

# It's about Space, It's about Time, Neuroeconomics and the Brain Sublime<sup>†</sup>

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**I**magine yourself lying on your back on a well-oiled high-tech sliding board, rather like the board of an auto mechanic who disappears under the front end of your car. You too will disappear head first into the narrow tunnel of the magnetic resonance imaging device—a brain scanner. Unlike a mechanic sliding under a car, however, you are tied with soft constraints around head and torso to minimize your movement and hold your head still while areas of your brain are scanned as you play an economic game. Based upon recent neuroeconomic studies, certain parts of the brain have been found to be more active in situations that involve calculation versus trust, or considerations of fairness, or problems of ambiguity versus risk, or other factors (for a review, see McCabe, 2008). Like previous studies in behavioral economics, neuroeconomic studies have established roles for both cognition and emotion in economic decision making. But the emphasis of most work thus far has been to discover their respective spatial locations in the human brain. We begin this essay by describing some examples of this work. We will also discuss some practical concerns suggesting that the findings of these studies, while an intuitive starting point, should be treated as provisional.

An alternative view of the brain has focused less on spatial locations and more on the brain's temporal dimension, using time series data from

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<sup>†</sup> To access the Appendix, visit <http://www.aeaweb.org/articles.php?doi=10.1257/jep.25.4.31>.  
doi=10.1257/jep.25.4.31

electroencephalography or EEG recordings. The EEG apparatus is sometimes called a “Frankenstein’s cap” because the head of a participant is covered with wires and stickers to record the electrical activity across the scalp, originating from neural activity within the brain. EEG signals are less precise in terms of discovering the source location of brain activity, but they accurately record the variation of brain activity across time. Subsequent patterns of brain activity evolving in time are studied using methods that derive from complexity science. These methods discover the self-organizing nature of brain activity, suggesting that the time dimension of brain activity may deserve far more attention as the field of neuroeconomics develops.

## **It’s About Space**

### **Perceived Unfairness in Economic Games**

We begin with an early study that used the “ultimatum game” to determine the brain areas associated with emotion and decision making (Sanfey, Rilling, Aronson, Nystrom, and Cohen, 2003). The ultimatum game has two players, a Proposer and a Responder, and an opening stake, which in this case was \$10. The Proposer decides how to divide that stake, and if the Responder agrees both players receive their share. However, if the Responder disagrees neither player receives any money. A purely logical Responder would accept any positive offer, because receiving any amount of money is better than receiving nothing. Yet ordinary people often reject offers perceived as “unfair” (for example, see Thaler, 1988 in this journal; Henrich et al., 2001; Sanfey, Rilling, Aronson, Nystrom, and Cohen, 2003, and the references therein). For instance, splits of \$2 or less are rejected about 50 percent of the time.

The purpose of scanning the brain while people play this game is to obtain more insight into why the ultimatum decisions deviate from the pure logic of self-interest. In this experiment, all the participants play the Responder role and they play 30 times: ten times with the Proposer identified as a human partner (participants were introduced to ten Proposers before the game began), ten times with the Proposer identified as a computer, and ten times in a “free-money condition” in which people receive money (in amounts ranging up to \$10) just for pressing a button. The purpose of the free-money condition is to control for a reaction to the monetary reinforcement by itself, and in actuality, all the Proposer interactions were determined by the computer, not by the people met beforehand, so that all the Responders faced the same range of offers.

Once the scans are taken, the brain images of the players are sorted into the free-money, computer, and human Proposer conditions and in each condition sorted between fair offers, in which the \$10 was split evenly, and unfair offers, in which it was split unevenly. These six piles of images are then collapsed into six average composites, and the six average composites are in turn morphed into a common brain format, a standardized brain made by adjusting away the

idiosyncrasies of each Responder's brain size and shape, changing each part of the Responder's brain image to the standard size, and then placing each in the standard location.

The corrections of the imaging data are meant to put all brains on an equal footing. Yet all imagers worth their salt know that these corrections are also distortions, and moreover are based on an assumption that the contributions of the individual parts of the brain are truly distinct such that they add up straightforwardly to the total contribution of the whole brain—the brain can be no more than the sum of its parts.

The standardized composites of fair and unfair offers are then contrasted in the free-money, computer, and human Proposer conditions. In each of these contrasts, the fair-offer composite is literally subtracted, point-by-point, from the unfair-offer composite, yielding an image of differences. The working assumption here is that the most extreme positive differences mark the parts of the brain that had worked the hardest during the unfair offers.

The subtraction is made possible because the images are composed of voxels, which are not unlike the pixels on your computer screen or television. Voxels have numerical values that estimate a ratio of oxyhemoglobin (HbO<sub>2</sub>) to deoxyhemoglobin, a ratio which increases as glucose is released from the blood to an active region of the brain. This ratio is called the BOLD signal, which estimates the glucose sustenance required by an active region after its hard work. The local numerical values of voxels also lend themselves to the mathematical operations that were necessary to generate the standardized images in the first place.

In this example, the subtraction yielded the largest differences in three specific regions of the brain: the bilateral anterior insula, dorsolateral prefrontal cortex, and anterior cingulate cortex. Although raw voxel values of brain activity show all of the brain working all of the time, these three areas worked slightly harder—albeit less than 5 percent harder (Raichle, 2010; Sokoloff, Mangold, Wechsler, Kenney, and Kety, 1955)—when judging unfair offers compared to fair offers, establishing an association between these three areas of the brain and the emotions that bias our judgments of unfair offers. (Brain images highlighting the location of these parts of the brain, along with a list of other functions that these parts of the brain may hold, are available with this paper in the Appendix Figure 1 at <http://e-jep.org>.)

By comparison, the brain regions highlighted during judgments of computer splits, or when taking free money in the control condition, were not the same areas as those highlighted by the human offers, establishing a dissociation of brain areas associated with human offers from those associated with other offers. Also, the magnitude of the difference between voxel values from a \$9/\$1 split was greater than the magnitude of difference from an \$8/\$2 split in the bilateral anterior insula, a correlation with the degree of unfairness in unfair offers.

Sanfey, Rilling, Aronson, Nystrom, and Cohen (2003) concluded that the anterior insula represents the negative emotions of someone who is confronted with an unfair offer—a conclusion consistent with previous associations between

the anterior insula and instances of pain, distress, hunger, thirst, autonomic arousal, and negative emotions generally (Calder, Lawrence, and Young, 2001). The dorso-lateral prefrontal cortex, on the other hand, represents cognitive processes during human offers, working harder here in unfair offers than in fair offers, which is consistent with previous associations of this area of the brain to goal maintenance and executive control, cognitive processing, and memory functions, but not with negative emotions (Levy and Goldman-Rakic, 2000) or with the acceptance rates of unfair offers. Thus, the cognitive work done in the prefrontal cortex complements the emotive work done in the anterior insula, the region of the emotions induced by unfair offers.

### **Trust and Altruism**

A “trust game” again begins with a Proposer and a Responder, and in this study, the original stake was \$20. The Proposer divided that amount, and then the Proposer’s offer was tripled by the experimenter so that the tripled amount was received by the Responder. Next, the Responder could return some amount to the Proposer. A purely rational Proposer would expect that the Responder would send nothing back; therefore, the Proposer would send nothing to the Responder. However, a trusting Proposer would give some amount to a Responder, and a Responder reacting to that implicit trust with altruism would send something back.

In a study by King-Casas, Tomlin, Anen, Camerer, Quartz, and Montague (2005), each participant played ten consecutive trust games with the same opponent in the same roles in all ten games. Consequently, if a Responder failed to reciprocate with a “fair” share of the tripled amount, the Proposer could make a stingy initial offer on the next round. Thus, there would presumably be carryover from each round of the game to the next. Both Proposers and Responders were scanned simultaneously while playing the multi-round game, one making the initial offers and the other deciding the ultimate outcome of each round. The focus of the study was on the place and time in the brain during the course of decision making wherein a person formulated an “intention to trust” (p. 80), which determined that a generous offer was made.

Each trial’s initial offer from the Proposer was first characterized in one of three ways: generous, which was defined as a larger proportion offered despite a lower proportion repaid in the previous round (compared to two rounds ago); ungenerous, defined as a smaller proportion offered despite a higher proportion repaid in the previous round (compared to two rounds ago); or neutral, which meant the same proportion offered as in the previous round. Then the pooled brain images of Respondents were compared in a number of different ways, including contrasting Responders who received unexpectedly generous offers with those who received unexpectedly ungenerous offers and contrasting immediate brain reactions with those that happened a few seconds later.

Four brain regions in the Responders were associated with either generous treatment or ungenerous treatment (that is, an offer from the Proposer that was better or worse than what would have been expected based on earlier offers): inferior

frontal sulcus, superior frontal sulcus, thalamus, and inferior/superior colliculli. The caudate nucleus (hereafter the caudate) was the region that worked hardest following generous offers. Also, the magnitude of differences in voxel values in the caudate of the Responder produced a larger net change six to ten seconds after the Responder received a generous offer, and the magnitude of differences in the caudate of the Responder were correlated with that of the Responder's anterior-cingulate cortex. (Images of brain scans highlighting these particular parts of the brain, along with a list of other functions identified for these parts of the brain, are in Appendix Figure 2 available online at <http://e-jep.org/>.)

Another set of analyses looked at correlations in brain activity of both participants and how these correlations changed over time. For example, the magnitude of differences in the Responder's caudate voxel values were correlated with the values of the Proposer's middle-cingulate cortex preceding the more generous offers by the Proposer. And the magnitude of change in the Proposer's middle-cingulate cortex region was correlated with the magnitude of change in the anterior-cingulate cortex of the Responder.

The maximum or peak correlation between the two brains' middle-cingulate cortex versus anterior-cingulate cortex trailed the appearance of the initial offer by about 14 seconds, and the location in time of this peak did not change much from the first few games to the last few games played. However, the peak correlation between the Proposer's middle-cingulate cortex with the caudate nucleus of the Responder did change over the multiple rounds of the game. Initially, this peak correlation between the brain of the Proposer and the brain of the Responder followed the initial offer by about 18 seconds, but by the final rounds of the game it trailed the initial offer by only 4 seconds.

A second peak correlation also changed its location in time. The peak correlation between the Responder's anterior-cingulate cortex and the Responder's caudate occurred about 7 seconds after seeing the initial offer in the first few games. However, by the seventh and eighth rounds of the game, the peak correlation *preceded* the revealed initial offer by about 9 seconds, which suggests that the decision to repay an offer generously was made before the offer was known, at about the same time that the Proposer appeared to formulate the initial offer.

Plainly, when we look at any one study by itself, it seems as if a picture of the interactions within brains and between brains is beginning to emerge. And yet a number of serious problems remain. For example, if we take the results concerning fairness and generosity from the trust game, together with the previous results concerning unfairness and punishment from the ultimatum game, it would appear that responses to fairness and unfairness are formulated in different parts of the brain. The anterior insula formulate the response to unfair offers, whereas the response to fair offers as an intention to trust is formulated in the head of the caudate nucleus. With experience, the intention to trust comes to precede the offer, as though a generous response is based on play across earlier games. However, if the intention to trust is formulated in a different part of the brain than the response to unfairness, it must follow that some other region or regions in the

brain must play the role of dispatcher, to send the correct emotional signals to the region making the brain's response. Yet we remain ignorant of how this happens.

These are some of the kinds of difficulties that arise when making comparisons across studies in neuroeconomics. For example, study conclusions disagree about which regions of the brain should be counted toward understanding an opponent's mental states, like a judgment of unfairness or an intention to trust. This may be because the studies are constructed in different ways: such as in their choice of a neutral condition, or choices among linear analyses, or the precise time intuited at which beliefs exist about an opponent's state of mind (for example, Sanfey, Rilling, Aronson, Nystrom, and Cohen, 2003; King-Casas, Tomlin, Anen, Camerer, Quartz, and Montague, 2005; McCabe, Houser, Ryan, Smith, and Trouard, 2001; Tomlin et al., 2006).

Indeed, McCabe, Houser, Ryan, Smith, and Trouard (2001) argue that the basis for cooperative behavior appears to be a network of regions that span the whole brain, including sensory and motor regions and both hemispheres—namely frontal cortex (middle frontal gyrus, frontal pole), the occipital lobe, the parietal lobe, and the thalamus, but which do not overlap with regions that appeared in images of uncooperative participants. Tomlin et al. (2006) also found that the middle cingulate regions were important to the Proposer, while the anterior and posterior cingulate regions were important to the Responder. The latter regions were not apparently important when the game was played against a computer, only against a human opponent, but neither were they apparent in the other studies that we have reviewed. Thus, a variety of contradictory results have emerged that remain to be sorted out in further studies. (To view the brain scans showing areas of the brain commonly associated with trust and altruism, as well as a list of other brain functions associated with these areas, see the Appendix Figure 3 online with this paper at (<http://e-jep.org>).)

### **Ambiguity and Risk**

The examples to this point have all had elements of ambiguity and risk, but in the context of social situations. What about ambiguity and risk by themselves? Medical students at the University of Minnesota were given an initial sum of \$190 to hold in their left hand while they were slid into a doughnut-shaped brain scanner, this time a positron emission tomography or PET scanner. Inside the scanner they were presented with choices between different gambles tailored to vary risk or ambiguity (Smith, Dickhaut, McCabe, and Pardo, 2002).

Each choice was between two gambles illustrated by different numbers of red, yellow, and blue marbles. A marble's color indicated its payoff, and the respective number of marbles of each color represented the probability of each payoff. Thus, in an urn containing 30 red, 30 blue, and 30 yellow marbles, each marble of each color would be equally likely to be chosen. Furthermore, if a red marble pays off \$50, blue \$6, and yellow \$4, the expected payoff would be  $(30 \times \$50) + (30 \times \$6) + (30 \times \$4) / (30 + 30 + 30) = \$20$ , an expected gain of \$20 on average. On loss trials, the same payoffs would appear with signs reversed from positive to negative.

Each gamble was constructed to force a choice based on either relative risk or relative ambiguity—with equal numbers of gains and losses in both the risk and the ambiguity conditions. Risk was varied using the range of payoff values. The expected payoff of 30 red marbles each paying \$30, 30 blue marbles paying \$30, and 30 yellow marbles paying \$0 is \$20, the same expected value as in the previous example, but the range of the payoffs across the marbles of \$0–\$30 is smaller than in the previous example of \$4–\$50, and a smaller range is perceived as a less-risky choice (Smith et al., 2002). Ambiguity was created by providing the exact number of marbles in one color while giving only the sum total of marbles in the other two colors.

After exiting the scanner, each medical school participant realized two actual gambles. One of the two gambles was for a gain and the other was for a loss, and both were drawn from among the gambles enacted when in the scanner. The sum of the gain outcome and the loss outcome, plus the \$190 given at the outset, equaled the amount of money pocketed by the student (Smith et al., 2002).

Medical students typically chose the less-risky gamble when choosing between two gains, and the more-risky gamble when choosing between two losses. Students trended toward choosing ambiguous gambles when choosing between two gains, but showed no preference for ambiguity when choosing between two losses. Overall, the pattern showed larger differences due to risk by comparison to ambiguity, and opposite effects of risk for gains versus losses (Smith et al., 2002).

The imaging contrasts also indicated an interaction effect: the difference in images changed between ambiguity versus risk depending on whether the payoff structure was a gain or a loss. In a first contrast, the aggregate standardized images of trials presenting risky losses were subtracted from images of risky gains, and the aggregate images of trials presenting ambiguous losses were subtracted from ambiguous gains. In a second contrast, these images of differences (the two outcomes of the previous contrasts) were subtracted from each other. This second subtraction of risk minus ambiguity highlighted ventromedial sites<sup>1</sup>—sites in bottom middle cortex—working harder in the risky judgments of gains.

Starting again with the same images, the scientists then reversed the previous subtractions. They subtracted the images of trials presenting risky gains from those presenting risky losses, and trials presenting ambiguous gains from those presenting ambiguous losses. After that they subtracted again the images of differences, but this time the subtraction was ambiguity minus risk. Thus, instead of gain minus loss, loss minus gain—and instead of risk minus ambiguity, ambiguity minus risk—such that the voxel values highlighted as positive in this latter contrast would have been the extreme negative voxel values in the previous contrast. The results of this last contrast discovered a larger presence of dorsomedial sites<sup>2</sup> (top middle cortex)

<sup>1</sup> Using the notational scheme of Brodmann Areas (in parentheses), the discovered areas of the ventromedial network included the regions orbitofrontal cortex (13b), gyrus rectus (14c), medial orbitofrontal (1m, r), intraparietal sulcus (7), brainstem, pons, frontal pole (10p), interior frontal gyrus (47/12m, l), entorhinal cortex (28), and parietal lobe (7/40).

<sup>2</sup> The brain regions and Brodmann Areas of the dorsomedial network included the regions cerebellum VIIB, middle temporal gyrus (21), superior frontal gyrus (6), paracentral lobule (5), pre-SMA (6),



working harder in the risky judgments of losses, completing the parallel with the behavioral interaction effect (Smith et al., 2002).

On the basis of these findings, Smith, Dickhaut, McCabe, and Pardo (2002, p. 717) concluded they had discovered two distinct and complementary choice systems, a dorsomedial network associated with “loss processing when evaluating risky gambles” and a “more primitive ventromedial system related to processing of other stimuli.” A few years later, a different study of risk and ambiguity found contradictory results, examining specific areas of the brain predicted from previous studies: the striatum (frontal middle primitive subcortical structure associated with reward anticipation), orbitofrontal cortex (frontal lobes just behind and above the eyes associated with uncertainty), and the amygdala (site in middle outside temporal cortex associated with ambiguous facial cues and vigilance) (Hsu, Bhatt, and Adolphs, 2005). (Brain images highlighting these parts of the brain, along with other functions that have been associated with these parts of the brain, are available online in the Appendix Figure 4 together with this paper at <http://e-jep.org>.)

The Hsu, Bhatt, Adolphs (2005) study used two tasks based on a gamble metaphor of drawing cards from a deck, rather than marbles from an urn, and a third task that varied risk and ambiguity in knowledge judgments. Ambiguity images were subtracted from risk images, and then risk from ambiguity. Regions working harder due to ambiguity included the orbitofrontal cortex and the amygdala, and the dorsomedial prefrontal cortex. Regions working harder due to risk included the dorsal (top) striatum (caudate nucleus), and the work demands of the dorsal striatum were found to be correlated with the average payoff of the gambles chosen, which was not the case for the orbitofrontal cortex or the amygdala.

A point of convergence of Smith et al. (2002) and Hsu et al. (2005) is that both discovered a harder-working orbitofrontal cortex, and both sets of authors see this region as a part of a larger functional network. While the function of this ventromedial network was only vaguely stated in Smith et al.’s hypothesis, Hsu et al. were more precise, proposing a network spanning two interacting systems, a system for vigilance and evaluation of uncertainty (the amygdala and the orbitofrontal cortex) and a second system downstream in the striatum that anticipates rewards. A point of divergence was that the vigilance–evaluation plus reward–anticipation systems were discovered in the condition that emphasized ambiguity, whereas the less-precisely described system of Smith, Dickhaut, McCabe, and Pardo (2002) was discovered in the condition that emphasized risk. Hsu, Bhatt, and Adolphs (2005) failed to corroborate the harder-working orbitofrontal location in their contrast that emphasized risk.

Of course the field of neuroeconomics is quite young, and these difficulties have been acknowledged. Possibly, as the neuroimaging technology improves and as the literature builds, studies will be sufficiently cross-referenced to converge upon a map of the brain with reliable locations for each type of emotional or logical

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cerebellar vermis VI, precuneus (7), inferior parietal lobe (39/40), precuneus (7/31), and cerebellum crus I.



decision (Roskies, 2010).<sup>3</sup> Certainly some association must exist between the brain and decision making! However, a skeptical view holds that it has not been the lack of exotic imaging technology that has delayed the development of lasting insights about brain function, cognition, and behavior. Rather, it has been a wrongheaded logic that seeks to equate spatial locations in the brain with the causes of behavior or mental functions (Uttal, 2001).

### **James and the Psychologist's Fallacy**

The pioneering psychologist William James (1890) coined the term psychologist's fallacy: the tendency to make attributions to others based on our first-person experience of cognition and behavior. In one version of this fallacy, the first-person experiences of reasoning or emoting, for example, become third-person categories or components of cognition and behavior (Ashworth, 2009). We reason, so there must be a seat of reason, and we emote, so there must be a seat of emotion. In cognitive neuroscience, we may take the fallacy one step further in placing the seats of reason or emotion in the brain. We emote, therefore we can isolate the cause of emotion in the brain, and so on. The psychologist's fallacy seems to be built on logic of cause and effect. However, the conflicting outcomes discussed here illustrate a general state of affairs across many studies using functional neuroimaging. Many of the studies that seek to trace particular kinds of decisions to particular areas of the brain have reached contradictory or inconsistent conclusions.

Early on, the scientists using subtractive brain imaging discovered that their results were not usually replicable, at least in the strict sense of producing overlapping active voxels in overlapping brain regions for the same brain function (Jennings, McIntosh, Kapur, Tulving, and Houle, 1997; Poeppel, 1996; Van Orden and Paap, 1997). These failures to replicate led scientists to relax the standards of evidence for what counts as a replication. For example, in some studies two brain images that contain at least one active voxel in the same brain region can be counted to be equivalent. The respective voxels need not overlap; they must only appear in the same region of the standardized brain (Knoch, Gianotti, Baumgartner, and Fehr, 2010; McCabe, Houser, Ryan, Smith, and Trouard, 2001).

The fact that similar tasks or methods highlight different brain regions has another interpretation: that mental functions must be distributed across networks of brain regions. This network hypothesis makes (apologetic) sense of the failures to replicate, but it runs into other problems. The extent of a brain network can grow with each new study—at least until it fills the whole brain, which defeats the underlying assumption of the analysis (for example, see Anderson, 2010). Also, studies inevitably discover spurious brain regions associated with spurious idiosyncratic task effects or strategies, present in one task contrast but no other. Coherent

<sup>3</sup> A related but different point of view is that the different entailments inherent in brain processes, behavior, or conscious experience can become a basis for triangulation, yielding a reliable empirical and phenomenological convergence (Roepstorff and Jack, 2004).

criteria have not yet emerged to reliably distinguish functional networks from functional anomalies.

When one considers the spatial methodology, the difficulty of finding false positives seems all too real—that is, finding regions of the brain that seem to be identified with a certain task in one study, but not in other studies. After all, a brain in these studies becomes an image landscape of measured voxel values, a topography undulating up and down in local variation. With any two non-identical images, if one is subtracted from the other, the results will include a region of maximum positive differences and a region of minimum negative differences. In this way, any contrast using brain images can be counted on to make “discoveries” (Uttal, 2001).

In the most notorious example of how discovery can go astray, Bennett, Baird, Miller, and Wolford (2010, p. 2) presented a dead (!) salmon with “a series of photographs of humans in social situations,” and using standard analyses of the images that resulted, they discovered a hard-working region of human social perception in the salmon’s brain. They point out that a standard fMRI produces 130,000 voxels, and so, depending on how one analyzes this mass of data and the inevitability of noise in the data, the possibility of a false positive outcome can be very high. They suggest that standard statistical tests may fail badly in this setting. The positive findings of their study, despite the previous death of the salmon, should perhaps humble the conclusions drawn from any single neuroimaging study and rein in some of the hype that so often accompanies a new neuroimaging result.

In effect, the spatial approach to studying the brain assumes that the brain can be treated as the sum of its parts. The assumption is called component-dominant dynamics, meaning interactions within the components dominate the interactions among the components (Van Orden, Holden, and Turvey, 2003). Component-dominant dynamics are necessary if components are to remain causally distinct. To do so, components must interact only locally. For example, an emotion component responding to fiduciary transactions could interact with a cognitive component that rationally evaluates transactions without having the guts of either response changed in the process. The component-dominant dynamics assumption encapsulates local effects of components such that they can be recovered in linear analyses of the measurements of the brain. This approach underlies what is often called the General Linear Model of the brain.

One reason to assume component-dominant dynamics is to justify the subtraction of one image of the brain from another, or to justify more complicated “factorial analyses” of brain or behavior (Van Orden, Pennington, and Stone, 2001). The assumption requires that brain dynamics are uniform fluctuations around equilibriums, even when contrasting average values from two different points in time. The existence of such equilibriums in the brain’s behavior could be turned around to corroborate component-dominant dynamics and would justify pooled values, means, and the standardized images so prominent in subtractive analyses. But brain dynamics are not uniform and do not contain stable equilibriums (Buzsáki, 2006; Kelso, 1995). Consequently, we believe that while some kind of spatial approach to analyzing the brain will eventually chalk

up reliable successes (Freeman, 2007), it will ultimately fail to capture, in a full way, how the brain works, unless it gives sufficient emphasis to the dimension of time (Freeman, 2006).

## It's About Time

Until recently, it was not clear how to envision brain activity without the accompanying notion that certain areas of the brain were the home of particular functions. A clear alternative has emerged, however, from a contemporary understanding of complex systems, inspired originally by “far from equilibrium” thermodynamics (Gregoire and Prigogine, 1977). The nature of voxel values in brain images suggests a look in this direction because voxel values directly reflect local thermodynamics (Davia, 2006). Voxel values estimate metabolism, the fuel required by the thermodynamic engine that is the brain. Given this fact, it seems at least potentially appropriate to borrow from thermodynamics and complexity theory (Hollis, Kloos, and Van Orden, 2009). Repeatedly measured voxel values reveal distinct patterns of change over time, as do other measures of brain activity, giving access to the dynamics of the brain in terms of how activity fluctuates over time.

### How Do the Components of the Brain Interact?

Measuring the behavior of the brain over time allows us to pose hypotheses about the dynamics of the brain. An alternative to the assumption of *component-dominant dynamics* discussed earlier is called *interaction-dominant dynamics*, a hypothesis based on the claim that the brain is different than the sum of its parts. Interaction-dominant dynamics allow the interacting components to change each other's intrinsic dynamics as they interact—at least within limits (Jensen, 1998; Van Orden, Holden, and Turvey, 2003).

Interaction-dominant dynamics and component-dominant dynamics predict different patterns in the time series of measured values of brain activity. Component-dominant dynamics predict that a time series of measured values of the brain should exhibit a uniform random pattern around a mean value (so long as all else remains equal). Large or small changes in one component will not be systematically related to large or small changes in other components. Brain components are coupled only loosely, or not at all (Newell, 1990; Simon, 1973).

Interaction-dominant dynamics imply that the brain is composed of interdependent components that “infect” each other with changes, and the changes can be amplified or damped in the interactions among components. Instead of a pattern of random variation, there exists an unstable balance between two different tendencies: a tendency among interdependent components to be dominated by changes due to a few stronger components versus a tendency for each component to behave independently. The actual activity of the brain differs in quality from either of these two tendencies—and a fractal pattern is predicted to emerge.

### Fractal Time in Brain Data

The middle graph in Figure 1 portrays results from a typical electroencephalography or EEG recording from a data bank available on the Internet (at <http://www.physionet.org>), 2011). Specifically, EEG recordings yield a time series of values from each electrode in the “Frankenstein’s cap,” reflecting the variation of activity within the brain. The middle, raw, EEG time series in Figure 1 was recorded from a healthy participant at an electrode located above the middle-posterior region during a no-task resting condition (see the EEG Motor Movement/Imagery Dataset at [www.physionet.org](http://www.physionet.org)) for descriptions of experimental conditions and data, ([www.physionet.org](http://www.physionet.org)), 2011). The signal consists of 9,760 data points recorded over the course of one minute.

EEG outputs may appear quite irregular, but several decades ago researchers discovered fractal structure in the brain signals of nonhuman animals (Anderson, Holroyd, Bressler, Selz, Mandell, and Nakamura, 1993; Freeman, 1989; Grüneis, Nakao, and Yamamoto, 1990; Kodama, Mushiake, Shima, Nakahama, and Yamamoto, 1989a, b; Selz and Mandell, 1991; Yamamoto, Nakahama, Shima, Kodama, and Mushiake, 1986). A decade later, these findings had been replicated in studies of human brains. For example, a fractal pattern like that illustrated by the middle data in Figure 1 was observed in the EEG recordings from human participants in a so-called resting state, in which no task was required while being scanned (Linkenkaer-Hansen, Nikouline, Palva, and Ilmoniemi, 2001).

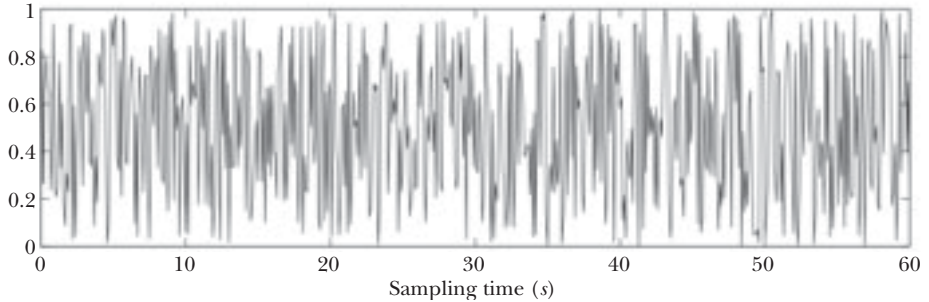
Economists have traditionally not worked much with fractal mathematics, and so we will provide a quick overview of the concepts and how they apply to brain research. Benoit Mandelbrot invented the term *fractal* in the 1970s to refer to a new geometry, synthesizing previously exceptional mathematical “monsters” within a geometry emphasizing the highly irregular phenomena of nature in the rough. Loosely speaking, fractal geometry is about patterns or shapes that have the property that when divided into parts—no matter how small—the shapes of the parts mimic exactly (or statistically) the shape of the whole. Parts and wholes are “self-similar.” Many naturally occurring phenomena are readily analyzed using fractal geometry, ranging from snowflakes and broccoli to cardiovascular networks or kidneys. But while these examples are fractal in space, physiological signals like heartbeat and EEG readings are fractal in time.

In Figure 1, the middle pattern is the EEG brain signal of the healthy, resting participant. The signal below that is the EEG signal of a brain in seizure, while the upper signal represents a random, synthetic “white noise” signal. All three patterns appear irregular, but even an untrained eye can see that the three signals are markedly different from each other. Indeed, it turns out that, with training and experience, the human eye is among the most reliable “devices” for distinguishing among these patterns.

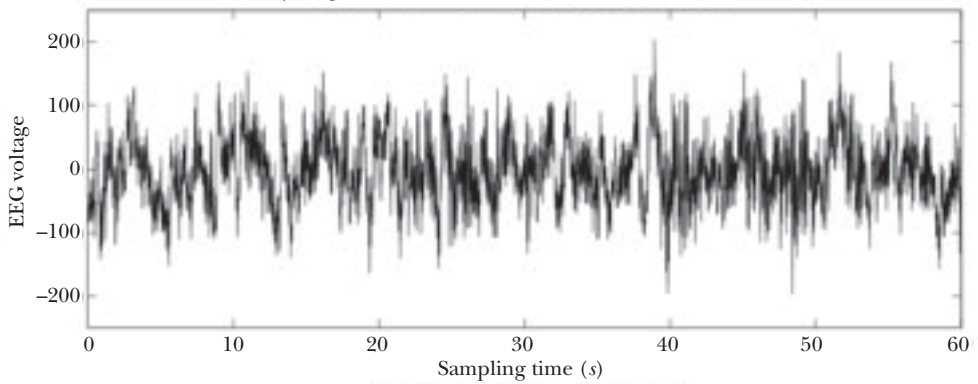
How is the fractal structure of a time series characterized? EEG data have a statistical fractal structure, although it is not the ideal repeating structures of the fractals made popular in posters and other popular art. The fractal structure of a time series can be evaluated using several kinds of statistical tools but the most

*Figure 1*  
**Three Examples of “Noise” in EEG Timeseries**

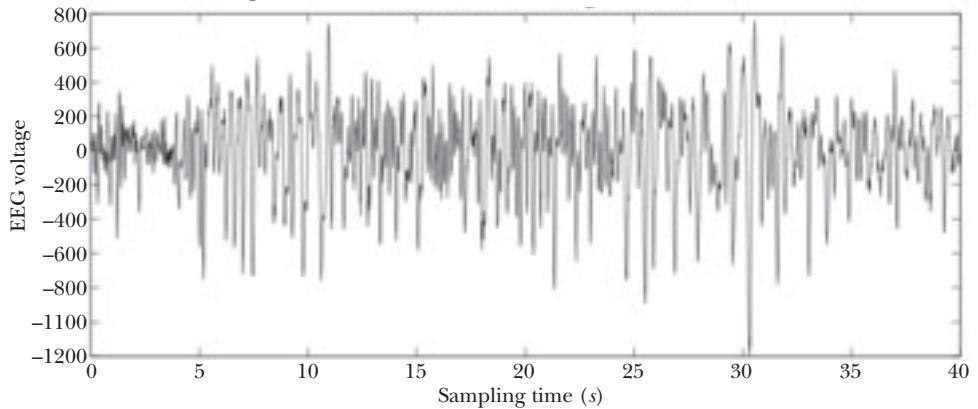
A: Synthetic White Noise



B: EEG Time Series of Healthy Subject at Rest



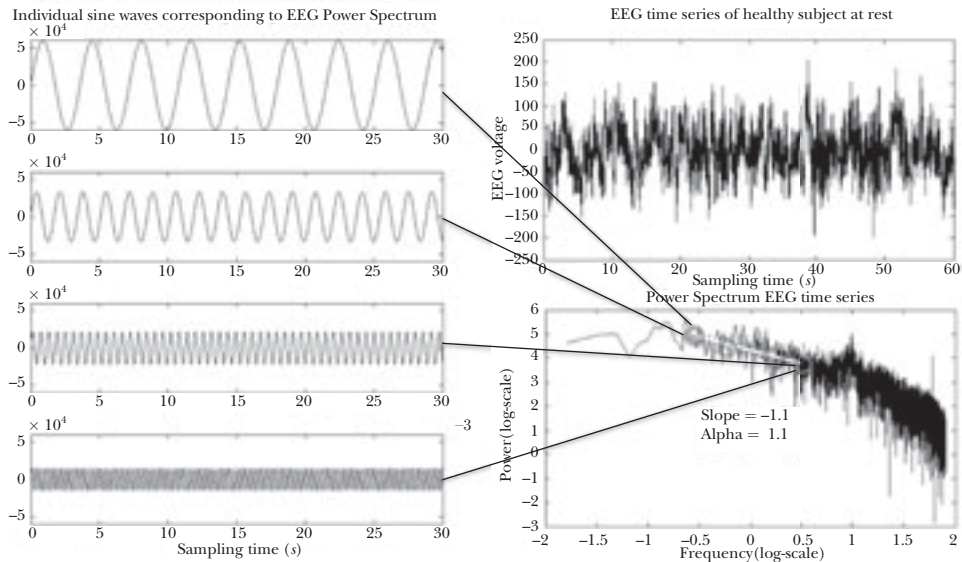
C: EEG Time Series during Seizure



*Source:* Authors.

*Notes:* Top: a synthetic signal of random white noise with  $\alpha \approx 0$ . Middle: EEG data from a healthy participant at rest. The time series resembles that of fractal time and  $\alpha \approx 1$  (known as “pink noise”). Bottom: EEG recording during a seizure in which the time series of EEG data resembles brown noise with  $\alpha \approx 2$  ([www.physionet.org](http://www.physionet.org)), CHB-MIT Scalp EEG Database).

**Figure 2**  
**Spectral Plot of an EEG Time Series**



Source: Authors.

Notes: Data from the middle panel of the earlier Figure 1, the participant at rest recorded for 60 seconds. On the lower right, the power spectrum is displayed on log-log scales. Four ordered pairs of amplitude (power) and frequency are highlighted with dots and lines that connect to the respective sine waves that they represent (see also Holden, 2005.)

common is to use a Fourier transformation, which approximates an irregular and aperiodic series of EEG data with wholly regular and periodic sine waves. Simply adding up sine waves of different frequencies and amplitudes can closely approximate any complicated curve. The next step is to transform these sine curves into what is called a spectral density function, which summarizes the relationship between the size of changes and how often those changes occur.

We first approximate the raw EEG data series at the upper right of Figure 2 using the Fourier transformation, which involves transforming the curve into the series of sine waves on the left. Then the sine waves are transformed in turn into the power spectral density function at the bottom right. Again, the spectral density plot summarizes the relation between the size (amplitude squared) of changes ( $S$ ) over time in the EEG signal versus how often or how frequently changes of that size occur ( $f$ ). This relation of size compared to frequency,  $S(f)$ , is the typical focus of a fractal analysis. The mathematics of fractal geometry is defined by invariant relations between the size (or magnitude) of structures and the number (or frequency) of structures at that size.

The decomposition of a pattern into sine waves, via the Fourier transformation, is portrayed on the left side of Figure 2. Each sine wave has a particular



frequency and amplitude, and these two values are graphed as an ordered pair with the (log) frequency spectrum on the  $x$ -axis and the (log) amplitude-squared (power) on the  $y$ -axis, as portrayed in the lower right-hand plot of Figure 2. Arrows in the figure connect the illustrated sine waves to their actual point coordinates in the spectral plot.

A fractal pattern is plausible when power or size of change lines up proportionally with frequency of change on the log-log axes. The regression line portrayed in Figure 2 expresses this relation, with a slope of  $-\alpha$ , where  $\alpha$  is called the scaling exponent. The name “scaling exponent” comes from the relation of  $S(f) = 1/f^\alpha$ , which translates as “the size of changes occurring with a particular frequency equals the inverse of frequency, itself, raised to the scaling exponent alpha.” The relation is called an “invariant scaling relation” because the proportional relation between size and frequency of change is equivalent at big scales of change, small scales of change, and all scales in between. The invariant relationship across all scales between size and frequency of changes is the defining feature of fractals.

The straight line of the spectral plot in Figure 2 is also called a “power law.” Power laws show up as straight lines when graphed on log-log scales. Power laws relating event sizes and event frequencies are found widely in nature, and a variety of power law values have been associated with a wide array of organisms, biological processes, and collective social activities (Bak, 1996; Farmer and Geanakoplos, 2005; Jensen, 1998; Jones, 2002; Mitzenmacher, 2003; Philippe, 2000; Van Orden, Kloos, and Wallot, 2011; West and Deering, 1995). Power laws also appear widely in measurements of human performance (for reviews, see Gilden, 2001; Kello et al., 2010; Kello and Van Orden, 2009; Riley and Turvey, 2002; Van Orden, Holden, and Turvey, 2003; Holden, Van Orden, and Turvey, 2009).

The power law value of  $\alpha = 1.1$  in Figure 2 is close to one, and  $\alpha = 1$  represents a mathematical ideal in fractal geometry. The ideal is here called “fractal time” because the fractal pattern unfolds in time instead of space.<sup>4</sup> Resting-state neural activity has been examined in a number of studies, and the general finding is fractal time (Buzsáki, 2006). EEG signals that exhibit fractal time are associated with healthy brains. Signals that depart from fractal time, becoming either overly random or overly regular, are associated with aging and disease (Van Orden, 2010; Van Orden, Kloos, and Wallot, 2011; West, 2006).

For example, signals resembling the white noise signal in Figure 1 are often associated with aging and, analyzed with these methods, yield  $\alpha \approx 0$ . If the data in the bottom panel of Figure 1 that came from a brain seizure were analyzed with these methods, then  $\alpha \approx 2$ . The value  $\alpha \approx 1$  is also the source of other names for the  $S(f) = 1/f^\alpha$  scaling relation, namely  $1/f$  scaling or  $1/f$  noise. It is also called pink noise because noise captures the arrhythmic irregularity of the raw EEG signal

<sup>4</sup> Loosely speaking, the fractal dimension estimates the extent to which the rough irregular raw EEG curve “leaks” from the first dimension of a straight line into the second dimension of a plane. The power law or scaling exponent of ideal fractal time is 1, and the fractal dimension of ideal fractal time is 1.2. Random white noise has a power law value or scaling exponent of 0 and a fractal dimension of 1.5.



and because the power spectrum of light with a similar scaling relation appears pink from the large amplitudes of reddish light in the low-frequency portion of the spectrum.

Of course, the data that stream from the “Frankenstein cap” of EEG recording form multiple time series—one for each of the electrodes. Thus, a key question for studying the behavior of the brain is the extent to which similar patterns of change are observed across the EEG nodes. This area of study was inspired by results from physics concerning how systems may self-organize their own behavior (Jensen, 1998). For example, when a pile of rice is formed by dropping one grain of rice at a time, it will self-organize to allow access to the widest possible range of rice avalanches. The brain analogy to avalanches is the tendency for coherent activity to spread among the nodes of the Frankenstein cap, the nodes distributed across a person’s scalp. Size, in this analogy, is the number or spatial extent of nodes that participate in coherent activity (Allegrini, Paradisi, Menicucci, and Gemignani, 2010).

In addition, each avalanche begins and ends in an observable rapid transition between two states of coherent activity, so each avalanche of coherent EEG can be measured in two ways: by the number of nodes participating in the coherent dynamics and the duration in time of each avalanche (the time from the rapid transition at the beginning of the avalanche until the rapid transition at the end). Fractal time across the size and duration of EEG avalanches has been observed for some years (Gong, Nikolaev, and van Leeuwen, 2003; Stam and de Bruin, 2004). More recent work finds that both ways of measuring brain avalanches yield power law behavior (Allegrini, Paradisi, Menicucci, and Gemignani, 2010), similar to the power law illustrated in Figure 2.

Variation in patterns of global synchronization is the paramount scale of global change in brain dynamics, and changes in the global organization of central nervous system activity unfold in the predicted fractal pattern. Interaction-dominant dynamics predict that ongoing interdependent changes in each of a system’s components participate in the global dynamical pattern. Consequently, no matter the scale or direction from which we enter the system, the repeated measurements should bear evidence of the fractal signature. Indeed, fractal characteristics have been observed from the smallest to the largest scales of brain dynamics. Fractal time is observed in the variation of current flow through neuronal ion channels (Banerjee, Verma, Manna, and Ghosh, 2006), in the rate of neurotransmitter secretion (Lowen, Cash, Poo, and Teich, 1997), in the intervals between action potentials (Bhattacharya, Edwards, Mamelak, and Schuman, 2005), in the variation of individual voxel values during functional magnetic resonance imaging (Thurner, Windischberger, Moser, Walla, and Barth, 2003; Zarahn, Aguirre, and D’Esposito, 1997), and in local field potentials (Leopold, Murayama, and Logothetis, 2003).

The unstable balance inherent in the dynamics of complex systems predicts the universal presence of fractal time. But why? What use is an unstable balance? In complex systems, the unstable balance serves as a tipping point or transition state for transition between different organizations of the brain. The brain stays

close to this tipping point (and  $\alpha \approx 1$ ), allowing it to transition quickly to new organizations as required. The transition state would be called a “critical state” in thermodynamics, which yields another name for fractal time as “critical behavior.” Pioneering studies using EEG with (SQUID) neuroimaging had previously verified multiple empirical flags of critical behavior, and these flags of criticality were discovered while observing transitions between different brain organizations, and the virtually coincident transitions between different organizations of behavior (Kelso, 1995).

### **Deviations from Fractal Time Due to Tasks and Feedback**

The central nervous system fluctuates as a fractal object, which means that it exhibits the same statistical signature of fractal time at all scales of system dynamics. This fractal signature is not always present to the same degree, however. For example, the avalanche study of EEG leads found that nodes near the center of the globally coherent activity produce fractal time, but with less clear signals of fractal time than nodes at the penumbra. Nodes less central to the globally coherent activity produced the clearest signals of fractal time (Allegrini, Paradisi, Menicucci, and Gemignani, 2010).

One explanation for this pattern is that behavioral states self-organize the brain, and brain activity reflects to some extent the dynamics of that content. Typically content will not fluctuate at the same pace as fractal brain dynamics, and so it will perturb the pattern of the fractal dynamics. Unsystematic perturbations of fractal time will tend to make the fractal signal resemble random white noise (Van Orden, Holden, and Turvey, 2003), and the amplitudes of the unsystematic perturbations determine the extent of the resemblance to white noise (Holden, Choi, Amazeen, and Van Orden, 2010). In the avalanche study (Allegrini, Paradisi, Menicucci, and Gemignani, 2010), the EEG nodes at the penumbra of coherent activity would participate less and be least perturbed by the fluctuations in content, thus preserving clearer signals of fractal time in their local dynamics.

Similar changes have been induced in healthy brain dynamics by manipulating the relation between task and participant—and here we begin to re-approach the kinds of studies that may have some economic application. A study to examine the acquisition of skill in task performance (in this case, drawing lines back and forth between two visible targets in a classic motor performance task) found clearer signals of fractal time as participants gained practice, converging toward an ideal signal as the practice progressed (Wijnants, Bosman, Hasselman, Cox, and Van Orden, 2009). When a participant is less practiced on a task, each measurement trial of the task creates unfamiliar task demands. Lacking extensive practice and task skills, task demands tend to take a participant by surprise, and unsystematic surprises from trial to trial make brain signals look less like fractal time and more like random white noise.

Often the tasks used in experiments include planned sources of unsystematic change from one measurement trial to another, such as randomized order of the choices that are being offered. Yet, in this crucial relation between participant and

task, sources of random change are always also sources of perturbation to outcome measurements, creating more random-like white-noise-like patterns. The direction of change in the scaling exponent  $\alpha$  between two conditions allows us to evaluate such outcomes. The earlier Figure 1, showing variation in  $\alpha$  from white noise, to the brain at rest, to a seizure episode, illustrates the previously observed span of variation in scaling exponents.

Some laboratory tasks provide explicit feedback on performance, such as “too fast” or “too slow,” or “correct” or “incorrect.” Buiatti, Papo, Baudonniere, and van Vreeswijk (2007) studied the effect of accuracy feedback on EEG signals. Participants had to decide whether three numbers illustrated a hidden rule. There were in fact no hidden rules behind the numbers, and although the students were led to believe that the feedback they got was based on their performance, the feedback was controlled by the experimenter. This study contrasted the noise structure of EEG with and without feedback, and when the feedback message was “correct” or “incorrect.” Without feedback, most participants (and most electrodes) produced values of  $\alpha$  close to 1, but slightly larger. On trials receiving “correct” feedback, the  $\alpha$  values of EEG recordings departed in the direction of a more random pattern, a pattern more like the  $\alpha = 0$  pattern of random white noise. EEG measurements on trials presenting “incorrect” feedback departed in the opposite direction, giving the appearance of a signal with  $\alpha$  closer to  $\alpha = 2$ .

One way to think about these results is that the feedback of “correct” implies that a trial requires no adjustment to the strategy of decision making. Feedback requiring no change would simply perturb performance unsystematically. Unsystematic perturbations contribute randomness to measured signals, which deviate toward white noise. Alternatively, feedback of “incorrect” will presumably engage the participant in a mindful effort to decipher their error. Mindful changes occur on the slower time-scales of the EEG signal, and amplified slow (lower frequency) time-scales give the appearance of signals with  $\alpha \approx 2$ . Relevant to the big picture we develop in this paper, neuroeconomic studies of spatial locations discovered narrowly circumscribed regions of the brain associated with emotions, while the hidden rule study found that the emotion-laden feedback of “incorrect” led to changes in the global signature of the entire brain.

### **Deviations from Fractal Time Due to Stimulation**

EEG signals of participants left to their own thoughts “at rest”—unoccupied with an experimenter’s task—show clear evidence of fractal time. Linkenkaer-Hansen, Nikulin, Palva, Kalia, and Ilmoniemi (2004) contrasted this resting condition with a stimulation condition designed to cause a behavior. Specifically, the participant’s brain was electrically stimulated, causing the participant’s thumb to twitch. Brain activity was recorded using both MEG (magnetoencephalography) and EEG technology. All the time series of data, in all the conditions and with both kinds of recordings, showed reliable evidence of fractal time. However, the electrically induced twitching of the thumb decreased the  $\alpha$  of the recorded signal in the direction of white noise.

Resting-state EEG has been contrasted with stimulation during passive listening to classical music, a short story read aloud, and also active mental rotation of figures (Shepard and Metzler, 1971). Listening to music showed the least deviation from fractal time in EEG ( $\alpha$  closest to one), followed by listening to the story, and then mental rotation (Bhattacharya and Petsche, 2001). Another EEG study compared visual stimulation due to viewing a painting with later mental imaging of the same painting, also comparing professional artists with nonartists. Mental imaging of the painting yielded the values of  $\alpha$  closest to the  $\alpha = 1$  of fractal time, and mental imaging by artists produced values closer to  $\alpha = 1$  than nonartists (Bhattacharya, 2009).

Mental imaging of a painting can be viewed as a production task; the participant controls production of the mental image. Production tasks and skilled performance appear to minimize external perturbation effects on signals of fractal time (Kloos and Van Orden, 2010). Behavioral studies using production tasks produce clear signals of fractal time (Kello and Van Orden, 2009). In addition, behavioral studies have found clearer signals of fractal time in skilled task performance than in less-skilled performance (Wijnants, Bosman, Hasselman, Cox, and Van Orden, 2009). The EEG data reflect the same directions of the effects found in the behavioral data.

### **Multifractal Time**

Estimates of the scaling exponent  $\alpha$  of fractal time can vary over time and space. The dynamics of brain activity are not stationary and are not adequately captured by a single estimate of the scaling exponent. Multifractal analyses reveal this variation. Multifractal analyses add a second dimension to fractal analyses, capturing the wide or narrow range of the  $\alpha$  values that are present in a time series of brain data, as well as a kind of central tendency of the scaling exponents in the single value of  $\alpha$  derived in a monofractal analyses (like that portrayed in Figure 2).

EEG signals have been examined for the presence of multifractal dynamics. In one study, a comparison was made between tracking a selected path through a map by eye versus tracking a dot through the map with a joystick-controlled cursor (Popivanov et al., 2006). The overall outcome was a clear presence of multifractal dynamics in all conditions, a finding that has also been established in fMRI dynamics using a face recognition test (Wink, Bullmore, Barnes, Bernard, and Suckling, 2008). Multifractal dynamics have been observed in behavioral studies as well (Ihlen and Vereijken, 2010; Wallot and Van Orden, 2011) and will assuredly be more widely explored in future studies of behavior and brain.

Some proponents of the complexity approach continue to presume that specialized functions exist in the different regions of the brain and even use local variation in the signal of fractal time to pick out local brain regions (for example, Bhattacharya, 2009; Bhattacharya and Petsche, 2001; Wink, Bullmore, Barnes, Bernard, and Suckling, 2008). However, the power law behavior in global avalanches of EEG activity, together with the global fractal time observed in the time intervals between phase transitions of coherent whole-brain activity in EEG, provide an alternative source of the local variation. From this perspective local variation stems from higher-order patterns in time and space, the variation in whole-brain fractal

dynamics (Allegrini, Paradisi, Menicucci, and Gemignani, 2010; Gong, Nikolaev, and van Leeuwen, 2003; Stam and de Bruin, 2004). Wider application of multifractal analyses may eventually decide this issue, because whole-brain multifractal dynamics would imply interaction-dominant dynamics among components at all levels below the whole brain (for discussion, see Ihlen and Verijken, 2010).

Other proponents of the complexity approach propose that the functionality of the brain is sufficiently context-sensitive that functions must be self-organized on the fly (Turvey, 2007). The idea of functional holism converges with the long-standing discovery that each movement trajectory is unique unto itself, even the repeated movements of a master carpenter pounding a nail, or a prima ballerina in repeated dance rehearsals (Bernstein, 1967). Studies of fractal time in behavior have elaborated this view as well, and these ideas are bolstered by recent discoveries of subtle body synchronies among unpracticed individuals, as in a conversation with a stranger (Shockley, Richardson, and Dale, 2009; Richardson, Marsh, Isenhower, Goodman, and Schmidt, 2007; Konvalinka et al., 2011). Finally, although the complexity approach has not as yet confronted all the regularities in brain and behavior that remain on the table, it comes to the table with a more varied and powerful set of explanatory concepts. Formally this power reflects the fact that the complexity approach generalizes the “linear” concepts that preceded it; practically it reflects methods and tools of analysis that continue to be developed (Marwan, 2011; Zbilut and Webber Jr., 1992).

## **The Brain Sublime**

In contrast to the astounding successes in describing the anatomy and physiology of the central nervous system, science has not yet produced a functional account of the brain that can withstand close empirical inquiry. We believe that complexity theory, corroborating the rather detailed predictions of interaction-dominant dynamics, offers a promising path toward such an account. The theoretical groundwork is in place to let empirical dynamics reveal the fundamentals of systems, such as how a system’s components interact. How components interact, in turn, dictates whether a system is simple and therefore amenable to linear analysis, or complex requiring the nonlinear methods of complexity science. Linear methods presume uniform dynamics and emphasize stable experimental control to get a clear picture of brain regions. Nonlinear methods first characterize the dynamics and then emphasize the phenomena of unstable dynamics using methods that induce loss of stability around the tipping points of phase transitions, revealing the nature of the system in the way its dynamics come apart (Kelso, 1995).

The two different approaches produce different scientific portraits of what the brain does—and thus how to study the brain. And thus far neither perspective has achieved a clear advantage in the democracy of scholarship, in which young scientists vote with their feet to choose a career path through neuroeconomics. Were we to gamble on the future potential of existing studies in neuroeconomics, however, our

money would be on the more pragmatic kinds of neuroeconomics studies, those that are relatively free of assumptions about just how the brain works, which have produced some intriguing results.

One example concerns a classic problem in economics. The values of public goods such as roads or water purity are notoriously difficult to estimate. Citizens have an incentive to minimize how much they would pay for new roads or pure water and then freeload on the contributions of others. In this context, Krajbich, Camerer, Ledyard, and Rangel (2009) constructed a lie detector, using brain images to deter potential freeloaders. Participants were first told (assigned) how much they value a public good (high or low value) while their brains were scanned in the fMRI machine. Subsequently, a machine-learning algorithm classified the participants' brain images to predict the previously assigned values of high or low. The algorithm could eventually sort brain images correctly about 60 percent of the time.

Participants were told about the 60 percent success rate of the algorithm; the incentive for truthfully reporting the personal value of new roads or pure water did not require that the machine classify all people perfectly, only that it scored reliably above chance. That was sufficient to induce truth telling. Notice that this solution to the classic problem of eliciting truthful preferences for public goods does not rely in any central way on a particular assumption about how the brain works but only on whether brain images contain some information of some kind about preferences.

Ultimately, the future of neuroeconomics is not wedded to a particular methodology for examining the brain, whether it is one that emphasizes space or time or uses a technology as yet undiscovered. As Camerer (2008, pp. 369) puts it: "The potential of neuroeconomics is in combining the clearest experimental paradigms and statistical methods in economics, with the unprecedented capacity to measure a range of neural and cognitive activity that economists like Edgeworth, Fisher, and Ramsey daydreamed about but did not have." We conclude then that, irrespective of where the real promise lies, bringing together reliable economic paradigms with reliable brain science holds a possibility for taking this new science beyond anyone's wildest dreams.

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