ANALYSIS OF INVESTMENT OPPORTUNITIES IN THE GAMING STOCK MARKET USING SOCIAL TRADING

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Abstract

Despite the gaming industry's growth, until 2016 there was no option to invest in the gaming stock market with a diversified financial product, and even in 2024, investment instruments are scarce. Furthermore, the literature lacks an explanation of the relationship between key game metrics and macroeconomic variables (Palma-Ruiz et al., 2022). This study aims to fill both these gaps. The 50 countries with the highest revenues for various markets and geographic regions are analysed to develop multivariate models that explain gaming revenues and player numbers using macroeconomic variables such as gross domestic product (GDP), private consumption, number of Internet users, and interest in online gaming via Google Trends. The main finding is that the games' revenues and the number of players can be effectively explained by the macroeconomic variables mentioned above and that the models also serve as a forecasting method with high model quality. In addition, a portfolio of gaming stocks is developed using the social trading platform (STP) wikifolio and compared to alternatives in terms of holding and performance. The findings suggest that STPs can serve as a bridge in markets with limited or non-existent tradable instruments and that social traders have outperformed conventional investment products in gaming.

Keywords: FinTech, Games, Gaming, Video Games, Social Trading, Wikifolio

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1. INTRODUCTION

An emerging trend in asset management is the rise of social trading platforms (STPs), which democratise investment decisions by providing a transparent and interactive environment for investors of all experience levels to share and implement strategies and insights, thereby extending access beyond wealthy individuals and institutional investors (Apesteguia et al., 2020; Deng et al., 2023; Röder & Walter, 2019). The STP wikifolio, established in Austria in 2012, enables individuals to invest in portfolios managed by traders through exchange-traded certificates (Kern, 2017; wikifolio [https://www.wikifolio.com/en/int/about-wikifolio]).

Individual traders on the wikifolio platform have been shown to outperform professional traders, suggesting that social trading can uncover and harness unconventional investment talent (Doering & Jonen, 2016; Lauterbach & Ziegler, 2019; Oehler et al., 2016). Dorfleitner and Scheckenbach (2022) find a strong negative correlation between overconfidence and trading performance on STPs, influenced by platform-specific compensation and risk management approaches, while Scheckenbach et al. (2021) reveal that convex incentive structures lead traders to reduce risk near the high-water mark, with social status indicators heavily affecting risk decisions. Lauterbach and Ziegler (2019) find that individual traders on the wikifolio platform significantly outperform professional traders and media firms, attributed to better selection and market timing, challenging the traditional view of professional investment superiority. The impact of wikifolios extends to user engagement, where platform features, social dynamics, and transparency play a key role in attracting both experienced and inexperienced investors (Glaser & Risius, 2018; Reith et al., 2020; Scheckenbach et al., 2021).

However, there is little research on wikifolios, especially regarding management, performance relative to benchmarks, and the sectors and trading strategies of wikifolios, such as in the computer and video game industry. Although the gaming industry is still young compared to traditional forms of entertainment, having emerged at the end of the 20th century, it has grown into a multi-billion-dollar ecosystem with three billion players worldwide, driven by rapid technological advances like mobile and cloud gaming, extended reality, and esports, with diverse revenue streams and increasing global engagement, projected to reach USD 282 billion by 2024, led by major markets in the United States (US), China, Japan, and Europe (Alomari et al., 2016; Baltezarević et al., 2018; Bányai et al., 2019; Cruz-Neira et al., 2018; Formosa et al., 2022; Newzoo, 2024; Statista, 2025).

The first research aim thus addresses the aforementioned research gap by conducting an analysis of 50 countries with the highest games revenue in the period from 2018 to 2023, which accounted for 96% of worldwide revenue in 2023 (Statista, 2025). The study develops multifactor models by region and market class, with the aim of revealing the relationships via multi-linear regression analyses between gaming data, such as game revenue and player count, and macroeconomic data, such as gross domestic product (GDP), private consumption, Internet users, and Google Trend data. Furthermore, there is no scientific literature on the performance of gaming stocks or a gaming fund, which represents a blatant research gap. There is also a literature gap regarding how social trading can be used to invest in gaming. The second research aim of this study is to close these gaps. Despite its rapid growth, based on extensive research in 2015, the author could not find a single investment vehicle that would allow investors to invest in the gaming industry and participate in its development. The only option for investors to benefit from the growth prospects of the gaming market was to acquire shares of gaming companies. This approach presents several challenges, including high research costs, increased risk due to a lack of diversification, and the need for a high level of industry knowledge to navigate the complexity of this rapidly evolving sector. There was a lack of a managed portfolio that summarised a broad range of gaming stocks, which precluded a more systematic and less risky form of investment and thus represented a gap in the market for investments in the gaming industry. However, the STP wikifolio offers the possibility to invest in portfolios of stocks by creating an investable certificate on these so-called wikifolios on its platform. This led the author to the idea of creating a public wikifolio on the games market (Tahvildari, 2025).

The study's results offer high-quality multivariate models that forecast gaming revenue and player count based on region and market while also contributing to the scientific literature through holdings and performance analyses. The findings show that gaming revenue correlates with combinations of the variables GDP, private consumption, number of Internet users, and Internet search interest in gaming, while the number of gamers correlates with combinations of GDP, private consumption, and the number of Internet users. The holding and performance analyses demonstrate that gaming wikifolios offer wider diversification, lower risk, and superior risk-adjusted performance compared to gaming exchange-traded funds (ETFs). This suggests that social traders in the gaming segment can outperform the market and provide investors with a superior alternative to traditional investment products. Additionally, wikifolio can accurately reflect the market by better-replicating equity sub-markets like gaming, where conventional investment opportunities are scarce.

The structure of this paper is as follows. Section 2 reviews the relevant literature. Section 3 analyses the methodology used to conduct empirical research into the relationship between gaming market variables, such as game revenue and number of players, GDP, private consumption, number of Internet users and gaming Internet search interest, as well as for the holdings and performance analyses between two gaming wikifolios and a gaming ETF. Section 4 documents and explains the results of this study and Section 5 discusses them in detail. Finally, Section 6 summarises the results of the study and identifies limitations and implications for research and practice.

2. LITERATURE REVIEW

Kern (2017) discusses how wikifolio merges Internet technology with finance through an innovative leader-follower model, democratising investment by allowing transparent, cost-effective trading of index certificates. Doering and Jonen (2016) examine how portfolio managers on STPs adjust their risk strategies in response to underperformance, revealing insights into dynamic risk management and the impact of diverse management approaches in environments free from traditional investment constraints. Lauterbach and Ziegler (2019) find that individual traders on the wikifolio platform outperform professional and media firm traders on returns and risk-return ratios, attributing this advantage to superior selection, risk management, and market timing, challenging the traditional belief in the superiority of professional investing. Röder and Walter (2019) show that investment flows into social trading portfolios depend on past performance, visibility, and active trader communication. Oehler et al. (2016) conclude that while most wikifolio certificates do not outperform market benchmarks, geographically focused portfolios and those managed by skilled traders can achieve significant excess returns, challenging the assumption of uniform underperformance among retail investors. A joint study by the Universities of Zurich and Geneva reveals that wikifolio certificates with high investment capital consistently outperform the market and traditional funds, offering superior risk-adjusted returns while highlighting the influence of investor personality traits on trading success.

Dorfleitner and Scheckenbach (2022) demonstrate a strong negative correlation between overconfidence and trading outcomes on STPs, emphasising how platform-specific compensation and risk management approaches shape trader behaviour and suggesting strategies to mitigate the risks of overconfident trading. Scheckenbach et al. (2021) discover that convex incentives and social dynamics, such as rankings and communication skills, influence traders on social platforms to reduce risk near the high-water mark, offering insights for platform design to mitigate moral hazard. Glaser and Risius (2018) argue that increased transparency and social interaction on trading platforms amplify behavioural biases such as the disposition effect, negatively impacting trader performance and challenging the efficient market hypothesis. Reith et al. (2020) observe that experienced users are driven by performance factors, while system complexity and security concerns deter inexperienced users, recommending enhanced security and usability to boost engagement on STPs. Yang et al. (2021) propose a strategic delay in trade information release to balance transparency and revenue optimisation on STPs, suggesting a dynamic delay policy tailored to trader profiles to mitigate free-riding and benefit both platforms and users. Deng et al. (2023) analyse STPs and identify that link formation is influenced by communication, financial performance, and demographics, while link dissolution is mainly driven by financial performance and communication.

Apesteguia et al. (2020) provide evidence that copy trading significantly increases investors' risk-taking, with the effect amplified when traders can directly replicate others' actions, concluding that copy trading encourages excessive risk-taking. Horn et al. (2024) imply that transactions on the STP wikifolio effectively predict aggregate private investor behaviour, with buy and sell transactions forecasting high-market-cap and low-market-cap stocks, respectively, in the following month. Oehler and Schneider (2023) note that STPs incentivise signal providers, especially underperformers, to engage in lottery-like stock trading due to convex reward structures, effectively exposing followers to a gambling-like return profile. Xi et al. (2022) evaluate technological innovation efficiency in China's video game industry using a meta-frontier approach, identifying significant regional disparities and emphasizing the role of human capital, research and development investment, economic development, and infrastructure in enhancing innovation performance. Palma-Ruiz et al. (2022) a positive correlation between per capita GDP and gaming revenues and players in European and North American countries, while the opposite is true in Asia. They also find a generally positive relationship between Google Trends in esports and revenues in the gaming market.

The literature on STPs such as wikifolios points to considerable development at the interface of social networking and financial investments with innovative investment opportunities that challenge traditional models. Social traders often outperform their professional peers, demonstrating the potential of STPs to exploit unique trading strategies and democratise access to financial markets. The lack of research on management styles, comparative benchmark performance, and sector-specific trading strategies within wikifolios, such as for the games industry, presents an opportunity for further study.

3. RESEARCH METHODOLOGY

The methodology consists of two phases. Inspired by Palma-Ruiz et al. (2022), the first phase involves gathering data on the gaming market for the top 50 countries with the highest gaming revenues from 2018 to 2023 from the statistical service provider Statista (2025), yielding 300 data points. These countries account for more than 96% of global gaming revenue in 2023, ensuring the data is representative of the entire games industry. The dataset includes revenue and players on an annual basis. Next, macroeconomic data such as GDP, Internet users, and private consumption for the same period 2018–2023, for the selected 50 countries are collected from the World Bank (https://data.worldbank.org/). In addition, Google Trends (https://trends.google.com/trends/) data on the search term "gaming" is collected for the period January 1, 2018–December 31, 2023. These are given a score between zero and 100 (highest search interest). For each year, average trend data is calculated for the year based on the monthly trend data provided.

The countries are categorised by market using Morgan Stanley Capital International (MSCI) market classifications and by region using United Nations Statistics Division (UNSD) geographical definitions to develop, compare, and discuss different models for each market and region. The MSCI classification assesses equity markets around the world and classifies them as developed, emerging, frontier, or standalone (MSCI, 2024). Of the 50 countries selected, MSCI classifies most as either developed or emerging markets, while four fall into the frontier category. The remaining are categorised as "other markets", as shown in Table 1.

The geographical breakdown is based on the United Nations (UN) classification (UNSD, n.d.). The regions are Africa, the Americas, Asia-Pacific, Europe, and the Middle East, as shown in Table 2.

Table 1. MSCI market classification of the 50 selected countries

MSCI market class	*Number of countries*	*Countries*
Developed markets (DM)	22	US, Japan, France, United Kingdom (UK), Germany, Canada, Italy, Australia, Spain, Netherlands, Switzerland, Sweden, Belgium, Austria, Norway, Israel, Denmark, New Zealand, Finland, Singapore, Portugal, Ireland
Emerging markets (EM)	18	China, India, South Korea, Brazil, Mexico, Indonesia, Philippines, Turkey, Thailand, Saudi Arabia, Egypt, Poland, Malaysia, South Africa, Colombia, Chile, United Arab Emirates (UAE), Peru
Frontier markets (FM)	4	Nigeria, Bangladesh, Vietnam, Pakistan
Other markets (OM)	6	Russia, Iran, Argentina, Iraq, Ethiopia, Algeria

Source: Author's elaboration based on MSCI (2024).

Table 2. United Nations classification by geographical region of the selected 50 countries

Region	*Number of countries*	*Countries*
Africa	5	Algeria, Egypt, Ethiopia, Nigeria, South Africa
Americas	8	Argentina, Brazil, Canada, Chile, Colombia, Mexico, Peru, US
Asia-Pacific	14	Australia, Bangladesh, China, India, Indonesia, Japan, Malaysia, New Zealand, Pakistan, Philippines, Singapore, South Korea, Thailand, Vietnam
Europe	17	Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Netherlands, Norway, Poland, Portugal, Russia, Spain, Sweden, Switzerland, UK
Middle East	6	Iran, Iraq, Israel, Saudi Arabia, Turkey, UAE

Source: Author's elaboration based on UNSD (n.d.).

After that, the following basic multilinear models with the (in)dependent variables described in Table 3 and parametrisations β_{GDP}, β_{IU}, β_C, β_{GT} with appropriate dimensions calculated statistically for all countries in a particular market class or region using multi-linear regressions, so that the resulting models apply to a country in the respective market class or region.

Model 1

$$Revenue = \alpha + \beta_{GDP} * GDP + \beta_{IU} * IU + \beta_C * C + \beta_{GT} * GT \quad (1)$$

Model 2

$$Players = \alpha + \beta_{GDP} * GDP + \beta_{IU} * IU + \beta_C * C + \beta_{GT} * GT \quad (2)$$

Table 3. Variable descriptions for multilinear Models 1 and 2 modelling games revenue and number of players

Variables	*Description*	*Unit*
Dependent variable		
Revenue	Games revenue	Billion USD
Player	Number of players	Million
Independent variable		
GDP	Gross domestic product	Billion USD
IU	Internet user	Million
C	Private consumption	Billion USD
GT	Google Trends	Points

Source: Author's elaboration.

Then, one by one, ten subsets of the total sample are selected. The first subset is the entire sample "top 50", followed by the four subsets for the markets in Table 1 and five subsets for the regions in Table 2. The two Models 1 and 2 are considered separately and the next steps are carried out individually for each subset to explain the endogenous variables on the left side of the equations. The process begins with the execution of multi-linear regressions for all possible combinations of the four exogenous model variables on the right side of the linear Eqs. (1) and (2). This is achieved by setting the "beta" coefficients β_{GDP}, β_{IU}, β_C, β_{GT} individually and sequentially to zero or retaining them. The brute force approach guarantees the examination of all potential relationships. Subsequently, only those models which contain statistically significant variables (p-value < 0.05) are retained. Hence, emphasis is placed on reliability, whereby it is ensured that each predictor makes a meaningful contribution to the explanation of the dependent variable. The assessment of multicollinearity is conducted using the variance inflation factor (VIF). Only models where all variables have a VIF < 10 are retained to enhance interpretability and stability. The presence of high multicollinearity leads to unreliable coefficient estimates and the obfuscation of individual effects, thereby undermining the interpretability of the results.

The subsequent step is to evaluate the adjusted R^2 from these non-multicollinear models and to choose the models with the highest values. This measure is selected based on its capacity to reflect the goodness of fit of the model while adjusting for the number of predictors and helps to avoid overfitting and maintain predictive accuracy. Lastly, the selection of the optimal model is evaluated through the Akaike information criterion (AIC) and Bayesian information criterion (BIC), where lower values are better. The AIC and BIC balance model fit and complexity, with the BIC tending to favour simpler models. This step serves to validate that the final model is parsimonious, reducing complexity while ensuring maximum generalizability. If the selection of the best model according to the presented criteria is not unique, the two or three best results are presented.

Alternative suitable methods, not applied in this study, include structural equation modelling, which identifies direct and indirect causal effects while incorporating market classifications or regional differences; non-parametric regression methods, which flexibly model non-linear relationships and regional variations; and time series analysis, which captures temporal dynamics to reveal both short-term adjustments and long-term trends in gaming and economic variables (Box et al., 2015; Reddy & Henze, 2023; Ullman & Bentler, 2012).

The second phase consists of data extraction and analysis of investment products in the games stock market, which includes two competing wikifolios and an ETF. The author developed a public wikifolio on the games market in 2015, launched it under the name "video games" in August 2016, and has managed it since. It is traded on the stock exchange as a certificate under the symbol WF000GAMES and has gained popularity since its inception with the highest assets under management (AUM) within the gaming market on the wikifolio platform, totalling EUR 330,000 in April 2024 (Börsen Radio Network [BRN], n.d.; Tahvildari, 2025).

A holdings analysis is applied to compare the components of WF000GAMES with the wikifolio (symbol WF00OGES15) managed by Dreher (2025) and the ETF (symbol ESPO) (VanEck, 2025). Furthermore, a performance analysis is carried out between the three portfolios. If S_t^i is the price of the portfolio π^i at time $t \in \tau$ for a daily interval τ, the cumulative return (CR) between $t_1 < t_2$ for $t_1, t_2 \in \tau$ is:

$$CR_{t_1,t_2}^i = \frac{S_{t_2}^i}{S_{t_1}^i} - 1 \tag{3}$$

Based on the CR, the annualised return (AR) is calculated as:

$$AR_\tau^i = \sqrt[|\tau|]{\left(1 + CR_\tau^i\right)^{252}} - 1 = \left(1 + CR_\tau^i\right)^{\frac{252}{|\tau|}} - 1 \tag{4}$$

where, $|\tau| = 1 + \max_{t\in\tau}\{\tau\} - \min_{t\in\tau}\{\tau\}$ is the length of the interval τ in (trading) days, and 252 the conventional count of trading days per year. The annualised volatility (AVol) (standard deviation of daily returns) is as follows with the empirical standard deviation: and the empirical mean:

$$AVol_\tau^i = \hat{\sigma}_\tau^i\sqrt{252} \tag{5}$$

$$\hat{\sigma}_\tau^i = \sqrt{\frac{1}{|\tau| - 1}\sum_{t\in\tau}\left(R_t^i - \bar{R}_\tau^i\right)^2} \tag{6}$$

$$\bar{R}_\tau^i = \frac{1}{|\tau|}\sum_{t\in\tau} R_t^i \tag{7}$$

where, $R_t^i = S_t^i / S_{t-1}^i - 1$ as the (ex-post) arithmetic daily return. These key figures are used to calculate risk-adjusted performance measures (RAPM). The maximum drawdown (MDD) during the period τ is:

$$MDD_\tau^i := \max_{t_2\in\tau}\left[\min\left\{0, \frac{S_{t_2}^i}{\max_{t_2 \geq t_1 \in\tau} S_{t_1}^i} - 1\right\}\right] \tag{8}$$

The MDD shows the largest loss in the entire observation period and represents the loss from having bought at the all-time high and sold at the all-time low. The ratio of the CR and the absolute value of MDD is the return to drawdown risk (RDR):

$$RDR_\tau^i = \frac{CR_\tau^i}{\left|MDD_\tau^i\right|} \tag{9}$$

While RDR is an asymmetric RAPM, the annualised return to volatility risk ratio (AVR) defines a symmetric RAPM:

$$AVR_\tau^i = \frac{AR_\tau^i}{AVol_\tau^i} \tag{10}$$

The Sharpe ratio (SR) is applied as a further asymmetric RAPM (Kourtis, 2016; Ray et al., 2009) and is as follows:

$$SR_\tau^i = \frac{\bar{R}_\tau^i}{\hat{\sigma}_\tau^i} \tag{11}$$

A risk-free interest rate of 0% is assumed for the calculation so that the RAPM is not distorted by another return variable not required for the performance comparison. In addition, the capital asset pricing model (CAPM) is used to calculate Jensen's α and β (Fama & French, 2004; Ray et al., 2009):

$$R_t^i = \alpha^i + \beta^i R_t^b + \varepsilon_t^i \tag{12}$$

where, $\varepsilon^i = \left(\varepsilon_t^i\right)_{t\in\tau}$ is a white noise process and R_t^b represents the return of the benchmark portfolio (market portfolio return). The CAPM is only applied for the period between 2 July 2019 and 1 March 2024 for which data on ESPO is available, since it is used as a benchmark as it physically tracks (MarketVector, n.d.; VanEck, 2025). The (excess) Treynor ratio (TR) is calculated as a systematic RAPM using the quotient of Jensen's α and β (Hubner, 2003):

$$TR^i = \frac{\alpha^i}{\beta^i} \tag{13}$$

The historical price data for the three portfolios is downloaded from the public financial data service provider finanzen.net[1]. Eqs. (3–13) are calculated based on the scraped historical price data of the portfolios. The (tradable) daily closing price data for WF000GAMES has been available since February 23, 2017, and for WF00OGES15 since May 18, 2017. The data for ESPO has been available since July 2, 2019. Hence, two time periods are defined. For the comparison of the two wikifolios, the period is from May 18, 2017, to March 1, 2024. The second period starts with ESPO historical price data on July 2, 2019, and ends on March 1, 2024. Alternative methods that would be suitable for performance analysis are holdings-based and returns-based style analyses, which are not applied in this study (Kaplan, 2012; Swinkels & van der Sluis, 2006).

4. RESULTS

The first phase includes numerous multilinear regression models, which are developed and presented in Table 4 for *Revenue* and Table 5 for *Player*, depending on the MSCI market class and UN region. In total, more than 300 multilinear regressions were calculated, with 15 combinations each for the entire sample "top 50" and the nine subsets for games revenue and number of players. Two models are given for most subsets explaining the *Revenue* or *Player*. Column 7 indicates whether all the independent variables specified in the model are statistically significant. Column 10 indicates whether the specified model has the smallest AIC and/or BIC values among all non-multicollinear significant models (if available). Otherwise, it refers to the set of all 15 possible model combinations per subset.

[1] https://www.finanzen.net/

Table 4 shows the models for *Revenue*. The regressions have high model qualities, which can be seen from the adjusted R^2, and serve to predict *Revenue* for a country from the subset based on the market and region. Depending on the subset, there are different numbers of significant factors. All independent variables — *GDP*, *IU*, *C*, and *GT* — appear as explanations for *Revenue* in individual models. There is a collinearity between *GDP* and *C*, so, in the models, either *GDP* or *C* serves as an explanation. Some models have the number of *IU* and/or *GT* as influencing variables. *GDP*, *C*, and *GT* always have a positive influence on *Revenue*. The number of *IU* has a positive influence on *Revenue*, except in the emerging markets and the Asia-Pacific region. There is a great overlap between the emerging markets and the Asia-Pacific region, so it is striking that there are countries in these groups where *Revenue* falls as the number of *IU* increases. This discrepancy stands out in comparison to other markets and regions. The model quality is lowest for frontier markets, likely due to the smallest data subset of these four countries.

Table 4. Multilinear regression modelling results for game revenue according to Model 1

Subset	α	β_{GDP}	β_{IU}	β_C	β_{GT}	*Significance*	*Adj. R^2*	*Max. VIF*	*Lowest AIC/BIC*
(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*
Top 50	-4482.9596	3.5564	19.9219	0	52.8456	Yes	0.9178	1.8028	Yes/Yes
Top 50	-5506.7251	0	40.5585	4.7793	70.2255	Yes	0.8598	1.3919	No/No
DM	-7160.9669	0	132.4253	0	46.5449	Yes	0.9283	1.0294	Yes/Yes
DM	-5578.3971	25.8645	0	0	62.0763	Yes	0.9197	1.0173	No/No
EM	-3743.0612	6.7175	-18.9637	0	35.7232	Yes	0.9769	7.2851	Yes/No
EM	-1849.7759	6.7470	-18.7713	0	0	No	0.9761	6.7868	No/Yes
FM	-1279.7479	6.0068	0	0	0	Yes	0.4913	1.0000	No/No
FM	-1479.2525	5.0585	8.7453	0	0	No	0.5443	1.1814	Yes/Yes
OM	-204.0333	0	24.6936	1.3616	0	Yes	0.9577	5.0535	Yes/Yes
OM	-163.0593	0.7500	23.4618	0	0	Yes	0.9560	6.5778	No/No
Africa	39.5194	0	20.0892	0	0	Yes	0.8409	1.0000	Yes/Yes
Americas	-763.1411	0	0	2.7764	0	Yes	0.9855	1.0000	Yes/Yes
Americas	-974.7340	3.4292	0	0	0	Yes	0.9855	1.0000	No/No
Asia-Pacific	-5483.2260	7.0519	-24.1280	0	80.4647	Yes	0.9706	4.3825	Yes/Yes
Asia-Pacific	-936.8668	7.1489	-24.3103	0	0	Yes	0.9687	4.2588	No/No
Asia-Pacific	-6475.7135	5.6137	0	0	85.4913	Yes	0.9521	1.0976	No/No
Europe	-923.2955	0	0	4.7537	13.8091	Yes	0.9139	1.0001	Yes/Yes
Europe	-139.4604	0	0	4.7496	0	Yes	0.9101	1.0000	No/No
Europe	-250.7051	2.5991	0	0	0	Yes	0.8676	1.0000	No/No
Middle East	-309.2332	0	14.5308	2.1495	7.8379	Yes	0.9572	1.2348	Yes/Yes
Middle East	-371.8674	1.0124	16.4666	0	7.6359	Yes	0.9379	1.1110	No/No

Source: Author's elaboration.

Table 5 shows the models for the *Player*. It is noticeable that *GT* has no significant influence in any of the models. There are three-factor models for Asia-Pacific and the Middle East, where both *GDP* and *C* appear in the models, although one of the two always has a negative influence on the *Player*. Therefore, the other two-factor models for these two subsets are more logical to use and have lower multicollinearity. No significant model was found for the entire top 50 sample. Therefore, the *Player* appears to be highly dependent on the specific market and region. Apart from frontier markets and Africa, the model fits very well and is suitable for forecasting.

Table 5. Multilinear regression modelling results for players according to Model 2

Subset	α	β_{GDP}	β_{IU}	β_C	β_{GT}	*Significance*	*Adj. R^2*	*Max. VIF*	*Lowest AIC/BIC*
(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*
DM	-3.7621	0	0.5797	0	0	Yes	0.9851	1.0000	Yes/Yes
DM	0.6036	0.0079	0	0	0	Yes	0.9755	1.0000	No/No
EM	−7.4722	0.0235	0.2489	0	0	Yes	0.9912	5.5350	Yes/Yes
EM	-17.5305	0	0.1773	0.0734	0	Yes	0.9881	8.2500	No/No
FM	-84.1973	0.3148	0	0	0	Yes	0.2675	1.0000	Yes/Yes
OM	5.1449	0	0.2577	0	0	Yes	0.8300	1.0000	Yes/Yes
Africa	-8.5226	0	0.8395	0	0	Yes	0.3908	1.0000	Yes/Yes
Africa	-6.5858	0.1215	0	0	0	Yes	0.2795	1.0000	No/No
Americas	-2.0900	0	0.5281	0.0013	0	Yes	0.9926	4.9630	Yes/Yes
Americas	-2.1893	0.0009	0.5293	0	0	Yes	0.9925	4.9545	No/No
Asia-Pacific	-1.7391	0.0452	0.3447	-0.0731	0	Yes	0.9903	0.9791	Yes/Yes
Asia-Pacific	-14.3841	0.0187	0.3162	0	0	Yes	0.9792	0.7652	No/No
Europe	-0.6889	0	0.2643	0.0061	0	Yes	0.9348	2.1968	Yes/Yes
Europe	-0.6485	0.0029	0.2766	0	0	Yes	0.9207	2.2727	No/No
Middle East	3.1376	-0.0126	0.2911	0.0130	0	Yes	0.9756	9.7300	Yes/Yes
Middle East	2.7498	-0.0067	0.3032	0	0	Yes	0.9694	5.7732	No/No
Middle East	1.7523	0	0.3082	-0.0110	0	Yes	0.9493	4.7662	No/No

Source: Author's elaboration.

The results of the second phase are presented as follows. The wikifolio dashboard of WF000GAMES shows key information about the wikifolio, including the chart, history, descriptions, ratios, trades and positions with their weights, and any comments from the asset manager Tahvildari (2025). It has achieved a cumulative performance of 171.4% (14.1% p.a.) since its launch on August 21, 2016, up to the reporting date of March 1, 2024. The holdings of WF000GAMES as of March 1, 2024, were scraped directly from the wikifolio dashboard page (Tahvildari, 2025). The snapshot reflects the changes in positions over the 7.5 years since the wikifolio's launch. Aside from the cash position, the portfolio consists of 35 stocks, each with an average weight of 2.72%, a median of 2.39%, a standard deviation of 2.18%, a range of 8.19%, a minimum of 0.26%, and a maximum of 8.45% (Tahvildari, 2025).

Microsoft (MSFT) is the largest holding at 8.45%, followed by chip manufacturer Advanced Micro Devices (AMD) at 6.91% and console and cloud gaming leader Sony at 6.9%. Microsoft's weight includes Activision Blizzard (ATVI) due to the USD 69 billion takeover (Pales, 2023). It is followed by publisher Electronic Arts (EA) with 6.27%, chip maker NVIDIA with 5.62%, and publisher Take-Two Interactive (T2) with 5.45%. This is followed by Japanese publisher Square Enix (SE) with 4.49% and Nintendo with 4.2%. Smaller positions include the Chinese publisher Netease (3.75%), the French publisher Ubisoft (3.55%), the Japanese publishers Konami (3.5%), Capcom (3.28%), and Bandai Namco (2.74%), the Chinese publisher Tencent (2.47%), chip manufacturer Intel (2.46%), and the US companies Alphabet (2.8%), Amazon (2.67%), Meta Platforms (2.39%), Disney (2.28%), and Apple (2.19%). There are minority shareholdings of less than 2%. The overall equity weight is 95.07%, with the remaining 4.93% held in cash, indicating a highly invested strategy. US equities account for nearly half of the portfolio (49.25%). Japan comes in second with around a quarter (26.22%), followed by China and Hong Kong with 6.73% and France with 5.80%. Sweden and Poland account for 4.34% and 1.85%, respectively. Singapore and South Korea are the least represented, with 0.49% and 0.39%, respectively (Tahvildari, 2025).

The wikifolio WF00OGES15 was published on November 23, 2015, and became tradable on May 18, 2017, making it the second tradable gaming wikifolio on the platform and has an AUM of EUR 292,000 at the time of analysis (Dreher, 2025). Except for the cash position with a weight of 4.5%, it comprises 34 stocks with average weights of 2.81% with a median of 1.05%, a standard deviation of 4.53%, a range of 21%, a minimum of 0.1%, and a maximum of 21.1%. Due to the higher standard deviation and range with a lower median of the weights, it is characterised by significantly less portfolio diversification compared to WF000GAMES, as almost half of the total assets (45%) are invested in just three stocks. Chip maker AMD has the largest weight at 21.1%, followed by competitor NVIDIA at 14.6%, which means that together they account for more than a third of assets at 35.7%. T2 comes in second with 9.3%, followed by MSFT with 8.2%. Nintendo, EA, and Sony account for 7.5%, 4.7%, and 3.3%, respectively. The first four titles account for more than half (53.2%) of the assets. The portfolio is overweight in chipmakers over common game stocks. Market leader Sony is underweighted at 3.3%. SE, Konami, Capcom, and Bandai Namco only have a small share of 3.6%, although together with Sony and Nintendo, they dominate almost the entire Japanese market (Statista, 2025). Instead, there are micro positions such as Fastly, Lions Gate Entertainment, or Alibaba with weights of less than 0.2%. Almost three quarters (72.5%) of the shares come from the US, 15.1% from Japan, 2.9% from China and Hong Kong, 1.4% from France, 1.1% from the Netherlands, 1% each from Germany and South Korea, 0.2% each from Poland and Sweden, and 0.1% from Canada (Dreher, 2025).

On June 24, 2019, the first gaming ETF ESPO was launched, which invests in companies that generate at least 50% of their revenue from video games and esports (MarketVector, n.d.; VanEck, 2025). As of March 1, 2024, the fund has an AUM of USD 577 million. The ETF comprises 25 stocks with an average weight of 4%, a median of 3.88%, a standard deviation of 2.79%, a range of 11.6%, a minimum of 0.7%, and a maximum of 12.3%. The ETF, which consists of 25 stocks, has 10 fewer positions than the wikifolio WF000GAMES. Even though WF00OGES15 has larger weight deviations, the ETF is less diversified based on descriptive statistics. The ETF is also heavily weighted towards chip manufacturers, with NVIDIA accounting for 12.3% and AMD for 10.32%, which together account for more than a fifth of its holdings (22.62%). Nintendo comes next with 6.69%, followed by Chinese companies like Tencent (6.04%) and Netease (5.5%). EA and Take-Two, the two largest independent publishers, have relatively low weights at 4.8% and 4.06%, respectively. Japanese publishers such as Capcom, Bandai Namco, Konami, and Square Enix tend to have low weights of 4.06%, 3.88%, 2.96%, and 1.36%, respectively. Instead, app developers such as Applovin (5.46%) and Unity Software (3.51%), mobile game developers Sea (5.06%), Roblox (3.96%), and Aristocrat Leisure (4.43%) are heavily weighted. Leading European publishers such as the French group Ubisoft are completely absent. 46.38% of the holdings come from the US, 22.23% from Japan, and 12.82% from China and Hong Kong. South Korea (9.15%), Australia (4.43%), Taiwan (2.84%), Poland (1.15%), and Sweden (1.01%) follow (VanEck, 2025).

The ETF replicates the MVESPGTR index. To qualify for inclusion in the index, companies must operate predominantly in gaming, with more than 50% (25% for the current components) of their revenues coming from video games and/or esports, have a market capitalisation of more than USD 150 million and a high level of trading activity. The index limits the weight of individual companies to 8% and excludes companies that do not adhere to ethical standards. The 50% revenue filter is flawed because to correctly capture a market, the market would need to be segmented by a metric, such as revenue, and then the shares of total revenue in gaming would need to be considered accordingly. The index makes the fundamental error of referring to individual companies (share of gaming revenue) and thus ignoring the size of the revenue or the share of total revenue in the gaming market. As a result, market leaders such as Sony and Microsoft, which together dominate the console and cloud gaming submarkets, are completely absent. Other platform providers, such as Alphabet and Apple, which earn money from their application stores via commissions and have a significant share of revenue, are also missing (Statista, 2024, 2025). Chip makers such as NVIDIA and AMD have long supplied not only the gaming market but also large parts of other industries, so the gaming share is significantly lower, but they are still represented in the index due to the 25% rule for current components and account for more than all major Japanese or American game developers combined, which is a substantial imbalance (AMD[2], NVIDIA[3]). Other European publishers, such as Ubisoft[4], are

[2] https://ir.amd.com/
[3] https://investor.nvidia.com/home/default.aspx
[4] https://www.ubisoft.com/en-us/company/about-us/investors

missing, which is incompatible with the index criteria. Despite the systematic constraints of the index, there is no other gaming index on the market that could be used as a benchmark, so the ESPO is used as a benchmark for the CAPM analyses. Despite the systematic constraints of the index, the ESPO serves as the benchmark. For the CAPM analyses, there is no other gaming index available on the market.

Table 6 shows the calculated performance figures for the two wikifolios, WF000GAMES and WF00OGES15, for the period from May 18, 2017, to March 1, 2024, using Eqs. (3–13) based on the price data from finanzen.net. The average daily return of WF00OGES15 at 0.0687% is slightly higher than that of WF000GAMES at 0.0524%. The higher standard deviation of the daily returns, 1.4671% for WF00OGES15 and 1.266% for WF000GAMES reflects the associated higher risk. The SR is similar for both wikifolios, although at 0.0468 it is slightly higher for WF00OGES15 than 0.0414 for WF000GAMES. The CR of WF00OGES15 at 171.42% is significantly higher than that of WF000GAMES at 115.01%, which is mainly due to the focus of WF00OGES15 on chip manufacturers such as NVIDIA and AMD, which have risen strongly in the hype surrounding artificial intelligence. For example, NVIDIA has increased sixfold since the beginning of 2023 (Krauskopf, 2024; NVIDIA, n.d.). The AVol and MDD also show that the WF00OGES15 has a significantly higher risk. The AVol of 23.19% (WF00OGES15) is higher than 20.10% (WF000GAMES), and the MDD of -34.97% (WF00OGES15) is significantly lower than -28.57% (WF000GAMES). However, WF00OGES15's higher CR and AR lead to an RDR of 4.90 and an AVR of 0.67, while wikifolio WF000GAMES achieves an RDR of 4.03 and an AVR of 0.59.

Table 6. Performance metrics for the two wikifolios WF000GAMES and WF00OGES15 for the period May 18, 2017–March 1, 2024, based on the Eqs. (3–13)

Portfolio	$\bar{R}_\tau^i$, (%)	$\hat{\sigma}_\tau^i$, (%)	SR_τ^i	CR_τ^i, (%)	AR_τ^i, (%)	$AVol_\tau^i$, (%)	MDD_τ^i, (%)	RDR_τ^i	AVR_τ^i
WF000GAMES	0.0524	1.2660	0.0414	115.01	11.84	20.10	-28.57	4.03	0.59
WF00OGES15	0.0687	1.4671	0.0468	171.42	15.71	23.29	-34.97	4.90	0.67

Source: Author's elaboration based on financial data provided by https://www.finanzen.net/.

Table 7 shows the same performance figures for the period July 2, 2019–March 1, 2024, for the three portfolios, including ESPO. The performance figures of WF00OGES15 are comparable to those of ESPO, primarily due to their similar portfolio composition. The average daily returns with the standard deviation are 0.0745% and 1.7491% (ESPO), 0.0717% and 1.484% (WF00OGES15), and 0.0524% and 1.285% (WF000GAMES), respectively. The higher returns come at the price of higher risk. With a CR of 102.38% and AR of 16.09%, the ESPO is slightly below the CR (105.96%) and AR (16.52%) of the wikifolio WF00OGES15. For WF000GAMES, CR and AR are lower at 69.24% and 11.78%, respectively. The SRs are quite similar at 0.0483 (WF00OGES15), 0.0426 (ESPO), and 0.0408 (WF000GAMES), with WF00OGES15 performing the best. ESPO has the highest AVol at 27.77%, while the other two have AVols of 23.56% (WF00OGES15) and 20.40% (WF000GAMES). The same applies to the MDD, which is very high for ESPO at 40.91%, compared to 34.97% (WF00OGES15) and 28.57% (WF000GAMES). The RDRs are 3.03 (WF00OGES15), 2.5 (ESPO), and 2.42 (WF000GAMES). In this respect, the wikifolio WF00OGES15 is ahead of the ESPO. In terms of AVR, ESPO and WF000GAMES share a value of 0.58, while WF00OGES15 boasts a higher AVR of 0.7. The performance figures to date indicate that the wikifolio WF00OGES15 outperforms ESPO and WF000GAMES in both risk-adjusted and absolute terms. The outperformance of WF00OGES15 and ESPO can be attributed to their heavy investments in NVIDIA and AMD.

Table 7. Performance metrics for the three portfolios WF000GAMES, WF00OGES15 and the ETF ESPO for the period July 2, 2019–March 1, 2024, based on the Eqs. (3–13)

Portfolio	$\bar{R}_\tau^i$, (%)	$\hat{\sigma}_\tau^i$, (%)	SR_τ^i	CR_τ^i, (%)	AR_τ^i, (%)	$AVol_\tau^i$, (%)	MDD_τ^i, (%)	RDR_τ^i	AVR_τ^i
WF000GAMES	0.0524	1.2850	0.0408	69.24	11.78	20.40	-28.57	2.42	0.58
WF00OGES15	0.0717	1.4840	0.0483	105.96	16.52	23.56	-34.97	3.03	0.70
ESPO	0.0745	1.7491	0.0426	102.38	16.09	27.77	-40.91	2.50	0.58

Source: Author's elaboration based on financial data provided by https://www.finanzen.net/.

Table 8 displays the CAPM results. The coefficient ρ shows a correlation of approx. 1/3 between the daily returns of the wikifolios and the benchmark. The coefficient of determination R^2 is 0.1181 (WF000GAMES) and 0.1144 (WF00OGES15), which means that approx. 11.8% of the variance of the wikifolio returns is explained by the benchmark returns. Both wikifolios outperform the benchmark market, as can be seen from the positive α of 0.0336% (WF000GAMES) and 0.0503% (WF00OGES15). With a market risk β of 0.2525 (WF000GAMES) and 0.287 (WF00OGES15), the systematic risk in the modelling is significantly lower than that of the benchmark. The TR for WF000GAMES is 0.1331%, and for WF00OGES15, it is slightly higher at 0.1754%, meaning that both wikifolios systematically outperform the ETF. However, the model quality based on the R^2 is quite low, which implies that the returns of the portfolios correlate less, which was to be expected due to the different portfolio allocations based on the holdings analysis.

Table 8. Capital asset pricing model results for the three portfolios WF000GAMES, WF00OGES15, and ESPO for the period July 2, 2019–March 1, 2024, with correlations $\rho^{i,b}$, Jensen's α^i, β^i, TR^i, and adjusted R^2

Portfolio	$\rho^{i,b}$	α^i, (%)	β^i	TR^i, (%)	R^2
WF000GAMES	0.3437	0.0336	0.2525	0.1331	0.1181
WF00OGES15	0.3382	0.0503	0.2870	0.1754	0.1144
ESPO	1.0000	0.0000	1.0000	0.0000	1.0000

Source: Author's elaboration based on financial data provided by https://www.finanzen.net/.

5. DISCUSSION

The results of the first phase provided numerous multi-linear models for explaining *Revenue* with various combinations of significant variables: 1) *GDP*, 2) *IU*, 3) *C*, and 4) *GT* searches for the keyword "gaming", depending on the market and region for a country. The models have very high model quality across the entire (sub)sets and serve as forecasts. For the frontier markets, it is recommended to expand the sample for future studies to optimise the model quality for this market. The remaining markets and regions also include alternative models with interchangeable variables (e.g., either *GDP* or *C*, depending on the model) and sometimes alternative models with fewer factors that are more feasible as forecast models. Two examples are the Americas and Europe regions, which are explained very well by only one factor, *C*, with a high model quality (R^2 of 0.986 and 0.91, respectively — values are rounded, see Table 4). On average, the models used to estimate the *Player* have very good model qualities, although their prediction quality is slightly lower than that of *Revenue*. For example, no significant model was found for the entire top 50 sample, meaning that the number of players can only be predicted with sufficient accuracy depending on a country within one of the MSCI markets or regions. An exception is again found for frontier markets, since the modelling has a low quality here due to the low number of countries in the sample. The modelling for the number of players shows that only *GDP*, *C*, and/or the number of *IU* have an influence, but not Google searches with the keyword "gaming" as an indicator of interest in gaming.

In contrast to the analysis by Palma-Ruiz et al. (2022), the results of this study provide a comprehensive basis for explaining the relationships between *Revenue* and the *Player* using three important macroeconomic variables: 1) *GDP*, 2) *C*, and 3) *IU*. Furthermore, the multifactor models consider interest in searching for games online when explaining *Revenue*. While Palma-Ruiz et al. (2022) conduct univariate analyses to calculate individual correlations and identify relationships, this study examined the totality of the available exogenous variables in order to ultimately establish multivariate models with very high model qualities without multicollinearity, which, due to their robustness and stability, serve as forecast models for one country from the defined markets and regions. Furthermore, unlike the findings of Palma-Ruiz et al. (2022), this analysis found no negative correlation between GDP and games revenue in Asian regions, as GDP had a positive influence. Additionally, this study covers a period that is twice as long and more up-to-date, specifically from 2018 to 2023. Due to the inclusion of a high number of 50 countries, it covers more than 96% of the worldwide games revenue in 2023, further enhancing its representation.

The author created the wikifolio WF000GAMES, which has been managing the games market for almost eight years. The wikifolio platform facilitated the establishment of the world's first financial instrument, enabling investors to invest in the gaming market and benefit from its promising positive performance. As of March 2024, the wikifolio had an AUM of EUR 330,000, making it the largest gaming wikifolio on the platform. A comparison of holdings with the second wikifolio, WF00OGES15, and the VanEck ETF ESPO shows that these two portfolios are significantly less diversified and have a strong overweight of American chip stocks AMD and NVIDIA, whereas other market leaders in gaming are underrepresented or, in the case of the ETF, are completely absent. The performance comparison between the two wikifolios, WF000GAMES and WF00OGES15, for the period from May 18, 2017, to March 1, 2024, showed a better return on sales for WF00OGES15 due to the better absolute performance resulting from the overweight of NVIDIA and AMD. On the other hand, the drawdown risk, volatility, and cluster risk are significantly higher than for the more diversified wikifolio WF000GAMES. In the period July 2, 2019–March 1, 2024, there were similar results in a direct comparison of the two wikifolios with the ETF. However, due to the lower diversification, the ETF showed significantly higher MDDs of up to almost -41% and high volatility, whereby the wikifolio WF00OGES15 performed slightly better than the ETF based on the RPM. The CAPM shows a systematic excess return for both wikifolios compared to the benchmark. The performance comparison of the three portfolios reveals a period of strong performance by US chipmakers, which benefited the ETF and WF00OGES15. However, the risks are higher due to overweighting compared to wikifolio WF000GAMES.

6. CONCLUSION

Despite the gaming industry's growth, until 2016, there was no option to invest in the gaming stock market using a diversified financial product. Furthermore, there was a lack of explanation of the relationships between key figures such as gaming revenue and the number of players. The study aimed to develop econometric models based on a representative sample of 50 countries from different developed markets and geographical regions. These models were designed to explain game revenues and player numbers using macroeconomic variables such as GDP, private consumption, number of Internet users, and search interest in games using Google Trends data. Another goal was to show investors the opportunity to invest in gaming using the STP wikifolio. To do this, the author created a gaming wikifolio and carried out holdings and performance analyses to compare it with two other competing gaming investment alternatives.

The study's results demonstrate that multilinear models can explain the relationships between game revenue, GDP, private consumption, the number of Internet users, and Google search interest in gaming across various markets and regions. Likewise, the respective numbers of gamers can be explained based on GDP, private consumption, and the number of Internet users. The findings represent significant models with very high average model quality, which can be used as forecasts and thus close the gap in terms of missing explanations for the correlation between the gaming key figures and the observed variables. Nevertheless, there are some limitations to the forecast, which, due to the design as a cross-sectional analysis by combining all time points from 2018–2023, groups the countries into markets and regions and were not conducted at the individual country level. A longitudinal analysis that focuses on a single country with a significantly longer time series could yield more accurate forecast results. However, this is challenging due to the limited data availability of the gaming metrics of revenue and number of players and can be addressed by future studies. The models derived in this study can serve as analytical and forecasting tools for practitioners and academics alike while also offering the potential for future research to optimise and refine them.

The holding and performance analyses showed that the gaming wikifolio WF000GAMES had a broader diversification at lower risk and good risk-adjusted performance compared to another gaming wikifolio, WF00OGES15, and the VanEck ETF. In addition, both wikifolios beat the ETF in terms of systematic risk-adjusted performance. The conclusion that can be drawn from this is that social traders can beat the market and can be a better alternative for investors than traditional investment products such as ETFs for the gaming sector. The results of the study contribute to the argument that financial instruments for the gaming stock market deserve more interest from researchers and practitioners, especially since there are hardly any investment alternatives. One limitation of the holdings analysis is that it shows a snapshot and not the holdings over time. Similarly, there is a limitation to the performance analysis because no stock-based and return-based style analysis was carried out to analyse the performance contribution of individual positions in the wikifolios and in the ETF. These offer scope for further research.

The models developed in this study are crucial for future research, as they not only explain the previously missing relationships between key gaming metrics and external macroeconomic factors but also serve as forecasting models for each market class and region. Future studies can also use the models to refine them at a more granular level. Furthermore, the results of the wikifolio solution are important for future research, as they show that social traders outperform conventional funds in the gaming sector. More research based on the methodology and results of this study is recommended on wikifolio as a solution for missing or inadequate financial instruments of other sectors like gaming, as wikifolio is a good alternative to fill the gaps in the investment landscape for retail investors.

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