

Piece-rates, salaries and tournaments: psychological and economic competition in a real effort task

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We explore the impact of different remuneration schemes on productivity using a cognitively challenging real effort task. The task we use requires participants to predict the value of a variable Z which is a function of two other variables X and Y with the values of X and Y changing from one round to the next. Participants do not know what the actual relationship is but they do know that there is a well-defined relationship between X , Y and Z and that while the values of X and Y change from one round to the next, the underlying function does not change over time. Prior to the start of the experiment they are shown ten examples of X , Y and Z . These examples are designed to help subjects figure out what the relationship may be. The metric of performance is the absolute error, which is the absolute value of the difference between the value of Z predicted by a subject in any round and the actual value of Z in that round, with smaller errors indicating better performance. The assumption here is that greater cognitive effort would lead to better decisions and therefore minimize the prediction error.

We look at a number of different incentive schemes such as fixed salaries (where payoff is independent of performance), piece rates (where performance depends on absolute performance) and tournaments (where payoff depends on relative performance). Given that tournaments are an oft-used mechanism in a variety of organizational context, we explore the effectiveness of tournaments as an incentive mechanism and ask what it is about tournaments that may lead to better performance.

Tournaments differ from piece-rates in at least three ways: (1) the psychological pleasure/pain of winning/losing respectively; (2) the economic payoff from winning/losing, where the payoffs are discrete and different from that under piece-rates and finally (3) tournaments provide information about how well one is doing vis-à-vis others and how well it is possible to do.

In order to get a benchmark on ability levels we have everyone playing under a piece-rate scheme for five rounds at the beginning before allocating them to different treatments. We find that overall the two treatments that lead to the smallest errors on average are: (1) A treatment that pays a fixed salary and (2) a treatment we call “piece-rate win/lose”. In the latter treatment participants are paid a piece rate according to their absolute performance but in addition are provided information on whether they did better or worse than others in the group. We also find that when pay depends on performance as in the case of piece rates, providing additional information in terms of winning/losing leads to improved performance. But when payment is performance independent as with fixed salaries providing winning/losing information makes performance worse (errors larger).

There is significant heterogeneity among participants and one reason why tournaments do not perform well overall is because subjects who are not good at the task perform significantly worse in the tournament condition than in the other treatments. This in turn leads to higher average errors overall in the tournament condition. However, because everyone plays under a piece-rate at the start, we can sort our subjects into “high” and “low” performers on the basis of their performance in the first five rounds. We find that while there is limited learning over time on the whole, it is the tournament treatment where there is most learning – in the form of errors declining over time – and

this learning is most pronounced among the “high” performers. Our results have significant implications for the design on incentive schemes in the work-place.

Piece rates, salaries and tournaments: economic and psychological competition in a real effort task

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How should you pay someone?

- Piece rates
 - Output – Pay based on absolute performance
 - Input – Pay based on time
- Salary
 - Pay independent of performance; no ***extrinsic*** incentive
- Tournaments
 - Pay based on relative performance;
 - Winner take all; Rank-order
 - *Lazear and Rosen (1981); Green and Stokey, (1983); Nalebuff and Stiglitz (1983)*

Voluminous literature looking at incentive mechanisms

- Field studies
 - Executive positions (Gibbons and Murphy, 1990), Chicken farmers (Knoeber, 1989, 1994), Law firms (Ferrall, 1996), Portfolio managers (Brown, 1996), Executives (Xu, 1997), Etc.
- Experimental work
 - Bull, Schotter and Weigelt (1987)
 - Harbring and Irlenbusch (2003)
 - Van Dijk et al (2001)
- Surveys
 - Prendergast (1999), Dechenaux, Kovenock, Sheremeta (2012)

Three ways tournaments differ from piece rates

- ***Psychological competition***
 - Act of competing against another 
 - pleasure of winning/ pain of losing
- ***Economic competition***
 - Performance dependent payoffs
 - “Bad” decisions leading to low payoff
- ***Information***
 - Information about how well you are doing
 - How well it is possible to do
 - Provides a reference for identifying attainable level

Objectives of our study

- *Study performance under different incentive schemes*
- Using a “real effort task”
- Cognitively difficult task ->
- People need to expend “effort” to perform the task well

The task used in this study

- Multiple Cue Probabilistic Learning Task
- In each round subjects asked to forecast price of fictitious “stock” given two cue-values A and B
- Stock price:
- $P_t^* = 10 + 0.3 * CUE A_t + 0.7 * CUE B_t + e_t$

The task used in this study

- Cue values change each round, but **not** the underlying relationship
- *Metric of good decision (good performance) ->*
- *Absolute forecasting error:*
- $e_{it} = |P_t^* - P_{it}|$

Experimental design

- Computerized experiments
- \$5 show up fee
- Instructions read out loud
- 5 minutes to study 10 examples of Price/Cue relationship provided on paper
- Experiment starts after that

Experimental design

- Shown Cue A and Cue B for 1st round
- Given time to enter decisions
- Results displayed
- New cue values for second round and so on
- Continue for 20 rounds

Three types of payment schemes

- **Piece rate:**
- $Earning_{it} = \$1.00 - e_{it}$

- **Two person (winner take all) tournament:**
- $Earning_{it} = \$1.00$ if $|e_{it}| < |e_{jt}|$
 $= \$0.00$ otherwise

- **Salary**
- Earnings = \$20 (announced before-hand)

Treatments

- *Piece rates*
- *Piece rates with win-loss information (Win-Lose)*
- *Tournament*
- *Tournament no information*
- *Salary*
- *Salary with win-loss information*

Piece rates

- Rounds 1 – 20
- Payment based on own absolute errors only
- $Earning_{it} = \$1.00 - e_{it}$
- If absolute error > 100 then receive \$0

Win-Lose

- ***Rounds 1 – 5***
 - Piece rate payment scheme exactly as before

 - ***Rounds 6 – 20***
 - Assigned partner each round; ***anonymous***
 - Partners randomly re-matched each period,
 - Same piece rate payment scheme but
 - At the end of the round subjects learn
1. ***Earnings***
 2. ***WIN or LOSE*** (*whether one's own error was smaller (larger) than pair member's error*)

Tournament

- ***Rounds 1 – 5***
- Piece rate payment scheme exactly as before

- ***Rounds 6 - 20***
- Assigned partner each round
- Provided extra \$4.00 in earnings account
- At the end of the round subjects learn
 - 1. Error***
 - 2. WIN or LOSE***
 - 3. Payment = \$1.00 or \$0.00***

Tournament no information

- ***Rounds 1 – 5***
- Piece rate payment scheme exactly as before

- ***Rounds 6 - 20***
- Assigned partner each round
- Provided extra \$4.00 in earnings account
- At the end of the round subjects learn
- 1. Error***
- At the end of ROUND 20 subjects learn
- 1. WIN or LOSE***
- 2. Payment = \$1.00 or \$0.00 for each round***

Salary

- Rounds 1 - 20
- Flat \$20 payment announced at the beginning
- Shown earnings based on Piece Rate
- At the end of the round subjects learn

1. Error

2. Earnings

- But made clear that they receive a flat amount at the end regardless of errors or “per round earnings”

Salary with Win-Loss

- Rounds 1 - 20
- Flat \$20 payment announced at the beginning
- Shown earnings based on Piece Rate
- At the end of the round subjects learn
- **Error**
- **Earnings**
- **Win or Lose**
- But made clear that they receive a flat amount at the end regardless of errors or “per round earnings”

Questions

1. Is winning/losing important in pay for performance schemes?

- Piece rate vs. Win/Lose
- Incentives the same, information different

2. Are payoffs important when paying for performance?

- Win/Lose vs. Tournament
- Information same, incentives different

Questions

3. Is information in tournaments important?

- Tournament vs. Tournament No Info
- Incentives the same, but info different

4. Extrinsic versus intrinsic motivation

- Compare piece rate with salary

5. Is winning/losing important when pay is independent of performance?

- Compare Salary vs. Salary Win-Lose

Questions

- Collect demographic information along with gender
- Prior to start of game, we measure
 - 1. *Trait Anxiety***
- Following game, we measure
 - 1. *Motivation***
 - 2. *Effort***
 - 3. *Competence***
 - 4. *Interest***

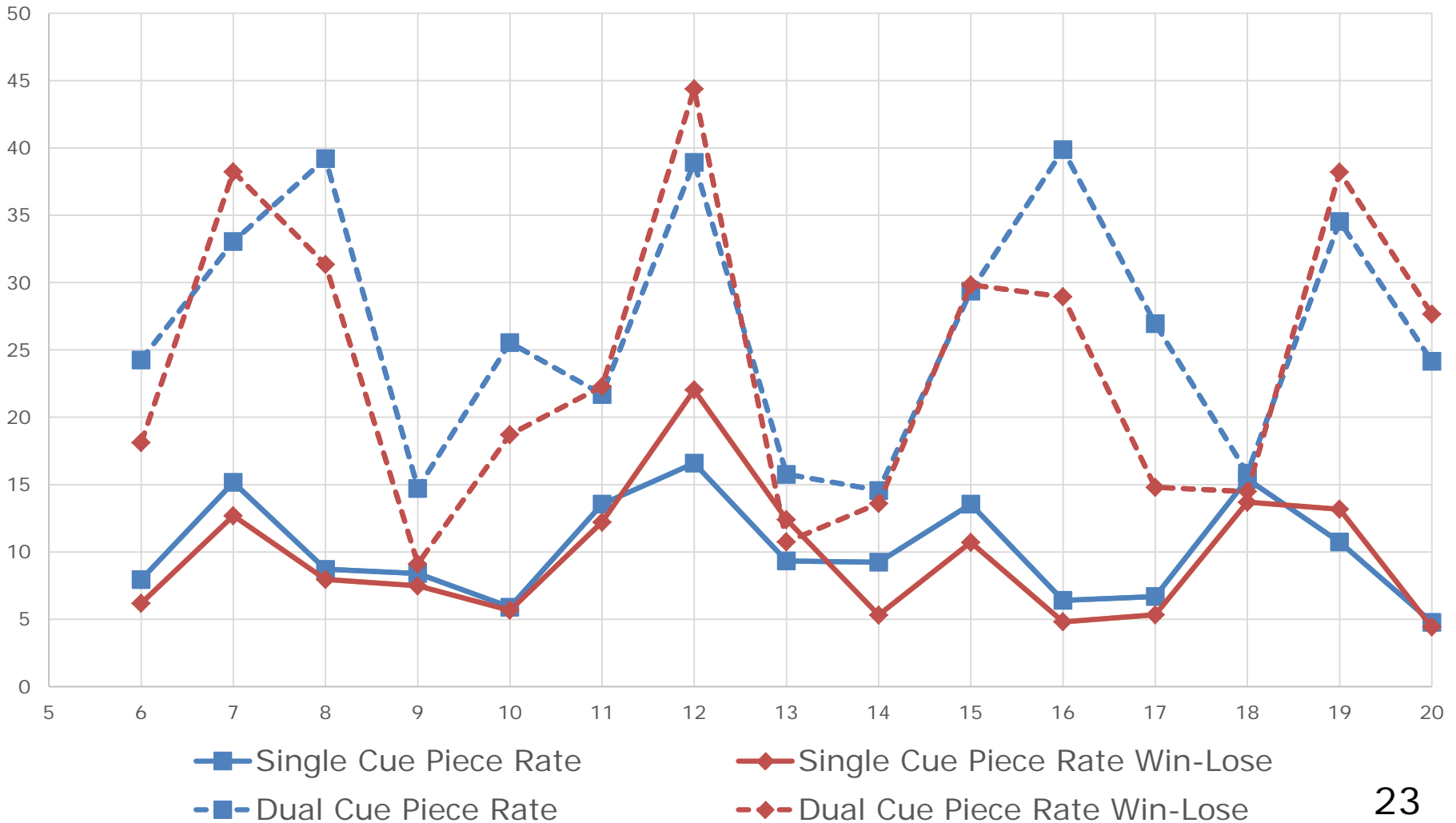
Experimental design

- Two separate experiments with 376 subjects
- *Experiment #1 with 176 subjects*
- **Here both cue values change from one round to the next**
- *Experiment #2 with 200 subjects*
- Here Cue A ***fixed at 150***; only Cue B changes

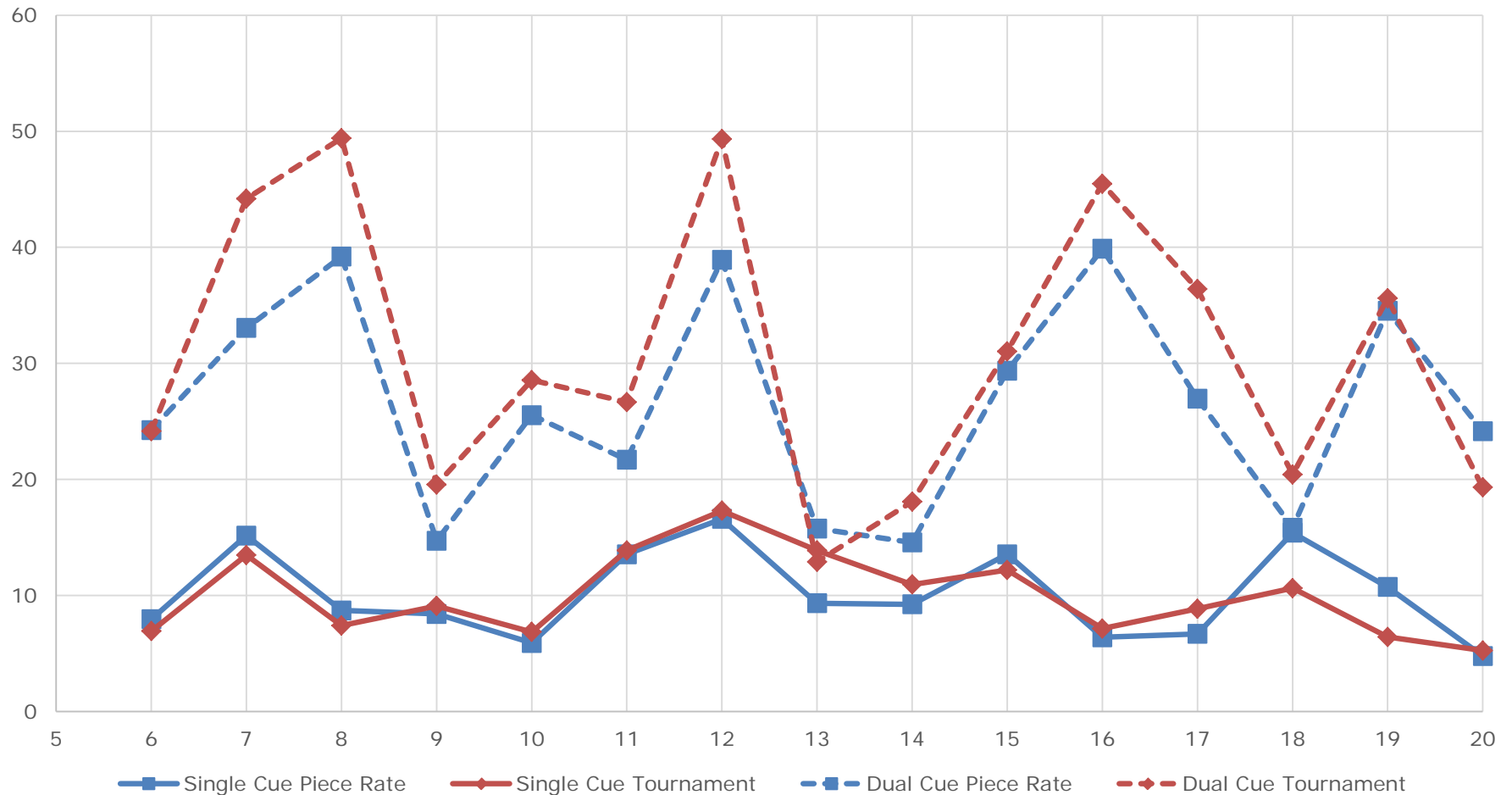
Overview of Results

	<i>Single Cue</i>		<i>Dual Cue</i>		<i>Overall</i>
	n	Average Errors	n	Average Errors	Average Errors
<i>Piece Rate</i>	42	10.2	39	26.6	18.1
<i>Win-Loss</i>	42	9.6	35	24.0	16.2
<i>Tournament</i>	40	10.0	38	30.7	20.1
<i>Salary</i>	42	9.0	34	25.1	16.2
<i>Salary Win-Loss</i>	34	10.2	30	31.4	20.2

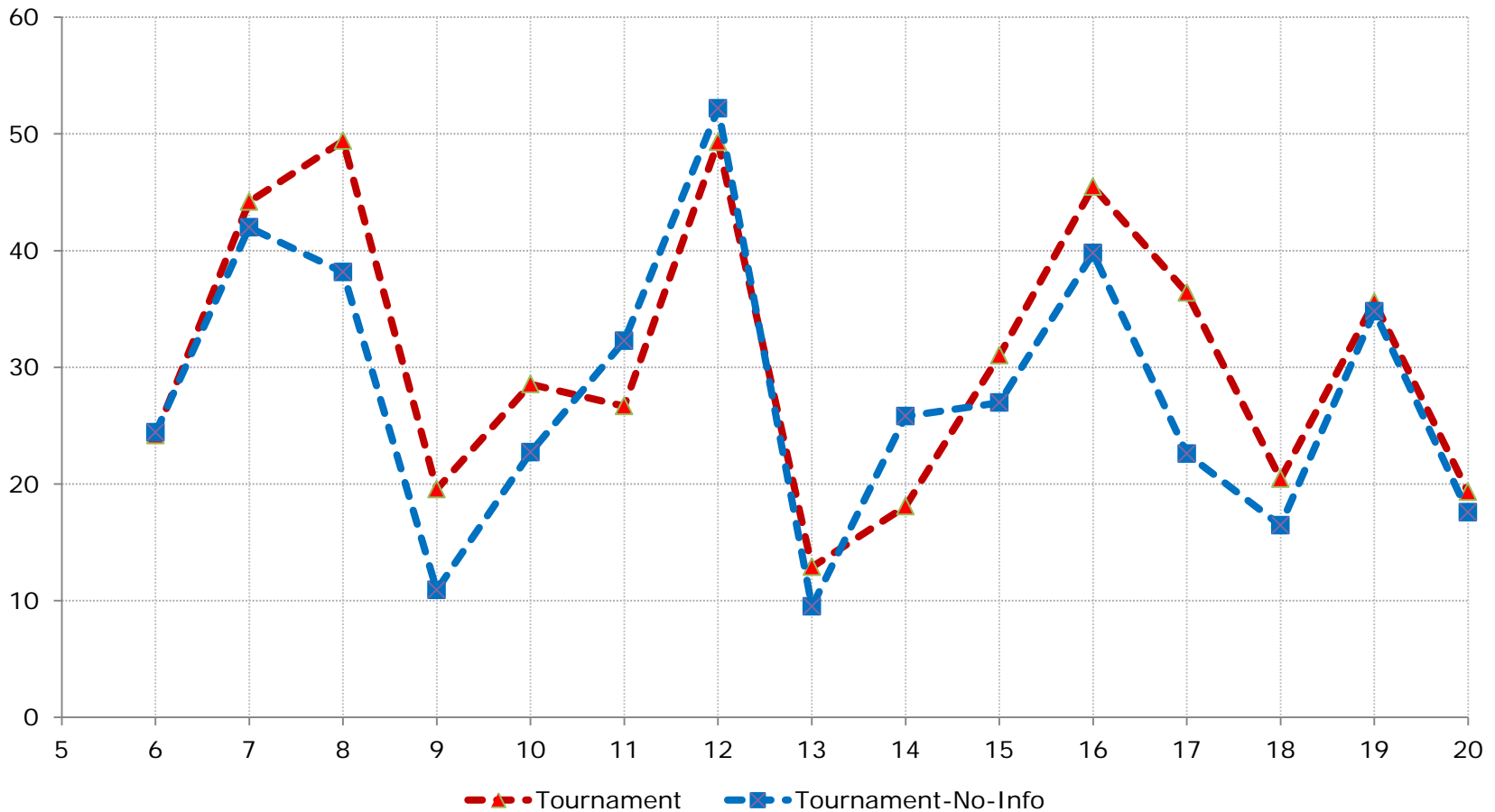
Piece Rate vs Piece-Rate Win-Lose



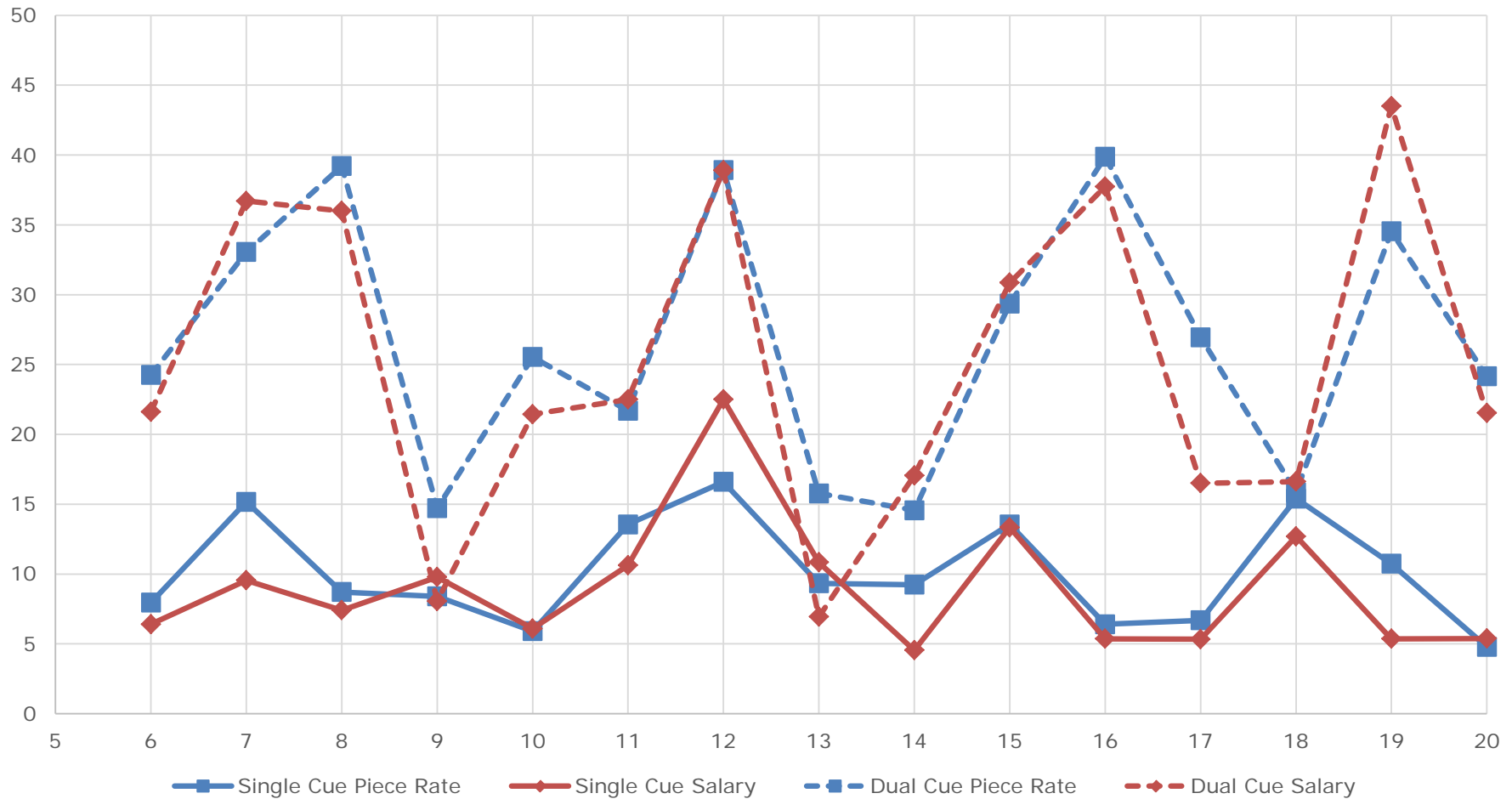
Piece-Rate Win-Lose vs Tournament



Dual Cue Tournament Vs Tournament No Information



Piece Rate vs Salary



Salary vs Salary-Win-Lose



Dependent variable: Absolute forecast error
(All Data)

	Model 1	Model 2	Model 3	Model 4
Piece Rate Win-Lose	-1.84 (2.10)	-1.79 (2.03)	-3.92* (2.23)	-5.49* (2.99)
Tournament	2.04 (2.66)	1.15 (2.68)	0.10 (2.90)	3.14 (3.16)
Salary	-1.80 (2.09)	-4.21 (2.78)	-6.00** (2.91)	-7.34** (3.00)
Salary Win-Lose	2.13 (2.62)	-0.29 (3.20)	-1.55 (3.46)	-2.84 (3.30)
Cuespread	0.08*** (0.00)	0.08*** (0.01)	0.08*** (0.01)	0.08*** (0.01)
Lagged Earnings		-2.94 * (1.60)	-2.50 (1.64)	-2.63 (1.65)
Trait Anxiety			0.10 (0.11)	0.10 (0.11)
Female			6.46*** (1.35)	6.45*** (1.34)
Round	0.17 *** (0.06)	0.17 *** (0.06)	0.17 ** (0.07)	0.15 (0.14)
Constant	6.39 *** (1.91)	8.48 *** (2.66)	2.01 (4.34)	2.27 (4.61)
With treatment-round interactions	No	No	No	Yes
Observations	5640	5640	5130	5130
Participants	376	376	342	342
R ²	0.082	0.090	0.110	0.110

p-values for Wald χ^2 test on treatment dummy coefficients

	Model 1	Model 2	Model 3	Model 4
P(PRWL = 0)	0.38	0.379	0.079	0.067
P(PRWL = T)	0.093	0.184	0.076	0.008
P(PRWL = S)	0.977	0.252	0.310	0.552
P (S = 0)	0.391	0.13	0.04	0.015
P (S = SWL)	0.082	0.082	0.06	0.09

Dependent Variable: Absolute Forecast error
(Dual cue)

	Model 1	Model 2	Model 3	Model 4
Piece Rate Win-Lose	-2.53 (3.43)	-2.43 (3.28)	-4.26 (3.35)	-6.51 (4.82)
Tournament	4.17 (4.41)	3.00 (4.35)	1.68 (4.57)	6.86 (4.79)
Salary	-1.50 (3.40)	-5.27 (4.40)	-7.28 (4.54)	-10.22 ** (4.95)
Salary Win-Lose	4.87 (4.32)	1.10 (5.14)	2.07 (5.37)	-4.42 (5.03)
Cuespread	0.11 *** (0.01)	0.11 *** (0.01)	0.12 *** (0.01)	0.12 *** (0.01)
Lagged Earnings		-5.06 * (2.65)	-3.80 (2.57)	-3.95 (2.61)
Trait Anxiety			0.07 (0.17)	0.07 (0.17)
Female			8.69 *** (2.14)	8.68 *** (2.14)
Round	0.52 *** (0.11)	0.52 *** (0.11)	0.54 *** (0.12)	0.47 * (0.24)
Constant	3.71 (3.30)	7.43 * (4.39)	-0.85 (6.85)	0.16 (7.26)
With treatment-round interactions	No	No	No	Yes
Observations	2640	2640	2430	2430
Participants	176	176	162	162
R ²	0.107	0.110	0.137	0.138
p(PRWL = T)	0.069	0.119	0.092	0.013
p(S = 0)	0.660	0.231	0.109	0.039
p(S = SWL)	0.073	0.073	0.017	0.249

Dependent Variable: Absolute Forecast error (Single cue)

Dep Var: Forecast Error	Single Cue	Single Cue	Single Cue	Single Cue
Piece Rate Win-Lose	-0.56 (1.49)	-0.55 (1.48)	-1.32 (1.71)	-2.88 (3.31)
Tournament	-0.15 (1.66)	-0.56 (1.64)	-0.85 (1.95)	-0.15 (3.25)
Salary	-1.15 (1.35)	-2.16 (1.71)	-3.29* (1.88)	-3.84 (3.08)
Salary Win-Lose	0.06 (1.47)	-0.95 (1.81)	-2.29 (1.95)	0.47 (3.67)
Cuespread	0.02 *** (0.00)	0.02 *** (0.00)	0.02 *** (0.00)	0.02 *** (0.00)
Lagged Earnings		-1.13 (1.14)	-1.41 (1.25)	-1.44 (1.24)
Trait Anxiety			0.03 (0.09)	0.03 (0.09)
Female			1.31 (1.01)	1.30 (1.01)
Round	-0.10 * (0.06)	-0.10 * (0.06)	-0.12 ** (0.06)	-0.11 (0.14)
Constant	8.74 *** (1.46)	9.79 *** (1.78)	9.35 ** (4.19)	9.22 * (4.87)
With treatment-round interactions	No	No	No	Yes
Observations	3000	3000	2700	2700
Participants	200	200	180	180
R ²	0.018	0.020	0.025	0.026
p(S = 0)	0.394	0.206	0.080	0.211

High versus low performers

Combined data

- Why do tournaments not perform well in general?
- It appears that those who are good at the task perform about the same in all treatments
- But those who are not good perform better in Win-Lose and Salary
- What does it mean to say – good or bad at the task?

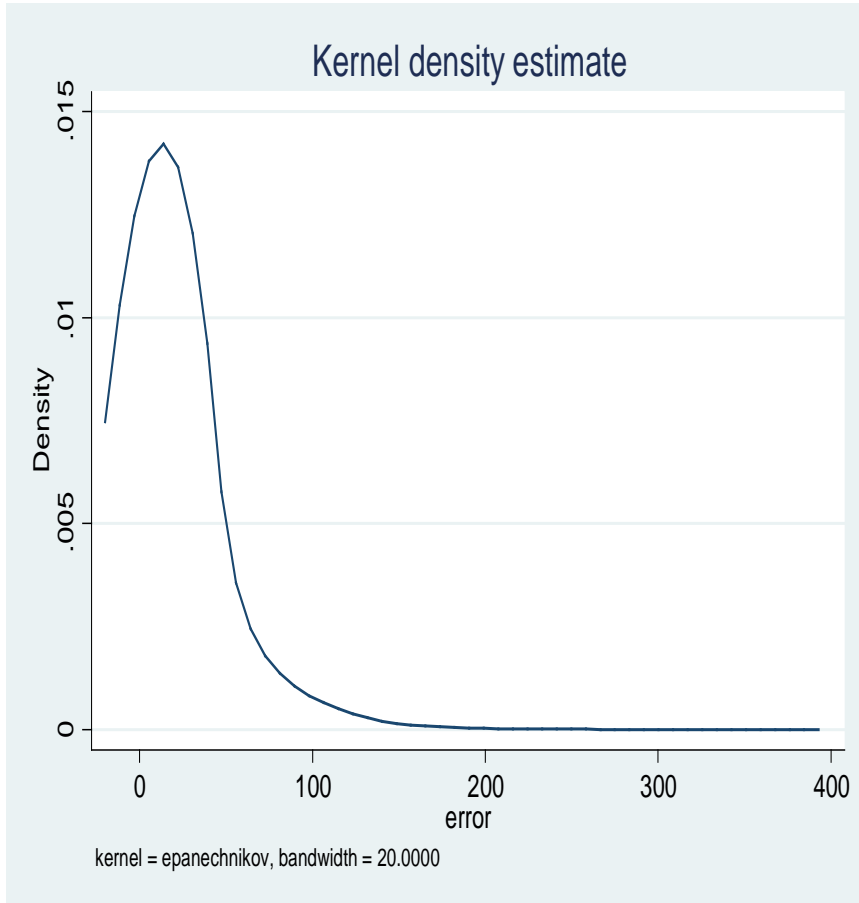
High versus low performers

Combined data

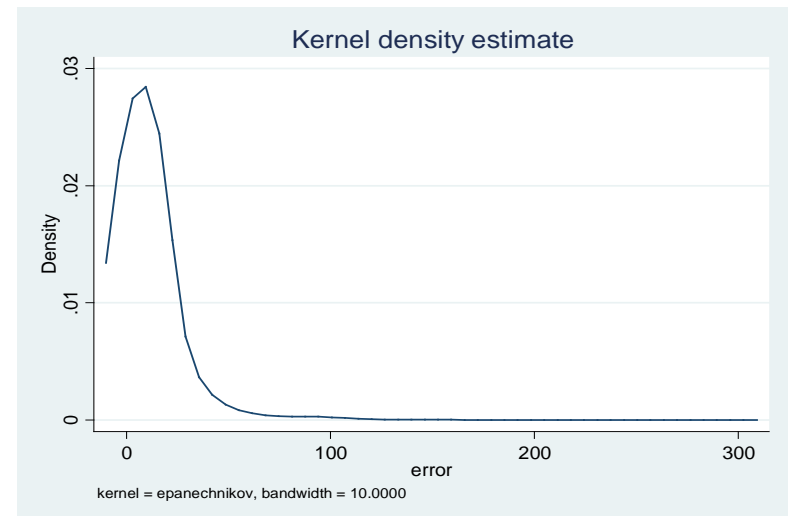
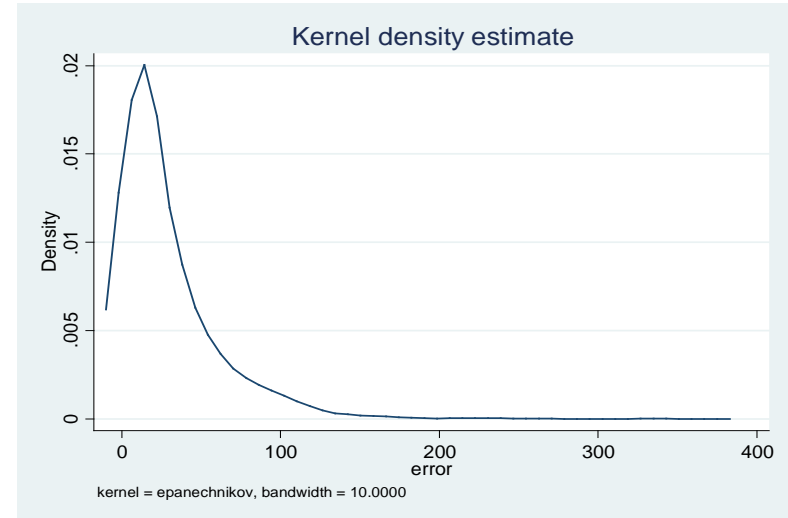
- Because everyone plays under a piece-rate condition during the first five rounds, we can look at performance in those rounds to split people up into “high” and “low” performers
- Split by Mean or Median?
 - *Data positive/right skewed (long right tail)*
- Below we present results for combined data and those above and below the mean (=22.7)
 - *Mean error of more -> LOW performer*
 - *Lower than mean -> HIGH performer*

Kernel Density Plots

DUAL CUE



ALL



SINGLE CUE

Regression of errors for high performers

Dep Var: Forecast Error	High Perf	High Perf	High Perf	High Perf
Piece Rate Win-Lose	2.63*	2.58*	1.51	2.21
	(1.48)	(1.46)	(1.60)	(2.45)
Tournament	2.14	1.60	1.43	3.83
	(1.68)	(1.59)	(1.75)	(2.65)
Salary	0.76	-0.69	-1.67	-1.03
	(1.35)	(1.91)	(2.00)	(2.63)
Salary Win-Lose	-0.17	-1.62	-3.10	-0.73
	(1.26)	(1.85)	(2.00)	(2.99)
Cuespread	0.05 ***	0.05 ***	0.05***	0.05 ***
	(0.00)	(0.01)	(0.01)	(0.01)
Lagged Earnings		-1.62	-1.96	-2.04
		(1.44)	(1.59)	(1.60)
Trait Anxiety			0.08	0.09
			(0.07)	(0.07)
Female			2.75 ***	2.75 **
			(1.07)	(1.07)
Round	-0.03	-0.03	-0.06	0.03
	(0.05)	(0.05)	(0.05)	(0.09)
Constant	4.61 ***	5.94 ***	2.52	1.41
	(1.13)	(1.71)	(3.37)	(3.63)
With treatment-round interactions	No	No	No	Yes
Observations	3240	3240	2940	2940
Participants	216	216	196	196
R ²	0.079	0.082	0.098	0.099
p(PRWL = 0)	0.076	0.077	0.347	0.367
p(PRWL = T)	0.787	0.559	0.963	0.539
p(PRWL = SWL)	0.044	0.023	0.015	0.320
p(S = 0)	0.572	0.716	0.404	0.695
p(S = SWL)	0.456	0.459	0.193	0.898

Regression of errors for low performers

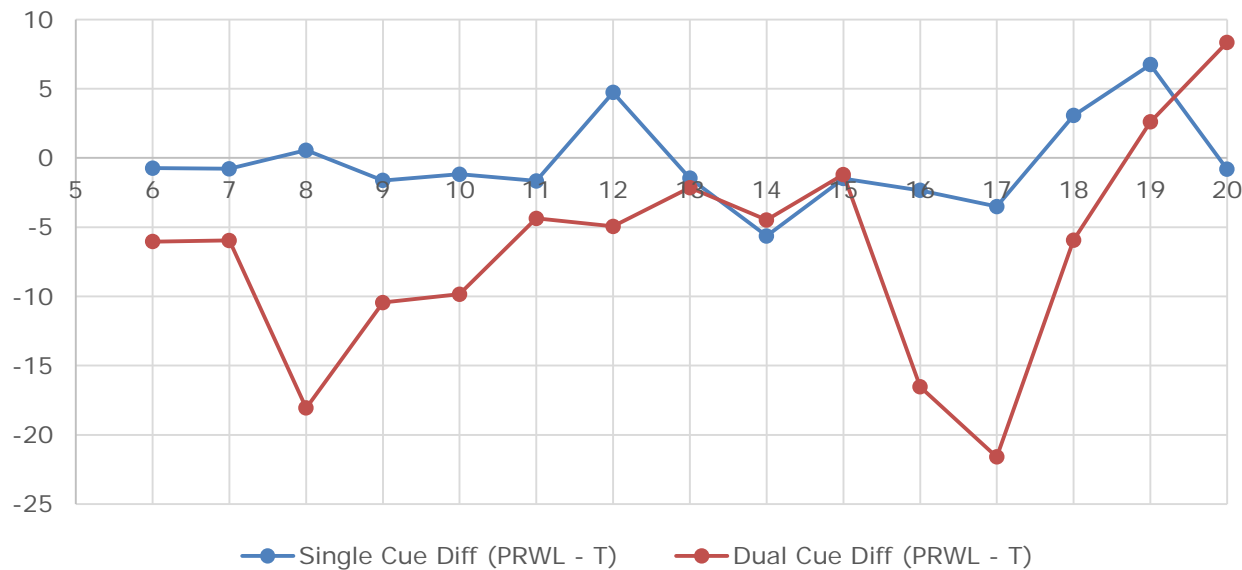
Dep Var: Forecast Error	Low Perf	Low Perf	Low Perf	Low Perf
Piece Rate Win-Lose	-4.54 (3.77)	-4.42 (3.66)	-6.87 * (3.91)	-13.65 ** (6.76)
Tournament	3.32 (4.81)	2.66 (4.90)	0.66 (5.11)	4.21 (5.55)
Salary	-4.26 (3.55)	-5.99 (4.70)	-8.87 * (5.11)	-13.11 ** (5.47)
Salary Win-Lose	0.63 (4.19)	-1.11 (5.20)	-0.69 (5.42)	-5.48 (5.18)
Cuespread	0.11 *** (0.01)	0.11 *** (0.01)	0.11 *** (0.01)	0.11 *** (0.01)
Lagged Earnings		-2.39 (2.92)	-1.38 (2.85)	-1.41 (2.88)
Trait Anxiety			0.04 (0.16)	0.04 (0.16)
Female			6.51 *** (2.51)	6.50 *** (2.51)
Round	0.45 *** (0.13)	0.46 *** (0.13)	0.49 *** (0.14)	0.32 (0.29)
Constant	8.23 ** (3.53)	9.74 ** (4.72)	3.97 (6.88)	6.17 (7.37)
With treatment-round interactions	No	No	No	Yes
Observations	2400	2400	2190	2190
Participants	160	160	146	146
R ²	0.091	0.095	0.106	0.107
p(PRWL = 0)	0.229	0.226	0.079	0.044
p(PRWL = T)	0.066	0.091	0.081	0.016
p(S = 0)	0.230	0.203	0.082	0.017
p(S = SWL)	0.142	0.142	0.028	0.127

Improvements in performance according to task difficulty

- Okay so tournaments do not do well overall
- But do tournaments perform relatively better when the task is easier?
- We can compare improvements in performance across the different tasks
- Many ways of doing this: we look at pairs of treatments and the differences in errors

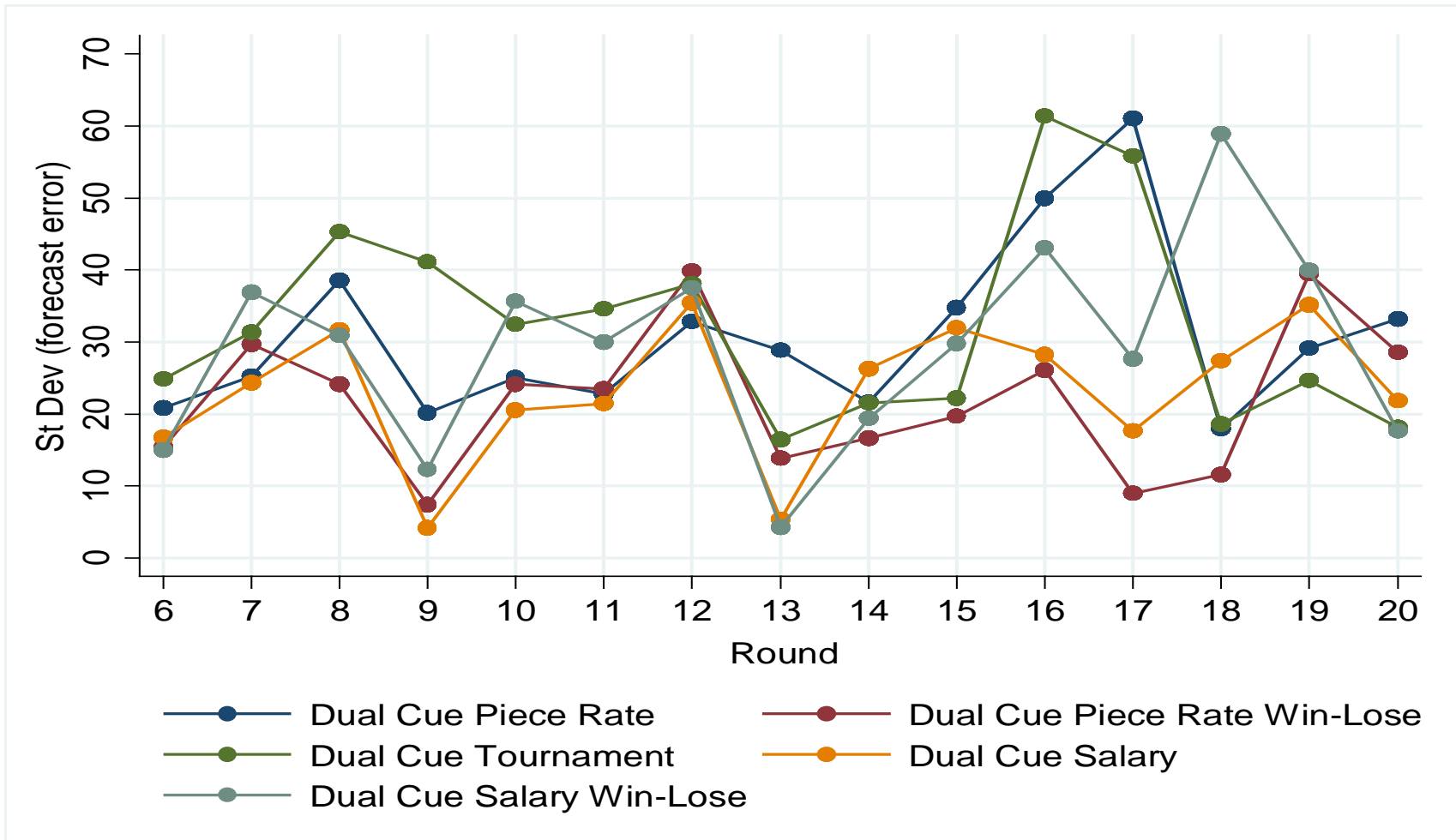
Piece Rate Win-Lose vs Tournament across task difficulty

Piece Rate Win-Lose errors - Tournament errors
Treatment Round Average Errors by Task

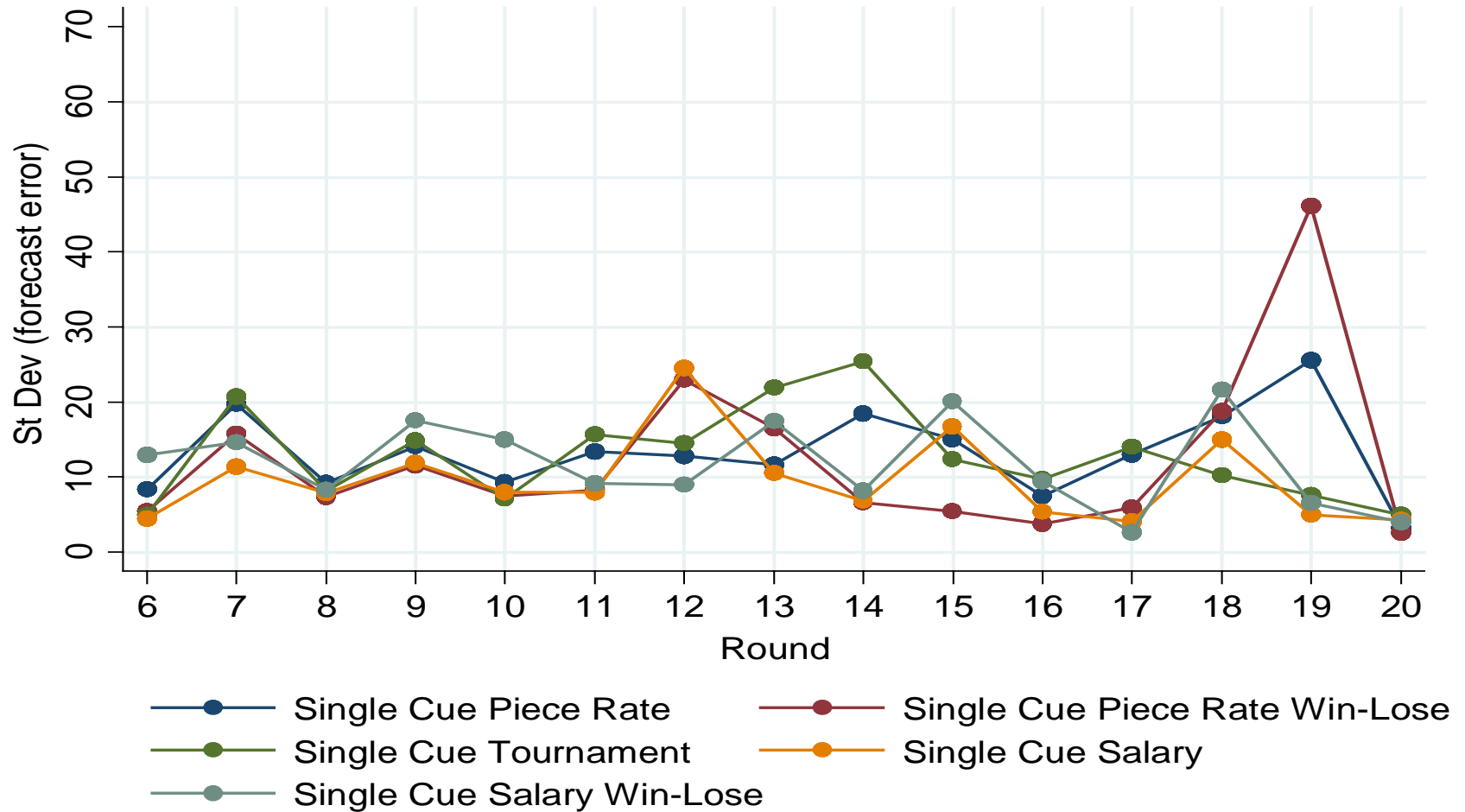


	Single Cue	Dual Cue	Ranksum
PRWL - T	-0.412 (3.135)	-6.707 (7.791)	z = 3.007 p = 0.0026

Learning over time?



Learning over time?



Dependent variable: Absolute forecast error
All Data – Partial Results for interaction terms

	Model 1 Rounds 5 - 20	Model 2 Rounds 10 - 20	Model 3 Rds 10–20 HIGH Perf	Model 4 Rds 10 – 20 LOW Perf	
Round	0.154 (0.144)	0.466** (0.22)	0.036 (0.189)	0.627 (0.417)	
Win-lose_round	0.121 (0.21)	-0.041 (0.388)	-0.239 (0.281)	0.441 (1.016)	
Tournament_round	-0.236 (0.188)	-0.551** (0.279)	-0.541*** (0.227)	-0.611 (0.544)	
Salary_round	0.095 (0.189)	-0.019 (0.353)	-0.42 (0.293)	0.568 (0.716)	
Salary Win-Lose_round	0.091 (0.222)	0.23 (0.343)	-0.174 (0.248)	0.437 (0.632)	
Constant	2.272 (4.61)	-1.01 (5.73)	5.075 (4.344)	0.444 (9.578)	
Observations	5130	3420	1960	1460	
Participants	342	342	196	146	
R ²	0.08	0.084	0.069	0.10	41

Accuracy of forecasts

Dep Var: Forecasts	Piece Rate	Win Lose	Tournament	Salary	Salary win-Lose
Cue A	0.34*** (0.02)	0.32*** (0.01)	0.30*** (0.02)	0.33*** (0.02)	0.36*** (0.02)
Cue B	0.63*** (0.02)	0.65*** (0.01)	0.62*** (0.02)	0.64*** (0.01)	0.61*** (0.02)
Constant	17.53*** (4.51)	15.13*** (1.96)	25.80*** (5.28)	17.53*** (2.00)	17.81*** (3.57)
Observations	1215	1155	1170	1140	960
Participants	81	77	78	76	64
R ²	0.873	0.906	0.846	0.910	0.860
Wald Chi ²	2018.92	11242.88	1465.87	8314.48	2321.44
p > chi ²	0.000	0.000	0.000	0.000	0.000
p(cue A = 0.3)	0.023	0.148	0.835	0.047	0.005
p(cue B = 0.7)	0.000	0.000	0.000	0.000	0.000
p(cons = 10)	0.095	0.009	0.003	0.000	0.029

High Performers

Dep Var: Forecasts	Piece Rate	Win Lose	Tournament	Salary	Salary win-Lose
Cue A	0.32 *** (0.02)	0.33 *** (0.01)	0.30 *** (0.03)	0.27 *** (0.01)	
Cue B	0.68 *** (0.01)	0.67 *** (0.01)	0.68 *** (0.02)	0.70 *** (0.01)	0.73 *** (0.01)
Constant	10.76 *** (1.97)	10.91 *** (2.36)	12.14 ** (5.05)	14.77 *** (2.84)	47.77 *** (1.90)
Observations	675	780	690	660	435
Participants	45	52	46	44	29
R ²	0.958	0.935	0.931	0.954	0.952
Wald Chi ²	7793.52	10004.43	2218.1	6774.69	5558.67
p > chi ²	0.000	0.000	0.000	0.000	0.0000
p(cue A = 0.3)	0.309	0.010	0.922	0.032	
p(cue B = 0.7)	0.153	0.019	0.232	0.835	0.007
p(cons = 10)	0.701	0.699	0.671	0.093	
p(cons = 55)					0.000

Low Performers

Dep Var: Forecasts	Piece Rate	Win Lose	Tournament	Salary	Salary win-Lose
Cue A	0.35 *** (0.02)	0.32 *** (0.03)	0.33 *** (0.03)	0.38 *** (0.02)	0.38 *** (0.02)
Cue B	0.59 *** (0.02)	0.63 *** (0.02)	0.55 *** (0.03)	0.58 *** (0.02)	0.56 *** (0.02)
Constant	22.45 *** (7.25)	19.03 *** (3.50)	33.44 *** (9.40)	19.83 *** (2.74)	21.46 *** (3.95)
Observations	540	375	480	480	525
Participants	36	25	32	32	35
R ²	0.813	0.863	0.778	0.881	0.837
Wald Chi ²	750.86	5967.71	517.41	5117.51	1930.74
p > chi ²	0.000	0.000	0.000	0.000	0.000
p(cue A = 0.3)	0.019	0.447	0.338	0.000	0.000
p(cue B = 0.7)	0.000	0.000	0.000	0.000	0.000
p(cons = 10)	0.086	0.010	0.013	0.000	0.004

Why does Salary Win-Lose do worse?

Data for rounds 6 - 20

	Salary Dual Cue	Salary Win- Lose Dual Cue	Salary Single Cue	Salary Win- Lose Single Cue
Cuespread	0.123*** (0.016)	0.154*** (0.021)	0.010*** (0.004)	0.025*** (0.007)
Round	0.692*** (0.234)	0.998*** (0.316)	-0.071 (0.0756)	-0.275** (0.128)
Trait Anxiety	NS	NS	0.158* (0.088)	0.361*** (0.092)
Female	NS	NS	NS	NS
Lagged Earnings	-10.95 (7.068)	-23.001** (9.168)	-2.365 (4.982)	-13.23* (7.51)
Constant	13.131 (8.274)	8.468 (17.668)	2.364 (7.0661)	8.105 (8.813)
Observations	465	405	600	480
Participants	31	27	40	32
R ²	0.196	0.175	0.04	0.118

Concluding thoughts

- Across our two experiments by and large the treatments that perform better are “salary” and “win/lose” with salary doing better overall
- Part of the reason why tournaments do not perform well is because “low” performers fare especially poorly in this treatment
- Providing win/loss information in pay for performance schemes improves performance

Concluding thoughts

- However, providing win/loss information when payment is independent of performance actually makes things worse
- Tournament shows greater improvement in performance between dual and single cue tasks
- *This suggests that when a task is intellectually challenging tournaments may not do well but they might perform better if the task is more menial (?)*

Concluding thoughts

- Limited evidence of learning overall across different treatments
- But there is some evidence of learning in the tournament treatment particularly in the later rounds
- And this learning seems most pronounced for the “high” performers

Concluding thoughts

- Why does the salary treatment do well?
- Merlo and Schotter (1999)
 - ***Learn-while-you-earn*** and ***Learn-before-your-earn*** (LBYE)
 - *find that subjects do much better in the LBYE treatment where every single decision does not count for payment*
- *Why does Salary Win-Lose perform worse?*
 - *More myopic focus on per round earnings and winning/losing even when those do not matter?*
 - *Subjects feel “more controlled” when winning/losing information provided?*

Concluding thoughts

What is the aim?

- ***Minimize aggregate errors***
 - *If pay independent of performance, then **Salary***
 - *If pay dependent on performance, then **Win-Lose***
- ***Learning over time***
 - ***Tournaments***
 - *especially for “highly skilled” workers*