Outline

1. Reference Dependence: Equity Premium
2. Reference Dependence: Job Search
3. Reference Points: Forward vs. Backward Looking
4. Reference Dependence: Endowment Effect
5. Reference Dependence-KR: Effort
6. Social Preferences Wave I: Altruism
7. Workplace Effort: Altruism
8. Shaping Social Preferences
1 Reference Dependence: Equity Premium

- Equity premium (Mehra and Prescott, 1985)
  - Stocks not so risky
  - Do not covary much with GDP growth
  - BUT equity premium 3.9% over bond returns (US, 1871-1993)

- Need very high risk aversion: \( RRA \geq 20 \)

- **Benartzi and Thaler (QJE 1995):** Loss aversion + narrow framing solve puzzle
  - Loss aversion from (nominal) losses—\( \Rightarrow \) Deter from stocks
  - Narrow framing: Evaluate returns from stocks every \( n \) months
• More frequent evaluation—>Losses more likely —> Fewer stock holdings

• Calibrate model with $\lambda$ (loss aversion) 2.25 and full prospect theory specification —> Horizon $n$ at which investors are indifferent between stocks and bonds

![Graph showing prospective utility over length of evaluation period]
• If evaluate every year, indifferent between stocks and bonds
• (Similar results with piecewise linear utility)
• Alternative way to see results: Equity premium implied as function on $n$
• **Barberis, Huang, and Santos (QJE 2001)**

• Piecewise linear utility, $\lambda = 2.25$

• Narrow framing at aggregate stock level

• Range of implications for asset pricing

• **Barberis and Huang (2001)**

• Narrowly frame at individual stock level (or mutual fund)
2 Reference Dependence: Job Search

- DellaVigna, Lindner, Reizer, Schmieder (QJE 2017)
- Insert slides
Large literature on understanding path of hazard rate from unemployment with different models.

**Typical finding:** There is a *spike* in the hazard rate at the *exhaustion point* of unemployment benefits.

⇒ Such a spike is *not easily explained* in the standard (McCall / Mortensen) model of job search.

⇒ To explain this path, one needs unobserved heterogeneity of a special kind, and/or storeable offers
Germany - Spike in Exit Hazard

Source: Schmieder, von Wachter, Bender (2012)
Simulation of Standard model

Predicted path of the hazard rate for a standard model with expiration of benefit at period 25
Model - Set-up

- We integrate **reference dependence** into standard McCall / Mortensen **discrete time** model of job search

- **Job Search:**
  - Search intensity comes at per-period **cost** of \( c(s_t) \), which is **increasing** and **convex**
  - With probability \( s_t \), a job is found with salary \( w \)
  - Once an individual finds a job the job is kept forever

- **Optimal consumption-savings choice**
  - Individuals choose optimal consumption \( c_t \) (hand-to-mouth \( c_t = y_t \) as special case)
  - Individuals are **forward looking** and have rational expectations
Utility Function

- Utility function $v(c)$
- Flow utility $u_t(c_t|r_t)$ depends on reference point $r_t$:
  
  $$u_t(c_t|r_t) = \begin{cases} 
  v(c_t) + \eta(v(c_t) - v(r_t)) & \text{if } c_t \geq r_t \\
  v(c_t) + \eta \lambda (v(c_t) - v(r_t)) & \text{if } c_t < r_t 
  \end{cases}$$

- $\eta$ is weight on gain-loss utility
- $\lambda$ indicates loss aversion
- Standard model is nested for $\eta = 0$

- Builds on Kahneman and Tversky (1979) and Kőszegi and Rabin (2006)

- Note: No probability weighting or diminishing sensitivity
Unlike in Kőszegi and Rabin (2006), but like in Bowman, Minehart, and Rabin (1999), reference point is backward-looking.

The reference point in period $t$ is the average income earned over the $N$ periods preceding period $t$ and the period $t$ income:

$$r_t = \frac{1}{N+1} \sum_{k=t-N}^{t} y_k$$
Key Equations

- An **unemployed** worker’s value function is

  \[ V_t^U(A_t) = \max_{s_t \in [0,1]; A_{t+1}} u(c_t| r_t) - c(s_t) + \delta \left[ s_t V_{t+1}^E(A_{t+1}) + (1 - s_t) V_{t+1}^U(A_{t+1}) \right] \]

- Value function when **employed**:

  \[ V_{t+1}^E(A_{t+1}) = \max_{c_{t+1}} u(c_{t+1}| r_{t+1}) + \delta V_{t+2}^E(A_{t+2}). \]

- Solution for **optimal search**:

  \[ c'(s_t^*) = \delta \left[ V_{t+1}^E(A_{t+1}) - V_{t+1}^U(A_{t+1}) \right] \]

- Solve for \( s_t^* \) and \( c_t^* \) using backward induction
How does the model work?

- Consider a step-wise benefit schedule

- What are the predictions of the standard vs. reference-dependent model without heterogeneity?
Example: Hazards under Two Models

Hazard Rate, Standard Model

Hazard Rate, Ref.-Dep. Model

Reference-Dependent Job Search
Example: Hazards under Two Models

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<tr>
<th>Periods</th>
<th>Benefit Level</th>
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<td>T</td>
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<td>T+N</td>
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<th>Periods</th>
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<tr>
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<td>0.07</td>
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<td>0.08</td>
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</table>

Hazard Rate, Standard Model

Hazard Rate, Ref.-Dep. Model

Reference-Dependent Job Search
Example: Hazards under Two Models

- Consider the introduction of an additional step-down after $T_1$ periods, such that total benefits paid until $T$ are identical:

- What are the predictions of the standard vs. ref.-dep. model?
Example: Hazards under Two Models

Hazard Rate, Standard Model

Hazard Rate, Ref.-Dep. Model

Reference-Dependent Job Search
Benefit schedule before and after the reform

Note: Eligible for 270 days in the first tier, base salary is higher than 114,000HUF ($570), younger than 50.
Define before and after

- Old UI, Old UA
- Old UI, New UA
- New UI, New UA

Reform occurred

- Before: Nov 1, 2004 to Feb 5, 2005

Dataset available: 2004, Jan 1 to 2007, Dec 31
Hazard rates before and after

Hazard by Duration

Number of days since UI claim

Samplesize: 11867

Survival Rate

Reemployment Wages

Reference-Dependent Job Search
Interrupted Time Series Analysis

Seasonally adjusted hazard rate

Quarter

hazard at 210–270 days

hazard at 270–330 days

Before Placebo Test

After Placebo Test

Reference-Dependent Job Search
Structural Estimation

We estimate model using **minimum distance** estimator:

\[
\min_{\xi} (m(\xi) - \hat{m})^\prime W (m(\xi) - \hat{m})
\]

\(\hat{m}\) - Empirical Moments (without controls)

- 35 15-day pre-reform hazard rates
- 35 15-day pre-reform hazard rates

\(W\) is the inverse of diagonal of variance-covariance matrix

Further assumptions about utility maximization:

- Log utility: \(v(c) = \log(c)\)
- Assets \(A_0 = 0\), Borrowing limit \(L = 0\), Interest rate \(R = 1\)
- Cost of effort \(c(s) = k j s^{1+\gamma} \frac{1}{1+\gamma}\)
Estimation Method

- Parameters $\xi$ to estimate:
  - $\lambda$ loss component in utility function
  - $N$ speed of adjustment of reference point
  - 15-day discount factor $\delta$ (fixed at $\delta = 0.995$ for hand-to-mouth case)
  - Cost of effort curvature $\gamma$
  - Unobserved Heterogeneity: $k_h$, $k_m$ and $k_l$ cost types, and their proportions (only one type for ref. dep. model)

- Fixed parameters:
  - Gain-loss utility weight $\eta = 0$ (standard model), $\eta = 1$ (ref.-dep. model)
  - Reemployment wage fixed at the empirical median
  - Start with hand-to-mouth estimates ($c_t = y_t$)
Standard Model, 3 types (Hand-to-Mouth)
Ref.-Dep. Model, 1 types (Hand-to-Mouth)
Incorporating Consumption-Savings

Previous results have key weakness
- Reference-dependent workers are aware of painful loss utility at benefit decrease
- Should save in anticipation
- Ruled out by hand-to-mouth assumption

Introduce optimal consumption:
- In each period $t$ individuals choose search effort $s_t^*$ and consumption $c_t^*$
- Estimate also degree of patience $\delta$ and $\beta, \delta$
Standard model (Optimal Consumption)

- Standard model with 3 cost types and estimated $\delta$ performs no better than with hand-to-mouth assumption
Ref.-Dep. model (Optimal Consumption)

- Reference-dependent model with estimated $\delta$ performs well
- BUT: estimated $\delta = .9$ (bi-weekly) – not realistic
The reference-dependent model with $\beta, \delta$ performs about equally well - Laibson (1997), O’Donoghue and Rabin (1999), Paserman (2008), Cockx, Ghirelli and van der Linden (2014)

Estimated $\hat{\beta} = 0.58$ with $\delta = .995$, reasonable

Noticed: maintained naiveté
# Benchmark Estimates (Optimal Consumption)

## Structural estimation of Standard and Ref.-Dep. models - Optimal Consumption

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
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<tbody>
<tr>
<td>Discounting:</td>
<td>Standard Delta</td>
<td>RefD. Delta</td>
<td>Standard Beta</td>
<td>RefD. Beta</td>
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<tr>
<td>Parameters of Utility function</td>
<td>log(b)</td>
<td>log(b)</td>
<td>log(b)</td>
<td>log(b)</td>
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<tr>
<td>Utility function $\nu(.)$</td>
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<td></td>
<td></td>
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<tr>
<td>Loss aversion $\lambda$</td>
<td>4.92</td>
<td>(0.58)</td>
<td>4.69</td>
<td>(0.62)</td>
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<tr>
<td>Gain utility $\eta$</td>
<td>1</td>
<td></td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Adjustment speed of reference point $N$ in days</td>
<td>184</td>
<td>(11)</td>
<td>167.5</td>
<td>(11.2)</td>
</tr>
<tr>
<td>$\delta$</td>
<td>0.93</td>
<td>(0.01)</td>
<td>0.995</td>
<td>0.995</td>
</tr>
<tr>
<td>$\beta$</td>
<td>1</td>
<td></td>
<td>0.92</td>
<td>0.58</td>
</tr>
<tr>
<td>Parameters of Search Cost Function</td>
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<tr>
<td>Elasticity of search cost $\gamma$</td>
<td>0.4</td>
<td>(0.04)</td>
<td>0.07</td>
<td>(0.01)</td>
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<tr>
<td>Model Fit</td>
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<tr>
<td>Goodness of fit</td>
<td>227.5</td>
<td>194.0</td>
<td>229.0</td>
<td>183.5</td>
</tr>
<tr>
<td>Number of cost-types</td>
<td>3</td>
<td>1</td>
<td>3</td>
<td>1</td>
</tr>
</tbody>
</table>
Goodness of fit by Impatience

- Extra dividend of optimal consumption: Estimate patience
- Unemployed workers estimated to be very impatient
- Impatience too high in $\delta$ model, but realistic with $\beta, \delta$ model
  $\Rightarrow$ Evidence supporting present-bias

![Graphs showing goodness of fit by impatience](image)
Ongoing Work: Survey

- Key prediction of different models on search effort

⇒ Ideally we would have individual level panel data on search effort
Ongoing Work: Survey

- Build on Krueger and Mueller (2011, 2014):
  - Large web based survey among UI recipients in NJ
  - 5% participation rate
  - No benefit expiration in their sample

![Graph: Last 7 days (weekly recall)]

Source: Authors’ calculations based on the survey data and on administrative data from LWD.
Ongoing Work: Survey

- Conduct SMS-based survey in 2017 in Germany with IAB
- Twice-a-week ‘How many hours did you spend on search effort yesterday?’
  - Follow around 10,000 UI recipients over 4 months.
  - Use discontinuity in benefit duration (6/8/10 months) to get control group
  - Examine in particular search effort around benefit expiration
- Advantages of SMS messages:
  - Very easy to reply / low cost to respondent.
  - A lot of control, easy to send reminders etc.
3 Reference Points: Forward vs. Backward Looking

• Most papers so far assume a backward-looking reference point
  – Salient past outcomes
    * Purchase price of home
    * Purchase price of shares
    * Amount withheld in taxes
    * Recent earnings
  – Status quo
    * Ownership in endowment effect
  – Cultural norm
∗ 52-week high for mergers
∗ Round numbers (as running goals)

• For bunching and shifting test, reference point needs to be
  – Deterministic
  – Clear to the researcher

• For other predictions, such as in job search, exact level less critical
• **Koszegi and Rabin** (*QJE* 2006; *AER* 2007): forward-looking reference points
  – Reference point is expectations of future outcomes
  – Reference point is stochastic
  – Solve with Personal Equilibria

• Motivations:
  – Motivation 1: It often makes sense for people to compare outcomes to expectations
  – Motivation 2: Reference point does not need to be assumed

• Evidence:
  – Reference point for police arbitration
  – Reference point for watching sports games
Drawbacks of forward-looking reference points:
  - Stochastic $\Rightarrow$ Lose sharpest tests of reference dependence (bunching and shifting)
  - (Reference point is often taken as expectation, rather than full distribution, to simplify)
  - Often multiplicity of equilibria

Next, cover papers designed to test reference points as expectations:
  - Endowment effect
  - Effort

Future research: Would be great to see papers with reference point $r$

$$r = \alpha r_0 + (1 - \alpha) r_f$$

- $r_0$ backward-looking reference point
- $r_f$ forward-looking reference point
- What weight on each component?
4 Reference Dependence: Endowment Effect

- Plott and Zeiler (AER 2005) replicating Kahneman, Knetsch, and Thaler (JPE 1990)
  - Half of the subjects are given a mug and asked for WTA
  - Half of the subjects are shown a mug and asked for WTP
  - Finding: \( WTA \simeq 2 * WTP \)

Table 2: Individual Subject Data and Summary Statistics from KKT Replication

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Individual Responses (in U.S. dollars)</th>
<th>Mean</th>
<th>Median</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>WTP</td>
<td>0, 0, 0, 0, 0.50, 0.50, 0.50, 0.50, 1, 1, 1, 1, 1.50, 2, 2, 2, 2, 2.50, 2.50, 2.50, 3, 3, 3.50, 4.50, 5, 5</td>
<td>1.74</td>
<td>1.50</td>
<td>1.46</td>
</tr>
<tr>
<td>WTA</td>
<td>0, 1.50, 2, 2, 2.50, 2.50, 3, 3.50, 3.50, 3.50, 3.50, 3.50, 3.50, 4, 4.50, 4.50, 5.50, 5.50, 5.50, 6, 6, 6.50, 7, 7, 7.50, 7.50, 7.50, 8.50</td>
<td>4.72</td>
<td>4.50</td>
<td>2.17</td>
</tr>
</tbody>
</table>
How do we interpret it? Use reference-dependence in piece-wise linear form

- Assume only gain-loss utility, and assume piece-wise linear formulation (1)+(3)

- Two components of utility: utility of owning the object $u(m)$ and (linear) utility of money $p$

- Assumption: No loss-aversion over money

- WTA: Given mug $\rightarrow r = \{mug\}$, so selling mug is a loss

- WTP: Not given mug $\rightarrow r = \{\emptyset\}$, so getting mug is a gain

- Assume $u(\emptyset) = 0$
• This implies:

- **WTA: Status-Quo ~ Selling Mug**
  
  \[ u\{mug\} - u\{mug\} = \lambda [u\{\emptyset\} - u\{mug\}] + p_{WTA} \text{ or} \]
  
  \[ p_{WTA} = \lambda u\{mug\} \]

- **WTP: Status-Quo ~ Buying Mug**
  
  \[ u\{\emptyset\} - u\{\emptyset\} = u\{mug\} - u\{\emptyset\} - p_{WTP} \text{ or} \]
  
  \[ p_{WTP} = u\{mug\} \]

- It follows that
  
  \[ p_{WTA} = \lambda u\{mug\} = \lambda p_{WTP} \]

- If loss-aversion over money,
  
  \[ p_{WTA} = \lambda^2 p_{WTP} \]
• Result $WTA \sim 2 \times WTP$ is consistent with loss-aversion $\lambda \sim 2$

• Plott and Zeiler (*AER* 2005): The result disappears with
  
  – appropriate training
  
  – practice rounds
  
  – incentive-compatible procedure
  
  – anonymity

<table>
<thead>
<tr>
<th>Pooled Data</th>
<th>WTP (n = 36)</th>
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<tbody>
<tr>
<td></td>
<td></td>
<td>6.62</td>
<td>6.00</td>
<td>4.20</td>
</tr>
<tr>
<td>WTA (n = 38)</td>
<td></td>
<td>5.56</td>
<td>5.00</td>
<td>3.58</td>
</tr>
</tbody>
</table>
• What interpretation?

• Interpretation 1. Endowment effect and loss-aversion interpretation are wrong
  
  – Subjects feel bad selling a ‘gift’

  – Not enough training

• Interpretation 2. In Plott-Zeiler (2005) experiment, subjects did not perceive the reference point to be the endowment
• Koszegi-Rabin: \textit{Assume} reference point \((.5, \{mug\}; .5, \{\emptyset\})\) in both cases

- WTA:

\[
\begin{bmatrix}
0.5 \ast [u\{mug\} - u\{mug\}] \\
+ 0.5 \ast [u\{mug\} - u\{\emptyset\}]
\end{bmatrix}
= \begin{bmatrix}
0.5 \ast \lambda [u\{\emptyset\} - u\{mug\}] \\
+ 0.5 \ast [u\{\emptyset\} - u\{\emptyset\}]
\end{bmatrix} + PWTA
\]

- WTP:

\[
\begin{bmatrix}
0.5 \ast \lambda [u\{\emptyset\} - u\{mug\}] \\
+ 0.5 \ast [u\{\emptyset\} - u\{\emptyset\}]
\end{bmatrix}
= \begin{bmatrix}
0.5 \ast [u\{mug\} - u\{mug\}] \\
+ 0.5 \ast [u\{mug\} - u\{\emptyset\}]
\end{bmatrix} - PWTP
\]

- This implies no endowment effect:

\[
PWTA = PWTP
\]
• Following papers: manipulate probability of exchange to test Koszegi-Rabin

  – **Ericson and Fuster (QJE 2011)**: KR evidence

  – **Heffetz and List (JEEA 2015)**: no KR evidence

• Go over **Goette, Harms, and Sprenger (2016)**

  – Endowment effect in classroom

  – Vary probability $p$ of forced exchange: owner must sell, buyer must buy

  – For probability $p = 0.5$, owner in KR sense is only owner with prob. 0.5, and buyer is owner with $p = 0.5$ → Should be no endowment effect
- For $p > 0.5 \rightarrow$ Reverse endowment effect
- What do they find? Mostly, full endowment effect, no KR.
5 Reference Dependence-KR: Effort

- Abeler, Falk, Goette, Huffman (AER 2011)

- Return to our earlier real-effort set up

- Individuals put in effort $e$, with cost $c(e)$

- Value of effort $v(e|r)$ affected by a reference point

- Assume now that the reference point $r$ is a la Koszegi-Rabin

- $\rightarrow$ Evidence that subjects shift effort and bunch at this reference point?

- Design to disentangle forward- versus backward-looking references points
• Individuals put real effort

  – First training: for 4 minutes count as many zeros in tables as can

  – Then, real task:

    * Decide how long to work, for up to 60 minutes (smart design choice, as higher elasticity of effort than tasks to do in fixed amount of time)

    * With probability 1/2, paid piece rate time effort, $p \cdot e$, $p = .2$

    * With probability 1/2, paid $T$ euros

    * Vary whether $T_{Low} = 3$ or $T_{Hi} = 7$
• Standard model:

\[
\max_e \frac{T + pe}{2} - c(e)
\]

\[\Rightarrow e^* = c'^{-1}(p/2)\]

- Solution does not depend on target \( T \)

• Reference-dependent model, with gain-loss utility

- Assume reference point is \( pe \) with prob. 1/2, \( T \) with prob. 1/2

- If \( pe < T \), utility \( v(e|r) \) is (with prob. 1/2 paid \( pe \), with prob. 1/2
paid $T$):

$$
\frac{T + pe}{2} + \frac{1}{2} \eta \left[ \frac{1}{2} (pe - pe) + \frac{1}{2} \lambda (pe - T) \right] + \\
+ \frac{1}{2} \eta \left[ \frac{1}{2} (T - T) + \frac{1}{2} (T - pe) \right]
$$

$$
= \frac{T + pe}{2} + \frac{1}{4} \eta (\lambda - 1) (pe - T)
$$

- If $pe > T$, utility is

$$
\frac{T + pe}{2} + \frac{1}{2} \eta \left[ \frac{1}{2} (pe - pe) + \frac{1}{2} (pe - T) \right] + \\
+ \frac{1}{2} \eta \left[ \frac{1}{2} (T - T) + \frac{1}{2} \lambda (T - pe) \right]
$$

$$
= \frac{T + pe}{2} - \frac{1}{4} \eta (\lambda - 1) (pe - T)
$$
– The f.o.c. for effort are

\[
\frac{p}{2} + \frac{p}{4} \eta (\lambda - 1) - c'(e^*) = 0 \text{ if } pe < T \\
\frac{p}{2} - \frac{p}{4} \eta (\lambda - 1) - c'(e^*) = 0 \text{ if } pe > T
\]

– Thus, should see

* bunching at $T$

* Higher effort for higher $T$
- KR effect on effort, though smaller than one would expect
  - Anchoring can be confound
• Much research remains to be done on reference point determination

• Need design that ‘reveals’ reference point

• Use bunching?
6 Social Preferences Wave I: Altruism

- First set of models (since 1970s): Pure altruism
  - Self with payoff $x_s$
  - Other with payoff $x_o$
  - Self assigns weight $\alpha$ to Other’s utility:
    \[ U = u(x_s) + \alpha u(x_o) \]

- First used to model within-family altruism (Becker, 1981; Becker and Barro, 1986)

- Still very useful benchmark model
7 Workplace Effort: Altruism

- Bandiera-Barankay-Rasul (QJE, 2005)
  - Impact of relative pay versus piece rate on productivity

- Standard model:
  - **Piece rate**: Worker \( i \) maximizes

\[
\max_{e_i} p e_i - c(e_i)
\]

\[
e^*_i = c'^{-1}(p)
\]

- **Relative pay**: Worker \( i \) maximizes

\[
\max_{e_i} p e_i - \gamma \sum_{j \neq i} \frac{e_j}{I-1} - c(e_i)
\]

\[
e^*_i_{RP} = e^*_P = c'^{-1}(p)
\]
• Assume simple altruism:

\[ U_i = u_i + \alpha \sum_{j \neq i} u_j \]

- Piece rate: Worker maximizes

\[ \max_{e_i} pe_i - c(e_i) + \alpha \sum_{j \neq i} [pe_j - c(e_j)] \]

- Same solution as with \( \alpha = 0 \)

- Relative pay: Worker \( i \) maximizes

\[ \max_{e_i} pe_i - \gamma \sum_{j \neq i} \frac{e_j}{I - 1} - c(e_i) + \alpha \sum_{j \neq i} \left[ pe_j - \gamma \sum_{q \neq j} \frac{e_q}{I - 1} - c(e_j) \right] \]

- Solution

\[ c'(e_{iRP}^*) = p - \alpha \gamma (I - 1) \Rightarrow e_{iRP}^* < e_{iP}^* \]
• Test for impact of social preferences in the workplace
  – Does productivity increase when switching to piece rate?
• Use personnel data from a fruit farm in the UK
• Measure productivity as a function of compensation scheme
• Timeline of quasi-field experiment:
  – First 8 weeks of the 2002 picking season → Fruit-pickers compensated on a relative performance scheme
    * Per-fruit piece rate is decreasing in the average productivity.
    * Workers that care about others have incentive to keep the productivity low
  – Next 8 weeks → Compensation switched to flat piece rate per fruit
  – Switch announced on the day change took place
- Dramatic 50 percent increase in productivity
- No other significant changes

<table>
<thead>
<tr>
<th></th>
<th>Relative incentives</th>
<th>Piece rates</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Worker productivity (kg/hr)</td>
<td>5.01 (0.243)</td>
<td>7.98 (0.208)</td>
<td>2.97***</td>
</tr>
<tr>
<td></td>
<td>[4.53, 5.49]</td>
<td>[7.57, 8.39]</td>
<td></td>
</tr>
<tr>
<td>Kilos picked per day</td>
<td>Confidential</td>
<td></td>
<td>23.2***</td>
</tr>
<tr>
<td>Hours worked per day</td>
<td>Confidential</td>
<td></td>
<td>−.475</td>
</tr>
<tr>
<td>Number of workers in same field</td>
<td>41.1 (2.38)</td>
<td>38.1 (1.29)</td>
<td>−3.11</td>
</tr>
<tr>
<td>Daily pay</td>
<td>Confidential</td>
<td></td>
<td>1.80</td>
</tr>
<tr>
<td>Unit wage per kilogram picked</td>
<td>Confidential</td>
<td></td>
<td>−.105***</td>
</tr>
</tbody>
</table>

*** denotes significance at 1 percent. Sample sizes are the same as those used for the productivity regressions. Standard errors and confidence intervals take account of the observations being clustered by field-day. Productivity is measured in kilograms per hour. Daily pay refers to pay from picking only. Both daily pay and the unit wage per kilogram picked are measured in UK Pounds Sterling. Some information in the table cannot be shown due to confidentiality requirements.

- Is this due to response to change in piece rate?
  - No, piece rate went down → Incentives to work less (susbt. effect)
• Results robust to controls

• Results are stronger the more friends are on the field

<table>
<thead>
<tr>
<th></th>
<th>(1a) Relative incentives</th>
<th>(1b) Relative incentives</th>
<th>(2a) Piece rates</th>
<th>(2b) Piece rates</th>
</tr>
</thead>
<tbody>
<tr>
<td>Share of workers in the field who are friends</td>
<td>-1.68*** (.647)</td>
<td>-5.52** (2.36)</td>
<td>.072 (1.60)</td>
<td>1.17 (.493)</td>
</tr>
<tr>
<td>Share of workers in the field who are friends × number of workers in same field</td>
<td>1.60** (.684)</td>
<td>- .285 (1.60)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of workers in same field</td>
<td>.182 (.117)</td>
<td>.085 (1.60)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Marginal effect of group size (at mean friends’ share)</td>
<td>.236** (.110)</td>
<td>.076 (.065)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Worker fixed effects: Yes Yes Yes Yes
Field fixed effects: Yes Yes Yes Yes
Other controls: Yes Yes Yes Yes
Adjusted $R^2$: .3470 .3620 .3065 .3081
Number of observations (worker-field-day): 2860 2860 4400 4400
Two Interpretations:

- Social Preferences:
  * Work less to help others
  * Work even less when friends benefit, since care more for them
- Repeated Game
  * Enforce low-effort equilibrium
  * Equilibrium changes when switch to flat pay

Test: Observe results for tall plant where cannot observe productivity of others (raspberries vs. strawberries)
• Compare Fruit Type 1 (Strawberries) to Fruit Type 2 (Raspberries)
  – No effect for Raspberries

• → No Pure Social Preferences. However, can be reciprocity

• Important to control for repeated game effects → Field experiments

<table>
<thead>
<tr>
<th></th>
<th>(1) Fruit type 2</th>
<th>(2) Fruit type 1</th>
<th>(3) Fruit types 1 and 2 combined</th>
</tr>
</thead>
<tbody>
<tr>
<td>Piece rate dummy ($P_r$)</td>
<td>-.063 (.129)</td>
<td>.483*** (.094)</td>
<td></td>
</tr>
<tr>
<td>Piece rate × fruit type 2</td>
<td></td>
<td></td>
<td>-.100 (.095)</td>
</tr>
<tr>
<td>Piece rate × fruit type 1</td>
<td></td>
<td></td>
<td>.490*** (.092)</td>
</tr>
</tbody>
</table>
• **Hjort (2014 QJE):** Social preferences among co-workers as function of ethnicity
  
  – Kenya flower plant
  
  – Teams of 3: one supplier, two processors
  
  – Piece rate (at least initially) for two processors, and supplier gets pay for average productivity
- Different team ethnicity configurations of Luos and Kikuyu:
  - Vertically mixed teams $\rightarrow$ Work less hard to sort flower
  - Horizontally mixed teams $\rightarrow$ Sort fewer flowers to non-coethnic
  - Findings strikingly aligned to predictions of model
• Two further pieces of evidence:
  1. Period of ethnic animosity and violence
  2. Switch to team pay for the processors
• Prediction of first change:
  – Exacerbate patterns
• Prediction of second change:
  – Reduce effect in horizontally-mixed teams
  – Not in vertically-mixed teams
Figure II
Output in homogeneous and mixed teams across time

Average number of roses produced

Election day  Conflict begins  Team pay introduced

Homogeneous teams  Horizontally mixed teams  Vertically mixed teams
8 Shaping Social Preferences

• In given economic setting, take preferences as given (Becker, ‘De Gustibus non est disputandum’)

• But over medium-term, preferences can shift

• Focus on evolution of social preferences

• Example 1: Hjort (2014 QJE) – conflict affects social preferences between workers of different ethnicities
Example 2: **Deckers, Falk, Kosse, Schildberg-Hörisch (2016)**

- Program in Germany for low income children ages 7-9, assign
  * 1.5 year mentoring program
  * OR control
- Measure 1: Children 6 stars (traded with toys) between themselves and another (anonymous) child, local or in Africa

- Measure 2: Ask ‘How much do you trust others’
• Example 3: **Rao (2014):** Consider the impact of exposure to students of different social class on preferences

• Remarkable impacts over just 1-2 years of exposure

• Slides courtesy of Gautam
Elite Private Schools in Delhi

Elite private schools are:

▶ **Expensive**: Tuition $500-$2500/year (25-110% of median annual household income)
  
  ▶ Public schools are free

▶ **Selective**: In my sample, accept $\approx 7\%$ of applicants
  
  ▶ Strictly regulated admissions criteria
    
    ▶ Neighborhood
    ▶ Older siblings in same school
    ▶ Parents alumni, parent interview
Policy Innovation

Policy change in Delhi in 2007:

- 20% admissions quota in private schools for poor students
  - Household income cutoff: $2000/year
- Schools which received subsidized land from state govt.
  - Over 90% of elite private schools
- No fees for poor children
- No tracking
Variation across classrooms

Sample for this paper:
▶ $k = 14$ schools
  ▶ 9 Treatment Schools
  ▶ 2 Delayed Treatment Schools
  ▶ 3 Control Schools
▶ $n = 2017$ randomly selected students in 14 schools
  ▶ in Grades 2-5
▶ Over-sample control, delayed treatment schools
  ▶ Treatment schools in same neighborhoods
Variation within classroom (IV strategy)

- 1 hr a day working in small groups of 2-4 students

- Some schools ($k = 7$) use alphabetic order of first name to assign study groups.
  - Exogeneous variation in personal interactions

- Other schools ($k = 4$) frequently shuffle groups
  - Only “direct” effect of name
Alphabetic Order Predicts Study Partners

First Stage of IV Has Predictive Power

Note: 95% confidence intervals around mean amount given.
Dictator Games

- Students endowed with 10 Rupees, choose to share $x \in [0, 10]$
  - Can exchange money for candy later (Rs. 1 per piece)

- Vary the identity of the recipient
  - **Game 1**: Poor student in a school for poor children
  - **Game 2**: Rich student in a private (control) school
  - Order randomized

- Name and photographs of school shown to subjects.
  - Debriefing: Subjects understood recipient poor / rich
Dictator Game with Poor Recipient

Adding Delayed Treatment Schools

Note: 95% confidence intervals around mean amount given.
Dictator Game with Poor Recipient

Note: 95% confidence intervals around mean amount given.
### Table 3. Generosity towards Poor Students

<table>
<thead>
<tr>
<th>Specification:</th>
<th>(1) DiD Full Sample</th>
<th>(2) DiD Younger Sibs</th>
<th>(3) IV Treated Class</th>
<th>(4) DiD+IV Full Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treated Classroom</td>
<td>12.22*** (1.901)</td>
<td>12.95*** (2.274)</td>
<td>8.747** (3.510)</td>
<td></td>
</tr>
<tr>
<td>Has Poor Study Partner</td>
<td></td>
<td>7.53** (3.147)</td>
<td>12.08*** (4.313)</td>
<td></td>
</tr>
<tr>
<td>Controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Fixed Effects</td>
<td>School, Grade</td>
<td>School, Grade</td>
<td>Classroom</td>
<td>School, Grade</td>
</tr>
<tr>
<td>p-value (CGM)</td>
<td>&lt; 0.01</td>
<td>&lt; 0.01</td>
<td>.</td>
<td>.</td>
</tr>
<tr>
<td>Control Mean</td>
<td>27.12</td>
<td>26.75</td>
<td>33.77</td>
<td>27.12</td>
</tr>
<tr>
<td>Control SD</td>
<td>27.22</td>
<td>26.53</td>
<td>28.13</td>
<td>27.22</td>
</tr>
<tr>
<td>N</td>
<td>2015</td>
<td>1141</td>
<td>677</td>
<td>2015</td>
</tr>
</tbody>
</table>

Dependent Variable: Share Given to Poor Recipient in Dictator Game (%)

* p < 0.10, ** p < 0.05, *** p < 0.01
Dictator Game with Rich Recipient

Poor Classmates Also Increase Generosity to Rich

Note: 95% confidence intervals around mean amount given.
Changes in amounts given to rich recipients

Change in Giving to Rich Recipient:
Less likely to give 0%, More likely to give 50%
Volunteering for charity

- Schools offer volunteer opportunity for charities
  - Spend two weekend afternoons in school to help fundraise for a children’s NGO

- Participation is strictly voluntary
  - Only 28% of students participate

- Administrative data on attendance
Having Poor Classmates Increases Volunteering for Charity

Note: 95% confidence intervals around mean amount given.
Field experiment on team selection

- Subjects are students from two elite private schools
  - One treatment school, one control school
  - We invite *athletic* poor students from a public school

- Students must choose teammates to run relay race
  - Tradeoff ability vs. social similarity

- $n = 342$
Stage 1: Randomization

- Randomized to sessions with varying stakes
  - Rs. 50, Rs. 200 or Rs. 500 per student for winning team
    - Rs. 500 ($10) approx. one month’s pocket money
  - Variation in “price” of discrimination
- Brief mixing to judge socioeconomic status
Team Selection Experiment Design

**Stage 2:** Ability revelation and team selection

- Observe a 2-person race
  - Usually one poor and one rich student
    - Neither is from your school
  - Uniforms make school identifiable

- Pick which of the two runners you want as your partner

- **Discrimination** Picking the slower runner
Team Selection Experiment Design

Stage 3: Choice implementation and relay race
- Students randomly picked to have their choices implemented
  - Plausible deniability provided
- Relay races held and prizes distributed as promised

Stage 4: Social interaction
- Must spend 2 hours playing with teammates
  - board games, sports, playground
- Was pre-announced
A quasi-demand curve for discrimination

Poor Classmates & Incentives Reduce Discrimination

Prize for Winning the Relay Race

Share Discriminating Against Poor

Note: 95% confidence intervals around mean.
Willingness to Play Experiment

Invite students to a “play date” at poor school

- Opportunity to make new friends in neighborhood

- Elicit incentivized Willingness To Accept to attend
  - Using simple BDM mechanism
  - Students require payments to attend
Increase in supply of social interactions

Treatment Increases Supply of Social Interaction

Share accepting playdate

Payment for attending (Rupees)

Control Classrooms

Treated Classrooms

Play Date Tables
What part of the treatment is crucial?

- Personal interactions explain a lot of the overall effect
  - 70% of the change in “willingness to play”
  - 38% of the increase in giving to the poor

- Likely an underestimate of importance of interaction
Mechanisms

What’s the mechanism? My speculation:

1. Interacting with poor children changes fairness notions
   ▶ Makes students care more about equality of payoffs
   ▶ Changes in preferences vs. norms / social image

2. Familiarity breeds fondness $\rightarrow$ discrimination $\downarrow$, socializing $\uparrow$
   ▶ Change in prefs due to ‘‘mere-exposure’’
   ▶ Changes in beliefs
     ▶ No effects on beliefs about niceness, intelligence, hard work.
Policy Relevance

- India-wide roll-out of this policy beginning in 2013-14
  - 400 million children under age 15
  - 30% of Indian students already attend private schools
  - Could have large-scale effects on social behaviors
    - Note unrepresentative sample
9 Next Lecture

- Social Preferences II
  - Warm Glow
  - Wave II: Inequity Aversion
  - Wave III: Social Pressure and Social Signalling