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What do coaches do?

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- Select players
- Motivate/inspire
- Strategy and tactics
- But this depends on the sport: less role for tactics and strategy in MLB and NBA; important in NFL
- Coaching/teaching role (Bridgewater et al on football, 2011; Goodall et al, 2011 on NBA)
- Division of labour: offensive/defensive coordinators in NFL; General Manager in MLB & NFL; Director of Football
- Role of different managerial levels in team performance considered by Goff (2011) and currently Peeters et al.

Billy Beane & Art Howe: The Moneyball Story





Lancaster 🎇 University Lancaster 🎦 University Moneyball Importance of managers? Billy Beane as General Manager was tasked with putting • Pep Guardiola: " I'm not an innovator, I'm an ideas thief!" together a winning MLB team on a limited budget Rene Girard, Montpellier. Ligue 1 winners 2011/12, 3 points • Art Howe as Manager; frictions between Howe and Beane clear of favourites Paris St. Germain: • So who was responsible for Oakland A's success in 2002? Beane "It just goes to show that everyone can beat everyone and that money isn't the be-all and end-all. We're a club of mates, a club or Howe or both? Beane credited with 'revolutionising' MLB through use of that brings young players through and gives them a chance.. We played some great football with a well-balanced team" statistical analysis- founder of sports analytics Girard went on to coach Lille and is now at Nantes. Montpellier • But statistics were already there: Bill James finished 12th in Ligue 1 2015/16 • So perhaps Billy Beane was just a very good GM Successful managers and coaches add value, raise player · Digression: Howe objected to his portrayal by Philip Seymour productivity Hoffman in the movie, called it 'character assassination' But success depends on expectations of performance

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Managerial efficiency

Stochastic frontier and DEA models. Evaluate impacts of managers and coaches on technical efficiency of teams

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- Managers not a direct input to team performance, players are. But coaches can alter levels of technical efficiency e.g. 2 step SF model
- Dawson et al, JSE 2000, English Premier League- technical efficiency falling over 1992/93 to 1997/98. Pressure for success and increasing turnover rates.
- Frick and Simmons, MDE, 2008: Bundesliga, bigger teams that pay higher head coach salaries found to be more efficient than smaller teams paying lower salaries
- Del Corral et al JSE forthcoming, Spanish basketball. Foreign coaches more
 efficient than Spanish nationals in 2 empirical approaches. Ex-players more
 efficient in SF model
- Kahane RIO 2005, NHL, head coaches who were former players reduce technical inefficiency



- Does this apply to team sports and to team owners?
- Fans chant to 'bad' managers (and referees): "You don't know what you're doing!"
- Palermo football team: 6 head coaches in 2012/13, got relegated; 8 head coaches in 2015/16, survived in last game of season
- Leeds United, new owner Massimo Cellino (Cagliari President) "the manager eater", 7 head coaches since February 2014

Davide Ballardini: 12th spell as head ^{Lancaster} at Cagliari



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Uns Nur 200		, stable ad coa	e France? iches since	Į	ancaster 🤧 Iniversity 😍
	Italy		France		
	Palermo	31	Ajaccio	13	
	Cagliari	27	Nantes	13	
	Lecce	20	Marseille	12	
	Torino	18	Monaco Sochaux	11	
	Fiorentina	9	Lille St. Etienne Toulouse Caen	5	
	Juventus	9	Nancy	4	
	AC Milan	9	Lorient	2	
	Napoli	6			
	Average	14	Average	8	

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Club	Arriving	Spells	Departing	Fire/quit
Empoli	G. Martuscilleo	0 (internal)	M. Giampaolo	F
Udinese	G. lachini	11	L. De Canio	F
Torino	S. Mihailovic	6	G. Ventura (national	Q

Udinese	G. lachini	11	L. De Canio	F
Torino	S. Mihajlovic	6	G. Ventura (national team)	Q
Genoa	I. Juric	2	G. P. Gasperini	Q
Atalanta	G. P. Gasperini	6	E. Reja	F
Crotone	D. Nicola	3	I. Juric	Q
Sampdoria	M. Giampaolo	9	V. Montella	Q
AC Milan	V. Montella	3	S. Mihajlovic	F
Lazio	S. Inzaghi (Caretaker)	1	S. Pioli	F
Internazionale	F. De Boer	1	R. Mancini	F

Coach recycling

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- Coaches are fired very frequently. Less so in France & Germany.
- D'Addona and Kind, JSE 2014- coach durations falling in English football league in post-war period; probability of firing has gone up
- Could reflect greater rewards and greater cost of failure (relegation)
- If a coach is fired then this does not necessarily imply stigma
- Pool of fired coaches, often on 'gardening leave' available to be hired
- somewhere else.
- Italian rule: coach fired by team A can't be hired by team B in same season but can return to team A (similar in Germany but not in England)
- Why not hire a rookie coach? Promote from within?
- Assistants may not make good head coaches; may be tainted with head coach failure

Tervio: Market for mediocre talent

- Industry-specific talent that can only be revealed on the job
- So they go to external market and bid excessively for the pool of incumbent
 managers at expense of trying out new talent
- Which is populated by fired managers who failed somewhere
- So market for mediocre managers is sustained- unfavourable selection of managers
- See Thomas Peeters presentation tomorrow
- But not everyone in pool of vacancies is mediocre
- Rafa Benitez: Real Madrid to Newcastle?
- Roberto di Matteo: Chelsea to Schalke 04 to Aston Villa
- But these coaches won Champions League! Now in English Championship. So are they mediocre?
- Didn't want to be out of work 'too long'- scarring effect of unemployment eventually

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Head coach profile

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- Must have UEFA coaching badge
- White- very few black head coaches; Rooney rule for European football?
- Male- 1 female head coach, Corinne Dacre at Clermont Foot
- Ex-player but not necessarily international, need not have played for team now coaching for- exception: Jose Mourinho
- Age 40-60
- Has managerial experience
- Most likely same nationality as league, though not true for EPL where 7/20 head coaches are British

Black head coaches: Chris Hughton (Brighton) & Antoine Kombouare (Lens)



Lancaster 🎦 University Lancaster Literature on Head Coach Survival Bryson/Buraimo/Simmons (1) Hypotheses Increased performance (absolutely and above expectations) reduces Barros, Frick & Prinz, AE, 2009: Bundesliga- hazard model likelihood of dismissal and increases likelihood of quitting Bachan, Reilly & Witt, JORS 2008, English Football League, 3 General human capital (e.g. experience) is valued by team owners seasons- also use a hazard model protecting coaches from dismissal even if performance is poor. Greater • Goddard (2014), English football human capital raises quit rates. Greater age raises dismissal probability given experience (reduced match-specific surplus; burn-out; salary). • Pieper, Nuesch & Franck, SBR, 2014: Bundesliga, uses expected More firm-specific human capital lowers dismissal probability without points via betting odds affecting quit probability (reduced information asymmetry; learning) Van Ours & Van Tuijl, EI, 2016: Dutch top division, 14 seasons Playing experience does not affect dismissal or quit probability, contrary to • Most literature uses logit or LPM; highlights role of recent Goodall et al. (2011) on NBA performance in firings; can put this in terms of 'surprise', points Dismissal probabilities are greater in top tier than second tier; greater for Spain and Italy ('trigger-happy owners' linked to governance structures) expected points.

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Data

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- 4 countries 2000/01 to 2014/15; France, Germany, Italy and Spain
- Similar management structures: Head coach + Director of football
- 8 divisions in total so 218 teams
- Larger data set than previous studies covering 638 coaches with 68,172 coach-game observations, 1,518 of which end in departure from the club
 Distinguish voluntary quits from firings (mutual consent & non-renewal of
- contract = firing; source = Wikipedia + newspaper reports);
- Team and manager covariates: account for firm-specific human capital
 Cumulative surprise: actual points expected points derived from betting odds; expected points = 3*win prob + 1*draw prob

Cox Proportional Hazard Results

Variable	All	Fires	Quits
Team: Position last season	-0.005	-0.002	-0.011
Team promoted	0.634***	0.397	0.742***
Team relegated	0.690***	0.992***	0.141
General Human Capital: Age	0.015***	0.022***	-0.004
Year of first job	0.008	0.018***	-0.018***
N previous spells	-0.001	0.024	-0.060***
Got team promoted	-0.182***	-0.218***	-0.035
Got team relegated	-0.154**	-0.052	-0.489***
Cup win	-0.159*	-0.348***	0.226
Title win	-0.089	-0.090	-0.041
Working in home country	-0.222***	-0.268***	-0.117

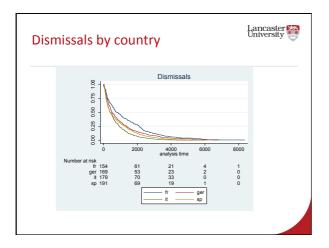
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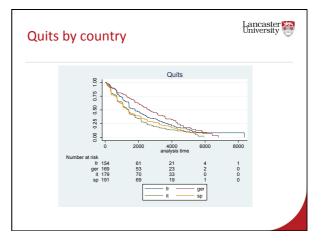
ox Proportiona	l Hazaro	l Results	Lancaster University
Variable	All	Fires	Quits
Firm-specific human capital			
Ex-player with club	-0.056	-0.055	-0.056
N previous spells with club	-0.184***	-0.291***	0.047
Hired from within	0.015***	0.022***	-0.004
Playing experience			
Played for country	-0.041	-0.067	-0.013
Years playing experience	0.015*	0.021*	-0.001
Played in top league	-0.091	-0.085	-0.055
Cup win	-0.159*	-0.348***	0.226
Never a professional player	-0.089	-0.090	-0.041
Working in home country	0.329***	0.411***	0.120

League and time-varying covariates

Variable	All	Fire	Quit
League Germany	0.060	0.154	-0.129
Italy	0.517***	0.561***	0.342
Spain	0.389***	0.452***	0.274
2 nd tier	0.051	0.057	-0.038
Time-varying covariates			
Points/game	-0.0004***	-0.0004***	-0.0001
Games left this season	-0.0004***	-0.0004***	-0.0004***
Last day of season	0.001***	0.001***	0.002***
Cumulative surprise	-0.0004***	-0.0004***	-0.0001
Pseudo R2	0.155	0.120	0.308
N managers	638	638	638
N games	68,172	68,172	68,172

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Previous literature on effects of head coach turnover

- Short-run within season: ordered probit- papers generally suggest little or no effect
 or even adverse effect (Audas et al, 2006, NHL). Forrest & Tena (2007) find a positive
 effect for home games following dismissal for 3 seasons in Spain.
- Problem here is Ashenfelter Dip- what would have happened to a team that had
 poor performances but did not fire its manager? Counterfactual problem with
 regression to the mean. Expect performances to improve.
- Short-run within season effects: matching- some papers suggest zero effect, e.g.. Van Ours & Van Tuijl (2016), ter Weel (2011) on Dutch league, De Paolo & Scoppa (2012) on Italy Serie A, also Goddard (2014) on England. An exception is Madum (2016) for Denmark, positive effects following a coach change.
- Fixed effects models- Cf. Bertrand & Schoar (2003) on CEOs. Hentschel et al (2014) on Bundesliga, manager Fes significant; Berri et al (2009) on NBA- coach/manager fixed effects were significant but differences in effects not great.
- Manager characteristics- Goodall et al (2011), NBA, coach playing experience important for team success after controlling for team payroll (considered endogenous) and team fixed effects.

Bryson, Buraimo & Simmons (2): Multi-league study of head coach turnover

Difference in-difference estimation

1. We create two distinct sets of game sequences. The first set is every sequence of 21 games (games 10.-9, -8, ..., 8, 9, 10) comprising a managerial change (fire or quit). The managerial change curst agame 0, therefore, games -10 to 0 is for the incumbent manager whilst games 1 to 10 is for the new manager. This first set of sequences is the treatment group. The second set is every sequence of 21 games in which there has been no managerial change. This second set of game sequences is the control group. Note that Palermo-type experience is therefore ruled out.

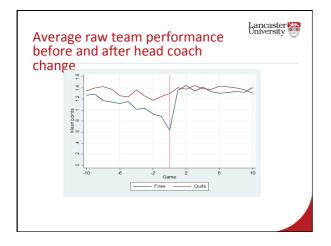
2. There are 1,185 game sequences involving the treatment group in which there is a managerial change (792 for fires and 383 for quits).

3. Across the two sets of game sequences, games 1 to 10 are the post-period following a managerial change. For the set of games sequences for the control group in which there is no managerial change, a synthetic change is assumed.

4. The difference in difference estimator is therefore Treatment x Post change. Regress points per game over 4 and 10 post-change games with controls.

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Covariates

- Team points t
- Team points t-1
- Cumulative points t-2 to t-5
- Cumulative points t-6 to t-10League position t
- League position t
 League position s -1
- Games left
- Last game of season

All coefficients significant except for Games left.

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Comments

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- Model is similar to Madum (2016)
- t = last game before coach departure; s = season
- Fewer points means greater probability of fire and quit with smaller effect on quit
- Worse league position now means greater probability of fire and quit
- · Some quits are 'jump before getting pushed'
- Better league position at end of previous season means higher probability of being fired and quitting- coach finds it difficult to sustain earlier team performance (cf. Mourinho at Chelsea)
- Can replace Points with Surprise (Actual Points Expected Points) and Cumulative Surprise; get similar results

Propensity Score Matching

- Find treatment group (games surrounding coach departure, T) and a control group (games not surrounding a coach departure, C)
- Assume <u>all</u> relevant differences between the groups pretreatment can be captured by observable characteristics
- Establish common support between T and C; assume Conditional Independence. For matching to be valid we need to observe games in treatment and control groups with same range of characteristics

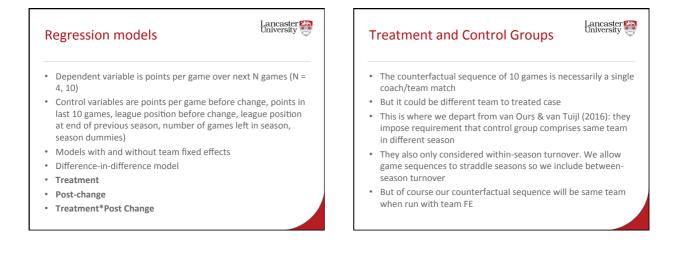
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Propensity Score Matching

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- In order to recover the average treatment-on-the-treated (ATT) effect of coach change we use the estimated propensity scores to identify those treated cases for whom there is common support in the untreated (control group) sample.
- pstest to show 'closeness' of covariates as between treated & control groups, unmatched vs matched- tests for common support
- Select from non-treated pool of games a control group where distribution of observed variables is similar as possible to distribution in treated group
- Calculate propensity score from probability of a game being in treatment group given game characteristics- probit model
- Match on basis of nearest neighbour; kernel method to estimate propensity scores didn't work. 5 neighbours gives more precision in estimates than 1.

Variable	All	Fired	Quit
Team points t	-0.220 (17.84)	-0.261 (2.61)	-0.050 (2.70)
Team points t-1	-0.135 (12.05)	-0.150 (12.03)	-0.052 (2.81)
Cumulative points t-2 to t-5	-0.086 (15.79)	-0.090 (15.03)	-0.045 (4.85)
Cumulative points t-6 to t-10	-0.026 (5.61)	-0.031 (6.24)	-0.004 (0.51)
League position t	0.019 (9.39)	0.022 (9.77)	0.008 (2.02)
League position s -1	-0.016 (7.72)	-0.016 (7.13)	-0.010 (2.78)
Games left	-0.001 (0.93)	-0.0008 (0.58)	-0.007 (2.46)
Last game of season	2.131 (46.38)	1.543 (29.73)	2.023 (29.25)
Pseudo R2	0.282	0.204	0.394



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ach effects er	compar	ison: 4	games	Lancaste University
	Unmatched	Nearest neighbour (1)	Nearest neighbour (5)	ebalance
All	0.279***	0.185***	0.252***	0.070***
All with team FEs	0.273***	0.139***	0.256***	0.048***
Fires	0.338***	0.438***	0.262***	0.088***
Fires with team FEs	0.330***	0.381***	0.242***	0.056***
Quits	0.147***	-0.133	-0.051	0.000
Quits with team FEs	0.145***	0.163	-0.157	-0.005

New method: Entropy Balancing

- ebalance in Stata- user-written routineImposes balancing on covariates as between treatment and
- control groups using mean, variance and skewness not just mean as in PSM
- Algorithm ensures balanced distributions of covariates without ad hoc choice of functions

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- Quick to compute
- Interpretation of PS tests is judgemental

				 Change in head coach following a firing leads to 0.2 to 0 	л
	Unmatched	Nearest neighbour (1)	Nearest neighbour (5)	points per game over 4 games, 0.2 to 0.3 points per game 10 games from a mean of 1.2 points per game	
All	0.219***	0.219***	0.236***	 Could make the difference between staying in a division 	and
All with team FEs	0.212***	0.136***	0.241***	getting relegated	un
Fires	0.275***	0.208***	0.271***	 Obviously depends on the right candidate being available 	~
Fires with team FEs	0.266***	0.210***	0.266***		
Quits	0.095***	0.139	0.220	 Sam Allardyce saved Sunderland; Rafa Benitez didn't sav 	е
Quits with team FEs	0.093***	0.141	0.422	Newcastle	
				 Smaller effect with entropy balance: 0.07 points/game c 	ver
				games	

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Interpretation

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- For fires we find that team performance improves in next 4 or 10 games following a coach change relative to our synthetic counterfactual
- This result is robust to different PSM estimations also to entropy balance
 For quits we find no change in team performance in next 4 or 10 games
- relative to counterfactual. Important to separate fires from quits.So managerial labour market does not look as irrational or inefficient as
- some commentators suggest
- Though we have ruled out team-seasons with high-frequency changes
- Why? Possibly our large sample size enable the data 'to speak'
- We allow games to roll over across seasons
- Different methods used here
- So next stage is to break sample down by league and see how results stand up

Conclusions

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- Head coach turnover is affected by both specific and general human capital
- Different determinants of fires and quits
- Differences across leagues
- Evidence that firing a head coach can generate improved performance for a team- unless you are Cagliari or Palermo
- Assortative matching among head coaches? E.g. Antonio Conte, Siena to
 Juventus to Chelsea; Allegri started at Cagliari; Mourinho at Porto
- Lots of work to do, especially on coach heterogeneity, roles of team owners, director of football, playing resources?
- Some interesting papers at this conference: Thomas Peeters tomorrow, Friday afternoon session on Coaches