# Neuroeconomics Lecture 1

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# Outline

- What is Neuroeconomics?
- Examples of Neuroeconomic Studies
- Why is Neuroeconomics Controversial
- Is there a role for Neuroeconomics Within Economics?
- Applying Decision Theory Tools to Neuroscience
    - Dopamine and Reward Prediction Error

# What is Neuroeconomics?

1. Studies that take the *process* of choice seriously
2. Studies that make use of data on the process by which choices are made

# Examples of Neuroeconomic Studies

- Locating correlates of economic concepts in the brain
- Causal studies
- A structural model of simple choice

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# Locating Economic Concepts in the Brain

- Run a behavioral experiment to get people to exhibit some behavior
    - e.g. Punishment
- Scan brain while they are doing so
- Find areas of brain whose activity correlates with behavior
- Conclude that this is where the related preference lives
    - Preference for equality (or punishment)

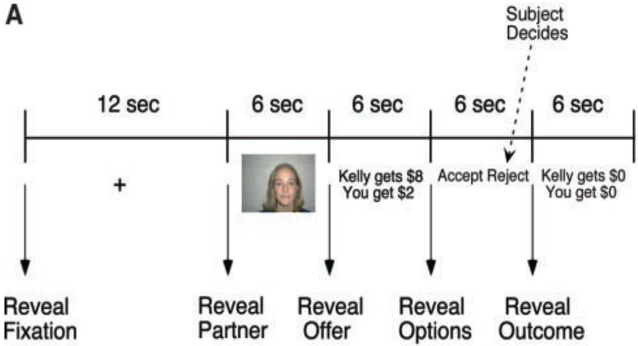
# Example: Ultimatum Game (Sanfey et al. 2003)

- Player A has \$10
- Makes an offer to player B of the form "I will take x and you take \$10-x"
- Player B can either accept offer, or reject offer in which case and both get \$0

# Example: Ultimatum Game (Sanfey et al. 2003)

- Responder's brain activations are measured by fMRI in a \$10 UG.
- A responder faces each of three conditions ten times.
  - Offers from a (supposed) human partner
  - Random offers from a computer partner
- Research Questions: Which brain areas are more activated when subjects face...
  - fair offers (3-5) relative to unfair offers (1-2).
  - the offer of a human proposer relative to a random computer offer.
- Method (very simplified):
  - Regression of activity in every voxel (i.e, 3D Pixel) in the brain on the treatment dummy (i.e., unfair offer dummy, human proposer dummy)

# Example: Ultimatum Game (Sanfey et al. 2003)



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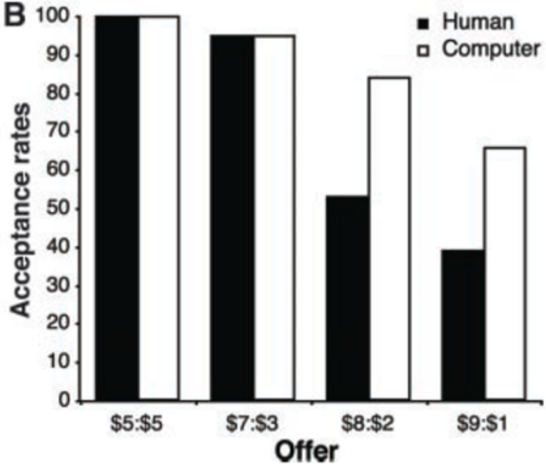
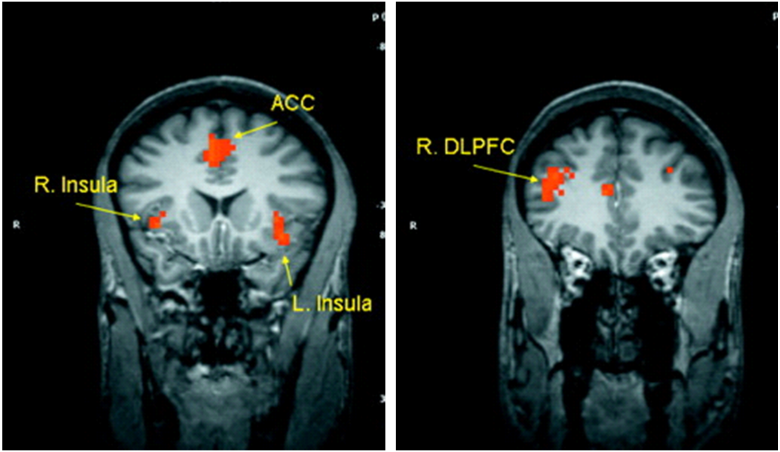


# Example: Ultimatum Game (Sanfey et al. 2003)

Differences in brain activity between unfair and fair offers from a human proposer



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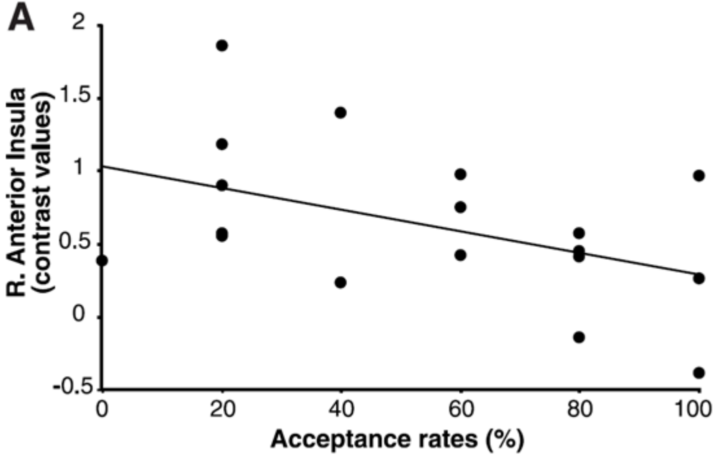


# Example: Ultimatum Game (Sanfey et al. 2003)

- Regions showing stronger activations if subjects face unfair human offers relative to fair human offers (the same regions also show more activation if the unfair human offer is compared to unfair random offers).
- Bilateral anterior Insula, anterior cingulate Cortex
  - Emotion-related region
  - Insula also has been associated with negative emotions such as disgust and anger.
- Dorsolateral prefrontal Cortex (DLPFC)
  - Cognition-related region
  - Associated with control of execution of actions
  - Associated with achievement of goals.
- Unfair offers are more likely to be rejected if insula activation is stronger.

# Other Examples

- Trust and reciprocity
  - Kosfeld et al. [2005]
- Temptation and self control
  - Mcclure et al. [2004]
- Ambiguity Aversion
  - Hsu and Camerer [2004]
- Reference dependence
  - Weber et al [2006]
- Origins of irrationality
  - Santos et al. [2007,2008]

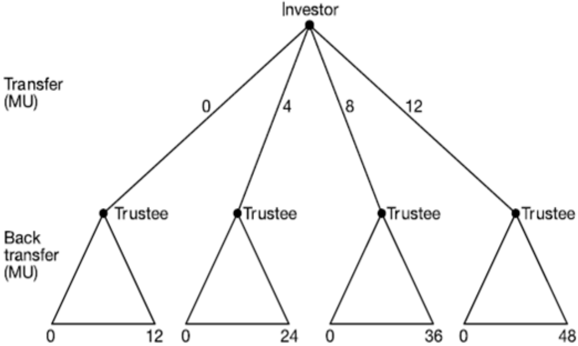
# Examples of Neuroeconomic Studies

- Locating correlates of economic concepts in the brain
- Causal Studies
- A structural model of simple choice

# Oxytocin, Trust and Trustworthiness (Kosfeld et al 2005)

- Step 1: Based on evidence from human and animal studies authors made an informed guess about how certain hormones may affect specific social behaviors in humans.
  - Oxytocin is a hormone, which induces labor in human and nonhuman mammals, during lactation of young animals and during mating.
- Step 2: Conduct a placebo-controlled hormone study that isolates the specific impact. This provides causal information about the impact of the hormone
  - Oxytocin is conjectured to play a key role in different social behaviors

# Oxytocin, Trust and Trustworthiness (Kosfeld et al 2005)



# Oxytocin, Trust and Trustworthiness (Kosfeld et al 2005)

- Does Oxytocin Affect Reciprocity/Inequality aversion?

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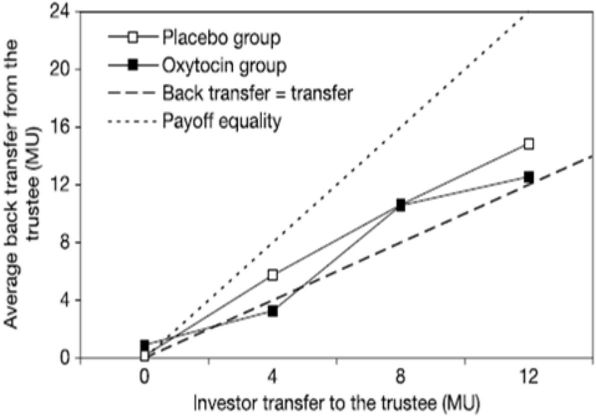

# Oxytocin, Trust and Trustworthiness (Kosfeld et al 2005)

- Does Oxytocin Affect Reciprocity/Inequality aversion?
  - No
- Does it affect investor behavior?

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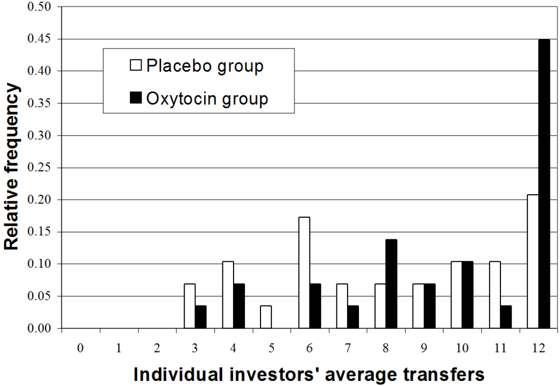

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  - Yes
- Is this just because of risk aversion?

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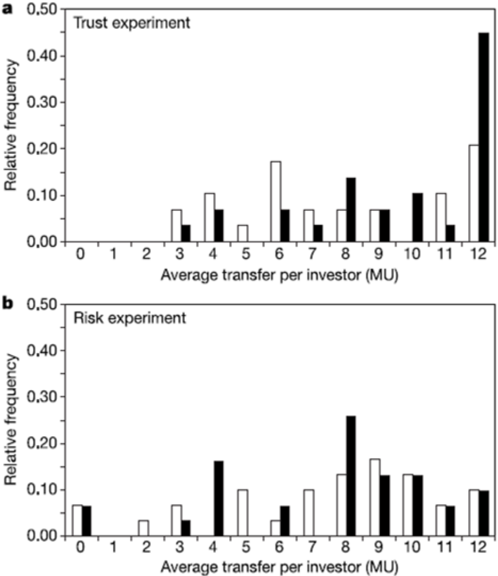

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- Does Oxytocin Affect Reciprocity/Inequality aversion?
  - No
- Does it affect investor behavior?
  - Yes
- Is this just because of risk aversion?
  - No
- Ocytocin seems to increase trust of first mover in the game

# Examples of Neuroeconomic Studies

- Locating correlates of economic concepts in the brain
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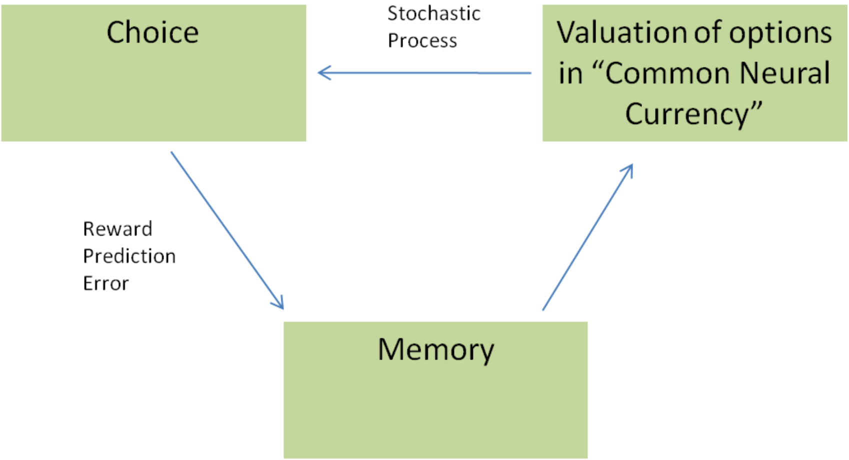
- A structural model of simple choice

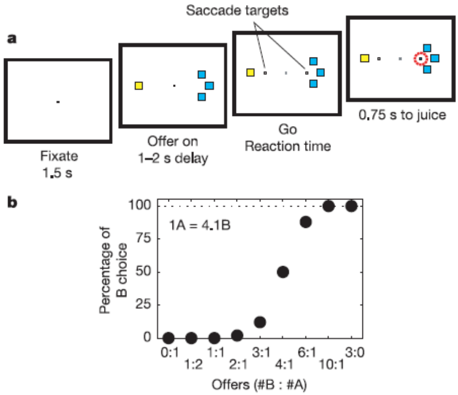
# A Model of Simple Choice



# Evidence of Single Neural Currency (Paddoa-Schioppa and Assad [2006])

- A monkey is offered the choice between different amounts and types of juice
- For example 3 ml or water or 1 ml of Kool Aid
- Record choices from different pairs
- Record activity from neurons in OFC

# Evidence of Single Neural Currency (Paddoa-Schioppa and Assad [2006])




- Calculate behavioral trade off between different types of juice

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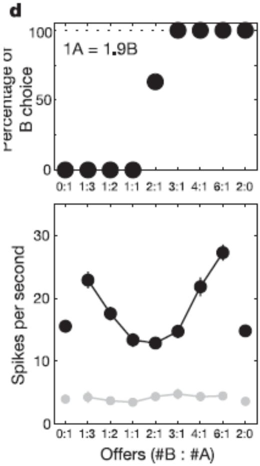
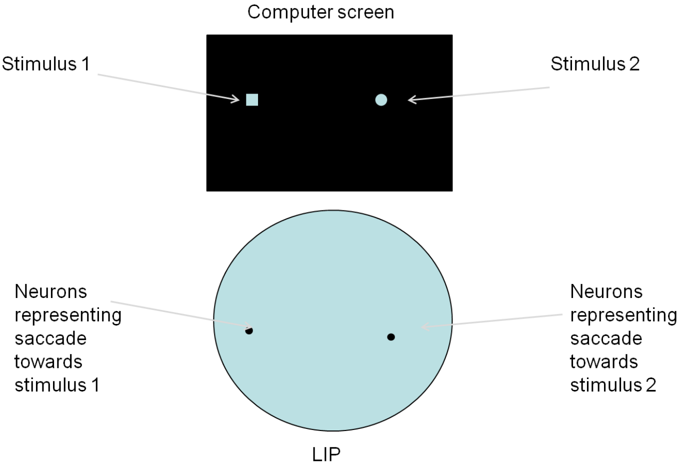


# Evidence of Single Neural Currency (Paddoa-Schioppa and Assad [2006])

- OFC neurons record ‘value’ of chosen option on a single scale
- Regression of activity on ‘utility’ of chosen object gives r-squared of 0.86
- Better fit than just amount of juice.
- Other studies show this area (straitum) values other items
  - Choosing between gambles [Tom et al 2007]
  - Current vs delayed monetary rewards [Kable and Glimcher, 2007]
  - Food items [Plassman et al. 2007; Hare et al. 2009]
- Activity in this area can (weakly) predict choice between consumer goods (Levy et al. 2011)

- LIP is an area of visual cortex that is related to choice
- Is a topological map of the visual field
- Activity in a particular area is linked to saccades (eye movements) to the same area.

# From Valuation To Choice [Platt and Glimcher 1999]



- Platt and Glimcher vary the magnitude and probability of juice reward from looking at each stimulus
- *Average* activity in the area related to stimulus 1 is proportional to the expected reward of looking at that stimulus
  - Later studies show it to be relative value
- Same for stimulus 2
- From previous studdies, we know that a saccade is triggered when activity in an area goes above a threshold
- This makes choice random
  - Activity in each area is stochastic, with mean determined by value of action
  - Probability that activity in an area goes above threshold proportional to value
  - Generates matching law type behavior

# Reward Prediction Error

- To be discussed later

- Following initial excitement there has been a backlash against neuroeconomics
- And particular is usefulness for economics
- One of the most influential articles was by Gul and Pesendorfer
- Note that this is *not* an argument that it is bad science

# Is Neuroeconomics Useful for Economics?

- Consider a set of possible environments $X$
  - prices, incomes, information states
- And a set of behavioral outcomes $Y$
  - demand for goods, labor supply
- Assume that economists are interesting in modelling $f : X \to Y$
- Neither $X$ nor $Y$ contain 'neuroeconomic variables'
  - Brain activity, eye movements etc

# Is Neuroeconomics Useful for Economics?

- Say that $f$ is in fact a reduced form of a sequence of mappings

$$\begin{aligned} h_1 &: X \rightarrow Z_1 \\ h_2 &: Z_1 \rightarrow Z_2 \\ &\vdots \\ h_n &: Z_n \rightarrow Y \end{aligned}$$

  such that $f = h_n.h_{n-1}...h_1$
- Is it useful for an economist to study the variables $Z_1, ...Z_n$?
- (For convenience we will consider the simple case where $f = hg$ and one intermediate variable $Z$

# Two Arguments for 'No'

- Economists are only interested in the mapping $f$ from $X$ to $Y$
- Two process models $\{h, g\}$ and $\{h', g'\}$ either imply different mappings $f$ and $f'$,
  - $g.h \neq g'.h'$
  - implies exists $x \in X$ such that $f(x) \neq f'(x)$
- or they don't
  - $g.h = g'.h'$
  - Economists need not differentiate between them

## Two Arguments for 'No'

- Economic models make no predictions about process ($h$ and $g$)
- Observations of process cannot be used to test economic models.
- Economic models are designed to predict the reduced form relationship $f$
- Evidence on $h$ and $g$ is orthogonal to this

# Possible Roles

- Inspiration
- Breaking up the problem
- Ruling out all mechanisms that could generate an $f$
- Robustness/Out of Sample Predictions
- Creating a 'Brain Map'

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# Inspiration

- If we have insight about process, this could lead us to new models
  - If we can guess $h$ and $g$ then this will tell us $f$
- Everyone (including G and P) agree that this would be useful if neuroeconomics could do it.
- Is there evidence that neuroeconomics has inspired new theories?

# Inspiration?

- Arguably, surprisingly little
- Most of the models that neuroscientists have given us had already been considered
  - Dual Self model of addiction [Bernheim and Rangel 2004]
  - Reinforcement Learning [Barto and Sutton 1998]
- This is arguably true of cognitive neuroscience more generally
- Most promising exception: Stochastic choice and optimal coding

# Possible Roles

- Inspiration
- Breaking up the problem
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# Breaking up the Problem

- There is a process between $X$ and $Y$ (whether economists like it or not)
- Explicitly learning about $h$ and $g$ (and observing $Z$) may help us guess the correct $f$
- May be easier to tackle $h$ and $g$ separately, rather than leaping straight to $f$
- Example Information Search and Choice
  - Environment tells subject what information to gather $h : X \to Z$
  - Choice then dependent on that information $g : Z \to Y$
  - May be easier to observe $Z$ and model $f$ and $g$ separately
- Example Oxytocin
  - We know from previous research mapping from environment to ocytocin release
  - Now know the relationship between oxytocin and trust game behavior

# Possible Roles

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- Ruling out all mechanisms that could generate an f
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# Ruling out all mechanisms that could generate an f

- A common claim: neuroscience can constrain models of economic decision making
- However, not enough to rule out *one* possible $h$ that could lead to an $f$
  - Satisficing and Utility Maximization
- Need to rule out *all* possible $h$'s that could generate an $f$
  - Eye tracking and backwards induction [Johnson et al 2002]

- Inspiration
- Breaking up the problem
- Ruling out all mechanisms that could generate an $f$
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# Out of Sample Predictions

- Comparing two models $f$ and $g'$ $h'$.
- Observe mapping from $\bar{X} \subset X$ to $Y$ and $Z$
- Both equally good at predicting relationship between $\bar{X}$ and $Y \setminus$
- $g'$ also is a good fit for $\bar{X} \rightarrow Z$, and $h'$ a good fit for $Z \rightarrow Y$.
- Do we conclude that $h'g$; will do a better job of predicting the relationship between $X/\bar{X}$ to $Y$ than would $f$?
- Example: McClure et al [2004] and the $\beta - \delta$ model
  - Present and future rewards (might be) encoded in different brain regions

# Out of Sample Predictions

- Bernheim: Depends on priors
- Can build a machine which
  - Exhibits exponential preferences that calculates present and future rewards separately
  - Exhibits hyperbolic preferences but calculates present and future rewards in the same place
- So is not ‘proof’, but may increase credence for ‘sensible’ priors
  - Example of a much more general inference problem
- Solves the 'Lucas critique' for microeconomics?

# Possible Roles

- Inspiration
- Breaking up the problem
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# Creating a Brain Map

- Much of (early) neuroeconomics is concerned with mapping economic concepts to brain areas
- What could we learn?
  1. Two types of economic behaviors are related to the same area of brain tissue
  2. That a particular type of economic behavior is related to an area of the brain that we know something about from previous research
- Could be useful from the point of view of inspiration
- But not really in terms of model testing
  - The fact that risk aversion and ambiguity aversion activate different brain areas does not make them any more real
  - Practical problem: fMRI not very precise

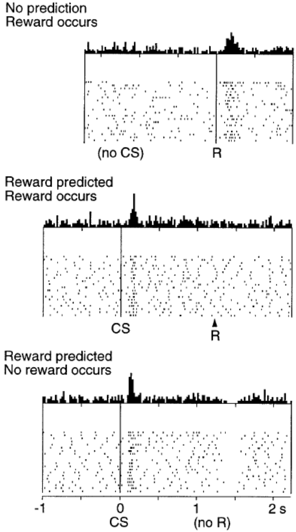
# Introduction

- *Dopamine* is a neurotransmitter
  - Transmits information between brain cells
  - Hypothesized to encode *Reward Prediction Error (RPE)*
- Difference between *experienced* and *predicted* rewards
  - RPE signal may then be used in learning and decision making
- If true, RPE hypothesis has big research benefits:
  - Makes 'reward' and 'belief' directly observable
  - First step towards a neurally-based theory of decision making
- We formalize and test RPE hypothesis
  - Show that activity in dopamine rich regions provides consistent information
  - Open question how this relates to traditional 'rewards' and 'beliefs'

# Early Evidence for RPE - Monkeys

Schultz et al. [1997]

- Dopamine fires only on receipt of *unpredicted* rewards
- Otherwise will fire at *first predictor* of reward
- If an expected reward is not received, dopamine firing will pause



# Early Evidence for RPE - Humans

O'Doherty et al. [2003]

- Thirsty human subjects placed in fMRI scanner
- Shown novel visual symbols, which signalled 'neutral' and 'tasty' juice rewards
- Assumptions made to operationalize RPE
  - Reward values of juice
  - Learning through TD algorithm
- RPE signal then correlated with brain activity
- Positive correlation with activity in Ventral Striatum taken as supporting RPE hypothesis
  - Ventral Striatum rich in dopaminergic neurons

# Problems with the Current Tests

- Current tests 'suggestive' rather than 'definitive'
- Several other theories for the role of dopamine
  - Salience hypothesis (e.g. Zink et al. 2003)
  - Incentive salience hypothesis (Berridge and Robinson, 1998)
  - Agency hypothesis (Redgrave and Gurney, 2006)
- These theories have been hard to differentiate
- Couched in terms of latent variable
  - 'Rewards', 'Beliefs', 'Salience', 'Valence' not directly observable
  - Tests rely on 'auxiliary assumptions' - not central to the underlying theory
- Experiments test both underlying theory *and* auxiliary assumptions

# An Axiomatic Approach

- Take an *axiomatic* approach to testing RPE hypothesis
  - A set of necessary and sufficient conditions on dopamine activity
  - Equivalent to the RPE model
  - Easily testable
- Similar to Samuelson's approach to testing utility maximization
  - Equivalent to the Weak Axiom of Revealed Preference
- Has several advantages
  - Provide a complete list of testable predictions of the RPE model
  - Non-parametric
  - Provide a common language between disciplines
  - Failure of particular axioms will aid model development

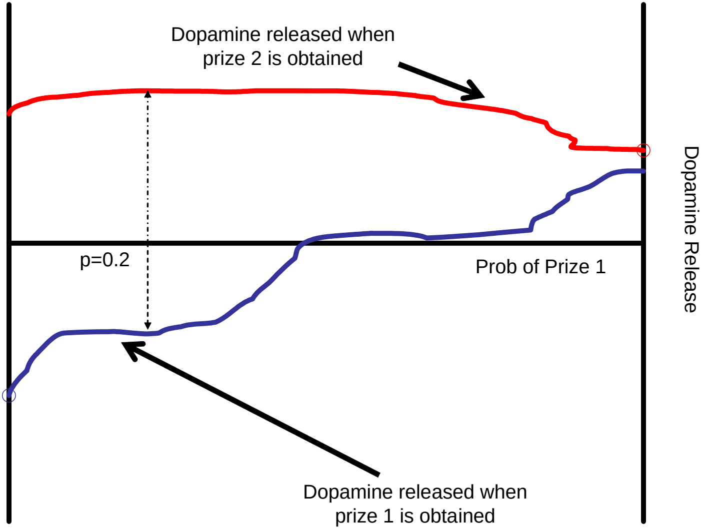
- Subjects receive prizes from lotteries:
  - $Z$: A space of prizes
  - $\Lambda$ : Set of all lotteries on $Z$
- $\Lambda(z)$: Set of all lotteries whose support includes $z$
- $e_z$: Lottery that gives prize $z$ with certainty

- Observable data is a Dopamine Release Function

$$\begin{aligned} \delta &: M \rightarrow \mathbb{R} \\ M &= \{(z,p) | z \in Z,\ p \in \Delta(z)\} \end{aligned}$$

$\delta(z,p)$ is dopamine activity when prize $z$ is obtained from a lottery $p$

- Note also that $\delta$ need not be 'dopamine'
    - Single unit recordings
    - fMRI activity in dopamine-rich regions


Dopamine released when
prize 2 is obtained
p=0.2
Prob of Prize 1
Dopamine Release
Dopamine released when
prize 1 is obtained

# A Formal Model of RPE

*The difference between how good an event was expected to be and how good it turned out to be*

- Under what conditions can we find
  - A Predicted reward function: $b : \Lambda \to \mathbb{R}$
  - An Experienced reward function: $r : Z \to \mathbb{R}$
- Such that there is an aggregator function $E$
  - Represents the dopamine release function

$$\delta(z, p) = E(r(z), b(p))$$

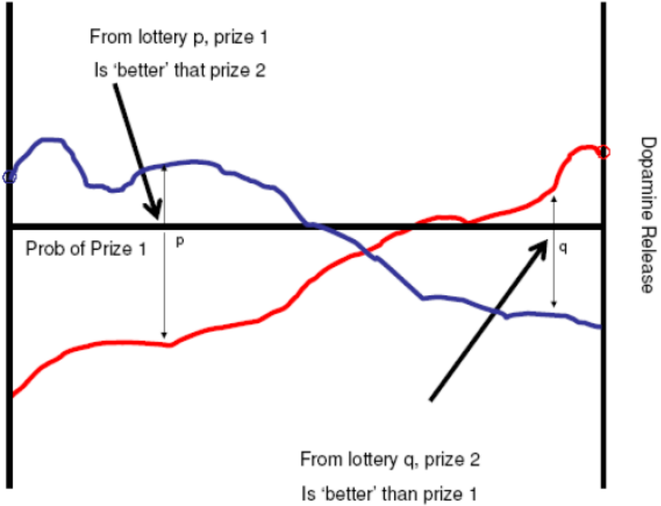
  - Is increasing in experienced and decreasing in predicted reward.
  - Obeys basic consistency

$$r(z) = b(e_z)$$

  - Treats 'no surprise' consistently:

$$E(x, x) = E(y, y)$$

# Necessary Condition 1: Consistent Prize Ordering



## Necessary Condition 1: Consistent Prize Ordering

- Consider two prizes, $z$ and $w$
- Say that, when $z$ is received from some lottery $p$, more dopamine is released than when $w$ is received from $p$
- Implies higher 'reward' for $z$ than $w$
- Implies that $z$ should give more dopamine than $w$ when received for *any* lottery $q$
- **Axiom A1: Coherent Prize Dominance**

$$\text{for all } (z,p),(w,p),(z,q),(w,q) \in M$$
$$\delta(z,p) > \delta(w,p) \Rightarrow \delta(z,q) > \delta(w,q)$$

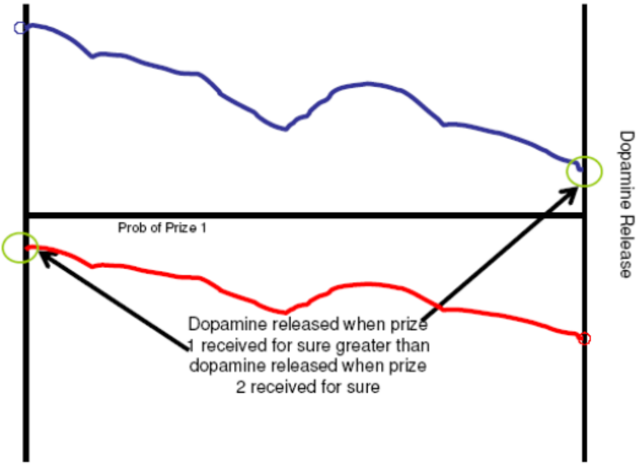
# Necessary Condition 2: Coherent Lottery Dominance

# Necessary Condition 2: Consistent Lottery Ordering

- Consider two lotteries $p$ and $q$ and a prize $z$ which is in the support of $p$ and $q$
- Say that more dopamine is released when $z$ is obtained from $p$ that when it is obtained from $q$
- Implies that predicted reward of $p$ must be *lower* that that of $q$
- Implies that whenever the same prize is obtained from $p$ and $q$ the dopamine released should be higher from lottery $p$ than from lottery $q$
- **Axiom A2: Coherent Lottery Dominance**

$$\text{for all } (z,p),(w,p),(z,q),(w,q) \quad \in \quad M$$
$$\delta(z,p) > \delta(z,q) \Rightarrow \delta(w,p) > \delta(w,q)$$

# Necessary Condition 3: No Surprise Equivalence



# Necessary Condition 3: Equivalence of Certainty

- 'Reward Prediction Error' is a comparison between predicted reward and actual reward
- If you know exactly what you are going to get, then there is no reward prediction error
- This is true whatever the prize we are talking about
- Thus, the reward prediction error of any prize should be zero when received for sure:
- **Axiom A3: No Surprise Equivalence**

$$\delta(z, e_z) = \delta(w, e_w) \ \forall \ z, w \in Z$$

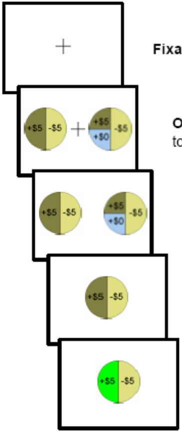
- In general, these conditions are necessary, but not sufficient for an RPE representation
- However, in the special case where we look only at lotteries with two prizes they are
- **Theorem 1:**
  If $|Z| = 2$, a dopamine release function $\delta$ satisfies axioms A1-A3 **if and only if** it admits an RPE representation
- Thus, in order to test RPE in case of two prizes, we need only to test A1-A3

# Aim

- Generate observations of $\delta$ in order to test axioms
- Use a data set containing:
  - Two prizes: win \$5, lose \$5
  - Five lotteries: $p \in \{0, 0.25, 0.5, 0.75.1\}$
- Do not observe dopamine directly
  - Use fMRI to observe activity in the Nucleus Accumbens
  - Brain area rich in dopaminergic neurons

# Experimental Design

Task design




**Fixation:** 12 seconds

**Options:** 3.6 seconds
to view options

Lottery 1 EV: $0
Lottery 2 EV: -$1.25

**Choice selection:** 1.2 seconds
to make a choice by button press
(fixation cross extinguished)

**Choice:** 8.4 seconds to
view the choice just made

**Outcome:** 3.6 seconds to
view outcome of choice
(outcome illuminated)

Trial length:

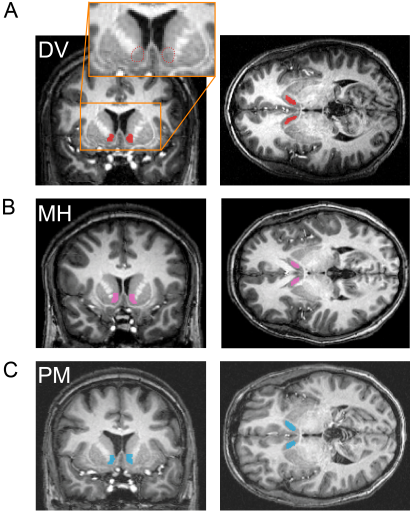
~29 seconds

# Experimental Details

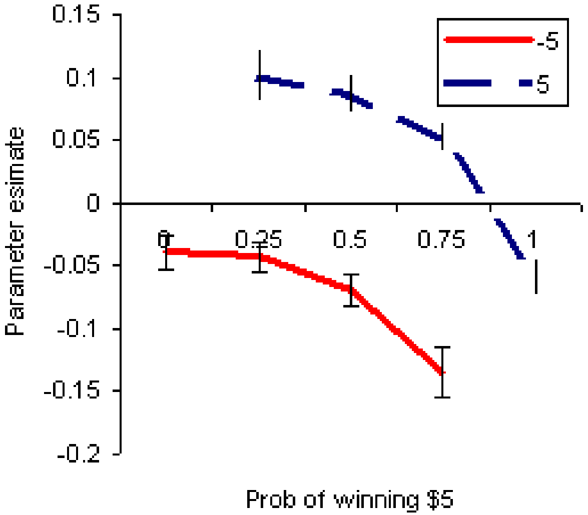
- 14 subjects (2 dropped for excess movement)
- ‘Practice Session’ (outside scanner) of 4 blocks of 16 trials
- 2 'Scanner Sessions' of 8 blocks of 16 trials
- For Scanner Sessions, subjects paid \$35 show up fee, + \$100 endowment + outcome of each trial
- In each trial, subject offered one option from ‘Observation Set’ and one from a ‘Decoy Set’

- Need to determine which area of the brain is the Nucleus Accumbens
- Two ways of doing so:
    - Anatomical ROIs: Defined by location
    - Functional ROIs: Defined by response to a particular stimulus
- We concentrate on anatomical ROI, but use functional ROIs to test results

## Anatomical Regions of Interest [Neto et al. 2008]

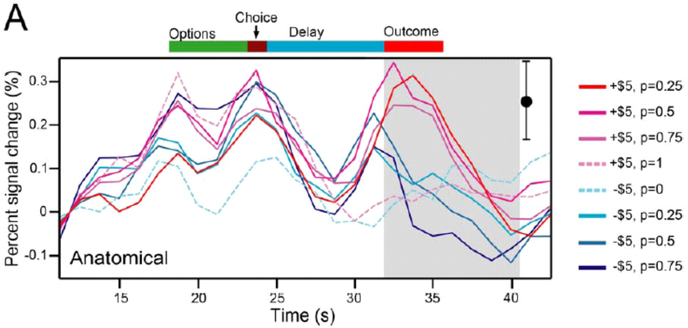


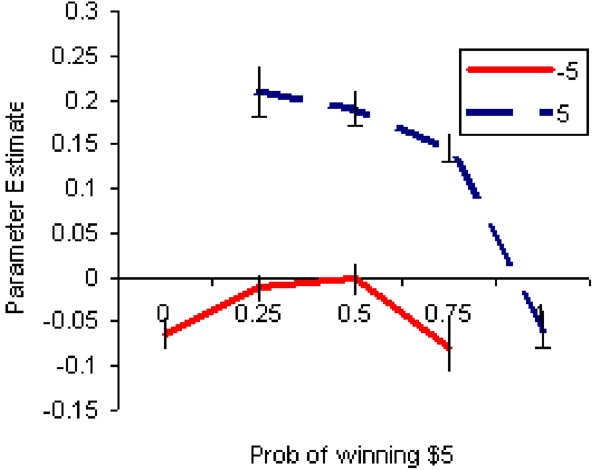
- We now need to estimate the function $\bar{\delta}$ using the data
- Use a between-subject design
  - Treat all data as coming from a single subject
- Create a single time series for an ROI
  - Average across voxels
  - Convert to percentage change from session baseline
- Regress time series on dummies for the revelation of each prize/lottery pair
  - $\bar{\delta}(x, p)$ is the estimated coefficient on the dummy which takes the value 1 when prize $x$ is obtained from lottery $p$


0.15
0.1
0.05
0
-0.05
-0.1
-0.15
-0.2
0
0.25
0.5
0.75
1
Parameter esimate
Prob of winning $5
-5
5

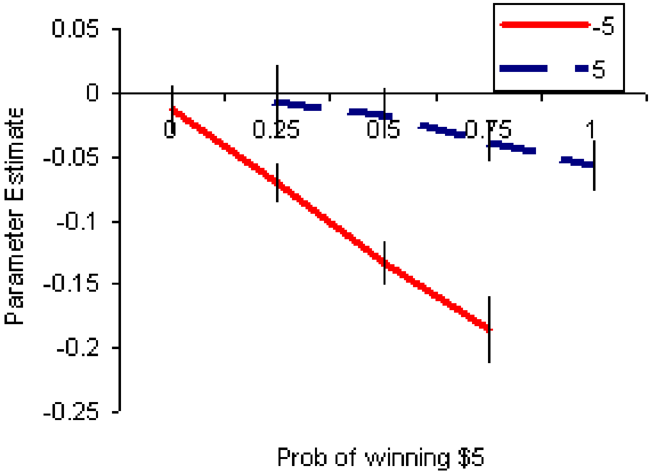
# Results

- Axioms hold
- Nucleus Accumbens activity in line with RPE model
- Experienced and predicted reward 'sensible'


A
Options
Choice
Delay
Outcome
Percent signal change (%)
0.3
0.2
0.1
0
-0.1
Anatomical
15
20
25
30
35
40
Time (s)
+$5, p=0.25
+$5, p=0.5
+$5, p=0.75
+$5, p=1
-$5, p=0
-$5, p=0.25
-$5, p=0.5
-$5, p=0.75

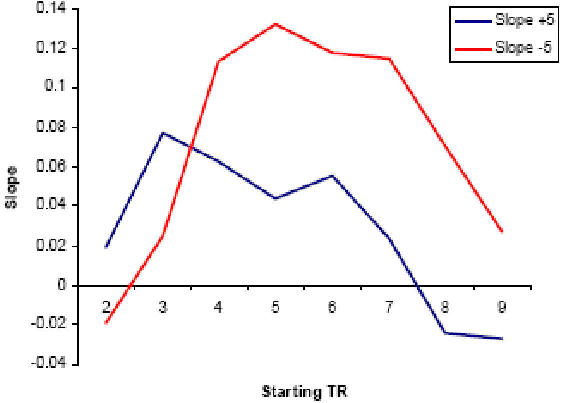

0.3
0.25
0.2
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
Parameter Estimate
0
0.25
0.5
0.75
1
Prob of winning $5
-5
5

# Late Period



-5
5
0.05
0
-0.05
-0.1
-0.15
-0.2
-0.25
0
0.25
0.5
0.75
1
Parameter Estimate
Prob of winning $5

# Two Different Signals?



# Key Results

- fMRI activity in Nucleus Accumbens does satisfy the necessary conditions for an RPE encoder
- However, this aggregate result may be the amalgamation of two separate signals
  - Vary in temporal lag
  - Vary in magnitude

- Axioms + experimental results tell us we can assign numbers to events such that NAcc activity encodes RPE according to those numbers
- Can we use these numbers to make inferences about beliefs and rewards?
  - Are they ‘beliefs’ and ‘rewards’ in the sense that people usually use the words?
  - Can we find any ‘external validity’ with respect to other observables?
    - Behavior?
    - Obviously rewarding events?
  - Can we then generalize to other situations?

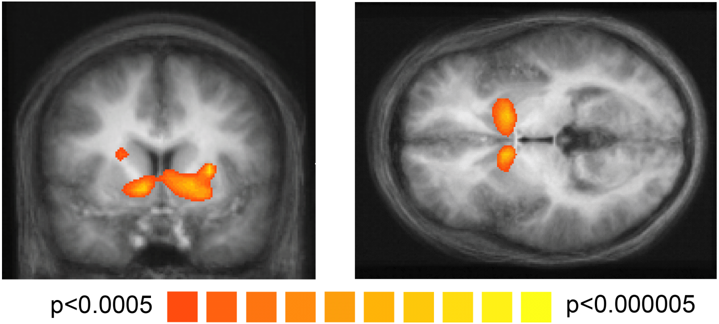
- New way of observing beliefs
- Makes ‘surprise’ directly observable
- Insights into mechanisms underlying learning
- Building blocks of ‘utility’

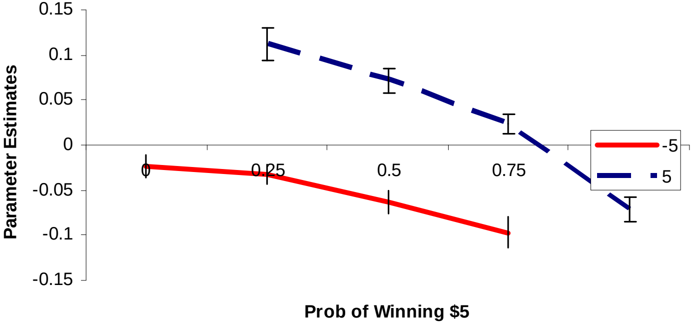
- We provide evidence that NAcc activity encodes RPE
- Can recover consistent dopaminergic 'beliefs' and 'rewards'
- Potential for important new insights into human behavior and 'state of mind'

# Functional Magnetic Resonance Imaging

- We test our theory in humans using fMRI
- fMRI detects differences in the ration of oxygenated to deoxygenated blood
- Brain activity affects level of blood oxygenation
- We can therefore detect brain activity in real time:
  - Temporal Resolution: c. 2 seconds
  - Spacial Resolution: c: 3 mm $\times$ 3 mm $\times$ 3 mm
- Data not as good as from 'single unit recording' from electrodes in the brain, but can be performed on humans

- Use the assumption that activity in dopamine rich regions likely to be correlated with difference in EV between lottery and prize
- Split data to make ROI definition independent of subsequent test
- ROI defined at the group level, not subject level


p<0.0005
p<0.000005



0.15
0.1
0.05
0
-0.05
-0.1
-0.15
Parameter Estimates
0
0.25
0.5
0.75
Prob of Winning $5
-5
5

- There are 4 steps to using this experimental data to test our axioms

1. Use fMRI to obtain data on brain activity.
2. Define regions of interest (ROIs) within the brain, the activity in which we will use as a proxy for dopaminergic activity.
3. Constructing a time series of activity in the ROI, and using this time series to construct observations of $\delta$.
4. Use these estimates of $\delta$ to test our axioms.