Deutsches Institut für
Wirtschaftsforschung

DIW BERLIN

Discussion Papers

1053

Sudipta Sarangi • Emre Unlu

Key Players and Key Groups in Teams: A Network Approach Using Soccer Data

Berlin, September 2010

Opinions expressed in this paper are those of the author(s) and do not necessarily reflect views of the institute.

IMPRESSUM

DIW Berlin
German Institute for Economic Research
Mohrenstr. 58
10117 Berlin

Tel. +49 (30) 897 89-0
Fax +49 (30) 897 89-200
http://www.diw.de

ISSN print edition 1433-0210
ISSN electronic edition 1619-4535

Key Players and Key Groups in Teams: A Network Approach Using Soccer Data*

Sudipta Sarangi[†] and Emre Unlu[‡]

September, 2010

Abstract

This paper provides a way of evaluating a player's contribution to her team and relates her effort to her salaries. We collect data from UEFA Euro 2008 Tournament and construct the passing network of each team. Then we determine the key player in the game while ranking all the other players too. Next, we identify key groups of players to determine which combination of players played more important role in the match. Using 2010 market values and observable characteristics of the players, we show that players having higher intercentrality measures regardless of their field position have significantly higher market values.

Keywords: Social Networks, Team Game, Centrality Measures

JEL Classification Codes: A14, C72, D85

---

*We would like to thank Coralio Ballester, Christophe Bravard, Kaj Gittings, Carter Hill, Matt Jackson, Jurjen Kamphorst, Naci Mocan, Christian Raschke, Adam Szeidl, Umed Temurshoev, Fatih Unlu, Zuhal Unlu, Yves Zenou and participants of Public Economic Theory Conference, LSU Network Conference and seminar participants at DIW for their insightful comments. This paper is supported by the US Department of Homeland Security under Award Number: 2008-ST-061-ND 0001. The views and conclusions contained in this document are those of the authors and should not be interpreted as necessarily representing the official policies, either expressed or implied, of the US Department of Homeland Security.

†*DIW* Berlin and Department of Economics, Louisiana State University; Baton Rouge, LA, 70803; e-mail: sarangi@lsu.edu.

‡Department of Economics, Louisiana State University; Baton Rouge, LA, 70803; e-mail: eunlu1@tigers.lsu.edu.

1 Introduction

Team like situations dominate many social and economic environments. Firms and organizations are usually made up of smaller groups or teams. In fact recommendation letters often mention person's ability to be a team player. An applicant's to be a team player is also tested in many interviews. Work environments like R&D groups, special task forces and even academia to a certain extent function as teams. Teamwork is an important feature of many games like soccer, basketball and voleyball. This makes understanding to contribution of individual members to a team very useful exercise. It can help design better teams and compensation packages. Identify the key players in teams is also very useful for retention issues. In this paper, we develop a method for identifying key players and key groups in teams.

There is a substantial literature on identifying the key node in a network. These may be degree based measures that take into account the number of links that emanate and end at a node. (see for instance Katz (1953), Freeman (1979), Hubbell (1965), Bonacich (1987) and Sade (1989)). Closeness measure like those developed by Sabidussi (1966) and Freeman (1979) use some type of topological distance in the network to identify the key players. Another measure called betweeness measure (see for instance Freeman (1979)) uses the number of paths going through a node to determine its importance. Borgatti and Everett (2006) develop a unified framework to measure the importance of a node. Borgatti (2006) identifies two types of key player problems (KPP). He argues that in KPP-positive situation key players are those who can optimally diffuse something in the network. In a KPP negative situation key players are individuals whose removal leads to maximal disruption in the network.

In a recent paper Ballester et al. (2006) provide microfoundation for the key player problem. Their model has two vital ingredients: individual actions and interaction between players. In the Nash equilibrium of the game each player chooses their individual action taking both components into account. The key player is the one whose removal leads to the greatest overall reduction in effort. Thus, their approach builds strategic behavior into the network, and combines both negative and positive aspects of the problem.

In this paper, we develop a Team Game based on the individual actions and interactions between players. Additionally, each player gains utility when the team achieves its desired outcome. This team outcome depends on individual effort and an ability term for each player. We then develop a new intercentrality measure that takes into account each player's contribution to their teammates and the team outcome in fact captures the contributions of other players to each player for achieving the team's objective. Another interesting feature is that following Ballester et al. (2006) we define key player problem from a social planner's perspective. In context of teams the chairman, team leader or head coaches can be regarded as the social planners.

This paper has two contributions. The first contribution is extending Ballester et al. (2006) model and introducing team (or network) outcome component into the analysis to rank players according to their contributions to their teammates. Nash Equilibrium of the model provides the optimal amount of individual efforts' of each player. It implies that if the player has a higher return for his individual actions or a higher ability parameter then she will have more incentives to perform individual actions. The second contribution is providing an empirical illustration of the approach using a team sport: soccer. We observe the passing effort of international soccer players to proxy the amount of interaction between players in UEFA European Championship 2008 and identify the key players and key groups in the network. It is important to note that we are not seeking the best player on the field. Rather, we are looking for the player whose contribution to his team is maximal. Finally, we show that players who have higher interactions (passings and receivings) have significantly higher ratings from experts and market values.

Determining a key group instead of a key player is an interesting aspect since more than one player may have equivalent level of contribution to their teammates. In addition to that, it is important to identify which combination of players have more importance within the network. This information is crucial for the team managers who wish to form a team with individuals who provide different adjacency to their teammates. It is important to note that the members of the of key groups are not the best working peers but they are the ones whose joint contribution to their team is maximal. Temurshoev (2008) extends Ballester et al.(2006) paper by introducing the key group dimension. Temurshoev (2008) searches for the key group, whose members are, in general, different from the players with highest individual intercentralities. We also apply Temurshoev's (2008) approach and determine the key groups of players.

The methods in this paper can be extended to the more general situations where people work in teams; however, in this paper, we provide an empirical example from international soccer matches.

Taking this approach has some advantages. First, soccer is a team sport and the payoff of players in the teams greatly depend on the team outcome. Second, interactions within soccer teams are observable and passing effort of players is a good metric to identify these interactions. We create a unique passing data from UEFA European Championship 2008 and identify the key players and key groups of teams which played in the Quarter Final, Semi-Final and Final stage of the tournament.[1]

After the introduction, the paper proceeds as follows: Section 2 defines the Team Game and various centrality measures, identifies the Nash Equilibrium and our team intercentrality measure. Section 3 motivates the use of soccer data as an empirical application. Section 4 identifies the empirical methodology. The paper concludes with discussions and possible extensions.

2 Team Game

In this section, we first define the team game. Then we introduce the various centrality measures and find the Nash Equilibrium of the game. Finally, we provide the relationship between the Nash equilibrium and team intercentrality measure.

2.1 Model Setup

We begin by introducing the Team Game. We define the individual player's payoff function using the notation of Ballester et al. (2006) as far as possible.

$$U_i(x_1, ..., x_n) = \alpha_i x_i + \frac{1}{2}\sigma_{ii} x_i^2 + \sum_{j \neq i} \sigma_{ij} x_i x_j + \theta Z. \tag{1}$$

The first two terms form a standard quadratic utility function where $x_i \geq 0$ is defined as the individual effort of player i. Here, $\alpha_i > 0$ stands for the coefficient of individual actions and $\sigma_{ii} < 0$, the coefficient of the second term, defines concavity in own effort i.e., $\partial^2 U_i / \partial x_i^2 = \sigma_{ii} < 0$. For simplicity we assume that these coefficients are identical for all players and we drop the subscript.[2] The third term captures the bilateral influences between players with σ_{ij} being the coefficient of this term. Note that σ_{ij} could be positive or negative depending on whether the interaction is a

[1] Fifty European National Teams played qualifying stages and only 16 of them were qualified for the UEFA Euro 2008. So, it is reasonable to expect that the quality of the players in the national tournaments are similar. Thus, interaction between players plays a crucial role in determining the outcome of the matches making our results more important.

[2] We relax this assumption and consider the cases when α_i and σ_{ii} can be different for every player in Proposition 1 (a)-(b).

strategic complement or substitute. We let $\mathbf{\Sigma} = [\sigma_{ij}]$ be the matrix of these coefficients. The last expression is the team outcome term which denotes the desired team goal. For instance, for a sales team this could be achieving sales. In a game soccer this could be winning the game or scoring more goals. This term contains a common set of variables for all players since they all share the same team outcome. For simplicity, let $Z = \sum_{i=1}^{n} \delta_i x_i$ where δ_i defines each individual's ability to help achieve the team's goal. The parameter θ is a scale factor that could be used to capture the importance of different events for the team.[3]

Our team game differs from that of Ballester et al. (2006) model in the last term. This allows us to consider the n players acting together towards a common objective. While alternative formulations are possible, we believe our framework has certain advantages. First, it allows for explicit comparison with Ballester et al. (2006). Second, while all effort by player provides a utility, the effort adjusted by the ability parameter is important for achieving the team outcome. This can be useful for empirical illustration since it may not be possible to obtain data on α_i and σ_{ii}. The ability parameter δ_i on the other hand could be obtained from available data.

Following Ballester et al. (2006), let $\underline{\sigma} = \min\ (\sigma_{ij}|i \neq j)$ and $\overline{\sigma} = \max\ (\sigma_{ij}|i \neq j)$. We assume that $\sigma < \min\ (\underline{\sigma}, 0)$. Let $\gamma = -\min\ \underline{\sigma}, 0 \geq 0$. If efforts are strategic substitutes for some pair of players, then $\underline{\sigma} < 0$ and $\gamma > 0$; otherwise, $\underline{\sigma} \geq 0$ and $\gamma = 0$. Let $\lambda = \overline{\sigma} + \gamma \geq 0$. We assume that $\lambda > 0$. Define $g_{ij} = (\sigma_{ij} + \gamma)/\lambda$. Note that, the g_{ij}'s are weighted and directed allowing us to obtain relative complementarity measures. Consequently, the elements g_{ij} of the weighted adjacency matrix lie between 0 and 1.[4] The adjacency matrix $\mathbf{G} = [g_{ij}]$ is defined as a zero diagonal nonnegative square matrix. The zero diagonal property assures that no player is connected to themselves (i.e, there are no direct loops from player i to i.) Then, $\mathbf{\Sigma}$ matrix which captures the cross effects can be decomposed into the following expression:

$$\mathbf{\Sigma} = -\beta\mathbf{I} - \gamma\mathbf{U} + \lambda\mathbf{G} \tag{2}$$

where $-\beta\mathbf{I}$ shows the concavity of the payoffs in terms of own actions, $-\gamma\mathbf{U}$ shows the global inter-

[3]In principle, one could define θ_Z to capture the importance of the team's objective. Here, for simplicity we assume it to be θ.

[4]If we do not use a weighted $\mathbf{G}$ matrix then $\mathbf{G}$ matrix involves only 0s and 1s as its elements. This will imply that the weight for having more connections with the same player is zero. So, $g_{ij} = 1$ then there is a connection and if $g_{ij} = 0$ then there is no connection between player i and player j. However, it is very important to identify the relative interaction between players rather than just considering if there is a connection between player i and j. Thus, using a weighted $\mathbf{G}$ matrix is important to illustrate team environments.

action effect, and $\lambda\mathbf{G}$ shows the complementarity in players' efforts. Using the above decomposition, Equation (1) becomes:

$$U_i(x_1, ..., x_n) = \alpha x_i - \frac{1}{2}(\beta - \gamma)x_i^2 - \gamma \sum_{j=1}^{n} x_i x_j + \lambda \sum_{j=1}^{n} g_{ij} x_i x_j + \theta_z Z \tag{3}$$

for all players $i = 1, ..., n$.

2.2 Centrality Measures

Here, we define the centrality measures needed to identify the key player. Let $\mathbf{M}$ be a matrix defined as follows:

$$\mathbf{M}(\mathbf{g}, a) = [\mathbf{I} - a\mathbf{G}]^{-1} = \sum_{k=0}^{\infty} a^k \mathbf{G}^k. \tag{4}$$

The above matrix keeps track of the number of paths that start from player i and end at player j with a decay factor, a and a given adjacency matrix $\mathbf{G}$. Note that players can also contribute to their teammates through indirect connections, but these have lower weights.

Following Ballester et al.(2006), we define the Bonacich centrality measure as:

$$\mathbf{b}(\mathbf{g}, a) = [\mathbf{I} - a\mathbf{G}]^{-1} \cdot \mathbf{1} \tag{5}$$

where $\mathbf{1}$ is a $n \times 1$ vector of ones, n is number of players in the team and $\mathbf{I}$ is a $n \times n$ identity matrix. The Bonacich centrality measure counts the total number of paths that originates from player i. Note that b_i is the row sum of the $\mathbf{M}$ matrix. Equivalently, the Bonacich centrality measure is $b_i(\mathbf{g}, a) = m_{ii}(\mathbf{g}, a) + \sum_{i \neq j} mij(\mathbf{g}, a)$. Next, we define a weighted Bonacich centrality measure with the ability parameter, δ_i as the weight:

$$\mathbf{b}_\delta(\mathbf{g}, a) = [\mathbf{I} - a\mathbf{G}]^{-1} \cdot \boldsymbol{\delta} \tag{6}$$

The Ballester et al. (2006) intercentrality measure (ICM) for an asymmetric $\mathbf{G}$ is given by:

$$\tilde{c}_i(\mathbf{g}, a) = b_i(\mathbf{g}, a) \times \frac{\sum_{j=1}^{n} m_{ji}(\mathbf{g}, a)}{m_{ii}(\mathbf{g}, a)} \tag{7}$$

We define another centrality measure which accounts for the weighted receivings of the players where the weights are given by δ_i:

$$r_i(\mathbf{g}, a) = \sum_{j=1}^{n} m_{ij}(\mathbf{g}, a) \times \delta_i \tag{8}$$

This (receiving) centrality measure takes into account the paths that end in player i weighted by the ability parameter of the player.

Note that, in the context of teams, the $\mathbf{\Sigma}$ matrix is unlikely to be symmetric since the number of paths from player i to player j will be different for at least one pair. Hence, an asymmetric $\mathbf{\Sigma}$ matrix will lead to an asymmetric $\mathbf{G}$ matrix. We now define a new intercentrality measure for determining the key players in the teams. The team intercentrality measure (TICM) for an asymmetric $\mathbf{G}$ matrix for the Team Game is given by:

$$\hat{c}_i(\mathbf{g}, a) = b_i(\mathbf{g}, a) \times \frac{\sum_{j=1}^{n} m_{ji}(\mathbf{g}, a)}{m_{ii}(\mathbf{g}, a)} + \sum_{j=1}^{n} m_{ij}(\mathbf{g}, a) \times \delta_i \tag{9}$$

Unlike the Bonacich centrality measure, ICM takes into account both the connections that player i sends to her teammates and the number of connections that player i receives. The primary difference between ICM and TICM is in the last term which measures player i's contribution to the team outcome by her ability parameter.

2.3 Nash Equilibrium of Team Game

In this section, we show that the Team Game has a unique interior Nash equilibrium.

Theorem 2.1. *Consider a matrix of cross-effects which can be decomposed into (3). Let $\sigma_{ij} \neq \sigma_{ji}$ for at least one $j \neq i$, $\beta/\lambda > (\rho(\boldsymbol{G}))$ and $\theta \leq |\alpha - \gamma \hat{x}^*|$. Define $\lambda^* = \lambda/\beta$. Then, there exists a unique, interior Nash Equilibrium of the team game given by:*

$$\boldsymbol{x}^*(\mathbf{\Sigma}) = \frac{\alpha \boldsymbol{b}(\boldsymbol{g}, \lambda^*) + \theta \boldsymbol{b}_\delta(\boldsymbol{g}, a)}{\beta + \gamma \hat{b}(\boldsymbol{g}, \lambda^*)}$$

where $\hat{b}(\boldsymbol{g}, \lambda^*) = \sum_{i=1}^{n} b_i(\boldsymbol{g}, \lambda^*)$.

Proof. The condition for a well defined interior Nash equilibrium of the Team Game is that the $[\beta \mathbf{I} - \lambda \mathbf{G}]^{-1}$ matrix must be invertible. We can rewrite the $[\beta \mathbf{I} - \lambda \mathbf{G}]^{-1}$ matrix as

$$\lambda[\frac{\beta}{\lambda}\mathbf{I} - \mathbf{G}]^{-1} \tag{10}$$

Let $(\rho_1(\mathbf{G}))$ be the spectral radius of $\mathbf{G}$ matrix.[5] Then, $\beta > \lambda(\rho_1(\mathbf{G}))$ ensures that Equation (9) is invertible by Theorem III of Debreu and Herstein (1953, pg.601). Once the condition is verified, an

[5] Spectral radius of $\mathbf{G}$ matrix is defined as the inverse of the norm of the highest eigenvalue of $\mathbf{G}$ matrix.

interior Nash equilibrium in pure strategies $x^* \in R^n_+$ satisfies:

$$\frac{\partial U_i}{\partial x_i}(x^*) = 0 \quad \text{and } x_i^* > 0 \quad \text{for all i=1, 2,...,n}$$

Hence, maximizing U_i with respect to x_i yields:

$$\frac{\partial U_i}{\partial x_i} = \alpha_i + \sigma_{ii} x_i + \sum_{j \neq i} \sigma_{ij} x_j + \theta \delta_i = \mathbf{0}$$

Therefore, $\boldsymbol{x^*}$ solves:

$$\alpha \mathbf{1} + \theta \mathbf{I} \boldsymbol{\delta} = (\beta \mathbf{I} + \gamma \mathbf{U} - \lambda \mathbf{G}) \boldsymbol{x^*}$$

Pre-multiplying both sides with $[\mathbf{I} - \lambda^* \mathbf{G}]^{-1}$ and using the definition of $\mathbf{b}_\delta(\mathbf{g}, \lambda^*)$, we obtain:

$$\beta \mathbf{x}^* = (\alpha - \gamma \hat{x}^*)[\mathbf{I} - \lambda^* \mathbf{G}]^{-1} \mathbf{1} + \theta \mathbf{b}_\delta(\mathbf{g}, \lambda^*)$$

where $\hat{x}^* = \sum_{i=1}^n x_i^*$. Using $\mathbf{U} \cdot \mathbf{x}^* = \hat{x} \cdot \mathbf{1}$ where $\mathbf{U}$ is a $n \times n$ matrix of ones and $\hat{x} = \sum_{i=1}^n x_i$. Rearranging terms yields:

$$x^*(\mathbf{\Sigma}) = \frac{\alpha \mathbf{b}(\mathbf{g}, \lambda^*) + \theta \mathbf{b}_\delta(\mathbf{g}, \lambda^*)}{\beta + \gamma \hat{b}(\mathbf{g}, \lambda^*)}$$

where $\hat{b}(\mathbf{g}, \lambda^*) = \sum_{i=1}^n b_i(\mathbf{g}, \lambda^*)$.

Given that $\alpha + \theta\delta > 0$ and $b_i(\mathbf{g}, \lambda^*) + b_\delta(\mathbf{g}, \lambda^*) \geq 1$ for all $i = 1, ..., n$, there is only one critical point and $\frac{\partial^2 U_i}{\partial x_i^2} = \sigma_{ii} < 0$ is always concave. This argument ensures that x^* is interior. Now, we establish uniqueness by dealing with the corner solutions.

Let $\beta(\mathbf{\Sigma}), \gamma(\mathbf{\Sigma}), \lambda(\mathbf{\Sigma})$ and $\mathbf{G}(\mathbf{\Sigma})$ be the elements of the decomposition of $\mathbf{\Sigma}$. For all matrices $\mathbf{Y}$, vector $\mathbf{y}$ and set $S \subset 1, 2, ..., n$, $\mathbf{Y}_s$ is a submatrix of Y with s rows and columns and $\mathbf{y}_s$ is the subvector of $\mathbf{y}$ with rows in s. Then, $\gamma(\mathbf{\Sigma}_{\boldsymbol{s}}) \leq \gamma(\mathbf{\Sigma})$, $\beta(\mathbf{\Sigma}_{\boldsymbol{s}}) \geq \beta(\mathbf{\Sigma})$ and $\lambda(\mathbf{\Sigma}_{\boldsymbol{s}}) \leq \lambda(\mathbf{\Sigma})$. Also, $\lambda(\mathbf{G}) = \mathbf{\Sigma} + \gamma(\mathbf{U} - \mathbf{I}) - \sigma_{ii}\mathbf{I} - \theta_z Z$ and the coefficients in $\lambda \mathbf{G}$ (s rows and columns) are at least as high as the the coefficients in $\lambda(\mathbf{\Sigma}_{\boldsymbol{s}})\mathbf{G}_s$. From Theorem I of Debreu and Herstein (1953, pg.600), $\rho_1(\lambda(\mathbf{\Sigma}_{\boldsymbol{s}})\mathbf{G}_s) \leq \rho_1(\lambda(\mathbf{\Sigma})\mathbf{G})$. Therefore, $\beta(\mathbf{\Sigma}) > \lambda(\mathbf{\Sigma})\rho_1(\mathbf{G})$ implies that $\beta(\mathbf{\Sigma}_{\boldsymbol{s}}) > \lambda(\mathbf{\Sigma}_{\boldsymbol{s}})\rho_1(\mathbf{G}_s)$.

Let $\boldsymbol{y^*}$ be a non interior Nash equilibrium of the Team Game. Let $S \subset 1, 2, ..., n$ such that $y_i^* = 0$ if and only if $i \in N \setminus S$. Thus, $y_i^* > 0$ for all $i \in S$.

$$\frac{\partial U_i}{\partial x_i} = \alpha - \beta x_i - \gamma \sum_{j \neq i}^n x_j + \lambda \sum_{i=1}^n g_{ij} x_j + \theta \delta_i$$
$$\frac{\partial U_i}{\partial x_i}(0) = \alpha_i + \theta \delta_i$$

and 0 cannot be a Nash Equilibrium. Then,

$$-\boldsymbol{\Sigma_s y_s^*} = (\beta \mathbf{I}_s + \gamma \mathbf{U}_s - \lambda \mathbf{G}_s)\boldsymbol{y_s^*} = \boldsymbol{\alpha} + \theta \boldsymbol{\delta}$$
$$\beta \boldsymbol{y_s^*} + \gamma \mathbf{U}_s \boldsymbol{y_s^*} - \lambda \mathbf{G}_s \boldsymbol{y_s^*} = \alpha + \theta \boldsymbol{\delta_s}$$
$$\beta[\mathbf{I}_s - \lambda^* \mathbf{G}_s]\boldsymbol{y_s^*} = \alpha + \theta \boldsymbol{\delta_s} - \gamma \hat{y_s^*} \cdot \mathbf{1_s}$$

where the last step utilizes $\mathbf{U}_s \mathbf{y}_s^* = \hat{y_s^*} \cdot \mathbf{1_s}$ and $\lambda^* = \lambda/\beta$. Pre-multiplying both sides by $[\mathbf{I}_s - \lambda^* \mathbf{G}_s]^{-1}$ yields:

$$\beta \boldsymbol{y_s^*} = [\mathbf{I} - \lambda^* \mathbf{G}_s]^{-1}\alpha + \theta[\mathbf{I} - \lambda^* \mathbf{G}_s]^{-1}\boldsymbol{\delta_s} - \gamma \hat{y_s^*}[\mathbf{I}_s - \lambda^* \mathbf{G}_s]^{-1} \cdot \mathbf{1_s} \tag{11}$$
$$\boldsymbol{y_s^*} = \frac{(\alpha - \gamma \hat{y_s^*})\mathbf{b}_s(\mathbf{g}, \lambda^*) + \theta \mathbf{b}_\delta^s(\mathbf{g}, \lambda^*)}{\beta} \tag{12}$$

Every player $i \in N \setminus S$ is best responding with $y_i^* = 0$ so that y_j^* is the action of the subset S of players.

$$\frac{\partial U_i}{\partial x_i}(y_i^*) = \alpha - \sum_{j \in S} \sigma_{ij} y_j^* + \theta \delta_i$$
$$\frac{\partial U_i}{\partial x_i}(y_i^*) = \alpha - \gamma \hat{y_s^*} + \lambda \sum_{j \in S} g_{ij} y_j^* + \theta \delta_i \leq 0$$

for all $i \in N \setminus S$. Now substitute y_s^* instead of y_j^* in the above equation:

$$\frac{\partial U_i}{\partial x_i}(\mathbf{y}^*) = \alpha - \gamma \hat{y_s^*} + \lambda \sum_{j \in S} g_{ij}\left(\frac{(\alpha - \gamma \hat{y_s^*}) b_j(\mathbf{g}, \lambda^*) + \theta \mathbf{b}_\delta^j(\mathbf{g}, \lambda^*)}{\beta}\right) \leq 0$$
$$\frac{\partial U_i}{\partial x_i}(\mathbf{y}^*) = (\alpha - \gamma \hat{y_s^*})[1 + \lambda^* \sum_{j \in S} g_{ij} \mathbf{b}_j(\mathbf{g}, \lambda^*)] + \theta \lambda^* \sum_{j \in S} \mathbf{b}_\delta^j(\mathbf{g}, \lambda^*) \leq 0$$

If $\theta \leq |\alpha - \gamma \hat{y_s^*}|$ then $y_i^* \leq 0$ using Equations (10) and (11), which is a contradiction. $\square$

The Nash equilibrium of the Team Game has interesting implications. First, it identifies the optimal effort of individuals in the network based on the given interactions between players. It explains why some players have low centrality values. For instance, players who have higher α and δ have greater incentives to perform individual actions. The Nash equilibrium of the game implies that when the ability parameter of the individual increases, the individuals will have greater incentives to perform individual actions.

A unique interior Nash equilibrium exists even when players have heterogeneity in returns (α_i) and concavity (σ_{ii}) in individual actions are proved in Proposition 1 (a) and (b).

Proposition 1

(a): If $\alpha_i \neq \alpha_j$ and $\theta \leq \max\, |\alpha_i - \gamma \hat{x^*}|$ then Nash equilibrium of the Team Game is:

$$\boldsymbol{x^*}(\boldsymbol{\Sigma}) = \frac{\mathbf{b}_{\alpha}(\mathbf{g}, \lambda^*) + \theta \mathbf{b}_{\delta}(\mathbf{g}, \lambda^*)}{\beta + \gamma \mathbf{b}(\mathbf{g}, \lambda^*)}$$

(b): If $\alpha_i \neq \alpha_j$, $\sigma_{ii} \neq \sigma_{jj}$ for at least one player and $\theta \leq \max\, |\alpha_i - \gamma \hat{x^*}|$, then Nash equilibrium of the team game is:

$$\boldsymbol{x^*}(\boldsymbol{\Sigma}) = \frac{\mathbf{b}_{\widetilde{\alpha}}(\mathbf{g}, \widetilde{\lambda}^*) + \theta \widetilde{\mathbf{b}_{\delta}}(\mathbf{g}, \lambda^*)}{\widetilde{\beta} + \widetilde{\gamma} \hat{\mathbf{b}}(\mathbf{g}, \widetilde{\lambda}^*)}$$

Proof: See Appendix.

2.4 Key Player

We now provide a method to identify the key player in the team from the social planner's perspective based on the relationship between TICM and the aggregate Nash equilibrium effort levels.

We denote by $\mathbf{G}^{-i}$ (resp. $\boldsymbol{\Sigma^{-i}}$) the new adjacency matrix (resp. matrix of cross-effects), obtained from $\mathbf{G}$ (resp. from $\boldsymbol{\Sigma}$) by setting all of its i^{th} row and column coefficients to zero. The resulting network is $\boldsymbol{g^{-i}}$. The planner's problem is to reduce $\mathbf{x}^*(\boldsymbol{\Sigma})$ optimally by picking the appropriate player from the population. Formally, she solves max $\{\mathbf{x}^*(\boldsymbol{\Sigma}) - \mathbf{x}^*(\boldsymbol{\Sigma}^{-i}) | i = 1, ..., n\}$. This is a finite optimization problem and has at least one solution. Let i^* be a solution. We call i^* the key player in Team Game, and removing i^* from the initial network $\mathbf{g}$ has the highest impact on the aggregate equilibrium level.

Theorem 2.2. *Let $\beta > \lambda \rho_1(\boldsymbol{G})$. The key player of the Team Game i^* solves max$\{\boldsymbol{x}^*(\boldsymbol{\Sigma}) - \boldsymbol{x}^*(\boldsymbol{\Sigma}^{-i}) | i = 1, ..., n\}$ and has the highest team intercentrality measure (TICM) in $\boldsymbol{g}$, that is $\hat{c_{i^*}}(\boldsymbol{g}, \lambda^*) > \hat{c_i}(\boldsymbol{g}, \lambda^*)$ for all $i = 1, ..., n$.*

In the proof, since we allow for asymmetric $\boldsymbol{\Sigma}$ and $\mathbf{G}$ matrices, we adapt Lemma 1 from Ballester et al.(2006) for this case.

Lemma 1: Let $\mathbf{M} = [\mathbf{I} - a\mathbf{G}]^{-1}$ matrix be well defined and nonnegative. Then $m_{ji}(\mathbf{g}, a) m_{ik}(\mathbf{g}, a) = m_{ii}(\mathbf{g}, a)[m_{jk}(\mathbf{g}, a) - m_{jk}(\mathbf{g}^{-i}, a)]$ for all $k \neq i \neq j$.

Proof. Aggregate Nash equilibrium in the Team Game depends on the Bonacich centrality and the Bonacich centrality weighted by the ability parameter of the player. Note that $\rho_1(\mathbf{G}) > \rho_1(\mathbf{G}^{-i})$. Thus, when $\mathbf{M}(\mathbf{g}, \lambda^*)$ is well defined and nonnegative then so is $\mathbf{M}(\mathbf{g}^{-i}, \lambda^*)$ for all $i = 1, ..., n$.

Let $b_{ji}(\mathbf{g}, \lambda^*) = b_j(\mathbf{g}, \lambda^*) - b_j(\mathbf{g}^{-i}, \lambda^*)$ for all $j \neq i$. This is the contribution of the player i to the player j's Bonacich centrality in $\mathbf{g}$. Recall $r_i(\mathbf{g}, a) = \sum_{j=1}^{n} m_{ij}(g, a) \times \delta_i$. Summing over all $j \neq i$ and adding $b_i(\mathbf{g}, \lambda^*)$ to both sides and adding the loss of the player's receivings centrality measure gives the aggregate effect of player i's removal from the Team Game.

$$b(\mathbf{g}, \lambda^*) - b(\mathbf{g}^{-i}, \lambda^*) + r_\delta^i(\mathbf{g}, \lambda^*) = b_i(\mathbf{g}, \lambda^*) + \sum_{j \neq i} b_{ji}(\mathbf{g}, \lambda^*) + r_\delta^i(\mathbf{g}, \lambda^*) \equiv e_i(\mathbf{g}, \lambda^*)$$

where e_i is the loss function when player i is removed from the network. Our goal is to find i^{th} player whose removal will result in the highest e_i such that $e_{i^*}(\mathbf{g}, \lambda^*) \geq e_i(\mathbf{g}, \lambda^*)$ for all $i = 1, ..., n$.

$$\begin{aligned}
e_i(\mathbf{g}, \lambda^*) &= b_i(\mathbf{g}, \lambda^*) + \sum_{j \neq i} [b_j(\mathbf{g}, \lambda^*) - b_j(\mathbf{g}^{-i}, \lambda^*)] + r_\delta^i(\mathbf{g}, \lambda^*) \\
&= b_i(\mathbf{g}, \lambda^*) + \sum_{j \neq i} \sum_{k=1}^{n} [m_{jk}(\mathbf{g}, \lambda_*) - m_{jk}(\mathbf{g}^{-i}, \lambda^*)] + r_\delta^i(\mathbf{g}, \lambda^*)
\end{aligned}$$

Using Lemma 1 for the asymmetric $\mathbf{G}$ matrix, the above expression becomes:

$$\begin{aligned}
e_i(\mathbf{g}, \lambda^*) &= b_i(\mathbf{g}, \lambda^*) + \sum_{j \neq i} \sum_{k=1}^{n} \frac{m_{ji}(\mathbf{g}, a) m_{ik}(\mathbf{g}, a)}{m_{ii}(\mathbf{g}, a)} + r_\delta^i(\mathbf{g}, \lambda^*) \\
e_i(\mathbf{g}, \lambda^*) &= b_i(\mathbf{g}, a) \times (\sum_{j=1}^{n} m_{ji}(\mathbf{g}, a))/m_{ii}(\mathbf{g}, a) + r_\delta^i(\mathbf{g}, \lambda^*)
\end{aligned}$$

□

3 Soccer: A Team Game and The Role of Passing

Modern soccer is very much a team game. The performance of players depends crucially on each other's actions and interaction between players forms a vital component of the game. Soccer coaches, training books and authorities emphasize the team aspect of the game. As the great Brazilian soccer player Pele said in a press conference in Singapore in November 2006, "I think the problem with Brazil was lack of teamwork because everybody used to say Brazil will be in the final." Pele added that Brazil had the best individual players against France, but they lost the game because they could not play as a team.[6] On November 29, 2007, Gerard Houllier, the famous technical director of the French Football Federation, speaking at the 9th UEFA Elite Youth Football Conference summed this up as "Teamwork is the crux of everything."[7]

[6]See http :// findarticles.com/p/articles/mi kmafp/is 200611/ai n16939060.

[7]See http://www.uefa.com/uefa/keytopics/kind=1024/newsid=629284.html

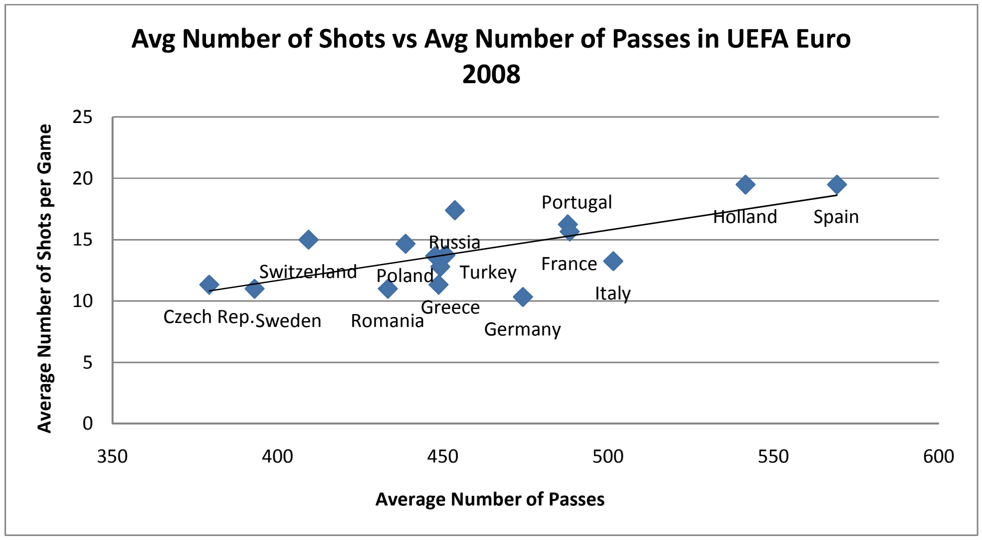

Figure 1: The relationship between average number of shots per game and average number of passes per game in UEFA Euro 2008.

One important aspect of soccer that makes it a team game is the fact that passing is a very crucial part of the game. In the early days of soccer, the game was based on individual skills such as tackling and dribbling. The Scots invented the passing game in the 1870s and everyone soon realized that it is easier move the ball than players, and the ball is faster than humans. Since then passing and receiving have become a key part of a soccer team's strategies. A soccer training manual by Luxbacher (2005) emphasizes the importance of passing in the following "Passing and receiving skills form the vital thread that allows 11 individuals to play as one - that is the whole to perform greater than the sum of its parts." Similarly, Miller and Wingert (1975) addresses the importance of passing in soccer by stating that "There are no more crucial skills than passing in soccer because soccer is a team sport. The most effective set plays involve accurately passing and receiving the ball."

Luhtanen et al. (2001) report that successful passes at the team level are important for explaining the success in the UEFA European Championship 2000. Specifically, Luhtanen et al. (2001) document that there is one to one relationship between the ranking of the team in Euro 2000 and the ranking of the team in terms of successful passing and receivings. Thus, it seems reasonable that passing is a good metric for identifying the interactions between players.

Figure 1 displays the relationship between average number of shots per game and average number of passes per game of the national teams in the UEFA European Championship 2008.[8] The correlation coefficient between these variables is 0.7. The regression coefficient obtained from regressing average number of shots on goal per game on average number of passes per game indicates that on the average 27 passes created 1 additional shot on goal for the team in Euro 2008. This is consistent with the idea that teams need ball possession to create goal scoring opportunities which directly affects the outcome of the match. Clearly, passing is an important interaction variable in our dataset.

There are some advantages to using passing for capturing player interactions. First, it is pairwise and both the sender and receiver of the pass must be successful to complete the action. So, the pairwise passing enables us to utilize the network theory to understand the contribution of each player to the team. Second, passing as a measure of interaction is observable and easily quantifiable. Data for other aspects of the soccer such as tackling, dribbling or off the ball movement of players are very hard to observe. In addition, often identifying the quality of these actions require subjective judgement. Finally, even if we had data about these aspects, it would be still difficult to quantify those variables exactly.

4 Empirical Methodology

This section illustrates our methodology for identifying the key player and key groups in soccer teams. First, we present the payoff function of players in soccer teams. Second, we describe our data collection process. Next, we calculate the ICM and TICM by using the corresponding definitions in the paper and provide our results for the key players and key groups. Finally, we conduct sensitivity checks for the model parameters used for identifying key players.

[8]This data was accessed from the following website http://www1.uefa.com/tournament/statistics/teams. It is available from the authors upon request.

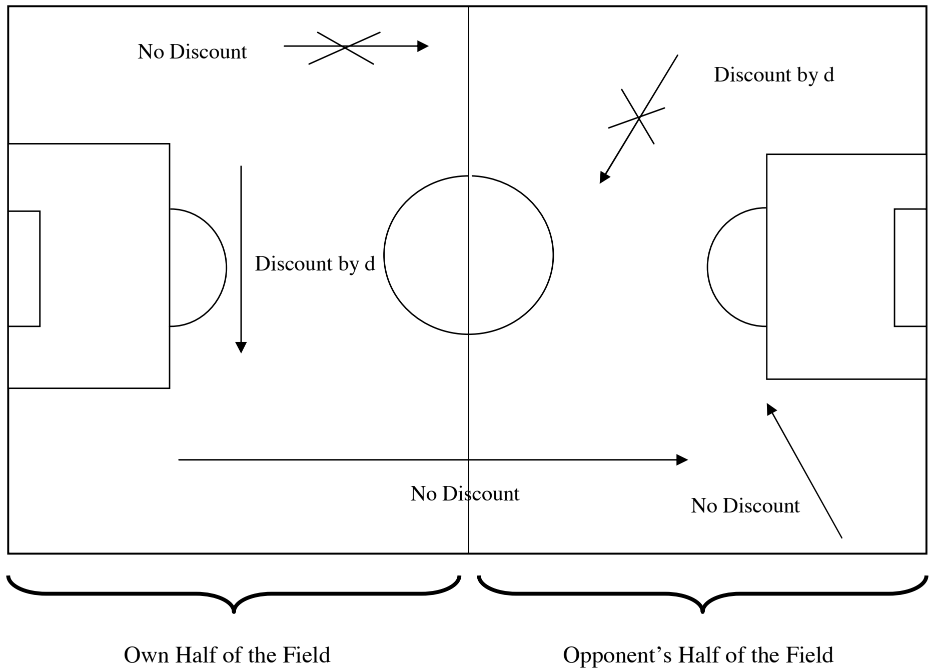

Figure 2: Discounting the successful passes and loses by "*d*".

4.1 Empirical Model

We return to the individual payoff function given in Equation (1) and interpret its terms for the game of soccer.[9]

$$U_i(x_1, ..., x_n) = \alpha_i x_i + \frac{1}{2}\sigma_{ii} x_i^2 + \sum_{j \neq i} \sigma_{ij} x_i x_j + \theta Z$$

where x_i is defined as how often the player i kicks the ball. This includes all passes, shots at the goal, corners and throw-ins of player i. The coefficient α_i measures the returns to individual effort. As before the utility function is quadratic in own effort with $\partial^2 U_i / \partial x_i^2 = \sigma_{ii} < 0$. The third term captures the interaction among players with σ_{ij} being the number of passes from player i to j. Thus, player i's utility from interacting with player j is weighted by how often he passes to j.

[9]Observe the payoff function shows only the actions of the team of interest. However, it does take the other team's effort into account implicitly. For example, as long as one of the team has ball possession, the other team cannot have any shots or passes.

In the above payoff function, σ_{ij} represents the complementary action of player i on player j. σ_{ij} indicates the number of (discounted) successful passes from player i to j minus the number of (discounted) unsuccessful passes from player i to j. This means that if σ_{ij} is positive, number of successful passes from player i to player j exceeds the number of unsuccessful passes from player i to j. While measuring the complementarity in players' effort, we introduce a discounting parameter, d in constructing the $\mathbf{\Sigma}$ matrix. Passes that are made far from the opponent's goal have little influence on creating a goal scoring opportunity. Therefore, we discount the passes that are made in own half of the field by a factor $0 < d < 1$. On the other hand, if player i successfully passes the ball to player j, and if player j is the opponent's half, then we do not discount that pass. Unsuccessful passes are discounted in the opposite way. If a player i losses the ball while trying to pass to player j, we look at the position of j. If player j is in the opponent's half, then we discount that loss by d. Similarly, if player i losses the ball while trying to pass to player j who is in his own half, then we do not discount that loss. Basically, if player i losses the ball near his own goal then that is a serious loss for the team. The intuition for not discounting the unsuccessful passes made in the own half is that players have to run back which hurts the team's play and may create an opportunity for the opponent to start an attack from an advantageous position.

The last term of the payoff function explains how an individual's utility depends on team outcome. We assume that the team outcome, Z is a linear function of each player's effort and ability parameter. The coefficient θ is a scale parameter that can be used to capture the importance of the game. In this framework, the ability parameter, δ_i is defined as the scoring probability of player i where $\delta_i =$ Number of goals scored by player i / Number of total shots on goal of player i. Alternatively, Z can also be defined as the outcome of the match. Specifically, Z can be assumed to be taking values of $\{1, 0, -1\}$ where $Z = 1$ implies that the team wins the game, $Z = 0$ implies that the match ended in a draw, and $Z = -1$ implies that the team lost the match. For the above definition of Z, the Nash equilibrium of the Team Game boils is identical to the Ballester et al. (2006) and allows us use the ICM provided by the authors in Remark 5 (note find page number).

4.2 Data and Results

Our data consists of all the matches from the Quarter Final onwards for the UEFA European Championship 2008. All the data that is used in the study is available from the authors on request.

Unfortunately, official passing data from UEFA's website is not adequate for our study due to a number of reasons. First, UEFA provides data only on the successful passes between player i and j and excludes the unsuccessful passes. Second, UEFA statistics do not provide the passing position of the players which is important for assessing the quality of passing. Finally, UEFA provides the total number of passes between player i and j in the entire tournament rather than match by match. Hence, we created a unique passing data set ourselves by watching the matches. This was done by freezing the frame at the time of the passing attempt and recording the player making the pass and the receiver in a matrix by noting the field position. We also discounted the passes using the method described in the previous section. Net discounted passes were used to create the interaction matrix, $\mathbf{\Sigma}$.[10] The net passes are used to determine the $\sigma_{ij}'s$ in $\mathbf{\Sigma}$ matrix. As expected, the $\mathbf{\Sigma}$ and $\mathbf{G}$ matrices are both asymmetric.

In order to facilitate comparisons across mathes we define a tournament wide λ and γ which are the same for every team. First we obtain the highest amount of positive and negative interaction between each pair of players throughout the tournament. Using this, the tournament wide γ and λ parameters are chosen as 5 and 20 respectively. This allows us to compare the same player's intercentrality measure from different matches as well as compare the intercentrality measure of different players from different matches. [11]

Data for creating the tournament wide scoring probabilities of each player was obtained from ESPN's website. [put the website here] Ideally, the life time scoring probability of a player would be δ_i in the theocratical model. However, this data is not available and we use the tournament wide measure as a proxy for this. Next, we calculate the $\mathbf{M}$ matrix, centrality vector ($\mathbf{b}$) and intercentrality vectors $\mathbf{c}$ and $\hat{\mathbf{c}}$ by using the definitions provided in Section 2. Note that assigning a value to a is crucial for obtaining a pure and interior Nash equilibrium. Ballester et al. (2006) note that for the case of asymmetric $\mathbf{\Sigma}$ and $\mathbf{G}$ matrices, a should be less than the spectral radius of $\mathbf{G}$, which is inverse of the norm of the highest eigenvalue of $\mathbf{G}$. The greatest eigenvalue of $\mathbf{G}$ matrices for the teams in the sample is 7.07 and hence following the above rule, the decay factor, a, is set to

[10] According to official statistics on average 800 successful passes occur in a match and it is a tedious exercise to record every passing attempt. Note that we also take into account the unsuccessful passing effort which is not reported by the official statistics.

[11] Note that the Netherlands vs Russia, Spain vs Italy and Croatia vs Turkey matches went into the extra time. Therefore, comparing the players in the these games with those ended in 90 minutes is not possible. The cross comparisons are valid for match lengths of the same duration. We discuss this issue in more detail in the next section.

0.125 for all matches. Since we did not have any guide lines for discount factor, $d \in [0, 1]$ we assume that $d = 0.5$ for all matches. Using all of these parameters we then compute TICM and ICM of each player.

The corresponding calculations for the Final, Semi Final and Quarter Final games for Euro 2008 are reported for each team in Tables 1-7. In those tables, $\hat{\boldsymbol{c}}$ refers to TICM and $\mathbf{c}$ indicates (ICM) of Ballester et al. (2006). We find that the results obtained by using TICM are better at capturing the players who have a direct influence on the outcome of the matches since it also incorporates the scoring probabilities. The highest value of TICM is observed in the Spain vs Italy Quarter Final game for Fabregas who has a value of 8.67. Note that this match ended in extra time. The highest value of TICM is observed in the Germany vs Portugal Quarter Final game for Deco of Portugal who has a value of 6.44 for a match which ended in normal time.[some arguments from slides interpret results not biased aganist forwards etc] However, since the data on scoring probabilities of players is not life time scoring probabilities, it also causes players who have very few shots in the tournament but scored a goal to have a high TICM in some matches.[provide example from data and explain] Therefore, we also report ICM results as a sensitivity check. [highest IM measure]

4.3 Sensitivity Checks

There is a concern that determination of the key player may depend on the our chosen values of the decay factor, a and discount factor, d. In fact, by means of an example Ballester et al.(2006) show that the key player may be different for different values of a. Similarly, the key player may change depending the value of discount factor, d. Hence, in order to check the robustness of our results, we conduct a simulation analysis by changing the values of those parameters. We allow a to vary from 0 to 0.125 in increments of 0.001. Simultaneously, we use the same increment and increase the value of d from 0 to 1. Since we perform the simulations for all matches and all teams, this gives us $14 \times 125{,}000 = 1.75$ million simulations. We find that the key player identified by ICM changes 15 percent of a time. On the other hand, the identified key players by using TICM change 40 percent of a time. There is a greater variability in TICM results because the scoring probability of the players are specific to the Euro 2008 tournament. Since the scoring probability itself shows great variability, it makes the TICM measure more idiosyncratic. The passign game on the other hand is more stable and therefore the ICM results have lesser variation.

4.4 Key Group

In this section, we determine the key groups of players following Temurshoev (2008). In fact the idea of the key groups [....Zenou.... put that in citation]Key groups of players in the matches provide information about the joint performance of players in the group. This is a valuable information for the soccer clubs, managers and coaches who wish the form their teams with individuals that provide different adjacencies to their teammates. In order to identify key groups of size k in a team, we take every possible combination of k players from the team and determine the reduction in the aggregate Nash equilibrium by their removal from the team. The key group consists of players whose removal leads to largest reduction in the aggregate Nash equilibrium.

We use Temurshoev's (2008) approach to compute the TICM of a group of k players. Removing players from the game creates a decrease in the expected number of goals in addition to the reduction in interaction between players. Therefore, the group intercentrality measure for TICM is defined as:

$$\hat{c_{\boldsymbol{g}}} = \mathbf{b}'\mathbf{E}(\mathbf{E}'\mathbf{M}\mathbf{E})^{-1}\mathbf{E}'\mathbf{b} + (\mathbf{1}'\mathbf{M}\mathbf{E})(\mathbf{E}'\boldsymbol{\delta}) \tag{13}$$

where $\mathbf{E}$ is the $n \times k$ matrix defined as $\mathbf{E} = (e_{i1}, ..., e_{ik})$ with e_{ir} being the i_r^{th} column of the identity matrix, k being the number of players in the group and $1 \leq k \leq n$. The first term captures the effect of the removal of a group of players in $\mathbf{g}$ and the second term captures the effect of reduction in the desired outcome of the team. It can be readily checked that for $k = 1$, the above expression boils down to the team intercentrality measure (TICM) of a player which is given in Equation (8). Note that the key group is not always comprised of the individuals having the highest intercentrality measure. As described in Borgatti (2006) and Temurshoev (2008), according to the *redundancy principle* key groups involve players who provide different adjacency to their teammates.

We choose key group sizes of $k = 2$ and $k = 3$ and calculate every possible group's intercentrality measure using ICM and TICM. The results for all the countries and matches in the sample are provided in Tables 8-12. In these tables, we report the top two key groups. In the key group tables, the column player position identifies the field position of the player. These positions are D (Defense), M (Midfield) and F (Forward). The rank in the $\hat{\boldsymbol{c}}$ column identifies the player's rank according to (TICM). The other key group results using ICM is available upon request. For an interesting comparison, we also provide the ICM key group results of Spain in Table 13. Generally, the key groups obtained by using TICM include more forward players. [..........Some info from slides explain why interesting......]

4.5 Player Ratings, Market Value and (Team) Intercentrality

In this subsection, the effect of intercentrality measure of the players who played in the Final, Semi-Final and Quarter Final games in Euro 2008 on their average ratings and market values will be discussed.

We introduce the average ratings that are given by the experts to the analysis to show that the performance of the players depend on their interactions with their teammates according to the experts. We obtained the average ratings from three sources: Goal.com, ESPN and SkySports. We create a variable of average rating for each player which is the obtained by taking of the average of the ratings.[12] We use these sources since they use the same scale and they also provide ratings for the substitute and substituted players in the matches. Also, these sources are outside the competing countries in UEFA EURO 2008 which eliminates potential bias in the ratings.

Next, we investigate whether having a higher ICM or TICM in Euro 2008 affects the market values of the players. Considering the effect of intercentrality on the salaries would be more interesting. However, the salaries of soccer players in Europe are private and not publicly available. Nevertheless, Frick (2007) and Battre et al. (2008) regard the estimated market value of the soccer players obtained from http://www.transfermarkt.de [13] as a good and reliable source to proxy the undisclosed salary of players. Battre et al.(2008) points out that there is a strong relationship between the market value of the players and their salaries for the players in Bundesliga, German First Division.[14] Using their argument, the estimated market value of the players are obtained for the year 2010 to proxy the salary of the players. The website also provides information about the other observable characteristics of the soccer players such as: Date of birth, club, nation, position, and number of international appearances, number of international goals, preferred foot and captaincy. We use the Club UEFA points and Nation UEFA points which are available from UEFA's website in order to capture the

[12]The correlation coefficient of ratings from the above sources are 0.7 thus we prefer to take the average of these ratings rather than using them one by one. Also, taking the average of the ratings will reduce the subjectivity in measuring the performance of the players.

[13]transfermarkt.de does not allow user to track the past market values. We saved the data about the players in March, 19 2010.

[14]Battre et al.(2006) obtains estimated market values of soccer players from a German sports magazine Kicker. However, Kicker only provides the market values of the players who only play at Bundesliga. However, they conduct a sensitivity check with transfermarkt data and they state that the correlation between those two sources are high.

quality and reputation of the players. Club and Nation points are announced by UEFA yearly and points are earned for being successful in UEFA club or national tournaments. The points that are provided by UEFA for the year 2008 are composed of the points earned in 2003-2008 period. We combine the available data from with the intercentrality measure, Club and Nation Rank measured by the UEFA points in 2008. The descriptive statistics about the data set are provided in Table 14.

In order to analyze whether there is a correlation between average ratings and (team) intercentrality measure, we consider the following base model:

$$AvgRating_{it} = \alpha_1 + \beta_1 (T)ICM_{it} + \gamma_1 Age_i + \theta_1 Age^2 + \lambda_1 Position_i + \psi_1 ClubRank_i + \phi_1 NationRank_i + \epsilon_{it}.$$

Similarly, we consider another base model to investigate the relationship between the market values of soccer players and their (team) intercentrality measure:

$$LogEMV_i = \alpha_2 + \beta_2 (T)ICM_i + \gamma_2 Age_i + \theta_1 Age^2 + \lambda_2 Position_i + \psi_2 ClubRank_i + \phi_2 NationRank_i + u_i.$$

In the above regression models, the i subscript represents the player i and the t subscript represents the match t. In model 1, average rating is the dependent variable and stands for the average ratings obtained from 3 reliable sources: Goal.com, ESPN and SkySports. In model 2, Log EMV is the dependent variable obtained from *transfermarkt.de* and represents the log of the estimated market value of the players in million euros. (T)ICM stands for the (team) intercentrality measure and identifies the contribution of player i to her teammates. Position is a dummy variable that identifies the position of the player. We consider three different positions for the players: Defense (D), Midfield (M) and Forward(F).[15] Club Rank and Nation Rank indicate the rank of the club and nation of the player measured by UEFA points. They are included to capture the reputation of the player as well as the individual quality. ϵ_i and u_i are the error terms for Model 1 and 2 respectively. In addition to the control variables in the base model, we regress the same dependent variables on a broader set of control variables including national team dummies, captaincy, height and preferred foot. The estimates are close and the coefficient of ICM and TICM variables are still significant. Since we have a small sample size, we prefer to use and report the results for the base models. Another important control variable is contract length of the players since according to the Bosman Rules in European football it is likely that players who are near to their contract expiration

[15] Goalkeepers are excluded from the regression analysis. Niko Kovac (Croatia) and Robert Kovac (Croatia) retired from professional soccer before 2010 and are also excluded.

dates have lower market values.[16] We checked the remaining duration of contracts of the players in our sample which is available in *transfermarkt.de*. There are only 12 players whose contracts' expire at the end of 2009-2010 season. Inclusion or exclusion of those players do not affect our results.

Some players are observed more than once in the tournament and they have different average ratings and intercentrality measures in different matches. However, we have only one observation for the market value of the players and the other control variables are time independent with the current setup. Model 1 can be estimated by using panel data methods (population average, pooled OLS or random effects) whereas Model 2 cannot be estimated by panel data methods. In order to deal with this issue, we take the average of the average ratings, (team) intercentrality measures and use GLS estimation in the estimation of Models 1 and 2. We provide the estimation results of Model 1 by using pooled OLS since average ratings and (team) intercentrality measures vary from match to match.

The estimation results for the relationship between average ratings and (team) intercentrality measures are provided in Tables 15 and 16. In the pooled OLS estimation, we estimate a linear regression model where the time variable is the match. Ideally, we could run a random effects model. However, there is not enough idiosyncratic variance in the data. In Model 15, we report the cluster-robust standard errors. We include a dummy variable ET to control for the minutes played of the players. ET takes the value of 1 if the corresponding player played more than 90 minutes in any match and 0 otherwise. In Table 16, we take the average of the average ratings and (team) intercentrality measures and have only one observation for each player and we report cluster-robust standard errors. The findings suggest that there is a strong relationship between the TICM and the average ratings. Specifically, players who have higher TICM performed better than their teammates according to the experts. For other sensitivity checks, we include the players who play enough time in the game specifically who played more than on the average 30 minutes. We lose 30 observations, but the results are robust. Another important factor to control for is whether or not the match ended in normal time. We define a dummy variable ET which is equal to 1 if the match ended in extra time and 0 otherwise. With the inclusion of this variable, TICM is significant whereas ICM is not. Therefore, we conclude that TICM better explains the average ratings since it also incorporates

[16] Bosman Rules is an important factor affecting the free movement of labor and had a profound effect on the transfers of football players within the EU. It allows professional football players in the European Union (EU) to move freely to another club at the end of their contract with their present team.

the goals scored by the players.

The estimation results investigating the relationship between the estimated market value and (team) intercentrality measures in Euro 2008 is provided in Table 17. We again report the results for both ICM and TICM. The standard errors are bootstrapped with 1000 replications.[17] According to the estimation results, intercentrality measure in UEFA Euro 2008 explains the 2010 market values of the players. One standard deviation increase in the intercentrality measure (ICM) creates on the average 9.84 percent increase in the market values of the players. On the other hand, one standard deviation increase in TICM yields on the average 10.88 percent increase in the market values of the players. It might be the case that, intercentrality measure is important for only a certain group of players (say midfielders) who play in the some certain position of the field. To test this hypothesis, we interact the intercentrality measure of players with their position dummies. The findings suggest that intercentrality measure is equally important at 5 percent significance level. (i.e, the effect of intercentrality measure is homogenous in the sample with respect to players' positions on the field.)

Note that the regression models use the (team) intercentrality measures which are calculated for specific parameters of $a = 0.125$ and $d = 0.5$. As a sensitivity check, we calculated the (team) intercentrality measures for $a = 0.1$ and $d = 0.4, 0.5, 0.6$ and $a = 0.125$ and $d = 0.4, 0.6$. The estimated coefficients and their significance are very similar.[18]

5 Conclusion and Discussion

In this paper, we introduce a Team Game and develop a measure of identifying the key player in the teams. Our work extends the intercentrality measure of Ballester et al.(2006) to contain an additional term. This additional term comes from the team outcome expression in the utility functions of players. This term suggests that a player gets utility when her team achieves its desired outcome. The calculated team intercentrality measure (TICM) can be regarded as team performance index of players. The calculated group team intercentrality measure ($\hat{c}_g$) can be interpreted as the joint contribution of players to their teams.

Our model measure also has some common features with intercentrality measure (ICM) of

[17]Since we have only one market value observation for the players, we lose significant amount of observations. To deal with this issue, we bootstrap the standard errors.

[18]We do not report the estimates obtained by using the above parameters but they are available upon request.

Ballester et al.(2006). We can say that a key player does not need to have the highest amount of individual payoff. In addition, a key player does not need to have the highest amount of individual action (number of kickings). It is important to note that both Ballester et al. (2006) and our framework are not seeking the best players in the network. The identified key players and key groups have the highest contribution to the corresponding aggregate Nash equilibrium. We show that there is a positive relationship between the average ratings and TICM and ICM in the sample. This fact reflects that soccer players having more interactions with their teammates get more credit in performance by the experts. More importantly, the market value of the soccer players increase with both TICM and ICM which is assumed to be reflected in their salaries. This effect is homogenous in the sample, it doesn't depend on the position of the player on the field.

One interesting extension of the approach in the paper might be considering the effort variable to be a vector and allowing different types of individual actions. This will require that we obtain a new set of theocratical results. Depending on the availability of data this model then can be empirically tested. In soccer for instance one could include tackling and dribbling data. Given the relationship between passing and scoring opportunities, this will not alter our primary results, but will provide us a more precise way to identify key players and key groups.

6 References

[1] Ballester, C., A. Calvo-Armengol, and Y. Zenou (2006). "Who's Who In Networks. Wanted: The Key Player". *Econometrica* **74**, pp. 1403-1417.

[2] Battre, M., Deutscher, C. and Frick, B. (2008). "Salary Determination in the German "Bundesliga: A Panel Study." No 0811, *IASE Conference Papers*, International Association of Sports Economists.

[3] Bonacich, P. (1987). "Power and Centrality: A Family of Measures". *American Jounal of Sociology* **92**, pp. 1170-1182.

[4] Borgatti, S. P. (2006). "Identifying Sets of Key Players In A Social Network". *Computational and Mathematical Organization Theory* **12**, pp. 21-34.

[5] Chen Y., G. Paul, R. Cohen, S. Havlin, S. P. Borgatti, F. Liljeros, and H. E. Stanley. (2007). "Percolation Theory and Fragmentation Measures in Social Networks", *Physica* **378**, 11-19.

[6] Debreu, G., and Herstein, I.N. (1953): "Nonnegative Square Matrices" *Econometrica*, **21**,

p.597607.

[7] Everett, M. G. and Borgatti, S. P. (1999). "The centrality of groups and classes". *Journal of Mathematical Sociology* **23**, pp. 181-201.

[8] Everett, M. G. and S. P. Borgatti (2006). "A Graph-Theoretic Perspective on Centrality". *Social Networks*, 28 (4), pp. 466-484

[9] Freeman, L. C. (1977). "A Set of Measures of Centrality Based on Betweenness". *Sociometry* **40**, pp. 35-41.

[10] Freeman, L. C. (1979). "Centrality In Social Networks: Conceptual Clarification". *Social Networks* **1**, pp. 215-239.

[11] Frick, B. (2007). "The Football Players' Labor Market: Empirical Evidence from the Major European Leagues." *Scottish Journal of Political Economy*, Vol. 54, No. 3, pp. 422-446.

[12] Hubbell, C. H. (1965). "An Input-Output Approach to Clique Information." *Sociometry* **28**, pp. 377-399.

[13] Katz, L. (1953). "A New Index Derived From Sociometric Data Analysis." *Psychometrika* **32**, pp. 241-254.

[14] Luhtanen P.; Belinskij A.; Hyrinen M.; Vnttinen T. (2001) "A Comparative Tournament Analysis Between the EURO 1996 and 2000 In Soccer." *International Journal of Performance Analysis in Sport*, volume 1, Number 1, July 2001, pp 74-82.

[15] Luxbacher, Joseph. "Soccer: Steps to Success" *Sports and Recreation*, 2005, pp 23.

[16] Miller, Al and Wingert, Norm. "Winning Soccer." H. Regnery Co., 1975, pp 62.

[17] Sabidussi, G. (1966). "The centrality index of a graph". *Psychometrica* **31**, pp. 581-603.

[18] Sade, D. S. (1972). "Sociometric of Macaca Mulatta I: Linkages and Cliques in Grooming Networks." *Folia Primatologica* **18**, pp. 196-223.

[19] Stephenson, K. and M. Zelen (1989). "Rethinking Centrality: Methods and Examples". *Social Networks* **11**, pp. 1-37.

[20] Temurshoev, U. (2008). "Who's Who In Networks. Wanted: The Key Group". Net Institute Working Paper 08-08.

7 Appendix

Proof of **Proposition 1.a**:

Proof. Note that equation (9) still holds for this case. $\mathbf{\Sigma}$ matrix is substituted in equation (10) to obtain:

$$(\beta\mathbf{I} + \gamma\mathbf{U} - \lambda\mathbf{G})x^* = \boldsymbol{\alpha} + \theta\boldsymbol{\delta}$$

where $\boldsymbol{\alpha}$ is now a $n \times 1$ column vector and its elements shows the returns to individual actions. Now, substitute $\mathbf{x} \cdot 1$ instead of $\mathbf{U} \cdot x^*$:

$$[\beta\mathbf{I} - \lambda\mathbf{G}]x^* = \boldsymbol{\alpha} - \gamma x^* \cdot \mathbf{1} + \theta\boldsymbol{\delta} \longrightarrow \beta[\mathbf{I} - \lambda^*\mathbf{G}]x^* = \boldsymbol{\alpha} - \gamma x^* \cdot 1 + \theta\boldsymbol{\delta}$$

And pre-multiply both sides by $[\mathbf{I} - \lambda^*\mathbf{G}]^{-1}$ matrix to obtain:

$$\begin{aligned}
\beta x^* &= [\mathbf{I} - \lambda^*\mathbf{G}]^{-1}(\boldsymbol{\alpha} + \theta\boldsymbol{\delta}) - \gamma x^*[\mathbf{I} - \lambda^*\mathbf{G}]^{-1} \cdot \mathbf{1} \\
\beta x^* &= \mathbf{b}_\alpha(\mathbf{g}, \lambda^*) + \theta\mathbf{b}_\delta + \gamma x^*\mathbf{b}(\mathbf{g}, \lambda^*) \\
x^*(\Sigma) &= \frac{\mathbf{b}_\alpha(\mathbf{g}, \lambda^*) + \theta\mathbf{b}_\delta(\mathbf{g}, \lambda^*)}{\beta + \gamma\mathbf{b}(\mathbf{g}, \lambda^*)}
\end{aligned}$$

□

Proof of **Proposition 1.b**: Define:

$$\widetilde{\alpha_i} = \frac{\alpha_i}{\sigma_{ii}} \quad , \quad \widetilde{\sigma_{ij}} = \frac{\sigma_{ij}}{\sigma_{ii}} \quad , \quad \widetilde{\delta_i} = \frac{\delta_i}{\sigma_{ii}}$$

Now, rewrite the payoff function by using the above definition such that:

$$\begin{aligned}
&U_i = \widetilde{\alpha} x_i + \frac{1}{2}\widetilde{\sigma}_{ii}x_i^2 + \sum_{j \neq i}\widetilde{\sigma}_{ij}x_i x_j + \theta\widetilde{Z} \\
&U_i = \frac{\sigma_i}{|\sigma_{ii}|}x_i + \frac{1}{2}\frac{\sigma_{ii}}{|\sigma_{ii}|}x_{ii}^2 + \sum_{j \neq i}\frac{\sigma_{ij}}{|\sigma_{ii}|}x_i x_j + \theta\widetilde{Z} \\
&\frac{\partial U_i}{\partial x_i} = \frac{\alpha_i}{|\sigma_{ii}|} + \frac{\sigma_{ii}}{|\sigma_{ii}|}x_i + \sum_{j \neq i}\frac{\sigma_{ij}}{|\sigma_{ii}|}x_j + \theta\frac{\delta_i}{|\sigma_{ii}|} = 0 \\
&\frac{\partial U_i}{\partial x_i} = \frac{1}{|\sigma_{ii}|}(\alpha_i + \sigma_{ii}x_i + \sum_{j \neq i} x_j + \theta\delta_i) = 0 \\
&\frac{1}{|\sigma_{ii}|}(\alpha_i + \sigma_{i1}x_1 + \sigma_{i2}, x_2 + ... + \sigma_{in}x_n + \theta\delta_i) = 0 \quad \forall\ i = 1, \ldots, n
\end{aligned}$$

Let $\widetilde{\mathbf{\Sigma}}$ be the following matrix:

$$\begin{bmatrix}
\frac{1}{\sigma_{11}} & 0 & 0 & \cdots & 0 \\
0 & \frac{1}{\sigma_{22}} & 0 & \cdots & 0 \\
0 & 0 & \frac{1}{\sigma_{33}} & \cdots & 0 \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
0 & \cdots & 0 & 0 & \frac{1}{\sigma_{nn}}
\end{bmatrix}$$

Then,

$$\widetilde{\boldsymbol{\Sigma}}(\boldsymbol{\alpha} + \boldsymbol{\Sigma}\mathbf{x} + \theta\boldsymbol{\delta}) = \mathbf{0}$$

In the above equation, $\widetilde{\boldsymbol{\Sigma}}$ is not zero matrix (since the diagonal elements are not equal to 0), then the second term must be equal to a zero vector. By using this, if the equation is solved for $\mathbf{x}$, then:

$$\mathbf{x}^*(\boldsymbol{\Sigma}) = \frac{\mathbf{b}_{\widetilde{\alpha}}(\mathbf{g}, \widetilde{\lambda}^*) + \theta\widetilde{\mathbf{b}_{\delta}(\mathbf{g}, \lambda^*)}}{\widetilde{\beta} + \widetilde{\gamma}\hat{b}(\mathbf{g}, \widetilde{\lambda}^*)} \tag{14}$$

8 Tables

Table 1: Spain vs Germany Final Game, a=0.125 and d=0.5

Name	**Position**	$\hat{c}_i$	c_i	**Name**	**Position**	$\hat{c}_i$	c_i
Xavi	M	4.31	3.97	Lahm	D	4.38	3.73
Fabregas	M	3.97	3.35	Schweinsteiger	M	4.31	3.57
Senna	M	3.66	3.66	Frings	M	4.02	4.02
Ramos	D	3.53	3.53	Podolski	M	4.01	3.45
Capdevila	D	3.49	3.49	Metzelder	D	3.88	3.88
Puyol	D	3.48	3.48	Mertesacker	D	3.77	3.77
Silva	M	3.47	3.36	Ballack	M	3.71	3.38
Guiza*	F	3.46	3.02	Klose	F	3.59	3.14
Marchena	D	3.46	3.46	Hitzlsperger	M	3.58	3.58
Iniesta	M	3.45	3.45	Friedrich	D	3.47	3.47
Torres	F	3.18	2.98	Lehmann	G	3.34	3.34
Xabi Alonso*	M	3.14	3.14	Jansen*	M	3.25	3.25
Cazorla*	M	3.11	3.11	Gomez*	F	3.12	3.12
Casillas	G	3.07	3.07	Kuranyi*	F	2.99	2.99

Table 1: In the above Table, the first 4 columns are for Spain and the remaining ones are for Germany. $\hat{c}_i$ represents TICM and c_i represents ICM. * indicates that player is a substitute.

Table 2: Spain vs Russia Semi-Final Game, a=0.125 and d=0.5

Name	**Position**	$\hat{c}_i$	c_i	**Name**	**Position**	$\hat{c}_i$	c_i
Ramos	D	5.37	5.37	Zyryanov	M	4.87	4.56
Silva	M	5.49	5.35	Semak	M	4.37	4.37
Fabregas*	M	6.02	5.24	Zhirkov	D	4.12	4.12
Xavi	M	5.48	5.09	Anyukov	D	4.10	4.10
Iniesta	D	4.97	4.97	Ignashevich	D	3.84	3.84
Senna	M	4.82	4.82	Berezutski	D	3.83	3.83
Capdevila	D	4.23	4.23	Arshavin	F	4.06	3.70
Xabi Alonso*	M	4.11	4.11	Saenko	M	3.63	3.63
Torres	F	4.28	4.06	Semshov	M	3.57	3.58
Marchena	D	4.02	4.02	Sychev*	F	3.46	3.46
Puyol	D	3.75	3.75	Akinfeev	G	3.36	3.36
Casillas	G	3.69	3.69	Pavlyuchenko	F	3.51	3.30
Villa	F	4.07	3.59	Biyaletdinov*	M	3.28	3.28
Guiza*	F	4.06	3.58				

Table 2: In the above Table, the first 4 columns are for Spain and the remaining ones are for Russia. $\hat{c}_i$ represents TICM and c_i represents ICM. * indicates that player is a substitute.

Table 3: Germany vs Turkey Semi-Final Game, a=0.125 and d=0.5

Name	**Position**	$\hat{c}_i$	c_i	**Name**	**Position**	$\hat{c}_i$	c_i
Schweinsteiger	M	4.96	4.15	Hamit	M	4.73	4.73
Mertesacker	D	3.84	3.85	Ayhan	M	4.65	4.65
Lahm	D	4.48	3.82	Sabri	D	4.64	4.64
Friedrich	D	3.75	3.75	Hakan	D	4.32	4.32
Hitzlsperger	M	3.75	3.75	Kazim	M	4.23	4.23
Frings*	M	3.68	3.68	Ugur	M	4.92	4.23
Metzelder	D	3.67	3.67	Aurelio	M	4.15	4.15
Podolski	M	4.12	3.55	Gokhan	D	4.14	4.14
Ballack	M	3.61	3.29	Mehmet	M	4.11	4.11
Rolfes	M	3.22	3.22	Semih	F	4.72	3.85
Klose	F	3.51	3.07	Gokdeniz*	M	3.45	3.45
Lehmann	G	2.98	2.98	Rustu	G	3.44	3.44
Jansen*	M	2.91	2.91	Tumer*	M	3.34	3.34
				Mevlut*	F	3.43	3.43

Table 3: In the above Table, the first 4 columns are for Germany and the remaining ones are for Turkey. $\hat{c}_i$ represents TICM and c_i represents ICM. * indicates that player is a substitute.

Table 4: Netherlands vs Russia Quarter Final Game, a=0.125 and d=0.5

Name	**Position**	$\hat{c}_i$	c_i	**Name**	**Position**	$\hat{c}_i$	c_i
Van Bronchorst	D	5.32	4.34	Arshavin	F	4.98	4.60
Van Der Vaart	M	5.08	5.08	Zhirkov	D	4.56	4.56
Nistelrooy	F	5.05	4.63	Pavlyuchenko	F	4.47	4.24
Sneijder	M	4.51	4.30	Zyryanov	M	4.46	4.16
Van Persie*	F	4.50	4.16	Semak	M	4.22	4.22
Heitinga*	D	4.43	4.43	Torbinski*	M	4.17	3.68
Boulahrouz	D	4.39	4.39	Anyukov	D	4.01	4.01
Oojer	D	4.35	4.35	Semshov	M	3.91	3.91
De Jong	M	4.24	4.24	Saenko	M	3.90	3.90
Kuyt	M	4.21	3.73	Kolodin	D	3.88	3.88
Afellay*	M	4.16	4.16	Ignashevich	D	3.76	3.76
Van Der Sarr	G	4.09	4.09	Bilyaletdinov*	M	3.76	3.68
Englaar	M	4.03	4.03	Akinfeev	G	3.52	3.52
Mathijsen	D	4.00	4.00	Sychev*	F	3.40	3.40

Table 4: In the above Table, the first 4 columns are for Netherlands and the remaining ones are for Russia. $\hat{c}_i$ represents TICM and c_i represents ICM. * indicates that player is a substitute.

Table 5: Germany vs Portugal Quarter Final Game, a=0.125 and d=0.5

Name	**Position**	$\hat{c}_i$	c_i	**Name**	**Position**	$\hat{c}_i$	c_i
Ballack	M	5.10	4.69	Deco	M	6.44	5.81
Schweinsteiger	M	5.47	4.58	Simao	M	5.39	5.39
Podolski	M	5.20	4.55	Ronaldo	M	5.47	5.31
Rolfes	M	4.38	4.38	Bosingwa	D	5.18	5.18
Lahm	D	4.95	4.25	Ferreira	D	4.70	4.70
Hitzlsperger	M	4.05	4.05	Pepe	D	5.15	4.63
Klose	F	5.01	3.96	Petit	M	4.51	4.51
Friedrich	D	3.87	3.87	Meireles*	M	4.91	4.48
Lehmann	G	3.60	3.60	Carvalho	D	4.40	4.40
Mertesacker	D	3.58	3.58	Moutinho	M	4.02	4.02
Metzelder	D	3.57	3.57	Nani*	M	4.02	4.02
Fritz*	M	3.39	3.39	Nuno Gomes	F	4.39	3.98
Borowski*	M	3.32	3.32	Postiga*	F	4.26	3.85
Jansen*	M	3.31	3.31	Ricardo	G	3.81	3.81

Table 5: In the above Table, the first 4 columns are for Germany and the remaining ones are for Portugal. $\hat{c}_i$ represents TICM and c_i represents ICM. * indicates that player is a substitute.

Table 6: Spain vs Italy Quarter Final Game, a=0.125 and d=0.5

Name	Position	$\hat{c}_i$	c_i	Name	Position	$\hat{c}_i$	c_i
Silva	M	8.14	7.97	Grosso	D	5.74	5.74
Capdevila	D	7.53	7.53	De Rossi	M	5.13	5.13
Fabregas*	M	8.47	7.49	Ambrossini	M	4.93	4.93
Senna	M	7.23	7.23	Aquilani	M	4.73	4.73
Xavi	M	7.61	7.13	Zambrotta	D	4.65	4.65
Ramos	D	6.52	6.52	Camoranesi*	M	4.65	4.65
Marchena	D	6.14	6.14	Chiellini	D	4.56	4.56
Villa	F	6.59	5.99	Toni	F	4.38	4.38
Iniesta	M	5.67	5.67	Panucci	D	4.99	4.29
Puyol	D	5.63	5.63	Cassano	F	4.28	4.28
Torres	F	5.54	5.29	Buffon	G	4.05	4.05
Cazorla*	M	5.18	5.18	Di Natale*	F	4.05	4.05
Guiza*	F	5.32	4.77	Perrotta	M	3.94	3.94
Casillas	G	4.72	4.72	Del Piero*	F	3.59	3.59

Table 6: In the above Table, the first 4 columns are for Spain and the remaining ones are for Italy. $\hat{c}_i$ represents TICM and c_i represents ICM. * indicates that player is a substitute.

Table 7: Croatia vs Turkey Quarter Final Game, a=0.125 and d=0.5

Name	Position	$\hat{c}_i$	c_i	Name	Position	$\hat{c}_i$	c_i
Modric	M	5.69	4.58	Arda	M	7.67	5.26
Pranjic	D	4.47	4.47	Hamit	M	5.24	5.24
Rakitic	M	4.18	4.18	Tuncay	M	5.24	5.24
N. Kovac	M	3.97	3.97	Hakan	D	5.11	5.11
Simunic	D	3.90	3.90	Nihat	F	5.03	4.40
Srna	M	4.06	3.83	Sabri	D	4.24	4.24
Corluka	D	3.77	3.77	Gokhan	D	4.14	4.14
R. Kovac	D	3.77	3.77	Emre	D	4.13	4.13
Kranjcar	M	3.66	3.66	Mehmet	M	4.09	4.09
Olic	F	3.64	3.37	Semih*	F	4.89	3.99
Petric*	F	3.32	3.32	Kazim	M	3.91	3.91
Klasnic*	F	4.05	3.31	Ugur*	M	4.48	3.82
Pletikosa	G	3.21	3.21	Rustu	G	3.69	3.69
				Gokdeniz*	M	3.43	3.43

Table 7: In the above Table, the first 4 columns are for Croatia and the remaining ones are for Turkey. $\hat{c}_i$ represents TICM and c_i represents ICM. * indicates that player is a substitute.

Table 8: Key Group of Spain in Euro 2008, TICM, a=0.125, d=0.5

Match	**Group Size**	**Player Position**	**Rank in $\hat{c}$**	**Player Names**	$\hat{c_g}$
Final	2	M, M	1,2	Xavi, Fabregas	7.78
Final	2	M, F	1,8	Xavi, Guiza	7.36
Final	3	M, M, F	1,2,8	Xavi, Fabregas, Guiza	10.58
Final	3	M, M, M	1,2,3	Xavi, Fabregas, Senna	10.49
Semi-Final	2	M, M	1,3	Fabregas, Xavi	10.48
Semi-Final	2	M, M	1,2	Fabregas, Silva	10.40
Semi-Final	3	M, M, M	1,2,3	Fabregas, Silva, Xavi	14.03
Semi-Final	3	M, M, D	1,2,4	Fabregas, Silva, Ramos	13.76
Quarter Final	2	M, M	1,3	Fabregas, Xavi	14.49
Quarter Final	2	M, M	1,2	Fabregas, Silva	14.15
Quarter Final	3	M, M, M	1,2,3	Fabregas, Silva, Xavi	18.87
Quarter Final	3	M, M, F	1,3,6	Fabregas, Xavi, Vila	18.66

Table 9: Key Group of Germany in Euro 2008, TICM, a=0.125, d=0.5

Match	**Group Size**	**Player Position**	**Rank in $\hat{c}$**	**Player Names**	$\hat{c_g}$
Final	2	D, M	1,2	Lahm, Schweinsteiger	8.28
Final	2	M, M	2,4	Schweinsteiger, Podolski	7.97
Final	3	D, M, M	1,2,4	Lahm, Schweinsteiger, Podolski	11.44
Final	3	M, M, M	2,3,4	Schweinsteiger, Frings, Podolski	11.25
Semi-Final	2	M, D	1,2	Schweinsteiger, Lahm	8.92
Semi-Final	2	M, M	1,3	Schweinsteiger, Podolski	8.52
Semi-Final	3	M, D, M	1,2,3	Schweinsteiger, Lahm, Podolski	11.93
Semi-Final	3	M, D, M	1,2,9	Schweinsteiger, Lahm, Ballack	11.69
Quarter Final	2	M, M	1,2	Schweinsteiger, Podolski	9.86
Quarter Final	2	M, F	1,4	Schweinsteiger, Klose	9.85
Quarter Final	3	M, M, F	1,2,4	Schweinsteiger, Podolski, Klose	13.71
Quarter Final	3	M, M, D	1,4,5	Schweinsteiger, Klose, Lahm	13.69

Table 10: Key Group of Russia in Euro 2008 TICM, a=0.125, d=0.5

Match	**Group Size**	**Player Position**	**Rank in $\hat{c}$**	**Player Names**	$\hat{c_g}$
Semi-Final	2	M, M	1,2	Zyryanov, Semak	8.36
Semi-Final	2	M, D	1, 4	Zyryanov, Anyukov	8.19
Semi-Final	3	M, M, F	1,2,5	Zyryanov, Semak, Arshavin	11.23
Semi-Final	3	M, D, F	1,4,5	Zyryanov, Anyukov, Arshavin	11.11
Quarter Final	2	F, M	1,4	Arshavin, Zyryanov	8.80
Quarter Final	2	F, F	1,3	Arshavin, Pavlyuchenko	8.79
Quarter Final	3	F, F, M	1,3,6	Arshavin, Pavlyuchenko, Torbinski	12.08
Quarter Final	3	F, D, F	1,2,3	Arshavin, Zhirkov, Pavlyuchenko	11.95

Table 11: Key Group of Turkey in Euro 2008 TICM, a=0.125, d=0.5

Match	**Group Size**	**Player Position**	**Rank in $\hat{c}$**	**Player Names**	$\hat{c_g}$
Semi-Final	2	M, F	1,2	Ugur, Semih	9.18
Semi-Final	2	F, D	2,5	Semih, Sabri	8.96
Semi-Final	3	M, F, D	1,2,5	Ugur, Semih, Sabri	12.60
Semi-Final	3	M, F, M	1,2,3	Ugur, Semih, Hamit	12.54
Quarter Final	2	M, F	1,5	Arda, Nihat	11.89
Quarter Final	2	M, F	1, 6	Arda, Semih	11.85
Quarter Final	3	M, F, F	1,5,6	Arda, Nihat, Semih	12.31
Quarter Final	3	M, M, F	1,2,6	Arda, Hamit, Semih	12.18

Table 12: Key Groups of Other Countries in Euro 2008 TICM, a=0.125, d=0.5

Match	**Group Size**	**Player Position**	**Rank in $\hat{c}$**	**Player Names**	$\hat{c_g}$
			Netherlands		
Quarter Final	2	D, F	1,3	Bronckhorst, Nistelrooy	9.81
Quarter Final	2	D, M	1,2	Bronckhorst, Vaart	9.64
Quarter Final	3	D, M, F	1,2,3	Bronckhorst, Vaart, Nistelrooy	13.27
Quarter Final	3	D, F, F	1,3,5	Bronckhorst, Nistelrooy, Persie	13.15
			Portugal		
Quarter Final	2	M, D	1,5	Deco, Pepe	10.73
Quarter Final	2	M, M	1,2	Deco, Ronaldo	10.60
Quarter Final	3	M, M, D	1,2,5	Deco, Ronaldo, Pepe	14.35
Quarter Final	3	M, D, M	1,5,6	Deco, Pepe, Meireles	14.15
			Italy		
Quarter Final	2	D, D	1,3	Grosso, Panucci	9.91
Quarter Final	2	D, M	1,2	Grosso, De Rossi	9.78
Quarter Final	3	D, M, D	1,2,3	Grosso, De Rossi, Panucci	13.47
Quarter Final	3	D, D, D	1,3,7	Grosso, Panucci, Zambrotta	13.25
			Croatia		
Quarter Final	2	F, M	1,5	Modric, Klasnic	9.21
Quarter Final	2	D, M	1,2	Modric, Pranjic	9.17
Quarter Final	3	D, F, M	1,2,5	Modric, Pranjic, Klasnic	12.31
Quarter Final	3	D, D, M	1,3,5	Modric, Rakitic, Klasnic	12.18

Table 13: Key Group of Spain in Euro 2008 ICM, a=0.125, d=0.5

Match	**Group Size**	**Player Position**	**Rank in $\hat{c}$**	**Player Names**	$\hat{c_g}$
Final	2	M, M	1, 2	Xavi, Senna	7.02
Final	2	M, D	1, 3	Xavi, Ramos	6.97
Final	3	M, D, D	1, 3, 4	Xavi, Ramos, Capdevila	9.61
Final	3	M, D, D	1, 3, 5	Xavi, Ramos, Puyol	9.60
Semi-Final	2	D, M	1,2	Ramos, Silva	9.52
Semi-Final	2	M, M	2,3	Silva, Fabregas	9.45
Semi-Final	3	M, D, M	5,1,3	Iniesta, Ramos, Fabregas	12.82
Semi-Final	3	M, M, M	5,4,8	Iniesta, Xavi, Xabi	12.73
Quarter Final	2	D, M	2,1	Capdevila, Silva	13.51
Quarter Final	2	M, M	4,1	Senna, Silva	13.13
Quarter Final	3	D, M, M	2,4,1	Capdevila, Senna, Silva	17.48
Quarter Final	3	D, M, M	2,4,3	Capdevila, Senna, Fabregas	17.39

Table 14: Descriptive Statistics

Variable	**Obs**	**Mean**	**Std. Dev**	**Min**	**Max**
Average Rating	110	6.18	0.86	3.33	8.17
Intercentrality (ICM)	110	4.18	0.60	2.99	5.81
Team Intercentrality (TICM)	110	4.379	0.741	2.986	7.671
Log Market Value	110	2.325	0.775	0.182	4.248
Age	110	27.035	3.741	20	38
Club UEFA Points	104	71.22	29.32	10.53	125.00
Nation UEFA Points	110	44.56	17.12	11.62	75.27
Germany	110	0.15	0.36	0.00	1.00
Croatia	110	0.10	0.29	0.00	1.00
Netherlands	110	0.12	0.33	0.00	1.00
Spain	110	0.13	0.34	0.00	1.00
Russia	110	0.12	0.33	0.00	1.00
Portugal	110	0.12	0.32	0.00	1.00
Turkey	110	0.16	0.36	0.00	1.00
Italy	110	0.12	0.33	0.00	1.00
Defender	110	0.28	0.45	0.00	1.00
Midfielder	110	0.45	0.50	0.00	1.00
Forward	110	0.22	0.41	0.00	1.00

Table 14: Average ratings for the players are obtained by taking the average of the player ratings available through Goal.com ESPN Soccer and Skysports. Log of the market value of players are obtained from *transfermarkt.de*. Spain, Germany, Russia Turkey, Netherlands, Croatia, Italy and Portugal are the dummy variables which are equal to 1 if player i is playing for the corresponding national team and 0 otherwise. D, M and F are dummy variables to indicate the field position of the players. They represent Defender, Midfielder and Forward respectively. Club and Nation UEFA points are available from UEFA's website. We use 2008 points, which is earned in 2003-2008 period by clubs or nations in UEFA tournaments.

Table 15: Average Ratings and (Team) Intercentrality Measure Pooled OLS Estimation

Variable	**I**	**II**	**III**	**IV**	**V**	**VI**
Intercentrality (ICM)	0.184*	0.158	0.161			
	(0.102)	(0.109)	(0.125)			
Team Intercentrality (TICM)				0.278***	0.253**	0.241**
				(0.096)	(0.100)	(0.106)
ET	0.262	0.338	0.339	0.173	0.239	0.237
	(0.242)	(0.259)	(0.263)	(0.232)	(0.251)	(0.256)
Age	0.031	0.158	0.155	0.085	0.198	0.161
	(0.272)	(0.268)	(0.269)	(0.248)	(0.244)	(0.246)
Age squared	-0.001	-0.003	-0.003	-0.002	-0.004	-0.003
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)
Club UEFA Points	0.001	0.000	0.000	0.000	0.000	-0.001
	(0.003)	(0.003)	(0.003)	-0.003	-0.003	-0.003
Nation UEFA Points	0.009*	0.010*	0.010*	0.009	0.010*	0.010*
	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)
Defender		-0.359**	-0.272		-0.313*	-0.036
		(0.171)	(0.735)		(0.166)	(0.734)
Forward		-0.21	-0.27		-0.208	-0.984
		(0.215)	(1.261)		(0.196)	(1.306)
DxICM			-0.02			
			(0.156)			
FxICM			0.016			
			(0.314)			
DxTICM						-0.063
						(0.149)
FxTICM						0.184
						(0.304)
Constant	4.836	3.303	3.317	3.731	2.378	2.934
	(3.634)	(3.573)	(3.605)	(3.341)	(3.287)	(3.321)
Observations	167	167	167	167	167	167
Number of Players	110	110	110	110	110	110
R-squared	0.09	0.111	0.112	0.126	0.143	0.148
Wald Chi Sq statistic	4.44	3.54	2.99	7.49	5.70	4.37

Table 15: The dependent variable is average ratings and the pooled OLS coefficients are reported in the above regressions. Cluster-robust standard errors are given in parentheses. ***, **, * indicate 1, 5 and 10 percent significance levels respectively. Goalkeepers are excluded from the sample. DxICM, FxICM, DxTICM and FxTICM are interaction variables obtained by interacting the (team) intercentrality measure with the position dummy. ET is a dummy variable which takes the value of 1 if the player played more than 90 minutes in any of the matches and 0 otherwise.

Table 16: Average Ratings and (Team) Intercentrality GLS Estimation

Variable	**I**	**II**	**III**	**IV**	**V**	**VI**
Intercentrality (ICM)	0.299**	0.229**	0.198			
	(0.120)	(0.113)	(0.150)			
Team Intercentrality (TICM)				0.310***	0.266***	0.231*
				(0.106)	(0.100)	(0.134)
Age	-0.181	-0.078	-0.089	-0.115	-0.012	-0.033
	(0.318)	(0.285)	(0.313)	(0.310)	(0.296)	(0.308)
Age Squared	0.003	0.001	0.001	0.002	0.000	0.000
	(0.006)	(0.005)	(0.006)	(0.006)	(0.005)	(0.006)
Club UEFA pts	-0.003	-0.002	-0.002	-0.003	-0.003	-0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Nation UEFA pts	0.001	0.001	0.001	0.001	0.001	0.002
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Defender		-0.145	-0.702		-0.118	-0.116
		(0.213)	(1.232)		(0.216)	(1.076)
Forward		-0.471*	-0.732		-0.479*	-2.067
		(0.262)	(1.613)		(0.251)	(1.494)
DxICM			0.130			
			(0.285)			
FxICM			0.065			
			(0.416)			
DxTICM						-0.002
						(0.242)
FxTICM						0.390
						(0.365)
Constant	7.910*	6.867*	7.163*	6.875	5.745	6.257
	(4.396)	(3.907)	(4.350)	(4.285)	(4.108)	(4.417)
Observations	104	104	104	104	104	104
R square	0.087	0.118	0.119	0.114	0.147	0.159
R square adj	0.041	0.053	0.035	0.069	0.085	0.079
Wald Chi Sq Statistic	9.46	13.91	12.03	10.87	16.88	18.52

Table 16: The dependent variable is average ratings and the GLS estimation results are reported in the above regressions. Bootstrapped robust standard errors are given in parentheses. ***, **, * indicate 1, 5 and 10 percent significance levels respectively. Goalkeepers are excluded from sample. DxICM, FxICM, DxTICM and FxTICM are interaction variables obtained by interacting the (team) intercentrality measure with the position dummy.

Table 17: Market Values and (Team) Intercentrality GLS Estimation

Variable	**I**	**II**	**III**	**IV**	**V**	**VI**
Intercentrality (ICM)	0.129*	0.164**	0.240***			
	(0.070)	(0.070)	(0.090)			
Team Intercentrality (TICM)				0.132**	0.145***	0.204***
				(0.056)	(0.053)	(0.061)
Age	0.314	0.301	0.329	0.341	0.33	0.344*
	(0.219)	(0.198)	(0.207)	(0.227)	(0.213)	(0.207)
Age squared	-0.008*	-0.007**	-0.008**	-0.008**	-0.008**	-0.008**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Club UEFA pts	0.007***	0.006**	0.006***	0.007***	0.006***	0.007***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Nation UEFA pts	0.013***	0.013***	0.012***	0.013***	0.013***	0.012***
	(0.005)	(0.004)	(0.005)	(0.005)	(0.004)	(0.005)
Defender		-0.163	1.223		-0.153	0.802
		(0.134)	(0.747)		(0.139)	(0.715)
Forward		0.184	0.761		0.153	1.296
		(0.148)	(0.802)		(0.148)	(0.817)
DxICM			-0.324*			
			(0.172)			
FxICM			-0.142			
			(0.200)			
DxTICM						-0.217
						(0.158)
FxTICM						-0.277
						(0.201)
Constant	-2.115	-2.084	-2.82	-2.541	-2.442	-2.994
	(2.985)	(2.667)	(2.790)	(3.084)	(2.931)	(2.843)
Observations	104	104	104	104	104	104
R square	0.483	0.501	0.523	0.489	0.509	0.524
R square adj	0.456	0.470	0.477	0.463	0.473	0.479
Wald Chi Sq Statistic	104.62	133.43	121.25	100.81	126.04	138.07

Table 17: The dependent variable is the log of 2010 market value of the players obtained from transfermarkt.de in the above regressions. Goalkeepers are excluded from the sample. DxICM, FxICM, DxTICM and FxTICM are variables obtained by interacting the (team) intercentrality measures with the position dummy of the player. Bootstrapped robust standard errors are reported in parentheses. ***, **, * indicate 1, 5 and 10 percent significance levels respectively.