Keynesian uncertainty and the shaky foundations of statistical risk assessment models

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1. Introduction

With the financialization of the economy, increasing reliance has been put on statistical models for derivatives pricing and for risk assessment in the day-to-day business of financial operators as well as in financial regulation, especially since Basel 1.5. This practice had already been criticized from many quarters and on different accounts before the crisis,[1] but these criticisms were simply ignored by the prevailing consensus.

In what follows, I shall try to reconsider such criticisms from a somewhat different standpoint. My point is that, though they are justified, they could have been put forward in even stronger terms had they relied on Keynes's work on probability and his notion of uncertainty, rather than (explicitly or implicitly) on Knight's distinction between risk and uncertainty. I shall thus focus on the views underlying statistical risk assessment techniques rather than on the techniques in themselves. Finally, I shall set out some policy implications for regulation.

2. Statistical risk assessment

Statistical risk assessment is by now a well-developed field of research, its growth over recent decades largely demand-stimulated by

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[1] Cf. for instance Danielsson (2002; 2008).

the needs of the financial sector of the economy, with high earnings attracting brilliant minds to solve precisely defined issues through refined mathematical and statistical techniques.

The basic issue is quite simple. On the one hand, financial operators take into account in their decisions the perspectives of gains and losses, and are often confronted with a trade-off between expected rates of return and risks. On the other hand, regulators, especially when supervising banks collecting savings deposits, devise rules such as to compel financial operators to cover risks, so as to limit the fragility of the individual institutions and of the financial sector as a whole.

Often the internal operating rules designed by the top management of financial institutions are modelled on the regulations and targets set by the regulators, though this need not be and is not always the case, due to the different perspectives of the two groups of agents, the financial institutions and the regulators. There is also the possibility of an opposite causal link, with regulators adopting procedures developed by skilled statisticians-mathematicians whose research was driven by demand from (and paid for by) financial institutions.

In any case, statistical models are based on an inductive method. This is true both at the level of the specification of the models and at the level of their application: data collected from past experience are utilized both for choosing the best specification of the model and for computing its parameters; such models and parameters, extrapolated into the future, provide then some knowledge of the amount of risk embedded in a given stream of financial contracts.

For instance, a series (possibly including as many as 250 data points)[2] of daily prices for IBM shares is taken; then the statistical characteristics of this series are considered (mainly, the moments of the distribution; commonly, the average and the variance); finally, some measure of risk such as VaR is computed. VaR means Value at Risk, and indicates the amount of the maximum potential loss that could be experienced on a given financial position over a certain time interval with a given probability. There are other measures of risk, but most of what

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[2] "The regulatory suggestion is (at least) 250 days, and most supervisors do not allow longer estimation horizons" (Danielsson, 2002, p. 1284).

can be said for VaR holds for them as well, so we shall focus on VaR, it being the most commonly utilized measure.

In applying VaR, there are many choices to be made. The main ones concern: method of computation, length and periodicity of the time series considered for the data, length of the period considered for the computation of the maximum loss and the target interval of confidence.[3]

Let us consider briefly three different methods of computation. The simplest one is the historical simulation: let us assume that the future distribution of the data will be equal to the past one; we then take out the worst x% of the outcomes (where 1-x is the required confidence interval) and the worst remaining outcome is the value at risk. This method is conceptually clear, and requires no assumptions on the shape of the distribution. Obviously, the assumption that the future be equal to the past is a very strong one, implying the absence of structural breaks or, in other terms, a non-evolving economy (in post-Keynesian terminology, an 'ergodic' economy). However, the factual reason for preferring other methods of computation of VaR to the one detailed here is its difficulty of computation, when considering a portfolio including many different assets.

Thus, two other methods for computing VaR are commonly preferred. The first are variance-covariance models; the second is the Monte Carlo method. Variance-covariance models assume an underlying normal distribution of the variable(s) being considered and estimate the variance of the distribution; very frequently such models add the assumption, in the case of portfolios including many different assets, that the returns for each individual asset are independent from the returns for all other assets. The Monte Carlo method instead relies on simulations: once the parameters of the distribution have been estimated, a series of values for the returns of the assets in the given portfolio are casually extracted from the estimated distribution thus computing the potential

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[3] Other choices are also relevant, such as accounting rules. Differences in how VaR is applied by individual financial institutions or within different national regulatory environments produce wide divergences in capital requirements, as it is by now well known in the literature. Cf. for instance Cannata *et al.* (2012).

gains and losses on the portfolio; then the desired percentile is taken out as the VaR measure.

These methods have been commonly adopted and have become part of a habit of thinking. Thus, in the aftermath of the 2007-2008 Stock Exchange crisis, leading financiers found no better excuse for their huge losses than that they had been confronted with an event with a probability of 1 in 10^{140}, in other words an event that should happen only once over a time span equal to fourteen times the life of the Universe.[4,5] Clearly, this means that something is wrong with these methods of computing risk.

3. A survey of critiques to statistical risk measurement

Many criticisms have been levelled at the failure of statistical risk measurement to foresee the financial crisis and its implications for the pricing of financial assets. First, the assumption of underlying normal distributions of the relevant variables has been called into question; 'fat tails' has become a catchword for this kind of criticism.[6] There is

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[4] According to David Vinier, Goldman's chief financial officer of Goldman Sachs, "We were seeing things that were 25-standard deviation moves, several days in a row" (*Financial Times*, August 13, 2007, quoted by Danielsson, 2008, p. 322, who also gives the corresponding probability and its equivalent in Universe lifetimes). The probability of the "several days in a row" event occurring is estimated to be even less likely by Cooper (2008, pp. 10-11).

[5] We find occasional references to a "black swan" event, as a very rare event which we are somewhat justified in not foreseeing. In fact, Taleb's (2007) reference to it has a different meaning, recalling a well-known example of the Popperian method of conjecture and refutation: the statement that "all swans are white" may be contradicted, after a hundred thousand encounters with white swans, by the discovery of a single counter-example, which when duly considered turns out to point to the existence of a previously unknown species of black swans in Australia, thus falsifying the original statement. In other terms, if the crisis was so extremely unlikely according to our theory, we should revise the theory rather than put the blame on our extreme misfortune. Popper's idea, in fact, is that rather than piling up new data taken at random (thus, quite often, in the same environment which generated previous data) in search for confirmation to our hypotheses, we should look around to different environments in active search for refutations; these will compel us to deepen our analysis, thus constituting real scientific progress. Cf. Popper (1969). Roubini and Mihan (2010, chapter 1) are correct in calling the 2007-2008 crisis "the white swan".

[6] The role of fat tails in financial markets is already recalled by Mandelbrot (1997).

however no element whatsoever for justifying any a priori assumption about the distribution. In other words, the issue is not whether we should assume a bell-shaped distribution with or without fat tails; the real issue is whether we have any justification for assuming the stability (between *ex ante* and *ex post*) of any distribution we may choose a priori. In this context, 'fat tails' turns out to be little more than an *ex post* adjustment for what in effect remains an unwarranted assumption.

Second, there is the correlation between different asset prices, and more generally between different events, which is very often underestimated, for instance when considering portfolio diversification as an adequate solution for risk management.[7]

Third, there are the subjective choices always necessary in such exercises. The length of the statistical time series chosen for analysis is a case in point. A long series increases the probability of internal 'structural breaks' that run counter the very aim of the analysis, namely deriving from the series some 'regular' statistical distribution on which to rely for projections. A short series can only be utilized as a guide for the operators in their day-to-day behaviour, certainly not for the long view required for regulators. The periodicity of the data is also important: assuming a daily series and a confidence target of 1%, we are allowed to assume away events that are estimated to happen 2.5 times each year: obviously, too often from the point of view of a regulator.

Fourth, there is the issue of what Soros calls "reflexivity",[8] namely the presence of circular causal links between the influence of events in shaping dominant market opinions, and in turn, the influence that market opinions have on events. In our case, when statistical risk measurement is a widespread rule of the game and determines the pricing of financial derivatives, then agents in the market adapt to it with the consequence that the underlying risk distribution is modified.[9]

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[7] For a shocking instance of such an underestimation we may refer to the case of CDOs (collateralized debt obligations), and the role they played in the 2007-2008 financial crisis. For an in-depth illustration of this case, cf. Gorton (2010).

[8] Cf. for instance Soros (2008).

[9] An instance of this is the case of the self-fulfilling expectations that played a relevant role in the recent euro crisis. Cf. D'Ippoliti and Roncaglia (2011). According to Soros (2008), reflexivity can give rise to financial (and real) bubbles, the explosion of which

Fifth, there is the problem of 'structural breaks': not only that the future is not alike the past; there can also be 'discontinuities', namely exceptional events or circumstances which disrupt the otherwise 'tranquil' path of the economy, thus disrupting the applicability of risk assessment models based on past experience.[10]

All this is already sufficient to cast strong doubts on the use of statistical risk measurements. Of course, private agents can choose the behavioural rules they prefer in their decision making processes, including reliance on the most dubious kinds of statistical risk measurement; a sufficiently well-working market will prove them right or wrong, *ex post*, punishing the grossest inadequacies. But the situation is quite different when we consider the viewpoint of regulatory authorities, who are tasked precisely with preventing situations that could give rise to financial fragility.

4. A more fundamental criticism

The critiques of statistical risk modelling surveyed in the previous section are but instances of a more basic criticism, well known to philosophers but somehow disregarded by economists. It is the critique to reasoning by induction already advanced by David Hume and repeated countless times since. The past can induce us to adopt certain conventions or certain behavioural habits but however large the database on which we rely, it is logically impossible to infer from the past that the future will conform to any pattern shown in past events.[11]

In principle, the Humean criticism to induction is commonly accepted. However, as Hume himself stressed, there is in practice the need for some guidance in decision-making, as far as possible founded on

originates crises; this can be considered as a reformulation of Minsky's theory of capitalist instability (Minsky, 1982).

[10] In a certain sense, what Popper – see footnote 6 above – recommends is to actively look for structural breaks, rather than relying on data series extracted from a tranquil environment.

[11] Cf. Hume (1939-40). Keynes, the proponent of the approach to probability taken up here, was a sophisticated Humean scholar: cf. Keynes and Sraffa (1938).

the objective grounds provided by past experience. Thus conventions are formed, which when shared within the reference community provide common behavioural rules and a common drive to individual decisions. But such conventions may change under the impact of events, and agents should keep this possibility in the back of their minds. Thus, the problem turns out to be: can the prevailing methods of statistical risk measurement provide a sufficiently stable convention not only for individual financial agents' decisions, but also for regulators?

My negative answer to this question requires a detour in the history of economic thought and consideration of the distinction between Knight's well-known dichotomy between risk and uncertainty and Keynes's often quoted but not equally well-known notion of uncertainty.

Knight's *Risk, Uncertainty and Profit* (1921) and Keynes's *A Treatise on Probability* (1921) are independent publications, tackling different issues, based on different perspectives, so that the same terms assume different meanings in the two works. As is well known, Knight (1921, especially p. 233) distinguishes between risk and uncertainty, the first being a case of quantitative probabilities and the second a case in which probabilities are non-measurable. Such a distinction, as we shall see, is not to be found in Keynes, who follows a completely different train of reasoning.

It is upon Knight's dichotomy that the use of statistical risk measurement relies, helped by the rise to dominance within the statistical field of the so-called subjective approach to probability. According to this latter approach, probability calculus can be utilized whenever there is room for a subjective statement of probability, hence whenever agents place bets on different possible outcomes. This happens whenever a derivative financial asset is bought or sold, so we are justified in applying risk (probability) analysis to this field, and we may find some objective foundation for our subjective assessment of probabilities by statistically estimating them on the basis of the agents' behaviour in the market as summarized by derivatives' prices and price movements.

This involves a certain amount of conceptual muddling, due – as we shall see – to circular reasoning and to the implicit assumption of a stable background to market events. However, if every financial or regulatory

institution concerned overlooks the muddle concurrently, statistical risk measurement can be established as the mainstream approach: hence, no longer subject to critical scrutiny. After all, something similar happened – even without the inducement of large monetary earnings – in the field of macroeconomics, where the inverse relationship between real wages and employment reigns supreme, though it has been shown to be devoid of sufficiently solid foundations in the course of the so-called capital theory debates of the 1970s.[12]

In trying to clarify this muddle, let us briefly survey the three main approaches to probability: the classical, the frequentist and the subjective. Classical probability calculus emerges from the study of 'regular' games, such as dice. It implies the full specification of the space of events in a finite number of atomic events (for instance, the six faces of a die), considered equiprobable on the basis of the so-called principle of insufficient reason, or principle of indifference: there is no reason to consider one face of a die more probable than any other. Probability calculus is then assigned the task of computing the probabilities of complex events, such as two or three throws of a die showing the same face, or totalling a pre-assigned value. It is a clear definition, but valid only within narrow limits. For instance, it is not applicable to other games (such as chess) where some element of human ability enters; or, more generally, whenever the very delimitation of the space of events and its partition into a finite number of atomic events proves difficult and/or involves an element of subjective evaluation. Thus, it cannot be applied to social, political and economic events, nor indeed to financial markets.

According to the second approach, the frequentist one, the probability of an event is the limit to which the relative frequency of the event tends in successive observations (stochastically independent from each other) of some variable, for instance the stature of conscripts, the throw of a die, or repeated independent measures of the same magnitude, when the number of observations tends to infinity. As with the classical definition, the frequentist definition implies an objective view of probability. The objective nature of the probability statement lies in the

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[12] For a survey of the debate, see Harcourt (1972).

fact that it is considered to depend on the intrinsic properties of the phenomenon under consideration.

Rigorously speaking, this definition can only be applied to 'collectives', namely to successions of uniform events only differing in some observable characteristic which is the object of scrutiny, when each observation is independent from the previous or the subsequent one and no regularity obtains. In some instances – different measurements of a same physical phenomenon or the stature of conscripts in a certain year – the aggregate of the observations displays a 'normal' shape: deviations from the average (or the median or the modal) value of the variable can be interpreted as probabilistic deviations from the 'norm', with increasingly smaller probabilities for increasingly larger deviations. Clearly, this definition excludes from the field of probability all 'singular' events, i.e. all events that are not part of a collective; in other words, it once again largely excludes the fields of social, political and economic events.

The subjective (or personalist) approach developed by De Finetti (1930; 1931) and Ramsey (1931), which triumphed after the Second World War in the formulation given to it by Savage (1954), implies a fully subjective notion of the probability statement: it is a state of the mind, not a state of nature. More precisely, to define it in operational terms, it can be determined as the lowest odds one would accept when betting on a given event. Each subject is considered able to quote betting odds for all sorts of events; the supply price and the demand price for each bet are assumed to be equal; that is, the subject is assumed to be indifferent between outcomes (as well as between betting and not betting). The mathematics of probability and the axiom of rational individual choice ensure the internal logical consistency of each subject's book of bet offers. Consistency is defined as the impossibility of devising a book of bets (a 'Dutch book') such as to ensure winning, whatever happens, against the book of bet offers under consideration; in other terms, consistency implies that no room be left for arbitrage trading. Thus subjective probabilities come to constitute the foundation for decision theory, with action (represented by a book of bet offers) based on a consistent set of probabilities dominant over all inconsistent ones. From

this point of view, however, consistency is all that matters: a coherent – and firmly believed in – system of rules for reading one's health in tea leaves is considered as equally 'rational' as asking the advice of the best physicians.

Clearly, individual financial operators can utilise the subjective approach in computing their supply and demand prices for derivatives, relying on their a priori probability distributions specified for the set of relevant states of the world, and for identifying arbitrage opportunities. The relevant states of the world considered in forming the subjective probability distributions are commonly reduced to a minimum, relying on drastically simplified views of the way the economy operates; indeed, quite often financial operators rely on the most recent market data for deriving their probability distributions, thus reducing the subjective approach to a frequentist one which implies structural stability of the economy. If this is the dominant convention in financial markets, adhering to it helps individual operators to adapt to the parcel of the world in which they work; we can notice however that the big winners among the operators (as well as the big losers) are those who look at the state of affairs with a fresh perspective: as Soros did in 1992 when betting on the devaluation of the British pound (or as Hunt did when trying to corner the silver market, beginning in the early 1970s and ending in bankruptcy in 1988).[13]

It is clear, in any case, that the subjective approach cannot provide firm foundations for risk measurement exercises aimed at regulatory purposes. There would be no need at all for a regulator if the market conventions on which financial operators rely were already sufficient for the purpose; but this can only be true in a fairytale world in which the market economy automatically reaches optimal equilibriums implying full employment of all kinds of resources, including labour, possibly driven by rational expectations: a fairytale world modelled by neoclassical economists in which – as Fama explained in 1970 – financial

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[13] For a perceptive discussion of the relationship between uncertainty and trading strategies, cf. Taleb (2001).

markets are efficient[14] and – as Lucas wrote in 2003 – crises are no longer possible,[15] once economists have taught politicians to avoid policy mistakes simply by abstaining from active interventions.

Knowledge of the 'true' model of the economy and rational expectations constitute then the foundation for leaving the economy vulnerable only to casual shocks, the adjustment to which is, in principle at least, instantaneous. Moreover, subjective probability distributions are by definition only attributable to individual operators and – unless all agents were equal – cannot be extended to an agent representing the whole of society, such as the regulator should be.[16] In a multi-commodities multi-agents world we are confronted with path dependence and uncertainty and we cannot assume a single and stable equilibrium; in such a world financial fragility cannot be fully avoided, it can only be limited by adequate regulations and by the active surveillance of regulators (cf. Minsky, 1982).

In fact, statistical risk measurement appears to be a contradictory mixture of the frequentist approach (for its reliance on data series referring to immediate past experience) and of the subjective approach (for the mathematical-statistical tools utilised in the analysis). Each of the two approaches – as we saw – is misleading if applied to the issue of regulating financial markets; their mixture, however sophisticated in nature, does not avoid any of the criticisms raised above concerning the individual approaches considered in isolation. The best that can be said for the application of statistical risk modelling to the regulation of

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[14] Even if "[…] the strong-form efficient markets model, in which prices are assumed to fully reflect all available information, is probably best viewed as a benchmark against which deviations from market efficiency (interpreted in its structural sense) can be judged" (Fama, 1970, p. 415), his analysis leads him to "[…] conclude that, with but a few exceptions, the efficient market model stands up well" (*id.* p. 383). Since then, the efficient market hypothesis has become the dominant foundation of the mainstream literature on financial markets.

[15] "Macroeconomics […] has succeeded: Its central problem of depression prevention has been solved, for all practical purposes, and has in fact been solved for many decades." (Lucas, 2003, p. 1).

[16] Aggregation of distinct individual agents into a single 'representative' agent implies the same well-known fallacies of aggregation that refer to the aggregate notion of capital. Cf. Forni and Lippi (1997).

financial markets is that the techniques are available and ready for use; however, this recalls the story of the drunk who looks for a lost key under a street lamp; though he happened to lose it some meters away in the dark, he explains that here he can see the ground better.

5. Keynes's approach to probability and his notion of uncertainty

Let us turn to Keynes's analysis of probability, recalling that it is the professional work of a mathematician – Keynes read mathematics at Cambridge, and *A Treatise on Probability* was written in the hope of earning a fellowship at King's College. Let us briefly consider its main aspects.[17]

In the first place, Keynes defines probability as the "degree of rational belief" in a proposition (hypothesis) on the basis of the available evidence. Hence, by itself probability is not an objective property of the phenomenon under examination, but a logical relation, established by the observer, between the available evidence on the one hand and the proposition under consideration ("primary proposition") on the other.

The logical relation (or "secondary proposition") may differ from one observer to another because of differences in knowledge, such as the extent of evidence available to each of them, but also because of differences in their individual intellectual abilities. At the same time, the probability statement retains some empirical correlate in its reference to the available evidence, which acts as a constraint on the expectations of the rational observer.

In Keynes's theory of probability, there is no objective rule to establish how the empirical evidence should affect the probability statement, or as to how additional evidence should change it. Thus, no bi-univocal correspondence can be established between evidence and a 'rational' probability statement. However, in Keynes's mind there clearly is the idea that the subject must somehow take the available evidence into

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[17] For a fuller treatment of Keynes's theory of probability, cf. Roncaglia (2009), which I draw from in part in the present paper.

account. In fact, together with internal consistency (no contradictions) in the system of beliefs, this is what distinguishes rational from irrational behaviour.

Thus, according to Keynes, the probability relation is an objective one, in that it is "independent of our opinion" (Keynes, 1921, p. 4), meaning by this that empirical evidence must dominate over subjective preferences in originating our probability statement. This is not contradicted by a point which Keynes also stresses, namely that the probability relation is a statement made by an individual agent at a specific moment in time, since it depends on the state of knowledge which may be different from one person to another and which may change over time. This point becomes important later in his research when, dealing with the stock exchange or the financial markets in general, Keynes constructs his theory on the basis of the fact that different agents may have (commonly have) different expectations, i.e. different evaluations of the situation and its perspectives.

Keynes interprets probability not as a set, possibly axiomatic, of theorems, but as a system of propositional logic, built in such a way as to contribute to our understanding of rational human behaviour under uncertainty. The probability statement is itself commonly 'uncertain' (not fully reliable), while perfect certainty and absolute ignorance are limit cases.

This means that there is an additional dimension: the 'weight' we can attribute to the logical statement of probability. Through it, we connect a proposition (hypothesis) to the available information: when information is abundant, the 'weight of the argument' is great, and it increases when we obtain new information on the issue under consideration. However, the weight of the argument should not be interpreted as a measurable magnitude. Thus, when we consider different probability propositions, only under special circumstances are we able to rank them in an increasing (or decreasing) sequence according to the weight of their argument. We should also stress that the weight of a probability statement depends on the evidence at the disposal of the individual agent; such evidence may not only be different from the

evidence available to other agents, but may also be differently interpreted.

6. Implications for statistical risk measurement and for regulatory policy

Keynes's views on how financial markets operate directly stem from his views on probability. First, a distinction is made between economic agents according to the different kinds of uncertainty involved in their decisions. Since there are wide differences in this respect between entrepreneurs, households and financiers, the theories concerning the determinants of their decisions are better constructed as belonging to different 'groups', in the sense indicated above. Analogously, entrepreneurs' decisions concerning investments have to be kept distinct from those concerning production levels, as well as from the decisions of different sets of agents operating in financial markets.

Second, uncertainty explains why agents prefer liquid assets to illiquid ones, and are correspondingly prepared to pay a premium for liquidity: liquidity is the way to keep options open (or rather, more open than would otherwise be the case) in the face of unforeseen developments in the state of affairs. In other terms, more liquid assets are those of which the value is less uncertain: for instance, in tranquil circumstances Treasury bills are more liquid than long-term bonds.

Third, financiers' decisions can be revised in a very short time span. Recent improvements in exchange technology brought this time horizon to less than a day for many kinds of financial tools. Hence, a change in perspective – for instance, the publication of new data or a new policy statement by some policy authority – brings with it immediate reaction in the form of changes in portfolio selection and investments or disinvestments across a wide range of financial assets. Correspondingly, the time horizon of agents operating in financial markets shrinks dramatically: buying or selling decisions are taken on the basis of expectations of asset prices in the next day, hour or even minute.

Fourth, under these circumstances herd behaviour is common: agents are constantly trying to foresee how other agents may view the situation, since this determines asset prices in the immediate future, and know that other agents do the same. An agent may have a correct evaluation of the fundamentals, but even if the market will finally converge to share these views any financier knows that the market can hold on to wrong opinions for longer than he or she can remain solvent by sticking to their own opinions, however correct they may be. This implies that there can be (and quite often are) sudden breaks of agents' views, or conventions. The agent who earns most profits is the one who succeeds in preceding the market's opinion by a short interval of time, not the one who clearly foresees how the economy evolves in the long run. This is clearly a source of instability, and thus of fragility for the financial sector as a whole.

What are the implications of these views for statistical risk evaluation? Let us consider briefly first the point of view of the agents, then the point of view of the regulators.

From the point of view of financial agents, statistical models of risk evaluation, as we have seen above, are a good way of expressing the set of conventions prevailing in the financial world at a given moment. The time span is relatively short because of the need to exclude structural breaks, even if not all changes in conventions are so dramatic as to involve changes in the parameters of the model. Thus, reference to a 100-day or 250-day interval of time allows for a systematic adjustment of the parameters and, until a substantive break of convention occurs, agents can rely on such models as a guide in their day-to-day operations (we can note that agents are likely to keep in mind the possibility of structural breaks, but may undervalue their impact because of the possibility of being rescued by public authorities concerned with systemic failures; in any case, in order to keep on the safe side they arrange their remunerations to be linked to short term rather than to long term results).

The situation is quite different if we turn to the point of view of the regulators. Their target is the avoidance of crises, which are by definition uncommon events. Thus, regulators should focus on structural breaks: precisely the events that make statistical risk evaluation misleading.

Statistical risk evaluation models are an unsuitable tool to keep the fragility of financial markets under control, and regulators should not rely on them.

This notwithstanding, such models have been utilized in order to evaluate the situation of financial institutions in the context of micro-prudential surveillance, which obviously implies keeping the risk implicit in individual portfolios under control. However, as we have seen, this cannot be anything but a first step, even in micro-prudential surveillance, since the regulator must be concerned with a time horizon sufficiently long as to make it necessary to take account of the possibility of structural breaks.

In any case, statistical risk evaluation models are – or, rather, should be – largely irrelevant for macro-prudential surveillance aimed at keeping under control the increasing fragility of the financial sector as a whole. Here, the mainstream climate of opinions subsequent to the 2007-8 financial crisis seems to favour reliance on statistical indicators of financial fragility, mostly focusing on macro-imbalances;[18] but, though this is a step forward compared to the pre-crisis mainstream tending to rely on the self-regulating abilities of the market, once again this assumes that the past is a good indicator of the future, which means implicitly assuming away (or at least directing attention away from) structural breaks, which may take place in the macro-economy as well.

Regulatory authorities should avoid rules based on risk measurement: these unavoidably generate endogenous reactions and incentivise manipulation. They should in fact shift the focus of their analysis away from risk measurement and towards singling out the causes of systemic fragility, in order to counter them. Thus, regulatory authorities should focus rather on 'structural' issues,[19] such as i) devising rules aimed at avoiding that the bankruptcy of individual financial institutions could engender a general financial crisis (hence limits to leverage or a maximum to total assets or to certain categories of assets;

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[18] Cf. for instance Banca d'Italia (2012). For a theoretical discussion of the issue, cf. Masera (2012).
[19] Cf. Tonveronachi (2010); Tonveronachi and Montanaro (2010); Montanaro and Tonveronachi (2012).

limits to the scope of activities allowed to be practiced by financial operators and taxation on financial transactions, and rules preventing the emergence of too-big-to-fail institutions and of excessive market power, and rules for the orderly resolution of financial operators crises and bankruptcies); ii) devising rules concerning a way of operating financial markets aimed at reducing their intrinsic instability (such as a Tobin tax on financial transactions, strict limits to leverage, to computer-generated transactions, to short selling, to over-the-counter derivatives and so on). Relying on statistical risk evaluation models – the Basel Way of regulating finance – is a methodologically wrong procedure for a regulatory agency to follow, from both a micro-surveillance and – even more so – from a macro-surveillance point of view.[20]

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[20] In other words, regulatory policy should take a path exactly opposite to the one suggested, among others, by Haldane (2012), namely simplifying the 'Basel tower' to the extreme, rather than turning the regulatory approach upside down.

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