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Explaining Financial Markets in Terms of Complex Systems

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Large changes of financial market prices without exogenous causes deviate significantly from the Gaussian behavior of random variables. This indicates that financial markets should be treated as complex systems, for which nonlinear interactions of its subunits/agents are crucial. I focus on how the complex systems perspective impacts the notion of explanations in economics. The mechanistic model seems to fit the bill, but problems surface on closer scrutiny. One characteristic of complex systems is that their behavior is surprisingly independent from microscopic details. Thus, mechanistic explanations in the microreductionist manner seem unavailable. Despite these conflicts, I defend a modified structural mechanistic approach.

1. Introduction. It is a commonplace that financial markets are complex systems. There are countless relevant influences, and each and every market participant is, being a human being, itself a highly complex entity.[1] In fact, financial markets are so complex that it is hardly possible to predict anything about their future behavior. So it seems that classifying financial markets as complex systems is correct but pretty useless. However, there is also a very specific notion of complex systems, which does not merely sharpen the ev-

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1. Note that this description also applies to the intelligence quotient (IQ), as Humphreys (2014) shows. Nevertheless, the distributions of IQs and of financial assets differ fundamentally. Although the formation of someone's IQ is highly "complex" in the everyday sense, this is not an instance of a complex system in the sense I will specify below (to be sure, Humphreys does not claim that it was such an instance). Even more so, certain deviations from processes such as the ones that form IQ are the best symptom, or "signature," for a complex system in this specific sense.

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eryday understanding. It highlights important features that are little known to many people and the significance of which is not immediately visible.

Much of what follows is not specific for financial markets and could just as well be said about ferromagnets, avalanches, heartbeats, or social networks. However, realizing that financial markets are complex systems opens the door to various helpful models and analytical tools that are not well known to be relevant. In the course of my considerations, in particular at the end, I delineate what this means specifically for the analysis of financial markets.

2. Financial Markets as Complex Systems. There are two seemingly contradictory characteristic effects in complex systems,[2] which are grounded in two fundamentally different kinds of complex systems behavior, namely, chaotic and robust complex behavior. The best-known example for chaotic complex behavior is the "butterfly effect": even extremely small variations of the initial conditions may drastically alter the behavior of the whole system (Bishop 2011, 108–11) and can make weather forecasts extremely difficult. The other effect is much less well known among nonexperts. It is the remarkable insensitivity to variations on the micro level, when it comes to the self-organized coordination of interacting parts of a complex system. This can give rise to macro effects such as the emergence of temporally and spatially highly coherent light in lasers. What unites both cases of complex behavior is that the undirected local interactions between the system's constituents lead to strong system-wide effects. In the case of *chaotic complex behavior*, tiniest differences on the micro level can, owing to the nonlinear interaction between the system's constituents, be amplified to an effect of any size. For the second kind of complex behavior, namely, *robust complex behavior*, for which the laser is a paradigmatic example, it is also the nonlinear interaction between the system's constituents that is essential. However, the crucial characteristic is that this interaction leads—in a statistically robust way (more on this below)—to a system-wide internal coordination that is surprisingly insensitive to the system's starting point on the micro level.

Financial markets display both chaotic and robust complex behavior. The following study is concerned with the latter, which is less obvious but more important for the explanation of financial markets. In fact, there is a whole

2. Note that the common practice of talking about "complex systems" simpliciter is misleading, although it is hard to avoid without cumbersome qualifications. A complex system is not something like a green ball: whether or not something is referred to as a complex system depends on the context. While the object that emits laser light is a complex system for the laser physicist, it is not a complex system for the engineer who designs the device that keeps the laser as steady as possible. Moreover, the same material object may sometimes display chaotic and sometimes robust complex behavior.

comparatively new interdisciplinary field that largely lives on treating financial markets as complex systems in this specific sense, called *econophysics* (see Mantegna and Stanley 2000; Johnson, Jeffries, and Hui 2003; Sornette 2003; for discussions of philosophical aspects of econophysics, see Rickles 2008; Kuhlmann 2011). Econophysics tries to analyze and explain certain economic phenomena by using methods, models, and theories from physics, primarily condensed matter physics. One particularly intuitive idea is to analyze financial market crashes by using the advanced physical theory of phase transitions (e.g., from a fluid to a solid state), where the common characteristic is the sudden occurrence of a comprehensive change of the state of affairs. But how is such a drastic interdisciplinary transfer possible?

Financial markets share a crucial statistical feature with known complex systems in physics, namely, the scale freedom (or scale invariance) of fluctuations. That is, there is no characteristic size for the fluctuation of financial market prices, for example, the changes of stock prices are distributed in the same way on any scale of magnitude and time (for more detailed accounts see Mantegna and Stanley 2000, chaps. 3–5; Goldberger 2006; Kuhlmann 2011, sec. 41.2.2). This means that small changes are governed by the same statistical distribution law as large changes. And this means in turn that large changes happen far more often than according to the Gaussian distribution function (the bell curve), which is not scale invariant and approaches zero very rapidly. To be more concrete, the probability distribution for large changes of prices of financial assets, such as stocks, follows a power law, which is well above the Gaussian bell curve. It has a "fat tail." And even more remarkably, this is not just sometimes the case. It is a generic feature of (speculative) financial markets, be they in London or New York, be it for stocks, derivatives, or currencies. The respective exponents are different, but we always encounter power laws. Another characteristic is that larger changes tend to occur in clusters. Economists call such partly qualitative descriptions of complicated statistical observations "stylized facts" (for a detailed discussion of this concept see Lawson 1989). They catch what is considered to be in need of an explanation. This kind of explanandum, which will concern us in the following, is thus quite peculiar: it is not a single event, but—although it is about statistics—neither is it a statistical law.

Within physics already we have several well-understood cases that share the same statistical phenomenology. We have learned to identify signatures that point to a common class of generating mechanisms, which often involve the "creation of long-range structure by short-range inter-molecular forces" (Binney et al. 1992, 30). This seems perfectly analogous to the fact that there are often large changes in financial markets without external causes, namely, in those cases where no incoming news is connected to the large changes. There is no guarantee that this analogy will hold in every new case that exhibits the same statistical phenomenology. However, such analogical reasoning can be tremendously helpful, and econophysics is built on the well-justified inference that financial markets are such a case.

The nontrivial analysis of the statistical characteristics of financial markets is one main enterprise where methods from physics can help. Another one is concerned with the explanation of these characteristics. Econophysics tries to tackle this task by constructing "microscopic models of financial markets," which reproduce the observed statistical features in financial markets—for example, fat-tailed return distributions, clustered volatility, crashes, and other stylized facts. Physics-based microscopic models of financial markets are highly idealized and work with large numbers of market participants or agents (for a survey of various approaches, see Samanidou et al. 2007). For instance, all agents can have identical properties, and the interaction between agents is modeled in a simple way. One approach is based on the Ising model—initially introduced in order to explain ferromagnetism—and assumes the agents to be on a grid, where they only interact with their nearest neighbors (Chowdhury and Stauffer 1999).[3] Another option is to have a few subgroups of traders with different behaviors, where switching between these groups is possible and depends probabilistically on the success or failure of other traders (Lux and Marchesi 1999). What is common to all these approaches is the fact that the endogenous interactions between market traders is the prime cause for the high fluctuations of stocks prices, and not exogenous events such as unforeseen economic developments or central bank decisions. This is in close analogy to ferromagnets, where the interaction between neighboring atomic spins is the dominant cause for the spontaneous macroscopic magnetization at sufficiently low temperatures, that is, when thermodynamic fluctuations become less important. Thus, in models for both financial markets and ferromagnets it is the internal interactions that are responsible for system-wide large changes. These and other closely related analogies (nonlinearity of interactions, power-law probability distribution of large changes, etc.) are the reason for assuming that financial markets should be treated as complex systems.

3. Explaining Complex Dynamics by Structural Mechanisms. In the following I want to argue that explanations of the generic behavior of complex systems may be best captured in terms of mechanisms. However, while the paradigmatic examples of mechanisms fit well into the existing accounts of the concept, complex systems require a more structural reading.[4] In order to

3. Today, the Ising model is used in various different contexts ranging from physical to social ones.

4. I use the term "structural" as opposed to "material" and not in the sense of contrasting a description of functions versus one of inner structure.

mend this deficiency, I will introduce the notion of *structural mechanisms*. With my analysis I want to explore an important class of cases that is just still inside the limits of mechanistic explanations.

3.1. Identifying Mechanisms. There are different options for fixing the identity criteria for causal mechanisms. One option is to cash out the notion of mechanisms in terms of physical processes (Dowe 2000). Quite obviously, it would not be very attractive to individuate a mechanism by a particular physical process in space and time, because then each mechanism would occur only once, making scientific generalizations impossible. We want to say that it is the same mechanism by which photosynthesis in different exemplars of some plants works. Thus, we should say that a mechanism can be specified by certain kinds of physical processes. Nevertheless, even then this approach has the incurable defect that it "obscures similarities between kinds of interactions among higher-level entities" (Glennan 2002, 346). If the interactions involved in mechanisms are understood as material processes, then tokens of interactions cannot be recognized as tokens of one common type of higher-level interaction because different physical instances of one type of interaction may be vastly diverse on the lower levels. My thermostat may work with different materials and thus involve different kinds of physical processes, but I still want to say that it works by the same mechanism.

Thus, it can be essential not to characterize mechanisms in terms of (fundamental) physical processes even though interactions between parts of a mechanism supervene on physics, that is, the higher-level interactions could not change without a corresponding change in the underlying physical basis. In other words, although higher-level interactions and thereby higher-level mechanisms are ultimately ontologically determined by the underlying physics, higher-level mechanisms are explanatorily autonomous. Describing a higher-level mechanism purely in terms of physical processes can even destroy its explanatory power. For instance, if a payment mechanism were described purely in terms of the physical, or material, processes that obtain between the computers, then the mechanism could never be appropriately understood. It is certainly physically realized in the end. However, in order to identify the mechanisms, one needs to abstract from its material manifestations. From these considerations we learn that it can be important to specify and individuate a mechanism by decomposing a given system into parts that fulfill certain functions—that is, we need a "functional decomposition" (Bechtel and Richardson 2010)—where it is irrelevant for the identification of a mechanism how the function of one of its parts is realized physically.

What I have said so far has nothing specifically to do with complex systems. However, when it comes to identifying a common mechanism across radically diverse complex systems, such as ferromagnets and financial markets, the identity criteria have to be even more abstract.[5] My thesis is that we need to focus on certain structural features.

3.2. Structural Mechanisms. The possibility of econophysics rests on the fact that there are certain similarities between systems in physics and economics. I want to claim that one, if not the, central explanatory issue here is mechanisms. Phase transitions in ferromagnets and financial markets can be studied in a common framework because the same structural mechanisms can be invoked in both cases. The reference to and the detailed analysis of such structural mechanisms are main reasons why econophysics is explanatorily fruitful. My aim is not to overcome the current explications of mechanism (three prominent accounts are Machamer, Darden, and Craver 2000; Glennan 2002; Bechtel and Abrahamsen 2005) but to show that their reading must be modified in order to accommodate complex systems of the kind explored in econophysics and similar fields.[6]

I propose to distinguish two different classes of structures in structural mechanisms, namely, (i) structural start and boundary conditions and (ii) emerging dynamical structures.[7] If one has identified a structural mechanism, then one knows that a certain set of structural start and boundary conditions (i) is essential for producing certain dynamical structures (ii). What one needs in order to be sure that one has really found a mechanism and not just an artifact is the fulfillment of the robustness condition, which I explicate in the next section.[8]

Structural start and boundary conditions may concern connectivity, dimensionality, topology, and certain symmetry properties. Connectivity is the most important structural aspect. The crucial issue in complex systems is the interaction between the system's parts, and neither their detailed behavior nor their minute spatiotemporal organization in the whole system. What really

5. In Kuhlmann (forthcoming) I pursue a related analysis regarding lasers.

6. It is difficult to formulate a more general definition of mechanisms, which comprises both the uncontroversial cases and what I call structural mechanisms, without arriving at a notion of mechanisms that is too general to be informative. What I intend instead, at least for now, is to show that structural mechanisms may still fit into the existing accounts of mechanisms if one reads them in more structural terms, as spelled out in the present section.

7. Note that this is close to what Bechtel and Richardson (2010, pt. 4) call "emergent mechanism." They conclude that there can be mechanistic explanations even in the absence of functional decomposition and localization, which is essential for classical mechanisms: "what is important in determining the behavior of the system in a network model is not the contribution of the parts, but their organization" (228).

8. Somewhat in contrast to my line of reasoning, Frigg argues that widely applicable complex systems models, more specifically those for self-organized criticality, are nothing but "vehicles for successful research" (2003, 630).

matters is the dynamical interactive organization of a complex system, and even there only certain structural aspects. A conventional mechanistic explanation shows how the often-sequential interactions of the different parts, which fulfill specific functions, produce a certain behavior. In complex systems it is usually impossible or at least not helpful to distinguish parts with different functions that play specific stable roles in the mechanism. Mostly all parts have identical properties and behavior. What is essential, instead, are the structural features of their interaction. For instance, the parts of a complex system—whatever they are, atomic spins or financial market traders—may be modeled to sit on a grid and only interact (nonlinearly) with their nearest neighbors, for example, by adopting their behavior. Moreover, the parts of a complex system usually all interact simultaneously. Thus, in contrast to conventional mechanisms, one could say that structural mechanisms in complex systems standardly have an egalitarian setup: all parts are governed by the same behavioral rules (and they may freely switch from one behavior to another), no external force tells them what to do, and they all interact at the same time.

Another surprisingly relevant structural feature is dimensionality. The analysis of universality classes in condensed matter physics, that is, classes of diverse physical systems with (almost) identical behavior in phase transitions—captured by the fact that they have (almost) identical critical exponents—has shown that something as general as spatial dimensionality can be essential (see Binney et al. 1992, 269ff.; Batterman 2002b, 42). For instance, in the above-mentioned Ising model the interacting parts of a complex system could be arranged on a line (i.e., one-dimensionally) or on a flat or a three-dimensional grid.

These examples show that the relevant start and boundary conditions for structural mechanisms in complex systems do not describe a specific configuration that already allows imagining what will happen if we let the system run. This is a crucial difference from conventional mechanisms, such as the one in a mechanical watch. In complex systems, for interesting things to happen, it suffices to have, in a sense, an amorphous setup with very general structural properties that apply to the whole system.

Now I come to the second class of structures in structural mechanisms, namely, the emerging dynamical structures. Robust complex behavior (see sec. 2) lives on the fact that nontrivial long-range effects (e.g., phase transitions) arise dynamically purely on the basis of short-range interactions.[9] The entire system behaves as if there were some external coordination, while in fact there is none. And I take it that this is one of the deep ideas behind the notion of mechanisms: once it is set up in the appropriate way, it runs largely

9. The qualification *nontrivial* is meant to exclude cases such as the one described in case (b) of sec. 3.5.

by itself without the need for any further coordination. But there is one pivotal issue that distinguishes conventional mechanisms from structural mechanisms in robust complex behavior—which is also the reason for the term "self-organization": in complex systems the "organization" that is crucial for the system behavior is not already present in the initial setup but only arises through the dynamics of the system, namely, by the interaction of its parts.

Coming back to the initial issue of the identity criteria for mechanisms, it is only possible to say that there is a common mechanism in diverse systems such as ferromagnets and financial markets if one stays on the structural level.[10] For example, one does not want to claim that market traders actually sit on a grid and only interact with their spatially nearest neighbors. Rather, the crucial point is more abstract or structural: large changes, be it phase transitions or financial market crashes, and other related phenomena can arise purely from the local interactions of the systems' parts without any external coordination. And it seems that complex systems theories can identify the common underlying structural mechanism.

3.3. Robustness of Dynamical Patterns and Statistical Properties. For mechanisms in complex systems the occurrence of the dynamical higher-level pattern one wants to explain, for example, a statistical phenomenon, must be robust.[11] For instance, econophysicists search for mechanisms that produce the phenomenon of volatility clustering. In contrast to a classical mechanism like a thermostat, from which we expect a predictable output in each single case of its working, mechanisms in complex systems mostly do not generate similar single outcomes but rather display a statistical pattern after many simulation runs (Weisberg 2013, chap. 9). Thus, when it comes to the explanation of statistical features,[12] the sensitivity to variations of the initial conditions in each single case can dissolve in the collective statistics, which is not sensitive to such perturbations, provided that the explanation is successful.[13] To put it the other way around, a mechanistic explanation of a statistical phenomenon in a complex system is only successful if the resulting

10. Alternatively, one could say that the structure of certain mechanisms in ferromagnets and financial markets is exactly similar. This may make a difference for ontological concerns. However, for explanations, which are my main interest, I think it amounts to the same thing.

11. Wimsatt (1994) argues that robustness is one of the crucial guidelines in order to "delineate the major structural features . . . which dominate our world." In Bedau's (2014) analysis, robustness is also crucial.

12. In econophysics these statistical features are the stylized fact (see sec. 2), such as the power-law decay in the tail of a probability distribution for returns.

13. Strevens (2003) focuses on the astonishing fact that complex systems can exhibit simple statistical regularities despite the chaotic details of their behavior (I would say in each token case).

collective statistics of many simulation runs is not sensitive to perturbations of the system's parameters in a reasonable range of values. Otherwise, one would rather classify the phenomenon as an artifact of the model, which does not help to identify an explanatory mechanism. The fact that robustness, or 'stability', is such an important requirement for the identification of mechanisms in complex systems is, I claim, the reason why most reports on explanatory approaches in econophysics finish with a consideration of their stability. Talk of mechanisms is only appropriate if the statistical patterns of the system behavior emerge in a robust way.[14]

3.4. Minimal Models as a Path toward Structural Mechanisms. Do many-agent models really supply causally efficacious mechanisms? After all, they are highly idealized, in particular regarding spatiotemporal aspects. I want to claim, however, that the aim of econophysics is not to construct models of financial markets that are as realistic as possible in as many aspects as possible. In particular, the modeled interacting parts of the financial market mechanism (i.e., the market participants), as well as the interaction itself, are not supplied with detailed realistic properties. Rather, the aim is to isolate those structural features of financial markets that are responsible for or at least sufficient to explain certain observed statistical features. Take the switching mechanism in Lux and Marchesi (1999), introduced above. It is largely irrelevant when, how often, or according to which rules traders switch their strategies. What matters is, first, the very possibility of switching and, second, that the probability for switching to occur is not purely random but depends on the behavior of the other traders, either collectively via the market price or individually via observation of what neighboring traders do.

Unrealistic explanations can be good or bad, of course. Approaches using the random walk model are, in some important contexts, explanatorily inferior to those using the more recent microscopic models of financial markets. However, in contrast to what one might expect, the main reason for this inferiority is not that the whole setting of the random walk model is less realistic than the one of microscopic models of financial markets. The crucial point is rather that the individual steps (or acts of coin tossing) are independent from each other. There is no interaction in the random walk model. Since this assumption leads to the well-known normal (or Gaussian) distribution, it does not account for the significant observed deviations from the normal distribution in the tails of the distribution function. What econophysics tries to isolate are those structural features in the underlying mechanism that lead to the observed fat tails of the probability distribution function of

14. Accordingly, in my analysis complex systems that exhibit chaotic behavior cannot be described in terms of mechanisms. Thus, complex systems and structural mechanisms only have a very important overlap, but there is also one without the other.

price changes. It is not essential that the models that realize the mechanism are completely realistic. It only matters that certain very general structural features are modeled, such as interaction between the parts of a multi-agent mechanism or the very possibility of strategy change. Once these features are incorporated, the employed microscopic models of financial markets may be surprisingly unrealistic in various details. Moreover, employing different more or less unrealistic models makes it possible to single out exactly which structural features are responsible for the statistical effects one wants to explain. In contrast, an approach with a detailed realistic model might not reveal what it is that is actually crucial for the explanation (Wimsatt 1987). My point is that econophysics explains by focusing on the essential structural features, while there is hardly any pretense to realism in many other respects.[15]

3.5. Is Mechanisms Talk Really Helpful? Humphreys rejects talk of *mechanisms*, since in his view the ambiguity of the term can produce the illusion of understanding (2014, n. 11). Instead, Humphreys prefers to speak of *processes*. I think both the rejection of the term "mechanism" and the choice of "process" as a preferable alternative are ill-founded. To begin with, there are also many other equally ambiguous and nevertheless helpful and widely used terms (not the least by Humphreys himself), such as causality, explanation, model, and process. But my main point is that employing the notion of mechanisms is particularly illuminating in the context of complex systems because it is apt to highlight their crucial and novel characteristics.

When we characterize what happens in complex systems, it is essential not to refer primarily to the concrete material processes—thus, the term "processes" tends to bring up the wrong connotations. In contrast, the notion of mechanism has the advantage that it is flexible enough to accommodate exactly the crucial point: very general structural aspects are more important for the dynamics of complex systems than the material realization or even a functional decomposition. I think that such a more structural read-

15. Similarly, Batterman (2002a) argues that for explaining "universal behavior" in phase transitions a highly idealized or "minimal" model is better than a detailed model in terms of microconstituents because the latter include irrelevant microdetails that make the explanandum phenomenon less perspicuous. See Weisberg (2013, chap. 6) for a review of different accounts of what he calls *minimalist idealization*. Note that the more well-known *Galilean idealization* introduces unrealistic models only for pragmatic computational purposes and thus usually temporarily. In contrast, *minimalist idealization* aims at models that capture "those factors that make a difference to the occurrence and essential character of the phenomenon in question" (Weisberg 2013, 100). Note that infinite-limit procedures play no crucial role in my study, so that there is no need to discuss the controversial status of "infinite idealizations," for which Norton (2012) argues that they are merely eliminable approximations.

ing of the notion of mechanisms is a very natural extension of the more common reading.

But are complex systems really so different from what we already know? Not every scientific finding, however interesting it may be, affects our general ideas about science, but I think it must be appreciated that complex systems do in fact constitute something genuinely new that does not fit comfortably into the standard philosophical categories. I want to describe this novelty in terms of multiple realization (without going any deeper into this debate):

a) On the one side of the spectrum there may be cases of multiple realization that pose an insurmountable problem for reductionism: the microrealizers, for example, for mental phenomena such as qualia (e.g., pain, taste, smell), have nothing at all in common. This seems to make their common higher-level features a mystery.
b) On the other side of the spectrum are harmless everyday cases of multiple realization: a rigid block falling down a table after its center of gravity has been pushed over an edge may be constituted in drastically different ways on its micro level. However, this is no surprise because it is obvious that, owing to the block's rigidity, only its geometrical structure and the distribution of mass matter in this context.
c) In complex systems, the situation seems somewhat similar to case (b) because here, too, only certain structural features matter, such as the dimension of a complex system and some very general properties of its connectivity (see sec. 3.2). However, this information about the initial setup would not allow us to predict its complex dynamics.[16] We only know this from computer simulations,[17] or by renormalization group methods that allow us to iteratively filter out the irrelevant microdetails (Morrison 2012, 2014). This may again look like the old example of the properties of salt being emergent. But here the detailed (quantum mechanical) microproperties were "simply" not sufficiently known in order to explain the properties of the compound. In complex systems, however, the properties of the system's constituents are usu-

16. Using the characterization by Butterfield (2011), which is compatible with reduction, the behavior of a complex system is emergent in the sense that it is novel and robust relative to the appropriate comparison class, here the component parts of the complex system.

17. Among other things, this is due to the fact that all the parts of the complex system interact with each other at the same time, as Bedau (2014) stresses. Of course, in principle this is also true for the solid block in my point (b). However, the interactions between the block's many parts simply maintain its solidity and do not contribute anything interesting to the dynamics. In contrast, for a complex system the whole dynamics only emerge through the interactions of all the system's parts.

> ally completely known. And even if they are not yet fully understood, as is obviously the case for economic agents, this lack of knowledge is not the reason why the dynamics of financial markets is complex (in the sense specified above).

Still, one might object, is it not always the case that only some features matter for an explanation, in particular for a mechanistic explanation? Well, yes and no. It is surely a matter of degree. In particular, when we keep the pragmatics of explanations in mind, it is completely normal that a huge proportion of details are irrelevant for any single aspect we may seek to explain. However, for explanations concerning the behavior of complex systems the irrelevance of microdetails is not only particularly drastic but very surprising and tells us something that is by no means obvious. Extreme changes on the level of the entire system can arise without being caused by extreme external events or any external coordination. Moreover, this happens with a probability that is much larger than for the case that by sheer luck all the system's parts would do the same.

4. Conclusion. The complex systems perspective shows that financial markets exhibit a dynamical complexity that is due neither to the complexities of human behavior nor to uncontrollable external influences. I have argued that the best way to capture this fact is in terms of what I call *structural mechanisms*. Mechanisms of this kind are characterized by surprisingly unspecific start conditions that seem far away from any realistic modeling. They only state very general but crucial assumptions about the structure of the system, such as its dimensionality and connectivity, for instance, under which conditions a part of the system adopts the behavior of its neighbors. The setup thus seems fairly amorphous and egalitarian, where all parts interact at the same time and according to the same simple rules. Nevertheless, it is sufficient for producing seemingly coordinated extreme events, such as crashes, with a probability that is much larger than for extreme IQs and similar random variables, and which is in accordance with empirical results. Thus, large changes are a generic feature of financial markets. This means that the failure of economic models may be not due to the fact that human behavior is not modeled in a sufficiently realistic way but because it is not fully realized how much complexity arises only through structural mechanisms of many interacting agents.

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