BEAUTIFUL GAME THEORY

How Soccer Can Help Economics

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CONTENTS

4

MAPPING MINIMAX IN THE BRAIN

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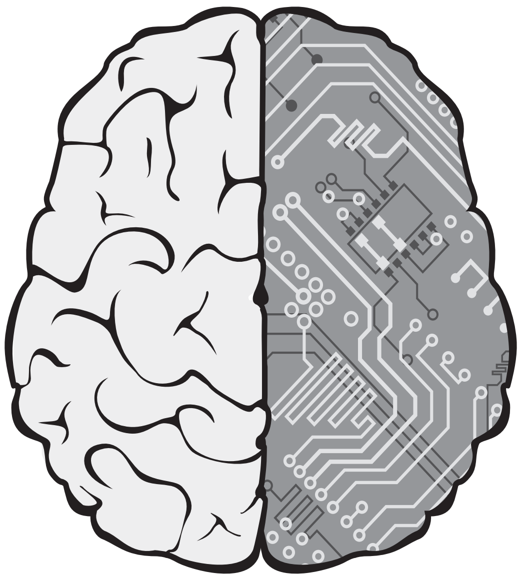

Soccer is a game you play with your brain.
—Johan Cruyff, quoted in Anderson and Sally 2013

Let there be granted to the science of pleasure what is granted to the science of energy; to imagine an ideally perfect instrument, a psychophysical machine, continually registering the height of pleasure experienced by an individual exactly according to the verdict of consciousness.
—Francis Y. Edgeworth 1881

The Obama administration and the European Commission are currently planning two different multiyear research efforts to produce an "activity map" that would show in unimaginable detail the working of the most complex organ in the body: the human brain. The first objective of these efforts is to gain a much deeper understanding of how the brain works. The final aim, probably unattainable for several decades, is to know how the brain generates perception, consciousness, memories, and thoughts and to find ways to intervene and influence such brain activities. Ideally, there will be many clinical benefits as well. The new knowledge could enable scientists to find better and cheaper ways to diagnose and treat depression, Parkinson's disease, stroke, schizophrenia, and other illnesses or injuries in the brain. Unfortunately, it is fair to say that we are a long way from such accurate understanding today.

Of the big scientific programs in the past century, few if any were as intimidating as these brain projects. The race between the United States and the USSR to put a man on the moon in the 1960s was relatively trivial because it was mostly achieved by technical processes, methods and knowledge that already existed at the time. The Human Genome Project to identify the complete sequence of genes on every chromosome in the body was completed a decade ago. There was no doubt that it was achievable; the only questions were when and at what cost. By contrast, the brain projects are not as clearly defined and will have to create new tools to explore the center of human cognition and behavior.

Thus far, "scientists have been able to infer the main function of certain regions of the human brain by studying patients with head injuries, brain tumors, and neurological diseases or by measuring oxygen levels and glucose consumption in the brains of healthy people" (Boffrey 2013).

In the past decade, this research has reached economics in what has become an entirely new field of scientific enterprise: neuroeconomics. This area combines mathematical frameworks, experimental methods, and lab and field behavioral data about peoples' choices with measures of neural activity. The goal is to relate formal theories of human choice to neural measures in an attempt to predict the effects of cognitive and emotional factors on individual choices.

Thus, using modern neuroimaging techniques—including functional magnetic resonance imaging (fMRI), positron emission tomography scans, and so on—economists have begun to look inside the brain and see what is going on when experimental subjects make economic decisions dealing with risk, uncertainty, gains, losses, endowments, temporal preferences, how to bid in auctions, and other behavior.[1]

"The data on say, dopamine release in the nucleus accumbens or bloody oxygen in the striatum when choosing between, say, an amount today or a bigger amount next month, are certainly fascinating in their own right. But can they improve our understanding of economic and social behavior?" (Maskin 2008). There is little agreement on this important question. Economists such as Colin Camerer, George Loewenstein, and

1 See, for instance, Camerer et al. (2005) and Glimcher et al. (2009).

Drazen Prelec (2005) predict that "we will eventually be able to replace the simple mathematical ideas that have been used in economics with more neurally-detailed descriptions." By contrast, economic theorists Faruk Gul and Wolfgang Pesendorfer (2008) argue that neuroscience evidence is irrelevant to economics because "the latter makes no assumptions and draws no conclusions about the physiology of the brain."[2]

In principle, the Gul–Pesendorfer critique would seem to be right, at least if we limit ourselves to current practice in economics. Basically, in a standard economic model, a person is presented with several options, and we try to predict which one he or she will choose. There is no need to know or infer anything about his or her brain as long as the prediction is correct. The problem is that predictions are sometimes far from correct, and so, in principle, we might improve the model by allowing behavior to depend not only on the economic options but also on sensual and neurological data about the person. From this perspective, neural findings show great potential for improving economic analysis. One can be cautiously optimistic and think that exploring new technologies and getting new data has option value.

With this objective in mind, this chapter is concerned with mixed strategies. Using fMRI techniques, we peer inside the brain when experimental subjects play the penalty kick game. As we have noted already, in interactive decision-making analysis, minimax is considered a cornerstone of game theory. More importantly, to the best of our knowledge, the minimax strategies have not been mapped in the brain previously by studying simultaneously the two testable implications of equilibrium.

SUBJECTS

The study was performed in the Hospital Nacional de Parapléjicos de Toledo (Spain) during 2012 with 20 healthy subjects. They formed 20 pairs. Twenty volunteers were studied in the MRI (6 women, mean age 30.7±6.0 (SD) years, range 21–40 years). Six subjects had low-medium education level (primary or high school), and 14 had high educational level (college degree or higher). Twenty subjects were studied outside the scanner (6 women, mean age 33.0±7.6 (SD) years, range 21–44 years). Six subjects had low-medium education level (primary or high school), and 14 had high educational level (college degree or higher). All subjects gave informed consent before participation. The study was approved by the local ethics committee and was conducted in accordance with the World Medical Association's Declaration of Helsinki.

2 See, however, the pioneering recent work by Brocas and Carrillo (2008) and Alonso et al. (2013).

EXPERIMENTAL SETUP

Two players were engaged in the penalty kick game. They were not friends and had not met before; recall that this aspect is important. One player was playing in a computer in a quiet room located outside the scanner room. The other player was lying down within the MRI room. For this player, the PC monitor was substituted by MRI-compatible goggles and the keyboard was substituted by a button box designed for the hand. Player location (inside or outside the MRI) was decided by flipping a coin. Both PC screen and goggles were always displaying the matrix in the middle and upper part of the screen that was studied in the previous chapters:

	A	*B*
A	60	95
B	90	70

In the lower part of the screen, the subjects saw a few lines of text where they received the "go" signal to make their decisions and where they also received the feedback about the opponent's decision and the identity of the winner. The prize was 1 euro per trial, and the subjects performed 100 to 120 trials (with the exception of one pair that performed 82 trials). Both players always received simultaneously the go signal and the feedback after each round (choices and outcomes).[3]

Table 4.1 collects the results of the Pearson tests of equality of payoffs across *A* and *B* strategies, as well as the runs tests, for each pair. As may be observed, quite remarkably, subjects play rather close to minimax. The subjects outside the MRI play in fact basically according to the equilibrium hypothesis with just two rejections in the Pearson tests and three in the runs tests at both the 5% and 10% levels. Perhaps even more remarkable is that 70% of the subjects within the MRI passed the Pearson test and 60% passed the runs test, something that is an order of magnitude closer to minimax than MLS players or friends.

SCANNING AND IMAGE PROCESSING

Some technicalities may be standard in neurological research but are probably unfamiliar to most economists. Each scanning session on a 3T Siemens Trio system comprised functional T2*-weighted MRI

3 The instructions and other details of the experimental procedure are available in Palacios-Huerta et al. (2013). They are almost identical to those in chapter 2, except for the aspects that concerned the fMRI that were included in the experimental instructions.

Table 4.1. Pearson and Runs Tests in the Penalty Kick fMRI Experimental Game

Pair	Player	N	L	R	Ls	Lf	Rs	Rf	p	χ^2 stat	p-value	r	$\Phi[r-1,s]$	$\Phi[r,s]$
1	MRI	82	37	45	30	7	34	11	0.78	0.36	0.547	41	0.401	0.490
	Out	82	42	40	32	10	32	8	0.78	0.17	0.677	38	0.159	0.219
2	MRI	103	72	31	57	15	26	5	0.81	0.31	0.580	33	0.002	0.005**
	Out	103	46	57	36	10	47	10	0.81	0.29	0.593	57	0.820	0.868
3	MRI	119	88	31	70	18	25	6	0.80	0.02	0.896	35	0.001	0.003**
	Out	119	52	67	44	8	51	16	0.80	1.31	0.252	60	0.495	0.570
4	MRI	117	74	43	61	13	36	7	0.83	0.03	0.858	61	0.846	0.888
	Out	117	58	59	48	10	49	10	0.83	0.00	0.967	83	0.999**	0.999
5	MRI	116	66	50	60	6	38	12	0.84	4.82	0.028**	45	0.005	0.009**
	Out	116	73	43	60	13	38	5	0.84	0.79	0.375	20	0.000	0.000**
6	MRI	119	69	50	54	15	43	7	0.82	1.15	0.283	54	0.150	0.198
	Out	119	46	73	7	39	15	58	0.18	0.53	0.466	59	0.581	0.655
7	MRI	116	63	53	53	10	40	13	0.80	1.36	0.244	68	0.953	0.968
	Out	116	65	51	51	14	42	9	0.80	0.27	0.602	47	0.013	0.021**
8	MRI	116	82	34	70	12	23	11	0.80	4.75	0.029**	40	0.015	0.026*
	Out	116	72	44	58	14	35	9	0.80	0.02	0.895	52	0.207	0.268
9	MRI	118	67	51	52	15	39	12	0.77	0.02	0.884	51	0.056	0.081
	Out	118	62	56	45	17	46	10	0.77	1.52	0.217	68	0.922	0.945
10	MRI	119	62	57	54	8	43	14	0.82	2.68	0.102	61	0.507	0.580
	Out	119	73	46	55	18	42	4	0.82	4.77	0.029**	51	0.088	0.124

11	MRI	100	64	36	57	7	26	10	0.83	4.63	0.031**	27	0.000	0.000**
	Out	100	62	38	51	11	32	6	0.83	0.06	0.801	49	0.532	0.615
12	MRI	105	61	44	53	8	35	9	0.84	1.01	0.314	68	0.999**	0.999
	Out	105	54	51	41	13	47	4	0.84	5.09	0.024**	48	0.121	0.165
13	MRI	113	75	38	57	18	27	11	0.74	0.32	0.569	47	0.147	0.201
	Out	113	49	64	14	35	15	49	0.26	0.38	0.536	56	0.423	0.499
14	MRI	114	78	36	67	11	20	16	0.76	12.55	0.000**	41	0.016	0.028*
	Out	114	72	42	17	55	10	32	0.24	0.00	0.981	61	0.903	0.934
15	MRI	104	47	57	39	8	38	19	0.74	3.57	0.059*	38	0.001	0.002**
	Out	104	59	45	18	41	9	36	0.26	1.47	0.226	45	0.064	0.094
16	MRI	115	62	53	52	10	40	13	0.80	1.26	0.262	58	0.451	0.526
	Out	115	56	59	14	42	9	50	0.20	1.71	0.192	57	0.356	0.428
17	MRI	114	83	31	74	9	23	8	0.85	3.98	0.046**	43	0.192	0.264
	Out	114	57	57	8	49	9	48	0.15	0.07	0.793	57	0.388	0.462
18	MRI	117	81	36	62	19	29	7	0.78	0.23	0.630	48	0.232	0.304
	Out	117	48	69	8	40	18	51	0.22	1.45	0.228	52	0.120	0.163
19	MRI	106	55	51	41	14	34	17	0.71	0.79	0.373	55	0.544	0.620
	Out	106	53	53	19	34	12	41	0.29	2.23	0.135	52	0.312	0.384
20	MRI	119	69	50	54	15	43	7	0.82	1.15	0.283	54	0.150	0.198
	Out	119	46	73	7	39	15	58	0.18	0.53	0.466	59	0.581	0.655

Notes: The columns *Ls, Lf, Rs,* and *Rf* denote successes (*s*) and failures (*f*) when choosing *L* and *R*, respectively. The variable p denotes the success rate obtained in the experiment and ** and * indicate rejection at the 5% and 10% levels, respectively.

transverse EPIs with blood oxygenation level-dependent (BOLD) contrast (40 slices per volume, TE: 61 ms; TR: 2.43 s; 3×3 mm in-plane resolution; 3-mm slice thickness), and one experimental session with 950 volumes was acquired for each participant. Additionally, a whole-head T1-weighted anatomical image was acquired after the experiment using a standard FLASH sequence with an isotropic resolution of 1 mm^3. Imaging data were analyzed using Statistical Parametric Mapping (SPM5, http://www.fil.ion.ucl.ac.uk/spm) implemented in MATLAB 10. The first five volumes were discarded for T1-signal equilibration effects. All remaining volumes were realigned to the first volume to correct for interscan head movements. Additionally, interactions of head motion and geometric distortions were removed using the "unwarp" toolbox as implemented in SPM5 (Andersson et al. 2001). The EPI images were normalized to a standard EPI template based on the Montreal Neurological Institute (MNI) reference brain in Talairach space. An AR(1) model accounted for serial autocorrelations of the data, and spatial smoothing of normalized images with an isotropic 8-mm full-width at half-maximum Gaussian kernel was conducted to allow for valid statistical inference according to Gaussian random field theory.

IMAGING ANALYSES

Here are more technicalities. Single-subject fixed-effects models were computed for each participant by multiple regression of the voxelwise time series onto a composite model containing the covariates of interest. These included the decision epoch, choice display epoch, and outcome epoch. Additionally, response key presses were included and modeled as delta functions. All covariates were convolved with a canonical synthetic hemodynamic response function in a general linear model (Friston et al. 1995, 1998) together with a single covariate representing the mean (constant) term over scans. Voxelwise parameter estimates for each covariate were calculated, resulting from the weighted least squares fit of the model to the data.

At a second (group) level of analysis, the contrast images for each participant and covariate were submitted to a 1-sample *t*-test for each covariate of interest in a random-effects analysis across participants.

GROUP ACTIVATION RESULTS

A second level analysis revealed activity increases in various bilateral prefrontal regions during the decision period. Interestingly, the data analysis suggested that activity in the left inferior prefrontal cortex related significantly to the ability to equate payoffs (as measured by the *p*-value), one of two key criteria for successfully playing the game (see figure 4.1). In other words, across the group, activity in this prefrontal region correlated with the performance measure for equating payoffs, with higher activity in participants who more effectively succeeded in equating payoffs. Conversely, a contralateral right inferior prefrontal region related to the ability to generate random sequences of choices (see figure 4.2). Activity in these regions was correlated with the performance score testing for the randomness of choices using the *p*-value of the runs test.

Together these pilot data suggest that two inferior prefrontal nodes jointly contribute to the ability to optimally play our asymmetric zero-sum penalty kick game by ensuring the appropriate equating of payoffs across strategies and the generating of random choices within the game, respectively.

This evidence, therefore, contributes to the neurophysiological literature studying competitive games. Vickery and Jiang (2009), for instance, find that the right inferior parietal lobule was systematically activated in the course of the play of a classic Matching Pennies game. In Hampton et al. (2008), models are built on the basis of various behavioral assumptions (such as fictitious play, reinforcement learning, or a formulation of the influence of one's actions on the others) that describe mentalizing in a version of a Matching Pennies game. They find that the medial prefrontal cortex (mPFC) and posterior superior temporal sulcus (pSTS) were activated.[4] Seo et al. (2009) record neural firing rates directly, and they show that firing rates are consistent with reinforcement learning in the Matching Pennies game. With respect to randomization per se (that is, not in the context of a strategic interaction), there is sound evidence using a variety of techniques that the dorsolateral prefrontal cortex is activated in the process of generating random sequences of numbers (see, e.g., Jahanshahi et al. 1998 and Daniels et al. 2003). In Ischebeck et al. (2008), the random generation of items from an ordered structure, such as numbers, activates the intraparietal sulcus more intensively than when using items from a nonordered structure, such as different animals.

The long-run goal of neuroeconomics is "to create a theory of economic choice and exchange that is neurally detailed, mathematically accurate, and behaviorally relevant" (Camerer 2008). This chapter contributes in this direction by combining the classic mathematical framework of strictly competitive games, experimental methods, and lab data on a strategic situation that is considered a cornerstone of interactive decision-making (minimax) and providing measures of neural activity in the two dimensions that characterize the equilibrium.

4 See also Kadota et al. (2010) and Vickery et al. (2011).

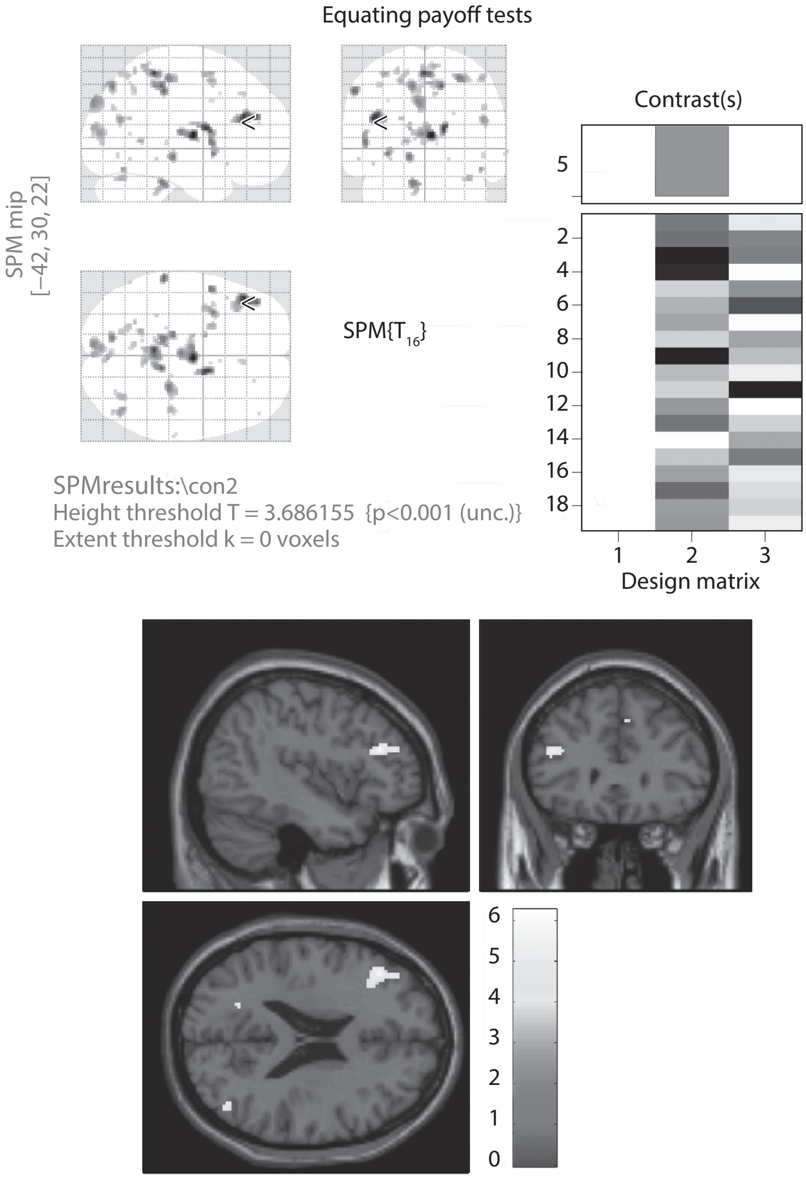

Figure 4.1. Brain activity when subjects equate payoffs across strategies.

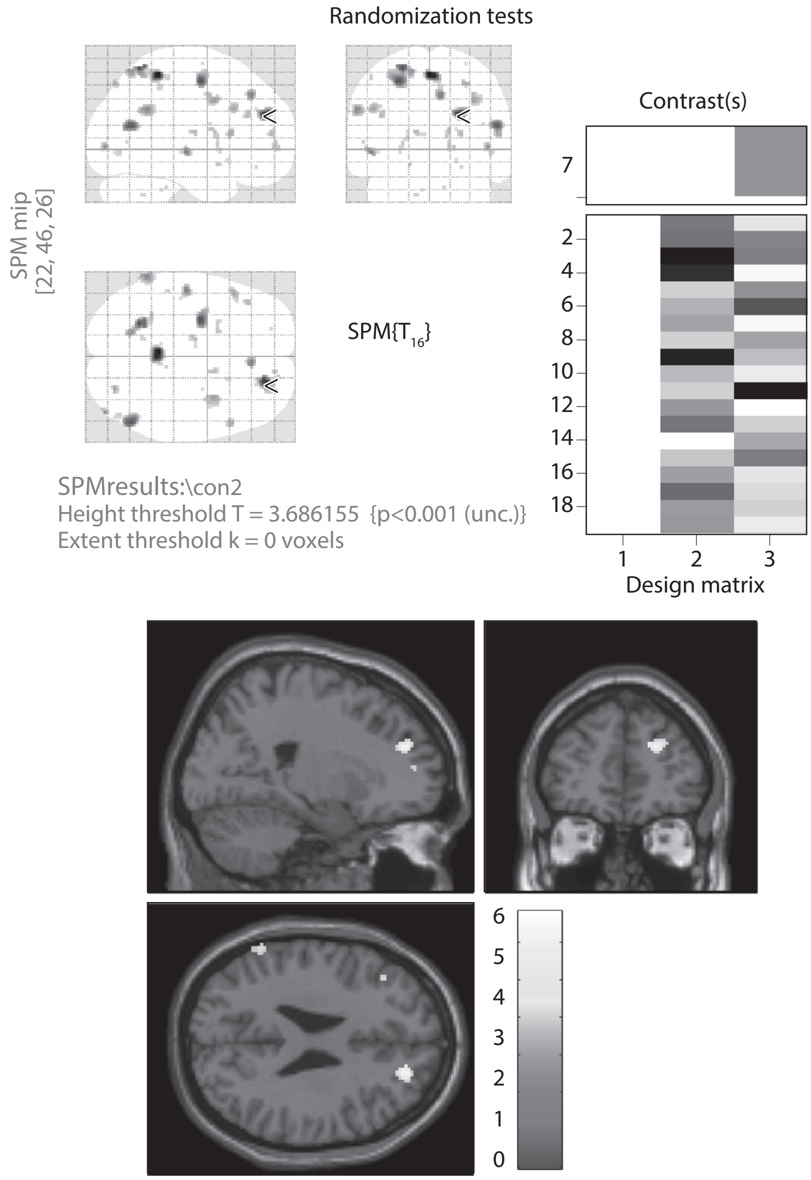

Figure 4.2. Brain activity when subjects randomize their strategies.