible hand" [93, 72], a

[2] Surprisingly, self-sufficiency of Human Computation sytems does not seem to have, so far, attracted much attention within the research community. The sytem's self-sufficiency has been one of the author's concerns in building the Human Computation platform metropolitalia.org [54].

[3] Past, present and even hidden information, depending on which of the Weak, Semi-Strong and Strong Efficient Market Hypotheses is considered.

metaphor expressing markets' capability of self-regulation, can be seen as a Human Computation *avant la lettre.*

A worthwhile question is thus not only whether today's financial markets are efficient, a question which has been much debated [70, 5, 81, 7], but also what can be done for ensuring, or improving, financial markets' efficiency. This chapter is a contribution to ensuring the efficiency of financial markets. Its thesis is, that Human Computation provides with novel means, that so far were unthinkable, for ensuring markets' efficiency. Since markets and certain forms of human computation are related, more insights into markets' efficiency may also have implications on the design of efficient Human Computation systems. In other words, approaches similar to the Human Computation enabled systemic credit risk rating proposed in this chapter could be conceived for regulating Human Computation systems.

Like credit risk on financial markets, reputation is a primary concern among the human contributors to many Human Computation systems (like Crowdsourcing marketplaces and immediate response Crowdsourcing systems) and of course among traders on online auction systems (like eBay). It is rather natural to think that a network analysis similar to the one proposed in this chapter for credit risk rating would be promising for assessing reputation. This view has recently been shown to be accurate [34, 25].

Prices are as important for the good working of a Human Computation labor market (like Amazon Turk) as a proper credit risk rating is for the good working of a financial market. So far, Human Computation labor markets are far from being efficient both, in the sense of Human Computation system efficiency mentioned at the beginning of this section, and in the sense of the Efficient Market Hypothesis [83, 28, 72]. Indeed, a major criticism of Mechanical Turk concerns its pricing of labor [82, 87, 88, 29]. This criticism is summarized as follows in [61, page 74]:

> "[...] there exists power asymmetry in Mechanical Turk, where requesters can reject work without providing justification, thereby not only forbidding payment but hurting the future chances of work by damaging the workers reputation."

On a labor market like Amazon Turk, a Human Computation-enabled network analysis of the type described in this chapter holds the promise of a better labor pricing, either through the detection of unfair requesters by a ranking of their reputations, through a "bipartite ranking" considering both, requesters' and workers' (or turkers') reputations, or through a ranking combining prices and reputation. What such a ranking may be, is an open issue. Undoubtedly, Network Analysis holds the promise of such rankings, that is, of making Human Computation labor markets more efficent in both senses mentioned above.

The author believes that Human Computation-enabled network analyses of the kind proposed in this chapter will, in the future, contribute to the good-working of many Human Computations systems and markets. In an age of progressing globalization [96], only a systematic collecting of information and its timely aggregation can ensure the efficiency of both, Human Computation systems and markets. Human Computation is needed for collecting all the information needed by humans contributing to Human Computation systems and markets because of the variety and complexity of goods, services, or taks dealt with on most Human Computation systems and markets.

7 Conclusion

This chapter has proposed a novel approach to credit risk rating based upon Network Analysis and enabled by Human Computation. The approach proposed is a dual-purpose participatory mechanism.

Section 2, an introduction into credit risk rating, derivatives, structured notes, and securitization, has stressed the need for a novel, systemic, assessment of credit risk on financial markets.

The system proposed in this chapter for computing a systemic credit risk rating consists of an incentive, the Grace Period Reward (GPR) introduced in Section 3, for humans to contribute with inputs and a network analysis for aggregating these human inputs. It is therefore a Human Computation algorithm.

The GPR, which resembles a credit risk insurance over a limited period of time, provides with an incentive for debtors to assess the risk of their own defaulting and to disclose these assessment to a system. The aggregation of the human inputs has been specified in Section 4 as eigenvector centralities expressing a systemic rating of the credit risk faced by the market's agents.

This systemic credit risk rating has been shown in Sections 3 and 5 to hold the promise of overcoming many deficiencies of current credit risk rating. The GPR has been described in Section 3.7 as an informationally productive transaction (or Tobin) tax and as making "bailouts in the small" possible.

The credit risk rating proposed in this chapter is unusual in several ways: It collects credit risks assessments from the debtors and not from the creditors; it propagates debtors' risk estimates through the risk dependency graph by computing eigenvector centralities; it is not based upon stochastic methods and statistical data; and it promises to deliver warnings of an increase in credit risk much earlier than current credit risk ranking methods. Furthermore, it gives a means to specify the regulatory capital of a depository financial institution depending on its "credit risk centrality" in the credit risk graph of the financial market.

Importantly, the credit risk rating proposed in this chapter does not require credits, derivatives or securitization instruments to be standardized. Thus, it imposes no constraints on the kind of financial instruments dealt with on the financial market and can accomodate new, so far not thought of, financial instruments.

The approach proposed in this chapter seems to have several advantages over current credit risk rating, which has been briefly introduced in Section 2: it is systemic in the sense that it not only considers the credit risk assumed by one agent but instead aggregates the credit risk along the debtor-creditor-liens, it is not affected by the complexity of financial instruments traded with, it is not based on statistics what makes it appropriate in exceptional situations too, it is not subject to the moral hazard of current credit risk, it provides time-dependent rankings, and it significantly reduces the speed differential between transactions and credit risk rating.

Deploying the approach on a financial market would, as it is discussed in Section 5, require further investigations, especially a calibration of the GPR.

Whether the proposed method would, in practice, hold its promises, is an open issue which is out of the scope of this chapter.

The main obstacle to a deployment of the systemic credit risk rating proposed in this chapter should be of cultural and political nature. Is the time ripe for financial markets and policy makers to understand and accept a network analysis enabled by Human Computation as a means to credit risk rating? If not, how many more financial crises will be needed for convincing of the value of techniques that, in other fields, are already well established?

Finally, this chapter has argued in Section 6 that Human Computation systems and markets share many commonalities. In that section, the view is expressed that Human Computation-enabled network analyses of the kinds proposed in this chapter will contribute, in the future, to the good-working of both, Human Computations systems and markets.

Acknowledgements The author is thankful to Norbert Eisinger (from the Institute for Informatics of the Ludwig-Maximilians University of Munich) for useful suggestions; to the team of the Play4Science research project for stimulating discussions on incentives in Human Computation systems; and to Pietro Michelucci, editor-in-chief of the "Handbook of Human Computation", and Haym Hirsh, editor of Section B "Application Domains" of that handbook, for useful advices on how to better present the research reported about in this chapter.

The work reported about in this chapter has benefited much from the knowledge and the experience the author gained through his contributions to the Human Computation platforms ARTigo.org and metropolitalia.org developped within the project Play4Science founded in part by the German Foundation for Research (DFG, project number 578416).

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