Performing Best when it Matters Most: Evidence from professional tennis

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University of London

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- In particular, part of this literature tries to understand how economic agents react to different forms of pressure
- Note that a perfectly **rational** agent's performance should be unaffected by changes in **pressure** or in the **stakes** (**importance** of the situation)
- This literature acknowledges the fact that these changes may affect an agent's ability to play optimally

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Why?

This heterogeneity should be taken into account when designing contracts and providing incentives

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Fairly recent literature

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Findings:

1. There is heterogeneity in agent's reactions to changes in the importance of the situation. **What changes is the importance of the points of a tennis match**
2. This heterogeneity has a significant impact on an agent's career. **What we measure is the impact of the ability to perform best when it matters the most on the ratings/rankings of elite tennis players**

Real-life scenarios

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Political campaigning

- U.S. presidential candidates campaign for years
- Many decisions to make, performances to give, along the way
- Some (nationally televised debates) have far more impact than others; some states are hugely influential
- Choking in an important performance/debate may mean losing the election

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⇒ High-quality information the context and on players' performance

Outline

Structure of a tennis match

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Points are not all equally important

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$s_2 \backslash s_1$	0	15	30	40
0	0	0	0	0
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30	0	0	0	0
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(Average serving percentage in our data set: $p_1 = 0.63$)

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Without using GiS and SiM!! **(Recall:** $PiM = PiG \cdot GiS \cdot SiM$**)**

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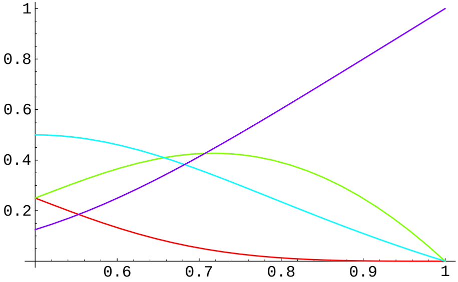

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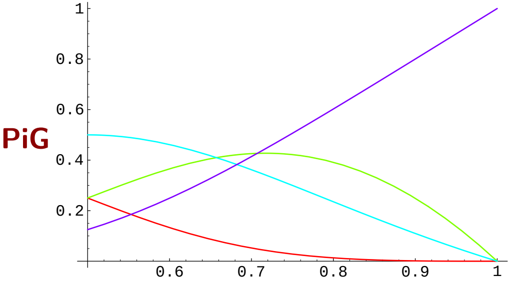

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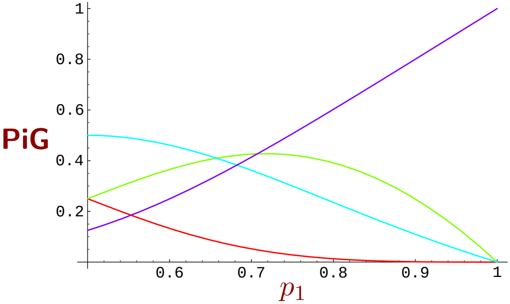

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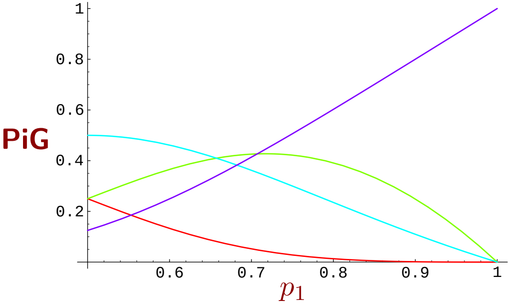

Figure: Red: 30-0, Turquoise: deuce, Green: 0-30, Purple: 0-40

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won \ lost	Federer-S	Federer-R	Nadal-S	Nadal-R	Roddick-S	Roddick-R
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Computing p_1 and p_2

- Main analysis: US Open data set (For each match, we need p_1 and p_2 to compute PiM variable)
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Defining PiM variable

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- We finally have all the ingredients to define PiM

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- Results robust to variations in the way to compute p_1 and p_2

The importance of a point varies substantially

1995 U.S. Open Finals: Agassi vs. Sampras

Point I

Point II

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- The winner earns $\$575,000$, the loser earns $\$287,500$

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1995 U.S. Open Finals: Agassi vs. Sampras

- The winner earns $\$575,000$, the loser earns $\$287,500$
- Compute from the match $p_A = .65$ and $p_S = .72$

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- $PiM = 8 \cdot 10^{-4}$
- $\$380$ in current dollars is at stake

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Point II

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- $PiM = .13$
- $\$64000$ in current dollars is at stake

Wrapping up

The importance variable: PiM

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- Depends on the players' relative abilities

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The importance variable: PiM

- Depends on the players' relative abilities
- Closer matches have more points with higher importance
- As players' abilities become different, almost all points converge to zero importance

Main Objectives

The goals

The data set

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- We want to identify, for each player, a serving ability, a returning ability, and a **critical ability**

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- Point by point data from 12 U.S. Open tournaments, 1994-2006
- Focus on men singles matches
- 1009 matches; 223140 points

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- We **can** say: “Federer is better than Nadal”
- We **can** say: “Roddick is worse than the average player in the data set”
- We **cannot** say: Federer is very good

The more, the better??

Pooling

Final data set

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Having more data may not be beneficial for the analysis

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- We pool all US-Open tournaments together (connectedness)

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- We take the maximal subset of our data set in which all the remaining players play, at least, 5 matches

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- We take the maximal subset of our data set in which all the remaining players play, at least, 5 matches
- We end up with 94 players and about 110000 points

Towards our first regression

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Computing importance of points

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- Compute **PiG**, **GiS**, **SiM** for each score.

Towards our first regression

Computing importance of points

- For each match, we already have p_1 and p_2
- Compute **PiG**, **GiS**, **SiM** for each score.
- Use them to compute **PiM** for each score, which is what we focus on.

Towards our first regression

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What should determine the outcome of a point?

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- Returner dummy variables
- Critical ability slope dummy variables

Regression specification

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- Suppose we have a point at score θ.

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$$P(\text{Nadal wins} \mid \theta) = \Phi\Big(\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad \Big)$$

Regression specification

- Suppose we have a point at score θ.
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$$P(\text{Nadal wins} \,|\, \theta) = \Phi\Big(\qquad \beta_N^S \qquad \Big)$$

Regression specification

- Suppose we have a point at score θ.
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$$P(\text{Nadal wins} \mid \theta) = \Phi\left(\beta_N^S + \beta_N^C \cdot PiM(\theta) \right)$$

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We want to identify the β parameters:

$$P\big(\text{server wins point } p \,|\, \theta\big) = \Phi\big(\beta_0 + \textstyle\sum_{i=1}^n (\beta_i^S \delta_i^S + \beta_i^R \delta_i^R + \beta_i^C \delta_i^C \cdot PiM)\big)$$

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Discrete Response Model (Logit regression with two outcomes)

Dependent variable y:

Regression specification

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Discrete Response Model (Logit regression with two outcomes)

Dependent variable y:

- $y = 1$ if "server wins point"

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- Nadal (N) serves
- Federer (F) returns

$$P(\text{Nadal wins} \,|\, \theta) = \Phi\big(\beta_0 + \beta_N^S + \beta_N^C \cdot PiM(\theta) - \beta_F^R - \beta_F^C \cdot PiM(\theta)\big)$$

We want to identify the β parameters:

$$P\big(\text{server wins point } p \,|\, \theta\big) = \Phi\big(\beta_0 + \textstyle\sum_{i=1}^{n} (\beta_i^S \delta_i^S + \beta_i^R \delta_i^R + \beta_i^C \delta_i^C \cdot PiM)\big)$$

Discrete Response Model (Logit regression with two outcomes)

Dependent variable y:

- $y = 1$ if “server wins point”
- $y = 0$ otherwise

Regression specification

- Suppose we have a point at score θ.
- Nadal (N) serves
- Federer (F) returns

$$P(\text{Nadal wins} \,|\, \theta) = \Phi\big(\beta_0 + \beta_N^S + \beta_N^C \cdot PiM(\theta) - \beta_F^R - \beta_F^C \cdot PiM(\theta)\big)$$

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Demeaning PiM

$$P(\text{Nadal wins} \,|\, \theta) = \Phi\left(\beta_0 + \beta_N^S + \beta_N^C \cdot PiM(\theta) - \beta_F^R - \beta_F^C \cdot PiM(\theta)\right)$$

Demeaning PiM

$$P(\text{Nadal wins} \mid \theta) = \Phi\big(\beta_0 + \beta_N^S + \beta_N^C \cdot PiM(\theta) - \beta_F^R - \beta_F^C \cdot PiM(\theta)\big)$$

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- PiM is defined as a positive variable
- Having a positive critical ability (β_N^C) implies winning more points in general

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- PiM is defined as a positive variable
- Having a positive critical ability (β_N^C) implies winning more points in general We do not want this!!

Demeaning PiM

$$P(\text{Nadal wins} \mid \theta) = \Phi\big(\beta_0 + \beta_N^S + \beta_N^C \cdot PiM(\theta) - \beta_F^R - \beta_F^C \cdot PiM(\theta)\big)$$

- PiM is defined as a positive variable
- Having a positive critical ability (β_N^C) implies winning more points in general
- We want critical ability to imply winning more important points and less unimportant points

Demeaning PiM

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- We want critical ability to imply winning more important points and less unimportant points
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Demeaning PiM

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- PiM is defined as a positive variable
- Having a positive critical ability (β_N^C) implies winning more points in general
- We want critical ability to imply winning more important points and less unimportant points
- We have to demean PiM

$$\text{PiM}_{\text{Demeaned}}(\theta) = \text{PiM}(\theta) \text{ - mean}(\text{PiM}(\theta))$$

Demeaning PiM

$$P(\text{Nadal wins} \mid \theta) = \Phi\big(\beta_0 + \beta_N^S + \beta_N^C \cdot PiM(\theta) - \beta_F^R - \beta_F^C \cdot PiM(\theta)\big)$$

- PiM is defined as a positive variable
- Having a positive critical ability (β_N^C) implies winning more points in general
- We want critical ability to imply winning more important points and less unimportant points
- We have to demean PiM at the match level

$$\text{PiM}_{\text{Demeaned}}(\theta) = \text{PiM}(\theta) \text{ - mean}(\text{PiM}(\theta))$$

Demeaning PiM

$$P(\text{Nadal wins} \mid \theta) = \Phi\big(\beta_0 + \beta_N^S + \beta_N^C \cdot PiM(\theta) - \beta_F^R - \beta_F^C \cdot PiM(\theta)\big)$$

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- We want critical ability to imply winning more important points and less unimportant points
- We have to demean PiM at the match level

$$\text{PiM}_{\text{Demeaned}}(\theta) = \text{PiM}(\theta) \text{ - mean}(\text{PiM}(\theta))$$

After the demeaning, the critical ability does not affect the average probability of winning a point

Results of the first regression

$$\boxed{y = \beta_0 + \sum_{i=1}^{n}(\beta_i^S \delta_i^S + \beta_i^R \delta_i^R + \beta_i^C \delta_i^C \cdot PiM)}$$

PiM represents demeaned PiM
94*3=282 variables. We do not run tests at the individual level

Results of the first regression

$$\boxed{y = \beta_0 + \sum_{i=1}^{n} (\beta_i^S \delta_i^S + \beta_i^R \delta_i^R + \beta_i^C \delta_i^C \cdot PiM)}$$

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94*3=282 variables. We do not run tests at the individual level

Joint significance tests

	p-value	p-value	p-value	p-value
Serving **Returning** **Critical (PiM)**				

Results of the first regression

$$\boxed{y = \beta_0 + \sum_{i=1}^{n} (\beta_i^S \delta_i^S + \beta_i^R \delta_i^R + \beta_i^C \delta_i^C \cdot PiM)}$$

PiM represents demeaned PiM

94*3=282 variables. We do not run tests at the individual level

Joint significance tests

	p-value	p-value	p-value	p-value
Serving	0^{***}			
Returning	0^{***}			
Critical (PiM)	0.06^{*}			

Results of the first regression

$$\boxed{y = \beta_0 + \sum_{i=1}^{n}(\beta_i^S \delta_i^S + \beta_i^R \delta_i^R + \beta_i^C \delta_i^C \cdot PiM)}$$

PiM represents demeaned PiM

94*3=282 variables. We do not run tests at the individual level

Joint significance tests

	p-value	p-value	p-value	p-value
Serving	0^{***}	0^{***}		
Returning	0^{***}	0^{***}		
Critical (PiM)	0.06^{*}			
Critical (BP)		0.79		

Results of the first regression

$$y = \beta_0 + \sum_{i=1}^{n} (\beta_i^S \delta_i^S + \beta_i^R \delta_i^R + \beta_i^C \delta_i^C \cdot PiM)$$

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Joint significance tests

	p-value	p-value	p-value	p-value
Serving	0^{***}	0^{***}	0^{***}	
Returning	0^{***}	0^{***}	0^{***}	
Critical (PiM)	0.06^{*}			
Critical (BP)		0.79		
Critical (PiM-0.63)			0.38	

Results of the first regression

$$\boxed{y = \beta_0 + \sum_{i=1}^{n} (\beta_i^S \delta_i^S + \beta_i^R \delta_i^R + \beta_i^C \delta_i^C \cdot PiM)}$$

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Critical (BP)		0.79		
Critical (PiM-0.63)			0.38	
Point id (demeaned)				

Results of the first regression

$$\boxed{y = \beta_0 + \sum_{i=1}^{n}(\beta_i^S \delta_i^S + \beta_i^R \delta_i^R + \beta_i^C \delta_i^C \cdot PiM)}$$

PiM represents demeaned PiM

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Joint significance tests

	p-value	p-value	p-value	p-value
Serving	0^{***}	0^{***}	0^{***}	0^{***}
Returning	0^{***}	0^{***}	0^{***}	0^{***}
Critical (PiM)	0.06^{*}			0.01^{***}
Critical (BP)		0.79		
Critical (PiM-0.63)			0.38	
Point id (demeaned)				0.0002^{***}

Results of the first regression

$$y = \beta_0 + \sum_{i=1}^{n} (\beta_i^S \delta_i^S + \beta_i^R \delta_i^R + \beta_i^C \delta_i^C \cdot PiM)$$

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Joint significance tests

	p-value	p-value	p-value	p-value
Serving	0^{***}	0^{***}	0^{***}	0^{***}
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Critical (PiM)	0.06^{*}			0.01^{***}
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Critical (PiM-0.63)			0.38	
Point id (demeaned)				0.0002^{***}

- There is heterogeneity in serving and returning abilities

Results of the first regression

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Joint significance tests

	p-value	p-value	p-value	p-value
Serving	0^{***}	0^{***}	0^{***}	0^{***}
Returning	0^{***}	0^{***}	0^{***}	0^{***}
Critical (PiM)	0.06^{*}			0.01^{***}
Critical (BP)		0.79		
Critical (PiM-0.63)			0.38	
Point id (demeaned)				0.0002^{***}

- There is heterogeneity in serving and returning abilities
- It seems there is also heterogeneity in critical abilities

Results of the first regression

Top 25	Serving	Point Estimate	Returning	Point Estimate	Critical	Point Estimate	ATP Rating	log(rating)
1	A.RODDICK	0.268	L.HEWITT	-0.457	T.ROBREDO	6.026	P.SAMPRAS	8.109
2	P.SAMPRAS	0.203	R.FEDERER	-0.485	A.CORRETJA	4.491	R.FEDERER	8.077
3	R.KRAJICEK	0.145	K.KUCERA	-0.5	J.FERRERO	2.892	M.STICH	7.856
4	R.FEDERER	0.065	A.AGASSI	-0.519	A.COSTA	2.631	L.HEWITT	7.813
5	M.MIRNYI	0.036	J.BJORKMAN	-0.534	M.ROSSET	1.434	A.AGASSI	7.78
6	M.STICH	0.017	M.YOUZHNY	-0.549	M.ZABALETA	1.43	A.RODDICK	7.779
7	A.AGASSI	0.	N.ESCUDE	-0.558	G.POZZI	1.324	Y.KAFELNIKOV	7.766
8	P.RAFTER	-0.002	Y.KAFELNIKOV	-0.562	R.SCHUETTLER	1.257	G.KUERTEN	7.742
9	G.RUSEDSKI	-0.005	D.NALBANDIAN	-0.574	A.RODDICK	1.043	T.MUSTER	7.702
10	N.ESCUDE	-0.024	G.CORIA	-0.577	G.IVANISEVIC	0.872	J.FERRERO	7.583
11	G.KUERTEN	-0.04	J.BLAKE	-0.582	B.BLACK	0.841	P.RAFTER	7.573
12	L.HEWITT	-0.047	P.KORDA	-0.587	M.WOODFORDE	0.799	R.NADAL	7.523
13	M.LARSSON	-0.047	A.RODDICK	-0.603	B.KARBACHER	0.762	P.KORDA	7.431
14	M.SAFIN	-0.081	G.CANAS	-0.617	P.SAMPRAS	0.655	T.HENMAN	7.407
15	B.BECKER	-0.087	D.HRBATY	-0.634	L.HEWITT	0.637	C.MOYA	7.377
16	T.MARTIN	-0.087	P.RAFTER	-0.638	N.ESCUDE	0.569	D.NALBANDIAN	7.37
17	J.BLAKE	-0.092	V.SPADEA	-0.651	A.MEDVEDEV	0.261	A.CORRETJA	7.293
18	X.MALISSE	-0.101	H.LEE	-0.655	P.RAFTER	0.151	M.SAFIN	7.281
19	W.ARTHURS	-0.104	S.SARGSIAN	-0.664	S.DOSEDEL	0.098	B.BECKER	7.264
20	M.ZABALETA	-0.112	J.COURIER	-0.674	M.SAFIN	0.096	R.KRAJICEK	7.236
21	M.DAMM	-0.121	M.ZABALETA	-0.678	W.ARTHURS	0.009	G.CORIA	7.22
22	J.COURIER	-0.134	T.ENQVIST	-0.68	A.AGASSI	0.	J.COURIER	7.192
23	D.NALBANDIAN	-0.135	A.CLEMENT	-0.683	R.FEDERER	-0.196	C.PIOLINE	7.188
24	R.GINEPRI	-0.135	T.HAAS	-0.685	C.PIOLINE	-0.236	T.ROBREDO	7.168
25	J.FERRERO	-0.139	M.SAFIN	-0.689	T.MARTIN	-0.238	A.MEDVEDEV	7.16

Towards our second regression

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- How much serving, returning, and critical abilities explain of a player's success?

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- We regress on ATP ratings and rankings

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$$\boxed{\textbf{ATP}_{\textbf{rating}} = \alpha_0 + \alpha_1 \cdot \textbf{Serving} + \alpha_2 \cdot \textbf{Returning} + \alpha_3 \cdot \textbf{Critical}}$$

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Actually, log(ratings) and log(rankings)

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$$\textbf{ATP}_{\textbf{rating}} = \alpha_0 + \alpha_1 \cdot \textbf{Serving} + \alpha_2 \cdot \textbf{Returning} + \alpha_3 \cdot \textbf{Critical}$$

$$\textbf{ATP}_{\textbf{ranking}} = \alpha_0 + \alpha_1 \cdot \textbf{Serving} + \alpha_2 \cdot \textbf{Returning} + \alpha_3 \cdot \textbf{Critical}$$

Actually, log(ratings) and log(rankings)

correlations	log(rating)	Serving	Returning	Critical
log(rating)	1	-	-	-
Serving	0.57	1	-	-
Returning	0.39	0.26	1	-
Critical	0.38	0.34	0.20	1

Towards our second regression

$$\boxed{\textbf{ATP}_{\textbf{rating}} = \alpha_0 + \alpha_1 \cdot \textbf{Serving} + \alpha_2 \cdot \textbf{Returning} + \alpha_3 \cdot \textbf{Critical}}$$

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Technical problems

Towards our second regression

$$\boxed{\textbf{ATP}_{\textbf{rating}} = \alpha_0 + \alpha_1 \cdot \textbf{Serving} + \alpha_2 \cdot \textbf{Returning} + \alpha_3 \cdot \textbf{Critical}}$$

Technical problems

- What regression to run? OLS?

Towards our second regression

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Technical problems

- What regression to run? OLS?
- Serving, Returning, and Critical are estimated variables

Towards our second regression

$$\boxed{\textbf{ATP}_{\textbf{rating}} = \alpha_0 + \alpha_1 \cdot \textbf{Serving} + \alpha_2 \cdot \textbf{Returning} + \alpha_3 \cdot \textbf{Critical}}$$

Technical problems

- What regression to run? OLS?
- Serving, Returning, and Critical are estimated variables
- Their errors may be correlated

Towards our second regression

$$\boxed{\textbf{ATP}_{\textbf{rating}} = \alpha_0 + \alpha_1 \cdot \textbf{Serving} + \alpha_2 \cdot \textbf{Returning} + \alpha_3 \cdot \textbf{Critical}}$$

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- What regression to run? OLS?
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What do we do?

Towards our second regression

$$\boxed{\mathbf{ATP}_{\mathbf{rating}} = \alpha_0 + \alpha_1 \cdot \mathbf{Serving} + \alpha_2 \cdot \mathbf{Returning} + \alpha_3 \cdot \mathbf{Critical}}$$

Technical problems

- What regression to run? OLS?
- Serving, Returning, and Critical are estimated variables
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- Standard OLS may lead to wrong confidence intervals

What do we do?

- We run a standard OLS

Towards our second regression

$$\boxed{\textbf{ATP}_{\textbf{rating}} = \alpha_0 + \alpha_1 \cdot \textbf{Serving} + \alpha_2 \cdot \textbf{Returning} + \alpha_3 \cdot \textbf{Critical}}$$

Technical problems

- What regression to run? OLS?
- Serving, Returning, and Critical are estimated variables
- Their errors may be correlated
- Standard OLS may lead to wrong confidence intervals

What do we do?

- We run a standard OLS
- We check robustness of results via GLS and bootstrap

Results of the second regression

	No controls	Some controls	More controls
(Intercept)			
Serving			
Returning			
Critical			

Results of the second regression

	No controls	Some controls	More controls
(Intercept)	7.86^{***}		
	(0.20)		
Serving	1.48^{***}		
	(0.29)		
Returning	0.78^{***}		
	(0.27)		
Critical	0.036^{**}		
	(0.016)		

Results of the second regression

	No controls	Some controls	More controls
(Intercept)	7.86***	7.32***	
	(0.20)	(0.15)	
Serving	1.48***	1.22***	
	(0.29)	(0.29)	
Returning	0.78***	0.77***	
	(0.27)	(0.29)	
Critical	0.036**	0.031**	
	(0.016)	(0.016)	
Endurance (via pointid)		66.85	
		(52.63)	

Results of the second regression

	No controls	Some controls	More controls
(Intercept)	7.86^{***}	7.32^{***}	6.14
	(0.20)	(0.15)	(20)
Serving	1.48^{***}	1.22^{***}	1.23^{***}
	(0.29)	(0.29)	(0.33)
Returning	0.78^{***}	0.77^{***}	0.87^{***}
	(0.27)	(0.29)	(0.33)
Critical	0.036^{**}	0.031^{**}	0.034^{**}
	(0.016)	(0.016)	(0.016)
Endurance (via pointid)		66.85	53.75
		(52.63)	(56.45)
Birth year			0.00056
			(0.001)
Height			0.00065
			(0.0077)
Lefty			0.098
			(0.12)
GDP			-0.0000003
			(0.0000002)
Bollettieri			0.15
			(0.13)
USA			-0.18
			(0.13)

Results of the second regression

	Coefficient in R2	Standard deviation	Impact
Serving			
Returning			
Critical			

Results of the second regression

	Coefficient in R2	Standard deviation	Impact
Serving	1.48		
Returning	0.78		
Critical	0.036		

Results of the second regression

	Coefficient in R2	Standard deviation	Impact
Serving	1.48	0.15	
Returning	0.78	0.15	
Critical	0.036	2.56	

Results of the second regression

	Coefficient in R2	Standard deviation	Impact
Serving	1.48	0.15	0.22
Returning	0.78	0.15	0.12
Critical	0.036	2.56	0.09

Conclusions

1. There is heterogeneity in agent's reactions to changes in the importance of the situation.
2. This heterogeneity has a significant impact on an agent's career.

Performing Best when it Matters Most: Evidence from professional tennis

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