

# Individual Attitudes and Market Dynamics Towards Imprecision

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## An Example

February 2021:

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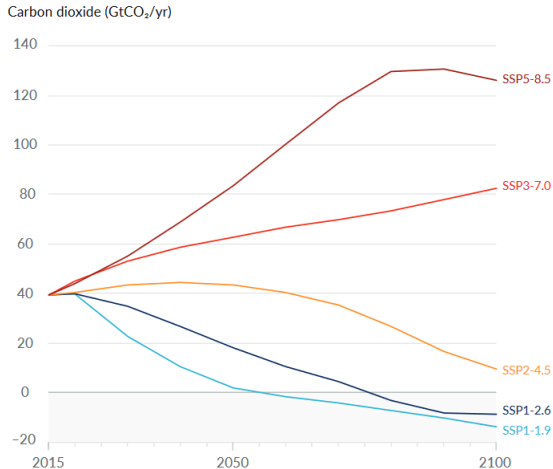
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  - ▶ death

## Another example

$CO_2$  scenarios for the climate

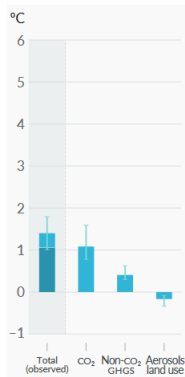




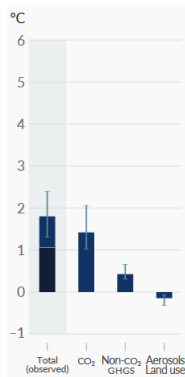
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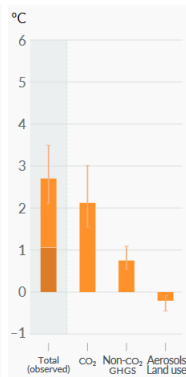
SSP1-1.9



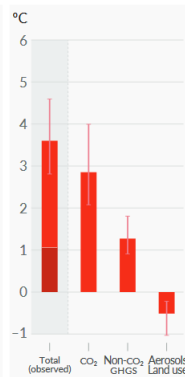
SSP1-2.6



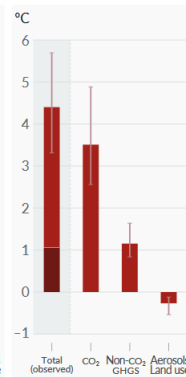
SSP2-4.5



SSP3-7.0



SSP5-8.5



## A related example

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- ▶ we can observe and measure the frequency of hurricane occurrence ex-post
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- ▶ we can observe and measure the frequency of hurricane occurrence ex-post
- ▶ but very little insights in how the likelihood of hurricanes in a specific region will be in a couple of years from now
- ▶ Even more concerning: the extent of damage they may cause is very much unclear!

# Motivation

- ▶ many situations in which both a prospects probability of occurrence and its consequences are unknown
- ▶ Standard economic models and experiments in this context distinguish between
  - ▶ risk, where both a prospects respective probabilities and its consequences are known, and
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  - ▶ uncertainty, where a prospects consequences are known, but the respective probabilities associated with the consequences are not.
- ▶ But: in many real-life situations there is even higher degree of unknownness
  - ▶ we often have some idea about consequences in the form of a range of potential outcomes
  - ▶ but we rarely have a clear idea of all potential outcomes, let alone the likelihood of each of them materializing

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- ▶ At the same time, there are often situations that are guided by a two-dimensional uncertainty, e.g. in financial markets:
  - ▶ probabilities over realizations are uncertain
  - ▶ actual outcome realizations are also uncertain

# Motivation

## Related findings

- ▶ Mixed results for ambiguity/imprecision in probabilities in asset market studies (Camerer & Kunreuther, 1989; Weber, 1989; Sarin & Weber, 1993; Bossaerts et al., 2010; Kocher & Trautmann, 2013; Füllbrunn et al., 2014)

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- ▶ For individual decision making: evidence for imprecision neutrality in probabilities, and imprecision seeking for imprecision in outcomes (using a similar task as ours - Du & Budescu, 2005)

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2. Relate investors individual attitudes towards imprecision to market outcomes

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- ▶ 2 tasks per treatment:
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    - ▶ 3 minutes of trading

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- ▶ 320 subjects, 1 hour, average payment €13.10

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IOP	[8, 108] [108, 208]	[0%; 100%] otherwise

# Screenshot - Individual Task

**WICHTIG**  
Bitte bestätigen Sie Ihre Eingabe **erst dann mit OK**, wenn Sie **das Feld** entsprechend ausgefüllt haben.

Lotterie		Ihre Entscheidung	
Ein Betrag im Intervall von [8;108] Talern	mit 50% Wahrscheinlichkeit	<input type="text"/>	<input type="button" value="Hilfe"/>
Ein Betrag im Intervall von [108;208] Talern	anderenfalls		

# Screenshot - Market

Periode

1 von 4

Die Urne besteht aus 20 **weißen** und **gelben** Ballen.

Die Mehrheit der Marktteilnehmer/-innen hat die Farbe **Weiß** gewählt.

Wird zufällig ein **weißer Ball** gezogen, so wird jede Aktie um einen zufälligen Preis **zwischen 0 und 100 Taler** zurückgekauft.

Wird zufällig ein **gelber Ball** gezogen, so wird jede Aktie um einen zufälligen Preis **zwischen 100 und 200 Taler** zurückgekauft.

Bisher keine Transaktionen

Kaufgebote

Preis

Stornieren

Verkauf

Verkaufsgebote

Preis

Stornieren

Kauf

Gebotsabgabe

Taler: 800.00

Aktien: 5

Letzter Preis: Kein Handel

Preis

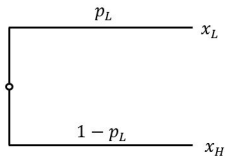
Kaufgebot

Verkaufsgebot



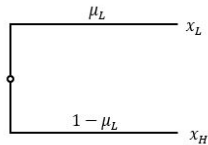
# Model and Hypotheses

# Illustration



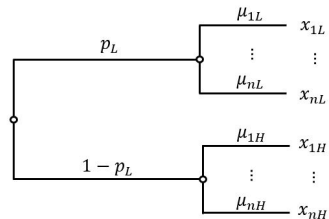
$$p_L = 0.5$$

(a) NI



$$\mu_L \in [0; 1]$$

(b) IP



$$p_L = 0.5$$

(c) IO

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- ▶ Allows us to do data fitting

## Model - NI

- ▶ two possible states, a low payoff  $x_L = 58$  and a high payoff  $x_H = 158$
- ▶ two objective probabilities associated with the possible outcomes,  $p_L$  and  $p_H$ , with  $p_H = (1 - p_L)$ , in our experiment  $p_L = p_H = 0.5$

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- ▶ we assume Expected Utility (EU)
- ▶ then under EU, a decision maker evaluates the prospect by

$$\begin{aligned} \text{EU}_{\text{ni}} &= p_L u(x_L) + (1 - p_L) u(x_H) \\ &= \frac{u(x_L) + u(x_H)}{2} \end{aligned} \tag{1}$$

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i.e., we assume  $\alpha$ -MEU
  - ▶ there is Bernoulli utility function  $u$  which is twice differentiable, strictly increasing, and concave

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- ▶ Then a decision maker with  $\alpha$ -MEU preferences evaluates the prospect by

$$\alpha - \text{MEU}_{IP} = \alpha \min_{\pi_L \in P} [\pi_L u(x_L) + (1 - \pi_L) u(x_H)] + (1 - \alpha) \max_{\pi_L \in P} [\pi_L u(x_L) + (1 - \pi_L) u(x_H)] \quad (2)$$

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- ▶ coefficient  $\alpha$  measures the degree of aversion to imprecision in probabilities (“ambiguity aversion”)
  - ▶  $\alpha = 1 \rightarrow$  imprecision-in-probabilities aversion
  - ▶  $\alpha = 0 \rightarrow$  imprecision-in-probabilities seeking

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- ▶ The “worst” case scenario corresponds to  $\pi_L = 1$ , and the “best” case scenario corresponds to  $\pi_L = 0$ . We can then rewrite

$$\begin{aligned}\alpha - \text{MEU}_{IP} &= \alpha \min_{\pi_L \in P} [\pi_L u(x_L) + (1 - \pi_L) u(x_H)] + \\ &\quad (1 - \alpha) \max_{\pi_L \in P} [\pi_L u(x_L) + (1 - \pi_L) u(x_H)] \\ &= \alpha u(x_L) + (1 - \alpha) u(x_H)\end{aligned}\tag{3}$$

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$$\alpha - \text{MEU}_{IP} = \alpha u(x_L) + (1 - \alpha)u(x_H) = \frac{u(x_L) + u(x_H)}{2} = \text{EU}_{NI} \quad (5)$$

# Model - IO

- ▶ modeled as a two-stage lottery (as in experimental design)
- ▶ two possible outcome ranges,  $[x_{L_1}, \dots, x_{L_n}]$  and  $[x_{H_1}, \dots, x_{H_n}]$



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- ▶ two objective probabilities associated with the possible outcome ranges,  $p_L$  and  $p_H$ , with  $p_H = (1 - p_L)$

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$$\begin{aligned} \alpha - \text{MEU}_{IO} = & p_L [\alpha \min_{\mu_{iL} \in Q_L} \text{EU}(\mu_{1L} : x_{1L}, \dots, \mu_{nL} : x_{nL}) \\ & + (1 - \alpha) \max_{(\mu_{iL} \in Q_L)} \text{EU}(\mu_{1L} : x_{1L}, \dots, \mu_{nL} : x_{nL})] \\ & + (1 - p_L) [\alpha \min_{\mu_{iH} \in Q_H} \text{EU}(\mu_{1H} : x_{1H}, \dots, \mu_{nH} : x_{nH}) \\ & + (1 - \alpha) \max_{\mu_{iH} \in Q_H} \text{EU}(\mu_{1H} : x_{1H}, \dots, \mu_{nH} : x_{nH})] \end{aligned} \quad (6)$$

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- ▶ this reflects our experimental design; instructions: “[...] payment of the lottery lies, with equal probability, either in the range [8:108] Taler or [108:208] Taler. That is, with a probability of 50% you receive an amount between 8 and 108 Taler, and with the complementary probability of  $100\% - 50\% = 50\%$  you receive an amount between 108 and 208 Taler. [...]”

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- ▶ The “worst” case scenario corresponds to a probability distribution that assigns a probability of 1 to the lowest possible outcome in the respective outcome range ( $\mu_{1L} = 1, \mu_{2L}, \dots, \mu_{nL} = 0$  for low outcome range,  $\mu_{1H} = 1, \mu_{2H}, \dots, \mu_{nH} = 0$ ),
- ▶ and the “best” case scenario corresponds to a probability distribution that assigns a probability of 1 to the highest possible outcome in the respective outcome range ( $\mu_{1L}, \dots, \mu_{(n-1)L} = 0, \mu_{nL} = 1$  for low outcome range,  $\mu_{1H}, \dots, \mu_{(n-1)H}, \mu_{nH} = 0$ )



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- ▶ assumption: the objective "worst" and "best" case scenarios are in set of subjective prior probabilities
- ▶ We can now rewrite to

$$\alpha - \text{MEU}_{IO} = p_L[\alpha u(x_{L1}) + (1 - \alpha)u(x_{Ln})] + (1 - p_L)[\alpha u(x_{H1}) + (1 - \alpha)u(x_{Hn})] \quad (7)$$

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- ▶ in case the decision maker is neutral towards imprecision in outcomes ( $\alpha = 0.5$ ) and has linear utility, then the expression is identical to NI with our calibration in the experiment:

$$\alpha - \text{MEU}_{IO} = p_L \left[ \frac{x_{L1} + x_{Ln}}{2} \right] + (1 - p_L) \left[ \frac{x_{H1} + x_{Hn}}{2} \right] = \frac{x_L + x_H}{2} = \text{EU}_{NI} \quad (8)$$

# Hypotheses

Based on the previous literature with a similar individual decision-making task (Budescu et al., 2002), we derive the following hypotheses:

- H1 On average, individuals are risk neutral.
- H2 On average, individuals are imprecision averse for IP.
- H3 On average, individuals are imprecision seeking for IO.

# Hypotheses

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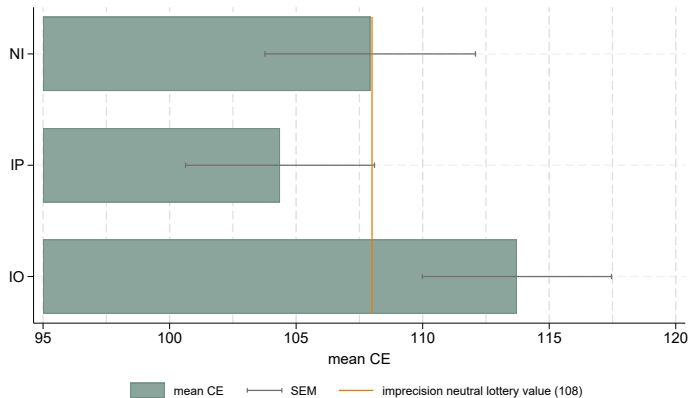
- H1 On average, individuals are risk neutral.
- H2 On average, individuals are imprecision averse for IP.
- H3 On average, individuals are imprecision seeking for IO.

In particular, we expect

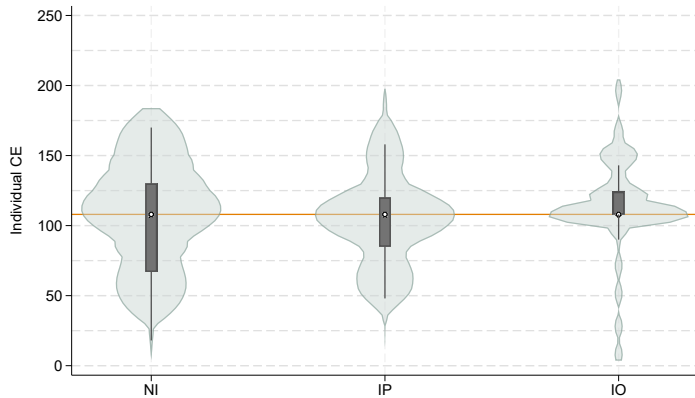
$$CE(IO) > CE(RISK) > CE(IP)$$

# Results

# Individual Task

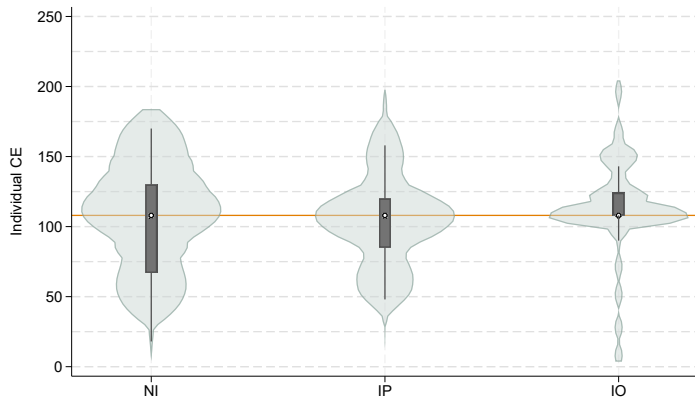


# Individual Task





# Individual Task



- Larger fraction above 108 in IO(  $p = 0.006$ , Wilcoxon signed-rank test)

# Individual Task

For our parameter estimations, we find:

- For NI estimating the model with power utility  $u(x) = x^r$ , we cannot reject linear utility with  $r = 0.356$ ,  $p = 0.098$ , Wald-test

# Individual Task

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- ▶ For the degree of imprecision aversion, we find
  - ▶ IP:  $\alpha = 0.536$ , we cannot reject imprecision neutrality ( $p = 0.333$ , Wald-test)

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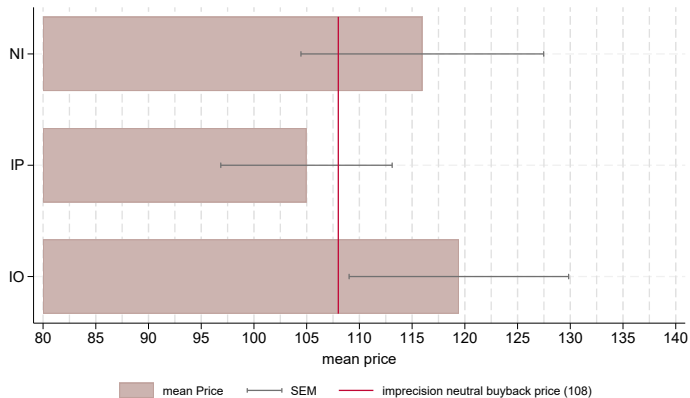
- ▶ For NI estimating the model with power utility  $u(x) = x^r$ , we cannot reject linear utility with  $r = 0.356$ ,  $p = 0.098$ , Wald-test
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  - ▶ IP:  $\alpha = 0.536$ , we cannot reject imprecision neutrality ( $p = 0.333$ , Wald-test)
  - ▶ IO:  $\alpha = 0.443$ , we also cannot reject imprecision neutrality ( $p = 0.130$ , Wald-test)

# Individual Task

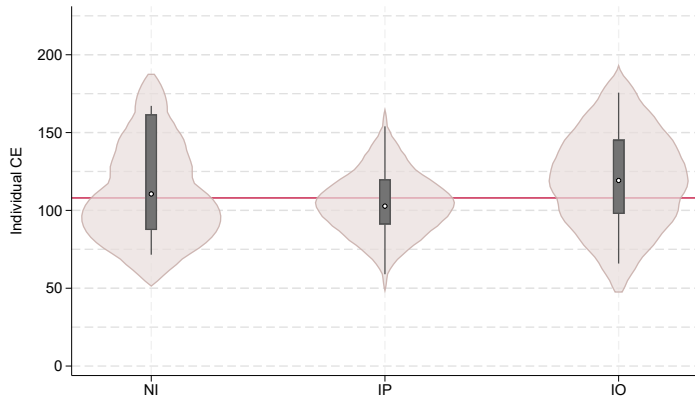
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  - ▶ IO:  $\alpha = 0.443$ , we also cannot reject imprecision neutrality ( $p = 0.130$ , Wald-test)
  - ▶ But: we find that  $\alpha_{IP} > \alpha_{IO}$  with  $p = 0.038$

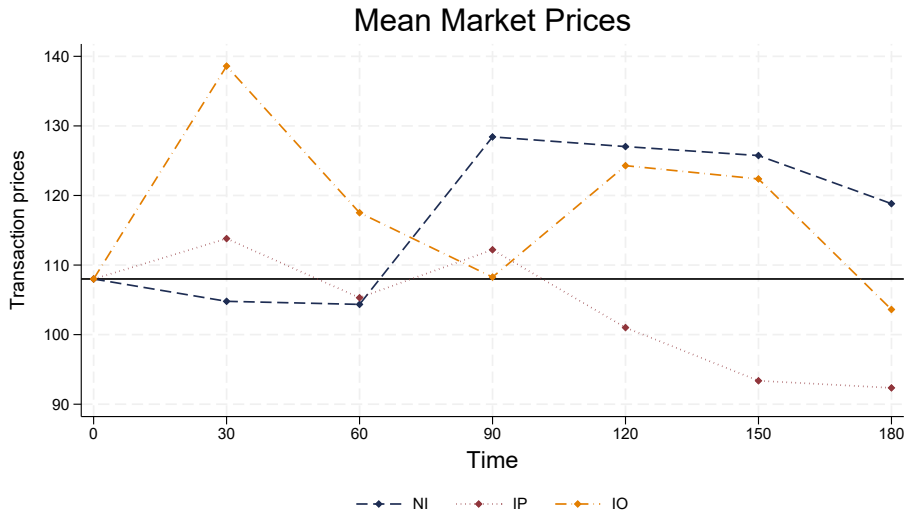
# Markets



# Markets



# Markets





# Markets

We compute market deviations  $MD_m^i$  per market and interval, dependent on the price  $P_m^i$  and expected value  $EV$ :

$$MD_m^i = \frac{P_m^i - EV}{EV} = \frac{P_m^i - 108}{108}$$

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$$MD_m^i = \frac{P_m^i - EV}{EV} = \frac{P_m^i - 108}{108}$$

Treatment	Interval 1			Interval 6		
	Mean	S.d.	$p$	Mean	S.d.	$p$
NI	0.078	(0.496)	0.846	0.100*	(0.182)	0.093
IP	0.054	(0.370)	0.553	-0.145*	(0.174)	0.051
IO	0.368*	(0.573)	0.075	-0.041	(0.353)	0.953

# Markets

For our parameter estimations, we find:

- ▶ For NI estimating the model with power utility  $u(x) = x^r$ , we cannot reject linear utility with  $r = 1.25$ ,  $p = 0.797$ , Wald-test

# Markets

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- ▶ For NI estimating the model with power utility  $u(x) = x^r$ , we cannot reject linear utility with  $r = 1.25$ ,  $p = 0.797$ , Wald-test
- ▶ For the degree of imprecision aversion, we find
  - ▶ IP:  $\alpha = 0.530$ , we cannot reject imprecision neutrality ( $p = 0.72$ , Wald-test)

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- ▶ For NI estimating the model with power utility  $u(x) = x^r$ , we cannot reject linear utility with  $r = 1.25$ ,  $p = 0.797$ , Wald-test
- ▶ For the degree of imprecision aversion, we find
  - ▶ IP:  $\alpha = 0.530$ , we cannot reject imprecision neutrality ( $p = 0.72$ , Wald-test)
  - ▶ IO:  $\alpha = 0.386$ , we also cannot reject imprecision neutrality ( $p = 0.30$ , Wald-test)

# Markets

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- ▶ For the degree of imprecision aversion, we find
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  - ▶ IO:  $\alpha = 0.386$ , we also cannot reject imprecision neutrality ( $p = 0.30$ , Wald-test)
  - ▶ we also cannot reject  $\alpha_{IP} = \alpha_{IO}$  ( $p = 0.26$ )

# Markets

Individual parameters (medians), individual task and markets

Treatment	NI		IP		IP	
	individual	market	individual	market	individual	market
$r$	1.00 (0.93)	1.23 (0.68)				
$\alpha$			0.50 (0.33)	0.55 (0.26)	0.50 (0.33)	0.39 (0.33)
$p$ -value	0.569		0.952		0.487	

# Markets

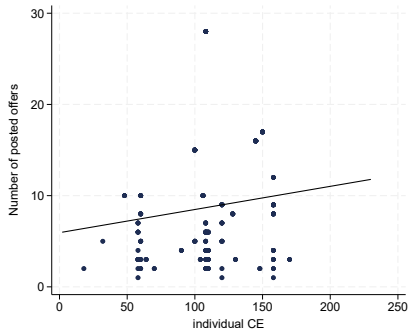
## Trading Behavior: Market Volume, Volatility, and Dispersion of Final Asset Holdings

	VOLUME			VOLA			DISPERSION		
	mean	<i>p</i> -value		mean	<i>p</i> -value		mean	<i>p</i> -value	
		IP	IO		IP	IO		IP	IO
NI	25.8 (8.97)	0.342	0.896	0.59 (0.56)	0.248	0.280	3.68 (0.74)	0.211	0.072
IP	22.9 (11.77)		0.403	0.36 (0.19)		0.063	3.29 (0.85)		0.565
IO	26.1 (11.84)			0.81 (0.70)			3.48 (1.68)		

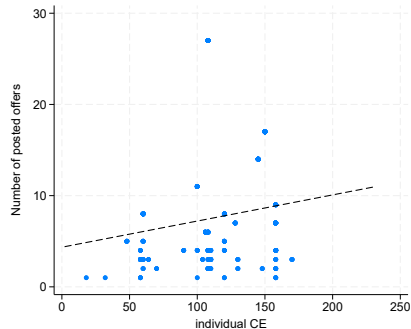


# Markets

no imprecision



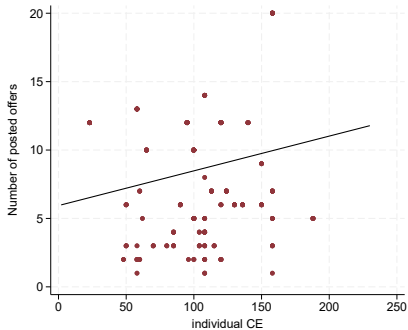
$$r = 0.119, p = 0.056$$



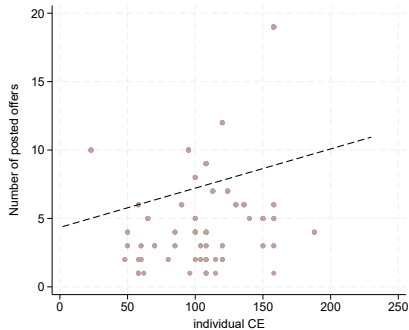
$$r = 0.145, p = 0.020$$

# Markets

imprecision in probabilities



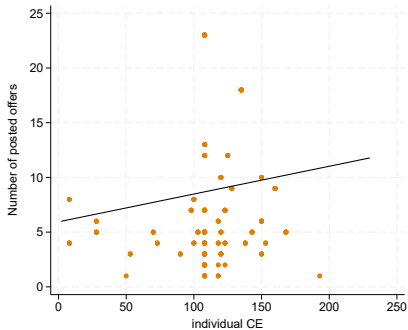
$$r = 0.200, p = 0.002$$



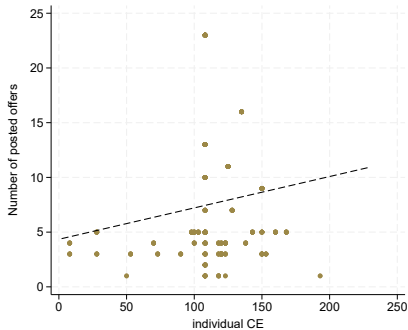
$$r = 0.298, p < 0.001$$

# Markets

imprecision in outcomes



$$r = 0.148, p = 0.017$$



$$r = 0.139, p = 0.025$$

# Summary

- ▶ we analyzed different dimensions of imprecision and their impact on individual choice and market dynamics
- ▶ findings support the importance of distinguishing between imprecision in probabilities and imprecision in outcomes
  - preference for imprecision in outcomes in individual task
  - higher prices with imprecision in outcomes vs. imprecision in probabilities
- ▶ parameter estimates align with observed market dynamics, indicating a translation of individual attitudes into market behavior

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