Petr Parshakov
TESE DE DOUTORAMENTO
THE ECONOMICS OF ESPORTS: ELEMENTS THAT AFFECT PERFORMANCE
2019
DOCTORAL DISSERTATION

THE ECONOMICS OF eSPORTS:
ELEMENTS THAT AFFECT PERFORMANCE

Supervised by:
Ángel Barajas
Dennis Coates

Year: 2019
Ángel Barajas and Dennis Coates

DECLARE that the present work, entitled “THE ECONOMICS OF ESPORTS: ELEMENTS THAT AFFECT PERFORMANCE”, submitted by Petr Parshakov to obtain the title of Doctor, was carried out under his supervision in the PhD programme “[V03D036V06] Análise Económica e Estratexia Empresarial”.

Vigo, July 24th 2019

The supervisors.

Dr. Angel Barajas  Dr. Dennis Coates
Acknowledgments

First of all, I want to I would like to express my sincere gratitude to my scientific advisors, professor Angel Barajas and professor Dennis Coates. I am deeply grateful to your support and your feedback. The fact that you decided to invest a substantial amount of your time in my thesis inspire me a lot.

Another gratitude goes out to Elena Shakina, who was crazy enough to believe in my research abilities. It is a unique opportunity to have such a boss.

For sure the thesis was not written without the help of the IDlab team. Thanks to Mariia Molodchik, Marina Zavertiaeva, Iuliia Naidenova, Sofia Paklina, Anna Bykova, Grigorii Teplykh, Carlos Maria Jardon, Felix Iturriaga and Thadeu Gaparetto for valuable comments. Your comments help me to grow up as a researcher (At least I hope so!). Thanks to Eduard Gabdukaev, who show me that eSports might be a substantial part of the life and inspire the topic of this thesis. Thanks to my friends Romych and Alex as well.

A special thanks are to my family. I’d like to thank my grandparents, parents and parents-in-law. You are those who taught me to ask “why” always. Your support is the thing which makes the preparation of this thesis possible. My wife Nastya and my daughter Katya – you are the most important part of my life, and I dedicate this milestone to you. Thank you for your love and support.
# Index

Resumen en español .......................................................................................................................................................... 4

Introduction ........................................................................................................................................................................ 10

Chapter 1. Macro-level analysis ......................................................................................................................................... 17

1.1 Determinants of country-level performance in eSports .......................................................................................... 17

1.1.1 Country performance in eSports: Problem statement ......................................................................................... 17

1.1.2 Determinants of performance in traditional sports ............................................................................................... 19

1.1.3 Macroeconomic and eSports indicators .................................................................................................................. 22

1.1.4 Hurdle model empirical approach .......................................................................................................................... 28

1.1.5 Revealed determinants of success in eSports .......................................................................................................... 30

1.2 eSports, video games and unemployment ................................................................................................................. 35

1.2.1 Work-leisure time distribution ............................................................................................................................... 36

1.2.2 Theoretical model of video games popularity and unemployment ........................................................................ 37

1.2.3 Comparative statics ................................................................................................................................................... 40

1.2.4 Empirical test of the model ...................................................................................................................................... 42

1.2.5 Empirical estimation of the effect of video games to unemployment rate .......................................................... 45

1.3 Conclusions on the macro-level analysis .................................................................................................................. 50

Chapter 2. Meso-level analysis .......................................................................................................................................... 52

2.1 Competitive Balance and League Growth in eSports: A test of Contestable Market Theory ........................................ 52

2.1.1 Competition and industry size: an overview ............................................................................................................. 52

2.1.2 Contestable market theory: a different perspective of competition ...................................................................... 55

2.1.3 Contestability and deregulation in eSports .............................................................................................................. 57

2.1.4 Five reasons to test the eSports industry for contestability ................................................................................... 59

2.1.5 Empirical test: Panel VAR approach ....................................................................................................................... 60

2.1.6 Impulse-response functions ..................................................................................................................................... 63

2.2 Video game publishers event promotion strategy: eSports tournaments and spillover effect .................................... 68

2.2.1 Promotion in eSports .................................................................................................................................................. 68

2.2.2 Event marketing and its effectiveness ....................................................................................................................... 70

2.2.3 Spillover effect ......................................................................................................................................................... 71

2.2.4 Video games and eSports tournaments .................................................................................................................... 72

2.2.5 Spillover effect: testable hypothesis ......................................................................................................................... 74

2.2.6 Spillover test: an empirical approach ..................................................................................................................... 75

2.2.7 Empirical results of spillover effects ......................................................................................................................... 80

2.3 Team vs. Individual Tournament: Video game publisher dilemma ........................................................................ 83
### Chapter 2.4 Conclusions on the meso-level analysis

#### 2.4.1 Conclusions on the meso-level analysis

Conclusions on the meso-level analysis are presented, detailing the findings and implications of the research. The chapter includes discussions on the managerial efficiency of eSports coaches, emphasizing the importance of team composition, diversity, and performance. The empirical test of team rank-order tournament is also analyzed, providing insights into the theoretical model of team rank-order tournaments and the equilibrium analysis.

#### 2.4.2 Implications of the Study

The study highlights the significance of micro-level analysis in understanding team dynamics and managerial efficiency in eSports. The empirical results suggest that diversity and communication play crucial roles in team performance and managerial effectiveness. The findings are further supported by the interpretation and implications for empirical test results, offering valuable insights for both managers and researchers.

#### 2.4.3 Recommendations for Future Research

Based on the conclusions, the chapter recommends avenues for future research to explore the micro-level dynamics in more depth. Suggestions include extending the empirical analysis to different game settings and examining the effects of various team compositions and communication strategies on performance.

### Chapter 3. Micro-level analysis

#### 3.1 Team composition, diversity and performance

The chapter delves into team composition and diversity, discussing their impact on performance. The analysis includes a detailed examination of team communication and performance as evidenced by Dota2 Videogame, focusing on the importance of team communication, empirical test results, and managerial efficiency.

#### 3.2 Managerial efficiency of eSports coaches

Managerial efficiency in eSports coaches is analyzed, with a focus on endogenous switching regression and empirical results. The chapter highlights the importance of effective communication and team composition in achieving managerial efficiency.

#### 3.3 Team Communication and Performance as Evidenced by Dota2 Videogame

The importance of team communication is explored, with an empirical test for Dota 2 setting and analysis of the intensity of communication. Words-based LASSO regression is used to further understand the relationship between communication and performance.

### References

The references section concludes with a comprehensive list of sources used in the research, ensuring a thorough understanding of the theoretical and empirical frameworks underlying the study.
Index of Tables

Table 1. The contribution of this work by level and stakeholder .................................................. 15
Table 2. Descriptive statistics of countries .................................................................................... 27
Table 3. Selections model estimation results .................................................................................. 31
Table 4. Outcome model estimation results .................................................................................... 32
Table 5. Comparative statics .......................................................................................................... 40
Table 6. Descriptive statistics of countries unemployment rates .................................................. 43
Table 7. Results of regression analysis (without IV) ...................................................................... 46
Table 8. First stage of IV estimates (tobit model) .......................................................................... 47
Table 9. Regression results of IV estimates .................................................................................... 48
Table 10. Regression results of lag(Labor productivity) indirect effect ........................................ 49
Table 11. Regression results with respect to the prize money (higher and lower than average) .............................................................................................................................. 50
Table 12. Descriptive statistics of video games sample .................................................................. 61
Table 13. Empirical results of VAR equation estimation ................................................................. 64
Table 14. Descriptive statistics of the sales (by region) .................................................................. 76
Table 15. Descriptive statistics of the sales (global) ...................................................................... 77
Table 3. Table 16. Estimation results of spillover effects ................................................................. 80
Table 17. Descriptive statistics of total prize and HHI ................................................................... 97
Table 18. Descriptive statistics of total prize and HHI by type ....................................................... 98
Table 19. Regression results of tournament theory test .................................................................. 104
Table 20. Regression results for the tournament theory test models with interactions ................ 105
Table 21. Descriptive statistics of teams characteristics ................................................................. 123
Table 22. Estimation results of the diversity effects ......................................................................... 128
Table 23. Descriptive statistics of team skills and experience ......................................................... 135
Table 24. Mean values of variables for teams with and without coaches ....................................... 136
Table 25. Results of the endogenous switching regression model for logarithm of prize money .......................................................... 138
Table 26. Summary statistics of Dota 2 matches .......................................................................... 144
Table 27. Estimation results of the intensity effect ......................................................................... 146
Index of Figures

Figure 1. Total eSports prize winnings by country (in US$), 1999–2015 .................................................. 23
Figure 2. Unemployment and hours spent on video games ................................................................... 41
Figure 3. Unemployment and hours spent on video games in case of an increase of population in one country .................................................................................................................. 41
Figure 4. Unemployment and hours spent on video games in case of simultaneous change in the $k_{11}$ and H. Panel (a) represents first, panel (b) – second .................................................. 42
Figure 5. Dynamics of unemployment rates and prize money .................................................................. 44
Figure 6. Scatterplot of the Gini ratio and Prize ...................................................................................... 62
Figure 7. Impulse-response function for Prize ........................................................................................ 65
Figure 8. Impulse-response function for Gini ratio .................................................................................. 66
Figure 9. Impulse-response function for Number of teams ....................................................................... 66
Figure 10. Impulse-response function for Number of tournaments ........................................................ 67
Figure 11. Total Sales of all game publishers by Region and Year. Source: Self-elaboration .......................... 77
Figure 12. Total number of tournaments of all game publishers by Region and Year (divided into two plots for the purpose of visualization) ................................................................. 78
Figure 13. Marginal effect for the nonlinear model for number of tournaments ...................................... 82
Figure 14. Game tree for tournaments’ organizer and players ................................................................. 90
Figure 15. The organizer’s utility in individual and team tournament ..................................................... 94
Figure 16. Optimal prize spread in individual and team tournament ....................................................... 94
Figure 17. Graphical visualization of the model result .............................................................................. 95
Figure 18. Number of tournaments and HHI dynamics - the shading of the bar reflects the average HHI of a particular year tournaments ........................................................................ 98
Figure 19. Relationship between the prize and the concentration (HHI) of prizes for team (left panel) and individuals (right panel). Scales for both graphs are the same. Although the maximum prize is truncated for the purpose of presentation, this does not affect ........................................................................ 99
Figure 20. Prize distribution by rank (from first to eighth) for team (left panel) and individual (right panel) games .................................................................................................................. 100
Figure 21. The comparison of prize spreads (only which are convex in rank order) of different types of tournaments and games ................................................................................................ 107
Figure 22. Four possible outcomes ......................................................................................................... 134
Figure 23. Number of teams with coaches by year .................................................................................. 137
Figure 24. Four possible outcomes for prize money and kill-to-death ratio ........................................... 140
Figure 25. Intensity distribution .............................................................................................................. 145
Figure 26. Marginal effect of intensity ...................................................................................................... 147
Figure 27. Top positive and negative words and their coefficients .......................................................... 149
Resumen en español

Los videojuegos y los juegos por ordenador son cada vez más populares. El desarrollo del software y los juegos por Internet involucra a numerosas personas en esta industria. Hace diez años, las competiciones de videojuegos se organizaron principalmente entre aficionados, pero ahora se ha convertido en un deporte profesional (Tassi 2012). La creciente popularidad de los juegos competitivos por ordenador y otras plataformas (eSports) ha generado un aumento en la cantidad de jugadores y en los premios –principalmente monetarios-. Aproximadamente 115 millones de entusiastas del hardcore \(^1\) vieron eSports en 2015 y otros tantos fueron espectadores ocasionales. Se espera que esas cifras sigan aumentando, alcanzando los 427 millones proyectados para 2019 (Rowell, 2016). A pesar de este hecho, no son muchos los estudios que analizan la economía de los deportes electrónicos. Nuestro objetivo es precisamente cubrir ese vacío. En particular, en esta tesis nos concentraremos en los determinantes del rendimiento. Siguiendo la idea de Blalock (1979), realizamos nuestro análisis en diferentes niveles: micro, meso y macro. Estos niveles no son necesariamente mutuamente excluyentes, pero dicha división se usa ampliamente en las ciencias sociales, en particular en la economía y en la gestión.

Abordamos los determinantes del desempeño de dos maneras. La primera es desde la perspectiva de la economía de los eSports. Analizamos aquellas características de los eSports que han sido ampliamente estudiados en el ámbito de los deportes tradicionales. La principal pregunta aquí es revelar los determinantes del éxito y compararlos con los de los deportes tradicionales. Estos resultados son potencialmente interesantes para los jugadores, los equipos y sus gestores, los organizadores de torneos y los editores de videojuegos. El segundo enfoque consiste en mirar, al mismo tiempo, las características únicas (peculiares) de los eSports. Aquellas características derivadas de la naturaleza "digital" de esta actividad. Si bien la mayoría de las empresas no son transparentes con respecto a su capital humano

\(^1\) anglicismo que resulta difícil de traducir y que puede indicar tanto personas que pasan muchas horas jugando como a los jugadores expertos y que gustan de juegos de elevada dificultad.
y, en el mejor de los casos, proporcionan información agregada, el deporte profesional es una buena plataforma para el análisis del capital humano, ya que se dispone de datos muy detallados sobre los individuos que participan en él (Kahn, 2000). Debido a la transmisión de las competencias, su amplia cobertura por parte de los medios y la existencia de un gran mercado de apuestas, una gran cantidad de datos estadísticos relacionados con los deportes profesionales está disponible y accesible al público. Esto ha llevado recientemente a un uso generalizado de los datos deportivos en la investigación económica y de gestión, tanto a nivel organizativo como individual.

A nivel organizacional, los datos deportivos se han utilizado para explorar temas como la transferencia de conocimiento (Yamamura 2009; Barthel y Wellbrock 2010; Berlinski, Schokkaert y Swinnen 2013; Frick y Simmons 2014), redes de transferencia de clubes (Lee, Hong y Jung 2015; Liu et al. 2016; Rossetti y Caproni 2016), redes de interacciones entre compañeros (Clemente et al. 2014; Clemente, Couceiro, et al. 2015; Clemente, Martins, et al. 2015), y la contribución del esfuerzo de los jugadores al rendimiento del equipo (Weimar y Wicker 2017). Además, la composición de los equipos y su influencia en su rendimiento representa un flujo separado de investigación. La existencia de datos deportivos precisos permite analizar la diversidad dentro de los equipos (Wilson y Ying 2003; Franck y Nüesch 2011, 2010; Ingersoll, Malesky y Saiegh 2014a), la comunicación interna en los equipos (Lausic et al. 2009) y las desigualdades en los pagos (Depken 2000; Frick, Prinz y Winkelmann 2003; Depken y Wilson 2004a; Frick 2007; Coates, Frick y Jewell 2016) y su impacto en el rendimiento del equipo.

A nivel individual, la investigación se ha centrado en los roles de los miembros individuales del equipo (atletas), así como en el ´administrador´ del equipo (entrenadores). Existen estudios que analizan, por ejemplo, la duración esperada y típica de la carrera de los jugadores (Burai et al. 2015; Miklós-Thal y Ullrich 2015), los elementos que determinan los salarios (Ashworth y Heyndels 2007) con un énfasis especial en la discriminación (Christiano 1986; Lavoie y Grenier 1992), y los sesgos en el comportamiento de los jugadores (Bar-Eli et al. 2007). Los datos precisos y detallados sobre la calidad de los miembros de los equipos y otras características permiten la identificación del rol particular del entrenador y su
contribución al éxito del equipo. Además de varias contribuciones sobre el impacto de la calidad de la gestión -representada en el entrenador- en el rendimiento del equipo (Kahn 1993; Dawson, Dobson y Gerrard 2000a, 2000c; Frick y Simmons 2008b; Frick, Barros y Prinz 2010; Paola y Scoppa 2012), también se han abordado otros temas como los determinantes de la compensación gerencial (Tomé, Naidenova y Oskolkova 2014) y las características psicológicas como la autoconfianza gerencial (Zavertiaeva, Naidenova y Parshakov 2018).

Objeto de la investigación y métodos empleados

Cada capítulo del presente trabajo se centra en un conjunto de temas combinados por el nivel de análisis. Cada uno de los análisis de cada tema en particular tiene su objetivo particular, así como su base teórica específica, su metodología y resultados.

En el primer capítulo se realiza un análisis a nivel macro, por lo que la unidad de observación es país. Comenzamos con un análisis de los determinantes del desempeño a nivel país. Este capítulo proporciona nueva información sobre los principales impulsores del rendimiento en el área emergente de los deportes electrónicos. Exploramos las características clave a nivel país que contribuyen al éxito de los jugadores. Dicho éxito se aproxima mediante el dinero ganado en competencias. Utilizamos los beneficios de los jugadores acumulados por país y un modelo de valla (hurdle model) para comprender los determinantes del rendimiento en cada país. Los resultados muestran que un aumento del 1% en el PIB per cápita conduce a un aumento del 2,2% en el premio monetario per cápita. La población del país no resulta estadísticamente significativa en el modelo. Este hallazgo puede indicar que el talento en los deportes electrónicos no se distribuye de manera uniforme entre la población mundial. Sorprendentemente, las economías post-soviéticas y planificadas o post-planificadas presentan más probabilidad de participar en deportes electrónicos.

A continuación, en este capítulo, analizamos el impacto en la tasa de desempleo de los deportes electrónicos, en general, y la popularidad de los videoguegos, en particular. Los videoguegos son tratados como una innovación en la actividad de ocio, lo que hace que estar parado puede ser más atractivo que antes de la aparición de estos. En este capítulo utilizamos los premios de competiciones en eSports como
proxy de la popularidad de los videojuegos para analizar su influencia en el desempleo. Utilizamos el dinero total ganado en premios por los representantes de un país en una temporada. Empleamos un modelo de regresión con datos de panel con país-año como unidad de observación. El principal resultado obtenido es que los videojuegos, como innovación en actividades de ocio, afectan la distribución del tiempo de trabajo y diversión de forma que la tasa de desempleo en los diferentes países aumenta. En general, esto prueba la idea de Greenwood y Vandenbroucke (2005), Vandenbroucke (2009), Kopecky (2011) y Aguiar et al. (2017) que las innovaciones de ocio afectan la oferta laboral.

En el segundo capítulo realizamos análisis a nivel meso. Aquí, la unidad de observación es un mercado o una industria. Primero utilizamos datos de eSports para construir un modelo empírico para medir el efecto de la competitividad de la liga en su popularidad. Los deportes electrónicos brindan una configuración perfecta para capturar el efecto de la concentración de la liga por las razones que se enumeran a continuación. Primero, no hay restricciones de competencia impuestas por un órgano regulador de la liga. En segundo lugar, los costes de entrada son significativamente más bajos en comparación con las otras ligas deportivas. En tercer lugar, los equipos de eSports maximizan su resultado como una empresa tiende a maximizar su beneficio. La recompensa en los deportes electrónicos se basa principalmente en el rendimiento mientras que, en la mayoría de los deportes tradicionales, una parte importante de la compensación económica de un atleta es independiente de sus resultados en las competiciones actuales. Esto hace que nuestros hallazgos sean potencialmente transferibles a otras industrias diferentes de los eSports. Finalmente, dado que los torneos en eSports, por equipos o individuales, se organizan de manera similar, es posible comparar la competencia entre equipos e individuos. Este capítulo utiliza como datos los premios de cada jugador para cada torneo (en dólares estadounidenses) para el período de 1999 a 2015. La conclusión general es que la competencia impulsa el desarrollo de la liga. Sin embargo, esto funciona solo para los juegos para equipos. Por lo tanto, el tipo de juego podría afectar la interdependencia entre la competencia y la popularidad de la liga.
Después de esto nos concentrarnos en los torneos de eSports. Las empresas han utilizado cada vez más la promoción de sus productos a través del marketing de eventos. Sin embargo, la evidencia empírica sobre si esos eventos inducen mayores ventas es mixta. Este apartado investiga los efectos secundarios derivados de la promoción para empresas multi-producto globales. La investigación se lleva a cabo usando datos de la industria de los videojuegos y de torneos de deportes electrónicos para el período 1997-2015. Los datos se recopilan a lo largo de 20 años, producto por producto en ventas de videojuegos, eventos, género e ubicación para todas las empresas de la industria. El método de análisis es regresión con datos de panel con efectos fijos. La conclusión principal de este apartado es que el uso del marketing de eventos tiene un claro impacto positivo en el aumento de las ventas para los productores de deportes electrónicos. Sin embargo, el efecto del número de eventos en una región particular sobre las ventas en la región es no lineal (en forma de U invertida). Además, encontramos evidencia empírica de los efectos secundarios de los eventos en diferentes regiones y géneros de videojuegos. Por el contrario, los eventos organizados por otros editores de videojuegos no afectan a las ventas de la compañía. Se ha proporcionado evidencia sobre los efectos de eventos de promoción a través de las regiones analizadas y entre categorías utilizando datos mundiales sobre ventas de videojuegos y torneos de deportes electrónicos. Para la industria de los videojuegos, se encontró un número óptimo de torneos de deportes electrónicos a organizar por año. Los productores de eSports deberían tener esto en cuenta al diseñar su estrategia de promoción a través de la organización o patrocinio de eventos.

A continuación, nos concentrarnos en el aspecto organizativo de los torneos. La teoría de torneos (tournament theory) ha sido corroborada por numerosas investigaciones empíricas en diferentes campos. Sin embargo, la literatura sobre teoría de torneos se centra principalmente en los incentivos para competidores individuales. En nuestro análisis, usamos datos de competencias de deportes electrónicos (videojuegos) tanto de torneos individuales como de equipo. Sugerimos un modelo teórico que proporcione información sobre la rentabilidad de

---

2 Sin ánimo de ser exhaustivos, hay que indicar que los géneros en videojuegos pueden ser principalmente de habilidad y acción —incluyen carreras, deportes, combate, disparos, laberinto,...— y cognitivos y de estrategia —comprender juegos de rol, de guerra, de aventuras y educacionales entre otros—.
la decisión "equipo frente a individual" por parte del organizador del torneo. A continuación, en la parte empírica, mostramos que tanto los torneos de eSports de equipo como los individuales siguen la teoría de torneos. Sin embargo, existe una diferencia entre la motivación para los grupos y los individuos. Esta diferencia está condicionada por el nivel competitivo. Nuestro estudio proporciona información sobre la estructura óptima de recompensa que debería maximizar el esfuerzo de los participantes y, en el caso de los torneos deportivos, el valor de entretenimiento de los eventos.

En el tercer capítulo realizamos análisis a nivel micro. Aquí la unidad de observación es el equipo. Primero utilizamos los datos de eSports para construir un modelo empírico para medir el efecto de la diversidad dentro de un equipo para medir su rendimiento. Entendemos que los equipos de profesionales eSports son mucho más similares a las empresas que operan en la "nueva economía" que a los equipos en otros deportes. Primero, el resultado depende más de las habilidades mentales que de la excelencia física. En segundo lugar, las diferencias idiomáticas pueden influir notablemente en el resultado. Esto es común para las empresas y los equipos de deportes electrónicos ya que requieren comunicación y un alto nivel de comprensión entre sus componentes. En tercer lugar, un equipo de eSports maximiza su resultado como una empresa tiende a maximizar su beneficio. La recompensa en los deportes electrónicos se basa principalmente en el rendimiento, mientras que en la mayoría de los deportes tradicionales, una parte importante de la compensación de un atleta es independiente de los resultados de los partidos actuales. Se consideran diferentes tipos de diversidades: en términos culturales, idiomáticos y de habilidad. Nuestros principales resultados son que la diversidad cultural es beneficiosa para el rendimiento del equipo, pero la existencia de varios de idiomas entre sus miembros y el diferente grado de experiencia entre los componentes del equipo afecta negativamente a los resultados. Teniendo en cuenta la diferencia en los resultados, llegamos a la conclusión de que las empresas no deben maximizar sin pensar la diversidad del equipo: los diferentes tipos de diversidad tienen diferentes costes de integración.

Posteriormente, en este capítulo, abordamos el tema de la eficiencia de la gestión, que es uno de los temas clave en la economía y la gestión laboral. El gestor es
responsible de la transformación de los recursos en resultados al menor coste posible. En la economía moderna, la importancia de los recursos humanos está creciendo, colocando el papel de los gerentes en el centro de la eficiencia de la empresa. Sin embargo, hay estudios que examinan la eficiencia de equipos sin un gerente o un entrenador. Son los llamados equipos autogestionados (Carte et al., 2006). Por lo tanto, a pesar del enfoque en la eficiencia gerencial en la literatura económica, la cuestión de si un equipo necesita un gerente está lejos de resolverse. En esta parte, utilizamos una configuración cuasi-experimental de eSports para entender si la presencia de un gerente es beneficioso para el rendimiento del equipo. 

El principal hallazgo de este estudio es que la contratación de un entrenador no aumenta el rendimiento del equipo. Esto plantea una pregunta sobre la eficiencia de la gestión, no solo en los deportes electrónicos, sino también en industrias similares, ya que los equipos de deportes electrónicos son similares a las nuevas profesiones donde el conocimiento informático y la comunicación por Internet son necesarios para todos los empleados.

Contribución

La contribución de este trabajo se puede dividir de dos maneras. La primera es con respecto al nivel de análisis: macro, meso y micro. La segunda forma es dividir por el grupo de interés: en deporte electrónico profesional o en economía en general.

A nivel macro, la contribución respecto al deporte electrónico profesional se resume en los siguientes puntos:

- Existen determinantes del desempeño a nivel de país.
- Un aumento del 1% en el PIB per cápita conduce a un aumento del 2,2% en el premio monetario per cápita.
- Las economías post-soviéticas y planificadas o post-planificadas tienen más probabilidades de participar en los deportes electrónicos.
- Los videojuegos afectan a la distribución del tiempo de trabajo y diversión y eso puede influir en la tasa de desempleo en los países.

En cuanto a los aspectos de economía general, las contribuciones se resumen en:

- Existe una distribución heterogénea del talento entre países.
- El desarrollo de las infraestructuras afecta en el desempeño a nivel de país.
The Economics Of Esports: Elements That Affect Performance

- Se presenta un modelo teórico del efecto de los eSports en la tasa de paro.
- Las innovaciones de ocio afectan la oferta laboral.

En nivel meso, considerando los deportes electrónicos, se presentan las siguientes contribuciones:

- En las competiciones de equipo de deportes electrónicos, el nivel de competencia impulsa el desarrollo de la liga.
- Existe un esquema óptimo de distribución de premios para organizadores de torneos de deportes electrónicos (por equipos e individual)
- Asimismo, existe una estructura óptima de distribución de premios para organizadores de torneos de deportes electrónicos (en vivo y online)
- Se estima un número óptimo de torneos por año y por juego.

Las contribuciones generales de carácter económico en este nivel son:

- Se ha realizado una estimación del efecto de la competencia dentro de la industria para su crecimiento.
- Se ha probado la teoría de torneos en el contexto de los eSports.
- Se ha desarrollado un modelo teórico de motivación grupal en torneo por equipos.
- El esquema de motivación óptimo es diferente para equipos e individuos.
- Existe efectos secundarios derivados de la promoción en términos de industria, región y producto para las empresas globales de multi-producto.

Finalmente, las contribuciones a nivel micro para los deportes electrónicos profesionales se sintetizan en:

- Recomendación para la composición de los equipos en Counter-Strike: Global Offensive (CS: GO).
- Se estima el efecto marginal de la habilidad individual medida por Kill to Death ratio en el desempeño del equipo.
- La contratación de un entrenador no aumenta el rendimiento del equipo en Counter-Strike: Global Offensive (CS: GO) en promedio.

Las contribuciones generales en este nivel se resumen en:
- Se estudia la diversidad en el rendimiento del equipo: la diversidad cultural es beneficiosa para el rendimiento del equipo, pero la diversidad de idiomas y experiencias afecta negativamente a los resultados del equipo.
- Diferentes tipos de diversidad tienen diferentes costes de integración.
- Los equipos autogestionados superan a los equipos con gestor (entrenador).

La principal contribución de los deportes electrónicos profesionales es revelar los factores de éxito en diferentes niveles. La gerencia del equipo, el organizador del torneo o las autoridades estatales pueden usar los hallazgos de esta tesis para maximizar sus ganancias o alcanzar sus objetivos. Nosotros, por ejemplo, sugerimos una estructura de distribución de premios para los organizadores de torneos y brindamos información sobre el número óptimo de eventos a organizar para los editores de juegos. La contribución a la economía general consiste en el análisis de cuestiones laborales y de gestión en un nuevo contexto. Encontramos que las innovaciones de ocio afectan la oferta de trabajo, sugerimos un modelo teórico de motivación grupal, probamos el efecto de la diversidad y la eficiencia gerencial en este nuevo contexto.
Introduction

Computer and video games are becoming more and more popular. The development of the Internet and gaming software involve many people in this industry. Ten years ago, video games competitions were organized mostly between amateurs, but now it has become professional (Tassi 2012). The growing popularity of competitive computer gaming (eSports) has caused an increase in the number of gamers and in the rewards given as prizes. Approximately 115 million hardcore enthusiasts watched eSports in 2015 and another 115 million were occasional viewers. Those numbers are expected to continue to increase, reaching a projected 427 million by 2019 (Rowell, 2016). Despite this fact, there are a few studies which analyze the economics of eSports, and our goal is to fill this void. In particular, we concentrate on the determinants of performance. Following the idea of Blalock (1979), we perform our analysis on different level: micro, meso and macro. These levels are not necessarily mutually exclusive, but such division is widely used in social science and in economics and management, in particular.

We address the issue performance determinants in two ways. The first is the economics of eSports perspective. We analyze features of eSports that have been extensively studied with regard to traditional sports. The main question here is to reveal the determinants of success and compare them to the traditional sports. These results would be potentially interesting for gamers, team, team management, tournament organizers and video game publishers. The second approach to look, at the same time, on the unique features of eSports, which are provided by the “digital” nature of this activity. While most firms are not transparent with respect to their human capital and provide aggregate information at best, professional sport is a good platform for human capital analysis as very detailed data on individuals is available (Kahn 2000). Due to the broadcasting of competitions, broad media coverage and existence of a large betting market, a lot of statistical data related to professional sports is publicly available and accessible. This has recently led to a widespread use of sports data in economics and management research at both, the organizational and the individual level.

At the organizational level, sports data have been used to explore issues such as knowledge transfer (Yamamura 2009; Barthel and Wellbrock 2010; Berlinschi,
Schokkaert, and Swinnen 2013; Frick and Simmons 2014), clubs’ transfer networks (Lee, Hong, and Jung* 2015; X. F. Liu et al. 2016; Rossetti and Caproni 2016), networks of interactions between teammates (Clemente et al. 2014; Clemente, Couceiro, et al. 2015; Clemente, Martins, et al. 2015), and contributions of players’ efforts to team performance (Weimar and Wicker 2017). Moreover, team composition and its influence on team performance is a separate stream of research. Precise sports data allow to analyze team diversity (Wilson and Ying 2003; Franck and Nüesch 2011, 2010; Ingersoll, Malesky, and Saiegh 2014a), intra-team communication (Lausic et al. 2009), and pay inequalities (Depken 2000; Frick, Prinz, and Winkelmann 2003; Depken and Wilson 2004a; Frick 2007; Coates, Frick, and Jewell 2016) and their impact on team performance.

At the individual level, research has addressed the roles of individual team members (athletes) as well as team manager (coaches). Available studies include analyses of e.g. expected and typical career length (Buraimo et al. 2015; Miklós-Thal and Ullrich 2015), salary drivers (Ashworth and Heyndels 2007) with a special emphasis on discrimination (Christiano 1986; Lavoie and Grenier 1992), and players’ behavioral biases (Bar-Eli et al. 2007). Moreover, precise and detailed data on team members’ quality and other features allows identification of the particular role and contribution of a coach. Apart from several contributions on the impact of managerial quality on team performance (Kahn 1993; Dawson, Dobson, and Gerrard 2000a, 2000c; Frick and Simmons 2008b; Frick, Barros, and Prinz 2010; Paola and Scoppa 2012), other topics such as managerial compensation drivers (Tomé, Naidenova, and Oskolkova 2014) and psychological perspectives as managerial self-confidence (Zavertiaeva, Naidenova, and Parshakov 2018) have been addressed too.

**Research Questions and Methods**

Each chapter of the present work focus on set of issues combined by the level of analysis. Each of the analysis of a particular issue has its particular aim as well as a specific theoretical background, methodology and results.

In the first chapter we perform macro-level analysis, so the unit of observation is a country. We start we an analysis of country-level determinants of performance.
This chapter provides with new information about key drivers of performance in the emerging area of eSports. We explore key country-level characteristics that contribute to players’ success, measured as money won. We use gamers’ prize earnings aggregated by country and a hurdle model to understand the determinants of performance. The results show that a 1% increase in GDP per capita leads to a 2.2% increase in prize money per capita. Country population is not statistically significant in the outcome model. This finding may indicate that eSports talents are not uniformly distributed across the world population. Surprisingly, post-Soviet and planned or post-planned economies are more likely to participate in eSports.

Next in this section we analysis the impact of eSports and, in general, video games popularity to the unemployment rate. Video games are treated as an innovation in leisure activity, which makes being unemployed more attractive than before. In this section we use eSports prizes as a proxy of video games popularity to analyze its influence on unemployment. We use the total prize money won by representatives of a country in a season in a panel regression model with country-year as a unit of observation. Our main result is that video games, as an innovation in leisure activities, affect work-fun time distribution and increase unemployment rate in countries. In general, this proves the idea of Greenwood and Vandenbroucke (2005), Vandenbroucke (2009), Kopecky (2011) and Aguiar et al. (2017) that leisure innovations affects labor supply.

In the second chapter we perform meso-level analysis. Here the unit of observation is a market or an industry. First we use eSports data to construct an empirical model to measure the effect of competitiveness of the league to its popularity. eSports provides us with a perfect setting to capture the effect of league’s concentration for the following reasons. First, there are no competition restrictions imposed by the league’s administration. Second, the entry costs are significantly lower comparing to the other sports leagues. Third, an eSports team maximizes its result like a firm tends to maximize its profit. Reward in eSports is mostly performance-based while in a majority of traditional sports a significant share of an athlete’s compensation is independent of current match results. This makes our findings potentially transferable to the other industries except for eSports. Finally, since in eSports tournaments in teams and individuals are organized in a similar
way, it is possible to compare the competition between teams and individuals. This section uses data on each gamer's prize earnings for each tournament (in US dollars) for the period from 1999 to 2015. The general conclusion is that competition drives league development. However, this works only for the team games. So, the type of the game might affect the interdependence between competition and league popularity.

After this we concentrate on the eSports tournaments. Companies have increasingly used promotion of their products through event marketing. However, empirical evidence on whether the events lead to higher sales is mixed. This section investigates spillover effects of promotion for global multiproduct firms. The research is carried out on data of the video game industry and eSports tournaments as events for the period of 1997–2015. The data is collected over 20 years, for product-by-product on game sales, events, genre, and location for all companies of the industry. The method of analysis is panel regression with fixed effects. The primary conclusion from this section is that the use of event marketing has a clear positive impact on the increase of sales for eSports producers. The effect of the number of events in a particular region on the sales in the region is nonlinear (inverted U-shaped). Moreover, we find empirical evidence of spillover effects of events across regions and game genres, whereas events of the other video game publishers do not affect company’s sales. Evidence on cross-regional and cross-category promotion effects of events using a worldwide data on video games sales and eSports tournaments has been provided. For the video gaming industry, a threshold number of eSports tournaments per year was found. eSports producers should consider this when designing their promotion strategy.

Next we concentrate on a tournament organizer task. Tournament theory has been supported by many pieces of empirical research in different fields. However, tournament theory literature focuses largely on the incentives of individual competitors. In our analysis, we use both individual and team tournaments data of eSports (video games) competitions. We suggest a theoretical model which provides insights of the profitability of “team vs. individual” decision of tournament organizer. Next in the empirical part we show that team and individual eSports tournaments follow tournament theory, however, there is a difference between the
motivation of groups and individuals. This difference is conditional on the level of competition. Our study provides insights on the optimal reward structure, which should maximize effort of contestants, and, in the case of sports tournaments, and entertainment value of the events.

In the third chapter we perform micro-level analysis. Here the unit of observation is team. First we use eSports data to construct an empirical model to measure the effect of diversity on team performance. We believe that professional eSports teams are much more similar to commercial firms, that operate in the “new economy”, than teams in other sports. First, the result depends more on mental abilities than on physical excellence. Second, language differences may heavily influence the result both in firms and eSports teams because they require communication and high level of understanding. Third, an eSports team maximizes its result like a firm tends to maximize its profit. Reward in eSports is mostly performance-based while in a majority of traditional sports a significant share of an athlete’s compensation is independent of current match results. Different kinds of diversities are considered, in terms of culture, language and skill. Our main results are that cultural diversity is beneficial for team performance, but language and experience diversity negatively affect results. Taking the difference in the results into account, we conclude that firms should not thoughtlessly maximize team diversity: different kinds of diversity have different integration costs.

Next in this section we address the issue of managerial efficiency, which 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 or a coach, so-called self-managed teams (Carte et al., 2006). 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 part, we use a quasi-experimental setting from eSports to understand whether the manager is of benefit to team performance. The main finding of this study is that hiring a coach does not increase team performance. This raises a question about management efficiency, not only in eSports but also in similar
industries because eSports teams are similar to modern professions since computer knowledge and Internet communication are necessary for all employees.

**Contribution**

The contribution of this work might be divided in two ways. The first is with respect to the level of analysis: macro, meso and micro. The second ways is to divide by the stakeholder: eSports professional or the general economist.

<table>
<thead>
<tr>
<th></th>
<th>eSports economics</th>
<th>General economics</th>
</tr>
</thead>
</table>
| **Macro**| - Determinants of country-level performance  
- 1% increase in GDP per capita leads to a 2.2% increase in prize money per capita  
- Post-Soviet and planned or post-planned economies are more likely to participate in eSports  
- Video games affect work-fun time distribution and increase unemployment rate in countries | - Talent distribution across countries  
- Infrastructure effect on country-level performance  
- Theoretical model of eSports effect to unemployment rate  
- We find that leisure innovations affects labor supply |
| **Meso** | - For team eSports competitions the level of competition drives league development  
- Optimal prize spread scheme for eSports tournament organizers (team and individual)  
- Optimal prize spread scheme for eSports tournament organizers (live and online)  
- Cross-regional, cross-genre and cross-publisher event promotion recommendation  
- An optimal number of tournaments per year and per game is estimated | - Estimation of the effect of competition in industry to the industry growth  
- Tournament theory test in the eSports context  
- Theoretical model of group motivation in team tournament  
- The optimal motivation scheme is different teams and individuals  
- Spillover effects of promotion in terms of industry, region and product for global multiproduct firms |
| **Micro**| - Recommendation for team composition in CS:GO  
- Marginal effect of individual skill measured by KD to the team performance is estimated  
- Hiring a coach does not increase team performance in CS:GO in average | - Diversity on team performance: cultural diversity is beneficial for team performance, but language and experience diversity negatively affect results  
- Different kinds of diversity have different integration costs  
- Self-managed teams outperforms managed teams |
The main contribution to the eSports professionals is revealing drivers of success at different levels. Team management, tournament organizer or state authorities might use our findings to maximize its profits, or, in case of state, to reach the other goals. We, for example, suggest the prize distribution scheme for tournament organizers or provide information about the optimal number of events for game publishers. The contribution to the general economic is the analysis of labor and management issues in the new context. We find that leisure innovations affects labor supply, suggest theoretical model of group motivation, test diversity effect and managerial efficiency in the new context.
Chapter 1. Macro-level analysis

1.1 Determinants of country-level performance in eSports

1.1.1 Country performance in eSports: Problem statement

The growing popularity of competitive computer gaming has caused an increase in the number of competitive gamers and determines the industry’s profits. The number of gamers and winnings varies greatly between games (e.g. Counter-Strike, Dota 2, League of Legends, StarCraft II). However, very few academic papers study this phenomenon, probably because eSports is a young industry. However, some recent papers discuss the definition of eSports and its possible implications (Seo 2013b; Seo and Jung 2014; Taylor 2012; Witkowski 2012) and others analyze the difference between eSports and traditional sports (Adamus, 2012; Seo, 2013). Although the data show strong country differences in gamers’ success, to the best of our knowledge, no research examines the country-level difference in gamers’ winnings.

We therefore analyze which characteristics of the gamer’s country contribute to his or her success in eSports. Although country-level determinants of success in traditional sports are well studied, several important differences exist between eSports and traditional sports. First, in eSports, players can switch from one game to another one much easily and still remain profitable, which is almost impossible in traditional sports. Second, the cost of participating in eSports is lower than in the majority of traditional sports. Third, some nations demonstrate better results in a particular sport. For example, Kenyans are known to be good in the sport of long-distance running, Norwegians are good in skiing due, in part, to the country’s climate, while Spain has a well-developed system for young soccer players, thus demonstrating strong results in adult competitions. In eSports factors such as established training schools, appropriate climate, and physical excellence are not relevant and thus therefore leaves open the question of why country-level effects exist. Fourth, governments often play a huge role in traditional sports. Governments distribute resources for sports development, organize needed infrastructure and competitions, invest in national teams, and reward the best players. Some countries

---

even use sports results to unite the nation and for propaganda purposes (Bernard & Busse, 2004; Rathke & Woitek, 2007). Because eSports is quite new, it is rarely even regarded by countries sports federations and governments as an actual sport. eSports is self-organized, and all the investments come from private sponsors. Fifth, every gamer in eSports who qualifies has the opportunity to participate in international championships. Contrarily, traditional sports may be subject to quotas and thus send only the country’s best players to competitions. This selectivity may bias the results of previous research, such as those dedicated to Olympics.

This study uses data on each gamer’s prize earnings for each tournament (in US dollars) for the period from 1999 to 2015 from the eSports Earnings project. We then aggregate the data by country. The tournaments are divided into offline and online because offline events are more prestigious and have higher prize money. We analyze the data following the approach suggested by Bernard and Busse (2004) for the Olympics success determinants; however, we modify the model to fit the particular eSports context. Particularly, we explain some of the proposed determinants differently and add two additional indicators, namely, percentage of Internet users and high-technology export. We implement a hurdle model to provide an empirical analysis.

This study adds to the literature in three main ways. First, we contribute to the literature on traditional sports. We review the well-established research on country-level determinants of traditional sport success and implement a similar approach to eSports. In so doing, we extend the understanding of important country-level factors. Second, we show that country has an effect on eSports performance. Unlike national teams of traditional sports that receive both organizational and financial government support, and may be subject to quota restrictions, eSports is self-organized and receives no government support. Nonetheless, our results show that country has a strong influence on eSports performance. Third, we develop a new area of eSports research by explaining gamers’ success. Even though eSports gamers appear to be more homogenous than players in traditional sports, we find that country can explain differences in prize earnings for both online and offline tournaments.

---

4 http://www.esportsearnings.com/
1.1.2 Determinants of performance in traditional sports

An extensive body of literature examines the determinants of country success in traditional sports competition. Bernard and Busse (2004) explore Olympics data from 1960 to 1996. This influential study identifies the most important country-level factors and makes predictions for the Sydney Olympics. Following studies usually extend Bernard and Busse by number of variables or the empirical method implemented. Subsequent research can be divided into three main groups by their purpose: (i) to reveal determinants of a country’s success; (ii) to use country-level factors to predict a national team’s Olympic success; or (iii) to propose a ranking system on the basis of country-level factors.

First, research that explores country-level causes of a national team’s success commonly employs the following factors in the model:

- **Economic situation.** The most popular indicators of a country’s economic situation are GDP (e.g., Bernard & Busse, 2004; Emrich, Pitsch, Klein, & Pierdzioch, 2012; Johnson & Ali, 2004) and GNP (Lozano et al. 2002). Some authors also use income per capita (Johnson & Ali, 2004; Lui & Suen, 2008; Noland & Stahler, 2016), export or import (Condon, Golden, and Wasil 1999; Gásquez and Royuela 2014), capital formation (Gásquez and Royuela 2014), or inflation (Gásquez and Royuela 2014).

- **Human resources characteristics.** Prior studies commonly implement population size or population growth (Condon, Golden, and Wasil 1999; Gásquez and Royuela 2014). More rarely authors use life expectancy (Churilov and Flitman 2006; Condon, Golden, and Wasil 1999; Gásquez and Royuela 2014), child survival (Churilov and Flitman 2006; Condon, Golden, and Wasil 1999), literacy rate (Gásquez and Royuela 2014), or education level (Noland & Stahler, 2016).

- **Country political situation and religion.** Johnson and Ali (2004) and Leeds and Marikova Leeds (2009) analyze present political regime and institutions while other researchers take into account communist (Bernard & Busse, 2004; Johnson & Ali, 2004; Otamendi & Doncel, 2014; Rathke & Woitek, 2007) or colonial heritage (Leeds and Marikova Leeds 2009).
Trivedi and Zimmer (2014) distinguish Islamic countries among others in their analysis.

- **Geography and natural resources.** A number of studies analyze weather conditions and climate as important determinants of success for a particular sport (Johnson & Ali, 2004; Noland & Stahler, 2016; Otamendi & Doncel, 2014). Condon et al. (1999) argue that land and water areas can serve as important factors.

- **Infrastructure.** Condon et al. (1999) find that a country’s infrastructure including airports, railroads, and highways is an important factor.

- **Hosting nation.** Prior studies show that hosting the Olympic Games increases both the governmental support and players’ efforts, which leads to greater success for the hosting nation team in general (Noland & Stahler, 2016; Rathke & Woitek, 2007; Trivedi & Zimmer, 2014).

Second, research that uses country-level factors to predict a national team’s Olympic success uses well-established determinants to predict future success of a national team. Thus, Condon, Golden, and Wasil (1999) use 17 independent variables, with the help of a regression model and neural network, to make predictions of Olympic performance. Despite the already high number of variables used, they conclude that more precise prediction may require the inclusion of additional factors. Emrich et al. (2012) find that population size and GDP better predict success on summer and winter Olympics, respectively. Otamendi and Doncel (2014) conclude that country-level factors should be added by sport type because categorizing models by specific sport increases the predictive power of the models.

Finally, studies that suggest an assessment or benchmarking tool commonly measure success with the help of a production function, where success determinants such as GDP or population size are inputs and number of medals or share are outputs. This area of research usually employs the data envelopment analysis technique (Churilov and Flitman 2006; Lins et al. 2003; Li 2016; Lozano et al. 2002; Wu, Liang, and Yang 2009) or stochastic frontier analysis (Rathke and Woitek 2007).

Previous research on country-level determinants of sport success uses data for national teams. The majority of prior studies are dedicated to Olympic competition, although a few studies on soccer use data on FIFA competitions (Leeds and
Marikova Leeds 2009; Gásquez and Royuela 2014). However, the scant research on non-national competitions has yet to explain adequately team or individual success by a country-level data.

To address the particular aspects of eSports, we must first understand the features of eSports that differ from traditional sports. Despite eSports’ growing popularity and huge audience, the sports economics literature on gaming is very limited. The majority of the existing studys focus on the definition of eSports and the possible implications (Seo 2013b; Seo and Jung 2014; Taylor 2012; Witkowski 2012). Even among these studys, a commonly accepted definition of eSports does not exist. Wagner (2006) defines eSports as “an area of sport activities in which people develop and train mental or physical abilities in the use of information and communication technologies”. Witkowski (2012) criticized this definition because many aspects of traditional sports are also computer-assisted or computer-mediated, so the definition does not fundamentally distinguish eSports from the traditional sports. Hamari and Sjöblom (2015) regard eSports as “a form of sports where the primary aspects of the sport are facilitated by electronic systems; the input of players and teams as well as the output of the eSports system are mediated by human-computer interfaces.”

Some prior studies analyze the difference between eSports and traditional sports. Adamus (2012) examines how eSports will develop and its potential impact on both eSports and traditional sports. Seo (2013) analyzes eSports from a marketing perspective and emphasizes that companies can use eSports for advertising and promotion purposes. Comparing traditional sports and eSports, Crawford (2005) argues that digital gaming may increase people’s interest in traditional sports.

Thus, based on prior research and the characteristics that distinguish eSports from traditional sports, we outline five important features of eSports that are the most relevant for our research.

1. The cost of participation is lower than in most traditional sports. Sport facilities, even for spectator gaming, are much cheaper those for traditional team sports. Investment in players is also lower, and, unlike traditional sports, one player can participate in multiple games on a professional level.
2. The gaming industry, which is still in its infancy, has no established professional schools to train players.

3. eSports offers two tournament types for most games: offline and online. Top tournaments are offline. No championships are awarded on the national level.

4. Rewards and prize money are mostly performance-based. No common fixed contracts exist in the industry.

5. Governments are not involved in eSports and do not invest any resources in its development.

Given the well-established link between success in traditional sports and country characteristics, we explore whether these characteristics apply to players’ success in eSports. We take into consideration the unique features of eSports, which makes our analysis novel as eSports is such a new phenomenon. In addition, this study extends the understanding of the importance of country-specific characteristics in sports in general by applying Bernard and Busse’s (2004) methodology to non-national competitions.

### 1.1.3 Macroeconomic and eSports indicators

To study the determinants of success in eSports, we use data on tournament prize winnings. We obtain this information from eSports Earnings.\(^5\) This resource, which is based on freely available public information, provides information on eSports tournaments, winners’ names (aliases), and the sums won. The eSports Earnings website contains information on each gamer’s prize earnings for every tournament (in dollars) for the period from 1999 to 2015. The earnings are divided into offline and online prize money. This division is important because the prize money is much higher in the offline (so-called LAN) events. Consequently, offline events attract better players, and the competition is stronger. We correct nominal prizes in line with the official U.S. inflation rates. Further we aggregate the data on the country-level.

Figure 1 present a distribution of total prize by country. The intensity of the grey color of the map represents the total prize for all years for a given country. The

---

\(^5\) http://www.esportsearnings.com/
figure provides no clear explanation for the countries’ success. The top five successful countries are United States, Brazil, Sweden, Republic of Korea, and China. These counties are very different in terms of population, GDP, and quality of life. Thus, statistical analysis is necessary to uncover the key determinants of performance. Figure 1 also shows many countries with zero prize awards. Specifically, 60% of counties have no reported eSports earnings, a factor that should be taken into account while determining the identification strategy.

Prior research uses numerous determinants of performance in traditional sports. In fact, in our review of literature, we find that approximately 25 determinants are commonly used to explain a country’s success in a traditional sport. We use five of these indicators that we believe also explain country differences in eSports results.

(a) Gross domestic product per capita has been and continues to be the most popular determinant among researchers on traditional sports (Bernard & Busse, 2004; Emrich et al, 2012; Johnson & Ali, 2004; Lins et al., 2003; Trivedi & Zimmer, 2014). It reflects the economic resources that can be used to prepare athletes, build and maintain training facilities, and develop
training methods (Rathke and Woitek 2007). It is the best predictor of
country success in Olympics and soccer. Even though eSports is not as
important on the country level as traditional sports and lacks national
teams, we believe that GDP strongly influences country-level results. First,
it reflects economic situation within a country, which is connected to its IT
development and computer and Internet access. Second, people in more
prosperous countries have a larger amount of leisure time and can thus
spend more time playing games. In poorer countries, children and their
parents spend the majority of their time in low-skilled labor. Third, in
countries with higher GDP, eSports teams are more likely to find investors
to pay for their training and participation in championships.

(b) Second, the literature also shows that, along with GDP, population is a good
explanatory variable of country success in traditional sports. It reflects the
demographic power of a nation (Wu, Liang, and Yang 2009) and thus the
number of potential players (Rathke and Woitek 2007). Lozano, Villa,
Guerrero, and Cortés (2002) argue that, despite of more precise metrics
such as population height or weight, the total number of people in a country
is a predictor of success for all types of traditional sports. Although eSports
is not closely connected to physical excellence,6 we argue that population
can be used as a proxy for the probability of talented eSports players within
a particular country.

(c) Third, following Gásquez and Royuela (2014), we use gross capital
formation, measured as total investments made by a particular country
relative to its GDP, as a predictor of country growth. On the one hand, fast-
growing countries may be characterized by a good economic that enhances
people’s interest and ability to spend time gaming and thus indicates a
more developed eSports industry. On the other hand, poor economic
conditions in fast-growing countries suggest a late diffusion of IT and
gaming. In these countries, the development of technology can spark
increased interest in gaming as something new and interesting to try. We
treat this indicator as a measure of the tangible orientation of a country

---

6 Some physically determined characteristics are important for gamers: the speed of reaction, the ability to
move fingers fast, the ability to overcome tiredness, etc.
whereas eSports requires a non-tangible orientation. For example, Sweden, which is top-five country in eSports, has a relatively low level of capital formation.

(d) Fourth, we use life expectancy at birth, which reflects the average level of population health (Condon, Golden, and Wasil 1999; Gásquez and Royuela 2014). Churilov and Flitman (2006) use a similar metric, adjusted for disability, to estimate the probability of finding young capable athletes. This indicator also reflects the physical quality of life within a country. Good health allows players to train hard and perform well, and its necessity contradicts the stereotype of gamers as unhealthy and unfit. Thus, we include life expectancy as a determinant in eSports performance.

(e) Fifth, we use post-Soviet bloc countries and post-planned economies as indicators of country performance of eSports. The seminal paper by Bernard and Busse (2004) as well as subsequent research (Johnson and Ali 2004; Otamendi and Doncel 2014; Rathke and Woitek 2007) explains the importance of these factors. Prior studies suggest that these countries have a specific approach to participation, training, and incentives for success in sports. Bernard and Busse, in fact, argue that post-Soviet countries seem to be able to “manufacture” gold medals. Rathke and Woitek (2007) show that resources allocation to sports in post-Soviet bloc and post-planned economies have some specificity. However, given our t-test results for post-Soviet bloc and post-planned economy countries, we cannot reject the null. Thus, we include this indicator for comparison with results of previous studies. The importance of these factors differs for several possible reasons. One explanation is that a Soviet past determines specific psychological and sociological features that are crucial for success in eSports (Parshakov and Zavertiaeva 2015a). Another explanation is that these countries developed new technologies more slowly, and thus, as IT improved, gaming acquired a sense of novelty that aroused great interest among new players.

In addition to the country characteristics that may influence the development of eSports, we add indicators to account for the unique features of eSports: coverage and popularity. While many determinants—from religion to family traditions—may
affect gamers’ performance, we chose two: popularity and coverage. Due to the lack of research on eSports performance, these indicators have no supporting literature.

We measure the popularity of eSports as the number of the Internet users per 100. We use the percentage of the Internet users as a proxy of a country’s IT advancement and computer saturation. Because eSports is highly connected to computer and Internet usage, we posit that a higher (lower) percentage of Internet users means a higher (lower) proportion of the population is involved in computer gaming. A higher number of gamers in a country increases the possibility that a country will have players who win eSports competitions.

We use high-technology export share in manufactured export to proxy for coverage. Some prior studies of the relation between sports and country development use a similar metric. For example, Condon et al. (1999) measure export and import share in GDP to analyze Olympics success. Gásquez & Royuela (2014) use openness, measured as the sum of exports plus imports relative to GDP, as a determinant of country success in soccer. These variables measure the extent to which an economy is open to the outside. Gásquez and Royuela argue that economic liberalization positively influences the efficiency of an economy and the probability of economic growth. We take into account not only the openness of an economy but also the development of IT. We argue that countries that export more high-tech products are more involved in the eSports industry (e.g., computer gaming production, eSports tournaments organization, etc.). Greater industry coverage may increase the time people spend on gaming and, therefore players’ prize earnings.

Similar to Bernard and Busse (2004), we also test the lag of total prizes won in a logarithm form. They suggest that a country’s investments in one Olympics may increase the chance of winning medals in subsequent Olympics. We include the lag to account for the effect of the previous country characteristics on the success in eSports and also to make our study comparable with the papers on traditional sports.

Table 2 presents descriptive statistics for the variables. Panel A presents the statistics for all countries, and Panel B provides statistics only for those countries with non-zero prize earnings. This comparison provides several important insights. First, the GDP per capita of prize-earning countries is approximately twice high as that of the full sample. However, the maximum GDP per capita for the full sample is
higher, which means that gamers from the richest countries (e.g., Monaco, Liechtenstein, Luxembourg) do not participate in eSports competitions. This result may be because in such counties people many more options for leisure than training in eSports.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>GDP per capita, thousands US$</td>
<td>1,721</td>
<td>13.55</td>
<td>19.49</td>
<td>0.21</td>
<td>145.22</td>
</tr>
<tr>
<td>Population, mill.</td>
<td>1,950</td>
<td>31.85</td>
<td>127.52</td>
<td>0.01</td>
<td>1364.27</td>
</tr>
<tr>
<td>Internet users per 100</td>
<td>1,820</td>
<td>34.37</td>
<td>28.17</td>
<td>0.0</td>
<td>98.16</td>
</tr>
<tr>
<td>Capital formation, % of GDP</td>
<td>1,576</td>
<td>24.53</td>
<td>8.85</td>
<td>0.0</td>
<td>69.32</td>
</tr>
<tr>
<td>Life expectancy, years</td>
<td>1,805</td>
<td>70.25</td>
<td>9.01</td>
<td>42.81</td>
<td>83.98</td>
</tr>
<tr>
<td>High-tech exports, % of manufactured exports</td>
<td>1,343</td>
<td>9.18</td>
<td>11.40</td>
<td>0.0</td>
<td>87.40</td>
</tr>
<tr>
<td>Post-Soviet</td>
<td>1,953</td>
<td>0.05</td>
<td>0.21</td>
<td>0.0</td>
<td>1.00</td>
</tr>
<tr>
<td>(Post-)planned</td>
<td>1,953</td>
<td>0.02</td>
<td>0.13</td>
<td>0.0</td>
<td>1.00</td>
</tr>
<tr>
<td>Have non-zero total prize</td>
<td>1,953</td>
<td>0.20</td>
<td>0.40</td>
<td>0.0</td>
<td>1.00</td>
</tr>
<tr>
<td>Have non-zero offline prize</td>
<td>1,953</td>
<td>0.19</td>
<td>0.39</td>
<td>0.0</td>
<td>1.00</td>
</tr>
<tr>
<td>Have non-zero online prize</td>
<td>1,953</td>
<td>0.16</td>
<td>0.36</td>
<td>0.0</td>
<td>1.00</td>
</tr>
</tbody>
</table>

Table 2: Descriptive statistics of countries

Table 2 also shows that the mean population in the non-zero prize sample is more than double the full sample. This result suggests that as a country’s population increases, the more successful gamers the country will produce, assuming the talent is uniformly distributed. Although life expectancy is only slightly higher in the
restricted sample, the \( t \)-test shows this difference is statistically significant. Compared to the full sample, non-zero prize countries with eSports prize winnings have twice as many Internet users per 100 and a higher percentage of high-technology export. These results are as expected, given that the level of IT development is of the great importance in such kind of sports. We include capital formation as the indicator of country growth and the country’s orientation toward a tangible strategy of growth. The full sample contains 5% post-Soviet counties and 2% counties with a planned or post-planned economy.\(^7\)

Because all major eSports tournaments are held offline (Coates and Parshakov 2016b), offline prize winnings are substantially higher than online prize winnings (Table 2, Panel B). Interestingly, the maximum prize is higher for the online competitions. However, because this variable is measured as the cumulative prize of all gamers for all tournaments during the year, a high number of minor online tournaments with relatively low prizes per tournament sums to a higher cumulative prize.

1.1.4 Hurdle model empirical approach

To study the determinants of the performance in eSports, we must take into account the structure of our data. Namely, 80% of the sample countries record zero total country winnings. This problem is typical for country-level studies of performance in traditional sports. Bernard and Busse (2004) address this problem by using a tobit regression with random effects. We use two different models that are forced to have the same covariates. A probit (or other binary outcome) model determines whether the dependent variable is censored, and then an ordinary least squares (OLS) regression determines the actual value of the dependent variable.

In our setting, the tobit model supposes that the same factors that influence the probability of being a non-zero prize country similarly affect the sum of the prize of those countries that have a non-zero prize. This assumption may be controversial. For this reason, we use a hurdle model. Cragg (1971) proposes a hurdle model to

---

\(^7\) Post-Soviet countries include Bulgaria, Czech Republic, Slovakia, Poland, Russian Federation, Hungary, Romania, Cuba, Kazakhstan, Armenia, Azerbaijan, Belarus, Bulgaria, Georgia, Kyrgyz Republic, Moldova, Tajikistan, Turkmenistan, Ukraine and Uzbekistan. Planned or post-planned economies include China, Democratic People’s Republic of Korea, Albania, Slovenia, Croatia, Bosnia and Herzegovina, Macedonia, and Uzbekistan.
explain the demand for durable goods. In our model, the probit model has one set of coefficients, and the OLS, which is done only on the positive country prize sample, has another. Consequently, the factors that determine whether a country has any prize winnings are different from those that determine the amount of a country’s prize money.

We use a panel probit with population-averaged effects for our selection model:

$$Pr[hp = 1|X] = \Phi(X^T\beta + \epsilon),$$

where $Pr$ denotes probability, $\Phi$ is the cumulative distribution function of the standard normal distribution, $hp$ is the dependent variable of positive prize winnings, and $X$ is a vector of covariates. We use the following covariates for the selection equation: log of GDP per capita, log of population, number of Internet users (per 100), gross capital formation (percentage of GDP), life expectancy at birth (in years), and high-technology exports (percentage of manufactured exports). We also include a dummy indicator for post-Soviet countries and planned or post-planned economies to compare the importance of these indicators between traditional sports and eSports.

In the outcome model, we use a panel model with fixed effects:

$$\log(prize) = X^T\beta + \sum \beta_i \cdot year_i + \sum \beta_n \cdot country_n,$$

where $year_i$ and $country_n$ indicate year and country dummies, respectively. A vector of covariates $X$ includes the log of GDP per capita, log of population, number of Internet users (per 100), gross capital formation (percentage of GDP), life expectancy at birth (in years), and high-technology exports (percentage of manufactured exports). Post-Soviet and post-planned dummies cannot be applied to the fixed effects model.

To make our results comparable with the results of studies of traditional sports, we also include the lag of prize winnings as an indicator of the importance of momentum for success in sports. OLS is inconsistent with a dynamic panel model because, by construction, the unobserved panel-level effects are correlated with the lagged dependent variables. To address this issue, we use Arellano and Bond’s (1991) estimator. Because Arellano and Bond recommend against using the two-
step nonrobust results for inference because the standard errors tend to be biased downward, we use Windmeijer bias-corrected robust standard errors, which Windmeijer (2005) show work well.

1.1.5 Revealed determinants of success in eSports

We estimate the selection model (Model 1) on the basis of the total sample; Models 2 and 3 use offline and online tournament data, respectively. We allow all coefficients to vary between online and offline games. Each specification includes year dummy variables to control for time effects; the year dummies are jointly significant. We correct the prize earnings for inflation, which provides a better indicator of the growing popularity of eSports.

Table 3 shows that we cannot reject the null of zero coefficients in any of the models for the logarithm of GDP per capita. This result means that infrastructure is not an important issue for eSports. This finding contradicts Bernard and Busse’s (2004) results for traditional sports, who find that wealthier countries are more likely to invest in sports infrastructure. However, GDP per capita is an important indicator for the outcome model (Table 3) although the elasticities differ a lot. Bernard and Busse find that a 1% increase in GDP per capita is associated with a 1.25% increase in medal share. Our analysis shows that a 1% increase in GDP per capita induces a 441% increase in total prize money. These results are robust to other dependent variables, such as offline and online prize. Such surprisingly high elasticity may be explained by the fact that competitiveness within eSports is not as strong as in the Olympics. Thus, the return on infrastructure is higher in eSports than in traditional sports, at least at the current stage. Given the average total prize of $341,803 and average population of approximately 70 million for non-zero prize countries, a 1% increase in GDP per capita will lead to a 2.2% increase in prize money per capita. This multiplier is quite high, suggesting that a country can quite easily build a brand in eSports, although wealthier countries are more likely to have the infrastructure and leisure time to devote to eSports.

A 1% increase in GDP per capita affects countries differently. The mean GDP per capita for non-zero prize countries is $26,049, compared to $9,915 for the total sample. This difference is statistically significant with a t-statistic of 15.2829. Sweden is the most successful country in eSports. Its GDP per capita is high, and a
1% increase would rank up the country from 18 to 11, according to World Bank data for 2015. GDP per capita is not statistically significant in the model with shares of prizes as dependent variable (see Table 4, Model 4). However, winning the same share of prize money in different years does not reflect similar performances: The total prize money award in eSports rose more than 400% from 2006 to 2014.

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total prize&gt;0</td>
<td>Offline prize&gt;0</td>
<td>Online prize&gt;0</td>
</tr>
<tr>
<td></td>
<td>coeff.</td>
<td>margins</td>
<td>coeff.</td>
</tr>
<tr>
<td>log(GDP)</td>
<td>0.0931</td>
<td>0.023</td>
<td>0.1117</td>
</tr>
<tr>
<td></td>
<td>(0.1014)</td>
<td></td>
<td>(0.1010)</td>
</tr>
<tr>
<td>log(population)</td>
<td>0.3711***</td>
<td>0.090</td>
<td>0.3738***</td>
</tr>
<tr>
<td></td>
<td>(0.0418)</td>
<td></td>
<td>(0.0415)</td>
</tr>
<tr>
<td>Internet users</td>
<td>0.0278***</td>
<td>0.007</td>
<td>0.0257***</td>
</tr>
<tr>
<td></td>
<td>(0.0042)</td>
<td></td>
<td>(0.0042)</td>
</tr>
<tr>
<td>Capital formation</td>
<td>0.0105</td>
<td>0.003</td>
<td>0.0032</td>
</tr>
<tr>
<td></td>
<td>(0.0091)</td>
<td></td>
<td>(0.0092)</td>
</tr>
<tr>
<td>Life expectancy</td>
<td>0.0337*</td>
<td>0.008</td>
<td>0.0340*</td>
</tr>
<tr>
<td></td>
<td>(0.0185)</td>
<td></td>
<td>(0.0182)</td>
</tr>
<tr>
<td>High-tech exports</td>
<td>0.0064</td>
<td>0.002</td>
<td>0.0079</td>
</tr>
<tr>
<td></td>
<td>(0.0053)</td>
<td></td>
<td>(0.0051)</td>
</tr>
<tr>
<td>Post-Soviet</td>
<td>1.4972***</td>
<td>0.517</td>
<td>1.3978***</td>
</tr>
<tr>
<td></td>
<td>(0.2096)</td>
<td></td>
<td>(0.2011)</td>
</tr>
<tr>
<td>Post-planned</td>
<td>1.6328***</td>
<td>0.574</td>
<td>1.5706***</td>
</tr>
<tr>
<td></td>
<td>(0.3377)</td>
<td></td>
<td>(0.3246)</td>
</tr>
<tr>
<td>Constant</td>
<td>-5.9307***</td>
<td></td>
<td>-5.7842***</td>
</tr>
<tr>
<td></td>
<td>(1.2435)</td>
<td></td>
<td>(1.2205)</td>
</tr>
<tr>
<td>Observations</td>
<td>1.219</td>
<td></td>
<td>1.219</td>
</tr>
<tr>
<td>Number of id</td>
<td>158</td>
<td></td>
<td>158</td>
</tr>
<tr>
<td>Chi-sq</td>
<td>254.15</td>
<td></td>
<td>251.73</td>
</tr>
</tbody>
</table>

*Note: Standard errors in parentheses.

*** p<0.01. ** p<0.05. * p<0.1.
The Economics Of Esports: Elements That Affect Performance

### Table 4. Outcome model estimation results

<table>
<thead>
<tr>
<th></th>
<th>(1) Total prize</th>
<th>(2) Offline prize</th>
<th>(3) Online prize</th>
<th>(4) Prize share</th>
<th>(5) Total prize</th>
</tr>
</thead>
<tbody>
<tr>
<td>log(GDP)</td>
<td>4.4139**</td>
<td>5.0892**</td>
<td>5.8019**</td>
<td>2.2852</td>
<td>15.1037***</td>
</tr>
<tr>
<td>log(population)</td>
<td>-4.5398</td>
<td>-3.9777</td>
<td>-9.9446</td>
<td>-7.1805</td>
<td>-18.6649*</td>
</tr>
<tr>
<td>Internet users</td>
<td>0.0043</td>
<td>-0.0126</td>
<td>0.0394</td>
<td>-0.0448</td>
<td>0.1177***</td>
</tr>
<tr>
<td>Capital formation</td>
<td>-0.1129***</td>
<td>-0.1689***</td>
<td>-0.1981***</td>
<td>-0.1292</td>
<td>0.0395</td>
</tr>
<tr>
<td>Life expectancy</td>
<td>-0.3540</td>
<td>-0.1218</td>
<td>-1.3873***</td>
<td>-0.6182</td>
<td>0.5566</td>
</tr>
<tr>
<td>High-tech exports</td>
<td>0.0302</td>
<td>0.0415</td>
<td>-0.0302</td>
<td>0.0252</td>
<td>0.0112</td>
</tr>
<tr>
<td>Lag of log (total prize)</td>
<td>(0.0222)</td>
<td>(0.0290)</td>
<td>(0.0359)</td>
<td>(0.0662)</td>
<td>(0.0493)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Included</th>
<th>Included</th>
<th>Included</th>
<th>Included</th>
</tr>
</thead>
<tbody>
<tr>
<td>Year controls</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>38.7156*</td>
<td>19.1252</td>
<td>126.1133***</td>
<td>68.3573</td>
</tr>
<tr>
<td></td>
<td>(23.1479)</td>
<td>(30.3137)</td>
<td>(37.4940)</td>
<td>(69.1195)</td>
</tr>
</tbody>
</table>

| Observations         | 368      | 368      | 368      | 368      | 904           |
| R²                   | 0.3562   | 0.2721   | 0.3362   | 0.0114   |               |
| Number of id         | 77       | 77       | 77       | 77       | 149           |

Note: Standard errors in parentheses.

*** p<0.01. ** p<0.05. * p<0.1.

The number of Internet users per 100 people is an important indicator for selection model. This result is robust through all the specifications (Table 3, Models 1–3). The marginal effect is, however, quite low: An additional user provides a 0.7% increase in the probability of having non-zero prize winnings. Interestingly, Table 4 shows that this indicator is not important for all of the outcome models. Although having a proper IT infrastructure is important to developing an eSports industry within a country, it likely loses its effect after reaching a certain threshold. The variance for the countries with a non-zero prize is 12% lower; this difference is statistically significant at the 1% level. Thus, successful eSport countries are more homogenous in terms of their IT infrastructure.

High-technology export (percentage of manufactured exports), which serves as an indicator of a country’s innovation structure, cannot reject the null in all models for both the selection and outcome models. We test the other indicators of innovation strategy, such as researchers in R&D (per million population) and
government expenditure on education (percentage of GDP), but the data are scarce or unavailable for many countries.\textsuperscript{8}

We include total population to be consistent with the previous studies of the determinants of success in traditional sports. Following research on traditional sports, we assume that talented eSports players are randomly distributed in the world population. Thus, the higher the population is, the more successful gamers a country has, and, consequently, the higher the prize winnings are. Interestingly, the log of population is important only in the selection model. The coefficients are positive, statistically significant, and robust to type of the prize (Table 3, Models 1–3). The marginal effect is 9%. Therefore, an increase of 1 million in a country’s population raises the probability of being a non-zero prize country by 9%.

Life expectancy, which represents the physical quality of life, reflects both infrastructure and population issues. It is statistically significant in all selection models (Table 3, Models 1–3). The marginal effect is 0.8%, which means that one additional year in life expectancy increases the probability of being a non-zero prize country by 0.8%. Despite its statistical significance, the economic impact of this indicator is relatively small. Life expectancy in the outcome model is statistically significant only for online prizes (Table 4, Model 3), and the coefficient is negative. Specifically, a one-year increase in life expectancy causes $100 \cdot (\exp(-1.3873) - 1 = -75\%$ decreases in online prize earnings. Thus, the better the infrastructure and physical quality of life of a country are, the lower a country’s prize earnings in online competitions are. Because online tournaments are low-level tournaments (Coates and Parshakov 2016b), this result suggests that countries with good infrastructure provide a greater number of possibilities to earn money or to become a professional gamer (and participate in higher-paying offline tournaments). However, in countries with a less developed infrastructure and lower physical quality of life, online gaming may be considered a more viable option for earning money, given the lack of opportunities to earn money or train professionally.

Results for the post-Soviet and planned or post-planned economies are surprising. Bernard and Busse (2004) study the ability of former Soviet Union and Eastern European countries “to ‘manufacture’ gold medals” (p. 415). The intuition

\textsuperscript{8} The results are available upon request
behind considering these counties in particular is based on their use of Olympic success for the propaganda purposes and their well-established traditions of success in many Olympic sports. However, this explanation does not fit the eSports context. Although we cannot identify the coefficients for these variables in the outcome model due to country fixed effects, both the post-Soviet and planned and post-planned dummies are positive and statistically significant in the selection model. In addition, the marginal effects are high. Being a post-Soviet country (planned or post-planned economy) increases the probability of being a non-zero prize country by 51% (57%). These coefficients differ across the three models for total sample, offline tournaments, and online tournaments (Table 3), but they all are relatively high.

An explanation for these results is not readily apparent. In these countries personal computers and computer games became available much later than in Western countries. In addition, Soviet computers were not at first compatible with US computers, and, therefore, the games were not compatible. Later, during the transition period, household financial constraints likely played a part. Thus, the large marginal effect may be explained by the peculiarities of gamers in post-Soviet and planned and post-planned economies as computer and gaming became more accessible. Given that the average age of gamer of 26, the current stars of eSports in these countries represent the first computer generation. Moreover, participating in safe outdoor activities may be problematic during the transitional period (Ceccato 2009) and computer gaming may be considered a viable option for entertainment. Cultural features may be important because a number of eSports tournaments competitors participate as a team rather than individuals. Also, communist ideology may somehow be beneficial to the development of eSports. Despite these possible explanations, further study is required to address the issues on post-Soviet counties success.

Finally, we estimate the model (Table 4, model 5) using lagged prize earnings to compare the results with the previous studies of traditional sports. The results differ among models, which is not unexpected given that year controls are not identifiable with our identification strategy. However, the lagged performance is positive and statistically significant compared to the models in Table 3. This finding is an evidence of a momentum effect in country performance in eSports.
1.2 eSports, video games and unemployment

In the last few decades, we have observed a huge transformation in everyday life and particularly in leisure activities. Digitalization has resulted in the emergence of new ways for people to spend their free time. The nature of digital leisure goods makes it easy for their popularity to grow. For example, Facebook, starting in 2004, grew from 12 million users in 2006 to 2.23 billion in 2018. Video games are another example – World of Warcraft started in 2004 and grew to 10 million monthly subscribers by 2010. In 2017, the number of frequent e-sports viewers and enthusiasts amounted to 143 million, which is almost equal to the population of Russia (147 million).

The growing popularity of video games affects the time distribution between work and leisure, and hence affects employment. Video gaming is an innovation in leisure activity which makes leisure, and therefore being unemployed and opting for gaming, more attractive. This results in a decrease in the labor supply, which is a negative shock to the labor market. However, it might be the case that through playing video games and related activities, employees acquire “digital” skills such as computer literacy. Such skills can potentially increase the productivity of workers. A report by the World Bank argues that the lack of digital skills might lead to greater inequality in society (World Bank, 2016). Nowadays, these skills are in great demand and more opportunities are available for companies that have access to vast quantities of data (The Boston Consulting Group, 2017). In this regard, video games might potentially benefit the quality of the labor supply.

In this study, we focus on the first part of this story. The purpose is to examine whether the popularity of video games increases the rate of total and youth unemployment in different countries. We analyze the information about e-sports prizes, unemployment rates and other macroeconomic indicators from 191 countries between 2000 and 2015. Two regression models are estimated – a linear regression model and a two-stage regression with IV.

Most studies on the topic highlight the difficulties in measuring work and leisure time allocation, since modern working activities often do not require a specific place of work or the use of specific equipment. For that reason, the authors use self-
reported survey data on time spent playing video games. However, people might underestimate the time spent, even they do not intend to do so. In our study, we use data on e-sports prizes by country to measure the popularity of video games, which means that we include data for professional e-sports players. Bernard and Busse (2004) showed that in traditional sport talent is distributed uniformly, and later Parshakov and Zavertiaeva (2018) proved this also in the context of e-sports, and therefore we assume that total prizes won by country correlates with the number of gamers. The number of gamers reflects the popularity of video games. Hence, we use e-sports prizes by country as a proxy for the popularity of video games.

1.2.1 Work-leisure time distribution

Digitalization influences the labor market in various ways (Brynjolfsson and McAfee 2011; Freeman 2002; Lent 2018). New jobs and positions have emerged, while existing ones have been significantly transformed or even substituted (Ducatel and Millard 1994; Loebbecke and Picot 2015). In turn, these changes have led to growing job polarization (Goos, Manning, and Salomons 2009; Goos and Manning 2007). Furthermore, new technologies require new skills from employees (Gibbs 2017; Lorenz et al. 2015) and change methods of management and the organization of work (Eichhorst et al. 2017; Rüßmann et al. 2015).

This study aims to examine another aspect of digitalization’s impact on the labor market, namely, the effect of digital leisure goods on the choice to work. We suppose that the new ways to spend free time appearing due to digitalization, influence people’s decisions about time allocation between work and entertainment. This focus is in line with the papers of Mincer (1962) and Becker (1965), which emphasize that labor supply is influenced by how time is allocated outside of work.

Greenwood and Vandenbroucke (2005), Kopecky (2011) and Vandenbroucke (2009) show that declining relative prices of leisure goods can help to explain employment declines over the last century. Extending this idea to the area of video games, Aguiar et al. (2017) find that over approximately the last decade, the increasing appeal of video games as a “leisure luxury” has led men in their twenties to reduce their working hours. Abraham and Kearney (2018), however, assert that
the conclusions of Aguiar et al. (2017) depend critically on the key structural assumptions of their model. In addition, in contrast to the ideas of Aguiar et al. (2017), Kimbrough (2018) considers the American Time Use Survey (ATUS) data and finds that an increase in gaming time is mitigated by a decrease in time spent on other electronic leisure activities.

Another reason why video games can influence employment is related to the nature of video games. Scholars argue that computer activities, including Internet surfing, online chatting, video games and others, can be addictive (Chiu, Lee, and Huang 2004; Griffiths 2000). A growing body of academic literature is aimed at investigating the nature of video game addiction and its consequences (Buckley and Anderson 2006; Carbonell et al. 2009; Sublette and Mullan 2012). Considering the negative effects of gaming for employment, employees can be distracted by video games from engaging with the workplace (Young, 2004). Moreover, video gaming addiction might be a cause of job loss or may influence the decision not to work (Chappell et al. 2006; Kim et al. 2008).

On the other hand, video games can promote the development of visual, spatial and ICT skills (Achtman, Green, and Bavelier 2008; Dondlinger 2007; Subrahmanyam and Greenfield 1994), improve digital literacy (Gee 2007; Steinkuehler 2010) and improve health-related outcomes (Primack et al. 2012). These positive effects of video gaming result in improvement of employees’ skills and performance (Buckley and Anderson 2006). Therefore, there is mixed empirical evidence on the effect of video games on unemployment. This study aims to provide some further insights into this relationship on the macro level.

1.2.2 Theoretical model of video games popularity and unemployment
To describe the relationship between the popularity of video games and total and youth unemployment in different countries, we developed a theoretical model. Let us consider two economies. We observe the countries’ populations \((n_1\) and \(n_2\)) and hourly wages \((w_1\) and \(w_2\)). \(W\) stands for the overall video game prize pool and \(H\) is an individual’s daily time budget that can be spent on three types of activities: work \((l)\), video games \((h)\) and rest \((H - l - h)\). Then \(l_{1i}\) and \(l_{2j}\) are the working times of
individuals $i$ and $j$ in countries 1 and 2 respectively, and $h_{1i}$ and $h_{2j}$ represent the time spent on video games for these individuals.

We assume that individuals are risk-neutral, so that their utility function from money is linear. Then, the utility function of individual $i$ from country 1 is as follows:

$$u_{1i} = w_{1i}l_{1i} + k_{11}\sqrt{h_{1i}} + \frac{1}{\sum_{s=1}^{n_1} h_{1s}} + \frac{1}{\sum_{s=1}^{n_2} h_{2s}} W + k_{12}\sqrt{H - l_{1i} - h_{1i}}, \quad i = \overline{1,n_1}$$

and the utility function of individual $j$ from country 2 is:

$$u_{2j} = w_{2j}l_{2j} + k_{21}\sqrt{h_{2j}} + \frac{1}{\sum_{s=1}^{n_1} h_{1s}} + \frac{1}{\sum_{s=1}^{n_2} h_{2s}} W + k_{12}\sqrt{H - l_{2j} - h_{2j}}, \quad j = \overline{1,n_2}$$

where $k_{11}, k_{12}, k_{21}$ and $k_{22}$ are constants.

The first terms from (1) and (2) represent the individuals' utility from their salary. The second terms represent the utility from playing video games. We suppose that each subsequent hour spent on video games yields less utility than the previous one. The third terms represent the utility from the expected share of the prize pool that each individual can earn. We assume that individuals in both countries have the same proficiency in video gaming, and hence, the expected prize money of each player is equal to the share of time spent on video games with respect to whole gaming time of all individuals from both countries. The fourth terms from (1) and (2) represent the utility from rest.

Individuals in both countries choose how much time they spend on work and video games to maximize their utility:

$$u_{1i} \rightarrow \max, \quad i = \overline{1,n_1};$$
$$u_{1i} \rightarrow \max, \quad j = \overline{1,n_2}.$$  

Hence the first order conditions are as follows:
Chapter 1. Macro-level analysis

\[ \begin{align*}
\left\{ \begin{array}{l}
\frac{\partial u_{1i}}{\partial l_{1i}} &= w_1 - \frac{k_{12}}{2\sqrt{H - l_{1i} - h_{1i}}} = 0, \\
\frac{\partial u_{1i}}{\partial h_{1i}} &= -\frac{k_{11}}{2\sqrt{h_{1i}}} + \frac{w}{\sum_{s=1}^{n_1} h_{1s} + \sum_{s=1}^{n_2} h_{2s}} - \left( \frac{h_{1i}W}{\sum_{s=1}^{n_1} h_{1s} + \sum_{s=1}^{n_2} h_{2s}} \right)^2 - \frac{k_{12}}{2\sqrt{H - l_{1i} - h_{1i}}} = 0, \\
\frac{\partial u_{2j}}{\partial l_{2j}} &= w_2 - \frac{k_{22}}{2\sqrt{l_{2j} - h_{2j}}} = 0, \\
\frac{\partial u_{2j}}{\partial h_{2j}} &= -\frac{k_{21}}{2\sqrt{h_{2j}}} + \frac{w}{\sum_{s=1}^{n_1} h_{1s} + \sum_{s=1}^{n_2} h_{2s}} - \left( \frac{h_{2j}W}{\sum_{s=1}^{n_1} h_{1s} + \sum_{s=1}^{n_2} h_{2s}} \right)^2 - \frac{k_{22}}{2\sqrt{H - l_{2j} - h_{2j}}} = 0.
\end{array} \right. \\
\end{align*} \]

From symmetry arguments we have:

\[
\begin{align*}
l_{1i} &= l_1, \quad h_{1i} = h_1, \quad i = 1, n_1; \\
l_{2j} &= l_2, \quad h_{2j} = h_2, \quad j = 1, n_2,
\end{align*}
\]

Hence, we can rewrite (4) as:

\[ \begin{align*}
\left\{ \begin{array}{l}
w_1 - \frac{k_{12}}{2\sqrt{H - l_1 - h_1}} = 0; \\
\frac{k_{11}}{2\sqrt{h_1}} + \frac{w}{n_1 h_1 + n_2 h_2} - \left( \frac{h_1W}{n_1 h_1 + n_2 h_2} \right)^2 - \frac{k_{12}}{2\sqrt{H - l_1 - h_1}} = 0; \\
w_2 - \frac{k_{22}}{2\sqrt{H - l_2 - h_2}} = 0; \\
\frac{k_{21}}{2\sqrt{h_2}} + \frac{w}{n_1 h_1 + n_2 h_2} - \left( \frac{h_2W}{n_1 h_1 + n_2 h_2} \right)^2 - \frac{k_{22}}{2\sqrt{H - l_2 - h_2}} = 0.
\end{array} \right. \\
\end{align*} \quad (6) \]

The solution of the system of equations (6) depends on the values of parameters \( k_{11}, k_{12}, k_{21}, k_{22}, n_1, n_2, H, w_1, w_2 \) and \( W \).

We assume the following values for these parameters:

\[
\begin{align*}
k_{11} &= 3, \quad k_{12} = 1, \quad k_{21} = 1, \quad k_{22} = 2, \quad n_1 = 100, \quad n_2 = 1,000, \\
H &= 12, \quad w_1 = 1, \quad w_2 = 1, \quad W = 5(n_1 + n_2) = 5,500
\end{align*}
\]

From (6) and (7), the optimal hours of working and resting are:

\[
\begin{align*}
h_1 &= 3.65, \quad h_2 = 6.47, \quad l_1 = 8.10, \quad l_2 = 4.53
\end{align*}
\]
If the labor demand in two countries equals \( L_1 = 6n_1 = 600 \) and \( L_2 = 4n_2 = 4,000 \) respectively, then the unemployment rates are calculated as \( un_i = 1 - \frac{l_i}{n_i} \) and are thus equal to \( un_1 = 0.26 \) and \( un_2 = 0.12 \).

### 1.2.3 Comparative statics

Consider the impact of changes in model parameters on the equilibrium level of unemployment. We change each parameter in the range:

\[
k_{11} \in \left[\frac{3}{4}, \frac{10}{11}\right], k_{12} \in [1, 11], k_{21} \in [1, 11], k_{22} \in [2, 12], n_1 \in [100, 200], n_2 \in [1,000, 2,100], H \in [12, 1.105 \cdot 12], w_1 \in \left[1, \frac{1}{5}\right], w_2 \in [1, 2], W \in [5,500, 11,000]
\]

The changes in the equilibrium levels of hours spent on work and video games are as follows:

<table>
<thead>
<tr>
<th>Parameter</th>
<th>( h_1 )</th>
<th>( l_1 )</th>
<th>( h_1 + l_1 )</th>
<th>( h_2 )</th>
<th>( l_2 )</th>
<th>( h_2 + l_2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( k_{11} )</td>
<td>↑</td>
<td>↓</td>
<td>const</td>
<td>↓</td>
<td>↑</td>
<td>const</td>
</tr>
<tr>
<td>( k_{12} )</td>
<td>const</td>
<td>↓</td>
<td>const</td>
<td>const</td>
<td>const</td>
<td>const</td>
</tr>
<tr>
<td>( k_{21} )</td>
<td>↓</td>
<td>↑</td>
<td>const</td>
<td>↑</td>
<td>↓</td>
<td>const</td>
</tr>
<tr>
<td>( k_{22} )</td>
<td>const</td>
<td>const</td>
<td>const</td>
<td>const</td>
<td>↓</td>
<td>const</td>
</tr>
<tr>
<td>( n_1 )</td>
<td>↑</td>
<td>const</td>
<td>const</td>
<td>↑</td>
<td>↓</td>
<td>const</td>
</tr>
<tr>
<td>( n_2 )</td>
<td>↓</td>
<td>↑</td>
<td>const</td>
<td>↓</td>
<td>↑</td>
<td>const</td>
</tr>
<tr>
<td>( H )</td>
<td>const</td>
<td>↑</td>
<td>↑</td>
<td>const</td>
<td>↑</td>
<td>↑</td>
</tr>
<tr>
<td>( w_1 )</td>
<td>↓</td>
<td>↑</td>
<td>↑</td>
<td>↑</td>
<td>↓</td>
<td>const</td>
</tr>
<tr>
<td>( w_2 )</td>
<td>↑</td>
<td>↓</td>
<td>const</td>
<td>↓</td>
<td>↑</td>
<td>↑</td>
</tr>
<tr>
<td>( W )</td>
<td>↑</td>
<td>↓</td>
<td>const</td>
<td>↑</td>
<td>↓</td>
<td>const</td>
</tr>
</tbody>
</table>

The changes in \( h_i \) and \( l_i \) are as one would expect and correspond to economic theory. The inverse relationship between \( l_i \) and \( un_i \) follows from (7); therefore, we obtain the following dependence of unemployment on the time spent on games.
As can be seen from Figure 2, unemployment depends negatively on the hours spent on video games. However, in cases where the population in one of the countries is growing, unemployment will positively depend on the time spent on games. Figure 3 illustrates this relation.

However, in practice, changes in the parameters shown in the table may occur simultaneously. In particular, with a simultaneous change in $k_{11}$ and $H$, the equilibrium values of $h_1$, $l_1$, $l_2$ increase and that of $h_2$ decreases. Therefore, the
dependence of unemployment on the hours spent on video games will differ for different countries. Figure 4 illustrates this relation.

![Graph](image)

**Figure 4. Unemployment and hours spent on video games in case of simultaneous change in the k_11 and H. Panel (a) represents first, panel (b) – second.**

Thus, depending on the parameters of the model, the effect of the hours spent on video games on unemployment might be positive or negative.

The model presented in this section provides us with the following testable implications:

1. There is a positive effect of video games on unemployment
2. The size of the effect depends on the country’s characteristics.

The following sections present the data and the methodology for empirical testing of these hypotheses.

### 1.2.4 Empirical test of the model

Considering e-sports prizes by country as a proxy for the popularity of video games, we obtained information from the e-sports earnings project[^9]. This resource is based on freely available public information on different e-sports tournaments, including the nicknames of winners in a particular tournament and the prize money won. The

[^9]: [https://www.esportsearnings.com/](https://www.esportsearnings.com/)
sample consists of 11,865 player-year observations for the period 2000-2015. The data are aggregated to country-year level. The data for 191 countries on total and youth unemployment rates and other macroeconomic indicators are taken from World Bank statistics. As control macroeconomic variables, we use GDP per capita, export to import ratio, labor productivity and ratio of Internet users (Baccaro and Rei 2007; Fedeli, Mariella, and Onofri 2018).

Table 6 shows summary statistics for our data set. As can be seen, the prizes vary considerably, and 84% of observations result in no prize. The variation in the number of Internet users per 100 people is also high – from zero to 98%. Interestingly, there is a difference between total and youth unemployment: youth unemployment is lower.

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>Mean</th>
<th>St. Dev.</th>
<th>Min</th>
<th>Pctl(25)</th>
<th>Pctl(75)</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>log(prize)</td>
<td>2,744</td>
<td>1.581</td>
<td>3.799</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>16</td>
</tr>
<tr>
<td>lag(GDP per capita)</td>
<td>2,744</td>
<td>15,865.7</td>
<td>18,609.5</td>
<td>442.5</td>
<td>2,950.5</td>
<td>22,799.7</td>
<td>129,349.9</td>
</tr>
<tr>
<td>lag(Export-to-import)</td>
<td>2,744</td>
<td>0.921</td>
<td>0.395</td>
<td>0.045</td>
<td>0.671</td>
<td>1.087</td>
<td>3.508</td>
</tr>
<tr>
<td>lag(Labor productivity)</td>
<td>2,744</td>
<td>33,540.6</td>
<td>34,800.8</td>
<td>948.6</td>
<td>7,427.0</td>
<td>49,287.8</td>
<td>211,332.9</td>
</tr>
<tr>
<td>Internet users (per 100 people)</td>
<td>2,744</td>
<td>28.283</td>
<td>28.129</td>
<td>0.000</td>
<td>3.857</td>
<td>48.950</td>
<td>98.240</td>
</tr>
<tr>
<td>Zero prize</td>
<td>2,744</td>
<td>0.844</td>
<td>0.363</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>log(youth unemployment)</td>
<td>2,744</td>
<td>2.581</td>
<td>0.820</td>
<td>1.184</td>
<td>2.161</td>
<td>3.144</td>
<td>4.185</td>
</tr>
<tr>
<td>log(total unemployment)</td>
<td>2,744</td>
<td>1.825</td>
<td>0.802</td>
<td>1.911</td>
<td>1.416</td>
<td>2.348</td>
<td>3.618</td>
</tr>
</tbody>
</table>

Figure 5 illustrates the dynamics of unemployment (youth and total) and the log of the prize money. As can be seen, all three series seem to be correlated, with a positive trend, which means that it is necessary to control for the time in the regression model.

---

10 The data and the replicating R code are available upon request.
To estimate the effect of the popularity of video games on unemployment, we use regression analysis. We estimate two regression models. First, we estimate the OLS regression model with time and country effects:

\[
\log(\text{unempl}_{it}) = \beta_0 + \beta_1 \cdot \text{lag}(\log(\text{prize})) + \beta_2 \cdot \text{lag}(\text{gdppc}_{it}) + \beta_3 \cdot \text{lag}(\text{exp.to.imp}_{it})
\]

\[
+ \beta_4 \cdot \text{lag}(%\text{exports})
\]

\[
+ \beta_5 \cdot \text{zeroprize}_{it} + \sum_t y_t \cdot \text{year}_t + \sum_t a_i \cdot \text{country}_i + \epsilon_{it}
\]

where \(\text{unempl}_{it}\) is the unemployment rate in country \(i\) in year \(t\), \(\text{prize}_{it}\) is the prize money won by the representatives of country \(i\), \(\text{exp.to.imp}_{it}\) is the ratio of exports to imports to control for the orientation of the economy, \(\text{gdppc}_{it}\) is an indicator of labor productivity to control for the labor demand, \(\text{gdppc}_{it}\) is the gross domestic product per capita, included to control for the labor demand and the economic cycle and \(\text{year}_t\) and \(\text{country}_i\) are time and country effects respectively, to control for unobservable sources of time and individual heterogeneity.

Since one might argue that the popularity of video games is endogenous to unemployment, we estimate a two-stage regression with IV. Our instruments are the lagged covariates from the main equation and Internet popularity measured as percentage of people with Internet access. Since our dependent variable in the first-
stage regression (prize money) is left-censored by zero, we use a tobit regression model:

\[
\log (prize_{it}^*) = \beta_0 + \beta_1 \cdot \text{lag}(inет_{it}) + \beta_2 \cdot \text{lag}(gdpc_{it}) + \beta_3 \cdot \\
\text{lag}(exp. to. imp_{it}) + \beta_4 \cdot \text{lag}(labor. prod_{it}) + \epsilon_{it}
\]

\[
\log (prize_{it}) = \begin{cases} 
\log (prize_{it}^*), & \text{if } \log (prize_{it}^*) > 0 \\
0, & \text{if } \log (prize_{it}^*) \leq 0
\end{cases}
\]

The question of using nonlinear projection in the first stage may arise. Although OLS estimation of the first stage with the correct IV is guaranteed to produce residuals that are uncorrelated with fitted values and covariates, estimated prize money may be negative. Therefore, we use a Tobit model for the first stage, since our aim is to have a correct prediction of prize money, and countries with zero prizes are definitely from the other data-generating process. However, as a robustness check, we also estimate the linear first-stage regression:

\[
\log (prize_{it}) = \beta_0 + \beta_1 \cdot \text{lag}(inет_{it}) + \beta_2 \cdot \text{lag}(gdpc_{it}) + \beta_3 \cdot \\
\text{lag}(exp. to. imp_{it}) + \beta_4 \cdot \text{lag}(labor. prod_{it}) + \epsilon_{it}
\]

In the second stage, for both tobit and linear predictions of prize money, we estimate the following regression equation:

\[
\log (unempl_{it}) = \beta_0 + \beta_1 \cdot \text{lag}(\log(prize)) + \beta_2 \cdot \text{lag}(gdpc_{it}) + \beta_3 \cdot \\
\text{lag}(exp. to. imp_{it}) + \beta_4 \cdot \text{lag}(labor. prod_{it}) + \beta_5 \cdot \text{zero prize}_{it} + \sum_t \gamma_t \cdot year_t + \sum_t \alpha_t \cdot country_t + \epsilon_{it}
\]

Where \(\log(prize)\) represents predicted values from the first-stage regression.

1.2.5 Empirical estimation of the effect of video games on unemployment rate

We begin the description of our results with the "naïve" regression without IV. Table 7 presents these results. As can be seen, the coefficients for the control variables are as expected. The higher the GDP, the lower the unemployment rate for both total and youth unemployment. Similarly, the higher the exports relative to imports, the higher the unemployment rate. Labor productivity also decreases the unemployment rate by reducing the labor demand.
Considering our main variable of interest, i.e., the prize money, the coefficient is positive and statistically significant for all specifications. Interestingly, comparing model 1 to model 3, we can see that the coefficient is almost the same for total and youth unemployment. Furthermore, comparing model 1 to model 2 and comparing model 3 to model 4, we observe different sizes of the effect for countries with different levels of income. The higher the income level, the lower the effect of the popularity of video games on unemployment.

Table 7. Results of regression analysis (without IV)

<table>
<thead>
<tr>
<th></th>
<th>log(total unemployment)</th>
<th>log(youth unemployment)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>lag(log(prize))</td>
<td>0.007**</td>
<td>0.017***</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>lag(GDP per capita)</td>
<td>-0.000***</td>
<td>-0.000***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>lag(Export-to-import)</td>
<td>0.122***</td>
<td>0.124***</td>
</tr>
<tr>
<td></td>
<td>(0.033)</td>
<td>(0.033)</td>
</tr>
<tr>
<td>lag(Labor productivity)</td>
<td>0.000***</td>
<td>0.000***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Zero prize</td>
<td>-0.050*</td>
<td>-0.059**</td>
</tr>
<tr>
<td></td>
<td>(0.029)</td>
<td>(0.029)</td>
</tr>
<tr>
<td>lag(log(prize)) × Low income</td>
<td>-0.002</td>
<td>-0.009</td>
</tr>
<tr>
<td></td>
<td>(0.036)</td>
<td>(0.036)</td>
</tr>
<tr>
<td>lag(log(prize)) × Lower middle income</td>
<td>-0.013*</td>
<td>-0.009</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>lag(log(prize)) × Upper middle income</td>
<td>-0.024***</td>
<td>-0.021***</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>Observations</td>
<td>2,646</td>
<td>2,630</td>
</tr>
<tr>
<td>R²</td>
<td>0.037</td>
<td>0.045</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>-0.037</td>
<td>-0.029</td>
</tr>
<tr>
<td>F Statistic</td>
<td>18.868*** (df = 5; 2457)</td>
<td>14.411*** (df = 8; 2439)</td>
</tr>
<tr>
<td></td>
<td>25.722*** (df = 5; 2457)</td>
<td>17.999*** (df = 8; 2439)</td>
</tr>
</tbody>
</table>
Chapter 1. Macro-level analysis

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

Table 8 presents the results of the first-stage tobit estimation. All instruments are statistically significant, indicating their validity.

### Table 8. First stage of IV estimates (tobit model)

<table>
<thead>
<tr>
<th></th>
<th>log(prize)</th>
</tr>
</thead>
<tbody>
<tr>
<td>lag(GDP per capita)</td>
<td>-0.0002927***</td>
</tr>
<tr>
<td></td>
<td>(0.00008344)</td>
</tr>
<tr>
<td>lag(Export-to-import)</td>
<td>2.71**</td>
</tr>
<tr>
<td></td>
<td>(1.25)</td>
</tr>
<tr>
<td>lag(Labor productivity)</td>
<td>0.00007103*</td>
</tr>
<tr>
<td></td>
<td>(0.00004307)</td>
</tr>
<tr>
<td>Lag(Internet users (per 100 people))</td>
<td>0.42***</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
</tr>
<tr>
<td>Constant 1</td>
<td>-27.2***</td>
</tr>
<tr>
<td></td>
<td>(0.163)</td>
</tr>
<tr>
<td>Constant 2</td>
<td>2.43***</td>
</tr>
<tr>
<td></td>
<td>(0.04)</td>
</tr>
<tr>
<td>Observations</td>
<td>2,744</td>
</tr>
<tr>
<td>Log-likelihood: -2131.707 on 5482 degrees of freedom</td>
<td></td>
</tr>
</tbody>
</table>

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

Table 9 represents the results of the second stage. Looking at the results for our main variable of interest (prizehat) one can conclude that the effect is positive but varies according to country income level. This corresponds to the results of the theoretical model suggested above. The effect is almost the same for total and youth unemployment. Appendix I contains the results of the linear first-stage and second-stage regression. The general findings are the same, which adds to the robustness of our results.
Table 9. Regression results of IV estimates

<table>
<thead>
<tr>
<th></th>
<th>log(total unemployment)</th>
<th>log(youth unemployment)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>lag(log(prizehat))</td>
<td>0.030***</td>
<td>0.037***</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>lag(GDP per capita)</td>
<td>-0.000***</td>
<td>-0.000***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>lag(Export-to-import)</td>
<td>0.143***</td>
<td>0.143***</td>
</tr>
<tr>
<td></td>
<td>(0.034)</td>
<td>(0.034)</td>
</tr>
<tr>
<td>lag(Labor productivity)</td>
<td>0.000***</td>
<td>0.000***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Zero prize</td>
<td>-0.068***</td>
<td>-0.068***</td>
</tr>
<tr>
<td></td>
<td>(0.026)</td>
<td>(0.026)</td>
</tr>
<tr>
<td>lag(log(prizehat)) ×</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low income</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>-0.135**</td>
<td>-0.115*</td>
</tr>
<tr>
<td></td>
<td>(0.062)</td>
<td>(0.061)</td>
</tr>
<tr>
<td>lag(log(prizehat)) ×</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lower middle income</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>-0.059***</td>
<td>-0.052**</td>
</tr>
<tr>
<td></td>
<td>(0.021)</td>
<td>(0.020)</td>
</tr>
<tr>
<td>Observations</td>
<td>2,562</td>
<td>2,562</td>
</tr>
<tr>
<td>R²</td>
<td>0.051</td>
<td>0.056</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>-0.024</td>
<td>-0.020</td>
</tr>
<tr>
<td>F Statistic</td>
<td>25.363*** (df = 5; 2374)</td>
<td>19.977*** (df = 7; 2372)</td>
</tr>
</tbody>
</table>

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

Following the idea that the effect might vary according to country characteristics, we further address the question of whether the size of an effect is conditional on the labor market productivity. Table 10 contains the results of the regression model with an interaction between the lagged prize money and a labor market productivity higher than the average. We find that the effect of the popularity of video games is
stronger for countries with higher productivity. Therefore, it seems that in these countries, productivity increases jointly with popularity of video games, also affecting labor demand and supply in such a way as to increase unemployment. Interestingly, we observe this effect only for adults, not for young people.

Finally, since the variation in prize money is huge, we divide our sample into countries with higher and lower prizes than the average. Table 11 shows these results. As can be seen, the effect for the “above average” countries, is smaller or even absent. Therefore, in countries where the popularity of video games is well established, there is no effect. Probably, in these countries, video games are not such an innovation in leisure, so their effect on unemployment is lower.

<table>
<thead>
<tr>
<th>Table 10. Regression results of lag(Labor productivity) indirect effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>log(total unemployment)</td>
</tr>
<tr>
<td>-------------------------</td>
</tr>
<tr>
<td>(1)</td>
</tr>
<tr>
<td>--------------------------</td>
</tr>
<tr>
<td>lag(log(prizehat))</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>High productivity</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>lag(log(prizehat)) × High productivity</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Control variables</td>
</tr>
<tr>
<td>Observations</td>
</tr>
<tr>
<td>R²</td>
</tr>
<tr>
<td>Adjusted R²</td>
</tr>
<tr>
<td>F Statistic (df = 7; 2372)</td>
</tr>
</tbody>
</table>

Notes: ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.
Table 11. Regression results with respect to the prize money (higher and lower than average)

<table>
<thead>
<tr>
<th></th>
<th>log(total unemployment)</th>
<th>log(youth unemployment)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Below</td>
<td>Above</td>
</tr>
<tr>
<td>lag(log(prizeshat))</td>
<td>0.182***</td>
<td>0.052</td>
</tr>
<tr>
<td></td>
<td>(0.028)</td>
<td>(0.034)</td>
</tr>
<tr>
<td>lag(log(prizeshat)) ×</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low income</td>
<td>-0.017</td>
<td>-0.044</td>
</tr>
<tr>
<td></td>
<td>(0.066)</td>
<td>(0.066)</td>
</tr>
<tr>
<td>lag(log(prizeshat)) ×</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lower middle income</td>
<td>-0.174***</td>
<td>-0.063**</td>
</tr>
<tr>
<td></td>
<td>(0.039)</td>
<td>(0.031)</td>
</tr>
<tr>
<td>lag(log(prizeshat) ×</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Upper middle income</td>
<td>-0.189***</td>
<td>-0.093***</td>
</tr>
<tr>
<td></td>
<td>(0.030)</td>
<td>(0.015)</td>
</tr>
<tr>
<td>Control variables</td>
<td>Included</td>
<td>Included</td>
</tr>
<tr>
<td>Observations</td>
<td>1,577</td>
<td>750</td>
</tr>
<tr>
<td>R²</td>
<td>0.074</td>
<td>0.138</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>-0.034</td>
<td>-0.040</td>
</tr>
<tr>
<td>F Statistic</td>
<td>14.182*** (df = 8; 1411)</td>
<td>18.638*** (df = 8; 1411)</td>
</tr>
</tbody>
</table>

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

1.3 Conclusions on the macro-level analysis

In this section we study the determinants of country-level performance in eSports and analyze if eSports and video games in general affects the unemployment rate. Our findings indicate that some determinants are important for both eSports and traditional sports. In our models, GDP per capita is important indicator for the outcome model, but it is not statistically significant for the selection model. This finding suggests that entry costs are relatively low in eSports. In addition, a country’s infrastructure affects performance in eSports: A 1% increase in GDP per
Chapter 1. Macro-level analysis

capita leads to a 2.2% increase in prize money per capita. In addition our results show that having a proper IT infrastructure is important to the initial development of eSports within a country, but this effect disappears after a certain threshold. Country population is not statistically significant in the outcome model, but it is important for the selection equation. This finding contradicts the evidence in the traditional sports literature. This result indicates that eSports talents are not uniformly distributed across the world population. Surprisingly, post-Soviet and planned or post-planned economies are more likely to participate in eSports: the marginal effect of being a post-Soviet country or planned or post-planned economy is 51%, and 57%, respectively. Given the lack of a clear explanation, further study is needed to address this effect to understand these countries’ success in eSports.

Regarding the effect of eSports to the unemployment rate, we aimed to find an answer to the question of whether video games, as an example of digital innovation in leisure activities, increase the rate of unemployment. This question arises due to the dual effect of gaming on the labor supply. On the one hand, spending time on video games might develop digital and computer literacy skills and thereby improve the quality of employees. On the other hand, video games might be addictive and might raise the value of leisure and influence decisions about time allocation between work and leisure. This results in a decrease in the labor supply. Since video games are a relatively recent invention, we analyze their effect on both total and youth employment, assuming that young people are more exposed to their influence. We provide a model which implies that the popularity of video games positively affects unemployment, and subsequently we perform an empirical test.

Our main result is that video games, as an innovation in leisure activities, do indeed affect work-leisure time distribution and increase unemployment rates at the country level. In general, this supports the ideas of Greenwood and Vandenbroucke (2005), Kopecky (2011), Vandenbroucke (2009) and Aguiar et al. (2017), who all claim that leisure innovations have an impact on the labor supply. The results of the OLS regression and the regression with IV showed that the negative effect of video games on employment is almost the same for adults and young people.

In addition, we tested whether this effect was similar for countries with different levels of income and labor productivity. The regression analysis showed a
significant inverse relationship between income level and the effect of the popularity of video games on total and youth unemployment. However, for adults this effect is stronger for countries with higher productivity.

Chapter 2. Meso-level analysis

1.1 Competitive Balance and League Growth in eSports: A test of Contestable Market Theory

1.1.1 Competition and industry size: an overview

The cyclical evolution of markets and competition has always been a debatable issue in industrial organization. In more traditional economic theories, it is assumed that competition is at the core of industry/market development. However, numerous studies address a reverse relation by asserting that industry growth, in turn, often affects the level of competition: bigger markets are more attractive for new companies. Early studies like those by Baumol (1982), Bailey and Baumol (1984), and Malerba and Orsenigo (1996a) mainly addressed regulation versus deregulation paradigms by looking for empirical evidence that a large number of competitive firms is not always the best solution for industry growth. The contestable market theory – tested on different oligopolistic and even monopolistic markets – demonstrates that natural entry barriers under low state regulation may create sufficient incentives for extensive and intensive growth. Hurdle et al. (1989) analyze one of the most obvious contestable markets – the airline industry – and affirm that no regulatory interference is required to induce industry development. An oligopolistic structure appears to be the most efficient way to enable long-term sustainability and growth. Morrison and Winston (1987), Langridge and Sealey (2000), and Graham (1998) conducted similar research on other oligopolistic markets. More recent studies examine the banking, insurance, and telecommunication sectors by testing a naturally established equilibrium with a high concentration of professional actors on the market. That is the case in papers by Pearcy and Savage (2015), Huang and Liu (2014), and Chen and Tanaka (2018). Traditional sports present a similar structure, with a limited number of teams or players that compete in leagues or tournaments.
Chapter 2. Meso-level analysis

This study contributes to the development of contestable market theory by challenging “the competition and industry growth” problem through an analysis of the emerging industry of eSports. Much potential exists for exploring this newly born industry, which appears to be developing as professional sports did. Meanwhile, eSports is the most unregulated sport in the sector.

The history of eSports tournaments is quite long. The first event took place at Stanford University in 1972. It was called the “Intergalactic Spacewar Olympics,” and the prize was a subscription to Rolling Stone magazine (Hiltscher & Scholz, 2015). However, the industry of eSports events has evolved considerably during the last decade (Parshakov and Zavertiaeva 2018). The main source of funding for this industry comes from game developers, which act as sponsors of tournaments on different levels. Unlike “traditional” sports, eSports still does not have any league structure and is not regulated in terms of revenue-sharing and competitive-balance rules. Video games attract people from all over the world. Initially, they were just a form of entertainment, and no professionalization of this industry was expected. However, in recent years, video games have become a recognized sport with professional players, very significant fundraising and viewership, and, as a result, new challenges for its governance. So-called eSports tournaments attract up to thousands of people who watch the competition among individuals or teams in a specific video game. With that, eSports industry has experienced exponential growth in recent years. The number of tournaments, teams and sportspersons, the volume of prizes, and the sales of producers are the main evidence of that growth. This advancement, being rather unexpected and rapid, has created in this industry a unique phenomenon within sports – an unregulated, self-developing market with practically no entry barriers or imposed regulation.

Given that the eSports industry is considered a sport, it shares some features with the “traditional” sports industry. However, it has some of its own particular features, as well. Precisely, sports leagues have used their own characteristics to justify avoiding some antitrust laws (Walter C. Neale 1964). The most developed professional sports are organized as leagues. They can be open – with promotion and relegation – as is the case of Europe, or closed, as in North America. But in both cases, the number of teams that take part in the sport competition does not change.
In fact, they are like oligopolies. The eSports industry is still in an early stage of its development and for that reason is not much regulated. In that sense, the number of competitors can vary, and this can influence the level of competition and prize-money sharing.

This study aims to study the effect of a tournament’s level of competition on its attractiveness and popularity. We use eSports data to construct an empirical model to measure this effect. eSports provides a perfect setting to capture the effect of a league’s concentration, for the following reasons. First, there are no competition restrictions imposed by the league’s administration. Second, the entry costs are significantly lower compared to other sports leagues. Third, an eSports team maximizes its results like a firm tends to maximize its profit. Fourth, leagues are not affected by any country-specific laws.

Rewards and, therefore, the revenue-sharing scheme, in eSports are mostly performance-based, while in a majority of traditional sports, a significant share of an athlete’s or a team’s compensation is independent of their current match results. This makes our findings potentially transferable to other industries, since eSports organizations have similar incentives to firms. Finally, since in eSports tournaments, teams and individuals are organized in a similar way, it is possible to compare competition between teams and individuals.

This study examines whether naturally developing competition in eSports has led this market to grow and the industry to become more attractive for viewers, sponsors, and business. We test contestable market theory, hypothesizing that any professional sport tends to higher concentration due to talent-driven performance and skills accumulation as key factors of sporting success. On the other hand, we address reverse causality to see whether greater attractiveness of this industry may lead to new entrants. If causality in at least one direction is found, does it imply new requirements for the governance of this fast-growing market, and can the eSports experience be transmitted to other professional sports, which are traditionally more regulated?

This study uses data on each gamer’s prize earnings for each tournament (in nominal US dollars) from 1999 to 2015, collected from the eSports Earnings project.
Chapter 2. Meso-level analysis

(http://www.esportsearnings.com/). In particular, we focus on games with the longest history so as to have a longer time span: Counter-Strike, StarCraft, and WarCraft. Note that StarCraft and WarCraft are individual games, while Counter-Strike is a team game.

The remainder of this study brings both a theoretical discussion and empirical tests of the hypothesis of contestable market theory in the specific context of the eSports industry. We expect to contribute to the development of this theory by analyzing a unique case of a barely regulated but fast-growing industry. This industry appears to have perfect conditions for demonstrating an unconstrained evolution of the market, which may converge to an oligopolistic structure due to its specific nature. If contestability in the eSports industry is evidenced, it might have several implications, including those that can classify this kind of sport within a special case of governance and development mechanisms.

1.1.2 Contestable market theory: a different perspective of competition

The concept of perfect competition had been dominating the evolution of economic thought until the 1980s. This idea underpinned most of the practice of antitrust regulation by putting special emphasis on firm size and market power as well as entry and exit barriers (Bailey and Baumol 1984). The first conceptual paper that introduced a holistic view of contestable market theory by Baumol (1982) shows that some markets are subject to economies of scale in a broad sense, including required knowledge and competencies accumulation. This study opened a new line of research of contestable markets more than 35 years ago. It was a continuation of Adam Smith’s “laissez faire” and deregulation movements, which, in turn, brought substantial implications for governmental interference in certain sectors and markets. One of the phenomena discovered in the contestability hypothesis was referred to as “hit and run.” It demonstrates opportunistic short-term behavior of new entrants in markets where no regulatory barriers on entrance and exit exist (Agliardi 1990; Paech 1998). This strategy, having a stable Nash-equilibrium, asserts that if small firms penetrate a market with a priori insufficient scale to sustainably win a competition, they seek to gain short-term benefits and exit this market as soon as possible. This behavior brings distortion and can even have fatal consequences for the development of an industry. Therefore, it is no wonder that
small firms are not pillars for the development of such markets and should not be supported, according to the followers of the contestability theory.

Notably, a body of empirical studies, leaning on vast statistics and quasi-experimental data, demonstrated that oligopolistic markets work better in transportation (Hurdle et al. 1989; Langridge and Sealey 2000; Graham 1998), finance (Dickens and Philippatos 1994; Carow 2001; Tri Mulyaningsih, Daly, and Miranti 2015; T. Mulyaningsih, Daly, and Miranti 2016;), and telecommunication (Pearcy and Savage 2015). Summing up the key findings of the above-mentioned papers, the following claim can be advocated: self-regulation of markets with naturally growing entry barriers appears to bring better general equilibrium for the market than imposed antitrust regulation. In the transportation and telecommunication industries, effortless oligopolistic competition with a low risk of collusion leads to a higher quality of services and pushes down prices, inducing demand and industry growth. In banking and insurance, higher capital consolidation allows for better diversification, with better warranties and client protection. Importantly, all cases redefine the role of professionalization, which serves as a key driver of development by attracting more investments and sustainability. Anticipating this empirical evidence, the importance of knowledge accumulation was discussed more than twenty years ago by Rashid (1988), followed by Malerba and Orsenigo (1996b). Furthermore, Bailey and Baumol (1984), at the start of contestability theory, suggested that excessive regulation of such markets may bring consequences that are adverse rather than just ineffective, finding regulation itself to be “among the primary causes of unsatisfactory industry performance.” A more recent empirical study by Chen and Tanaka (2018) supports this fact, explicitly pointing out why firms in contestable industries should not be regulated by conventional methods. For that, permit and product markets under imperfect competition and imperfect intertemporal arbitrage have been examined.

Upon the whole, the main stream of contestability theory followers seems to be consistent in providing new evidence of the “invisible hand” as the best solution for oligopolistic and monopolistic competition. However, looking more carefully at the examples of contestable markets, one can notice that nearly all of them experience specific regulation, even though firm enlargement and high entry barriers are not a
result of external pressure. This makes the results of experiments and hypothesis testing somewhat distorted and probably biased since the isolation of all other interference is not plausible. Moving away from the conventional consideration of industrial-organization settings but trying to mitigate possible criticism of noisy experimental data, we suggest testing the hypothesis on the emerging eSports industry. The state of the art regarding the current stage of its development and regulation is given in the next section.

1.1.3 Contestability and deregulation in eSports

The “traditional” professional sports industry is characterized by dominant leagues that, together with the clubs, exercise economic power unconstrained by rivals or the threat of entry, often featuring market-division schemes (Ross 2003). But also, when entry barriers are high, as in the case of sports, the teams might have to compete with other entertainment industries (Alexander 2001). However, the panorama could be different when no high entry barriers exists, as Byford and Gans (2019) analyze. As for now, the eSports industry is not regulated in the way that traditional sports are. This provides an interesting ground to investigate the growth of that particular market and to analyze what could happen in the future with it. Meanwhile, there is a current discussion about whether regulation of eSports ought to be introduced and whether this interference should be similar to other sports or be specific to the nature of the new emerging professional video gaming tournaments (Chao 2017).

The issues of market structure and regulation are the central points in most of the operations of professional sports leagues (Cyrenne 2009). In the case of eSports, there is not a clear line of operation, as there are not many professional leagues yet. As Coates and Parshakov (2016) mention, major eSports tournaments usually are live events, but there are also lower-level online events. A tournament may be a part of a larger competition that consists of several events (e.g. Dreamhack), or a competition may consist of just one major event (e.g. World Cyber Games). Note that in eSports, the difference between leagues and tournaments is not significant. Even the most popular “league,” ESL (Electronic Sports League), organizes series of tournaments in different games. Therefore, during one year, each team can decide
in which tournament to participate and form its own schedule. Round-robin tournaments, which are typical for traditional sports leagues, are not popular in eSports. The only exceptions are the first 6 seasons Starladder Starseries of Dota2 and regional-level tournaments in the League of Legends.

Despite their participation in different tournaments, teams can be compared at any time by the prize money won; unofficial ratings are available at https://esportsearnings.com. In our analysis, we use the term “league” for the group of teams which participate in tournaments in a particular eSports discipline or game (e.g. Counter-Strike). The number of tournaments and leagues has been rising constantly in recent years, but the number of international events has grown more slowly. In 2018, there were 13 international tournaments/leagues. The number of tournaments per year might be treated as the number of matches a team participates in within the league.

Rottenberg (1956) and Neale (1964), in their seminal papers, show that excessive dominance of a particular team will reduce interest in the competition and develop the so-called Uncertainty of Outcome Hypothesis (UOH). Borland (1987) tested the UOH using data from Australian Rules football; Soebbing (2008) used MLB data to test it. At the same time, however, evidence for the UOH is not always convincing: for example, Parshakov and Baidina (2017) tended to reject it for Russian football.

It should be noted that in most leagues, revenue sharing has been introduced to reduce sports-dominance affects. A team is interested in increasing its sports performance to increase its prestige and revenues. However, if one team really dominates the other teams, this might decrease the popularity of the competition and therefore decrease team revenue. For this reason, leagues have introduced different schemes of revenue sharing. There is evidence that revenue sharing in general contributes to keep leagues competitive (El-Hodiri and Quirk 1971; Kesenne 2000; Szymanski and Kéenne 2004), thought there are different results for regulation and self-regulation schemes (Vrooman 1995; Szymanski 2003). That is not the case in eSports and makes it interesting to study it.
1.1.4 Five reasons to test the eSports industry for contestability

Esports, not being a traditional industry for either sports or business, should be precisely dissected to make it understandable for analysis. On the other hand, there are evident traits that relate to its commercial capacity and pursuit. On the one hand, eSports teams raise funds from winning tournaments. Therefore, the reward is mostly performance-based, and all teams compete for the same prize pool, or revenue. In this sense, teams are similar to traditional firms. In addition, eSports teams do not act as traditional clubs in other professional sports and do not perform as a conventional firm on the market. They are seeking to regularly win prize money in tournaments and ensure their sustainable professional development; only a few teams have stated financial provisions and professional management. This conditions the specific nature of the entire industry.

However, five reasons to expose the eSports industry to a test of the contestability hypothesis can be claimed:

1. **eSports is a predominately knowledge-led industry.** Knowledge and skills consolidation drive the professionalization of teams. It creates natural barriers where newcomers barely can win competitions and receive prizes, which makes them not sustainable in the long-term. However, “hit and run” behavior may take place, since entry costs are fairly low and no substantial risk of taking part in tournaments exists, even if the probability to defeat more experienced rivals is tiny.

2. **The main source of capital comes from game developers who are using these tournaments as sales drivers.** That implies that capital providers seek for more spectacular professional competition and would prefer a “fierce battle” among fewer relatively equal rivals rather than the predictable outcome of a big number of beginners. Meanwhile, attractiveness for game developers alone may induce industry growth. It means that sponsors of eSports tournaments may prefer monopolistic or oligopolistic markets rather than perfect competition.

3. **The absence of regulation, which enables pure experimental data.** Unlike other professional sports, no league structure and revenue sharing is imposed on
eSports tournaments. That allows for the examination of historical and current data, which has documented the natural evolution of this industry, mitigating all possible consequences of regulatory interference. The same applies to antitrust control, which substantially affects all other industries and sectors by restricting the consolidation of capital in a small number of firms.

4. **Evident information asymmetry in the industry.** Asymmetry and implicit knowledge are considered two of the key markers of contestability. If the natural leaders of the market are significantly better informed about the hidden mechanisms that underpin success in the industry, new entrants have fewer chances to outperform their more-experienced rivals. Such a situation appears to exist in the eSports industry, where no technologies have been published and become common knowledge so far.

5. **ESports is one of the most data-rich professional sports.** Due to its nature, eSports tournaments generate huge amount of data that can be structured and processed for empirical analysis. That makes eSports not just fit within the scope of contestable markets but also able to be used for testing hypotheses relevant for contestable markets.

### 1.1.5 Empirical test: Panel VAR approach

We use data from the [www.esportsearnings.com](http://www.esportsearnings.com) project. It is a community-driven eSports resource based on freely available public information for both major and minor tournaments. We have scraped the data with R script (R Core Team 2015), which is available upon request. The number of observations in the original dataset is 41,982. For the purpose of the analysis, the data has been aggregated to game-year level. Descriptive statistics are presented in Table 12.

The Gini coefficient is used as the metric of competitiveness, but the results are robust to other metrics (Theil index, coefficient of variation, and Herfindal-Hinchman index). As one can see, the degree of competitiveness varies considerably: the minimum for the Gini coefficient is slightly above zero, and the maximum is close
to one. The prize varies even more: from 140 USD to 39 million USD by year (note that this is the prize money of tournaments of different games by year). The number of teams varies from 2 to 109. Interestingly, the mean value is 17, which is close to the number of teams in some traditional sports leagues (e.g. European football leagues). The number of tournaments ranges from 1 to 631. The average number of events each year is 57.

Such huge variation should be the result of the difference among games. This is important from an empirical point of view. First, we should address this issue with an appropriate methodology. Second, high variation potentially improves the validity of our analysis: we have the proper amount of variation, which allows us to capture the effect. In traditional sports leagues, the number of teams, games, and tournaments is almost the same during recent decades, whereas in eSports the number of teams, prize size, and number of events are changing dramatically.

<table>
<thead>
<tr>
<th>Statistic</th>
<th>N</th>
<th>Mean</th>
<th>St. Dev.</th>
<th>Min</th>
<th>Pctl(25)</th>
<th>Pctl(75)</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gini</td>
<td>254</td>
<td>0.514</td>
<td>0.184</td>
<td>0.020</td>
<td>0.395</td>
<td>0.662</td>
<td>0.844</td>
</tr>
<tr>
<td>Prize (USD)</td>
<td>254</td>
<td>1,556,564</td>
<td>4,918,450</td>
<td>140</td>
<td>20,623</td>
<td>852,976</td>
<td>38,867,941</td>
</tr>
<tr>
<td>N teams</td>
<td>254</td>
<td>16.634</td>
<td>22.910</td>
<td>2</td>
<td>3</td>
<td>22</td>
<td>109</td>
</tr>
<tr>
<td>N tournaments</td>
<td>254</td>
<td>57.012</td>
<td>115.236</td>
<td>1</td>
<td>5</td>
<td>52</td>
<td>631</td>
</tr>
</tbody>
</table>

Table 12. Descriptive statistics of video games sample

Figure 6 illustrates the correlation between the logarithm of the prize and the Gini coefficient. As one can see, there is interdependence between these variables. However, we need to understand the causal effects. This is what we will do next.
In order to empirically test the contestable market theory, we estimate the relationship between competition and prize. It is challenging because these variables simultaneously affect each other. For this reason, we use vector autoregression (VAR). Using this approach, one can build the orthogonal response functions (impulse response functions, hereinafter IRF) to estimate the reaction of one variable (for example, the Gini coefficient) to a shock in another variable (for example, Prize).

This method was proposed to be used in economics context by Sims (1980), who applied it to macro-level analysis. Sims argues that VAR models provide a theory-free method to estimate economic relationships, thus being an alternative to the “incredible identification restrictions” in structural models (Sims 1980). This approach might be used as an exploratory tool which helps to reveal causal relations without a well-developed underlying theory.

Since the data present a panel structure, the estimation is done using panel VAR. This technique helps to combine the advantages of VAR (all variables can be assumed as endogenous) with the advantages of panel data, allowing us to take into
account the individual heterogeneity of games (Love and Zicchino 2006; Naidenova and Parshakov 2013).

We estimate panel VAR of the second order. The choice of order is based on the information criteria. We perform four tests, which indicate that the order should be 1 or 2 (AIC = 2, HQ = 1, SC = 1, FPE = 2). We have chosen 2 to make sure our model is able to capture the relationship of different lags.

\[ z_{i,t} = \alpha + z_{i,t-1} \cdot \beta_1 + z_{i,t-2} \cdot \beta_2 + f_i + e_{it}, \]

where \( z_{i,t} \) is a vector of four variables (Prize, Gini, Number of teams, Number of tournaments) and \( f_i \) is the company’s individual fixed effect.

To analyze the impact of a shock to one variable on another variable, we estimate impulse-response functions (IRF). These functions allow for an understanding of how a shocked variable (e.g. Gini) affects another variable (e.g. Prize), keeping other shocks to other variables (e.g. Number of teams) constant.

Since games are heterogeneous, each one has its own features. Therefore, for a correct analysis, it is necessary to allow for individual heterogeneity within the cross-section, i.e., to use a model with “fixed effects.” Technically, a fixed-effects model can be estimated in two ways: using a set of dummies, and using within-transformation (mean-differencing). The latter removes the average value and keeps transformed and lagged regressors orthogonal. To estimate the confidence intervals for IRF, we use the bootstrap approach, since it is difficult to derive the distribution of IRF analytically. The bootstrap approach allows for an approximation of this distribution empirically. We use “vars” package by Pfaff (2008) for the empirical analysis.

1.1.6 Impulse-response functions

Table 13 contains the results of the estimations. Note that since we have four endogenous variables, it is challenging to understand the marginal effects from this table. For that reason, we report below the IRFs. However, it should be noted that all models are statistically significant: the lowest value of F joint test statistics is 2.465. This allows us to interpret the IRFs.
Table 13. Empirical results of VAR equation estimation

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Prize</th>
<th>Gini</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prize.l1</td>
<td>0.193**</td>
<td>0.015*</td>
</tr>
<tr>
<td></td>
<td>(0.091)</td>
<td>(0.009)</td>
</tr>
<tr>
<td>Gini.l1</td>
<td>0.685</td>
<td>-0.027</td>
</tr>
<tr>
<td></td>
<td>(0.794)</td>
<td>(0.075)</td>
</tr>
<tr>
<td>N_teams.l1</td>
<td>0.010</td>
<td>-0.001</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>N_tournaments.l1</td>
<td>0.004**</td>
<td>0.0003</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.0002)</td>
</tr>
<tr>
<td>Prize.l2</td>
<td>-0.125</td>
<td>-0.017**</td>
</tr>
<tr>
<td></td>
<td>(0.090)</td>
<td>(0.009)</td>
</tr>
<tr>
<td>Gini.l2</td>
<td>0.740</td>
<td>0.110</td>
</tr>
<tr>
<td></td>
<td>(0.796)</td>
<td>(0.075)</td>
</tr>
<tr>
<td>N_teams.l2</td>
<td>0.004</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>N_tournaments.l2</td>
<td>-0.003</td>
<td>-0.0001</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.0002)</td>
</tr>
<tr>
<td>Const</td>
<td>-0.002</td>
<td>-0.0001</td>
</tr>
<tr>
<td></td>
<td>(0.085)</td>
<td>(0.008)</td>
</tr>
</tbody>
</table>

Observations: 252  252  252  252
R²: 0.175  0.075  0.458  0.631
Adjusted R²: 0.147  0.045  0.440  0.619
Residual Std. Error (df = 243): 1.354  0.128  10.732  54.215
F Statistic (df = 8; 243): 6.426***  2.465**  25.660***  52.032***

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

The rest of the section contains IRF plots. For each variable we have four plots. Each plot contains the response of one variable to a shock to all of the other variables. The x-axis represents the time period (in years) for all of the plots. Figure 7 presents IRFs for the Prize variable. The first plot of the figure shows that if there is a shock (positive increase with a size of 1 standard deviation) to prize in the current period, this would cause an increase of prize also in the next two years. The confidence
interval for the next plot of Figure 7 is too wide and shows no significant effect of Gini on Prize. Therefore, we do not have evidence that competition affects industry size. The bottom plots of Figure 7 show that the number of teams and number of tournaments positively affect Prize with a one-year lag. Therefore, competition does not increase the industry’s size.

Figure 8 shows the IRFs for Gini. First, the shock of Prize increases Gini, but the effect lasts for only one year. The same holds for the Gini coefficient itself. The bottom plots show that the number of tournaments does not affect competition, but the effect of the number of teams on Gini is positive after two years. Therefore, the number of teams decreases competition with a significant time delay.

Figures 9-10 contain the IRFs for the number of teams and tournaments, respectively. The common result is that they are not affected by competition. Still, an increase in prize money has a positive effect on them.
Figure 8. Impulse-response function for Gini

Figure 9. Impulse-response function for Number of teams
Figure 10. Impulse-response function for Number of tournaments
1.2 Video game publishers event promotion strategy: eSports tournaments and spillover effect

1.1.1 Promotion in eSports

Promotion plays a crucial role in any business and companies try to find new, more efficient ways and tools of communication with consumers. However, the estimation of the effect of promotion can be confounded by external factors. This is especially true for global multiproduct firms due to spillover effects among products and markets. Globalization and increasing ease and speed of the spread of information leads to high interconnection of markets, and makes large-scale promotion actions international as well. Therefore, companies should develop promotional strategies that take into account potential spillover effects of promotion actions.

Compared to traditional promotion, event marketing is a relatively new promotion technique and potentially can be beneficial for companies. Specifically, event marketing can help companies to achieve their marketing objectives, particularly in terms of increasing sales (Zarantonello and Schmitt 2013). In event marketing, the product is more closely related to the sponsor than in traditional sponsorship (Close, Finney, Lacey, & Sneath, 2006), and therefore event marketing can be more effective and efficient, at least in some industries. For example, it shows high potential for service marketing due to the intangibility and heterogeneity of a product (Vila-López and Rodríguez-Molina 2013). In promoting a brand, an event and its sponsors can project brand image, personality, and popularity (Vila-López and Rodríguez-Molina 2013).

Still it is not clear how to evaluate the effectiveness of event marketing (Gupta 2003; Martensen et al. 2007; Wood 2009; Zarantonello and Schmitt 2013). Most studies have focussed on different elements of the brand or brand equity, but few have focussed on increased sales. The empirical results on whether event marketing improves company financial performance are mixed. Martensen, Grønholdt, Bendtsen, and Jensen (2007) found a high and positive value transfer from event to brand in the case of a golf tournament from survey data. Moreover, brand attitude and positive brand emotions were found to increase purchase intention.
Chapter 2. Meso-level analysis

We investigate effects of event marketing by means of a case from the video gaming industry with eSports (electronic sports) tournaments as the category of video games promotion.

Video gaming is a recent and rapidly developing industry. It attracts people of different ages all over the world. Started as entertainment, video games have now transformed into a recognized sport with professional players. eSports tournaments attract up to thousands of people who watch the competition among individuals or teams playing a specific video game.

Video game publishers, and hardware and software producers generally organize or sponsor electronic sports competitions. Tournaments provide professional gamers the opportunity to experience the newest hardware and software, and players and spectators can evaluate new game versions or modifications played at the top level of skill. Therefore, it could be expected that eSports tournaments motivate people to buy new games and foster loyalty to particular producers. From the viewpoint of game producers, eSports tournaments can be considered as marketing events to promote their products.

Marketing through organizing or sponsoring events or so-called event marketing is quite widespread in particular industries. A report by the Event Marketing Institute (2015) emphasize the fast development and efficiency of event marketing. The report show that spending within the category of event marketing grew by 6.1% annually, mostly funded directly by corporations. In the follow-up report in 2018, still the increase in event and experiential marketing budgets has been of 5.6%, indicating a steady growth in this kind of marketing. Moreover, consumers report that live events and experiential marketing are more effective than other advertising and marketing channels in fostering brand awareness (Event Marketer 2018). However, analysis of the efficiency of event marketing is generally based on case studies or survey data because of the limitation in data availability and the significant differences among events and products. This significantly restricts the analysis of possible spillover effects. However, eSports as a part of the digital era provide good data for statistical analysis.
Considering all of this, eSports offer an excellent platform to address interesting research questions, especially the effectiveness of eSports tournaments as a marketing tool. We are going to investigate how eSports tournaments affect the publisher’s sales of video games, and what would be the optimal strategy of tournament organization considering multiple products and regional differentiation. In other words, we study the potential spillover effects that can arise as consequence of large-scale promotional events of a global multiproduct firm.

1.1.2 Event marketing and its effectiveness

According to Wood (2009), an event is a live ‘occurrence’ with an audience, and all events can be used as ‘marketing’ events. Events are growing in popularity as alternative promotional tools, and marketers are investing heavily in them because events can create a greater connection with consumers through these experiences than through traditional advertising11 (Tafesse 2016). The promotion of goods and services through events is now called ‘event marketing’.

Event marketing assumes that a company organizes or sponsors (Close et al. 2006) a special event generally related to its product to support corporate objectives, including sales, brand awareness, and image enhancement (Sneath, Finney, and Close 2006). Events allow for direct, highly interactive encounters between consumers and the brands (Zarantonello and Schmitt 2013) and provide a communication platform (Nufer 2013). Tafesse (2016) stressed such features of event marketing as high audience involvement, novelty, experiential richness, and spatial and temporal transiency.

Sports events are frequently used for promotional purposes (Kahle and Close 2011). Therefore, event marketing can be compared with the sponsorship of sporting events. The majority of studies on sponsorship effectiveness found a positive effect (Deitz, Evans, and Hansen 2013; Reiser, Breuer, and Wicker 2012), however, some studies found no effect. (Naidenova, Parshakov, and Chmykhov

---

11 Traditional advertising is what most people think of when talking about advertising or marketing. This includes the usual venues for media placement, such as newspaper, radio, broadcast television, cable television, or outdoor billboard. Advertising on the usual venues is sometimes referred to as mass marketing.
2016) Frequently in the case of sponsorship of sports events, companies tend to promote their brands, not particular products. In contrast, event marketing assumes a very tight relationship between an event and the product.

1.1.3 Spillover effect

Bo, Bi, Hengyun, & Hailin (2016) point out that there is substantial body of literature that studies tourism spillover effects. The spillover effect in tourism refers to the phenomenon in which the tourism activities in one region benefit those in neighbouring regions. As eSports is a globalised industry, spillovers can be expected in different regions. Not because of proximity as in the case of tourism industry but because the organization of an eSports event can influence the sales of related product in the hosting area and also the other regions.

Erdem & Sun (2002) found spillover effects of promotions in umbrella branding. Considering an individual’s market basket, previous studies supported both between-category complementary effects and between-category substitution effects (Hruschka, Lukinowicz, and Buchta 1999; Leeflang et al. 2008). Nair (2007) empirically found that cross-price effects across games are low, indicating that games are imperfect substitutes for one another. Moreover, it was found that the entry of big hit games does not have significant effects on sales and prices of games within the genre.

The spillover effects has been also studied in the pharmaceutical industry. In particular, Liu, Liu, & Chintagunta (2017) analyse the effect of promotions when products from different companies are consumed in a bundle, and they point out the problem of free riding when other firms can benefit of the marketing efforts. The spillover effect can be positive or negative. The negative case can be related to unethical behaviour of a competitor. Offtimes brands may be damaged by misconduct of competitors (Trump and Newman 2017). Moreover, perceived

---

12 One of the branding strategies is Umbrella branding, also known as the family branding. The concept of umbrella branding represents a marketing practice which involves selling many related products under a single brand name. Umbrella branding can be effective if a consumer uses positive from knowledge of one product to make decisions about another product within the same umbrella brand. Naturally there is a drawback if the consumer has a negative experience with a product, with this negative affect spreading to other products under the brand and the brand itself.
corruption generates negative spillover effects on the consumer population’s attitude toward the event (Kulczycki and Koenigstorfer 2016), and consequently toward its sponsors. In general, the negative impacts of spillovers have received some attention, see, e.g., Mackalski & Belisle (2015).

In sports, there are interesting studies about the spillover effect in the case of the productivity of civil servants that are football fans and focus their attention and time on the results of their teams. Negative events in sports are prone to spillover to work with negative effects on employees’ work engagement and performance (Gkorezis et al. 2016). Positive effects have also been found. For example, in Korean baseball, postseason success has shown a positive spillover effect on the firms affiliated with sponsoring successful teams (Sung et al. 2016).

In more relevant results for this study is that Kumar & Tan (2015) found that introducing videos with other product promotions resulted in a significantly higher effect of videos on product demand. We expect to find in the eSport industry this kind of spillover effect.

1.1.4 Video games and eSports tournaments

The video game is a somewhat unique product as its essence is intangible. First, video games are classified as experience goods, which means that the game cannot be accurately evaluated before the purchase and consumption. Thus, the quality of a new video game can be estimated based on brand of the publisher and consumer ratings if available. Second, the physical attributes of video games minimally depreciate but the consumption value to owners depreciates quickly due to satiation (Ishihara and Ching 2012). Experiencing pressure from the used-games market, the publishers have to decrease prices for older games. Therefore, forward-looking consumers can strategically delay purchases to avail of lower prices (Nair 2007). Third, the utility derived from video games’ consumption depend on the hardware used and player’s skills. Thus, eSports tournaments allow potential customers to evaluate the game with the highest settings and enhance customers’ loyalty.
Electronic sports are becoming more and more popular (Bräutigam 2015). This kind of sports implies individual or team competition facilitated by electronic systems; video games are of particular importance within this category of sports. Bräutigam found that in the last five years, the number of eSports events has tripled, total prizes in 2015 exceeded $50 million, and the number of both active players and average prizes per player are also growing.

There are two kinds of eSports tournaments. Low-level tournaments usually are organized as online events, but all major tournaments are live events in front of an audience. A tournament might be part of a bigger event, such as DreamHack. The most common formats are single and double elimination, usually with a round-robin group stage (Coates & Parshakov, 2016). Major tournaments include the Electronic Sports World Cup, World Cyber Games, Major League Gaming, and the World eSports Games.

Organizing an eSports tournament requires significant funds. The prize pool for the top games of major tournaments reaches millions of USD per year (Goldfarb 2012). Usually, game developers themselves provide prize money for tournament competition, but sponsorship may also come from companies selling computer hardware, energy drinks, or computer software (Goldfarb 2012). It is important that companies consider a tournament as a marketing investment, understanding that an event itself might not be profitable. Riot Games, the organizers of the Legends Championship Series, states that this tournament is ‘a significant investment that we’re not making money from’ (Zacny 2013).

ESports tournaments clearly fit the features of event marketing pointed out by Tafesse (2016). They can create an atmosphere where participants and attendees are highly involved. Most of the attendees for these kinds of events are already consumers of a similar product. As each event has an uncertain outcome, there is a novelty effect. Moreover, game producers take the opportunity to present new developments. The event offers a rich experience where consumers can observe the best performances on their favourite games. Finally, they have an element of

---

13 DreamHack is the world's largest digital festival and hosts a series of events around the world and attract over 300,000 esport enthusiasts annually, gamers and fans. DreamHack events are the center of live broadcasts reaching millions of people.
transiency because typical eSports tournaments take about three days. Thus, one can consider eSports tournaments as event marketing actions of computer game producers and analyse their efficiency.

1.1.5 Spillover effect: testable hypothesis

This study focusses specifically on eSports tournaments, which computer game publishers can use for promotion of their games. Of course, other companies, such as computer hardware manufacturers, can also sponsor these kinds of events. Such tournaments can be local or international, offline or online (Seo 2016, 2013b). A specific feature of such events is that they can be easily streamed via the Internet. Such events provide a good opportunity to study the effect of promotion event on product sales.

As one of the topics that needs to be researched in this field is the effectiveness of event marketing (Gupta, 2003; Martensen, Grønholdt, Bendtsen, & Jensen, 2007; Wood, 2009; Zarantonello & Schmitt, 2013), the aim of this study is to study whether eSports tournaments have a positive impact on company sales.

We specify video game’s sales (in units) as the measure of eSports tournaments’ organizational effectiveness. In other words, we assume that eSports tournaments as a marketing tool should increase the company’s sales of the game the tournament is based on. We aggregated the games of a publisher by genres. Moreover, as previous research found country differences in market concentration and consumer price sensitivity (Erdem, Zhao, and Valenzuela 2004), and consumer behaviour due to national culture (de Mooij and Hofstede 2002). Therefore, we consider sales by region of the world. Thus, our first hypothesis is as follows:

**H1:** The number of e-Sports tournaments of publisher’s games in one genre has a positive effect on the regional sales of the games of the genre in the region the tournaments are held.

Liu, Zhang, & Keh, (2017) found positive but diminishing marginal returns of event marketing on brand value and firm sales. Therefore, we test non-linear effect of event marketing:
Chapter 2. Meso-level analysis

H1.1: Number of e-Sports tournaments of publisher’s games in one genre has a non-linear effect on the regional sales of the games of the genre in the region the tournaments were held.

Even if eSports tournament should mainly promote the played game, it promotes the brand as well. Thus, cross-product spillover effects can take place. Taking into account the findings of Nair (2007), we can hypothesize that computer games of one publisher are mostly complements:

H2: Number of e-Sports tournaments of all publisher’s games in other genres of the publisher has a positive effect on the regional sales of the games of the genre in the region the tournaments were held (between-genre spillover).

As was already mentioned, country features can affect the relationship between tournaments and game sales. We assume positive but smaller cross-regional effects of eSports tournaments:

H3: Number of e-Sports tournaments of the publisher’s games in one genre in all other regions has a positive effect on the regional sales of the games of the genre (regional spillover).

Finally, video games of other publishers can be substitutes or complements. The mechanism is the same as for the other games of the same publisher except for the brand effect. Assuming players’ loyalty to a genre due to fast satiation with a particular game, we hypothesize the predominance of complementation effect:

H4: Number of e-Sports tournaments of other publishers in one genre has a positive effect on the sales of the games of the genre in the region the tournaments were held (cross-publisher spillover).

1.1.6 Spillover test: an empirical approach

We use data on video games, which cover all games with sales greater than 100,000 copies per year. The dataset was generated by a scrape of vgchartz.com and

14 A complementary good or complement is a good with a negative cross elasticity of demand, in contrast to a substitute good. This means a good’s demand is increased when the price of another good is decreased. Conversely, the demand for a good is decreased when the price of another goods is decreased.
uploaded to the Kaggle project\textsuperscript{15}. Our data include the names of games, their genre, publisher, and annual sales in North America, Europe, Japan, and other regions for the period 1997–2014. We aggregated data by the platforms of the games’ release (i.e., PC, PS4, etc.). In the data, 12 genres of games are distinguished: action, adventure, fighting, strategy, platform, puzzle, racing, role-playing, shooter, simulation, sports, and miscellaneous. Six genres were excluded from the sample because of zero number of tournaments for them. Moreover, data on average scores assigned to these games by users, as well as the number of reviews, was collected from Metacritic.com. We obtained the information on tournaments, prize structure, and total prize pool from the results of the eSports Earnings project. This resource is based on freely available public information on different tournaments in eSports, including the nicknames of winners and the sums won. The eSports Earnings website contains information on each gamer and team prize earnings for each tournament (in US dollars) for the period from 1999 to 2014.

The unit of observation of aggregated sample is publisher-genre-region-year. However, since we also use information on the number of tournament all over the world, we report two tables with descriptive statistics: with and without division by regions. Table 14 contains information with respect to regions; Table 15 represents indicators, which do not vary from region to region. As one can see, publisher companies vary in size and sales dynamics. Average game rating is 7 of 10 based on 177 reviews. The variation in the number of tournament is huge with maximum value of 165.

\begin{table}[h]
\begin{center}
\begin{tabular}{lccccc}
\hline
 & N & Mean & St. Dev. & Min & Max \\
\hline
Sales (mln. copies) & 7,120 & 0.687 & 1.805 & 0 & 42.48 \\
Game rating & 7,120 & 7.246 & 1.316 & 0.7 & 9.6 \\
Number of reviews (th.) & 7,120 & 0.177 & 0.491 & 0.004 & 8.039 \\
Number of tournaments & 7,120 & 0.104 & 2.258 & 0 & 165 \\
Number of tournaments (all genres) & 7,120 & 121.297 & 91.461 & 17 & 263 \\
Number of tournaments in other regions & 7,120 & 0.316 & 2.966 & 0 & 165 \\
Number of tournaments of other genres & 7,120 & 6.771 & 17.487 & 0 & 166 \\
\hline
\end{tabular}
\end{center}
\caption{Descriptive statistics of the sales (by region)}
\end{table}

\textsuperscript{15}https://www.kaggle.com/gregoruvideogamesales
Table 15. Descriptive statistics of the sales (global)

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>Mean</th>
<th>St. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sales (mln. copies)</td>
<td>827</td>
<td>7.965</td>
<td>14.681</td>
<td>0.01</td>
<td>120.01</td>
</tr>
<tr>
<td>Game rating (of 10)</td>
<td>827</td>
<td>7.13</td>
<td>1.267</td>
<td>1.2</td>
<td>9.4</td>
</tr>
<tr>
<td>Number of reviews</td>
<td>827</td>
<td>0.186</td>
<td>0.426</td>
<td>0.004</td>
<td>6.165</td>
</tr>
<tr>
<td>Number of tournaments</td>
<td>827</td>
<td>1.814</td>
<td>8.965</td>
<td>0</td>
<td>165</td>
</tr>
</tbody>
</table>

Figure 11 illustrates the dynamics of game publishers’ sales in different regions. Interestingly, the pattern is almost the same for different regions: the sales of game producers was rising until 2008 and declining after this point. The highest drop is observed in the North American market. The largest video game markets are North America and the European Union.

Figure 11. Total Sales of all game publishers by Region and Year. Source: Self-elaboration
The Economics Of Esports: Elements That Affect Performance

![Graphs showing the total number of tournaments by region and year](Image)

**Figure 12.** Total number of tournaments of all game publishers by Region and Year (divided into two plots for the purpose of visualization)

Figure 12 represents the number of tournaments. We have split the figure in 2 as from 2005 there is a proliferation of tournaments. Moreover, it allows to see that until that time, tournaments were organized on North America and Europe. There were a few tournaments each year until 2005, when 43 eSports tournaments were organized. During the period from 2003 to 2011, the number of annual tournaments fluctuated around 40. In 2012 and 2013, the number of tournaments soared to around 200 each year. Such stair-step development of the eSports industry is mostly the result of changes in the relationship between video game developers and tournament organizers and broadcasters (Popper 2013). Among all of the game publishers analysed, only 25 firms have organized eSports tournaments. Moreover, the top four publishers—Electronic Arts, Warner Bros. International, Activision, and Starfish—have organized most of the tournaments (77%).

To estimate the effect of tournaments we use regression analysis. We estimate different models to measure the effect of different spillovers. The dependent variable in all models is product unit sales (in millions of copies sold). The set of control variables is also the same for all models. We include user game rating and number of reviews as a proxy of video game popularity. We also include fixed effects for genres, years and selected publishers. Unfortunately, we do not have historical information on price of the game. We try to address this issue by estimating our models only on subsamples of so called free-to-play games. The price of such game
is zero, and the publisher gains funds when players spend real money to buy some in-game products. The results are the same both in terms of magnitude and significance of the coefficient. This leads us to the conclusion that price might be not a significant determinant of demand of the video games, since usually the price is much lower than the cost of equipment (PC or console). Still, we add publisher and genres effects to address this issue, since they should capture the effect of the price: it is the publisher who is deciding on the price of its product, taking into account competitors’ prices in this genre of game.

Using these indicators, we estimate three regressions models (1), (2) and (3) where \( S \) is the total sales of each publisher \( i \) of games in genre \( j \) generated in region \( r \) and year \( t \). \( Genre, \ region, \ year, \) and \( publisher \) are the sets of dummy variables for each genre, region, year, and publisher, respectively, \( rating \) is the user rating of video games of these genre, \( reviews \) is an indicator of the number of user reviews.

Number of tournaments \( (N_{ijrt}) \) of the genre is included in all the models. Before testing the spillovers in promotion, one needs to control for the effect of the own promotion of the publisher. For the test of spillovers, we have constructed the following indicators:

1. regional spillover – for each publisher-genre-year we calculate the number of tournaments of the same genre of the same year but in the different regions \( (N_{-rijt}) \);
2. in-genre spillover – for each publisher-genre-year we calculate the number of tournaments of the same genre of the same year in the same region organizer by the other publishers \( (N_{ijrt}) \);
3. between-genre spillover – for each publisher-genre-year we calculate the number of tournaments of the different genres of the same year in the same region \( (N_{-ijrt}) \).

For all of the number of tournament indicators \( (N_{ijrt}, N_{-rijt}, N_{ijrt}, N_{-ijrt}) \) one might suggest a nonlinear relationship with publisher sales. For these reasons, in each of models 1, 2, and 3, we include the number of tournaments as a linear term and as both a linear and squared term. If linear and squared terms were jointly
statistically significant we include both of them in the final model and conclude a nonlinear relationship between these indicators.

\[ S_{ijrt} = \gamma_0 + \gamma_1 \cdot N_{ijrt} + \alpha \cdot N_{-ijt} + \mathbf{CV} \cdot \beta + \varepsilon_{ijpt} \]

\[ S_{ijt} = \gamma_0 + \gamma_1 \cdot N_{ijt} + \alpha \cdot N_{-ijt} + \mathbf{CV} \cdot \beta + \varepsilon_{ijpt} \]

\[ S_{ijt} = \gamma_0 + \gamma_1 \cdot N_{ijt} + \alpha \cdot N_{-ijt} + \mathbf{CV} \cdot \beta + \varepsilon_{ijpt} \]

Where \( \mathbf{CV} \) is a vector of control variables, which includes game rating, number of reviews, genre, region, publisher and year effects.

1.1.7 Empirical results of spillover effects

Table 16 contains the results of regression models discussed above. In all models, we include dummy indicators for each game publisher, year, region, and genre as control variables. Each set of dummies is jointly significant, indicating the importance of these controls.

Both indicators of popularity are statistically significant, the coefficients show positive effects. Moreover, the marginal effects are stable across all of the models 1-3. One unit increase in user rating provide publisher with 50,000 more copies sold, which is 7% of average number of copies sold. An increase of one thousand in the number of reviews leads to a huge boost of sales (70%); note that the maximum number of reviews is 8,000, so a one thousand increase is an extraordinary event.

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of tournaments (of the genre)</td>
<td>0.392***</td>
<td>0.392***</td>
<td>0.363***</td>
</tr>
<tr>
<td>Number of tournaments (of the genre) sq.</td>
<td>-0.002***</td>
<td>-0.002***</td>
<td>-0.002***</td>
</tr>
<tr>
<td>Number of tournaments (of the genre) in other regions</td>
<td>0.020***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of tournaments (of the genre) of games of other publishers</td>
<td></td>
<td>-0.000</td>
<td></td>
</tr>
<tr>
<td>Number of tournaments of other genres</td>
<td></td>
<td></td>
<td>0.107***</td>
</tr>
</tbody>
</table>
According to the tests described above, number of tournaments affects sales in a nonlinear way in all the models. The coefficients are stable from one regression to another, indicating inverted U-shape relation. Figure 13, panels (a), (b) and (c) represents the marginal effect for the model 1-3, respectively. The turning point for the all models is about 83 tournaments. Note that the number of tournaments varies from 0 to 165, so there are companies on both sides of the curve. Marginal effect is different for each number of tournaments; it is positive until 83 and negative after. Therefore, 83 events per year is indicated by our analyses to be the optimal number.
Figure 13. Marginal effect for the nonlinear model for number of tournaments

Model 1 is designed to estimate regional spillover. The coefficient of the number of tournaments in the other regions is statistically significant and positive. There is no evidence of nonlinear relationships from the test described above, so we include it in the linear term. Marginal effect in averages is lower than for tournaments organized in the same region: one additional tournament provides a company with 20,000 additional copies sold. Still, this effect is substantial considering the average number of copies sold is 687,000.

Model 2 is designed to test cross-publisher spillover. The coefficient is not statistically significant, so the tournaments of competitors (the same genre, the same year, the same region) do not affect sales. This is an interesting finding, indicating the publishers do not have to fear the free-rider effect or that their competitors get the benefits of their marketing efforts.
Model 3 represents the results for between-genre spillover. According to the tests, there is a statistically significant nonlinear relationship. Figure 13, panel (d) shows the marginal effect. Interestingly, the turning point is the same, but the effect, according to the coefficient is half of that for the number of tournament of the same genre.

1.3 Team vs. Individual Tournament: Video game publisher dilemma

1.1.8 Rank-order tournaments in economics and management

Professional video gaming is a growing industry. Competitions take both a league and a tournament format and competitors can be individuals or teams. A growing phenomenon is investing in an e-sport team. For example, Magic Johnson, Shaquile O’Neal, and Alex Rodriguez are individuals with stakes in video game teams (“The Most High-Profile Investments in Esports Teams so Far” 2016). The fluid and rapidly changing e-sports industry raises numerous questions. Labor-management relations, player compensation and the industrial organization of the league are among the issues. This study addresses a simple question: are e-sport tournament prizes structured to maximize effort of the participants?

Lazear and Rosen (1981) introduced rank order tournaments as optimal labor contracts and suggested large salary dispersion can lead to greater effort and higher productivity. Workers compete by exerting effort, and greater effort results in the individual achieving a higher rank and, consequently, winning a larger prize, a higher salary. Ehrenberg and Bognanno (1990) tested this tournament theory by examining the impact of prize structure in golf tournaments on performance of golfers and concluded that both the size and the structure of prizes influenced player performance. Since that time, the predictions of tournament theory have been studied in a number of sporting contexts including auto racing (B. E. Becker and Huselid 1992; Allmen 2001; Depken and Wilson 2004b), marathons (Frick and Prinz, 2007), tennis (Sunde 2009) and golf (Brown 2011). The theory also suggests that heterogenous ability of the competitors will affect effort, an issue addressed by several researchers (Brown 2011; Frick, Prinz, and others 2007; Sunde 2009).
Brown (2011) specifically addresses the presence of a dominant superstar (Tiger Woods) in the field. In each of these studies of tournament effects in sports, the researchers have a measure of competitor “effort”, the speed of a race or the score in the match.

The upshot of this research is that there is support for the predictions of tournament theory with regard to rank order tournaments, but that the context of the competition introduces nuances that are not inherent in the basic theory. For example, Allmen (2001) considers the two part compensation scheme of NASCAR and shows that a winner-take-all type structure could lead to excessive risk-taking by drivers and, consequently, more crashes. Frick and Prinz (2007) find that spreading out the prizes to more competitors in a marathon may lead to a bigger and more competitive field. If prizes are too concentrated, some competitors may opt to participate in competitions below their talent level where they are more certain of capturing some earnings.

Rosen (1986) extended the Lazear and Rosen (1981) analysis to elimination tournaments; players compete in rounds, with the winner advancing to the next round and the loser eliminated from the competition. In order to maintain and encourage effort as the tournament progresses, the prize from advancing another round has to increase relative to the prize for the current round. In the extreme case of winner-take-all, Rosen’s analysis predicts low effort in the early rounds of the tournament and greatest effort in the final round. Gilsdorf and Sukhatme (2008a, 2008b), Hill (2014), Sunde (2009), and Brown and Minor (2014) are studies of elimination tournaments. In each of these studies, the models explicitly introduce heterogeneous ability among the competitors.

The tournament theory literature focuses largely on incentives of individual competitors. Here our analysis will use both individual and team competitors because a substantial number of the competitions are for teams. The existing literature focuses on individual sports, golf, tennis, marathons and auto racing, of which only tennis is of the elimination tournament variety. Each of the competitions we analyze is an elimination tournament; we have no observations on a competition like a marathon, automobile race or a golf tournament in which the winner is the first past the post. Additionally, about one third of team and two thirds of individual competitions in our analysis are winner-take-all. Given the Frick and Prinz (2007)
findings, this characteristic of the prize structure in our data suggests small and
uncompetitive fields of competitors. Unfortunately, the data is limited to the prize
earnings of the top eight finishers with no information on the total number of
competitors or a ranking of the players or teams. As a result, we cannot assess the

Because so many competitors in our analysis are teams, the issue of proper
incentives potentially becomes more complicated than in the usual tournament
model (Che and Yoo 2001; Holmstrom 1982). There is a large literature on
production in teams which focuses on getting the incentives of the individual team
members to align with maximizing team results rather than individual net gains.
Despite the teams in the data, we argue that the analysis can treat the teams
essentially as individuals. While team members may find it individually optimal to
raise or lower their effort in response to the efforts of their teammates, monitoring
of this behavior is essentially costless suggesting that shirking would be identified
and punished by removal from the team. Moreover, the circumstances of team
training and recruitment make shirking extremely costly to the individual.
Nonetheless, data on effort is unavailable for individual competitors making testing
for shirking impossible. Below we describe compensation within the team, training
and team organization and the nature of the competition to draw inferences about
individual effort.

The study begins by describing video game competitions including
documenting the growth in competitive video gaming and in the value of prizes to
be won. There is an active player market as well, with players being recruited to top
teams by investors and compensation sufficiently large that players need not have
other jobs. The study describes tournament theory and provides an overview of the
empirical literature before turning to the data for this analysis and the methodology.
The study ends with a presentation and discussion of empirical results and a

1.1.9 eSports Background

To date there is no common definition of eSports. Wagner (2006) defines
eSports as “an area of sport activities in which people develop and train mental or
physical abilities in the use of information and communication technologies”.

85
Witkowski, (2012) criticized this definition because many aspects of traditional sports are computer-assisted or computer-mediated. Another definition is available from Hamari and Sjöblom (2015), who regard eSports as “a form of sports where the primary aspects of the sport are facilitated by electronic systems; the input of players and teams as well as the output of the eSports system are mediated by human-computer interfaces”. Holden, Kaburakis and Rodenberg (2017) in their study analyze if eSports can be determined as sports, concluding that “a number of the organized leagues are beginning to function similarly to other sports leagues even without a proclamation that competitive video gaming is a sport” (p.67).

Since eSports are an emerging form of activity, there are only a few studies devoted to this particular field. In general, the literature on eSports is very limited, with most work focusing on the definition of this phenomenon and its future implications (Seo 2013a; Seo and Jung 2014; Taylor and Witkowski 2010; Taylor 2012). However, Taylor (2012) provides a great deal of insight into the activity, from the journey from playing for fun to becoming a professional player, to organizing a league or tournaments, and the problems that arise between league and tournament organizers, sport governing bodies and game producers from this new form of competition. For example, Taylor highlights a problem between game producers and tournament organizers with respect to the way a tournament is organized or the game is played. Consider that a tournament organizer may purchase the game then charge an entry fee to a tournament for players of that game. The game producer might reasonably argue that such a usage violates the copyright as the tournament organizer is making commercial use of the game. Alternatively, software may have been developed by third parties to automate or speed certain types of activities within a game; the game producer may object to this also as a copyright violation. Neale (1964) discussed the peculiar economics of sporting competitions in which the teams needed to cooperate with each other to produce their product, competition on the field, while also competing off the field for ticket sales. eSports has a further complication, the game in which the teams meet to produce the match is the intellectual property of a third party. It is as if James Naismith, inventor of basketball, was around to assert property rights over the use of the sport for commercial purposes by the National Basketball Association.
Chapter 2. Meso-level analysis

The history of eSports tournaments is quite long. The first such event took place at Stanford University in 1972. It was called the “Intergalactic Spacewar Olympics” and the prize was a subscription to Rolling Stone magazine (Hiltscher and Scholz 2015). However, the industry of eSports events evolved considerably during the 1990s. With the establishment of the Cyberathlete Professional League (CPL) in 1997, tournament prize pools became larger due to corporate sponsorship and an increasing number of spectators, both online and live (Gaudiosi 2013). For now, CPL is inactive and has been substituted by the Electronic Sports League (ESL). Until 2011, the largest eSports event was the World Cyber Games (WCG). This event was regarded as the eSports Olympics (Svoboda 2004), whereas the biggest event is currently DreamHack, which comprises tournaments for the most popular games. Sponsorship is the core funding system for eSports tournaments (Taylor 2012). There are different kinds of sponsors. Game producers are interested in promoting their games through these tournaments. Hardware producers are also natural eSports sponsors (SteelSeries, MSI, Intel). There are also companies that promote their goods using eSports, such as Coca-Cola (“Coca-Cola and Riot Games Renew Partnership for 2015: The Coca-Cola Company” 2015). (Seo 2013a) study was one of the first attempts to analyze the marketing aspects of eSports.

eSports games can be categorized into different genres. For example, games can be multiplayer online battle arena games, real-time strategy games or tactical first-person shooter games. There are sports games, racing games and fighting games. However, based on cumulative tournament prize money, the top five games come from the multiplayer online battle arena, real-time strategy or tactical first-person shooter genres. These games are Dota 2, League of Legends, StarCraft II, Counter-Strike: Global Offensive, and Counter-Strike (“Top 50 Games Awarding Prize Money - eSports Game Rankings: eSports Earnings”, 2015).

A typical eSport competition is structured as a sequential elimination tournament. The number of participants varies a lot, but the mode is 32. Some teams/players are invited directly by the tournament organizers and the rest go through a qualification stage to fill spots not taken by the invited teams. Qualification is usually organized as a round-robin tournament, to reach this group of 32. A match is between two teams or two individuals with the winner determined by a best of three playoff system: one team must win two games to win the series. So, the
competition is structured as the pair-wise elimination tournaments of Rosen (1986).

Tournaments are usually organized by game producers, or by organizations licensed by the game producers, in order to promote their games. The incentive is to maximize the entertainment value across all matches, which in turn pulls in viewers, sponsors, ad revenue and gamers. Since the contestant effort is an important determinant of the quality of entertainment, the organizers are interested in maximizing the effort. Tournament theory suggests the prize structure that maximizes effort.

There are offline (so called “LAN” tournaments; LAN is a local area network in contrast to internet-based or online tournaments) and online competitions for most games. The leading tournaments are held offline and take place in front of live spectators. The most common format is a double-elimination system, whereas the format in the case of a low number of participants is a single-elimination system. Big events also have a group stage as a preliminary competition before the playoffs stage. Parshakov and Zavertiaeva (2015) underline the difference between prizes for online and offline tournaments. They show that 78% of gamers prize money is earned from offline tournaments. eSport competitions are structured like many regular sport competitions and a natural question is to what extent their incentive structure follows tournament theory.

1.1.10 Tournament theory and prize structure

Tournament theory is concerned with groups of agents that compete for a prize. The key feature of tournament theory is that the reward is based on relative rank (Lazear and Rosen 1981). The reward for tournament winners is designed to maximize the effort of all contestants. Since the reward can be either monetary or nonmonetary, tournament theory has implications in a wide range of fields. For example, tournament theory explains how judges compete for the ultimate prize, an appointment to the US Supreme Court (Choi and Gulati 2004), or how contract growers vie to supply broiler chickens to Perdue and Tyson (Knoeber and Thurman 1994). Messersmith, Guthrie, Ji, & Lee (2011) use tournament theory to explain compensation and executive turnover. Sporting events provide a natural context for tournament theory (Depken and Wilson 2004b; Melton and Zorn 2000).
To maximize effort, tournament organizers choose the prize spread. By prize spread, we mean the difference between the prize for winning the current round and the prize for winning the next round in sequential elimination tournaments (B. E. Becker and Huselid 1992; Messersmith et al. 2011). A sequential elimination tournament is organized in such a way that winners of the current stage compete in the next stage against other winning actors (Choi and Gulati 2004; O’Neill and O’Reilly 2010). As such, the optimal prize structure involves a prize spread that maximizes the ratio of actor effort to the prize. If it is too small, actors do not have an incentive to maximize their effort. If the spread is too high, actors take on an additional risk of losing and need to be separately compensated for such a risk (DeVaro 2006; Kepes, Delery, and Gupta 2009). Using data from automobile racing, some studies find that nonlinear rewards may be associated with more risky behavior (Allmen 2001; Depken and Wilson 2004b; Schwartz, Isaacs, and Carilli 2007). Moreover, the optimal spread may depend on the size of the tournament (Baye 1998). For example, Krishna and Morgan (1998) show that in small tournaments it is optimal to pay prizes only for first and second place or for the tournament to be winner-take-all.

A number of theoretical tournament theory papers show the reward structure that allows a competition to be organized to incite optimal effort (Baker, Jensen, and Murphy 1988; Lazear 1999b; Lazear and Rosen 1981; Prendergast 1999). (Rosen 1986) shows that, for risk-neutral contestants, the inter-rank spreads are constant until the final stages, but the final stage prize is substantially higher. Rosen also demonstrated that “if players are risk-averse, the incentive maintaining prize structure requires strictly increasing inter-rank spreads, with an even larger increment between first and second place.” (Rosen 1986). We formulate two research hypotheses concerning the structure of prizes in eSports:

1. the function describing the relationship between prize and rank is convex in the rank order;
2. the inter-rank spread for the final stage contestants is larger than for the lower stages.

Such hypotheses were tested in the business context: Lambert, Larcker and Weigelt (1993) and Conyon, Peck and Sadler (2001) found convex relationships between executive pay and organizational levels. However, in business, there are
significant nonmonetary incentives for the contestants. This presents a limitation in such research, since tournament theory supposes that “the prize is presumed to be the actors’ predominant motive. Research that incorporates more complex social understandings of actor objectives may be beneficial” (Connelly, Tihanyi, Crook & Gangloff, 2013, p.29). However, since the reward is mostly performance-based in eSports Parshakov and Zavertiaeva (2015), this provides us with perfect data for testing the implications of tournament theory. Unfortunately, it is not possible with existing data to test whether eSport tournament prize structures are efficient in the sense of eliciting maximum effort from the players.

1.1.11 Theoretical model of team rank-order tournaments

Figure 14 describes a tree of the game. On the first step (node 1 of the game tree) the organizer decides on the type of tournament to manage: individual or team tournament. Each tournament type has a paired-comparison structure, that has only one stage with 2 competitors. The winner and the loser get prize $W_1^{ind}$ and $W_2^{ind}$ in individual tournament respectively, and they get prize $W_1^{team}$ and $W_2^{team}$ in team tournament respectively. For chosen tournament type, the organizer decides on the prize level and the prize spread $\Delta W^j = W_1^j - W_2^j$, where $W_1^j > W_2^j > 0$ and $j \in \{ind, team\}$.

![Game tree for tournaments' organizer and players](Image)

Given the prize spread, in the individual tournament 2 people compete by choosing a level of effort (node 4 of the game tree, let’s define it as subgame 1). Let $x$ and $y$ be an effort level of person 1 and 2. And let $h^{ind}(x)$ be a function of effort that produces “effective” effort. The nature of the function $h(x)$ is a topic in the contest theory literature which we wish to avoid. For simplicity, let’s assume that $h^{ind}(x) = x$. The
Chapter 2. Meso-level analysis

probability of person 1 to win can be written as the following contest success function:

\[ P_i = \frac{h^{ind}(x)}{h^{ind}(x) + h^{ind}(y)}. \]

The cost of effort function increases monotonically in effort level, let it be \( c^{ind}(x) = x^2 \). Our assumption is that the marginal cost of effort is increasing. Following Rosen (1986), each competitor has the following utility function:

\[ U_i^{ind} = \frac{x}{x+y} W_1^{ind} + \frac{y}{x+y} W_2^{ind} - x^2, \quad i = 1,2. \]

According to the prize spread, the utility function can be rewritten in the following form:

\[ U_i^{ind} = \frac{x}{x+y} \Delta W^{ind} + W_2^{ind} - x^2. \]

In the team tournament 2 teams of 2 members compete and decide on the effort of the whole team \( x \) and \( y \) respectively (node 5 of the game tree, let’s define it as subgame 2). The whole team effort can be presented as a sum of personal efforts of team members \( x = x_1 + x_2 \). The probability of team \( i \) to win is the same contest success function and \( h(x) \) in this case is a production function of the team. We assume that it has a form of Cobb–Douglas production function: \( h(x) = x_1^\alpha x_2^\beta \), where \( \alpha \) and \( \beta \) are the output elasticities of each team member. The cost of effort to the team is as follows: \( c^{team}(x) = x_1^2 + x_2^2 \). Let’s suppose that we cannot differentiate the effort of each team member of a given team. Consequently, the team shares the prize equally between members and each member \( k \) of team \( i \) has the following utility function:

\[ U_{team}^{k,i} = \frac{x_1^\alpha x_2^\beta}{x_1^\alpha x_2^\beta + y_1^\alpha y_2^\beta} \Delta W^{team} + \frac{W_2^{team}}{2} - x_k^2, \quad k = 1,2, \quad i = 1,2. \]

In this case the optimal level of effort of the whole team will be equal to the sum of optimal for a member levels of effort.

The organizer chooses the prize spread comparing his utility from individual and team tournaments. The utility consists of two components. Firstly, it is a cost of a tournament, which is equal to prizes for the tournament. Secondly, the organizer wants to maximize the spectators’ value of the competition \( \varphi(x,y) \) that depends on effort levels of contestants. Assume spectator value is equal to the minimum of the
“effective” effort from the competitors. For that reason suppose, that the spectator value of competition can be represented as a Leontief production function with
\[ \varphi(x, y) = \min \{ h^j(x), h^j(y) \} \]. The value of a competition of type \( j \) is
\[ V^j = \min \{ h^j(x), h^j(y) \} - W^j_1 - W^j_2, j = \{ \text{ind, team} \}. \]
The organizer chooses competition type \( j \) for which \( V \) is greatest.

1.1.12 Equilibrium analysis

The game presented in Figure 14 is a sequential game with perfect information. The solution of the game can be found as a subgame Nash equilibrium.

In the individual tournament (subgame 1) each contestant maximizes his utility function with respect to his effort. Differentiating (1) with respect to \( x \) gives first order condition:
\[ \frac{x_2 \Delta W^{\text{ind}}}{(x_1 + x_2)^2} - 2x_1 = 0. \]

Without difference between players, in Nash equilibrium optimal players’ effort is identical and equal to \( x^{\text{ind}} = \frac{\sqrt{\Delta W^{\text{ind}}}}{2} \). The more the prize spread the more effort each individual exerts.

In the team tournament (subgame 2) each team member maximizes her utility function. Suppose, that members in each team are equally talented. That leads to \( \alpha = \beta \). And the maximum of the team utility is attained when members maximize their own utility. Teammates maximize utility with respect to effort \( x_k \). The first order condition for the team 1 is
\[ \frac{x_1^{a-1}x_2^a}{x_1^{a}x_2^{2a} + y_2^{2a}y_2^{2a}} = \frac{x_1^{2a-1}x_2^{2a}}{(x_1^{a}x_2^{2a} + y_2^{2a}y_2^{2a})^2} = \frac{4x_1}{a \Delta W^{\text{team}}} \]

Given equal talented teams and teammates, (6) leads to the symmetric equilibria, where each member of the team chooses effort \( x^{\text{team}} = \frac{\sqrt{\Delta W^{\text{team}}}}{4} \). In the equilibria teammate effort is positively related with the prize spread as in the individual tournament. Moreover, the effort is positively related with the output elasticity of the team.
In the subgame 3, the organizer decides on the type of tournament and prize spread. As the game has perfect information, the organizer knows equilibrium effort of contestants in each type of tournaments. By substitute \( x^{\text{ind}} \) and \( x^{\text{team}} \) into the formula we obtain the organizer’s utility function for individual and for team tournaments. In the individual tournament the organizer’s utility function is as follows:

\[
V^{\text{ind}} = \frac{\sqrt{\Delta W^{\text{ind}}}}{2 \sqrt{2}} - \Delta W^{\text{ind}} - 2 W^{\text{ind}}.
\]

Maximizing this with respect to prize spread gives an optimal spread \( \Delta W^{\text{ind}}_* = \frac{1}{32} \).

In the team tournament the organizer’s utility function is

\[
V^{\text{team}} = \min\{h^{\text{team}}(x), h^{\text{team}}(y)\} - \Delta W^{\text{team}} - 2 W^{\text{team}}.
\]

Accounting for symmetric Nash equilibrium in the subgame 2, we can rewrite production function as \( \min\{h^{\text{team}}(x), h^{\text{team}}(y)\} = h^{\text{team}}(x^{\text{team}}) \) and (8) is as follows:

\[
V^{\text{team}} = \left( \frac{\sqrt{\Delta W^{\text{team}}}}{4} \right)^{2a} - \Delta W^{\text{team}} - 2 W^{\text{team}}. \tag{9}
\]

Given team tournament, the organizer maximizes (9) with respect to prize spread. First order condition of (9) leads to optimal spread of \( \Delta W^{\text{team}}* = \left( \frac{16^a}{a^{a+1}} \right)^{\frac{1}{a^2-1}} \).

Consequently, if the organizer chooses to conduct an individual or team tournament, he will establish a prize spread \( \Delta W^{\text{ind}}* \) or \( \Delta W^{\text{team}}* \) respectively. Figure 15 compares utilities that the organizer gets with \( \Delta W^{\text{ind}}* \) or \( \Delta W^{\text{team}}* \) established as prize spreads.
Comparing optimal utilities, if \( \alpha < 0.39 \), then the organizer conducts team tournament. With \( \alpha > 0.39 \), the organizer conducts an individual tournament.

Figure 16 compares optimal prize spreads for both tournaments types. If \( \alpha \epsilon [0.05; 0.31] \), then the organizer will conduct team tournament and moreover optimal prize spread in team tournament is higher that prize spread in an individual tournament.
1.1.13 Interpretation and implications for empirical test

1. Organizer utility equals for team and individual tournament at an $\alpha = 0.39$, that is greater than alpha at which optimal team spread equals optimal individual spread ($\alpha = 0.31$).

2. Maximum team spread greater than individual spread for range of alpha $\alpha [0.05; 0.31]$, alpha for greatest of which is smaller than organizer indifference between team and individual tournament in terms of alpha.

3. Team spreads greater than individual spreads for some range of production decreasing returns to scale in effort $\alpha [0.05; 0.31]$; team spreads smaller than individual spreads if increasing returns.
4. Organizer’s decision about optimal tournament type is as follows. When alpha is high, in our case that means an increasing return to scale (alpha more than 0.5), the organizer should choose an individual tournament. The explanation can be as follows. In this case the team has “overmuch potential”. If each member recognizes it, then there are no incentives to exert the maximum level of effort within the team, what leads to free-rider problem. Consequently, the whole team performs at the lower level, than it can. And that is the reason for the organizer not to choose a team tournament. This is presented at the Figure 18.

Given small alpha and declining return to scale (according to the graph alpha less than 0.39), overall team potential is small. In this case teammates individual utility can be maximized only by maximizing utility of the whole team. Free-rider problem is neglected by synergy in the team. And the organizer should choose team tournament.

1.1.14 Empirical test of team rank-order tournament

To test the implications of tournament theory in the context of eSports, we use data on prizes that players win in tournaments. We obtained this information from the results of the eSports Earnings project. This resource is based on freely available public information on different tournaments in eSports, the nicknames of winners and the sums won. The eSports Earnings website contains information on each gamer's prize earnings for each tournament (in dollars) for the period from 1999 to 2014. Nominal prizes are inflation adjusted using the official US inflation rates.

Table 17 presents some descriptive statistics for prizes and prize concentration for the tournaments in our data. A typical tournament has prizes for the top eight winners. For some tournaments, especially individual competitions, this number might be lower. For descriptive purposes, we calculate the Herfindahl-Hirschman Index (HHI) to estimate the concentration of the prizes. HHI is calculated as follows:

$$HHI_i = \sum_{i=1}^{n} \left( \frac{prize_i}{\sum_{i=1}^{n} prize_i} \cdot 100 \right)^2$$
Chapter 2. Meso-level analysis

where \( p_{ri} \) is the prize of the gamer of rank \( i \) and \( n \) is the number of competitors that win a prize. The higher the HHI, the bigger the spread between winners’ prizes. For the perfectly concentrated tournament, where the winner takes all of the prize pool, HHI is equal to 10,000.

As seen from Table 17, the total prize pool varies game by game. However, even for one game, the variation in prize pool is large. For example, for the Multiplayer Online Battle Arena genre, the prizes vary from USD 3 million to USD 10 million. First Person Shooter is the genre with the highest mean prize. HHI varies largely according to genre. For most genres, there are tournaments in which only the winner gets a prize. Mean HHI is about 5,000 to 6,000, with the exception of the Sports Simulator genre, which is significantly more concentrated.

<table>
<thead>
<tr>
<th>Genre</th>
<th>Total prize</th>
<th>HHI</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Min.</td>
<td>Mean</td>
</tr>
<tr>
<td>First person Shooter</td>
<td>25</td>
<td>11,161</td>
</tr>
<tr>
<td>Sports</td>
<td>52</td>
<td>1,142</td>
</tr>
<tr>
<td>Role playing game</td>
<td>500</td>
<td>1,551</td>
</tr>
<tr>
<td>Fighting game</td>
<td>20</td>
<td>2,244</td>
</tr>
<tr>
<td>Multiplayer Online battle arena Collectible card Game strategy</td>
<td>3</td>
<td>25,213</td>
</tr>
<tr>
<td></td>
<td>54</td>
<td>6,700</td>
</tr>
<tr>
<td></td>
<td>18</td>
<td>7,064</td>
</tr>
</tbody>
</table>

Figure 18 illustrates the evolution of the average prize pool and HHI over time. There is a clear positive trend in the total prize pool with a boom in 2011, where the average prize pool doubled. Regarding the spread measured by HHI, there is no obvious trend.
Figure 18. Number of tournaments and HHI dynamics - the shading of the bar reflects the average HHI of a particular year tournaments.

Table 18 contains the mean prize and HHI for different types of game and types of tournament organization. The mean prize for team games is significantly higher, although it should be noted that this prize is divided among the team members. Given that the average team size is four to five, the mean prize per player is more or less the same between team and individual competitions. The concentration of prizes in individual games is slightly higher. Regarding the “location” of the tournament, the mean prize for an offline tournament is much higher than for an online tournament. This is because all of the top tournaments are held offline (so called “LAN” tournaments; LAN is a local area network in contrast to internet-based or online tournaments). The prize structure of online tournaments is more concentrated.

<table>
<thead>
<tr>
<th>Game type</th>
<th>N</th>
<th>Mean HHI</th>
<th>Mean prize</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Team vs. Individual</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- Individual game</td>
<td>5,622</td>
<td>6,692</td>
<td>6,112</td>
</tr>
<tr>
<td>- Team game</td>
<td>3,903</td>
<td>5,893</td>
<td>19,917</td>
</tr>
<tr>
<td><strong>Offline vs. online</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- Offline tournaments</td>
<td>24,863</td>
<td>3,959</td>
<td>27,392</td>
</tr>
<tr>
<td>- Online tournaments</td>
<td>39,968</td>
<td>7,855</td>
<td>2,076</td>
</tr>
</tbody>
</table>
Figure 19 illustrates the relationship between the prize and HHI. As one can see, there are perfectly concentrated team and individual tournaments. Interestingly, the prize pool for most of these tournaments is relatively low which is consistent with the implications in Krishna and Morgan (1998). More formally, testing for equality of the mean prize in winner-take-all versus tournaments with multiple prize winners, the data show that winner-take-all tournaments pay lower prizes on average. Moreover, this difference is substantial for both team ($28,867) and individual competitor ($10,174) tournaments. The winner-take-all tournaments are, therefore, consistent with tournament theory. Including these with the other tournaments may bias the results toward finding support for tournament theory, so we exclude the perfectly concentrated tournaments (HHI=10 000) from further analysis. This represents dropping 40% of the sample, 34% of team games and 62% of the individual games.

![Image](image.png)

Figure 19. Relationship between the prize and the concentration (HHI) of prizes for team (left panel) and individuals (right panel). Scales for both graphs are the same. Although the maximum prize is truncated for the purpose of presentation, this does not affect

Figure 20 shows the spread between prizes for places from first through eighth for team and individual tournaments. The spreads appear as to be expected from tournament theory: the spread for the top ranks is much higher than for the lower ranks. In what follows, we test formally if the prize spreads in eSports follow tournament theory.
Next we estimate the following regression:

\[
\log(prize_{ij}) = \alpha + \sum_{j=1}^{7} \beta_j rank_{ij} + \gamma totalprizespaid_i + \sum \beta_g game_{ig} \\
+ \sum \beta_k country_{ik} + \sum \beta_t year_{it} + \varepsilon_{ij},
\]

where \(i\) indexes the tournament and \(j\) the rank, \(rank_{ij}\) represents dummy indicators of the final tournament rank \(j\) of the gamer/team in the \(i\)th tournament. \(totalprizespaid_i\) is the $US value of all prizes paid in the \(i\)th tournament.. The eighth rank is the omitted category. The dummy indicators \(game_{ig}, country_{ik}\) and \(year_{it}\) represent controls for game, country of tournament and year, respectively. We use OLS with robust standard errors for the estimations. The theory is about differences in the level of prizes, not differences in log of prizes. Lambert, Larcker and Weigelt (1993) estimate the model in logs while and Conyon, Peck and Sadler (2001) estimate it in levels. We have done it both ways and both sets of results are consistent. Lambert, Larcker and Weigelt (1993) include several variables identifying the size of the company, group or division overseen by a specific executive as a determinant of the salary; Conyon, Peck and Sadler (2001) account for firm size using total capital employed. Our \(totalprizespaid_i\) is included to capture this size effect.
The first hypothesis we test supposes the convex relationship between rank and prize. In such a case, we should observe the following conditions:

$$\beta_7 \geq 0$$

$$(\beta_6 - \beta_7) \geq \beta_7$$

$$(\beta_5 - \beta_6) \geq (\beta_6 - \beta_7)$$

$$(\beta_4 - \beta_5) \geq (\beta_5 - \beta_6)$$

$$(\beta_3 - \beta_4) \geq (\beta_4 - \beta_5)$$

$$(\beta_2 - \beta_3) \geq (\beta_3 - \beta_4)$$

$$(\beta_1 - \beta_2) \geq (\beta_2 - \beta_3)$$

In words, seventh place has a larger prize than eighth place, the increment for sixth over seventh is greater than the increment of seventh place over eighth place, and so on. Each move up the ranking gives a larger boost to the payoff than did the previous move up in rank. This test procedure is outlined in Lambert, Larcker and Weigelt (1993) and Conyon, Peck and Sadler (2001). One can test each successive difference individually or test them jointly. For example, testing each successive difference implies seven tests, the one sided hypothesis test that the coefficient $\beta_7$ is positive followed by tests of the null hypothesis that $\beta_{i+2} \beta_{i+1+} \beta_{i+2}=0$, $i=1,...,6$, and $\beta_8=0$. Given there are seven tests, there are seven alternative hypotheses and some nulls may be rejected while others are not. Of course, each successive test is conditional on the conclusion from the previous test. Testing them jointly, the null hypothesis is $\beta_1 - \beta_2= \beta_2 - \beta_3= \beta_3 - \beta_4= \beta_4 - \beta_5= \beta_5 - \beta_6= \beta_6 - \beta_7= \beta_7$. The alternative hypothesis is that at least one of the equalities does not hold. We have done both types of tests and will report on them in the next section.

### 1.1.15 Discussion of empirical results

The results of the regression analysis are presented in Table 19. Models 1 to 3 are estimated based on the total sample, while models 4 to 6 are estimated only on data from offline tournaments and models 7 to 9 concern only online tournaments. Models 4 and 7 are the offline versus online subsamples of the full sample, models 5 and 8 are the offline and online subsamples of the team observations, and models 6 and 9 are the offline and online subsamples of the individual gamer observations. Each specification includes year, game and tournament host country indicator variables as well as rank positions one through seven and the dollar value of all
prizes paid by the tournament. As estimated here, all coefficients are allowed to vary between online and offline and between team and individual games. An alternative approach is to use interaction terms of the rank variables with identifiers for whether the observation represents a team, comes from an online tournament or both. Results of these estimations are available upon request but will be described below.

Consider model 1. Each of the set of year, host country, and game identifiers reject the null of all zero coefficients. An extra thousand dollars in prize money raises the prize to any given rank by about one-tenth of a percent. However, some games pay out total prizes in the hundreds of thousands and even millions of dollars. Suppose that a game raises its total prize payout by $50,000. Each individual prize would rise by 5%. This positive effect of size is consistent with the findings of (Conyon, Peck, and Sadler 2001; Lambert, Larcker, and Weigelt 1993). Competitions played online earn lower prizes than LAN tournaments. The coefficient, -0.70299, implies online game prizes are about 50% lower than those for LAN tournaments, all other things held constant.

The coefficients of most interest are those on the rank variables. Each of the first five rank coefficients is significantly different from zero at the 5% level. Neither the rank 6 nor the rank 7 coefficients is statistically different from zero. Since $\beta_6$ and $\beta_7$ are not different from zero, we treat them as zero. Doing so, the results indicate that $\beta_5 > 0, \beta_4 > \beta_5, \beta_2 = \beta_3, \beta_4$ and $\beta_1 = \beta_2 = \beta_3$. However, $\beta_3 - \beta_4 < \beta_4 - \beta_5$, contrary to the theory. More precisely, the coefficient on rank 1 is nearly double that on rank 2 which is more than double that on rank 3. The rank 3 coefficient is only slightly larger than the rank 4 coefficient which is about 3 times larger than the rank 5 coefficient. Each coefficient indicates how the prize at a specified rank differs from the prize for eighth place. Converting these coefficients to percentage differences, first prize is over 400% larger than eighth prize, second prize is nearly 140% larger, third prize is 48% larger, fourth prize 40% and fifth prize 11% larger than the eighth place prize. Clearly, while not perfect in matching the predictions of tournament theory, the evidence is strongly supportive of that theory.

The formal hypothesis tests described in the previous section are also supportive of the theory. One easily rejects the null hypothesis of no differences in the increments in favor of the alternative that at least one increment is bigger than
the previous increase in prize money. The F-statistic, with 6 and 17326 degrees of freedom, is 170.69. Taking each step individually, only the increases from 7th place to 6th place and from 6th to 5th place cannot reject the null of equality.

Model 2 presents similar evidence except only for team games. Through the first five places, the coefficients decline as place of finish becomes worse. The joint hypothesis test that all increments are equal is again rejected, $F(6,7460)=79.19$. Only the increment from third to second over that from fourth place to third place, and the boost from second place to first prize over the boost from third to second place are statistically significant in the team game subsample. These results are, perhaps, somewhat weaker than in model 1. Interestingly, the boosts to prizes for specific ranks are affected less by the total payout in team games than in the sample of all games. Additionally, online game prizes are reduced even more relative to LAN prizes in the team game subsample.

Model 3 looks at prizes in individual games. Total prize money has a far larger effect on prizes in the individual game setting than in the team game setting. An extra thousand dollars in total prizes increases the prize at each rank by about 2.7%. Even more interesting is the finding that online games are not penalized at all with respect to prizes compared to LAN games in the individual game setting. As for the prize structure, the data reject the null that all increments in prizes from one rank to the next are equal, $F(6,9808)=124.86$. In the tests of each step up the prize ranking, the null of equal steps cannot be rejected for the move from 7th to 6th equal to that from 8th to 7th and from 7th to 6th compared to 6th to 5th.

Specific discussion of models 4 through 9 is omitted to avoid redundancy. In each case, the rank coefficients show the basic tournament theory predictions through the first four or five places. Sixth and seventh place are generally not individually significant and the increase in the prize from 8th to 7th and from 7th to 6th place never reject the null of equality. The effect of an increase in the total prize pool is always statistically significant and always substantially larger in the individual than in the team tournaments. The effect of the prize pool is also larger in online than in offline tournaments, though this is at least partially explained by online prizes starting from a smaller base of prizes than offline tournaments.

The last issues we address are whether the effect of rank on prize is different between online and offline games and between team and individual games. As
indicated previously, the results in Table 19 allow all coefficients, including the year, host country and game type, to vary. Here we impose equality of the year, host country and game type effects and allow only the coefficients on the ranks and the total prizes paid to vary. In the first case, we interact ranks and total prizes with the dummy variable identifying online tournaments; in the second we include interactions of the ranks and total prizes with the dummy variable identifying online games; in the third, both sets of interactions are included as is a set of interactions of rank and total prizes with both the team and the online dummy. Table 20 reports the results of these estimations.

The primary results are simply that online versus offline matters, team versus individual matters and putting all the interactions in the same model, all interactions, including the three way interactions are jointly significant. The very large team rank interaction coefficients might seem unreasonable but it is important to remember that the prizes in the team games must be shared, generally with 3 or 4 others. Consequently, team size explains in large measure the very large boost in team game rank coefficients over those of individual games. The fully interacted model makes clear that while online matches suffer relative to offline tournaments in terms of prizes paid, the effect is not as large for the team online matches. A further interesting result is that in the fully interacted specification all eight ranks interacted with team are individually statistically significant. Moreover, from rank 1 through rank 5 the coefficient rises as the team rank becomes worse. From rank 5 through 8 the boost from the team game compared to the individual game is very similar. In other words, the boost from competing in a team rather than an individual game is larger at rank 8 than at rank 1.

Table 19. Regression results of tournament theory test

<table>
<thead>
<tr>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
<th>(9)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Offline + Online</td>
<td>Offline</td>
<td>Online</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All</td>
<td>Team</td>
<td>Individual</td>
<td>All</td>
<td>Team</td>
<td>Individual</td>
<td>All</td>
<td>Team</td>
<td>Individual</td>
</tr>
<tr>
<td>Rank 1</td>
<td>1.6372*</td>
<td>1.6967*</td>
<td>1.9684**</td>
<td>2.0027*</td>
<td>1.9668*</td>
<td>2.2974**</td>
<td>1.4851*</td>
<td>1.5502*</td>
</tr>
<tr>
<td></td>
<td>(0.0440)</td>
<td>(0.0625)</td>
<td>(0.0475)</td>
<td>(0.0475)</td>
<td>(0.0711)</td>
<td>(0.0501)</td>
<td>(0.0726)</td>
<td>(0.1062)</td>
</tr>
<tr>
<td>Rank 2</td>
<td>0.8747*</td>
<td>0.9559*</td>
<td>1.1886**</td>
<td>1.2409*</td>
<td>1.2413*</td>
<td>1.5028**</td>
<td>0.7214*</td>
<td>0.7854*</td>
</tr>
<tr>
<td></td>
<td>(0.0441)</td>
<td>(0.0628)</td>
<td>(0.0476)</td>
<td>(0.0475)</td>
<td>(0.0712)</td>
<td>(0.0501)</td>
<td>(0.0728)</td>
<td>(0.1068)</td>
</tr>
<tr>
<td>Rank 3</td>
<td>0.3921*</td>
<td>0.5206*</td>
<td>0.6367**</td>
<td>0.6497*</td>
<td>0.6882*</td>
<td>0.8419**</td>
<td>0.2978*</td>
<td>0.4596*</td>
</tr>
<tr>
<td></td>
<td>(0.0451)</td>
<td>(0.0635)</td>
<td>(0.0493)</td>
<td>(0.0476)</td>
<td>(0.0712)</td>
<td>(0.0508)</td>
<td>(0.0758)</td>
<td>(0.1106)</td>
</tr>
</tbody>
</table>
Chapter 2. Meso-level analysis

### Table 20. Regression results for the tournament theory test models with interactions

<table>
<thead>
<tr>
<th>Rank</th>
<th>Online interactions</th>
<th>Team interactions</th>
<th>Team and online interactions</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.9568*** (0.0476)</td>
<td>1.9481*** (0.0479)</td>
<td>2.2937*** (0.053)</td>
</tr>
<tr>
<td>2</td>
<td>1.1950*** (0.0476)</td>
<td>1.1684*** (0.0480)</td>
<td>1.4992*** (0.053)</td>
</tr>
<tr>
<td>3</td>
<td>0.6054*** (0.0478)</td>
<td>0.6272*** (0.0498)</td>
<td>0.8441*** (0.053)</td>
</tr>
<tr>
<td>4</td>
<td>0.4944*** (0.0505)</td>
<td>0.5582*** (0.0528)</td>
<td>0.6822*** (0.057)</td>
</tr>
<tr>
<td>5</td>
<td>0.1300*** (0.0548)</td>
<td>0.1213*** (0.0576)</td>
<td>0.1519*** (0.060)</td>
</tr>
<tr>
<td>6</td>
<td>0.1052*** (0.0554)</td>
<td>0.0998* (0.0576)</td>
<td>0.1295** (0.060)</td>
</tr>
<tr>
<td>7</td>
<td>0.0374 (0.0567)</td>
<td>0.0241 (0.0582)</td>
<td>0.0323 (0.060)</td>
</tr>
<tr>
<td>Total prizes paid</td>
<td>0.0009*** (0.0001)</td>
<td>0.0262*** (0.0007)</td>
<td>0.0203*** (0.001)</td>
</tr>
<tr>
<td>Rank 1 × Online</td>
<td>-0.4668*** (0.0859)</td>
<td>-0.7980*** (0.095)</td>
<td></td>
</tr>
<tr>
<td>Rank 2 × Online</td>
<td>-0.4684*** (0.0860)</td>
<td>-0.7665*** (0.096)</td>
<td></td>
</tr>
<tr>
<td>Rank 3 × Online</td>
<td>-0.2906*** (0.0888)</td>
<td>-0.5636*** (0.100)</td>
<td></td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1
The Economics Of Esports: Elements That Affect Performance

<table>
<thead>
<tr>
<th>Term</th>
<th>Coefficient</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rank 4 × Online</td>
<td>-0.2434***</td>
<td>(0.0929)</td>
</tr>
<tr>
<td>Rank 5 × Online</td>
<td>0.0022</td>
<td>(0.1061)</td>
</tr>
<tr>
<td>Rank 6 × Online</td>
<td>-0.0244</td>
<td>(0.1079)</td>
</tr>
<tr>
<td>Rank 7 × Online</td>
<td>-0.0514</td>
<td>(0.1137)</td>
</tr>
<tr>
<td>Total prizes paid × Online</td>
<td>0.0312***</td>
<td>(0.0018)</td>
</tr>
<tr>
<td>Rank 1 × Team Game</td>
<td>1.2802***</td>
<td>(0.1137)</td>
</tr>
<tr>
<td>Rank 2 × Team Game</td>
<td>1.3184***</td>
<td>(0.1136)</td>
</tr>
<tr>
<td>Rank 3 × Team Game</td>
<td>1.4181***</td>
<td>(0.1147)</td>
</tr>
<tr>
<td>Rank 4 × Team Game</td>
<td>1.3352***</td>
<td>(0.1182)</td>
</tr>
<tr>
<td>Rank 5 × Team Game</td>
<td>1.6285***</td>
<td>(0.1282)</td>
</tr>
<tr>
<td>Rank 6 × Team Game</td>
<td>1.6041***</td>
<td>(0.1297)</td>
</tr>
<tr>
<td>Rank 7 × Team Game</td>
<td>1.5753***</td>
<td>(0.1327)</td>
</tr>
<tr>
<td>Rank 8 × Team Game</td>
<td>1.5764***</td>
<td>(0.1320)</td>
</tr>
<tr>
<td>Total prizes paid × Team Game</td>
<td>-0.0253***</td>
<td>(0.0007)</td>
</tr>
<tr>
<td>Rank 1 × Team Game × Online</td>
<td>0.4331***</td>
<td>(0.070)</td>
</tr>
<tr>
<td>Rank 2 × Team Game × Online</td>
<td>0.3642***</td>
<td>(0.071)</td>
</tr>
<tr>
<td>Rank 3 × Team Game × Online</td>
<td>0.3829***</td>
<td>(0.084)</td>
</tr>
<tr>
<td>Rank 4 × Team Game × Online</td>
<td>0.0893</td>
<td>(0.101)</td>
</tr>
<tr>
<td>Rank 5 × Team Game × Online</td>
<td>0.1010</td>
<td>(0.137)</td>
</tr>
<tr>
<td>Rank 6 × Team Game × Online</td>
<td>0.0489</td>
<td>(0.147)</td>
</tr>
<tr>
<td>Rank 7 × Team Game × Online</td>
<td>-0.1041</td>
<td>(0.166)</td>
</tr>
<tr>
<td>Rank 8 × Team Game × Online</td>
<td>-0.0223</td>
<td>(0.148)</td>
</tr>
<tr>
<td>Total prizes paid × Team Game × Online</td>
<td>-0.0048**</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Game, Year, Country dummies</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Included</td>
<td>6.3985***</td>
<td>(0.3230)</td>
</tr>
<tr>
<td>Included</td>
<td>5.3487***</td>
<td>(0.2696)</td>
</tr>
<tr>
<td>Included</td>
<td>5.2186***</td>
<td>(0.283)</td>
</tr>
<tr>
<td>Observations</td>
<td>17,435</td>
<td></td>
</tr>
<tr>
<td>R-squared</td>
<td>0.6690</td>
<td>0.6760</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

The baseline category for the model (1) is Rank 8, for the model (2) – Rank 8 in the individual games, model (3) – Prize in individual offline games.
Figure 21 presents a comparison of prize spreads, which take into account both dimensions. It only contains coefficients for those ranks that significantly differ from lower ranks, for example, \((\beta_1 - \beta_2) \geq (\beta_2 - \beta_3)\), as discussed in the methodology section. As this graph shows, even for offline tournaments, the spreads are different with respect to the game type (individual and team). This difference is much higher for online tournaments. There is a difference between the motivation of groups and individuals, such that this difference increases along with the reward and the status of the competition. The structure of incentives might reflect the fact that they are designed to attract different types of players.

![Figure 21. The comparison of prize spreads (only which are convex in rank order) of different types of tournaments and games](image)

### 1.4 Conclusions on the meso-level analysis

In this section we performed meso-level analysis with a market or an industry as a unit of observation. First, we use eSports data to construct an empirical model to measure the effect of competitiveness of the league to its popularity. After we concentrate on the tournament analysis from the view of organizers. We test if there are spillover effects in promotion through events and later analyze the motivation scheme in team tournaments.

Regarding the first part, we have tested the contestable theory using data from one of the non-conventional industries which evidently has a tendency to converge
to natural oligopolistic or monopolistic competition and has not been affected by any regulation so far. eSports is considered an emerging, fast-growing market in professional sports, attracting significant financial resources and inducing new individuals and teams to enter tournaments. This issue appears to be relevant for the research exercise, contributing to empirical evidence of the well-known contestable hypothesis. We believe that eSports also represents a unique case of a pure self-developing market and can be considered as a good example for reshaping sports governance, which is not usually questioned in other professional sports. Furthermore, eSports provides us with a relevant setting to estimate this effect mainly because of the absence of country-specific law regulations. Eventually, a number of interesting findings that are highlighted hereafter provoke a discussion of governance regimes not only for eSports but also for other industries and markets.

For this study, prize money paid has been used as a proxy of the size of the market. The main result is that competition does not increase industry size. Size is mainly explained by the number of tournaments in the previous year. We could expect that as the number of tournaments is increasing, the absolute money paid increases as well. The number of teams and number of tournaments also positively affect industry size with a one-year lag.

Interestingly, the reverse relation is significant: industry size decreases competition, but the effect disappears after one year. In fact, what has been observed is that the prizes tend to concentrate in a smaller number of competitors. The other effect that we have observed is that the number of teams and new entries affects competition with a significant time delay and a controversial outcome. It could have been expected that with higher number of competitors, competition would increase. However, here it has been found that as there are no entry barriers, new competitors can enter, but their chances to get a share of the market are scarce. At the same time, strong competitors are getting stronger and dominating the prize pool. This can lead in the medium-term to the differentiation of leagues that are now appearing and result in an industry with a concentration of talent in those competitors that will be able to attract money, as currently happens with the “traditional” sports leagues.
Chapter 2. Meso-level analysis

With respect to the second part, we conclude that events in general increase sales, but marginal effect varies. The saturation point is about 83. Over that number of tournaments, the marginal effect on copies sold will decline. This result is in line with findings of Martensen, Grønholdt, Bendtsen, and Jensen (2007), who study the influences of events on the buying intention. However, in our case the results are about real purchases rather than the intention to purchase. Also, this is in line with the studies of Zarantonello and Schmitt (2013) and Vila-López and Rodriguez-Molina (2013), who argue that event marketing can help companies to achieve their marketing objectives, such as increasing sales. eSports tournaments belong to this kind of event or experiential marketing. Organizing tournaments provide attendees with the excitement of an experience at the highest level of competition that can make them prone to acquire games. This study could be complemented with an analysis in monetary terms. It would be interesting to observe the variation in prices and also to study if the increment in sales (monetary terms) would cover the cost of organizing the tournaments.

With respect to spillovers, we find an empirical evidence of regional spillover and between-genre spillover. There is no evidence of in-genre spillover. An optimal strategy of a company is to organize events in different regions, because they help to promote products in all regions. Organizing events to promote another product of a particular company well be also beneficial for the all of the products of company. This is in line with the findings of studies of between-category effects (Hruschka, Lukanowicz, and Buchta 1999; Leeflang et al. 2008). However, according to our data, a company neither benefits from nor is harmed by the events of the other companies, even when they are promoting nearly the same product. In that sense, the publishers that decide to promote their products organizing events do not have to fear free-riders.

For the third part, base on the Lazear and Rosen’s tournament theory which is devoted to optimal labor contracts. It has been supported by many subsequent pieces of empirical research in different fields (Choi and Gulati 2004; Depken and Wilson 2004b; Knoeber and Thurman 1994; Melton and Zorn 2000; Messersmith et al. 2011). In our study we find empirical evidence that prize spreads in eSports tournaments follow the tournament theory of Lazear and Rosen (1981) and Rosen
Taylor organizers teammates. course, share terms team for Interestingly, games second tournaments tournaments. tournaments between (Conyon, Peck, and Sadler 2001; Lambert, Larcker, and Weigelt 1993) in terms of risk-aversion.

Interestingly, for the low-level (online) tournaments the prize spread is smaller. Since in tournament theory prize spread can be treated as an indicator of the degree of risk-aversion, this suggests that the risk aversion of contestants varies between online and offline competitions. Moreover, this finding suggests that in tournaments without much at stake, participants may be more risk loving than in tournaments with large prizes on the line. It is also possible that these low-level tournaments attract predominantly hobbyists whose primary purpose in playing in tournaments is to find better competition than they find otherwise. Taylor (2012) suggests the move from playing against one’s friends to playing in online tournaments is a step toward becoming a professional gamer. Prize money is of second order importance to these players.

The results for the team games are similar to the results for the individual games to the extent that they follow tournament theory. However, there is significant difference between the motivation of groups and individual. Interestingly, this difference depends on the level of competition. The size difference for team tournaments compensates for the fact that prizes are shared equally in the team tournaments. This raises interesting questions about production in teams and payoffs to performance. For example, is it optimal to share prize money equally in terms of incentivizing effort? Team members face a moral hazard because their share of the prize is the same with or without great effort (Holmstrom 1982). Of course, in the eSport setting, it is likely quite easy to observe shirking in your teammates. Moreover, eSport teams often live together (Taylor 2012, 46). Team organizers frequently pay players in-kind, with room and board, as well as a salary (Taylor 2012, 257). The room and board brings the team members together in a single location where they practice intensively. One hypothesis is that building the
team through cohabitation minimizes the possible shirking outside the game, that is, not practicing sufficiently. Contracts are notoriously short in eSports (Taylor 2012, 152), so cohabitation may also be a way of minimizing team member contact with other team organizers.
Chapter 3. Micro-level analysis

1.5 Team composition, diversity and performance

1.1.16 Diversity in eSports: motivation

Alchian and Demsetz (1972) first discussed production in a team setting with the focus on how team members can be rewarded and induced to work together efficiently; Marschak & Radner (1972) address the structure of teams, particularly with respect to sharing of information. The issues of organization and reward are especially topical today because labor markets, and production teams, are increasingly internationalized due to globalization (Rama 2003). Team composition and team diversity issues may be important factors that influence team performance. On the one hand, multinational teams may offer a greater variety of skills, knowledge and perspectives that are culturally determined and which raise productivity. On the other hand, highly diverse teams might involve higher integration and communication costs than culturally homogenous teams. Alesina and La Ferrara (2005) survey the literature on diversity and economic performance.

The relationship between diversity and performance is difficult to estimate empirically in the general business production context due to a lack of data on team members’ nationalities and other sources of diversity. However, sports provide a good setting in which to test for such an effect, and has been the focus of several papers (Brandes, Franck, and Theiler 2009; Franck and Nuesch 2010; Ingersoll, Malesky, and Saiegh 2014b; L. Kahane, Longley, and Simmons 2013). We use eSports data to understand whether diversity affects team results. eSports is competitive video gaming; in the literature section below, we provide a definition and a discussion of eSports competitions. We believe that professional eSports teams are much more similar to commercial firms, that operate in the “new economy”, than teams in other sports. First, the result depends more on mental abilities than on physical excellence. Second, language differences may heavily influence the result both in firms and eSports teams because they require communication and high level of understanding. Third, an eSports team maximizes its result like a firm tends to maximize its profit. Reward in eSports is mostly performance-based while in a majority of traditional sports a significant share of an athlete's compensation is independent of current match results.
In Counter-Strike: Global Offensive (CS:GO) teams, the particular game we analyze, there are representatives from 23 countries. By contrast, there were only 20 nations represented on the National Hockey League teams analyzed by (L. Kahane, Longley, and Simmons 2013). There are 17 nationalities represented in Major League Baseball, and 15 in the National Football League. Among North American professional sports, the National Basketball Association has the most countries represented among its players, 41. The most diverse sport leagues are the football leagues of Europe. For example, an article on ESPN FC dated August 11, 2015, reported that there were 64 different nationalities represented in the English Premier League, 55 in the Bundesliga, 51 in Serie A, 50 in La Liga, and 48 in Ligue 1.16 In the next section, we provide a discussion of other features of eSports that allow us to extend our findings to broader sport and business contexts.

We construct an empirical model to measure the effect of diversity of different types on team performance. Following the previous studies of Ingersoll et al. (2014), Kahane et al. (2013) and Ottaviano & Peri (2005), we consider cultural diversity, reflected by the country of origin of each teammate. We also try to understand which cultural characteristics are important, evaluating the effect of diversity in Hofstede characteristics, which describe dimensions of national cultures (Hofstede 1984). Since in a more globalized world cultural diversity might be less important, we also analyze the effect of language diversity. American players might have different cultural backgrounds than, say, their UK teammates, however, they both speak the same language. That might be more important than their cultural differences. Finally, we consider an effect of diversity in skill and experience. A team may be only as strong as its weakest link, so one poor player may waste the efforts of many talented teammates; a team of average or slightly above average players could be better than a team of several excellent players with one weak player.

1.1.17 Diversity in economics and management studies
Two seminal papers by Lazear (1999a, 1999b) study culturally diverse work teams and how they might affect the labor market decisions of a firm. However, Lazear develops only a theoretical model, arguing that “at the empirical level, it is difficult,
if not impossible, to obtain direct measures of who works with whom. Even if this could be done, it would then be necessary to obtain information on the characteristics, skills, and knowledge of the individuals who are engaged in team production” (Lazear, 1999b, p.37). Prat (2002) addresses the question of whether it is optimal for teams to be homogeneous or heterogeneous. Teams are modeled as groups of individuals who are joint payoff maximizers and the impact of their decisions may be complementary or they may be substitutes. Prat’s results indicate when the decisions of the members are complementary that homogeneous groups are better but when the impacts are substitutable heterogeneous groups have higher payoffs.

Some papers have tried to empirically test the relationship between diversity and performance in general (Ottaviano and Peri, 2005, 2006) or in specific non-sport industries (Hamilton et al., 2003; Leonard and Levine, 2003). For example, Ottaviano and Peri (2005) find that average wages and employment density are higher in US cities that have greater linguistic diversity. Moreover, Ottaviano and Peri (2006) also show that the productivity of the native population rises as the workforce becomes more culturally diverse. Hamilton et al. (2003) analyze teams working on sewers and find that greater diversity in skills across workers leads to higher team productivity. Leonard and Levine (2003), by contrast, found no evidence that variation in sales (and sales growth) in retail stores are predicted by the degree of gender or ethnic diversity of those stores. Their evidence does indicate, however, that sales are negatively affected by age diversity. A weakness of these papers on diversity of teams is that they often study only one firm, focusing largely on low-skill workers or industries with low coworker interaction.

Team diversity in sports presents an opportunity to test hypotheses regarding interaction of team members precisely because workers bring varied skills to the team and must communicate to perform effectively. Sport teams may be more homogeneous than other firms in some regards, for example, there is often no gender diversity and age diversity is rather limited, but ethnic and skill diversity can be quite substantial. Moreover, sports teams’ interactions are far more transparent than are interactions among workers in firms. For instance, Timmerman (2000) studies the effect of age and racial diversity on team performance in basketball and baseball. He finds that age diversity and racial diversity are negatively associated
with basketball team performance. Regarding baseball, neither diversity indicator shows any effect on performance. This might be a result of lower importance of coworker interaction in baseball. Later, Idson and Kahane (2004, 2000) examine the NHL and find that teammates’ attributes affect the pay of other individual players. Kahane et al. (2013) also find that the presence of foreign players increases NHL team-level performance, but teams perform better when European players all come from the same country rather than from numerous European countries. This finding suggests benefits arising from communication but also perhaps a shared playing style. Smith and Hou (2014) analyze structurally redundant heterogeneity. They define this as heterogeneity among people within a hierarchical level where homogenous subgroups exist between levels. Using NBA data, they find that redundant heterogeneity positively affects performance. Stura and Lepadatu (2014) underline that diversity might have both positive and negative effects on performance in sports contexts.

A number of papers have addressed football team diversity (Brandes, Franck, and Theiler 2009; Franck and Nuesch 2010; Ingersoll, Malesky, and Saiegh 2014b). Brandes et al. (2009) attempts to test the model of Lazear, (1999a) specifically with respect to different cultures having different inherent capabilities, the extent to which these capabilities are relevant for production, and the ability of teammates to learn them. While the evidence is that productivity differs by culture, Brandes et al. (2009) do not find evidence that these differences matter for team production. Franck and Nuesch (2010) focus on the difference between the homogeneity of the players on the pitch and the players on the roster. They argue that greater homogeneity among the players on the pitch will lead to greater performance of the team; a team is only as strong as its weakest link. On the other hand, greater heterogeneity within the roster may be better for training and developing skills. Franck and Nuesch (2010) posit a team production function in which individual playing abilities enter both additively and multiplicatively. The marginal productivity of an individual player’s ability will, if the multiplicative term coefficient is not zero, depend upon the playing talent of his or her teammates. If the coefficient is positive, each player is more productive the greater the product of the abilities of the teammates. For a given average ability, this product will be largest when ability is homogeneous. On the other hand, when the coefficient is
negative, individual player marginal productivity will be greatest when the disparity in ability is greatest. Examining the players on the pitch, what they call the competition team, they find that higher mean ability and lower variation in ability both increase team productivity at the match level. However, looking at productivity over the season, higher mean ability and higher variation in ability produce greater team productivity.

Ingersoll et al. (2014) utilize data on the UEFA Champions League. They argue that existing papers that focus predominantly on the Bundesliga suffer from a selection problem. The wealthy clubs are best able to afford expensive foreign players so there may be a spurious correlation. By focusing on the Champions League clubs, they contend, the influence of this wealth disparity may be minimized. In addition, they address the cultural diversity in unique ways. In the main specification they measure linguistic distance among the players on the squad, finding robust evidence that greater diversity leads to a larger per game goal differential. The impact is sufficiently large that added diversity could make the difference between advancing and not advancing in the tournament. As a robustness check, Ingersoll et al. (2014) use data measuring attributes of culture from Hofstede (1984); this is a direct approach to including cultural diversity that is a unique contribution. Specifically, Ingersoll et al. (2014) construct a measure of culture diversity from Hofstede’s (1984) “individualism” variable. The variable is analogous to the linguistic distance in averaging the distance between players on the individualism metric. In no case do Ingersoll et al. (2014) estimate a model that includes both language and cultural diversity.

This study uses data on team diversity in an emerging sport: eSports. eSports is competitive computer gaming. While 10 years ago, these competitions were primarily organized by and for amateurs, they have since become much more professionalized (Bernard and Busse, 2004) and include a rapidly growing fan base. Approximately 115 million hardcore enthusiasts watched eSports in 2015 and another 115 million were occasional viewers. Those numbers are expected to continue to increase, reaching a projected 427 million by 2019 (Rowell, 2016). Despite its growing popularity and huge audience, the literature on eSports is very limited. The majority of existing papers focus on the definition of this phenomenon (Seo 2013a; Seo and Jung 2014; Taylor and Witkowski 2010; Taylor 2012). Even
among these papers, there is no commonly accepted definition of eSports. For example, Wagner (2006) defines eSports as “an area of sport activities in which people develop and train mental or physical abilities in the use of information and communication technologies”. This definition was later criticized by Witkowski (2012) because many aspects of traditional sports are computer-assisted or computer-mediated, so the definition does not distinguish such gaming from traditional sports. Hamari and Sjöblom (2015) regard eSports as “a form of sports where the primary aspects of the sport are facilitated by electronic systems; the input of players and teams as well as the output of the eSports system are mediated by human-computer interfaces”.

We believe that eSports team diversity and its influence on team performance warrants attention for several reasons. First, a lot of eSports teams are not diverse at all. This is quite unusual for top sports leagues. Top European soccer leagues, like English Football Premier League, Spanish La Liga or German Bundesliga are diverse in terms of team composition. Among the top US leagues, NHL seems to be the least diverse, the NFL and MLB somewhat more diverse, and the NBA the most diverse, but all of them are diverse to some extent. So, eSports provide us with a good setting to test the effect of diversity on team results. Second, the skills of eSports players are more akin to those required in modern professions than are the skills of hockey or basketball players. Computer knowledge and communication by internet are more important for employees than is physical development. Third, the role of the players is paramount in eSport teams. The coach is not nearly as significant as in traditional sports. Indeed, many teams that participate in large tournaments do not even have a coach. Fourth, it is very easy to initiate participation: gamers do not need expensive equipment or training with the best coaches to become competitive. Each team can begin by entering less prestigious online tournaments. Moreover, there are few barriers to entry in the form of rigidly rule-bound closed leagues and other structures that limit entry to traditional professional sports. This suggests eSports has a more efficient labor market than in traditional sports. Fifth, Parshakov and Zavertiaeva (2015) find that gamers’ countries of origin influence performance, indicating that some skills or knowledge is country-specific. Consequently, country diversity within a team may be an important issue. To conclude, we believe that the
eSports context provides a good setting within which to test the effect of diversity on performance.

1.1.18 Research framework of empirical test of diversity effect

To estimate the effect of diversity on performance, which we measure as total earnings (or prize money) for a year, we use data on the top 100 teams in CS:GO for the period of 2013-2015. CS:GO is a multiplayer strategic first-person shooter game. There are five members in each team per match but the team roster can change during the season. Each team is either the Terrorist or Counter-Terrorist team and attempts to complete specific objectives or eliminate, kill, all members of the enemy team. For some maps there might be a natural advantage to be on the terrorist or counterterrorist team, however, since during the game each team plays both sides for each map, there is no advantage for the entire game.

The game operates in short rounds that end when all players on one side are dead or a team’s objective is completed. Players purchase weapons and equipment at the beginning of every round using money awarded based on their performance in the previous round. Each weapon has its own price, which usually depends on the damage output. Sniper guns are one of the most powerful, the rivals can be eliminated with one shot from long distance. It should be highlighted that the choice of weapon might affect individual player statistics, since sniper weapons provide a player with an advantage. However, because such weapons are expensive, teams usually would not buy more than one sniper gun which means the composition of team weapons is very consistent: the distribution of weapons is available at https://www.hltv.org/stats. The four most popular weapons (ak47, m4a1, awp, m4a1silencer) are 80% of the total weapon variety. This makes team-level performance indicators reliable.

CS:GO fits the purpose of this study as there are clear roles in CS:GO teams. Usually the roles are in-game leader (IGL), lurk, sniper, support and entry. These roles have different primary tasks. However, Drenthe (2016) also shows that there are “informal roles” in the game. Having roles in a team implies that cultural diversity might be important, since the particular cultural background of a team member might be important for a particular role. Furthermore, because the roles differ, communication between the players will be important. Since the reward in
eSports is performance-based (Coates and Parshakov 2016a), a team and the individuals within that team share the same incentives.

As may be obvious, several types of diversity are of interest in the literature. The first type is diversity of skills. The issue here is whether it is better for the team for all players to be equally skilled at all phases of the game, for a given average level of skill, or for each player to be a specialist in some role. We will call this skill diversity. Of course, in addressing the importance of diversity in skill we must also control for the average level of skill. Game statistics are aggregated to capture the overall ability of the team, and the standard deviation between team members in these statistics measures skill diversity.

Individual skill is captured by the headshot percentage variable. In the game, a headshot is a definite kill of an opposing player. Any other hit to an opposing player may leave that player capable of continuing in the game. The basic indicator of team skill is the kill-to-death (KD) ratio. Obviously, being killed fewer times than the number of opponents you kill indicates a greater likelihood of winning the match and earning prize money. Experience is also a possible determinant of good performance. Experience is reflected in the number of played by a player. For example, teams that are eliminated early in tournaments will play fewer maps in the tournament and hence have less experience. Alternatively, very good teams may win each match with a minimum of lost maps, and that team would thus also have a small number of maps played. Consequently, both very good and very bad teams may have a small number of maps played. As our data cover only the top 100 teams, it is unlikely that we have any very bad teams. Nonetheless, the top five or ten teams are clearly better at the game than the teams in the bottom half of the list. Consequently, one issue to address is how to identify the distinct impact of number of maps played between the good and the bad teams. All of these indicators are averaged by team. Since there are team members who participate in relatively few games, we construct weighted averages of the headshot percentage and KD ratio with a player’s share of the number of maps played as his weight.

We also calculate weighted standard deviations of these variables as indicators of the diversity of skill within a team. A higher standard deviation in, say, headshot percentage means that the players on the team are not equally adept at this skill.
However, this disparity may be good if the sniper has a very high headshot percentage where the IGL does not. High disparity would be less desirable if the IGL had a high headshot percentage but the sniper did not. One might consider team skill diversity relative to the mean team skill. A high standard deviation around a low mean might be better than a low variation around a low mean as it would indicate some player(s) on the team are better skilled, but low variation around a high mean would be better than high variation around a high mean as the latter is akin to the weakest link scenario described above.

The second type of diversity of interest is cultural/linguistic. Five players from different countries without a common language would surely struggle in this game as rapid and clear communication is required. To capture cultural diversity, we construct the Herfindahl-Hirschman index: \( HHI = \sum \left( \frac{N_{\text{country maps}}}{N_{\text{total maps}}} \right)^2 \). \( N_{\text{country maps}} \) represents the number of maps played by all team members from a particular country, while \( N_{\text{total maps}} \) is the total number of maps played by each member of a team over the course of a year. An additional metric of cultural diversity is the total number of countries represented by the team members. Our hypothesis is that teams with greater cultural/linguistic diversity will perform worse than teams that are more homogeneous.

To measure language diversity, we construct a similar index, but in calculating maps played by all team members from a particular country we treat players from all post-Soviet countries as speaking the same language. We also consider all players from countries in which more than 50% of the population speaks English as English speaking. The idea is to avoid treating as diverse teams in which teammates’ share a common native language but not a common home country. For instance, our assumption is that players from the UK and Australia while from different countries are not from totally different cultures and languages.

Next, we analyze if there are particular country-level cultural features that are important for team composition and performance. We use Geert Hofstede’s cultural dimensions for this purpose. Professor Hofstede and his research team developed measurements of dimensions of national culture (Hofstede 1984). All dimensions are evaluated in the form of indexes with a minimum value of 1 and a
maximum value of 120. Hofstede’s website\textsuperscript{17} contains information on six cultural dimensions, estimated for different countries\textsuperscript{18}.

\textit{Individualism.} Individualistic countries are characterized by poor ties between individuals. According to the Hofstede center, people in such countries stress personal achievements and individual rights and expect others to fulfill their own needs. We suppose this type of diversity might affect team performance as a high degree of individualism will negatively affect teamwork.

\textit{Uncertainty avoidance.} This metric indicates “to what extent a culture programs its members to feel either uncomfortable or comfortable in unstructured situations”. We assume diversity in uncertainty avoidance might negatively affect team strategy and team decisions as interpersonal conflicts may arise between players with very different degrees of uncertainty avoidance.

\textit{Long-term orientation.} According to the Hofstede center, nations with long-term orientations “prefer to maintain time-honored traditions and norms while viewing societal change with suspicion”. This dimension reflects the readiness of team members to accept delayed gratification of material, social and emotional needs. Diversity in long-term orientation might affect a team’s strategy in terms of proper objective setting: in long-term oriented cultures, professional gamers are accustomed to not expecting immediate results during a game, match, tournament or season. In short-term oriented cultures, the current result is a major concern. So, if one team member wants to maximize the present tournament prize, while another wishes to maximize the season reward, they will experience conflict regarding their proper training schedule, choice of tournament and effort in a game. Still, diversity in long-term orientation might have a positive effect, since it is better for performance when players with different roles are differently oriented.

\textit{Masculinity.} This dimension refers to the preference of a society with regard to achievement, heroism, assertiveness and material rewards for success. It might be important to have diversity regarding masculinity in CS:GO because, among the

\textsuperscript{17} http://www.clearlycultural.com/geert-hofstede-cultural-dimensions
\textsuperscript{18} By implementation of the Hofstede dimensions we implicitly assume that gamers are a representative sample of the whole country population. That is why a country population cultural means measured by Hofstede are equal to the sample means
different roles, there is the IGL. For such a role, it might be beneficial for the individual player to have a high masculinity score. This characteristic might also be beneficial for the so-called “entry fragger” – a person who tries to eliminate one or two representatives of the rival team at the start of a game. However, high masculinity scores might be unacceptable for the sniper or lurk, who are supposed to wait for good opportunities to arise to eliminate rivals.

*Power distance.* This index measures how well a society accepts an unequal distribution of power. In our setting, this dimension might affect a team member’s willingness to follow the team leader, which is important for team performance. However, diversity in this characteristic might be both beneficial and harmful for team performance. On the one hand, low diversity supposes a relatively high level of discipline. On the other hand, low diversity might negatively affect the audacity of team members and render team decisions predictable by rivals.

*Indulgence.* This sixth dimension to the Hofstede index has been developed recently and built on the base of Minkov’s World Values Survey data. This dimension is related to enjoying life and having fun. Since it is a developing dimension which has not been used widely in previous research, we choose to exclude it in favor of the previous five dimensions that are validated in many empirical studies, in particular, to study diversity in sport teams (Ingersoll et al., 2014).

1.1.19 *Data and methodology for the empirical test*

We use data on the total prize won by a team as an indicator of that team’s performance. The source of these data is the project “eSport earnings”. This resource is based on freely available public information on different tournaments in eSports, the nicknames of winners and the sums won. The website contains information on each gamer’s prize (in dollars) for the period from 1999 to 2016. We use the data only for the period from 2013 to 2015, since in 2012 the new version of the Counter-Strike game, CS:GO, was introduced, and professional gamers were not yet accustomed to the new gameplay.

To compile a list of each year’s best CS:GO teams we use the ratings available on the Liquipedia Counter-Strike web page (“The Counter-Strike Encyclopedia”).
Data on in-game performance (headshot percentage, KD ratio and number of maps played) are collected from HLTV.org. HLTV.org is the leading CS:GO statistics site in the world. The World Bank is the source of data on the GDP and USD deflator.

Table 21 contains the descriptive statistics for our indicators.

<table>
<thead>
<tr>
<th>Statistic</th>
<th>N</th>
<th>Mean</th>
<th>St. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prize, USD</td>
<td>277</td>
<td>28,248.790</td>
<td>83,835.180</td>
<td>100,000</td>
<td>863,698.800</td>
</tr>
<tr>
<td>HHI</td>
<td>246</td>
<td>0.840</td>
<td>0.215</td>
<td>0.197</td>
<td>1.000</td>
</tr>
<tr>
<td>HHI language</td>
<td>246</td>
<td>0.932</td>
<td>0.143</td>
<td>0.363</td>
<td>1.000</td>
</tr>
<tr>
<td>Headshot percentage</td>
<td>245</td>
<td>39.852</td>
<td>13.758</td>
<td>0.383</td>
<td>78.640</td>
</tr>
<tr>
<td>KD ratio</td>
<td>245</td>
<td>0.988</td>
<td>0.106</td>
<td>0.310</td>
<td>1.232</td>
</tr>
<tr>
<td>Maps played</td>
<td>245</td>
<td>96.181</td>
<td>88.496</td>
<td>1.000</td>
<td>584.145</td>
</tr>
<tr>
<td>GDP per capita, USD</td>
<td>244</td>
<td>40,069.180</td>
<td>18,824.840</td>
<td>3,703.366</td>
<td>89,338.740</td>
</tr>
<tr>
<td>Number of gamers</td>
<td>277</td>
<td>11.480</td>
<td>8.767</td>
<td>5</td>
<td>42</td>
</tr>
<tr>
<td>SD (headshot percentage)</td>
<td>240</td>
<td>8.609</td>
<td>4.701</td>
<td>0.063</td>
<td>33.465</td>
</tr>
<tr>
<td>SD (KD ratio)</td>
<td>240</td>
<td>0.127</td>
<td>0.053</td>
<td>0.021</td>
<td>0.417</td>
</tr>
<tr>
<td>SD (Maps played)</td>
<td>240</td>
<td>35.976</td>
<td>34.896</td>
<td>0.000</td>
<td>333.466</td>
</tr>
<tr>
<td>SD (GDP)</td>
<td>237</td>
<td>0</td>
<td>6419.235</td>
<td>0.000</td>
<td>28347.421</td>
</tr>
<tr>
<td>SD (Power distance)</td>
<td>225</td>
<td>2.812</td>
<td>5.331</td>
<td>0.000</td>
<td>23.445</td>
</tr>
<tr>
<td>SD (Individualism)</td>
<td>225</td>
<td>3.137</td>
<td>4.99</td>
<td>0.000</td>
<td>20.958</td>
</tr>
<tr>
<td>SD (Masculinity)</td>
<td>225</td>
<td>4.420</td>
<td>7.723</td>
<td>0.000</td>
<td>44.265</td>
</tr>
<tr>
<td>SD (Uncertainty avoidance)</td>
<td>225</td>
<td>4.194</td>
<td>7.627</td>
<td>0.000</td>
<td>33.780</td>
</tr>
<tr>
<td>SD (LR Orientation)</td>
<td>225</td>
<td>3.382</td>
<td>4.822</td>
<td>0.000</td>
<td>24.119</td>
</tr>
<tr>
<td>Number of countries</td>
<td>277</td>
<td>2.162</td>
<td>1.601</td>
<td>1</td>
<td>11</td>
</tr>
<tr>
<td>Almost English</td>
<td>277</td>
<td>14.755</td>
<td>35.179</td>
<td>0</td>
<td>99</td>
</tr>
<tr>
<td>From USSR</td>
<td>277</td>
<td>0.108</td>
<td>0.311</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>One country team</td>
<td>277</td>
<td>0.310</td>
<td>0.464</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

As one can see, the variation in prize money is large and the distribution is positively skewed. For that reason, we take its natural logarithm as the dependent variable. Regarding the skill indicators, one can see high variation across the board,
indicating that our sample comprises teams of different abilities despite including only top-level teams.

The average number of gamers to play for a team in a year is 11. This indicates high turnover among the team members, which makes the question of diversity even more important for the teams. New team members must quickly become acquainted with team strategy and communication rules if the team is to succeed. An average team consists of representatives from two countries, so even the average team is culturally diverse. Interestingly, only one third of teams are composed entirely of members from just one country. Regarding language diversity, 11% of teams are entirely composed of representatives of post-Soviet countries. In 15% of teams, gamers are born in countries in which over half the population speaks English. Almost a half of teams (49%) consist of members who come from countries with a common language.

We estimate the following regression:

$$\log(\text{prize}_i) = \alpha + \mathbf{CV} \cdot \delta + \mathbf{DIV} \cdot \beta + \varepsilon_i,$$

where $i$ indexes the team. Since only 23% of teams are observed for all three years, we do not include team fixed effects. We did test a specification with year fixed effects, but these effects were neither individually nor jointly significant. $\mathbf{CV}$ represents a vector of control variables, which includes headshot percentage, KD ratio, number of maps played and number of gamers who played for the team during a year (to control for roster turnover), as well as an interaction term of the number of gamers and number of countries of origin. $\mathbf{DIV}$ is a vector of diversity indicators. We estimate a set of regressions for different types of diversity. In the first three models, we analyze the effect of cultural diversity. We use different proxies of diversity in the first and second models. Diversity in Hofstede characteristics is studied in the third model. Models 4 and 5 are for language and skill diversity, respectively. Finally, we include all diversity metrics in a single regression in order to study their joint effect.
1.1.20 Empirical results

Table 22 contains the results of the regression analysis. The first three models consider country-specific (cultural) diversity, the fourth considers language diversity, the fifth considers diversity in skill, and the sixth considers all forms of diversity in one regression. Models 1-3 use different metrics of diversity. In the first model, we use the Herfindahl-Hirschman index (HHI) as the diversity metric, while we use the number of countries in the second. In the third, we use five Hofstede dimensions to study particular cultural diversity perspectives.

The results concerning the control variables are as one would expect. The average headshot percentage for the team is statistically significant and positive. Since our dependent variable is in logs, we evaluate marginal effects as \((e^\beta - 1) \cdot \frac{1}{100}\) in order to determine the percentage change in the dependent variable. The KD ratio is also statistically significant and positive. A 0.01 increase in this ratio increases the total prize by 5.41%. As an indicator of experience, the number of maps played positively affects the prize. The other functional forms regarding experience were also tested, with linear seemingly the best. The marginal effect is relatively high: one additional map as a unit of experience adds approximately 1% to the prize money. All these results are robust with regard to different specifications, while the coefficients for the skill and experience indicators are consistent across Models 1-6.

To capture the effect of diversity, we must control for the number of gamers as an indicator of the turnover in the team. For this purpose, the annual total number of gamers in the team is included. The interaction of the number of gamers and the number of countries of origin of these gamers is included to control the joint effect of turnover and country differences. The coefficients for these indicators are not consistent across Models 1-6 in terms of sign. However, the effect of turnover itself, measured by the number of gamers, is not statistically significant. The interaction term is statistically significant in Models 1 and 4. Therefore, one might conclude that, despite the fact that turnover itself does not matter, the effect of diversity should be analyzed more thoroughly.

We begin the description of the diversity results from the perspective of cultural diversity. We use three metrics of cultural diversity. First, in Model 1, the
HHI is employed as a diversity indicator to consider the number of games played by players from different countries. The coefficient is not statistically significant. However, the coefficient of the dummy indicating a team comprised of representatives of just one country is statistically significant and negative. Such teams receive 30% less prize money on average. In turn, one might conclude that diversity is not significant regarding team performance, although the absence of diversity should be considered to be a negative factor in terms of performance.

In Model 2, we use the number of countries represented in a team as an indicator of diversity. With such a proxy, we do not relate diversity to the number of games played. The coefficient is statistically significant and positive. A representative from an additional country would increase the prize money by almost 32%, all else being equal. The dummy for the one-country team is not statistically significant, since this effect is captured when the value of the country indicator is one. Here we might conclude that diversity is beneficial to the team.

Next, in Model 3, we look more closely at the problem of cultural diversity. We not only analyze the marginal effects of countries, but also try to identify particular cultural characteristics that might be important to team composition. For this purpose, Hofstede’s cultural dimensions are employed. Diversity in power distance, which indicates differences in the attitudes of team members to the inequalities of power distribution within society, negatively affects team performance. The coefficient is statistically significant and negative. An increase of one standard deviation in the power distance diversity decreases team prize money by 27%. Diversity in individualism, which is defined as the willingness of a player to only take care of themselves and their families, is beneficial to the team. The marginal effect is of the same magnitude as that for power distance diversity: one standard deviation in individualism diversity leads to a 27% increase in prize money. This might be explained by the fact that there are different roles in CS:GO teams and that, for some (e.g., snipers), individualism is beneficial. Diversity in masculinity is also beneficial to team performance. Masculinity is defined as a societal preference for achievement, heroism, assertiveness and material rewards for success (Hofstede 1984). One standard deviation increase in masculinity diversity leads to a 20% increase in prize money, such that the effect of masculinity
diversity is less than that of individualism diversity. The remaining cultural diversity characteristics are not statistically significant. Surprisingly, diversity in terms of GDP per capita does not affect team performance. GDP is an indicator of the economic welfare of a country, which might be expected to influence a given player's attitude, way of thinking, ability to study and use something new, etc. It also indicates the ability to buy a PC, which influences a gamer's skills because it is connected with the ability to train for longer periods. This might be explained by the relatively low entry costs in eSports, meaning that, in almost all countries, buying a PC or a console is affordable for gamers, allowing them to train. It should be noted that, in eSports, the difference between amateur and professional equipment is low.

In Model 4, we analyze the impact of language diversity. We include the HHI in the regression as a language concentration indicator. In contrast to the HHI from Model 1, the language HHI is statistically significant and positive. The more a team is concentrated in terms of language, the better its performance. This is in line with gamers’ own thoughts: Sergey “starix” Ischuk, the former player and coach of the Natus Vincere CS:GO team, said: “Of course, it is desirable that all the players talk the same language. So much easier to communicate and explain their ideas about gaming moments. On a professional level, this factor is very important” (Gabinski 2016).

The binary indicator for the teams comprising gamers from post-Soviet countries is statistically significant and negative: such teams win 93% less prize money on average. Interestingly, the indicator of the dummy for teams consisting of gamers from countries in which over half the population speaks English is also significant, but the marginal effect is 8%, which is less than one eleventh the effect for post-Soviet countries. Still, both dummies indicate a negative effect of language concentration. There might be at least two interpretations of this result. First, speaking the same language in a team is beneficial to performance; however, a representative of another country might introduce a certain country-specific ability, which could also be beneficial, even though it increases language diversity. In other words, the benefits of diversity outweigh the drawbacks. Second, these dummies are included in order to take into account those countries with similar languages. This might be inappropriate: in post-Soviet countries, people do not speak Russian as
well as their native language. Indeed, among young people, Russian is probably not so popular for everyday communication. To some extent, a similar effect might apply to the dummy indicator of countries with a significant English-speaking population.

Next, we consider the impact of diversity in terms of skill on team performance. We include the standard deviation of headshot percentage, KD ratio and maps played as the indicators of skill diversity. Interestingly, diversity in skill does not affect performance: the coefficients of standard deviation in headshot percentage and KD ratio are not statistically significant. This might be due to the sample: since we only analyze top-level teams, the variation in skill is relatively low. The number of maps played might also be considered an indicator of experience. It has a negative statistically significant effect on team performance: one standard deviation increase in experience diversity reduces prize money by 49%.

In Model 6, we include all the diversity indicators in the same regression. As there are few individually significant coefficients due to multicollinearity, we perform joint hypothesis tests regarding different kinds of diversity. Skill diversity indicators are statistically significant at the 1% level \(F(3, 188) = 3.50\), cultural diversity indicators are not statistically significant \(F(9, 188) = 1.38\), and language diversity indicators are also statistically significant at the 1% level \(F(3, 188) = 2.99\). One can conclude that language and skill diversity are more important in terms of team construction than is cultural diversity.

### Table 22: Estimation results of the diversity effects

<table>
<thead>
<tr>
<th></th>
<th>(1) Cultural</th>
<th>(2) Cultural</th>
<th>(3) Cultural</th>
<th>(4) Language</th>
<th>(5) Skill</th>
<th>(6) All</th>
</tr>
</thead>
<tbody>
<tr>
<td>Headshot percentage</td>
<td>0.010***</td>
<td>0.006</td>
<td>0.011**</td>
<td>0.013***</td>
<td>0.007*</td>
<td>0.011**</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>KD ratio</td>
<td>1.858**</td>
<td>1.823*</td>
<td>2.458*</td>
<td>1.700*</td>
<td>1.741**</td>
<td>1.761**</td>
</tr>
<tr>
<td></td>
<td>(0.920)</td>
<td>(0.951)</td>
<td>(1.265)</td>
<td>(0.875)</td>
<td>(0.728)</td>
<td>(0.890)</td>
</tr>
<tr>
<td>Maps played</td>
<td>0.011***</td>
<td>0.011***</td>
<td>0.012***</td>
<td>0.012***</td>
<td>0.016***</td>
<td>0.015***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Number of gamers</td>
<td>-0.011</td>
<td>0.009</td>
<td>-0.001</td>
<td>-0.022</td>
<td>0.017</td>
<td>0.018</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.018)</td>
<td>(0.015)</td>
<td>(0.013)</td>
<td>(0.013)</td>
<td>(0.020)</td>
</tr>
<tr>
<td>N gamers (\times) N counties</td>
<td>0.004**</td>
<td>-0.006</td>
<td>0.003</td>
<td>0.003*</td>
<td>0.003</td>
<td>-0.004</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.004)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.005)</td>
</tr>
<tr>
<td></td>
<td>Estimate</td>
<td>Std. Error</td>
<td>z</td>
<td>p-value</td>
<td></td>
<td></td>
</tr>
<tr>
<td>--------------------------</td>
<td>----------</td>
<td>------------</td>
<td>------</td>
<td>-----------</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SD (headshot percentage)</td>
<td>0.013</td>
<td>0.012</td>
<td>1.31</td>
<td>0.189</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SD (KD ratio)</td>
<td>1.231</td>
<td>0.132</td>
<td>9.28</td>
<td>&lt;0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SD (maps_played)</td>
<td>-0.018***</td>
<td>0.004</td>
<td>-5.74</td>
<td>&lt;0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SD (GDP)</td>
<td>0.000</td>
<td>0.000</td>
<td>0.00</td>
<td>1.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SD (Power distance)</td>
<td>-0.051*</td>
<td>0.028</td>
<td>-1.95</td>
<td>0.052</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SD (Individualism)</td>
<td>0.054***</td>
<td>0.021</td>
<td>2.60</td>
<td>0.009</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SD (Masculinity)</td>
<td>0.026*</td>
<td>0.014</td>
<td>2.16</td>
<td>0.031</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SD (uncertainty avoidance)</td>
<td>-0.012</td>
<td>0.026</td>
<td>-0.47</td>
<td>0.637</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SD (LR Orientation)</td>
<td>-0.001</td>
<td>0.022</td>
<td>-0.05</td>
<td>0.958</td>
<td></td>
<td></td>
</tr>
<tr>
<td>HHI</td>
<td>0.312</td>
<td>0.374</td>
<td>0.83</td>
<td>0.409</td>
<td></td>
<td></td>
</tr>
<tr>
<td>One country team</td>
<td>-0.301*</td>
<td>0.179</td>
<td>-1.69</td>
<td>0.091</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of countries</td>
<td>0.279***</td>
<td>0.162</td>
<td>1.72</td>
<td>0.085</td>
<td></td>
<td></td>
</tr>
<tr>
<td>HHI language</td>
<td>0.960*</td>
<td>0.521</td>
<td>1.84</td>
<td>0.067</td>
<td></td>
<td></td>
</tr>
<tr>
<td>From USSR</td>
<td>-0.663***</td>
<td>0.236</td>
<td>-2.80</td>
<td>0.005</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Almost English</td>
<td>-0.008**</td>
<td>0.003</td>
<td>-5.84</td>
<td>&lt;0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>5.475***</td>
<td>0.885</td>
<td>6.20</td>
<td>&lt;0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>229</td>
<td>0.567</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R-squared</td>
<td>0.593</td>
<td>0.663</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
1.6 Managerial efficiency of eSports coaches

1.1.21 Managerial efficiency in eSports

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 or a coach, so-called self-managed teams (Carte, Chidambaram, and Becker 2006). 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 study, we use a quasi-experimental setting from eSports to understand whether the manager is of benefit to team performance.

There is a considerable amount of research on managerial efficiency in the sports industry due to the availability of data on professional sports teams. The coach is usually treated as an input in terms of the production function of the team. Rottenberg’s (1956) study of Major League Baseball (MLB) teams introduced the concept of the production function with regard to professional sports teams. He considered the quantity of talent and other factors, including infrastructure and management, to be the main inputs in the team production function. Scully (1974) empirically estimated the team production function while studying the relation between wages and the players’ marginal revenue product in MLB. His analysis was extended by Zech (1981) and became a common framework for the estimation of production functions in American football (Atkinson, Stanley, and Tschirhart 1988; Berri and Jewell 2004; F. Carmichael and Thomas 1995; L. H. Kahane 2005; Schofield 1988). A substantial part of this literature is devoted to association football where a positive relationship between the talent of players and team success was also found (Fiona Carmichael, Thomas, and Ward 2000; Frick and Simmons 2008a; Kuypers and Szymanski 1999; Szymanski and Smith 1997).

Most of these studies focus more on team quality than on managerial or coaching efficiency. However, the authors generally include indicators that reflect the contribution that coaching makes to production. Zech (1981) found that his proxies for coach quality were statistically insignificant. Carmichael et al. (2000)
also concluded that coach experience was not statistically significant in their estimation of the production function. However, Porter and Scully (1982) found that the coach’s contribution to team success was comparable to that of a “star” player. Frick and Simmons (2008) found that a team with a better coach 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 coach efficiency were sensitive to the choice of the model. One also might expect that a better team might hire a more skilled coach, hence, reverse causality might be an issue.

All of these studies focus on the issue of managerial efficiency, in other words, whether a better coach helps a team to improve its results. However, it might be beneficial for a team to refuse to hire a coach. There is a growing literature that analyzes self-managing teams and shows that these teams might be more efficient than teams with managers (Carte, Chidambaram, and Becker 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, Doverspike, and Cober 2002). The question of whether a better coach improves team performance has not been settled but there is a lack of studies on the question of whether a team actually needs a coach.

In this study, we address the question of whether a team needs a coach and we estimate the treatment effect of coaches on team performance. Coaches in eSports 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 coach is a given. However, over the last five years in eSports, top teams have been hiring coaches, that is, they have added a coach to the team management. For that reason, eSports provides us with a quasi-experimental setting with which to test the treatment effect of coaches.

eSports is competitive computer gaming. This sport has been growing rapidly for at least the last 10 years. In 2014, the number of viewers of League of Legends (one of eSports primary disciplines) exceeded the audience of the National Basketball Association (NBA) and National Hockey League (NHL) finals. In 2022,
eSports will be a medal event at the Asian Games—the biggest regional international comprehensive sports event. Rowell (2016) has predicted that the number of eSports viewers will continue to increase, reaching a projected 427 million by 2019. Despite its growing popularity, eSports is not well studied in academic research, particularly from the perspective of business and economics.

We concentrate on a particular eSports discipline: Counter-Strike: Global Offensive (CS:GO). There are some features of CS:GO that make it a good platform for analyzing coach efficiency. The team production function in CS:GO is similar to that of traditional team sports (Parshakov, Coates, and Zavertiaeva 2018). The rewards are performance-based, so the team prize money is a good proxy of its skill (Coates and Parshakov 2016b; Parshakov and Zavertiaeva 2018). The role of the coach in CS:GO and in eSports, in general, is similar to traditional sports. An important difference is that in CS:GO the coaches can talk only during pause times and before/after games. They cannot communicate during the game. Each team has an in-game leader (IGL) that plays and communicates at the same time. A coach usually has an analyst as his deputy. A coach’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, especially the smaller ones, the coach and the analyst may be the same person. In other larger organizations, a team of many individuals supports the coach.

---

19 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 money awarded on the basis of their performance in the previous round.
Chapter 3. Micro-level analysis

1.1.22 Endogenous switching regression

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 coach:

\[
I_i = 1 \quad \text{if} \quad \gamma Z_i + u_i > 0 \\
I_i = 0 \quad \text{if} \quad \gamma Z_i + u_i \leq 0
\]

\[Regime \ 1: \quad y_{1i} = \beta_1 X_{1i} + \epsilon_{1i} \quad \text{if} \quad I_i = 1\]

\[Regime \ 2: \quad y_{2i} = \beta_2 X_{2i} + \epsilon_{2i} \quad \text{if} \quad I_i = 0\]

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 coach. Of course, the presence of a coach 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 coach. It does so by using a probit model to predict which teams will have a coach 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 probit equation includes the number of teams within the eSports organization to which each team belongs and the age of that organization in both linear and squared terms. 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 coach decision 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).

Following the estimation, we calculate and compare the expected prize money according to four possible outcomes. Outcome I predicts the logarithm of the prize money for those teams that had a coach 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 coach using the coefficients from the prize money regression estimated on the sample of teams that did not have a coach. Outcomes II and IV are counterfactual predictions. Using the coefficients from the coefficients from the regression on teams with coaches, outcome II predicts the prize money that would have been won by teams that did not have a coach; outcome IV predicts the prize money of teams that did have a coach using the coefficients from the no-coach prize money regression.

These four outcomes can be presented as follows (Figure 22):

![Figure 22. Four possible outcomes](image)

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

In the current section, 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 coach. In order to control for competitors’ skills,
we use the average kill-to-death ratio of rival teams. With the exception of the
presence of a coach, all of these variables were normalized by dividing by the mean
in order to control for one team being better than the other teams, rather than them
simply being good at the game.

In order to model the probability of a team having a coach in the first stage,
we used two additional variables—team age and the number of teams within the
eSports organization to which each team belongs. In eSports, there are professional
organizations that usually have several teams for different eSports games. For
instance, Fnatic, one of the most famous and successful eSports 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 eSports
organization and the age of a team reflect its professionalism and can be positively
correlated with the probability of hiring a coach without determining the
performance of the individual teams. On average, there are three teams in eSports
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 23. 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.

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>N</th>
<th>Mean</th>
<th>SD</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>General team information</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Prize money (in USD)</td>
<td>463</td>
<td>84,258.2</td>
<td>201,747.5</td>
<td>100</td>
<td>1,558,756</td>
</tr>
<tr>
<td>Presence of coach</td>
<td>463</td>
<td>0.350</td>
<td>0.477</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Age of organization</td>
<td>463</td>
<td>4.091</td>
<td>4.834</td>
<td>0</td>
<td>20</td>
</tr>
<tr>
<td>Number of teams in</td>
<td>463</td>
<td>3.192</td>
<td>2.474</td>
<td>1</td>
<td>12</td>
</tr>
</tbody>
</table>
organization

**Team skills and experience**

<table>
<thead>
<tr>
<th>Variables</th>
<th>Teams without coach</th>
<th>Teams with coach</th>
<th>Difference between teams</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of played maps</td>
<td>463</td>
<td>101.7</td>
<td>79.20</td>
</tr>
<tr>
<td>Headshot, %</td>
<td>463</td>
<td>42.12</td>
<td>11.76</td>
</tr>
<tr>
<td>Kill-to-death ratio</td>
<td>463</td>
<td>0.990</td>
<td>0.0992</td>
</tr>
</tbody>
</table>

Some insights can also be extracted from the analysis of differences in the means of variables between the teams with and without a coach (Table 24). First, on average, coached teams earn almost 5.4 times more prize money than self-managed teams. Of course, the difference in mean prize money between coached and uncoached teams may simply reflect the rise in the number of teams with coaches over recent years when the prize money has also been higher. The speed of this rise in coached teams can be seen in Figure 23. In 2013, about 2.5% of the top 100 CS:GO teams were trained by coaches, while in 2016, this value reached its peak at 70.4%. Indeed, from 2015 to 2016, the number of teams with coaches increased by almost 40 percentage points. However, in 2017, the share of coached 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 coach in eSports.

Second, teams with a coach 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 coach appeared to be statistically significant—on average coached 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 coach appeared to be statistically significant. These simple tests of the difference in the means support the intuition that a coach positively influences team performance.

*Table 24. Mean values of variables for teams with and without coaches*
In this section, we present the results of the endogenous switching regression model. The first column in Table 25 reports the probit estimates of the probability that a team has a coach. This model is statistically significant at the 1% significance level. In addition, we calculated the predicted value of the dependent variable (whether or not a team has a coach) and compared this with the actual values. The model correctly predicts that a team has a coach 63.3% of the time and does not have a coach 60.5% of the time and it makes an incorrect prediction 33.3% of the time. The results indicate that the number of teams within an eSports organization and the age of that organization are relevant instruments for the presence of a coach.
As expected, the more teams in an organization the higher the likelihood a
team has a coach. In this case, one additional team within the organization increases
the probability that a team has a coach 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 coach is U-shaped, reaching its minimum at the
organizational age at 7 years.

The second and third columns of Table 25 present the logarithm of prize
money estimates for teams without and with coaches, respectively. For teams
without coaches, 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 coach 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 coaches, only one variable is statistically
significant—the number of played maps (at the 1% level). For coached teams, an
increase in the number of played maps by one unit will increase the prize money by
1.1%.

Table 25. Results of the endogenous switching regression model for logarithm of prize money

<table>
<thead>
<tr>
<th>Selection equation</th>
<th>Log of prize money Without coach</th>
<th>Log of prize money With coach</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of played maps</td>
<td>0.0106*** (0.00130)</td>
<td>0.0110*** (0.00117)</td>
</tr>
<tr>
<td>Headshot, %</td>
<td>0.0148*** (0.00569)</td>
<td>0.0197 (0.0176)</td>
</tr>
<tr>
<td>Kill-to-death ratio</td>
<td>0.127*** (0.0227)</td>
<td>1.491* (0.845) 1.612 (1.122)</td>
</tr>
</tbody>
</table>
Finally, to see whether a coach 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 22. These predicted values for prize money are shown in Figures 24.

As can be seen, on average, the teams that have a coach and continue to have a coach (outcome I) earn more prize money compared with teams who do not have a coach and are not going to hire a coach (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 coach, we observe the following changes in prize money. If a team without coach decides to hire a coach (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 coach (outcome IV). Alternatively, if a team with a coach decides to fire the coach (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.
To sum up, these estimations fail to prove that in the case of eSports gaming (in particular, CS:GO Global Offensive), switching from not having a coach to having a coach 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 coach (IV) showed that, on average, teams with coaches still earn more than self-managed teams but this is not due to the presence of a coach.
1.7 Team Communication and Performance as Evidenced by Dota2 Videogame

1.7.24 The importance of team communication

Communication plays an important role in teamwork. The dependence of teamwork on the ways the members of the team use to communicate is undeniable: “Communication is the cornerstone of team interaction, without which teams would not be able to share information and knowledge, discuss and debate issues or strategies, or develop solutions to problems” (Hassal 2009, p. 16); “Issues such as leadership, collective efficacy, team cohesion, and group goal setting undoubtedly have great theoretical and practical value within sport teams. These issues all rely on one social process that may be the most important component of intra-team interactions. This process is communication” (Sullivan & Feltz 2003, p. 1693). Communication is regarded as team-level cognitive processing in (Letsky 2008). Thus, the investigation of communication and it relation to team performance is an essential issue.

Globalization trends in business lead to distributed multinational teams with significant part of remote communication. The collaboration of team members from the different locations is generally facilitated by tools like email, chat, etc. Chang, Chuang, & Chao (2011) argue that such virtual teams significantly differ from other small groups in terms of communication.

The purpose of the current study is to investigate the team text-based communication intensity and its interdependence with team performance using data of non-professional computer game teams. Unlike professional teams, there is high rotation of players in such teams. Thus, the coordination of the players is based mainly on communication during the game, not on trainings or previous experience. However, the communication of computer game teams is a good setting to investigate the efficiency of text-based communication in the context of urgent decision-making.

Team sport is among many other types of activities which highlight this inherent human necessity to be a part of a larger whole. Similar to other activities team sport has recently gone digital. Competitive computer gaming become popular
worldwide. Moreover, now it is becoming the recognized professional sport (e-sports or cybersports) (Leavitt, Keegan, and Clark 2016). Yet the field of communication of computer game teams remains sufficiently understudied.

Computer gaming enables us to analyze communication patterns and identify the most efficient ones for team performance. Communication of computer game teams falls under the category of computer mediated communication defined as “communication that takes place through a variety of media and provides distributed group members with video, audio, and text-based messaging capabilities” (Harris & Sherblom, 2008, p. 296). Players make use of audio and text chats of which the present research will concentrate only on the latter.

The phenomenon of virtual teams which members work together from a distance and mostly communicate via specific tools become very widespread in many spheres (Chang, Chuang, and Chao 2011). Such teams can be multinational, culturally diverse and work together for a short period of time for particular project. The authors mention the necessity of adaptation for communication in virtual teams (Chang, Chuang, and Chao 2011; Newlands, Anderson, and Mullin 2003).

There is a significant difference in communication style in face-to-face and computer-mediated communication. Namely, Newlands et al. (2003) found that new users of text-based computer-mediated communication have to adapt to a precise, highly specified style of giving directions which required little interpretation by addressees. According to Harris & Jenkins (2006), teams using computer mediated communication perform better than face-to-face communicating teams on idea-generating tasks and their members participate more equally. However, the authors note that computer mediated communication is less efficient way for tasks with social-emotional interaction. On the other hand, the study of virtual teams of Cheshin, Rafaeli, & Bos (2011) shown that emotion contagion occurs in teams even when communication is only text-based.

The role of forms of communication has been studied in relation to various teams: design teams (Stempfle & Badke-Schaub, 2002), software project teams (He, Butler, and King 2007) or cyber security teams (Jariwala et al. 2012) – and in various aspects: computer-assisted communication in team decision-making process
(Colquitt et al. 2002), team performance approached via information sharing (Mesmer-Magnus and DeChurch 2009) or via individual extraversion reflected in communication (Macht et al. 2014). At any given time, group members may use verbal communication to convey any of the four types of messages: problem-solving talk, role-assumption talk, consciousness-raising talk, or encounter talk (Harris & Sherblom, 2008, p. 112).

Empirical studies on communication are frequently based on experimental design (Colquitt et al. 2002; Newlands, Anderson, and Mullin 2003; He, Butler, and King 2007; Cheshin, Rafaeli, and Bos 2011; McKendrick et al. 2014), questionnaire survey (Sullivan and Short 2011) and interviews (Chang, Chuang, and Chao 2011). While experimental design allow to control the conditions, it can affect individuals’ behavior particularly the way people communicate. Questionnaire surveys and interviews rely on subjective memory-based information that can lead to biased empirical results. The alternative approach to investigate team communication is related to usage of communication log records (for example, see Leavitt et al., 2016). Online video games provide a setting to analyze large sets of game log data to investigate virtual team communication in real-life conditions.

Communication intensity is one of core features of team communication and generally assumed to have a positive influence on team performance. The findings of McKendrick et al. (2014) have shown that the frequency of communication is positively related to team performance whereas word count affect team performance negatively. He et al. (2007) have found that frequency of meetings and phone calls were positively related to the formation of team cognition, while e-mail use had no effect. The analysis of frequency of easy-to-activate communicative alerts (“pings”) in the study of Leavitt et al. (2016) has shown that pings have a positive but concave relationship with player performance.

The content of communication also affects team performance. However, it is task-specific and is more difficult to analyze. Sullivan and Short (2011) analyze situations in which the team interacts. The authors distinguish four factors of effective team communication: acceptance of each other; distinctiveness from other social units; intra-team conflict that is constructive or positive in nature, and intra-team conflict that is destructive or negative in nature. Empirical analysis of this
Factors on a sample of athletes from different types of sports has revealed that team performance is negatively related to the communication of distinctiveness at the team level. Other three factors have been found not significant. McKendrick et al. (2014) identified five main topics in communication within a networked supervisory control setting and found that the communication related to particular topics improve team performance.

In this part we analyze the link between team communication and performance in the context of fast decision-making. We address this question in two ways. First, we analyze the “quantity” using communication intensity indicator. Following previous papers, we assume that higher communication intensity corresponds to higher team performance. Additionally, taking into account the feature of fast-decision making context, we test whether there is an optimal communication intensity. Second, we analyze the content of messages to identify difference in communication patterns of successful and unsuccessful teams. Namely, we reveal the words which are frequently used by the teams. We use text mining and machine learning techniques for this purpose.

1.1.25 An empirical test: Dota 2 setting

Our dataset contains 50000 ranked ladder matches from the Dota 2 data dump created by Opendota. It was inspired by the Dota 2 Matches data published here by Joe Ramir. This dataset is available on Kaggle\textsuperscript{20}. Dota 2 is a popular MOBA available as free to play, and can take up thousands of hours of your life. The number of matches in this dataset is 95 thousands. We use information on the matches results and about text chat of the players. For each match we have all characters each team member type in text chat. Table 26 contains summary statistics for our indicators, Figure 25 represents the distribution of intensity of communication. We evaluate intensity of the communication by characters per player per minute, after the data was aggregated on the team-match level. We also perform an analysis of the words which are correlated with the winning probability.

\begin{table}[h]
\centering
\caption{Summary statistics of Dota 2 matches}
\end{table}

\textsuperscript{20} https://www.kaggle.com/devinanzelmo/dota-2-matches/home
As a preliminary analysis, we perform Welch Two Sample t-test to compare intensity by winning dummy. We reject the null of the same mean with $t = 10.252$, $df = 93264$, $p$-value < $2.2e-16$. So, the intensity of communication of winners is higher.

There are two parts in our analysis. First, we address the issue of communication intensity and its effect on team performance. For this purpose we estimate probit regression. Note that we do not include control variables, so one should not interpret our results in terms of causal relation. So, one should interpret our results in terms of correlation, but not causation.

$$win_{ij} = \varphi(\beta_1 + \beta_2 \cdot intensity_{ij} + \beta_3 \cdot intensity_{ij}^2) + \varepsilon_{ij},$$

where win is a dummy indicator of winning of team i in match j, intensity is an intensity of communication and $\varepsilon$ is an error term.
In the second part, we address the issue of the correlation between particular words frequency and winning probability. Since the number of words is high, we use lasso regression of Tibshirani (1996). This is a popular machine learning approach, which allows variable selection and coefficient estimation at the same time. In particular, we estimate linear model by penalized maximum likelihood. We use gaussian distribution, so the objective function is \[
\frac{1}{2} \frac{\text{RSS}}{N} + \lambda \cdot \text{penalty}.
\]
Since for each value of \(\lambda\) we have different set of coefficients, we use cross-validation to select this parameter. All estimations are performed in R (R Core Team 2015) with Friedman, Hastie and Tibshirani (2010) glmnet package. The data and replicating scripts are available upon a request.

1.1.26 Intensity of communication

Table 27 contains the results of probit estimations. We include intensity in a linear and squared term to test the nonlinear effect of intensity. In both regressions, communication intensity is statistically significant. Figure 26 report the marginal effect of communication intensity. Blue line represents median intensity, while red line is the optimal intensity. As one can see, most of the teams are slightly below the optimum, but close.

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>win</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td>Intensity</td>
<td>-0.010***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
</tr>
<tr>
<td>Intensity sq.</td>
<td>-0.002***</td>
</tr>
<tr>
<td></td>
<td>(0.0001)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.061***</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
</tr>
<tr>
<td>Observations</td>
<td>95,316</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-66,001.210</td>
</tr>
<tr>
<td>Akaike Inf. Crit.</td>
<td>132,006.400</td>
</tr>
</tbody>
</table>

*Note:* *p*<0.1; **p**<0.05; ***p***<0.01
1.1.27 Words-based LASSO regression

Before the regression, we perform the following procedures, which are standard for natural language processing. First, we tokenize the texts by words. Each token is a word or a combination of them (e.g. “New York”). Second, we remove so-called stop words. Stop words are those that are not useful for an analysis, for example, “the”, “of”, “to”. There are three dictionaries (“onix”, “SMART”, or “snowball”), we use combined list of such words. Third, we prepare “sparse” words matrix, there each row is a match, and each column is a word. We use tidytext package of Queiroz et al. (2018) for these purposes. Finally we have 76,352 observations and 8,075 of words.

Using LASSO-type regression we select 698 words. We do not report the coefficients for all of them, but they are available online at https://goo.gl/5fp6XA. Figure 27 contains top 20 positive and negative coefficients. So, those are the words which are correlated with the probability of winning.

We have discussed these results with a professional gamer. Below is the interpretation. First, as one can see, there are a lot of typos in the text due to the speed of game. Second, there are some words, which are used for the communication between teams or between teammates but do not have an important meaning, so-called as “trash talk” (blo**ob, cheaters, acaben (correctly gaben), hd (laugh smiley XD), perras (Spanish curse word). Most of such words are negatively correlated with
the probability of winning. Third, different words which contain the information are both positively (couriers, slakr (slark), melt (meld)) and negatively (kampe (camp), pode (pudge), murdered) correlated with the winning probability.
Figure 27. Top positive and negative words and their coefficients
1.8 Conclusions on the micro-level analysis

In this section we performed micro-level analysis with a team as a unit of observation. We believe that professional eSports teams are much more similar to commercial firms, that operate in the “new economy”, than teams in other sports. First, the result depends more on mental abilities than on physical excellence. First we use eSports data to construct an empirical model to measure the effect of diversity on team performance. Second, we analyze managerial efficiency in the context of eSports. Third, we analyze the relationship between the intensity of communication and team performance.

Regarding the first part, the main result of this study is that companies might benefit from diversity in their workforces: the absence of diversity reduces performance by 30%. However, different aspects of diversity affect performance in different ways. This is in line with Lazear’s (1999) idea that an increase in communication costs reduces the gains attainable through skill diversity.

In our study we construct cultural distance measures which are similar to Ingersoll’s et al. (2014) measures of language diversity. With respect to cultural diversity, our results suggest that diversity is beneficial, consistent with the results of Hamilton, Nickerson and Owan (2004), Ottaviano and Peri (2006) and Kahane, Longley and Simmons (2013). However, not all types of cultural diversity are equally beneficial. For an optimal team composition in a firm, it is necessary to consider the particular cultural features of different countries, for example, individualism or perceptions of power distance. An optimal matching of teammates with respect to the cultural perspectives of their countries of origin is an intriguing topic for future research.

According to our results, the benefits of language diversity do not outweigh the costs of such diversity. However, since our results for different metrics of language diversity differ, we can conclude that, in some cases, the benefits of some country-specific skills might be more important than an increase in communication costs. Further studies of the effect of language diversity will be required to address the points raised in this research.

Surprisingly, skill diversity does not affect team performance, according to our results. Diversity in experience has a negative effect on team performance. Since experience might be considered as a proxy indicator of age, the question of knowledge transfer might be tested using similar data. Diversity in age seems to have a negative effect for short-term
performance, but it might be an important source for success in the long run, as well as for the sustainability of a team.

We believe that specific data from the eSport industry can be used as a laboratory for analyzing profit-maximizing firms. First, teams in eSport have strong business orientation: their results are performance-based (Parshakov, Zavertiaeva, 2018). Moreover, to the extent that the incentives in the eSport team match the incentives in ordinary jobs, then there is no reason to believe that individual responses will differ between settings. Indeed, one lesson of these findings could be to encourage team-production incentives in business, which may be less clear and highly uncertain, to more closely mirror the incentives in eSport competitions. Second, in eSport the management of human resources is facilitated by electronic systems as in many businesses currently and likely even more so as digitalization of the economy progresses. Third, eSport reflects the digitalization trend in business. Fourth, in eSport the physical excellence of the athletes is less important than their mental abilities which makes expectations for workers in eSport similar to those expectations for workers in many modern firms.

To summarize, our main result with respect to diversity is that it might be beneficial, however, firms should not thoughtlessly maximize team diversity: different kinds of diversity have different integration costs. Another important conclusion, which is more general, is that eSport seems to be a good laboratory for testing different aspects of labor economics theories. The industry is rising, and the incentives of participants and teams are similar to those in commercial firms, since the reward is mostly performance-based. Finally, the data are extensive since the core aspects of the sport are facilitated by electronic systems.

Regarding the second part, the main finding of this study is that hiring a coach does not increase team performance. This raises a question about management efficiency, not only in eSport but also in similar industries because eSport 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, Coates, and Zavertiaeva 2018). This in-game leader might, to some extent, also be treated as the unofficial coach 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 coach, there might be a leader that partly fulfills the responsibilities of a coach. This raises potentially interesting questions about team management and team leadership: should the same person perform the roles of
both a coach 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 coach show that only young or well-experienced teams have a coach. 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 coach 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 coaches earn more prize money but this is not due to the coach. Still, a coach somehow changes the strategy of the team. For the self-managed teams, individual performance is the important determinant of success, while for teams with coaches, the only important determinant is experience. Thus, the coach makes 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 coaches’ efforts.

With respect to the third part, we performed the analysis of text-based communication of members of virtual teams in a context of online Dota2. Dota2 is a multiplayer online battle arena video game which is played in matches between two teams of five players, with each team occupying and defending their own separate base on the map.

The analysis of communication intensity in terms of number of characters texted by team members per minute has shown that there is inverted U-shape relationship between communication intensity and team performance. This result confirms the results of Leavitt et al. (2016). Therefore, most teams’ communication is less intensive than optimum. This result corresponds to the hypotheses and results of other authors that assume positive relationship.

Communication content during the game is mainly related to players’ coordination and their emotions. On the current stage of the study there were found no specific communication patterns attributed to only winning or only losing teams. Both kinds of teams share information as well as express emotions. However, losing teams tend to be more emotional.
The main limitation of the study is that we cannot identify the causal relationship between communication and team performance. However, we supported that the behavior of successful and unsuccessful virtual teams is different. Further investigation can be also related to team members’ features and its influence on communication and team performance.
Conclusions

This study comes to investigate the determinants of performance in emerging area of eSports on three levels. Despite the boost in the popularity of eSports a gap both in the theoretical and empirical foundations has been discovered. This study attempts to fill this gap in two ways. The first is the contribution to the eSports professionals is revealing drivers of success at different levels. The second is the contribution to the general economic is the analysis of labor and management issues in the new context.

The research has been presented in this thesis in three steps:

1. Macro-level analysis of eSports determinants of success and eSports impact to labor market.
2. Meso-level analysis of competitiveness of eSports, spillover effects and team tournaments motivation schemes.

In the conclusion of our research we would like to emphasize the following findings.

Theoretical contribution:

1. Theoretical model which describes the relationship between the popularity of video games and unemployment in different countries.
   a. Unemployment rate negatively depends on the hours spent on video games.
   b. However, in cases where the population is growing, unemployment will positively depend on the time spent on games.
   c. Depending on the utility from playing video games, the effect of the hours spent on video games on unemployment might be positive or negative.
2. Theoretical model of group motivation in team tournaments.
   a. Prize spreads in team tournaments are greater than individual spreads for some range of production function with decreasing returns to scale in effort; team spreads smaller than individual spreads in case of increasing returns.
   b. When returns to scale in effort is high the organizer should choose an individual tournament. In this case the team has “overmuch potential".
If each member recognizes it, then there are no incentives to exert the maximum level of effort within the team, what leads to free-rider problem. Consequently, the whole team performs at the lower level, than it can. And that is the reason for the organizer not to choose a team tournament.

Methodological contribution:

3. We suggest the metric of video games popularity through eSports prize money.
4. Panel VAR approach is suggested for the empirical tests of contestable market theory.
5. New metrics of skill and language diversity are suggested.
6. Endogenous switching regression model as an approach for the empirical test of managerial efficiency is suggested.
7. Text mining and lasso regression for the empirical studies of team communication are suggested.

Empirical contribution:

8. Determinants of country-level performance in eSports.
   a. GDP per capita is significant indicator for the outcome model, but it is not statistically significant for the selection model. This finding suggests that entry costs are relatively low in eSports.
   b. A country’s infrastructure affects performance in eSports: A 1% increase in GDP per capita leads to a 2.2% increase in prize money per capita.
   c. A proper IT infrastructure is important to the initial development of eSports within a country, but this effect disappears after a certain threshold.
   d. Country population is not statistically significant in the outcome model, but it is important for the selection equation. This finding contradicts the evidence in the traditional sports literature.
9. The empirical estimation of digital leisure innovations effect to the work-leisure time distribution of individuals.
a. Video games, as an innovation in leisure activities, do affect work-leisure time distribution and increase unemployment rates at the country level.

b. There is a significant inverse relationship between income level and the effect of the popularity of video games on total and youth unemployment. For adults this effect is stronger for countries with higher productivity.

10. The empirical test of contestable market theory in the context of eSports.

a. The main result is that competition does not increase industry size.

b. The reverse relation is significant: industry size decreases competition, but the effect disappears after one year. In fact, what has been observed is that the prizes tend to concentrate in a smaller number of competitors.

c. The number of teams and new entries affects competition with a significant time delay and a controversial outcome

11. The empirical test of spillover effects in promotion through events.

a. The events in general increase sales, but marginal effect varies. The saturation point is about 83 event per year.

b. We find an empirical evidence of regional spillover and between-genre spillover. There is no evidence of in-genre spillover. An optimal strategy of a company is to organize events in different regions, because they help to promote products in all regions.


a. The results for the team games are similar to the results for the individual games to the extent that they follow tournament theory.

b. However, there is significant difference between the motivation of groups and individual. Interestingly, this difference depends on the level of competition.

13. Regarding the team performance, the major findings are the following.

a. The teams benefit from diversity in their workforces: the absence of diversity reduces performance by 30%. However, different aspects of diversity affect performance in different ways.

b. The benefits of language diversity do not outweigh the costs of such diversity.
c. Hiring a coach does not increase team performance. This raises a question about management efficiency, not only in eSports but also in similar industries because eSports teams are similar to modern professions since computer knowledge and Internet communication are necessary for all employees.

d. The analysis of communication intensity in terms of number of characters texted by team members per minute has shown that there is inverted U-shape relationship between communication intensity and team performance

The findings established in this study might be a valuable contribution to the development of eSports and video games as an object of research. The contribution of this study is spread across theoretical, methodological and empirical areas with the focus on empirical studies.
References


References


Kimbrough, Gray. 2018. “Xboxes and Ex-Workers? Gaming and Labor Supply of Young Adults in the US.”


References


References


