The new new neuroscience: extending the reach of modern approaches to brain and mind

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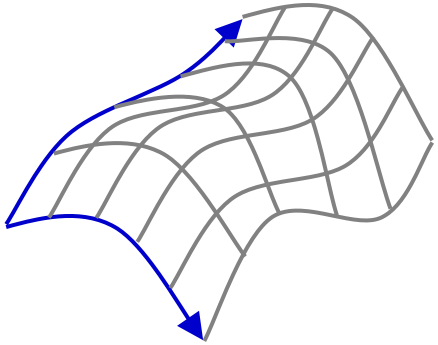
The prevailing model (ambition)

Growing body of cellular & molecular data

Behavior, thoughts, moods, etc.

Computational Models and methods

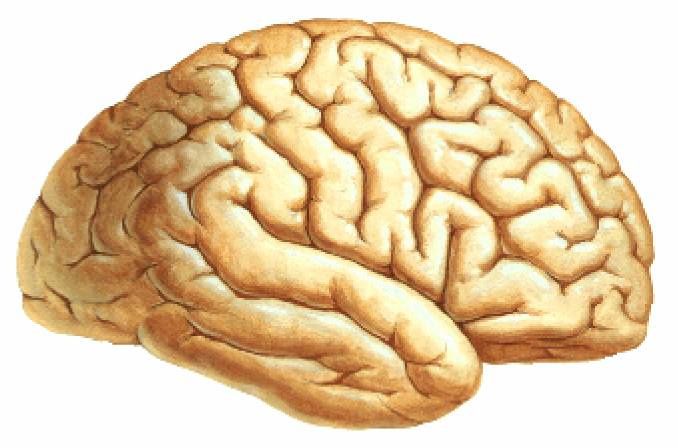


Describe complex behaviors, thoughts, moods, etc as **computations**.

↕

Describe neuronal responses and interactions as **computations**.

A shift to prediction, decoding, and groups



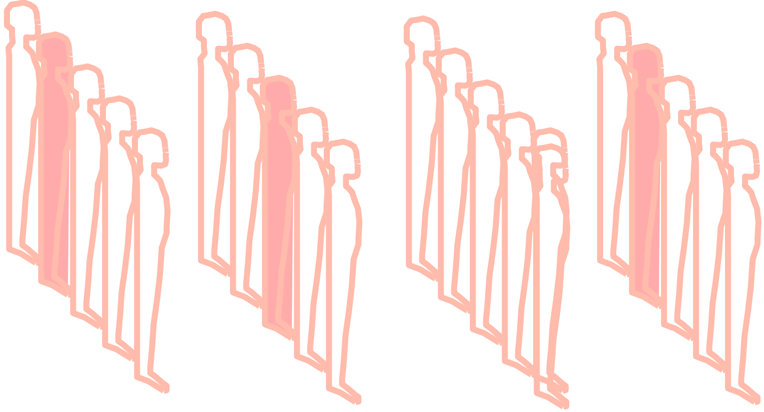
2 examples

1.

evocative visual stimulus (IAPS)

decode political ideology (Wilson-Patterson)

2.



market price (human, agent)

bubbles (overvaluation)

worms and brains

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Report

Nonpolitical Images Evoke Neural Predictors of Political Ideology

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Summary

Political ideologies summarize dimensions of life that define how a person organizes their public and private behavior, including their attitudes associated with

Results

We carried out a passive picture-viewing experiment to test the hypothesis that nonpolitical but affectively evocative images elicit brain responses that predict political ideology as assessed by a standard political ideology measure. Healthy volunteers (n = 83) were instructed to look at presented pictures while lying in the scanner, and, to control for attentiveness, we instructed them to press a button when a fixation cross appeared on the screen (Figure 1). Images were sampled from the International Affective Pictures database [14] and included disgusting, threatening, pleasant, and neutral images (see Appendix S1 available online). Each emotional condition had two subconditions (see the Supplemental Experimental Procedures). After the fMRI session, participants completed a behavioral rating session in which they rated all pictures they had seen in the scanner (using a nine-point Likert scale) as disgusting, threatening, or pleasant. Lastly, participants filled out computer-based questionnaires assessing their political attitudes, disgust sensitivity, and state/trait anxiety level. See the Supplemental Experimental Procedures for details of the behavioral rating and survey sessions.

Political ideology was summed from several survey items (Appendix S2), including ideological position, partisan affiliation, and policy preferences (e.g., gun control and immigration, presented in the well-known Wilson-Patterson format [15]).

IAPS images on random time boundaries

Elastic Net

Wilson-Pattern Political ideology survey

Wilson-Patterson Issue Battery

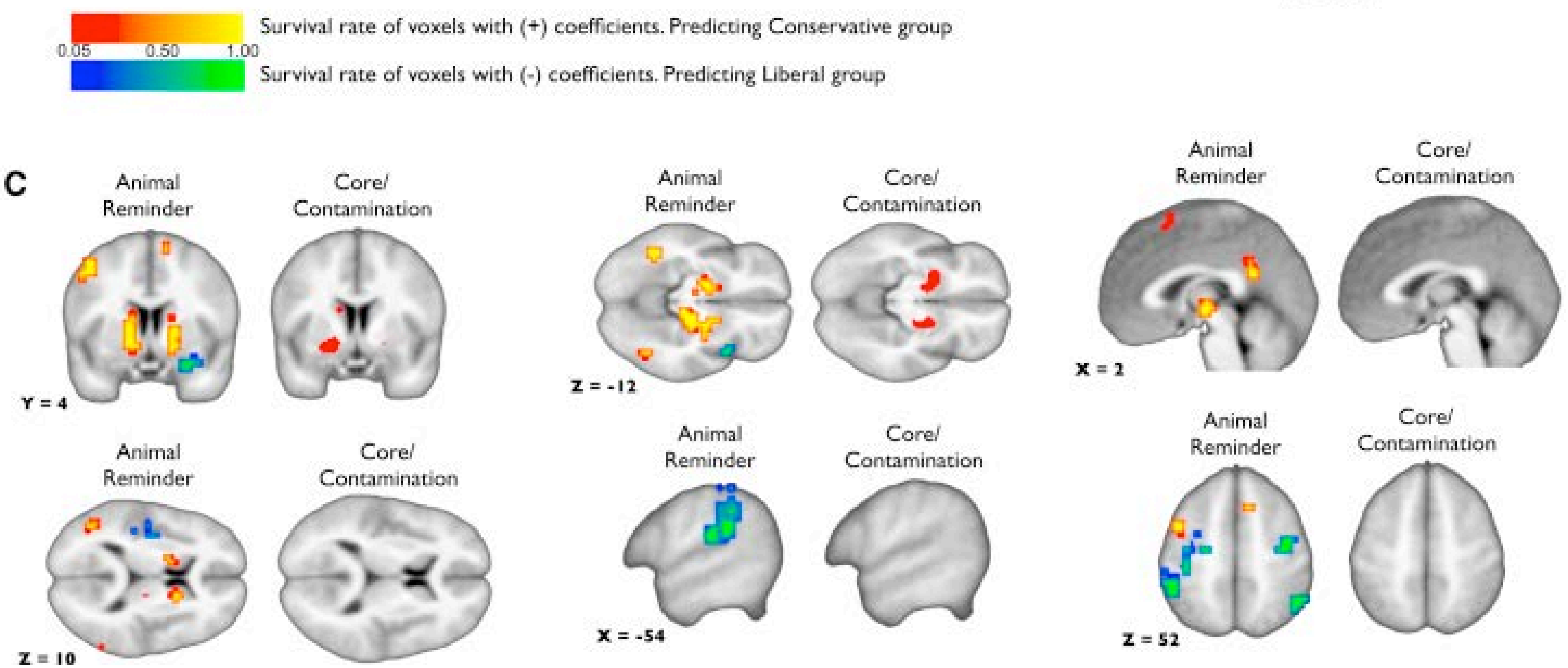
Here is a list of various topics. Please indicate how you feel about each topic.

1. strongly agree
2. agree
3. uncertain
4. disagree
5. strongly disagree

a. School prayer
b. Pacifism
c. Stop immigration
d. Death penalty
e. Government-arranged healthcare
f. Premarital sex
g. Gay marriage
h. Abortion rights
i. Evolution
j. Biblical truth
k. Increase welfare spending
l. Protect gun rights
m. Increase military spending
n. Government regulation of business
o. Small government
p. Foreign aide
q. Lower taxes

What does the brain say?

Separate networks predict conservative and liberal scores



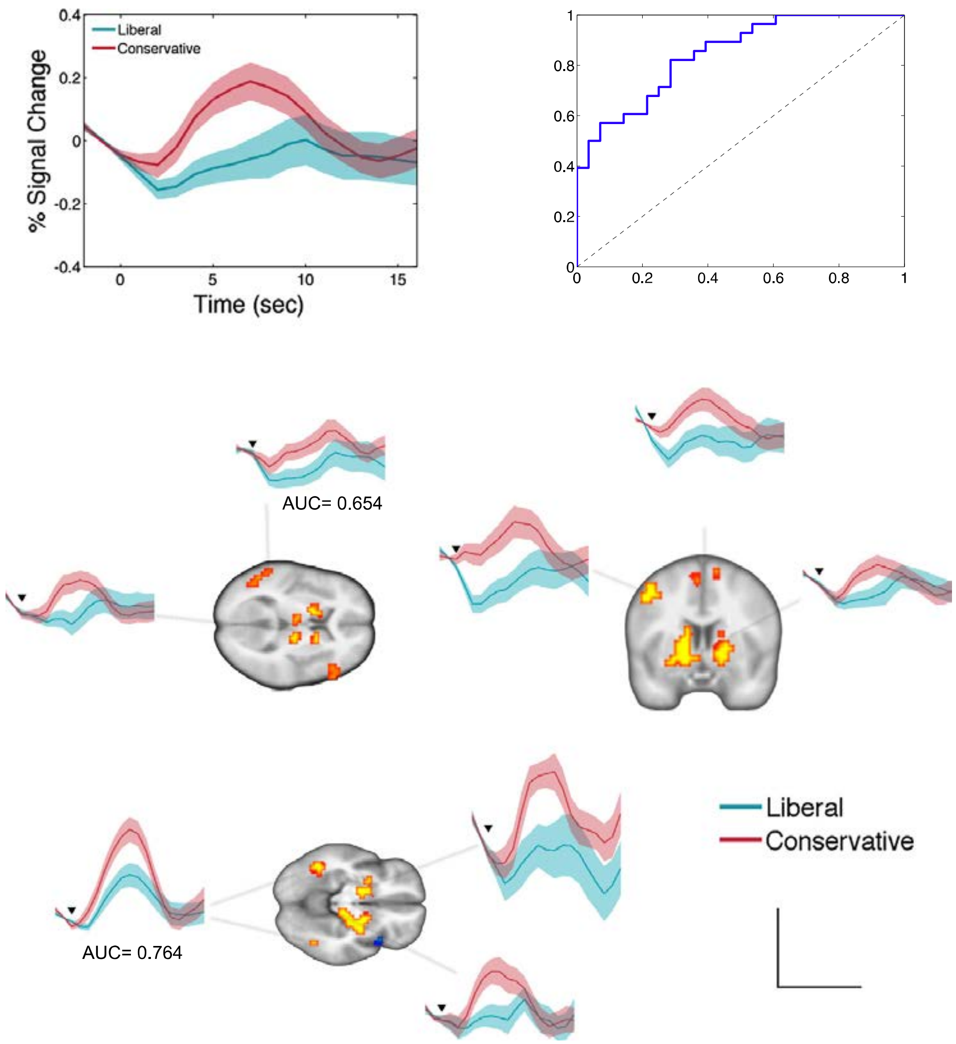
Ahn et al., (2014) ***Current Biology*** 24:1-7

What does conscious behavior say?

All the pictures are rated the same

Ahn et al., (2014) ***Current Biology*** 24:1-7

Single stimulus prediction of political ideology score



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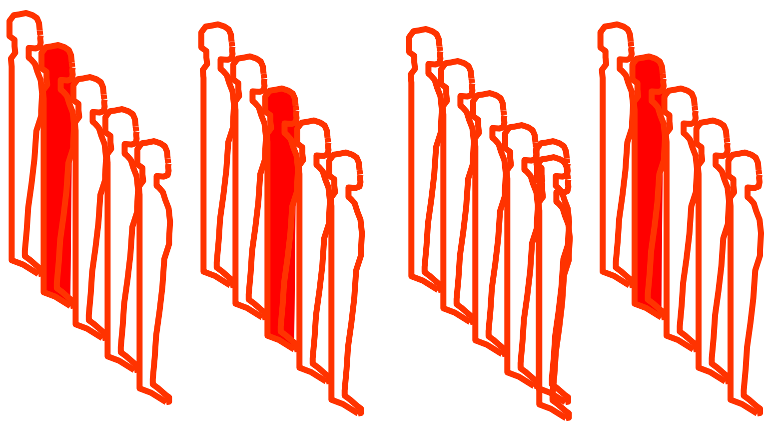


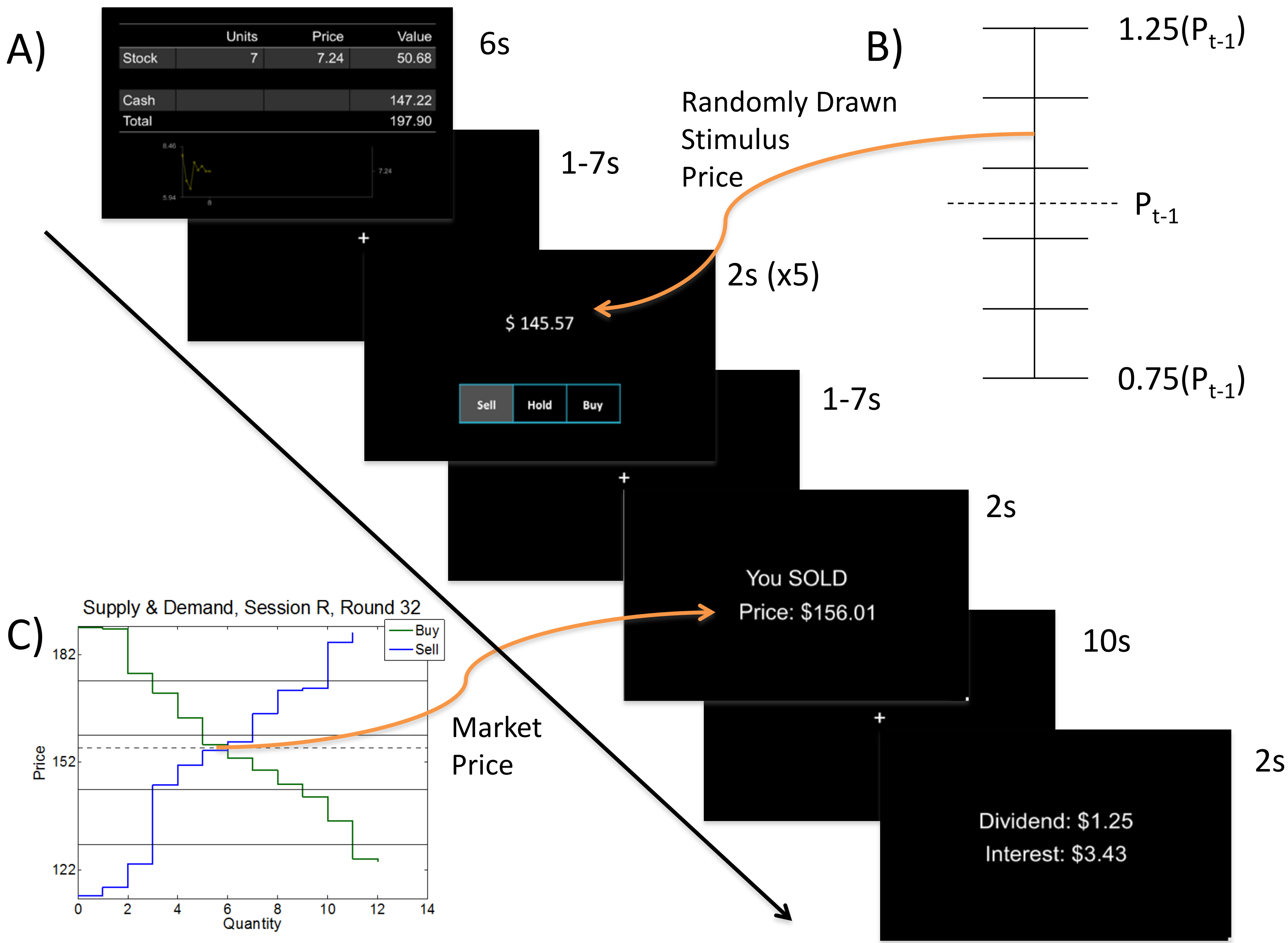
market price (human, agent)

bubbles (overvaluation)

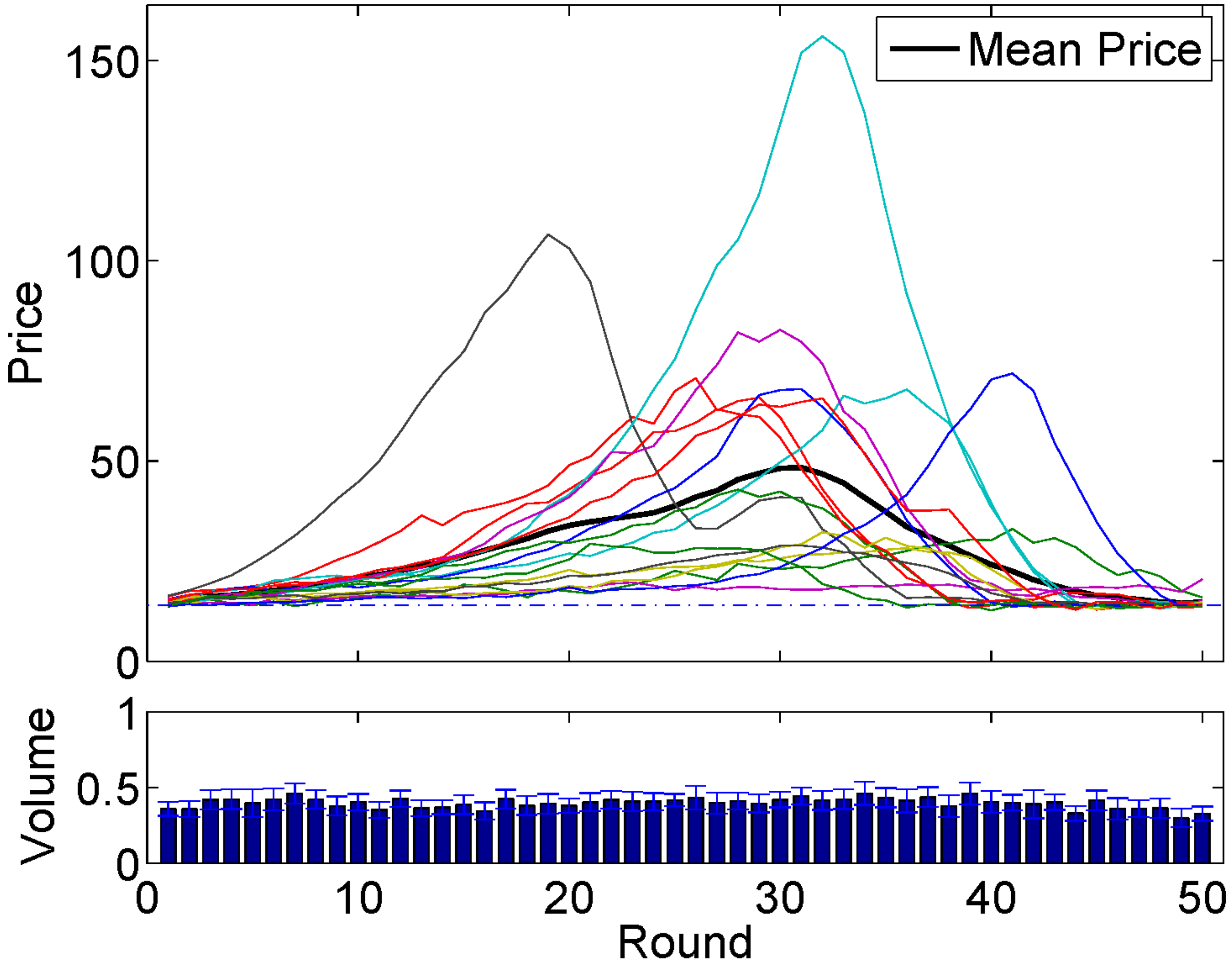
Neural and computational underpinnings of collective choice

Irrational Exuberance in Laboratory Markets

with Alec Smith (Caltech),
Terry Lohrenz (Virginia Tech),
Justin King (Virginia Tech),
Colin Camerer (Caltech)

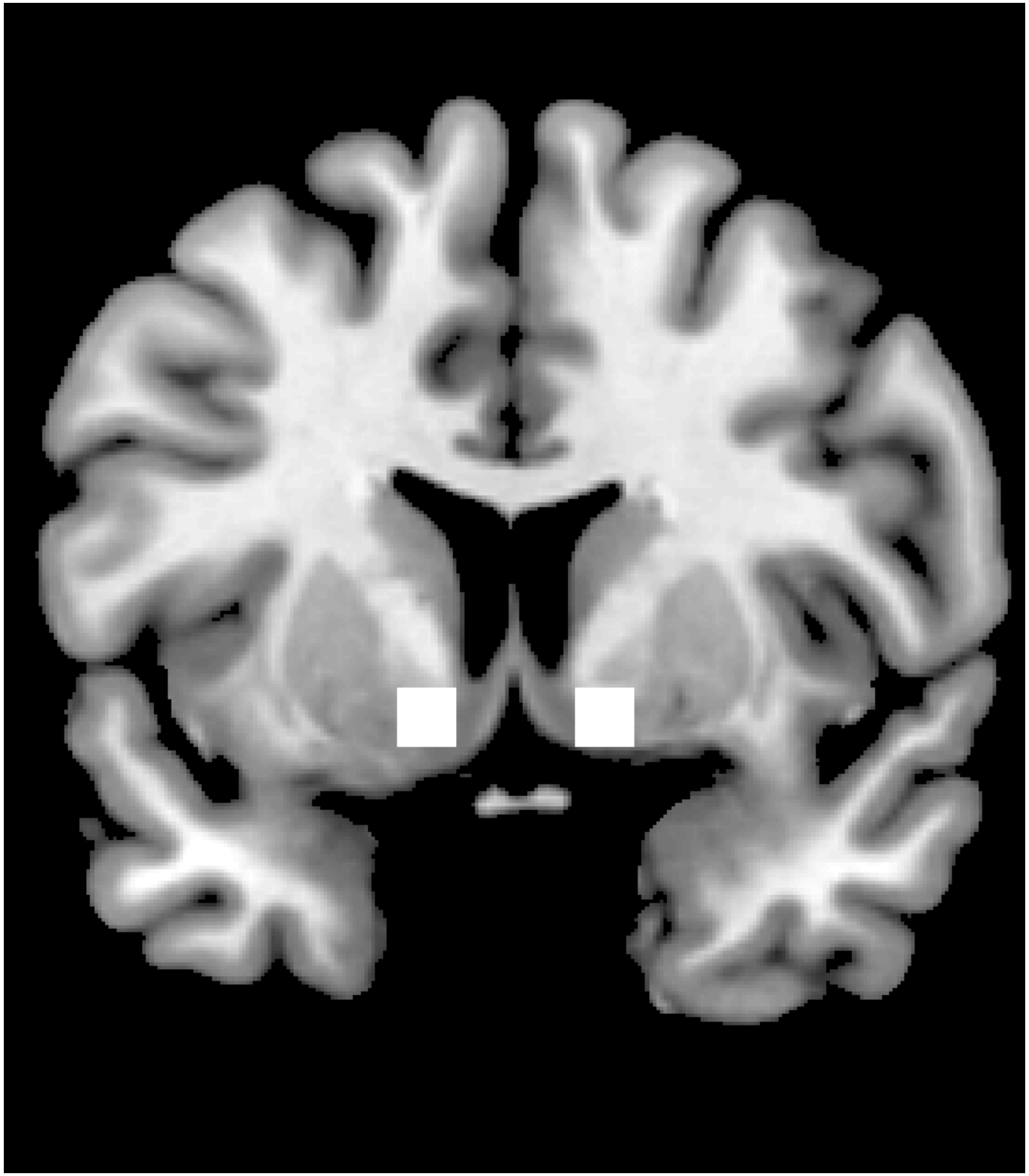

A)
Units Price Value
Stock 7 7.24 50.68
Cash 147.22
Total 197.90
6s
1-7s
$ 145.57
Sell Hold Buy
2s (x5)
1-7s
You SOLD
Price: $156.01
2s
10s
Dividend: $1.25
Interest: $3.43
2s
B)
Randomly Drawn Stimulus Price
1.25(P_{t-1})
P_{t-1}
0.75(P_{t-1})
C)
Supply & Demand, Session R, Round 32
Buy
Sell
Price
Quantity
Market Price

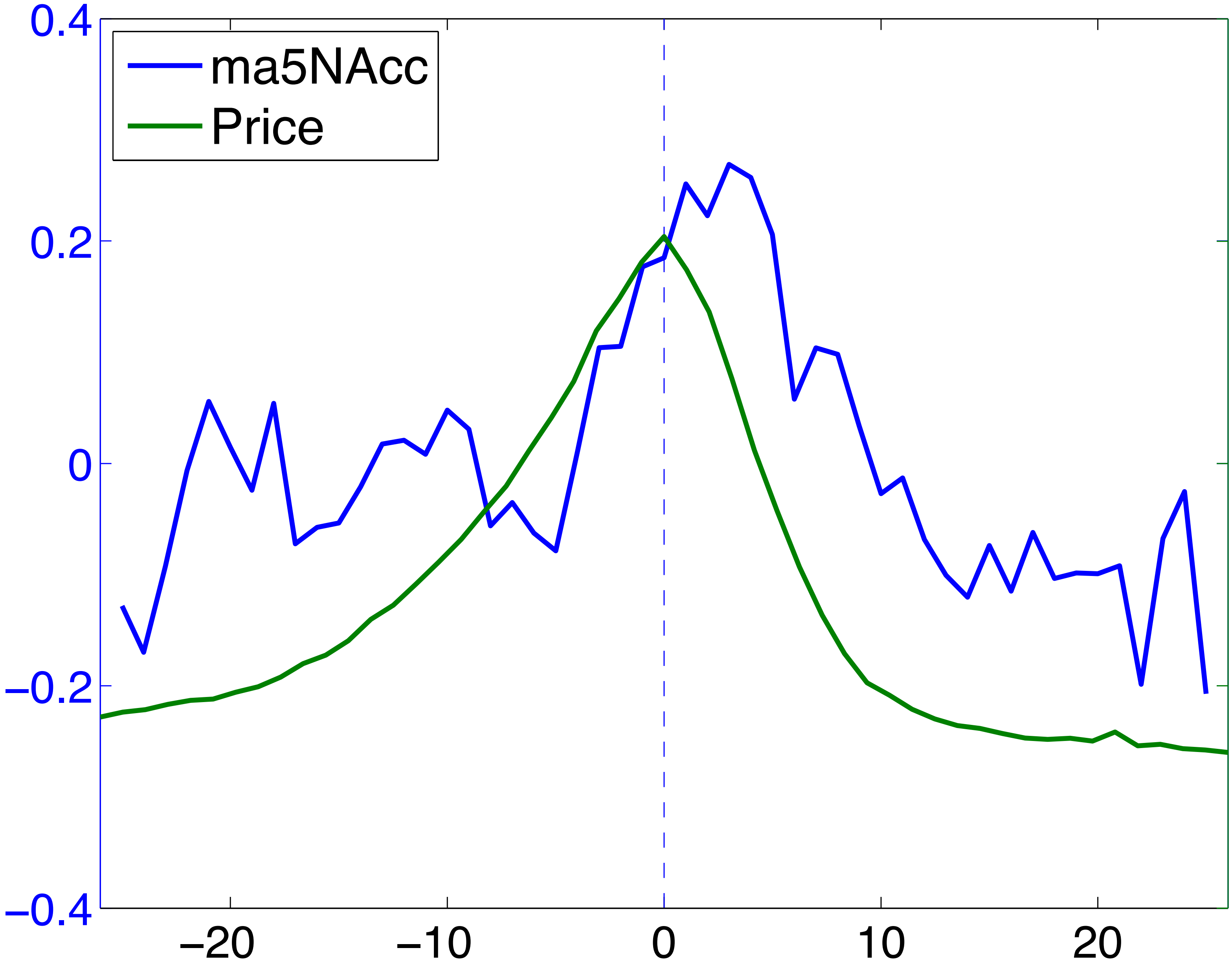
Bubbles form despite ‘flat’ fundamental value



Nucleus Accumbens ROI

- A Priori Mask
- MNI (+/-12,8,-8)
- 24 voxels total
- Trial-by-trial peak response to “Trading Results”



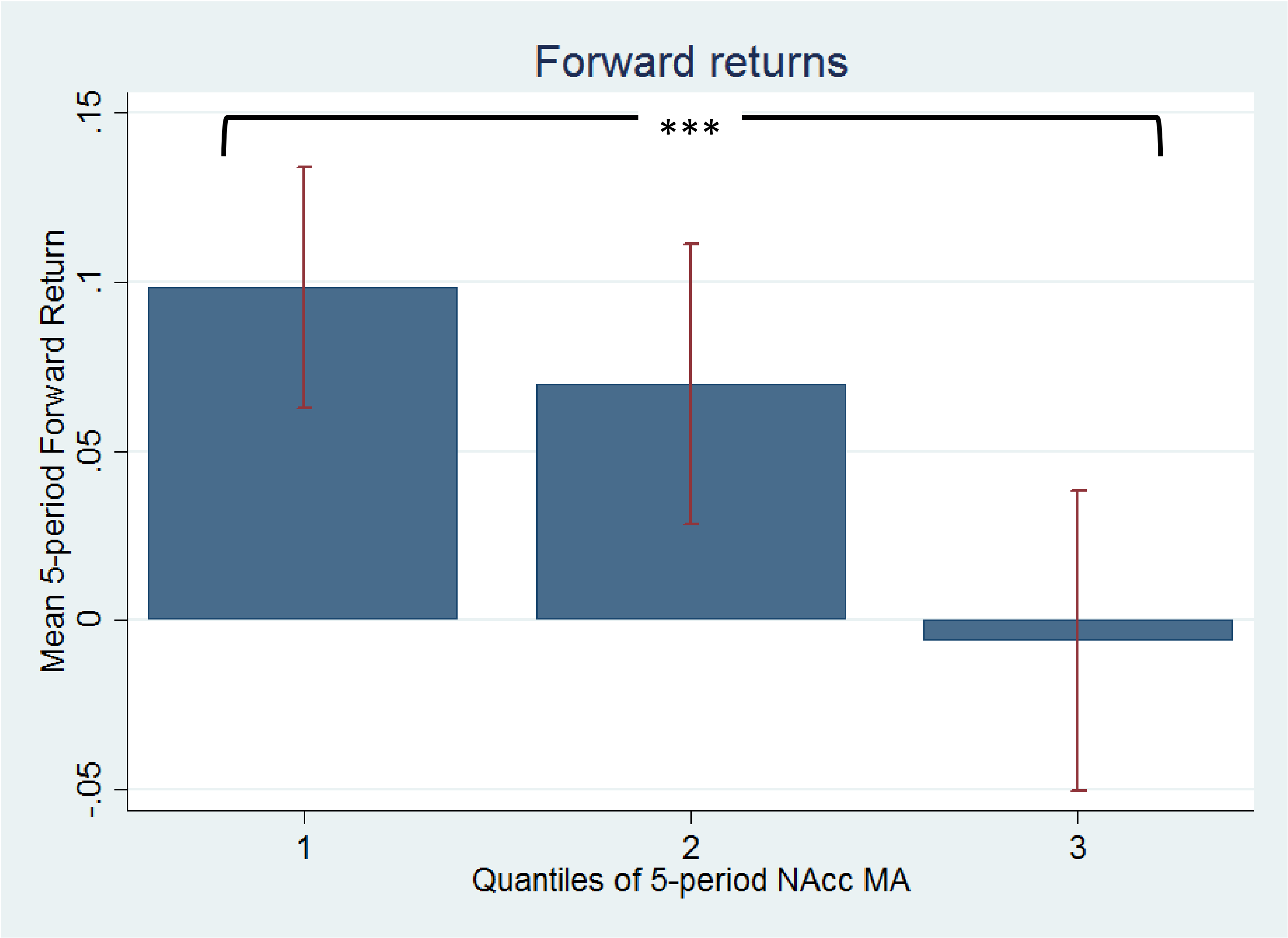


ma5NAcc
Price
0.4
0.2
0
−0.2
−0.4
−20
−10
0
10
20

Discussion: NAcc

- NAcc activity tracks prices
- NAcc activity predicts returns & crashes
- Subjects for whom NAcc predicts buying do worse
- Bubbles as a collective behavioral pathology
- Common biological foundations with addiction and impulse control disorders

Within-market NAcc Activity as Indicator of Future Price Changes



PLOS ONE

RESEARCH ARTICLE

On the Potential of a New Generation of Magnetometers for MEG: A Beamformer Simulation Study

Elena Boto[1], Richard Bowtell[1], Peter Krüger[2], T. Mark Fromhold[2], Peter G. Morris[1], Sofie S. Meyer[3], Gareth R. Barnes[3], Matthew J. Brookes[1]*

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Artificial intelligence and Biological Brains

LETTER

doi:10.1038/nature14236

Human-level control through deep reinforcement learning

Volodymyr Mnih[1]*, Koray Kavukcuoglu[1]*, David Silver[1]*, Andrei A. Rusu[1], Joel Veness[1], Marc G. Bellemare[1], Alex Graves[1], Martin Riedmiller[1], Andreas K. Fidjeland[1], Georg Ostrovski[1], Stig Petersen[1], Charles Beattie[1], Amir Sadik[1], Ioannis Antonoglou[1], Helen King[1], Dharshan Kumaran[1], Daan Wierstra[1], Shane Legg[1] & Demis Hassabis[1]

The theory of reinforcement learning provides a normative account[1], deeply rooted in psychological[2] and neuroscientific[3] perspectives on animal behaviour, of how agents may optimize their control of an environment. To use reinforcement learning successfully in situations approaching real-world complexity, however, agents are confronted with a difficult task: they must derive efficient representations of the

agent is to select actions in a fashion that maximizes cumulative future reward. More formally, we use a deep convolutional neural network to approximate the optimal action-value function

$$Q^*(s,a) = \max_{\pi} \mathbb{E}$$

26 February, 2015 ***Nature*** 518:529 -

Collaborators

Virginia Tech - Terry Lohrenz, Ken Kishida, Ann Harvey, Justin King, Meghana Bhatt, Rosalyn Moran

University College London - Peter Dayan, Karl Friston, Xiaosi Gu, Andreas Hula, Peter Fonagy, Ray Dolan, Tobi Nolte, Christof Mathys, Sarah Carr, and UCL interns

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Mark Klinger
Families of autistic subjects

Stanford University
Sam McClure

Princeton University
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NYU
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Peter Fonagy
Ray Dolan
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Salk Institute
Terry Sejnowski