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DOES MANAGER MATTER? EVIDENCE FROM E-SPORTS

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Abstract

Growing importance of human resources places the role of managers at the core of company efficiency. However, there are studies that demonstrate the efficiency of teams without a manager, so-called self-managed teams, is higher comparing with managed teams. Thus, despite the focus on managerial efficiency in the economic literature, the issue of whether a team needs a manager is far from settled. In this paper, we use a quasi-experimental setting from e-Sports (competitive video gaming) to understand whether the hiring a manager is of benefit to team performance. The empirical part of the study is based an endogenous switching regression model. This method allows investigating what performance of self-managed team would be if it will have a manager and vice versa. The dataset includes the information of prize money and features of top e-Sports teams in *Counter-Strike: Global Offensive* (e-Sports discipline) from 2013 to 2017. The main finding of this study is that managed teams perform better than self-managed ones but this is not due to the manager.

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Managerial efficiency is one of the key issues in labor economics and management. The manager is responsible for the transformation of resources into output or revenue at the least possible cost. In the modern economy, the importance of human resources is growing, placing the role of managers at the core of company efficiency. However, there are studies that examine the efficiency of teams without a manager, so-called self-managed teams (Carte et al., 2006; Cohen and Ledford, 1994; Cummings, 1978). Thus, despite the focus on managerial efficiency in the economics literature, the issue of whether a team needs a manager is far from settled. In this paper, we use a quasi-experimental setting from e-Sports to understand whether the manager is of benefit to team performance.

There is a considerable amount of research on production and in particular managerial efficiency in the sports industry due to the availability of data on professional sports teams (Carmichael and Thomas, 1995; Frick and Simmons, 2008; Kahane, 2005; Kuypers and Szymanski, 1999; Porter and Scully, 1982; Schofield, 1988; Zech, 1981). The authors generally include indicators that reflect the contribution that management makes to production. Zech (1981) found that his proxies for manager quality were statistically insignificant. Carmichael et al. (2000) also concluded that manager experience was not statistically significant in their estimation of the production function. However, Porter and Scully (1982) found that the manager's contribution to team success was comparable to that of a "star" player. Frick and Simmons (2008) found that a team with a better manager was more efficient.

The mixed evidence from these papers could be partly explained by the difficulties entailed in the empirical estimation of the team production function. Dawson et al. (2000) found, for example, that the estimates of managerial efficiency were sensitive to the choice of the model. Another pitfall is the choice of method to analyze efficiency: various techniques such as data envelopment analysis, stochastic frontier approach, betting odds efficiencies and others yield contradicting results (del Corral et al., 2017; Haas, 2003). One also might expect that a better team might hire a more skilled manager, hence, reverse causality might be an issue.

All of these studies focus on the issue of managerial efficiency, in other words, whether a better manager helps a team to improve its results. However, it might be beneficial for a team to refuse to hire a manager. There is a growing literature that analyzes self-managing teams and shows that these teams might be more efficient than teams with managers (Carte et al., 2006; Stewart, 2006). Self-managed teams are defined as teams in which team members are the only ones who take responsibility for the quality and the results of the work process and product, thus, the management function is shared among team members (O'Connell et al., 2002).

There are several reasons why self-managed teams can outperform managed ones: higher flexibility in the face of changing conditions and higher motivation when leadership responsibilities and rewards are shared across all team members (Cohen and Ledford, 1994; Pearce III and Ravlin, 1987; Wall et al., 1986). Besides, self-managed teams are characterized by task feedback that allows monitoring and improving current activities (Hackman and Oldham, 1976; Pasmore, 1988). All these advantages are likely to encourage employees from self-managed teams to perform better (Cohen et al., 1996; Goodman and Haran, 2009). The influence of team autonomy on its performance was empirically investigated; however, the results are contradictory (Chaston, 1998; Cohen and Ledford, 1994; Kozlowski and Bell, 2003; Stewart, 2006).

In this paper, we address the question of whether a team needs a manager and we estimate the treatment effect of managers on team performance. Managers in e-Sports play the same role as the manager of a team in any other context; they help to transform the players' resources into team performance. In the majority of team sports, the presence of a manager is a given. However, over the last five years in e-Sports, top teams have been hiring managers, that is, they have added a manager to the team management. For that reason, e-Sports provides us with a quasi-experimental setting with which to test the treatment effect of managers. Thus this paper contributes to the literature on self-managed teams and sheds light on the consequences of hiring or firing a manager in terms of team performance.

E-Sports is competitive computer gaming that has been growing rapidly at least since 2010 and is increasingly recognized as a sport (Funk et al., 2018; Hallmann and Giel, 2018). In 2014, the number of viewers of *League of Legends* (one of e-Sports primary disciplines) exceeded the audience of the National Basketball Association (NBA) and National Hockey League (NHL) finals (Dorsey, 2014). In 2022, e-Sports will be a medal event at the Asian Games—the biggest regional international comprehensive sports event. Rowell (2016) has predicted that the number of e-Sports viewers will continue to increase. Despite its growing popularity, e-Sports is not well studied in academic research, particularly from the perspective of business and economics (Karhulahti, 2017; Wagner, 2006). From a managerial point of view, any e-Sports team addresses the typical issues such as team composition, leadership and work environment. From an economic point of view, the e-Sport team can be considered as a company because its main aim is to earn money. In this sense, the analysis of e-Sports data can provide fruitful insights for non-sport companies.

We concentrate on a particular e-Sports discipline: *Counter-Strike: Global Offensive* (CS:GO)⁴. There are some features of CS:GO that make it a good platform for analyzing managerial efficiency. The team production function in CS:GO is similar to that of traditional team sports (Parshakov et al., 2018). The rewards are performance-based, so the team prize money is a good proxy of its skill (Coates and Parshakov, 2016; Parshakov and Zavertiaeva, 2018)⁵.

The role of the manager in CS:GO and in e-Sports, in general, is similar to traditional sports. However, there are important differences. First, in CS:GO the managers can talk only during pause times and before/after games. They cannot communicate during the game. Second, usually there are no "bench" players, so the manager is not deciding on the team for a particular match. Third, the manager is rarely involved in the process of team composition and transfers. In both self-managed teams and teams with managers, the owner or his deputy are those who decide on transfers, hiring and resigning of the players. The team members are also involved in this process. Each team has an in-game leader (IGL) that plays and communicates at the same time. A manager usually has an analyst as his deputy. A manager's role is to show the team the right direction based on experience, such as instructing players on how to best use their individual and group skills and by providing encouragement to the team. In some organizations,

⁴ *Counter-Strike: Global Offensive* is a multiplayer first-person shooting game. There are five players on each team. Each team is either a terrorist or a counter-terrorist team and attempts to complete specific objectives or to eliminate all members of the rival team. There is no natural advantage to being the terrorist or the counter-terrorist team. The game operates in short rounds that end when all players on one side are dead or when a team's objective has been completed. Players purchase weapons and equipment at the beginning of every round using the money awarded on the basis of their performance in the previous round.

⁵ An appendix contains the scatterplot of the log of prize money and the kill-to-death ratio as an indicator of team skill. It indicates a positive relation between prize money (in logs) and the kill-to-death ratio. The better teams seem to get higher prize money.

especially the smaller ones, the manager and the analyst may be the same person. In other larger organizations, a team of many individuals supports the manager.

1. METHODOLOGY

The empirical analysis of this study utilizes an endogenous switching regression model (Lokshin and Sajaia, 2004). This model describes the performance of teams by using two regression equations and a criterion function (I) that determines whether or not a team has a manager:

$$\begin{aligned} I_i &= 1 & \text{if } \gamma Z_i + u_i > 0 \\ I_i &= 0 & \text{if } \gamma Z_i + u_i \leq 0 \end{aligned}$$

$$\begin{aligned} \text{Regime 1: } y_{1i} &= \beta_1 X_{1i} + \epsilon_{1i} & \text{if } I_i = 1 \\ \text{Regime 2: } y_{2i} &= \beta_2 X_{2i} + \epsilon_{2i} & \text{if } I_i = 0 \end{aligned}$$

A naïve model would estimate an equation that explains team performance and includes variables that measure influences such as the ability of the players, turnover among players in the team and whether or not the team has a manager. Of course, the presence of a manager is a choice variable and this choice may be correlated with unobservable factors that explain team performance. The switching regression model addresses the possible endogeneity of the decision about whether to have a manager. It does so by using a probit model to predict which teams will have a manager and it then uses the probit equation to construct the inverse Mills' ratio that is included as an explanatory variable in the performance regression.

The switching model relies upon identification of the choice to have a manager or not that does not also explain performance, that is, there should be a variable or variables in Z_i that do not also belong in the vectors X_{1i} and X_{2i} . The inverse Mills' ratio is a nonlinear function of the variables in Z_i ; if Z and the X 's are identical then the Mills' ratio is just a nonlinear function of the X s. In such a case, the significance of the Mills' ratio may indicate that the functional form of the performance regression is nonlinear rather than controlling for the omitted unobservable factors that explain the decision to have a manager and are correlated with the performance regression error. In this analysis, variables which predict the presence or absence of a manager, that identify the inverse Mills' ratio, include the number of teams within the e-Sports organization to which each team belongs and the age of that organization and its square. Our hypothesis is that these variables relate to factors at the organizational and sponsorship level and outside the interpersonal relationships within the individual team, the abilities of individual players, and in-game cooperation and communication among teammates. We do not include lagged values of performance, because it costs a very large number of observations. We also do not include the current period performance indicators, because the decision to have a manager occurred prior to these variables.

The performance equations include the average kill-to-death ratio and average headshots percentage (to control for the skill of a team), the average number of maps played (to account for team experience), the number of players during a year (to control for turnover in the team). We use lagged performance indicators for two reasons. First, because of the turnover of players', the previous value of the performance indicator would not reflect the current team skill. Second, prize money might affect team prize in case of roster changes, but the transfers during the season are quite rare.

Following the estimation, we calculate and compare the expected prize money according to four possible outcomes. The outcome I predicts the logarithm of the prize money for those teams that had a manager using the coefficients from the regression on those same teams. Outcome III analogously predicts the logarithm of the prize money for teams that did not have a manager using the coefficients from the prize money regression estimated on the sample of

teams that did not have a manager. Outcomes II and IV are counterfactual predictions. Using the coefficients from the regression on teams with managers, outcome II predicts the prize money that would have been won by teams that did not have a manager; outcome IV predicts the prize money of teams that did have a manager using the coefficients from the no-manager prize money regression.

These four outcomes can be presented as follows (Figure 1):

[Please insert Figure 1 here]

To sum up, we observe whether or not a team has a manager and the team's prize money. We then calculate what the prize money of a team without a manager would be if it had a manager and vice versa. A t-test on the equality of means was performed to test the statistical significance of the differences among these outcomes.

2. DATA DESCRIPTION

We use CS:GO team data in the empirical part. The data includes the prize of all professional teams in all tournaments from the HLTV webpage. HLTV is a major source of data in CS:GO. This organization decides on which teams to include in the ranking of professional teams. Note that even the teams with low prize might be treated as professionals if CS:GO is the activity team members do for a living. Low prizes at the start might be compensated by contracts with sponsors, but such a model is not sustainable in the long run⁶.

Note that the teams are located in different regions. It is difficult to define the country of the team. First, most of the teams consist of representatives from different countries. Second, the countries in which they train might differ from the countries in which they live regularly. Third, a player might switch teams more easily than in traditional sports.

In the current study, team performance is measured as the logarithm of prize money earned by a team in each particular year. This variable demonstrates substantial variation, from a low of 100 USD to a high of 1,558,756 USD. The determinants of team performance include players' skills (measured by average kill-to-death ratio and average headshots), players' experience (average number of played maps) and the presence of a manager. Kill-to-death ratio is evaluated as the number of kills divided by deaths. For example, if a player gets 10 kills and 5 deaths in a given game, they have a kill-to-death ratio of 2. It means they got 2 kills for each time they die. The headshot is the percentage of the player's shots into the opponents' head. This statistic reflects individual skill since one shot into the head almost always is enough to kill the opponent. It should be said that kill-to-death ratio depends on the competitors' kill-to-death ratio, so it might be biased if the competition is has an unbalanced structure. However, since each team participates in a lot of tournaments during a year, the majority of teams face each other.

There is a time trend in the prize money indicating the growth of the popularity of eSports and CS:GO in particular. However, the system of equations could not be estimated with the year effects. It might be that time trend is highly correlated with the performance indicator (there is a statistically significant correlation between kill-to-death ratio and the prize). So the performance indicator should capture the time trend effect.

⁶ We also run the regressions dropping part of the sample with the extremely low prize money (less than 1,000 USD). The coefficients differ, but the general results are the same (available upon request).

In order to model the probability of a team having a manager in the first stage, we used two additional variables—team age and the number of teams within the e-Sports organization to which each team belongs. In e-Sports, there are professional organizations that usually have several teams for different e-Sports games. For instance, *Fnatic*, one of the most famous and successful e-Sports organizations, has a team for each of *Counter-Strike: Global Offensive*, *Call of Duty*, *Counter-Strike: Global Offensive Academy*, *Dota 2* and *FIFA*. The number of teams within one e-Sports organization and the age of a team reflect its professionalism and can be positively correlated with the probability of hiring a manager without determining the performance of the individual teams. On average, there are three teams in e-Sports organizations and the average team age is four years.

The mean, standard deviation, minimum and maximum values for the variables used in the analysis are presented in Table 1. The data is of longitudinal structure. However, we observe only 69% of the teams for more than one season and 20% of the teams are observed for all four seasons. This is because of the huge turnover of the bottom-ranking teams. In one year, an average team earns 84.2 thousand USD. The variation in players' experience is huge: the most experienced team has 516 times more maps played than the least experienced team and the standard deviation in maps played is 79, while the mean is only 101.7. The variation in skill is harder to characterize. The mean headshot percentage is almost four times its standard deviation and the range is large, from 0.309 up to 78.64. The mean kill-to-death ratio is about 10 times larger than its standard deviation with the range covering 0.310 up to 1.314.

[Please insert Table 1 here]

Some insights can also be extracted from the analysis of differences in the means of variables between the teams with and without a manager (Table 2). First, on average, managed teams earn almost 5.4 times more prize money than self-managed teams. Of course, the difference in mean prize money between managed and self-managed teams may simply reflect the rise in the number of teams with managers over recent years when the prize money has also been higher. The speed of this rise in managed teams can be seen in Figure 2. In 2013, about 2.5% of the top 100 CS:GO teams were trained by managers, while in 2016, this value reached its peak at 70.4%. Indeed, from 2015 to 2016, the number of teams with managers increased by almost 40 percentage points. However, in 2017, the share of managed teams among the top 100 CS:GO teams decreased and was equal to 54%, which might indicate a changing trend with respect to hiring a manager in e-Sports. This might be explained by the fact that self-managed teams won a lot of major tournaments, which indicate for the whole community that managers are not vital for the team success. Also, in 2015, it was trendy to hire a manager even to show the professionalism of a team. Later, the teams might take these decisions more thoughtfully, since the manager adds to the costs of the organizations.

Second, teams with a manager show the higher professionalism of the organizations to which they belong; measured as the number of teams in such organizations. Further, differences in the skills and experience between teams with and without a manager appeared to be statistically significant—on average managed teams are more skilled and experienced. Moreover, such teams have less strong competitors compared with self-managed teams. Even small differences in the competitors' kill-to-death ratio between the teams with and without a manager appeared to be statistically significant. These simple tests of the difference in the means support the intuition that a manager positively influences team performance.

[Please insert Table 2 here]

[Please insert Figure 2 here]

3. RESULTS

In this section, we present the results of the endogenous switching regression model. The first column in Table 3 reports the probit estimates of the probability that a team has a manager. This model is statistically significant at the 1% significance level. In total, 67.17% of observation are correctly classified. R squared need not be high, because we do not need a perfect fit for the first-stage regression. The results indicate that the number of teams within an e-Sports organization and the age of that organization are relevant instruments for the presence of a manager. The correlation coefficients reported by the movestay command of Lokshin and Sajaia (2004) ρ_1 and ρ_2 are both positive. However, only the correlation between the manager selection equation and the prize equation for the teams with the manager is statistically significant. This suggests that the teams who continue to have a manager win less prizes than a random team⁷.

As expected, the more teams in an organization the higher the likelihood a team has a manager. In this case, one additional team within the organization increases the probability that a team has a manager by 4.6% (at the 1% significance level). The age of the organization to which a team belongs and its squared form also appear to be statistically significant. The relationship between the age of an organization and the probability of having a manager is U-shaped, reaching its minimum at the organizational age of 7 years.

The second and third columns of Table 3 present the logarithm of prize money estimates for teams without and with managers, respectively. For teams without managers, regime 2, three variables are statistically significant—the number of played maps, the headshot percentage (both are significant at the 1% level) and the kill-to-death ratio (at the 10% level). All of these have a positive influence on team performance measured as a logarithm of prize money. According to these results, if teams without a manager increase the number of played maps that reflect its experience by one unit, they will improve their prize money by 1.06%. Increasing the headshot percentage by 1% will bring 1.48% more prize money. Finally, if self-managed teams enhance their kill-to-death ratio by a unit of 0.1, this will result in a 14.9% increase in prize money.

In the first regime, teams with managers, only one variable is statistically significant—the number of played maps (at the 1% level). For managed teams, an increase in the number of played maps by one unit will increase the prize money by 1.1%.

[Please insert Table 3 here]

⁷ The movestay command reports only the coefficients of the number of teams in the organization and the organization's age and age squared in the probit first stage. We estimated the probit using all variables in the model, constructed the inverse Mills' ratio and estimated the performance regression including the inverse Mills' ratio and the excluded variables. A joint test of the null hypothesis that the excluded variables all have a zero coefficient in the performance equation cannot reject the null, suggesting our valid identification of the switching effect.

Finally, to see whether a manager has a positive effect on prize money as a proxy of team performance, we calculated the predicted values for the dependent variable for four possible outcomes, as presented in the methodology section in Figure 1. These predicted values for prize money are shown in Figures 3.

As can be seen, on average, the teams that have a manager and continue to have a manager (the outcome I) earn more prize money compared with teams that do not have a manager and are not going to hire a manager (outcome IV)—67,167.2 USD against 7,373.4 USD. With regard to the teams that might switch to having or not having a manager, we observe the following changes in prize money. If a team without manager decides to hire a manager (outcome III), on average, it will earn less money—from 7,373.4 USD to 4,667.9 USD—compared with continuing to either have or not have a manager (outcome IV). Alternatively, if a team with a manager decides to fire the manager (outcome II), it will increase its prize money from 67,167.2 USD to 149,529.6 USD. The predicted values for these four outcomes were pairwise compared by performing a t-test that showed the statistical significance of the difference in means.

[Please insert Figure 3 here]

To sum up, these estimations fail to prove that in the case of e-Sports gaming (in particular, CS:GO *Global Offensive*), switching from not having a manager to having a manager positively affects the team performance measured in terms of prize money. However, a comparison of the predicted prize money for the two observable outcomes when teams have (I) and do not have a manager (IV) showed that, on average, teams with managers still earn more than self-managed teams but this is not due to the presence of a manager.

4. CONCLUSION

The main finding of this study is that hiring a manager does not increase team performance. This raises a question about management efficiency, not only in e-Sports but also in similar industries because e-Sports teams are similar to modern professions since computer knowledge and Internet communication are necessary for all employees. This might be partly explained by the features of CS:GO teams, i.e., there are so-called “in-game leaders” in such teams (Parshakov et al., 2018). This in-game leader might, to some extent, also be treated as the unofficial manager because he is supposed to manage the team during the game, which also requires elaborating on team strategy prior to the game. Hence, even in teams without a manager, there might be a leader that partly fulfills the responsibilities of a manager. This raises potentially interesting questions about team management and team leadership: should the same person perform the roles of both a manager and a leader? Carte et al. (2006) partly address this issue by analyzing virtual teams. Their study shows that better self-managed teams displayed more leadership behaviors.

Our findings for the determinants of hiring a manager show that only young or well-experienced teams have a manager. This shows that the benefits of having an official manager might be different at different stages of the team life cycle. Young teams treat the manager as a driver to boost team performance, whereas well-experienced teams might need an official manager for the other reasons, e.g., as an instrument to deal with the turnover of players (our data shows the positive correlation between the age of the team and the turnover of the players).

According to our results, teams with managers earn more prize money but this is not due to the manager. Still, a manager somehow changes the strategy of the team. For the self-managed teams, individual performance is the important determinant of success, while for teams with managers, the only important determinant is an experience. Thus, the manager makes the individual performance less important, which might or might not be beneficial for the team. The answer might depend on the presence of star players on the team as such players can counteract managers' efforts.

To sum up, we believe that due to its digital nature, e-Sports provides an interesting setting from which to test a variety of theories of labor economics and management. This reflects the digitalization trend in business and provides both academics and practitioners with a huge amount of data that has already been quantified and is publicly available.

REFERENCES

- Carmichael, F. and Thomas, D. (1995), "Production and efficiency in team sports: an investigation of rugby league football", *Applied Economics*, Vol. 27 No. 9, pp. 859–869.
- Carmichael, F., Thomas, D. and Ward, R. (2000), "Team performance: the case of English premiership football", *Managerial and Decision Economics*, pp. 31–45.
- Carte, T.A., Chidambaram, L. and Becker, A. (2006), "Emergent Leadership in Self-Managed Virtual Teams: A Longitudinal Study of Concentrated and Shared Leadership Behaviors", *Group Decision and Negotiation*, Vol. 15 No. 4, pp. 323–343.
- Chaston, I. (1998), "Self-managed Teams: Assessing the Benefits for Small Service- sector Firms", *British Journal of Management*, Vol. 9 No. 1, pp. 1–12.
- Coates, D. and Parshakov, P. (2016), *Team vs. Individual Tournaments: Evidence from Prize Structure in ESports*, SSRN Scholarly Paper No. ID 2787819, Social Science Research Network, available at: <http://papers.ssrn.com/abstract=2787819> (accessed 27 July 2016).
- Cohen, S.G. and Ledford, G.E. (1994), "The effectiveness of self-managing teams: A quasi-experiment", *Human Relations*, Vol. 47 No. 1, pp. 13–43.
- Cohen, S.G., Ledford, G.E. and Spreitzer, G.M. (1996), "A predictive model of self-managing work team effectiveness", *Human Relations*, Vol. 49 No. 5, pp. 643–676.
- del Corral, J., Maroto, A. and Gallardo, A. (2017), "Are former professional athletes and native better coaches? Evidence from Spanish basketball", *Journal of Sports Economics*, Vol. 18 No. 7, pp. 698–719.
- Cummings, T.G. (1978), "Self-Regulating Work Groups: A Socio-Technical Synthesis", *Academy of Management Review*, Vol. 3 No. 3, pp. 625–634.
- Dawson, P., Dobson, S. and Gerrard, B. (2000), "Estimating coaching efficiency in professional team sports: Evidence from English association football", *Scottish Journal of Political Economy*, Vol. 47 No. 4, pp. 399–421.
- Dorsey, P. (2014), "'League of Legends' ratings top NBA Finals, World Series clinchers", available at: http://www.espn.com/espn/story/_/page/instantawesome-leagueoflegends-141201/league-legends-championships-watched-more-people-nba-finals-world-series-clinchers.
- Frick, B. and Simmons, R. (2008), "The impact of managerial quality on organizational performance: evidence from German soccer", *Managerial and Decision Economics*, Vol. 29 No. 7, pp. 593–600.
- Funk, D.C., Pizzo, A.D. and Baker, B.J. (2018), "eSport management: Embracing eSport education and research opportunities", *Sport Management Review*, Vol. 21 No. 1, pp. 7–13.
- Goodman, P.S. and Haran, U.J. (2009), *Self-Managing Teams*, Encyclopedia of Group Processes and Intergroup Relations., Sage Publications, Thousand Oaks, CA.
- Haas, D.J. (2003), "Productive efficiency of English football teams—a data envelopment analysis approach", *Managerial and Decision Economics*, Vol. 24 No. 5, pp. 403–410.
- Hackman, J.R. and Oldham, G.R. (1976), "Motivation through the design of work: Test of a theory", *Organizational Behavior and Human Performance*, Vol. 16 No. 2, pp. 250–279.
- Hallmann, K. and Giel, T. (2018), "eSports—Competitive sports or recreational activity?", *Sport Management Review*, Vol. 21 No. 1, pp. 14–20.
- Kahane, L.H. (2005), "Production efficiency and discriminatory hiring practices in the National Hockey League: a stochastic frontier approach", *Review of Industrial Organization*, Vol. 27 No. 1, pp. 47–71.
- Karhulahti, V.M. (2017), "Reconsidering esports: Economics and executive ownership", *Physical Culture and Sport. Studies and Research*, Vol. 74 No. 1, pp. 43–53.
- Kozlowski, S. and Bell, B. (2003), "Work groups and teams in organizations. Review update", *Handbook of Psychology*, Vol. 12, pp. 412–469.

- Kuypers, T. and Szymanski, S. (1999), "Winners and Losers, the Business Strategy of Football", *London: Viking*.
- Lokshin, M. and Sajaia, Z. (2004), "Maximum likelihood estimation of endogenous switching regression models", *Stata Journal*, Vol. 4, pp. 282–289.
- O'Connell, M.S., Doverspike, D. and Cober, A.B. (2002), "Leadership and semiautonomous work team performance: A field study", *Group & Organization Management*, Vol. 27 No. 1, pp. 50–65.
- Parshakov, P., Coates, D. and Zavertiaeva, M. (2018), "Is diversity good or bad? Evidence from eSports teams analysis", *Applied Economics*, pp. 1–12.
- Parshakov, P. and Zavertiaeva, M.A. (2018), "Determinants of Performance in eSports: A Country-Level Analysis", *International Journal of Sport Finance*, Vol. 13 No. 1, available at: <http://fitpublishing.com/articles/determinants-performance-esports-country-level-analysis> (accessed 18 February 2018).
- Pasmore, W.A. (1988), *Designing Effective Organizations: The Sociotechnical Systems Perspective*, Vol. 6, John Wiley & Sons Inc.
- Pearce III, J.A. and Ravlin, E.C. (1987), "The design and activation of self-regulating work groups", *Human Relations*, Vol. 40 No. 11, pp. 751–782.
- Porter, P.K. and Scully, G.W. (1982), "Measuring Managerial Efficiency: The Case of Baseball", *Southern Economic Journal*, Vol. 48 No. 3, p. 642.
- Rowell, D. (2016), "427 million people will be watching esports by 2019", available at: http://www.espn.com/esports/story/_/id/15508214/427-million-peo-ple-watching-esports-2019-reports-newzoo.
- Schofield, J.A. (1988), "Production functions in the sports industry: an empirical analysis of professional cricket", *Applied Economics*, Vol. 20 No. 2, pp. 177–193.
- Stewart, G.L. (2006), "A meta-analytic review of relationships between team design features and team performance", *Journal of Management*, Vol. 32 No. 1, pp. 29–55.
- Wagner, M.G. (2006), "On the Scientific Relevance of eSports", *International Conference on Internet Computing*, pp. 437–442.
- Wall, T.D., Kemp, N.J., Jackson, P.R. and Clegg, C.W. (1986), "Outcomes of autonomous workgroups: A long-term field experiment", *Academy of Management Journal*, Vol. 29 No. 2, pp. 280–304.
- Zech, C.E. (1981), "An empirical estimation of a production function: The case of Major League Baseball", *The American Economist*, Vol. 25 No. 2, pp. 19–23.

FIGURE 1. Four possible outcomes

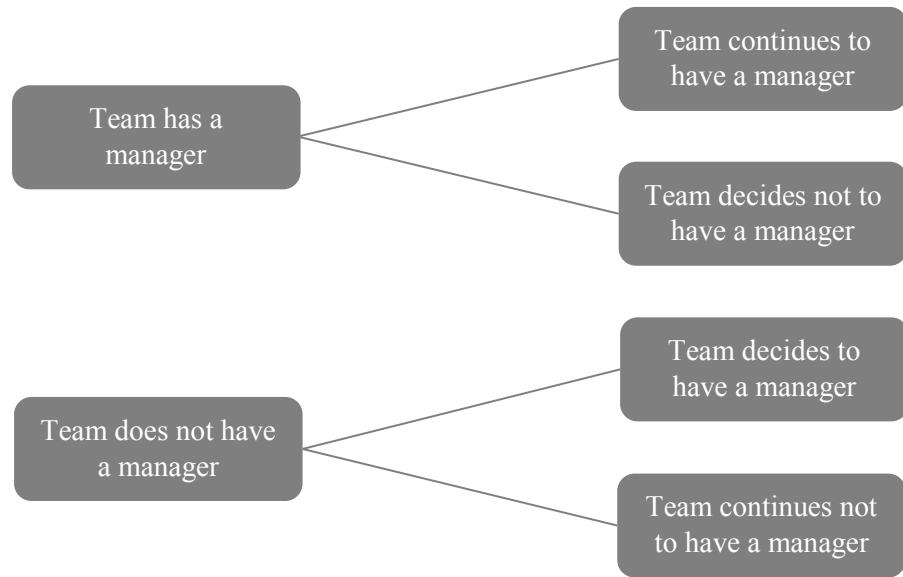


TABLE 1
Descriptive statistics

VARIABLES	N	Mean	SD	Min	Max
<i>General team information</i>					
Prize money (in USD)	463	84,258.2	201,747.5	100	1,558,756
Presence of manager	463	0.350	0.477	0	1
Age of organization	463	4.091	4.834	0	20
Number of teams in organization	463	3.192	2.474	1	12
<i>Team skills and experience</i>					
Number of played maps	463	101.7	79.20	1	516.8
Headshot, %	463	42.12	11.76	0.309	78.64
Kill-to-death ratio	463	0.990	0.0992	0.310	1.314

TABLE 2
Mean values of variables for teams with and without managers

VARIABLES	Teams without manager	Teams with manager	Difference between teams with and without manager
<i>General team information</i>			
Prize money (in USD)	32,936	179,615	146,679***
Age of organization	3.874	4.494	0.62
Number of teams in organization	2.817	3.889	1.072***
<i>Team skills and experience</i>			
Number of played maps	77.69	146.4	68.71***
Headshot, %	40.81	44.54	3.73***
Kill-to-death ratio	0.973	1.021	0.048***

Notes: ***Significant at the 1 percent level.
 **Significant at the 5 percent level.
 *Significant at the 10 percent level.

FIGURE 2. Number of teams with managers by year

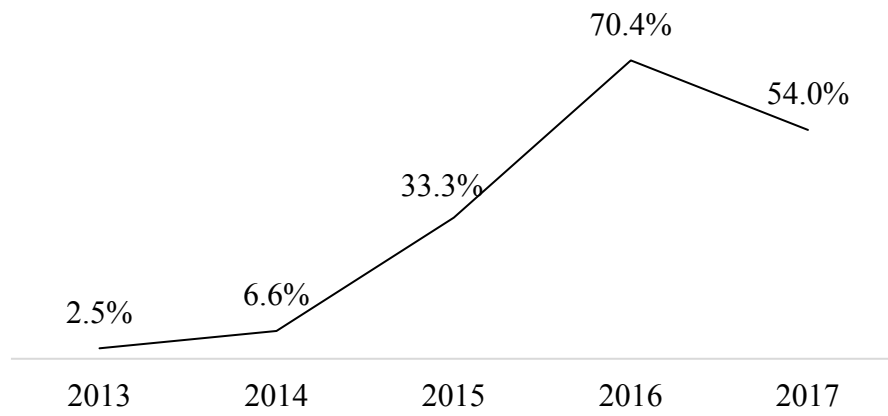


TABLE 3

Results of the endogenous switching regression model for logarithm of prize money

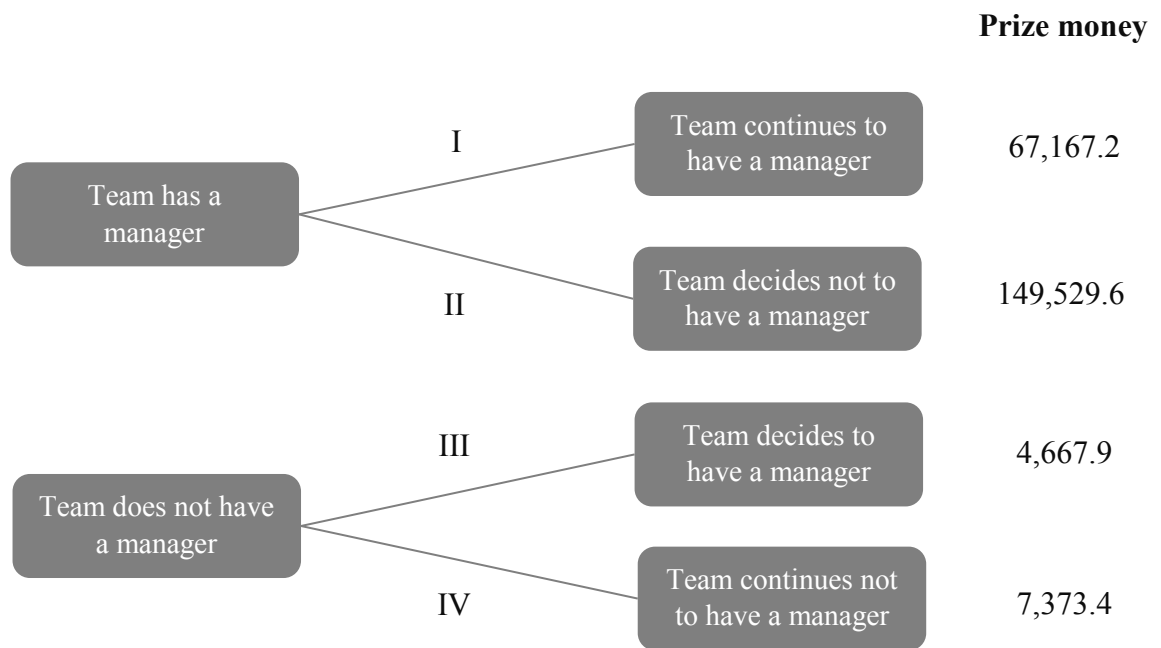
	Selection equation	Log of prize money Without manager	Log of prize money With manager
Number of played maps		0.0106*** (0.00130)	0.0110*** (0.00117)
Headshot, %		0.0148*** (0.00569)	0.0197 (0.0176)
Kill-to-death ratio		1.491* (0.845)	1.612 (1.122)
Number of teams in organization	0.127*** (0.0227) [0.0466]		
Age of organization	-0.0830** (0.0379) [-0.0306]		
Age of organization sq.	0.00710*** (0.00248) [0.0026]		
Constant	-0.748*** (0.101)	5.565*** (0.829)	8.093*** (1.397)
Observations	463	463	463
Rho 1	0.07		
Rho 2	0.71***		

Standard errors in parentheses

Marginal effects for selection equation in squared brackets

*** p<0.01, ** p<0.05, * p<0.1

FIGURE 3. Four possible outcomes for prize money and kill-to-death ratio



Appendix 1. The relation between the kill-to-death ratio and the log of prize as the performance indicator.

