DIVERSITY AND PERFORMANCE:
ESPORTS TEAM-LEVEL ANALYSIS

by

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Kyiv School of Economics

Abstract

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In this paper, we study how the diversity of culture, language, experience, and skill affect the performance of a team using the data from esports. The dataset covers the top 50 Counter-Strike teams by prize earnings in the period 2016-2021.

We use prize money as a proxy for performance and try different indicators to capture team diversity: Herfindahl–Hirschman Index, number of countries represented, Hofstede dimensions, number of maps played, and popular index of individual players' skill based on in-game statistics.

The results obtained suggest that cultural diversity does not affect team performance, but differences in terms of language are associated with worse results. Teams with higher skill diversity perform better than more homogeneous ones.

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LIST OF ABBREVIATIONS

HHI. Herfindahl-Hirschman Index

FE. Fixed effects

RE. Random effects

GDP. Gross domestic product

CS:GO. Counter-Strike: Global Offensive

Chapter 1

INTRODUCTION

Over the last years, working in teams has become mainstream in organizations. According to the surveys (Druskat and Wheeler, 2004), almost 80% of Fortune 1000 companies use self-managed teams. For decades, the optimal team structure has been a topic of academic discussion, starting from Marschak and Radner (1972) to Usher and Barak (2020). Among other determinants of team performance, particular interest is devoted to different kinds of team diversity (Knippenberg and Mell, 2016). Previous studies showed mixed results regarding the link between team diversity and performance. However, most recent studies also suggested that gender and ethnic diversity can enhance collaboration in science (Hofstra et al., 2020) and business (Horwitz, 2007). The subject matter is becoming exceptionally relevant today due to globalization, labor market internationalization (Rama 2003), and social policy concerns surrounding diversity issues (Jackson, May, & Whitney, 1995).

Despite the importance, a lack of firm-level data on different production teams' diversity makes it hard to estimate its effect on team performance in general terms. This creates an opportunity for alternative ways to assess the issue, one of which is to use a sports environment. Such an approach is applied in several articles (e.g., Franck and Nuesch 2010; Ingersoll, Malesky, and Saiegh 2014). In this thesis, we use data from esports to study the cost and benefits of diversity regarding team performance.

By standard definition, electronic sports (esports) “refer to competitive (pro and amateur) video gaming that is often coordinated by different leagues, ladders, and tournaments, and where players customarily belong to teams or other 'sporting' organizations" (Hamari and Sjöblom, 2017).

Since the first consumer game in 1971, video games have grown to a global market with an estimated 2.9 billion players (Global Games Market Report, NewZoo, 2021). As a result, a new form of competition between players has developed. In the last 15 years, eSport transformed from minor local rivalries for amateurs to a global professional environment. The phenomenon has gained a considerable amount of attention in recent years. COVID-19 pandemic also accelerated this process, as esports became one of the few entertainment events available for the public through online broadcasting technologies. The industry has grown significantly: total prize money reached more than $1,1 billion in 2021 alone (esports Earnings, 2021), and the global esports audience is estimated to be 474 million (Global Games Market Report, NewZoo, 2021).

Esports includes different disciplines. Counter-Strike: Global Offensive, the particular game we analyze, is one of the most popular. CS:GO provides an excellent setting to test the question of team diversity: there are five people in a team, the game requires quick and clear communication, and the chances for a team to win depend on the individual performance of each member and teamwork. Moreover, as was argued in Parshakov et al. (2018), "professional esports teams are much more similar to commercial firms that operate in the 'new economy' than teams in other sports". Several factors explain this: the results depend on mental abilities rather than physical, and eSport teams strive to maximize their results as firms to maximize their profits.

Players from our sample represent 60 different countries. It is comparable to big Europe football leagues, regarded as the most diverse sports leagues. On average they represent 66 nationalities (Football Statistics and History, 2022).

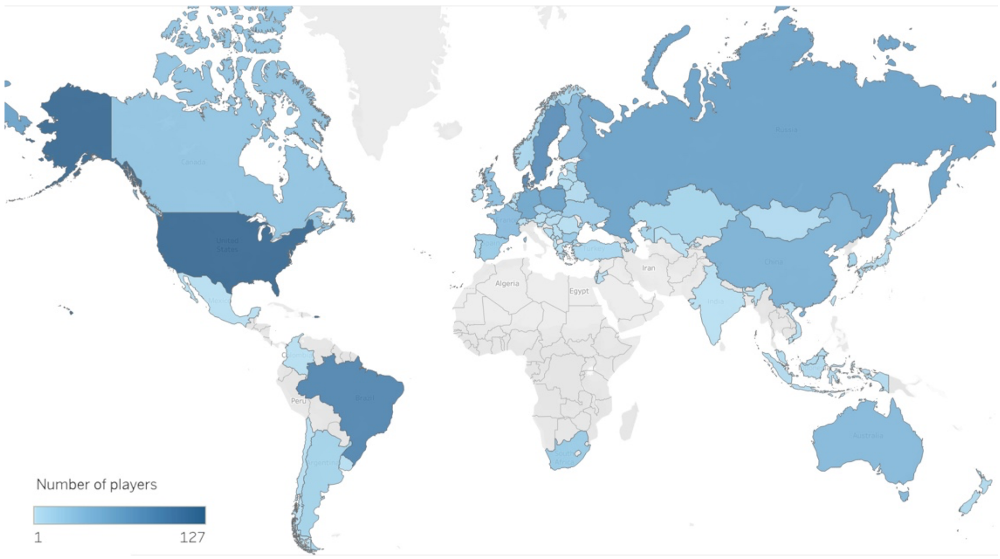

Figure 1. Geography of the top CS:GO players

Another advantage of esports is that all the needed demographic data, in-game statistics on individuals and team-level are available online. We discuss the sources of our dataset in Chapter 3.

For this study, we identify several kinds of diversity: culture, language, and skill that could be crucial for the optimal CS:GO team composition.

Therefore, the main objective of this study is to estimate the effects of team cultural, language, and skill diversities on the performance of a team (measured as prize money won) using the data from esports through an empirical model. The hypothesis is that eSport organizations might benefit (in terms of prize money won) from team diversity.

The rest of this article is organized in the following way. Chapter 2 describes the relevant literature. Chapter 3 describes the data used in the analysis. The methodology of the thesis is described in Chapter 4. The results and discussion are presented in Chapter 5. Chapter 6 serves as a summary of the main findings.

Chapter 2

LITERATURE REVIEW

Researchers found that teams with heterogeneous worker abilities are more productive, but if we fix abilities among the team, ethnically homogeneous cohorts are more productive. For example, Prat (2002) studied the question of optimal team homogeneity within the framework of team theory. The model includes agents of different types that form a team to maximize their joint payoff. The results suggest that workforce homogeneity is optimal if the agents' decisions are complementary, and heterogeneity of a team is optimal if the jobs are substitutable. This is in line with Hamilton et al. (2012), who used panel data from a garment plant that shifted from individual piece rate to group rate production.

Some research aimed to examine the link between diversity and performance in general. For example, Ottaviano and Peri (2005) investigated whether cultural diversity across US cities affects their productivity. The results indicate that wages and employment density were systematically higher in cities with richer linguistic diversity. Furthermore, Ottaviano and Peri (2006) find a positive association between cultural diversity and the productivity of the native population.

Some studies use data from a particular industry. For example, Alexandre and Moretti (2009) used data from a supermarket chain to indicate a positive association between productivity and skill diversity during a shift.

Such approaches usually consider only one firm and focus on low-skill jobs in industries where the data is available. One could argue about its representative characteristics.

On the other hand, sports teams are generally represented by highly skilled individuals and are required to communicate at a high level, creating an excellent opportunity to estimate the effects of different types of team diversity. Still, there are characteristics specific to this environment, such as little gender and age diversities.

Ingersoll et al. (2014) use data on the UEFA Champions League to study the impact of diversity on group performance. Results show that a one-standard-deviation increase in the linguistic difference representing cultural diversity is associated with twice as big a team's goal differential during the tournament.

Guryan et al. (2009) examined the peer effects using the data from professional golf tournaments and found no evidence that playing partners' ability affects performance.

Although the research in this field has mushroomed, there are still many limitations. Most of the previous studies use limited data and simple statistical analysis.

All the research on esports has been developed relatively recently. Wagner (2006) is the fundamental study that tries to lay a foundation for proper academic treatment of esports, followed by the latest paper on structuring the esports agenda (Cranmer et al., 2020). After this work, several interesting research topics appeared, among which was the National Research University Higher School of Economics project on esports economics. It includes the study of implications of tournament theory using data on esports (Coates and Parshakov, 2016), which suggests that contestants in esports tournaments are risk-averse, and Country-Level Analysis of Determinants of Performance (Parshakov and Zavertiaeva, 2018). The results of the latter work show that a 1% increase in GDP per capita leads to a 2.2% increase in prize money per capita, the country population is not statistically significant, but post-Soviet countries are more likely to participate in esports.

This project also includes the related study of team diversity and its effect on performance which showed that different kinds of diversity have opposite effects (Petr Parshakov et al., 2018) – cultural diversity is beneficial for team performance. However, language and experience diversity have adverse effects.

Chapter 3

DATA

The sources for the data are open-source websites, where accessible public data is captured. The Liquipedia Counter-Strike web page ('The Counter-Strike Encyclopedia') contains various data on top Counter-Strike teams. We used the "Statistics" section to collect prize earnings on the best 50 teams (Liquipedia Statistics, 2022). The portal also offers information on professional gamers in "Players" part, where we gather data on the age and native country of each individual. Similarly, "Teams" section of the website was utilized to fetch the date when the team hired a coach for the first time.

HLTV (2022), the leading CS:GO statistics site, is used for in-game metrics – HLTV Rating and the number of maps. Data on Greet Hofstede's cultural dimensions were obtained through Hofstede's website (Dimensions Data Matrix, 2015). Data on GPD is from World Bank.

4.1. Dependent variable

We use prize money won by a team within a year as a dependent variable. The sample spans the period of 2016-2021 for 296 teams. Team prize earnings in a year range from \$39 thousand to almost \$4 million, with a mean value of \$290 thousand and a median of \$140 thousand.

The distribution is right-skewed, meaning only a few teams enjoy the highest rewards, which is common in the superstar market esports represents (Ward, 2019). Thus, we will use the natural logarithm form of the response variable in our analysis to bring it close to the normal distribution, which implies a log-linear model.

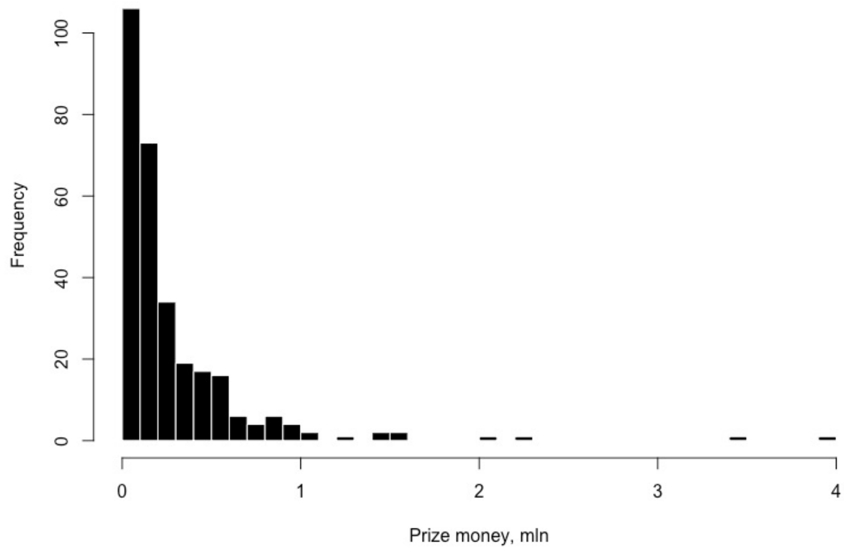

Figure 2. Distribution of Prize money won, millions

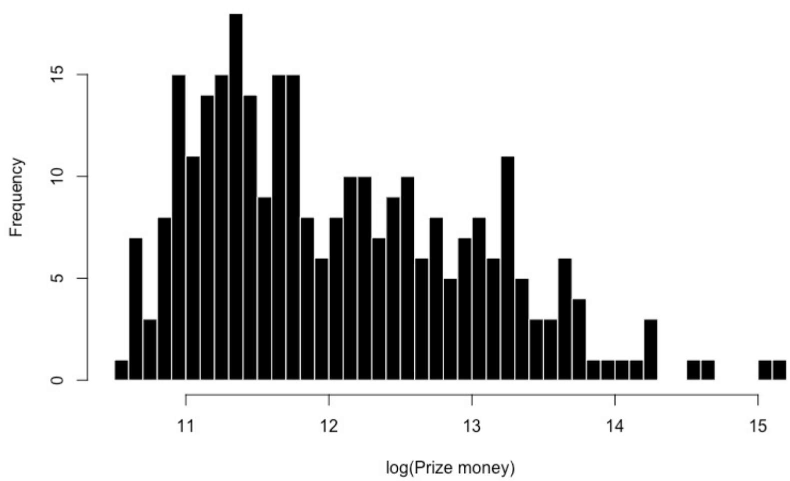

Figure 3. Distribution of log of Prize money won

4.1. Independent variables

As our methodology covers different models for different measures of diversity we conditionally divide the set of explanatory variables into two groups – control variables and diversity indicators. The control group is present throughout all models and includes variables listed in Table 1.

Table 1. Control variables

Variable	Description
Mean rating	Simple average of team members' HLTV Rating during a year
Mean number of maps	Simple average of team members' number of maps played during a year
Number of gamers	Number of team members during a year
Mean age	Simple average of team members' age in a particular year

Mean rating is constructed using the HLTV Rating index. It is a relative measure of a player's skill that is calculated and published by HLTV.org and is updated after every professional game. Having statistics on every pro gamer, HLTV computes the expected value (average) for various in-game measures, such as the number of kills per round, and then checks how many standard deviations the player is above or below the average. HLTV player Rating is scaled so that the mean value is 1.00; anything higher indicates a skilled professional gamer and a less skilled score lower than 1.00.

Team averages were calculated for each year separately using the data on individual members that played for that team during the year.

Table 2. Diversity indicators

Variable	Diversity type(model)	Description
HHI	Cultural(1)	Herfindahl-Hirschman concentration index built on the country's shares
Number of countries	Cultural(2)	Number of countries represented by team members during a year
SD(GDP, Hofstede)	Cultural(3)	Standard deviations of GDP of the country of origin and Hofstede Dimensions within a team
HHI Language	Language(4)	Herfindahl-Hirschman concentration index built on languages shares
SD(HLTV Rating, No of maps)	Skill(5)	Standard deviations of HLTV Rating and number of maps played within a team

To estimate the effects of diversity we test different metrics: three separate methods to capture cultural diversity and one for each language and skill diversity. Method applied to construct HHI indices is discussed in Chapter 4. Variations of GDP, Hofstede dimensions score, HLTV Rating, and the number of maps played are represented in a form of the standard deviation of those values within a team in a year.

Descriptive statistics on the final dataset is available in Table 3 below. The difference in cultural and language indices is dictated by the assumptions we made – people from certain countries know the same languages. Thus, the Herfindahl-Hirschman index on language level is higher.

On average, the team during a year consists of 9 players representing at least three different counties – a quite high turnover and cultural diversity, which confirms the relevance of our study. Moreover, only 11 teams have been included in the top 50 for six years straight, pointing to the high level of competition at the team level.

Counter-Strike Global Offensive is a high-paced game that requires quick reflexes from the gamer, so it is expected that performance will start to diminish before the player reaches 30 (Ward, 2019). This is in line with the mean age of team members, which is close to 23.

HLTV rating is 1.06, indicating good average team performance, which is expected from the top 50 teams in the world.

The mean number of maps played by a team within a year is 117, with a standard deviation of 52. Considering it follows near-normal distribution, meaning for around 68% of the teams in the sample, this value ranges from 65 to 169.

The coefficients of variation regarding Hofstede's dimensions are about on the same level, except for Masculinity, which is substantially higher on average – there is higher diversity in terms of this dimension compared to all the others.

Also, 12% of the teams only consist of representatives of one country. In a similar sample covering 2013-2015 (Parshakov, 2018), this value was more than 30%, another demonstration of a tendency to assemble more diverse teams. A similar situation is for language diversity – the share of teams that consist of players from countries with a common language dropped by 22 percentage points, from 49% to 27%.

Regarding the predictor variables, we expect few special properties. The assumption is that the relation between prize money won and the average age of teammates is non-linear due to the human body's physical abilities, as discussed above. We expect the effect of age on performance for a Counter-Strike player to be positive on average up to some peak age and decline gradually after that peak is reached.

We will also test the interaction term between the number of players in a team and the number of countries of origin during a year. It will show if the effect of one variable depends on the value of another.

Table 3. Descriptive statistics of variables

Statistic	N	Mean	St. Dev.	Min	Median	Max
Prize money	296	291 432	419 886	39 339	140 616	3 937 071
Log (prize money)	296	12.06	0.94	10.58	11.85	15.19
HHI	296	0.63	0.27	0.14	0.63	1
HHI language	296	0.76	0.23	0.18	0.8	1
No of countries	296	3.27	1.89	1	3	11
Mean age	296	22.92	1.58	17.4	23	27.17
Mean rating	296	1.06	0.04	0.93	1.06	1.21
Mean no. maps	296	117.66	52.19	11	109.1	305
No. gamers	296	9.29	3.32	5	9	25
SD (age)	296	3.27	1.05	0.55	3.37	7.35
SD (rating)	296	0.08	0.03	0.03	0.08	0.2
SD (nmaps)	296	75	39.84	0	75.64	201.36
SD (GDP)	294	7 998	8 339	0	5 094	35 317
SD (power dist)	284	7.81	9.23	0	4.6	41.01
SD (individualism)	284	6.41	7.54	0	3.72	35.36
SD (masculinity)	284	8.72	10.89	0	4.46	52.33
SD (uncert_avoid)	284	7.97	9.05	0	3.33	42.43
SD (lr_orient)	290	7.52	7.44	0	5.68	29.5
SD (indulgence)	290	6.37	7.59	0	3.21	36.06
CV (power_dist)	284	0.16	0.2	0	0.09	0.77
CV (individualism)	284	0.11	0.13	0	0.06	0.78
CV (masculinity)	284	0.23	0.32	0	0.09	1.65
CV (uncert_avoid)	284	0.15	0.17	0	0.08	0.76
CV (lr_orient)	290	0.16	0.16	0	0.14	0.76
CV (indulgence)	290	0.14	0.17	0	0.10	0.91
Coach	296	0.95	0.22	0	1	1
One country	296	0.12	0.33	0	0	1
One language	296	0.27	0.44	0	0	1

Chapter 4

METHODOLOGY

The panel structure of our data set allows us to empirically analyze our hypotheses. To do so, we begin with a pooled regression model for the effects of diversity on team performance and then test fixed and random effects specifications.

4.1. Game settings

It is important to understand the game design in which teams operate. Counter-Strike Global Offensive (CS: GO) is a multiplayer first-person shooter game where two teams, five players each, compete in specific objective-based models. The most popular game mode and one used on a professional esports scene is where the Terrorist side's objective is to plant the bomb and the Counter-Terrorist tries to stop them. The game is run in short rounds that finish when one of the teams either accomplishes an objective or eliminates every opponent. Each team plays both Terrorist and Counter-Terrorist sides during the game, eliminating the advantage one could have on a particular map.

At the start of each round, team members buy weapons and utility on the rewarded money. These rewards depend on the individual and team results of the previous round. Weapons vary by many parameters, among which price and damage, although 4 top used rifles cover 65%+ (hltv.org/stats) of game situations and are used whenever teams' budget allows. This factor contributes to in-game elements homogeneity for teams and allows us to perform the team-level study. Another essential feature of CS:GO team composition is that there are in-game and "informal" roles Drenthe (2016) for each player.

4.2. Hypotheses and assumptions regarding diversity

Separation into roles and required quick communication in teams indicate that cultural, skill, and language diversities could be essential. In this section, we discuss our approach to including them in the model and their possible effect on the performance.

4.2.1 Cultural and language diversities

Diversity of culture, as well as language diversity, are captured by the data on individual players. We test three separate measures of cultural diversity: HHI, number of countries, and Hofstede dimensions.

Herfindahl–Hirschman index (HHI) is commonly used in studies of ethnolinguistic diversity. In our case we calculate it by applying the following formula:

$$HHI = \sum\left(\frac{N_{countrymaps}}{N_{totalmaps}}\right)^2 \tag{1}$$

Where, $N_{countrymaps}$ stands for the number of maps played by team members from one native country, a $N_{totalmaps}$ represents total maps played.

The same approach is used for the linguistic part, although with the assumption that countries where 50%+ of the population speak English, Spanish, or Russian are the same.

As an alternative, we also test specification with the number of countries represented by the team members in a year.

We hypothesize that culturally diverse teams could benefit from the new ideas that players with different backgrounds bring together as discussed in Mohammadi et al. (2017). On the other hand, high cultural diversity generally comes with the cost of lower communication quality. Therefore, linguistic diversity could harm team performance. Also, skill and experience diversity should be beneficial for the team as differently skilled players can occupy contrasting roles in a squad. We expect this relationship to be non-linear – skill and job-related experience will boost team performance up to a certain extent. But too diverse groups would suffer from burdensome coordination and communication, which is in line with the relevant literature (Hoisl et al., 2016).

Our third variant to capture the effect of cultural diversity on team performance is utilizing Greet Hofstede's cultural dimensions theory (Hofstede 1984). It consists of six dimensions along which cultural values could be analyzed on a country level. They include individualism, uncertainty avoidance, long-term orientation, masculinity, power distance, and indulgence. Using this approach we assume the players are a representative sample of the country of origin population. Thus, we incorporate Hofstede dimensions variation within a team, measured by standard deviation, in our third model.

4.2.2 Skill and experience diversity

To study how skill and experience diversity is connected with team performance, we calculate standard deviations of HLTV Rating and the number of maps. While controlling for the averages, these indicators allow us to estimate relative disparity in a team. High skill diversity with a moderate mean should be favorable to a more balanced distribution, as it allows for highly talented individuals. Contrastingly, highly diverse teams with elevated average could be disadvantageous – the "weakest link" hypothesis as discussed in Franck and Nuesch (2010).

Resulting table 4 concludes the diversity specifications discussion and their expected effects:

Table 4. Expected effects of diversity

Specification	Expected effect	Description
Cultural diversity	+	Teams could benefit from cultural diversity, but the expected effect is non-linear
Language diversity	-	High linguistically diversity could affect the quickness and clearness of communication
Skill and experience	Ambiguous	The expected effect from skill diversity could depend on the team's average values

4.3. Resulting research framework

The sum of prize money in a year is used as the response variable to estimate the elasticities of team-level performance. It is a results-based parameter that is influenced only by the performance of the tournaments and the scope of those competitions. Three kinds of diversity indicators are skill and experience, language, and cultural diversities.

In-game statistics are used as a proxy for skill and experience level. Average HLTV rating represents the number of kills by the player in relation to the number of deaths and number of maps played. The higher Rating is, the higher the chances of winning more matches and prize money; the higher the number of maps played by the player on a professional level, the higher the experience.

To estimate the team's diversity of skill and experience, we use the standard deviation of the two variables above while controlling for team averages.

The resulting equation of panel data model specification for each of the teams will look like this:

$$\log(prize) = \alpha + \delta \cdot \boldsymbol{CV} + \beta \cdot \boldsymbol{DIV} + \varepsilon, \tag{2}$$

Where CV is a vector of control variables and DIV is a diversity indicators vector.

Chapter 5

ESTIMATION RESULTS

First, we estimated all five models covering different kinds of diversities and a resulting one that includes all of the variables using the pooled method. Then, we also tested specifications with fixed and random effects estimators.

We ran the Hausman test for fixed versus random effects to decide these two. The null hypothesis is that FE coefficients do not significantly differ from RE coefficients.

Table 5. Hausman test

Model	chisq	df	p-value
(1) HHI	6.03	14	0.96
(2) No. Countries	7.29	14	0.92
(3) Hofstede	11.56	18	0.86
(4) Language	5.49	14	0.97
(5) Skill	12.18	15	0.66
(6) Joint	22.89	26	0.63

Accordingly, we cannot reject the null for all the models and use the RE estimator because it is efficient.

Test results could be a consequence of the nature of the dataset. As less than 5% of teams are represented in all six years, our panel is unbalanced. Besides, over 20% of the teams are included in one year only, and fixed effects specification disregard them.

Then, to test the panel effect itself, we employ the Breusch-Pagan Lagrange multiplier to decide between Pooled and Random Effects models.

Table 6. Lagrange Multiplier Test (Breusch-Pagan) for unbalanced panels

Model	chisq	df	p-value
(1) HHI	163	1	0.00
(2) No. Countries	158	1	0.00
(3) Hofstede	121	1	0.00
(4) Language	150	1	0.00
(5) Skill	177	1	0.00
(6) Joint	113	1	0.00

Thus, the null hypothesis of zero variance across the teams was rejected for all models. We proceed with the Random Effect specification in our analysis.

Estimation results for the final specification covering all models with different types of diversity are available in Table 7. Models 1-3 are devoted to capturing cultural diversity specific to the country of origin. Although they differ in terms of diversity measurements – in the first model, we utilize the Herfindahl-

Hirschman index. For the second model, the number of countries is used as a proxy for cultural diversity. Hofstede's cultural dimensions capture diversity concerning five distinct cultural values in the third model. In Model 4, we estimate the effects of language diversity through HHI with assumptions we described in Chapter 3. The fifth model explores skill diversity within a team using deviations from in-game statistics.

Empirical results for the control variables are as expected. The average HLTV rating of a team has a significant positive impact on the amount of earnings from prizes across the models. Since our model is log-linear, we will calculate marginal effects as $(e^{\beta} - 1) \cdot 100$ to obtain the change of response variable in percent. Accordingly, a 0.01 increase in team HLTV rating is associated with a 4.7% increase in total prize money. The quadratic functional form of the average number of maps is statistically significant, suggesting a non-linear relationship with the dependent variable. Around the mean, this effect is positive – one additional map on average adds 0.8% to the prize money, keeping everything else constant. After the team average reaches 212 maps within one year, the effect turns negative for every extra map. One could assume that both too few and too many games during a year are not beneficial for the team. The explanation lies in the competitive nature of the sphere – teams that perform poorly do not have a chance to play many games, as they are getting eliminated quickly. On the contrary, teams that manage to survive during the tournament but are still not that productive will require more maps than stronger ones.

Control for the total number of players during a year demonstrates a negative coefficient in all the models, but it is not statistically significant. Interaction term with the number of countries of origin is consistently positive and is significant inside HHI, language, and skill specifications. Thus, there is no general effect neither of turnover or cultural diversity, but crossover interaction. Nevertheless, we can state that the effect of country-specific diversity on team performance depends on player turnover.

The mean age of the players in a team is another vital factor about the experience and skill level. It also follows a non-linear relationship with team productiveness. Approximately, up to the mean of 23, the effect is positive with the slow decline afterward. This might be regarded as the peak form of an esports athlete in terms of age.

Regarding cultural diversity, the first model with the HHI as a proxy shows no statistically significant effect on team performance. The same is valid for Model 2, where we use the number of countries represented to capture the effect of diversity. Hence, we find no significant effect of cultural diversity on the team performance with the first two specifications.

For Model 3, we employed Hofstede's cultural dimensions framework to look at the effects of particular cultural characteristics that may be crucial for the team structure. The only statistically significant factor is diversity in long-term orientation. One standard deviation increase in this dimension for a team is associated with a reduced total prize by 1.6%. According to Hofstede (2001), this cultural value reflects the ability for perseverance and thrift. This is an essential factor in team building – too diverse teams will suffer from conflicts during the goal-setting stage. Short-term cultures will tend to maximize the momentary payoff, while long-term-oriented players will think in terms of season reward.

Diversity in terms of GDP per capita in a team is statistically significant, but the effect is negligible; therefore, it is not economically meaningful. This reflects the point that esports is accessible and does not require significant capital to enter.

Language diversity is analyzed in the fourth model by introducing the language HHI. The coefficient is significant and positive, contrary to the HHI for cultural diversity. The more concentrated the team is in the matter of language, the higher performance it shows compared to more diverse teams.

In respect of skill and experience diversities, we used the variation of the HLTV rating, and the number of maps played accordingly in Model 5. Both effects are positive, yet only the effect of the skill diversity is significantly different from zero. An increase in standard deviation by 0.1 in the team's HLTV Rating indicator is associated with a 33.6% increase in the total prize outcomes. This result could be explained by the fact the players of CS:GO team generally perform different functions. Hence, it might be natural for the specific role to be associated with a certain level of HLTV Rating. And, as our dataset contains only the year's top teams, the overall skill level is very high. Thus, a good team composition requires players with different average Ratings to be balanced. This result could be explained by the fact the players of CS:GO team generally perform different functions. Hence, it might be natural for the specific role to be associated with a certain level of HLTV Rating. And, as our dataset contains only the year's top teams, the overall skill level is very high. Thus, a good team composition requires players with different average Ratings to be balanced.

The effect of the coach dummy has no statistical significance. We suppose to better estimate the result of the introduction of professional coaches on the Counter-Strike: Global Offensive scene one would need more data, as in our sample almost all of the teams have a coach starting from the first year.

Table 7. Estimation results

	Dependent variable:		Prize money won			
	(1) HHI	(2) No counties	(3) Hofstede	(4) HHI lang	(5) Skill	(6) All
HLTV Rating	4.832***	4.908***	4.495***	4.848***	4.631***	4.495***
	(1.117)	(1.114)	(1.275)	(1.135)	(1.142)	(1.245)
Number of maps	0.017***	0.017***	0.017***	0.017***	0.015***	0.015***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
(Number of maps)^2	-0.00004***	-0.00004***	-0.00004***	-0.00004***	-0.00003***	-0.00003***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Number of gamers	-0.028	-0.006	-0.018	-0.030	-0.021	-0.016
	(0.021)	(0.032)	(0.019)	(0.020)	(0.017)	(0.033)
(Number of gamers*	0.006**	0.001	0.003	0.006**	0.004*	0.001
Number of countries)	(0.003)	(0.007)	(0.002)	(0.003)	(0.002)	(0.007)
Age	1.082*	1.082*	1.048*	1.035*	1.013*	0.992*
	(0.556)	(0.566)	(0.550)	(0.560)	(0.575)	(0.579)
(Age)^2	-0.023*	-0.023*	-0.022*	-0.022*	-0.022*	-0.021
	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)	(0.013)
HHI	0.280					0.062
	(0.232)					(0.449)
Number of countries		-0.048				-0.131
		(0.071)				(0.126)

Table 7. Estimation results – continued

(Number of countries)^2	0.008				0.013*
	(0.007)				(0.009)
SD (GDP)		0.00002**			0.00003***
		(0.00001)			(0.00001)
SD (Power distance)		0.001			0.005
		(0.009)			(0.010)
SD (Individualism)		-0.002			-0.001
		(0.010)			(0.010)
SD (Masculinity)		0.004			0.007
		(0.005)			(0.005)
SD (Uncertainty avoidance)		-0.011			-0.007
		(0.008)			(0.008)
SD (Long-term orientation)		-0.016*			-0.013
		(0.009)			(0.010)
SD (Indulgence)		0.006			0.002
		(0.012)			(0.013)
HHI Language			0.454*		0.457
			(0.254)		(0.365)
SD(HLTV Rating)				2.912*	2.700
				(1.763)	(1.992)
SD (Number of maps)				0.001	0.001
				(0.001)	(0.002)

Table 7. Estimation results – continued

Coach					0.258	0.292
					(0.170)	(0.196)
yr2017	-0.365***	-0.381***	-0.355**	-0.375***	-0.378***	-0.379**
	(0.141)	(0.139)	(0.160)	(0.143)	(0.137)	(0.165)
yr2018	-0.239	-0.255	-0.246	-0.253	-0.269*	-0.279
	(0.165)	(0.162)	(0.176)	(0.162)	(0.162)	(0.185)
yr2019	-0.115	-0.136	-0.139	-0.130	-0.140	-0.199
	(0.154)	(0.156)	(0.163)	(0.151)	(0.154)	(0.168)
yr2020	-0.540***	-0.566***	-0.553***	-0.554***	-0.552***	-0.566***
	(0.148)	(0.147)	(0.162)	(0.144)	(0.146)	(0.163)
yr2021	-0.398**	-0.424**	-0.422**	-0.431***	-0.447***	-0.501***
	(0.168)	(0.166)	(0.181)	(0.161)	(0.163)	(0.183)
Constant	-7.096	-6.958	-6.093	-6.764	-6.265	-6.085
	(6.403)	(6.489)	(6.358)	(6.424)	(6.662)	(6.631)
Observations	296	296	284	296	296	284
R2	0.844	0.844	0.840	0.839	0.847	0.845
Adjusted R2	0.836	0.836	0.829	0.832	0.839	0.829
F Statistic	103.442***	102.394***	104.843***	105.849***	107.105***	119.104***

Note: *p<0.1; **p<0.05; ***p<0.01

Chapter 5

CONCLUSIONS AND RECOMMENDATIONS

In this thesis, we examined the effect of cultural, language, and skill diversity on team performance using the data from esports. Applying different indicators of team diversity we constructed 5 empirical models and a resulting one.

We found no evidence of the general effect of cultural diversity on team performance. Although, with a high variation of team members regarding long-term orientation Hofstede's dimension is associated with lower winnings during a year. Thus, this aspect could be crucial in the optimal team structure.

Also, the higher linguistic distance between players affects team accomplishments negatively. This is expected behavior with a history of empirical evidence (Lyons 2017; Kahane, Longley, and Simmons 2013).

Teams with higher skill diversity, on average, perform better than more homogeneous ones. This might be due to the fact the Counter-Strike teams usually operate with preassigned in-game roles. As a consequence, players with specific level and set of skills fit a certain position in a team.

Thus, building an international team is not a trivial task and requires a thorough approach. In our recommendation to the team managers, we would not advise purposely avoiding cultural diversity in a team, as it doesn't affect performance. At the same time, results show that linguistic heterogeneity leads to lower team performance. Therefore, a diverse international team performs no worse than a more homogeneous one, as long as it does not creates language differences. However, high variation in specific cultural attributes, Hofstede's long-term orientation dimension in particular, is associated with lower team performance.

Additionally, combining individuals with different levels of skill could be beneficial for team performance.

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