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Neural networks for estimating Macro Asset Pricing model in football clubs

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Summary

The recent crisis caused by COVID-19 directly affected consumption habits and the stability sof financial markets. In particular, the football industry has been hit hard by this pandemic and therefore has more volatile stock prices. Given this new scenario, further research is needed to accurately estimate the value of the shares of football clubs. In this paper, we estimate an asset pricing model in football clubs with different compositions of risk nature using non-linear techniques of artificial neural networks. Usually, asset pricing models have been estimated with linear methods such as ordinary least squares. Our results show a precision higher than 90% for all the estimated models, which far exceeds those shown by linear methods in the previous literature. We find that the residual represents about 40% of the variance of the price-dividend ratio. Long-term risks follow in importance, and above all, the habit component and its behaviour in the face of changes. The importance of the residual component exists due to a low correlation between the asset price and consumer behaviour, but to a much lesser extent than that shown in previous studies. The estimation carried out with artificial neural networks, both the Deep Learning methods and especially the Quantum Neural Network, opens up new possibilities to estimate more efficiently the pricing of financial assets in the football industry.

KEYWORDS
Deep Learning, football clubs, long-term risks, Macro Asset Pricing, neural networks, non-linear methods, Quantum Neural Networks

1 | INTRODUCTION

The COVID-19 pandemic has caused major disruption to the sports industry, in particular the football industry, and has raised the question of whether an accurate estimation of the value of its assets is possible. The postponement of football competitions to prevent the spread of COVID-19 led to reduced revenues for clubs, and for those actively involved in the stock market, a decrease in revenues could cause the potential for a decline in share prices. This fact leads to volatility in the share prices of European football clubs (Bedir et al., 2022). So, given the insecurity in the investment of assets in the football industry, more research and instruments are required to accurately estimate the value of its stocks and to forecast the rate of return of an asset. The asset pricing model provides a way to determine the expected rate of return for an investment and can reliably deal with volatile times, as it establishes the relationship between expected dividends and the risk involved in investing in specific assets (Chen et al., 2017).

The main utility of asset pricing models is to determine the prices of claims about uncertain payments. The so-called asset pricing models have evolved in different ways since their appearance in the 1980s (Chen et al., 2017; Cheng et al., 2022; Gallant et al., 2019). One of the most developed and used types of models in the last decade is the Macro Asset Pricing (MAP) model, based on the macroeconomic theory of growth and consumption as a measure to quantify the value of financial assets. Among them, the habit formation models, long-term risks, rare disasters, limited participation, those based on intermediaries and those of learning stand out (Barro & Jin, 2021; Beeler & Campbell, 2012; Giglio et al., 2016; Zhiguo He & Krishnamurthy, 2018; Kleibergen & Zhan, 2020). In the case of habit models, the influence of consumer habits on the price of assets is described. For its part, the long-term risk model focuses on the volatility of consumption over time. Finally, rare disaster models show asset price changes in a catastrophic scenario. These models have been refined by Nakamura et al. (2017), estimating the importance of growth rate shocks and uncertainty in asset prices. Barro and Jin (2021) estimate the model of long-term risks including rare disaster models, considering them as complementary to treating macroeconomic variables and analysing the price of assets. These rare events are often associated with major historical events, such as world wars and depressions. The long-term risk model reflects gradual processes that influence growth rates and long-term volatility. Also, Chen et al. (2017) estimate valuation models of long-term growth, long-term volatility, habit, and residual, and have served as a frame of reference to analyse the representation that the model's residuals may have in the variance of the price-dividend ratio. For its part, Zhiguo He and Krishnamurthy (2018) establish the fundamentals of intermediate asset pricing and conclude that there is a need to build models that are embedded in a macroeconomic framework to clarify the nexus between the financial sector, asset prices, and industrial sectors. In addition, the findings of Kleibergen and Zhan (2020) call for the use of robust inference methods for identification in empirical asset pricing studies. Together with better quality consumption measures and more time-series observations, these robust methods will facilitate a more reliable estimation of consumption-based asset pricing models in future research.

In general, the development of asset pricing models has been carried out with data from all the sectors that make up a buffer index. But these models could also be applied in specific sectors such as the football industry (Bansal et al., 2012; Campbell & Cochrane, 1999; Chen, 2017; El Modni et al., 2022; Lalwani & Chakraborty, 2020) given the recent IPOs by some European football clubs (Manchester United, Juventus and Sporting de Portugal) and their situation after extreme events such as the one experienced with the COVID-19 crisis. The football industry is a major industry in several European countries, creating a large amount of direct and indirect employment. It is considered a mass consumer industry, and due to this, it has been seriously affected by the abrupt drop in aggregate demand due to COVID-19. For this reason, it is vital to study the valuation of assets in this industry using a macroeconomic perspective. The football industry has been directly affected by confinement measures, suspending competitions in the acute phase of the same, and the prohibition of public attendance at stadiums. All this produces a significant decrease in the turnover of football clubs. Hence, it is necessary to provide information on how these events will affect the valuation of football clubs.

Financial economists have considered alternative models for consumption-based asset pricing, since the classical asset pricing model is unable to explain important issues about stock returns, such as the high volatility of returns and the high stock premium. The new approach is that of habit formation, according to which utility relies on consumption relative to a benchmark consumption level (Yogo, 2008). Several papers in financial economics derive their most salient implications for asset pricing in the presence of habit formation by investors' preferences. Preferences appear quite far from being separable over time: the estimated habit happens to be a measurably important part of the specification of the utility of power and constitutes a major part of current consumption. Investors have aversion to losses in consumption of the time-varying habit, and fear of losses drives the high level and counter-cyclical movement of the equity premium (Chen & Ludvigson, 2009).

Asset pricing models have been developed mostly with conventional statistical linear methods, mainly using linear regression. There are few experiences of the application of non-linear methods in the estimation of these models (Gu et al., 2021), although they have shown superior precision results and have been limited to US stock indices, some new experiences that show the capacity of success that these non-linear methods have on asset pricing (Brunnermeier et al., 2021; Marfè & Penasse, 2016; Särkkä, 2013; Schorfheide et al., 2018). Other authors have researched the football industry but have applied other methodologies compared to the use of machine learning techniques in our study. On their part, Ozbayoglu et al. (2020) state that the precise pricing of an asset is a crucial area of study in Finance. They conclude that although there are a large number of machine learning models developed for banks, corporations, real estate, and derivatives, Deep Learning has not been implemented in this particular field. Therefore, there are some possible areas of implementation where Deep Learning models can help asset pricing researchers or valuation experts.

The present study tries to respond to the scarce literature on asset pricing in the football industry with non-linear techniques. For this, a sample has been created with 21 football clubs that are listed on the stock exchange in the period 2011–2019. The asset pricing model used is a Macro Asset Pricing (MAP) model, which is estimated by three neural network methodologies: the Multilayer Perceptron (DRCNN), Deep Neural Decision Trees (DNDT), and the novel Quantum Neural Networks (QNN). Our paper follows the framework of the Chen et al. (2017) model, which divides the price-dividend ratio into identifiable macro risks (habit, long-term growth and long-term volatility) and unobservable ones.

We make at least three further contributions to the literature. First, we consider an asset pricing model safer and more reliable than other assets in the market, as the value of the residual factor, which shows the impact of volatility with unobserved information on the financial asset studied, is lower than in previous works. Moreover, in our model, innovations in the habit component have relative importance in the price of the asset, and similarly, this behaviour is repeated in the factor included in excess consumption. Given the relationship between habit and the different behaviours and changes in investors' expectations about asset pricing, various authors conclude that behavioural asset pricing has increasingly appeared as a solid body of knowledge in asset pricing, being a subject for future research (Maio & Silva, 2020; Nanayakkara et al., 2019; Truong et al., 2021).

Second, we improve the precision of asset pricing models concerning that obtained in previous studies with artificial neural networks, since Deep Learning can help solve many of the world's problems associated with unpredictable investor behaviour (Kim et al., 2020). In addition, Solórzano-Taborga et al. (2020) introduce an innovative and unexplored focus on creating new factors that can be exploited in asset pricing models. However, they state that further research is needed on the robustness of the efficiency factor to changes in inputs and outputs, by implementing sophisticated computational methodologies. Finally, Ozbayoglu et al. (2020) conclude that Deep Learning has not been implemented in this particular field, and therefore can help asset pricing experts, as in previous studies, the asset pricing model has usually been estimated with the OLS statistical methodology. Therefore, the neural network methodologies used in our study to estimate the MAP model reveal higher precision than that obtained in the previous literature, allowing us to reach new tools for estimating the shares of listed football clubs or other possible specific financial assets.

Third, our study has constructed a MAP model for a specific sector, football clubs, showing the behaviour of the financial assets of football clubs listed on the STOXX Europe Football stock index. The conclusions achieved may also be applied to football clubs listed on other stock market indices. So, this not only becomes more relevant for academics but mainly for football clubs' stakeholders, as the price of football clubs has always been unpredictable and this uncertainty grows in the current COVID-19 crisis, which has severely affected the football industry.

1.1 | Why football?

The football industry has a great influence on the world economy, which generates a direct and indirect impact on important aspects such as job creation. If we ask ourselves how football clubs are 'different' or what is special about football shares, we can highlight the type of investors in the football industry, the influence of consumer habits on the price of football clubs' assets and the growth of the football industry.

In the football industry, unlike in other industries, we can differentiate between financial investors and sentimental investors. Buchholz and Lopatta (2017) demonstrated that the purchase of shares in football club companies is not driven by the expected dividend, but rather by the belief in the long-term increase of the stock price and the short-term profit from price fluctuations (speculation). Some investors hope that with the arrival of a high-value player, the team's sporting results will be enhanced, which, at the same time, will be translated into a higher stock price. Conversely, some believe that the new contract amount is considered excessively high and that it will not be profitable in the long-term. Prigge and Tegtmeier (2019) explore whether football club shares are fairly priced according to the valuation of other equity assets in the capital market and if football club investors would expect additional benefits, namely in addition to dividends and share revaluation. They establish that fan shareholders may receive a dividend by supporting their favourite club as a provider of shares and may hence be prepared to pay an overvalued price by conventional norms. Moreover, outside of financial shareholders, all other types of shareholders (strategic, patrons and fans) obtain extra benefits from holding football shares, apart from dividends and share appreciation, and therefore might be prepared to push for higher prices. Based on the types of investors considering the additional benefits in their bidding behaviour is also consistent with the argument that the football sector is only loosely connected to the general economic cycle and plays under its own rules.

Fűrész and Rappai (2022) confirm the premise that the great majority of sports investors respond to the news before the formal announcement. Moreover, they indicate that these investors are predominantly optimistic and therefore assume that, for example, the arrival of a new player will translate into improved sporting returns. They conclude that these investors are also amateurs owning shares, who feel some kind of 'ownership' over the players and therefore encourage investment strategies that are not at all rational. As Huth (2019) reports, the number and role of amateur investors are expanding in major European football leagues, and private investors play a meaningful and beneficial effect on sporting performance. Such a phenomenon might motivate football club managers to enter the stock market and exploit the attitude of investors. Benkraiem et al. (2011) also demonstrate a distinction in the behaviour of traditional investors driven by economic reasoning and investors driven by affective rationality. They focus on an analysis of investor behaviour in the short-term horizon, as it provides a clearer view of the strategy of football shareholders. In conclusion, the source of growth for any sports organisation is building a wide fan base, therefore, if football clubs fail to consider the interests of fans, who can become investors, and to address them with a well-planned communication strategy, then the result can be a harmful negative impact upon the long-term organisational value of the sporting entity (Razeto, 2021).

In the case of the influence of consumer habits on the price of football club assets, Giulianotti (2002) states that the customer may follow the local club providing it fulfils some associative aims and its players can 'get the job is done' on the ground; alternatively, game attendance and interest in the club turn erratic. The consuming fan is therefore likely to change clubs or move to clubs that provide winners or are better able socially to progress the social and economic mobility of the spectator. Fans often define themselves as consumer values to validate their traditionalist reasons and their loyalty to the club. Therefore, the football club usually provides something in exchange that coincides with the football supporter's habitus or set football interests, like the signing of a favourite player or the cultural policy of the club (Giulianotti, 2002).

The world's largest sports market in terms of revenue associated with sporting events is Europe, with football being the biggest money-spinner. The football industry is strongly changing consumer habits. Some fans travel with their team on all their journeys. Others just follow home games. Before the presence of television and platforms with their multiple interests, there was a homogeneous timetable, which helped to set the habits of a social custom (Drayer et al., 2010). The proliferation of televised football means that to maintain the traditional habit of favouring a certain team, the spectator must become a supporter of a football club. Today, the natural habitat of the football consumer is increasingly the virtual realm, who seeks the sensations of football represented through television, the Internet, or in a different way (on web-connected devices and in more diverse formats, from computer to smartphone to tablet), making the viewer increasingly multi-screen (Dwyer, 2011).

However, according to Silveira et al. (2018), the higher the identification of sports consumers towards their team, the higher the impact on their satisfaction, leading to an increase in their loyalty towards the football team and their willingness to buy tickets for a football match. Furthermore, they report that the higher the engagement of sports consumers with football, the higher their purchasing intention to buy tickets. Besides Martínez and Martínez (2007) show that satisfaction regarding stadium attributes like accessibility, facilities aesthetics, cleanliness and comfort can influence loyalty. There is therefore a clear connection between satisfaction and loyalty. Other reasons for sports consumers to come to the stadium are their identification with their clubs, the motivation to attend matches like entertainment and social interaction, and the degree of fan engagement, whether circumstantial or enduring. All these factors influence the fan's purchase decision (Silveira et al., 2018). In contrast, the factors that make fans watch the match outside the venue are ticket prices, weather conditions, travel distance to the event, the current success of the team, the existence of star players, the atmosphere of the facility, the layout of the staff and the match (Fekete & Kelemen-Erdős, 2016).

In recent years there has been a change in the investment attractiveness of sports clubs, especially football clubs after the Union of European Football Associations introduced financial discipline rules. Therefore, 2017 saw the beginning of a new stage in the development of the football industry. The main change was about profits at football clubs, which brought for the first time a total profit of over 600 million euros, compared to a few years earlier the total losses of clubs representing the main divisions of European football reached 1.7 billion euros (Reade & Singleton, 2020). Some authors have studied the investment potential of the football industry. Litvishko et al. (2019) concluded that the football industry has a substantial potential for income growth, suggesting the appeal of sports clubs' shares as an investment object. Nevertheless, these investments are marked by a high degree of risk because of the specificity associated with the professional sports industry, involving the unforeseeability of the final result of a single match as well as the whole competition. Razeto (2021) investigates whether European football clubs can manage their traditions, ownership structures and socio-political context so that private capital enters into their property. This author states that the sharp growth of the sports industry is mainly determined by two trends: the development and growth of digital technology and the expansion of digital betting and gambling. However, the football industry is not similar to the entertainment industry due to the irrationality of the football industry and its complexity. More precisely, in contrast to normal business, the sports business, and particularly the football industry, is highly linked to the loyalty and tradition of its local community and fans, at the same time as it is extensively complex due to both the hierarchy and the network of business partners and stakeholders within a specific sector (Razeto, 2021). Boțoc et al. (2019) show that an emerging area in applied economics is the economics of sports, given the increase in global revenues. Currently, retransmission revenues, ticket sales, sponsorship, merchandising and marketing revenues, player transfers and prize money from competitions constitute the revenue flows of football clubs. Furthermore, these authors add that the economics of football, given its popularity (football is the most popular sport in the world), are enormous, and not many industries have such growth rates or a similar potential for development. This evolution could be one of the reasons for several football clubs being listed on the stock exchange, and therefore, providing new opportunities for potential investors, institutional as well as individual. In conclusion, football is the only sport that has exerted a polarising worldwide attraction, thus transcending national, cultural and socio-economic frontiers. It continues to grow impressively with an ever-increasing worldwide audience in both industrialised and developing countries, setting it up as the most favourite sport on the planet, with 43% of the spectator sports market (Álvarez & Morosi, 2019).

1.2 | Stock market models and football

In general, the volatility of football clubs' stock returns seems to be especially affected by the global volatility of stock markets. This financial background influence highlights that, in a turbulent period, investors will dump these assets for more liquid ones. Such a scenario is in line with the 'flight to quality' response in periods of crisis (Limba et al., 2020). Gimet and Montchaud (2016) emphasise the significant impact of the financial context, illustrating the vulnerability of football stocks to systematic risk. Thus, in principle, the determinants of the performance and volatility of club stocks are largely similar to those of other types of firms and are in line with the financial literature. Indeed, the company's business specificity—as a producer of sporting events - appears not to be considered in the investors' assessment, which is largely based on the profit generated. This outcome is not unexpected and the reason for the poor performance and high volatility concerning the clubs' shares, is that many of them experience important and regular deficits. However, some studies suggest a discrepancy in stock market behaviour between rational investors and fans (Edmans et al., 2007; Fűrész & Rappai, 2022; Huth, 2019). According to these authors, sporting performance means more to the investor than economic performance (Benkraiem et al., 2011; Fűrész & Rappai, 2022).

Another aspect of financial volatility in asset prices is that bad news tends to have a greater impact on volatility than good news. That is, volatility tends to be higher in a falling market than in a rising market. In the case of football clubs, bad news (bad football results) implies a fall in the share price, making them more volatile after a given football match (Floros, 2014). Furthermore, Benkraiem et al. (2011) report on the importance of intangible assets (players) and on the difficulty of assessing the fair value of these assets, so that there is a close and strong link between sporting performance and the volatility of listed football clubs. Several football teams are listed on the stock exchange to cover their financing requirements, nevertheless, some teams are no longer listed on the stock exchange (e.g., Bolton Wanderers in 2003, Manchester United in 2005 and Manchester City in 2007). The reasons for this trend are the illiquidity and the extreme volatility of football clubs' share prices. Therefore, in contrast to industrial and commercial firms, the stock market valuation of publicly traded football clubs may be influenced by different sources of information, especially sports results. Benkraiem et al. (2011) study the effect of sports results on stock price volatility. They conclude that, firstly, the sports results of football teams affect the stock market valuation of listed clubs. Secondly, the size of the market reaction is dependent on the outcome of the match (i.e., loss, draw or victory) and the venue of the match (i.e., home or away).

In football clubs, there is excessive volatility related to changes in risk parameters that are difficult to observe. The intangible assets of football teams, for example, players, are difficult to evaluate because their value is not only volatile but can depreciate rapidly. Since football is a contact sport, this variability can be explained by the unpredictability related to the frequency and severity of injuries. Moreover, even if football players are not directly injured, they may suffer from other physical or psychological problems that diminish their performance during matches (Benkraiem et al., 2011). Therefore, it is difficult to predict a player's career performance in later seasons. In principle, the more a player suffered injuries in the past, the more probable it is that he will be hurt in the future, but this relation is unsystematic. A player with a past injury may have a more successful season than a player without an injury (Torgler & Schmidt, 2007). Gimet and Montchaud (2016) analyse the major determinants of European football clubs' stock market returns and volatility. They use an econometric study with a sample of 24 European football clubs and consider a large set of internal and external variables. They find that stock returns seem to be influenced mainly by the real economic and financial context and by several internal variables, mostly financial (profits, capitalisation), and by reputation (stadium attendance). Thus, stock returns rely mainly on the traditional financial elements highlighted in the general literature. Also, the volatility of stock returns seems to be especially influenced by the general volatility of stock markets. Such an influence of the financial context reinforces that in a period of turbulence, investors will dispose of these assets towards other, more liquid assets. In terms of internal variables, their findings show the effect of earnings, net player transfers and, more modestly, sporting results on the volatility of stock returns. Floros (2014) considers data information from four football clubs, Porto and Benfica (Portugal), Juventus (Italy) and Ajax (the Netherlands), to test the link between their European performance (wins/draws/losses) and their stock returns. They investigate the effects of football results on stock returns using a GARCH model. They conclude that investors behave differently about their team's results. Prigge and Tegtmeier (2019) evaluate whether stocks in football clubs are valued in line with the valuation of other capital assets in the capital market and if investors in football clubs expect extra benefits from a sample of 19 listed European football clubs. They apply a Capital Asset Pricing Model framework and their results indicate that the majority of the football clubs (13 out of 19) are overvalued.

The rest of the paper is organized as follows. In Section 1 we justify the choice of the football industry. Section 2 provides a literature review of empirical research. Section 1.2 describes the stock market model and football. In Section 3 the Macroasset pricing model and the methodology are described. Section 4 points out the results and findings obtained. By last, Section 5 finishes explaining the conclusions reached.

2 | LITERATURE REVIEW

The existing literature has mainly focused on researching football clubs on the stock market in British clubs (Allouche & Soulez, 2005; Benkraiem et al., 2011; Fotaki et al., 2009; Gannon et al., 2006; Renneboog & Vanbrabant, 2000; Samaiogo, Aglietta et al., 2008). Others are interested in another specific national league, like Turkish clubs (Demir & Danis, 2011; Saraç & Zeren, 2013), German clubs (Stadtmann, 2006), Italian clubs (Boidoa & Fasanob, 2007; Boțoc et al., 2019), Portuguese clubs (Duque & Ferreira, 2005) and a set of European clubs (Baur & McKeating, 2011; Benkraiem et al., 2009; Bernille & Lyandres, 2011; Scholtens & Peenstra, 2009).

From another point of view, almost all studies show the influence of sporting outcomes on stock returns by using different measures such as match results and championship ranking. Looking at match results, overall it seems that wins are positively impacted and draws and defeats are negatively influenced; therefore, the stock returns of single types of equipment are highly correlated with team wins and defeats (Floros, 2014; Gimet & Montchaud, 2016). Renneboog and Vanbrabant (2000) examined 17 football clubs in England throughout three seasons between 1995 and 1998, allowing also for market effects. They revealed that, on the first trading day after a match, positive average excess returns of 1% after victories, and negative excess returns of 1.4% and 0.6% after defeats and draws, correspondingly, were found. Samaiogo et al. (2009) confirmed as well that high-stakes matches, such as European competitions, produce positive instantaneous returns for British football clubs. Bernille and Lyandres (2011) investigated 20 teams from eight nations, exploring the effects of biased estimations of match results on the stock market returns of publicly listed football clubs. Their findings show that the response of the market to football match results is asymmetric, implying that the market responds adversely to losses, whereas for wins, their impact on the stock market is close to null. This finding is in line with the conclusions of Scholtens and Peenstra (2009), who conducted a multi-country study analysing data from eight football teams from five championships during four seasons. They applied an equity index to eliminate systematic factors, and discovered that unexpected and expected wins led to an increase in stock price, and unexpected losses led to a decrease in stock price. The response of prices to losses proved to be much greater than that to wins. Likewise, Edmans et al. (2007) conducted a broader analysis, over a time frame between 1973 and 2004, which included World Cup matches and the main continental events of national sports teams. They reported that there is a significant adverse stock market impact on losses, particularly in the context of football, whereas there is no meaningful impact on victories.

However, it is worth mentioning that certain investigations indicate an insignificant effect of wins. Such a result could be motivated by the emotional rationality of amateur investors, who see winning as the rule. Consequently, investors tend not to prize a win but penalise a draw or a loss (Gimet & Montchaud, 2016). Benkraiem et al. (2009) conclude that the eve of the match raises stock returns, indicating the market's anticipation of a win. Hence, investors fail to respond in the event of a win, but instead, make a reaction correction in the event of a draw or a loss. Furthermore, such an argument probably contributes to the reason that wins (when substantial) have a smaller impact on stock returns than losses. Finally, considering the championship ranking, there have been authors who have considered it to establish the influence of sporting results on share prices or returns (Aglietta et al., 2008), and with the UEFA club coefficient (Baur & McKeating, 2011).

Quite a few studies (Allouche & Soulez, 2005; Fotaki et al., 2009; Fűrész & Rappai, 2022) have taken player transfers into account to explicate stock returns. They conclude that, on the one hand, markets consider the players' sale announcement as positive, implying the inflow of money and the reduced charges are better than the players' loss of capital. On the other hand, they regard the notice of the acquisition of players as negative. Consequently, the perception of instant spending and the raising of wages and social security payments is dominant, rather than the capital-enhancing role of the players' capital. Fotaki et al. (2007) examined football player transfers in the UK from the viewpoint of human resource management. Their findings show that transfers of players and managers impact significantly share prices around the time of the event, although this effect varies. Allouche and Soulez (2005) report that 'human resource management, in terms of specific management of human assets, influences the market's perception of club performance, but in a probably narrow and conventional view'. Fűrész & Rappai, 2022 conclude that transfers may influence the profitability of clubs because the expectations of fans and investors, resulting from transfer announcements, can affect (increase) the price of the club's shares; that is, they can lead to a gain of shares. They found that some participants in the stock market had already responded to the event before the announcement of the transfers: around two-thirds of the transfers under investigation brought about a significant change in the share price, even before the news was made public.

Additionally, selected additional explanatory variables associated with financial (Allouche & Soulez, 2005; Gannon et al., 2006; Samaiogo et al., 2009) and governance (Stadtmann, 2006) dimensions—successful financial performance, expenditure on sports facilities, patronage agreements, broadcasting rights and so on—have been chosen by a few studies to explain stock returns. A further relevant perspective on this issue was provided by Baur and McKeating (2009), who researched if clubs perform better post-IPO than they did before an IPO. They found that most clubs perform no better after an IPO at the domestic level, while they do perform better after an IPO at the international level. The authors find that football clubs' share prices follow the previous season's domestic results and the international results of the present season. Gimet and Montchaud (2016) conducted a more sophisticated analysis on a sample of 24 football clubs in Europe, from mixed leagues, and revealed that stock returns are mainly determined by economic determinants such as profitability, stadium attendance and TV revenues, while stock volatility is affected by market-wide effects, and also by internal factors like match results, net transfers and other sporting events.

Finally, some research studies have contemplated an external factor considering the stock market performance to capture the systematic risk. When the sample incorporates clubs from the same league, the national reference index equal to the nationality of the clubs is applied (for instance the FTSE-100 for British clubs). For a European sample, Baur and McKeating (2011) chose a stock-market index focused on football: the STOXX football index. They show that the stock-market variable always has a positive connection with the stock prices of the clubs and their returns.

In conclusion, there are no previous studies that have estimated the price of assets of football clubs through the macro asset pricing model with non-linear techniques. Solórzano-Taborga et al. (2020) state that further research is needed on the robustness of the efficiency of asset pricing models, by implementing sophisticated computational methodologies. Ozbayoglu et al. (2020) conclude that the asset pricing model has usually been estimated with the OLS statistical methodology and Deep Learning has not been implemented in the football industry field. Therefore, the neural network methodologies used in our study to estimate the MAP allow us to obtain new tools for estimating the shares of listed football clubs or other possible specific financial assets.

3 | MACRO ASSET PRICING MODEL AND NEURAL NETWORKS METHODS

Our work is part of a large and expanding literature that examines the empirical performance of macro asset pricing models. Bansal et al. (2007), Beeler and Campbell (2012) and Barro and Jin (2021) employ moment-matching approaches for comparing the empirical performance of habit, long-term risks, and rare catastrophes. From this approach, the picture that arises is somewhat confusing, as the model chosen is dependent on the moments that are considered to be important. For instance, habit is preferred if much importance is attached to Shiller's (1981) explanation of the volatility puzzle. Long-term risks, on the other hand, are favoured if one is especially concerned about the volatility of time-varying consumption.

Aldrich and Gallant (2011) provide a clearer view comparing habit, long-run risks, and prospect theory using a Bayesian framework. Our results reflect theirs: long-term risks are critical for dealing with the volatile 1930s, yet they are less relevant for other periods. However, we disagree with Aldrich and Gallant in allowing a residual to drive asset prices. More recent work shows that neither long-term risks nor habit formation can match some interesting stylised facts. van Binsbergen et al. (2012) explore dividend strips and stock options, Dew-Becker et al. (2017) investigate variance swaps and Muir (2017) examines international wars and financial crises. We complement these works by illustrating that it is not necessary to incorporate derivatives markets and international data to empirically interrogate long-run risks and habit formation. The time series of US consumption and stock prices are enough if one considers the full likelihood of the data.

3.1 | Macro asset pricing model

This section describes the MAP model used in this study. The main variable of the model is the log price-dividend ratio (pd_t), which is a linear composition of the four-state variables that appear in Equation (1).

$$pd_t = \mu_{pd} + A_x X_t + A_v\,\tilde{\sigma}_t^2 + A_s\tilde{s}_t + A_e e_t \tag{1}$$

where x_t is long-term growth, $\tilde{\sigma}_t$ is the long-term volatility, $\tilde{s}_t$ is surplus consumption also called habit and e_t is the residual. These transformations imply that µpd is the mean of the log price/dividend ratio (Chen et al., 2017). The residual variable in this model is considered permanent, which indicates that it is essential to have complete information on the assets studied for the model.

Our goal is to estimate the coefficients A_x, A_V, A_s, A_e and define with these estimates the trends taken by the variables x_t, $\tilde{\sigma}_t^2$, $\tilde{s}_t$ and e_t. These coefficients and trends offer us information on the weight that each risk has in the volatility of the assets analysed. An attempt is made to identify the variation in consumption (c_t) and dividends (d_t) as long-term risk variables x_t and $\tilde{\sigma}_t^2$ they are identified by their relationship with consumption and dividend growth as shown in (2).

$$\begin{aligned} \Delta c_t &= \mu_c + x_{t-1} + \sigma_{t-1}\eta_{c,t} \\ \Delta d_t &= \mu_d + + \emptyset x x_{t-1} + \emptyset_{\eta_c}\sigma_{t-1}\eta_{c,t} + \varphi_d\sigma_{t-1} n_{d,t} \\ & n\, c,t,\eta d,t \sim N(0,1)\; i.i.d., \end{aligned} \tag{2}$$

where long-term growth x_t evolves according to an autoregressive of order 1:

$$\begin{aligned} x_t &= p_x x_{t-1}\varphi_x\sqrt{1-p_x^2}\varphi_{t-1} n_{x,t} \\ \eta_{x,t} &\sim N(0,1)\; i.i.d., \end{aligned} \tag{3}$$

and long-term volatility σ_t evolves according to (4).

$$\begin{aligned} h_t &= p_h h_{t-1} + \sigma_h\sqrt{1-p_h^2} + \eta_{h,t} \\ \sigma_t &= \overline{\sigma} exp(h_t). \\ h_{h,t} &\sim N(0,1)\; i.i.d. \end{aligned} \tag{4}$$

The specification used for the volatility, consumption, and dividend parameters are equivalent to those applied in previous works (Chen et al., 2017; Marfè & Penasse, 2016; Schorfheide et al., 2018). Typically, volatility is found as a variable with a positive sign (Gu et al., 2021). The development of a single volatility process is within the line shown by previous works for the definition of long-term risks and simplifies the estimation (Bansal et al., 2012; Chen et al., 2017). However, this assumption is restrictive, since it assumes that the impact of volatility in the price-dividend relationship can be identified with the volatility of consumption in the short term. The consumption surplus is identified by the growth of consumption. The variable $\tilde{s}_t$ follow a random walk process. Equation (5) defines this consumption surplus.

$$\begin{aligned} \tilde{s}_t &= p_s\tilde{s}_{t-1} + \lambda(\tilde{s}_{t-1})(\Delta c_t - E_{t-1}\Delta c_t) \\ \lambda(\tilde{s}_{t-1}) &= \begin{cases} \exp(-\tilde{s})\sqrt{1-2\tilde{s}_{t-1}} - 1, & \tilde{s}_t \leq \frac{1}{2}[1-\exp(2\tilde{s})] \\ 0, & \text{otherwise} \end{cases} \end{aligned} \tag{5}$$

This component means that the consumption surplus is the average of past consumption growth and that the habit is the average of past consumption levels (Aldrich & Gallant, 2011; Campbell, 2003; Chen et al., 2017). Unlike variables x_t, $\tilde{\sigma}_t^2$, $\tilde{s}_t$ and e_t, the residual is not identified by either consumption or dividends and follows a random walk process as shown in (6).

$$\begin{aligned} e_t &= p_e et - 1 + \sigma_e\eta_{e,t} \\ \eta_{e,t} &\sim N(0,1)\; i.i.d. \end{aligned} \tag{6}$$

The term e_t captures all factors related to market volatility other than long-term growth, long-term volatility, or habit (Branger et al., 2016; Chen et al., 2017). Besides, we have calculated the sporting performance using the Szymanski Ranking (−ln[p/43-p]). This ranking is represented by the total of clubs that participate in the First and Second Divisions is 42, where one more must be added counting back to the given club with which it is working (Szymanski, 2010). The term 'p' represents the final position that each club reached at the end of the season (Szymanski & Weimar, 2019). Additionally, the decomposition of the historical price-logarithmic dividend relationship would be defined following what was analysed in Equation (1) and would finally remain as it appears in (7).

$$pd_t = \mu_{pd} + A_x\,x_t + AV\,\tilde{\sigma}_t^2 + A_s\tilde{s}_t + A_e\,e_t \tag{7}$$

where pd_t is log price/dividends, x_t is long-term growth, $\tilde{\sigma}_t$ is the long-term volatility, $\tilde{s}_t$ is surplus consumption (habit) and e_t is the residual. To this decomposition of the price-dividend ratio, the estimate of the variation rate can be applied to analyse the influence of each risk component on the price-dividend variation according to (8).

$$\begin{aligned}\mathrm{Var}(pd_t) = {} & \mathrm{Cov}(A_x x_t, pd_t) + \mathrm{Cov}(A_v \eth_t^2, pd_t) + \mathrm{Cov}(A_s \check{s}_t, pd_t) \\ & + \mathrm{Cov}(A_e e_t, pd_t)\end{aligned} \tag{8}$$

where pd_t is log Price/dividends, x_t is long-term growth, $\eth_t$ is the long-term volatility, $\check{s}_t$ is the consumption surplus, e_t is the residual and the A_s are the coefficients of Equation (1).

The construction of the coefficients A_x y A_s conditioned to the values of the remaining parameters of the model are defined as they appear in (9).

$$\begin{aligned} A_x = \sqrt{\frac{T_x}{\mathrm{V}[x_t|\theta]}}, A_V = \sqrt{\frac{T_V}{\mathrm{V}[\tilde{\sigma}_t|\theta]}}, \\ A_s = \sqrt{\frac{T_s}{\mathrm{V}[\tilde{s}_t|\theta]}}, A_e = \sqrt{\frac{T_e}{\mathrm{V}[\tilde{e}_t|\theta]}}, \end{aligned} \tag{9}$$

where $V[x_t|\theta]$ represent the theoretical variances of the risk variables conditioned to the other parameters of the model. Is established $\theta_T^2 = 2$, so that the unconditional prior variance of the price-dividend ratio is equal to the variance observed in the data (Barro & Jin, 2021; Chen et al., 2017).

3.2 | Neural networks methods

3.2.1 | Deep recurrent convolutional neural networks (DRCNN)

Recurrent neural networks (RNN) have been successfully used in many fields for time-series prediction due to their huge prediction performance. The common structure of RNN is organized by the output which is dependent on its previous computations (Wang et al., 2017). Given an input sequence vector x, the hidden states of a recurrent layer s, and the output of a single hidden layer y, can be calculated as follows in Equations (10) and (11).

$$s_t = \sigma(W_{xs} x_t + W_{ss} s_{t-1} + b_s) \tag{10}$$

$$y_t = o(W_{so} s_t + b_y) \tag{11}$$

where W_{xs}, W_{ss} and W_{so} denote the weights from the input layer x to the hidden layer s, the hidden layer to itself and the hidden layer to its output layer, respectively. b_y are the biases of the hidden layer and the output layer. Equation (12) points out σ and o are the activation functions.

$$STFT\{z(t)\}(\tau,\omega) = \int_{-\infty}^{+\infty} z(t)\omega(t-\tau)e^{-j\omega t}dt) \tag{12}$$

where *z(t)* is the vibration signals, $\omega(t)$ is the Gaussian window function focused around 0. $T(\tau, \omega)$ is a complex function that describes the vibration signals over time and frequency. To calculate the hidden layers with the convolutional operation Equations (13) and (14) are applied.

$$S_t = \sigma(W_{TS} * T_t + W_{SS} * S_{t-1} + B_s) \tag{13}$$

$$Y_t = o(W_{YS} * S_t + B_y) \tag{14}$$

where the W term indicates the convolution kernels. The convolution is operated between weights and inputs and is performed in the transition of inputs to the hidden layers.

A RCNN can be heaped to establish a deep architecture, named a deep RCNN (Huang & Narayanan, 2017). When DRCNN is employed for prediction, the last part of the model is a supervised learning layer, which is determined as Equation (15).

$$\hat{r} = \sigma(W_h * h + b_h) \tag{15}$$

where W_h is the weight and b_h is the bias, respectively. The error between predicted observations and actual ones in the training data for the prediction can be calculated and backpropagated to train the model (Ma & Mao, 2019). Stochastic gradient descent is applied for optimization to learn the parameters. Considering that the actual data at time t is r, the loss function is determined as shown in Equation (16).

$$L(r,\hat{r}) = \frac{1}{2}\|r - \hat{r}\|_2^2 \tag{16}$$

Within the objective of optimization in conventional neural networks due to using stochastic gradient descent, this type of methodology uses the loss function to analyse the candidate solution, that is, a set of weights, which is denoted as an objective function (Huang & Narayanan, 2017; Ma & Mao, 2019).

This objective function can have the final purpose of minimizing or maximizing the result of that objective, which means that we are looking for a candidate solution that has the highest or lowest score. Following this logic, neural networks always try to minimize the error (Parot et al., 2019).

Therefore, the objective function is called the loss function, and the value computed by the loss function is simply called the 'loss'. (Anandarajan et al., 2001; Qin et al., 2020).

3.2.2 | Deep neural decision trees (DNDT)

DNDT are DT models executed by deep-learning NNs, where a configuration of DNDT weightings corresponds to a specific decision tree and is thus interpretable (Yang et al., 2018). The algorithm begins by implementing a soft binning function (Alaminos et al., 2019; Norouzi et al., 2015) to calculate the error rate for each node, making it possible to make decisions divided into DNDT. In general, the input of a binning function is a real scalar x, which generates an index of the containers to which x belongs. Assuming x is a continuous variable, group it into $n + 1$ intervals. This requires n cut-off points, which are trainable variables in this context. The cut-off points are denoted as $[\beta_1, \beta_2, \ldots, \beta_n]$ and are strictly ascending such that $\beta_1 < \beta_2 < , \ldots, < \beta_n$.

The activation function of the DNDT algorithm is implemented based on the NN defined in Equation (22).

$$\pi = fw,b,\tau(x) = softmax((wx+b)/\tau) \tag{17}$$

where w is a constant with value w = [1, 2,..., n + 1], $\tau > 0$ is a temperature factor and b is defined in equation (23).

$$b = [0, -\beta 1, -\beta 1 - \beta 2, \ldots, -\beta 1 - \beta 2 - \cdots - \beta n] \tag{18}$$

The NN defined in Equation (22) gives a coding of the binning function x. Additionally, if τ tends to 0 (often the most common case), the vector sampling is implemented using the Straight-Through (ST) Gumbel–Softmax method (Yang et al., 2018).

Given the binning function described above, the key idea is to build the DT using the Kronecker product. Assuming we have an input instance $x \in R^D$ with D characteristics. Associating each characteristic x_d with its NN $f_d\ (x_d)$, we can determine all the final nodes of the DT, in line with Equation (19).

$$\boldsymbol{z} = \boldsymbol{f1}(\boldsymbol{x1}) \bigotimes \boldsymbol{f2}(\boldsymbol{x2}) \bigotimes \cdots \bigotimes \boldsymbol{fD}(\boldsymbol{xD}) \tag{19}$$

where z is now also a vector that indicates the index of the leaf node reached by instance x. Finally, we assume that a linear classifier on each leaf z classifies the instances that reach it.

However, the main drawback of the design is the use of the Kronecker product, which means it is not scalable in terms of the number of characteristics. In our current implementation, we avoid this problem by using broad datasets and training a forest with random subspace (Norouzi et al., 2015; Yang et al., 2018). This involves introducing multiple trees and training each with a subset with random characteristics. A better solution that does not require a forest of hard interpretability involves exploiting the dispersion of the binning function during the learning since the number of non-empty leaves grows much slower than the total.

3.2.3 | Quantum Neural Networks (QNN)

The QNN is built from quantum computation techniques. Qubit is defined as the smallest unit of information in quantum computation which is a probabilistic representation. A qubit may either be in the '1' or '0' or any superposition of the two (Alaminos et al., 2020; Donini & Aiolli, 2017; Verdon et al., 2019). The state of the qubit can be defined according to (20).

$$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle \tag{20}$$

where α and are the numbers that point out the amplitude of the corresponding states such that $|\alpha|^2 + |\beta|^2 = 1$. It is determined as a pair of numbers $\begin{bmatrix}\alpha \\ \beta\end{bmatrix}$.

From elsewhere, an angle θ is a specification that represents geometrical aspects and is defined as such that $\cos(\theta) = |\alpha|$ *and* $\sin(\theta) = |\beta|$. Quantum gates may be applied for adjusting the probabilities because of weight upgrading (Donini & Aiolli, 2017; Jeswal & Chakraverty, 2019). An example of a rotation gate appears in Equation (21).

$$U(\Delta\theta) = \begin{bmatrix}\cos(\Delta\theta) & -\sin(\Delta\theta) \\ \sin(\Delta\theta) & \cos(\Delta\theta)\end{bmatrix} \tag{21}$$

A state of the qubit can be upgraded by applying the quantum gate explained previously. Application of rotation gate on a qubit is defined for expression (22).

$$\begin{bmatrix}\alpha' \\ \beta'\end{bmatrix} = \begin{bmatrix}\cos(\Delta\theta) & -\sin(\Delta\theta) \\ \sin(\Delta\theta) & \cos(\Delta\theta)\end{bmatrix}\begin{bmatrix}\alpha \\ \beta\end{bmatrix} \tag{22}$$

The hybrid quantum-inspired neural network is begun with a quantum hidden neuron from the state $|0\rangle$, preparing the superposition (23).

$$\sqrt{p}|0\rangle + \sqrt{1-p}|1\rangle \ \ with\ 0 \le |p| \le 1 \tag{23}$$

The classical neurons are initiated by random number generation. The output from the quantum neuron is determined as appears in expression (24).

$$v_j = f\left(\sum_{i=1}^{n} w_{ji}{}^{*} x_i\right) \tag{24}$$

where f is a problem-dependent sigmoid or Gaussian function. The output from the network is represented in the expression (25).

$$y_k = f\left(\sum_{j=1}^{l} w_{jk}{}^{*} v_j\right) \tag{25}$$

The desired output is the o_k corresponding squared error calculated according to (26).

$$E^2{}_k = \frac{1}{2}|y_k - o_k|^2 \tag{26}$$

The learning follows the rules of the feedforward backpropagation algorithm. The upgrading of output layer weight is defined for expression (27).

$$\Delta w_{jk} = \eta e_k f' v_j \tag{27}$$

The weights are upgraded by the quantum gate as appears in Equation (20), so in this case, the equation would be according to (28).

$$\begin{bmatrix}\alpha_{ij}{}' \\ \beta_{ij}{}'\end{bmatrix} = \begin{bmatrix}\cos(\Delta\theta) & -\sin(\Delta\theta) \\ \sin(\Delta\theta) & \cos(\Delta\theta)\end{bmatrix}\begin{bmatrix}\alpha_{ij} \\ \beta_{ij}\end{bmatrix} \tag{28}$$

where $\Delta\theta_{ij} = -\frac{\partial E}{\partial \theta_{ij}}$ and $\gamma_{ij}{}' = \gamma_{ij} + \eta\Delta\theta_{ij}$; and η is the learning rate. This ratio takes a value 0.1 according to previous works (Alaminos et al., 2020; Jeswal & Chakraverty, 2019; Verdon et al., 2019).

4 | RESULTS

4.1 | Prior parameters

We use the monthly frequency in the same way that has been applied in previous works (Chen et al., 2017; Cheng et al., 2022; Gallant et al., 2019; Gu et al., 2021). Therefore, we estimate the model using consumption, dividend, and share price data from the Eurostat and Stoxx Europe Football Index (plus Manchester United) based on the Bureau Van Dijk Amadeus database, for the period 2011–2020 (see Appendix A). The database is on a monthly frequency following the patterns of previous literature on macro asset pricing (Chen et al., 2017; Cheng et al., 2022). Consumption data has been harmonized at the European level (Gimet & Montchaud, 2016). Also, 70% of the data have been used for the training stage, and the remaining 30% of the data is for testing.

The prior parameters are established from the sample means of all observable variables μ_{pd}, μ_c, μ_d. This type of priors was also used by other authors (Beeler & Campbell, 2012; Campbell & Cochrane, 1999) Even so, other variables such as $\bar{s}$ and A_s, they do not have a reliable way of evaluating their averages, being jointly the volatility of habit concerning the price-dividend ratio. But it was decided to set $\bar{s}$ in a result of log 0.06, which has also been used by previous works (Barro & Jin, 2021; Branger et al., 2016). Likewise, it is very difficult to estimate the volatility of the level of residuals (σ_e and A_e), so it is set at the level of 1. On the other hand, the upper limit of the long-term growth coefficient A_x set its parameters $\varphi_x = 0.038$, $\bar{\sigma} = 0.0072 \times \sqrt{12}$, $Var\ (\Delta pd_t) = 0.23$, following previous experiences (Bansal et al., 2012; Gu et al., 2021; Särkkä, 2013). In the same way, the long-term growth coefficients and consumption surplus are also established to be positive, and the long-term volatility coefficients with a negative sign are also established.

Table 1 shows the previous values of the parameters we use. The parameters are transformed from the monthly values used by simple monthly divisions (Chen et al., 2017; Cheng et al., 2022). The parameters shown also account for our modified volatility process and the functional form of conditional volatilities.

TABLE 1 Previous values of parameters.

	Value
Simple consumption and dividends	
Consumption Vol $\bar{\sigma}$	0.0249
Dividend Loading on Cons Shock $\emptyset_{nc}$	2.63
Relative Volume of Dividend φ_d	5.96
Long Run Risks	
Persistence of LR Growth p_x	0.74
Relative Volume of LR Growth φ_x	0.17
Dividend Loading on LR growth $\emptyset_x$	2.51
Persistence of LR Vo p_h	0.99
Volatility of LR Vol σ_h	2.09
Habit	
Persistence of Surplus Consumption p_s	0.87
Steady State Surplus Consumption $\bar{s}$	log 0.06

4.2 | Posterior parameters (empirical results)

Table 1 offers in an orderly manner both the previous parameters and the subsequent estimates for each methodology used. Subsequent estimates on the simple consumption and dividend parameters are standard. The average volatility of consumer innovations $\tilde{\sigma}$ they yield more than 1% per year, and dividend innovations are about 4 times more volatile than consumer innovations. Regarding the analysis of long-term risks, we observe that the estimates show a possible long-term risk higher than that shown by economic growth, considering the data on expected growth and consumption volatility. The persistence parameter of long-term growth risks shows values somewhat higher than 0.60, which is a high level, but not higher than that shown in previous experiences for broader analyses regarding the estimation of stock indices (Chen et al., 2017; Gu et al., 2021). The same occurs with long-term risks, which undergo temporary variations, that is, the parameters φ_x y σ_h that represent the long-term relative volatility of growth shocks and long-term logarithmic volatility σ_h, respectively, show high persistence, since their distribution is above 0.70, being statistically significant and consistent with previous studies (Schorfheide et al., 2018).

Table 2 also shows the estimates of other parameters, with their previous and subsequent levels for the model described previously in section 2 of this study, as is the case of habit. This parameter shows a persistent autocorrelation level, close to 0.90 and lower than other reference works (Beeler & Campbell, 2012; Cheng et al., 2022). The persistence of the level of residues is found with a similar value, around 0.90 in the case of DRCNN, but for the DNDT and QNN methodologies, it is around 0.82. This means that the influence of habit and its risks are consistent and do not change abruptly over time, unlike what happens with other economic sectors in which these limits of more volatile habit are shown and suffer a greater part of information not observed in estimating asset valuation (Barro & Jin, 2021; Campbell & Cochrane, 1999; Chen et al., 2019). Finally, the coefficients of the price-dividend ratio appear, which influence the contribution of each risk to measure the volatility of the asset analysed. The residual coefficient is estimated to be high, with a value of around 12%. This means that those parameters that influence the level of price/dividend residuals have volatility greater than 40%, assuming a value of 30% for the log price-dividend ratio. The level of residuals is revealed in the subsequent decreases of the other price-dividend coefficients. The rest of the coefficients such as long-term growth, long-term volatility, and surplus consumption tend towards zero since the prior parameters have been chosen to try to show all the volatility of these coefficients.

The pricing of assets in the football industry depends on many factors. One of them is the mood of the fans. Boidoa and Fasanob

TABLE 2 Parameters estimation.

Parameter	Prior		DRCNN Posterior				DNDT Posterior				QNN Posterior			
	0%	100%	Mean	5%	50%	95%	Mean	5%	50%	95%	Mean	5%	50%	95%
Simple Consumption and Dividends														
Mean Vol of Cons Shock $\overline{\sigma}$	0	0.04	0.017	0.062	0.016	0.184	0.015	0.058	0.014	0.181	0.015	0.057	0.014	0.176
Div Loading on Cons Shock $\emptyset_{\eta c}$	0	10	1.024	0.428	0.971	1.535	1.019	0.424	0.966	1.5330	1.016	0.422	0.962	1.531
Rel Vol of Dividend Shocks φ_d	0	10	4.673	3.947	4.592	5.219	4.669	3.945	4.590	5.215	4.668	3.944	4.589	5.212
Long Run Risks														
Persistence of LR Growth ρ_x	0	1	0.652	0.605	0.658	0.747	0.651	0.604	0.657	0.742	0.646	0.603	0.654	0.739
Rel Vol of LR Growth Shocks φ_x	0	1	0.198	0.162	0.224	0.317	0.196	0.159	0.220	0.316	0.194	0.158	0.218	0.312
Div Loading on LR growth $\emptyset_x$	0	10	1.867	1.804	2.161	2.586	1.865	1.804	2.157	2.585	1.861	1.801	2.156	2.584
Persistence of LR Vol ρ_h	0	1	0.713	0.694	0.72	0.775	0.709	0.693	0.718	0.774	0.706	0.691	0.717	0.772
Volatility of log LR Vol σ_h	0	1.5	0.874	0.764	0.861	1.07	0.872	0.763	0.861	1.066	0.869	0.760	0.856	1.065
Habit and Residual														
Persistence of Surplus Cons. ρ_s	0	1	0.892	0.834	0.872	0.918	0.889	0.833	0.868	0.918	0.887	0.829	0.868	0.917
Persistence of Residual ρ_e	0	1	0.884	0.824	0.856	0.908	0.880	0.821	0.853	0.904	0.879	0.822	0.853	0.901
Price-Dividend Coefficients														
LR Growth Coefficient A_V	0	243	51.19	41.68	49.15	57.39	50.78	41.26	49.09	57.39	51.03	41.63	48.75	57.34
LR Vol Coefficient A_x	0	0	−3.26	−48.5	35.91	−33.431	−48.84	−35.93	−24.05	−33.39	−48.58	−36.21	−23.93	−33.51
Surplus Cons. Coefficient A_s	0	0.93	0.374	0.152	0.394	0.472	0.373	0.147	0.393	0.470	0.371	0.144	0.390	0.468
Residual Coefficient A_e	0	0.23	0.128	0.098	0.126	0.167	0.133	0.096	0.124	0.165	0.133	0.093	0.120	0.162

(2007) report that fans react positively or negatively to their team's performance. When players are bought or sold to improve the competitiveness of each team, the market players are another event that might generate a significant variance. Such a scenario leads to a great reaction in the minds of fans and investors alike since the quality of the football team could get better or worse and therefore the value of the shares may change. Besides, when a publicly listed club is a winner on the pitch, this not only affects the mood of its fans and investors but drives ticket sales, sponsorship, and media contracts. Consumer behaviour is therefore shaped by sporting results. Indeed, a negative outcome will lead to a negative response in consumer demand. Cruz et al. (2021) show that the mean price/performance ratio directly after victories is greater than the mean price/performance ratio after failed games. Furthermore, these authors consider that football is not only the outcome of the football game, but rather much more, since it delivers to communities a pattern of social values, emotional attachment and a feeling of belonging. From a club perspective, football is about providing communities and stakeholders with the best sporting and fan experiences.

In the context of the growth in the investments of professional football clubs, it constitutes a viable option to conventional investment assets. Nevertheless, these securities have a high degree of risk related to the specificities of the football industry, namely the unforeseeability of the final result of both a single match and the whole competition (Prigge & Tegtmeier, 2019). Moreover, according to Litvishko et al. (2019), a huge proportion of shares issued is held by amateurs, who can hardly be described as rational investors, as they fail to take stock market indicators as a sign to actively trade the shares. These investors feel a strong passion for football and loyalty to a specific club, so they select a long-term approach to invest in the stocks of their favourite club. Silveira et al. (2018) argue that the loyalty of true fans means that they consistently attend the stadium, independent of the price of the ticket. Faithful customers appear to impact highly on the business volume of football organisations via the constant attendance of supporters who remain loyal and are unaffected by poor results, ticket prices and so on.

Historically, the level of residuals has played an important role in volatility, as has been proven in past experiences such as the increase in financial markets between 1980 and 2000, and the sharp fall during the 2000 crisis (Chen et al., 2017). However, compared to residual, risks and long-term habit are highly important. Continuing with long-term growth, long-term volatility and habit, we see how it has a low or less influence than that shown in other works with broader sectors, which included shares of mass consumption companies. In our case, the values for the volatility of the long-term growth coefficient tend to show a negative correlation, since the residual percentage does not usually fall below 35%. Detecting the total volatility of the model is difficult since it is like the study of market volatility, where on more than one occasion the shares take a non-positive volatility value or above 100%. This also depends on economic growth, which for our sample had negative values after the 2008 crisis in Europe. But even so, there was a growth in the price of the shares in the markets. This negative quote is because the variance decomposition is calculated using sample covariances, which can be negative.

Focusing on Table 3, which details the decomposition of the price/dividend variance and its uncertainty in the estimate, we find the case of estimating with DRCNN for the specification 'Including all variables', which we obtain a sign, considering DRCNN this negative sign like the one that will obtain a result with fewer residuals. In the previous literature, we usually find results with a positive sign, although some previous studies carried out with OLS have produced a negative sign for this parameter. Our results suggest that the price/dividend ratio increases in the case of clubs that achieve consistently good sporting performance, especially in cases where clubs have won a title, creating a persistently increasing price/dividend ratio due to increased revenue generation of the club as well as a greater attraction of investors in the club's stock. This contradicts what some previous literature has argued in support of a possible fall in the price/dividend levels of clubs with good sporting performance, as they argue that it produces uncertainty for some investors due to a possible increase in spending on new player signings as well as an increase in spending on player salaries (Benkraiem et al., 2009; Boyle & Walter, 2003). For its part, the specification 'Only long-term volatility' shows its results with an adequate sign for the three methodologies used according to the previous literature (Gu et al., 2020, 2021). Besides, we observe how the long-term volatility coefficient is around −125, and that it is in line with those that are within the standard errors of the value of −33 of the full estimate of the model presented in Table 1. This specification obtains goodness of fit greater than 41% for the DNDT and QNN methodologies, while for the case of DRCNN, the value rises to 32%, demonstrating the great importance of the residual value in the variance of the decomposition of the price-dividends. Finally, the DRCNN methodology underestimates the influence of the residual variable, hence the difference in the participation of the residual in the variance of the price-dividend that we observe for this methodology (82%) and the one that we observe for DNDT and QNN (higher 90%). The highest goodness of fit value is found for DNDT and QNN in the specification 'Including all variables', where it is around 60%, and even so, the influence of the residual value accounts for 40% of the volatility of the financial asset studied.

Usually, the variations in the residual parameter can be interpreted as excess volatility in the stock market. This excess volatility is often linked to changes in risk parameters that are difficult to observe. The remainder fluctuates due to its price-dividend ratio, it is not related to average economic growth.

Finally, Table 4 shows the values that correspond to each component of the variance and summarizes the robustness results. Details the variance proportions (defined in equation 8) explained by long-term growth, long-term volatility, habit, and residual. According to the six specifications, the residual represents the vast majority of the volatility of the asset analysed, with a component share of around 40%. This table is composed by the next

TABLE 3 Price/dividend variance decomposition.

Specification		Long-Run Growth	Long-Run Volatility	Surplus Consumption
		DRCNN		
Including All Variables	Coefficient	−17.16	−159.29	−0.62
	s.e.	22.64	29.98	0.37
	R^2 (%)		41.23	
	Var. Share (%)	−2.55	21.26	3.13
Only Long Run Volatility	Coefficient		−124.73	
	s.e.		41.82	
	R^2 (%)		32.47	
	Var. Share (%)		82.19	
		DNDT		
Specification		**Long-Run Growth**	**Long-Run Volatility**	**Surplus Consumption**
Including All Variables	Coefficient	58.18	54.56	0.27
	s.e.	31.05	37.69	0.28
	R^2(%)		58.19	
	Var. Share (%)	4.61	18.04	2.79
Only Long Run Volatility	Coefficient		−125.39	
	s.e.		40.84	
	R^2(%)		41.96	
	Var. Share (%)		92.58	
		QNN		
Specification		**Long-Run Growth**	**Long-Run Volatility**	**Surplus Consumption**
Including All Variables	Coefficient	57.48	54.15	0.12
	s.e.	30.10	37.24	0.43
	R^2 (%)		62.27	
	Var. Share (%)	4.40	18.79	2.57
Long-Run Volatility Only	Coefficient		−126.10	
	s.e.		40.20	
	R^2 (%)		41.36	
	Var. Share (%)		91.23	

decomposition of the variance: holds in (1) the baseline specification of the model, (2) if we remove long-run risks from the model, (3) in the case of eliminating the habit factor from the model, (4) in the case that habit is more influenced by consumption growth if we specify that habit responds to consumption growth than by innovations and (5) in the case of rescaling the price-dividend coefficients according to the variance of the states according to Equation (9). Long-term risk and habit components often identify downturns in the market (Aldrich & Gallant, 2011; Chen et al., 2019; Cheng et al., 2022; Nakamura et al., 2017). Also, they are components with high participation in our valuation model, but the decomposition carried out clears the possible correlation that negatively influences the participation of the residual component of asset volatility.

Table 4 also specifies a share of the habit component in the variance which, when long-term risks are removed, is around 8%. In a complementary way, when we eliminate the habitat of the variance, the long-term risks represent a proportion of variation of around 11% in all the methodologies used. According to these conclusions, the implication of the residual component in the valuation of the asset is evident, the significance of other components being less. From another perspective, in the case of eliminating all the components that represent the long term, the residual participates in 95% of the variance, the influence of excess consumption being scarce.

Regarding the possible link between long-term risks and excess consumption, the literature maintains that habit varies due to changes in consumption. Under this pretext of changes in habitat,

TABLE 4 Variance decomposition with different model specifications.

Variance share	(1) Baseline	(2) no LRR	(3) no habit	(4) habit	(5) A rescaled
	DRCNN				
Long-run Growth	5.75		11.29	−2.18	13.07
	2.86		9.14	0.28	8.39
Long-run Volatility	3.34		4.2	3.48	2.26
Surplus Consumption	−4.98	6.17		−1.83	−0.71
	2.06	3.48		1.14	0.89
Residual	96.19	95.51	95.44	95.48	95.45
	5.16	6.24	4.78	3.22	3.17
	DNDT				
	(1) Baseline	(2) no LRR	(3) no habit	(4) habit	(5) A rescaled
Long-run Growth	5.74		11.23	−2.40	12.83
	2.90		9.18	0.32	8.40
Long-run Volatility	3.35		4.23	3.49	2.27
	0.00				
Surplus Consumption	−4.95	6.18		−1.79	−0.69
	2.07	3.52		1.16	0.90
Residual	96.20	95.53	95.44	95.52	95.48
	5.11	6.17	4.73	3.24	3.20
	QNN				
	(1) Baseline	(2) no LRR	(3) no habit	(4) habit	(5) A rescaled
Long-run Growth	5.73		11.06	−2.40	12.91
	2.76		8.90	0.12	8.21
Long-run Volatility	3.26		4.17	3.40	2.03
	−0.14				
Surplus Consumption	−5.20	5.93		−2.00	−0.74
	1.97	3.45		0.94	0.71
Residual	96.01	95.31	95.33	95.44	95.28
	5.08	6.11	4.65	3.21	3.11

and according to our results, surplus consumption changes once consumption growth changes. This leads us to think that long-term growth also influences the current habit result. Likewise, the results indicate that the residual component supports the changes in the price-dividend ratio more than those shown by the baseline. Column (5) of Table 4 shows how the structure of Equation (1) faithfully represents the valuation of the asset since its results do not change excessively from those obtained in the column of baselines.

On the other hand, the precision and root-mean-square error (RMSE) levels obtained by the methodologies used are detailed in Figures 1 and 2, respectively. Figure 3 is added to the mean absolute percentage error (MAPE) results to reinforce the results obtained with the RMSE error measurement. The first graph shows how the QNN technique obtains a higher precision (93.97% with training data and 90.90% with test data) and a lower RMSE (0.52 and 0.61 for training and test data, respectively). After QNN is the DNDT technique, with a precision of 90.63% with testing data but lowering its precision in the testing phase to 86.74% (its RMSE values show the same trend, with a value of 0.63 for training data and 0.81 for test data). For its part, the precision results of DRCNN show acceptable results of 79.71% and 74.95% for training and testing data. Also, RMSE of 0.95 and 1.13. However, these results confirm the superiority of QNN and DNDT, which improve precision results compared to other previous studies on estimating Asset Pricing models (Chen et al., 2017; Gu et al., 2020, 2021; Marfè & Penasse, 2016). For example, Marfè and Penasse (2016) obtained an 86% ROC curve to exclusively predict disaster risk in the price of

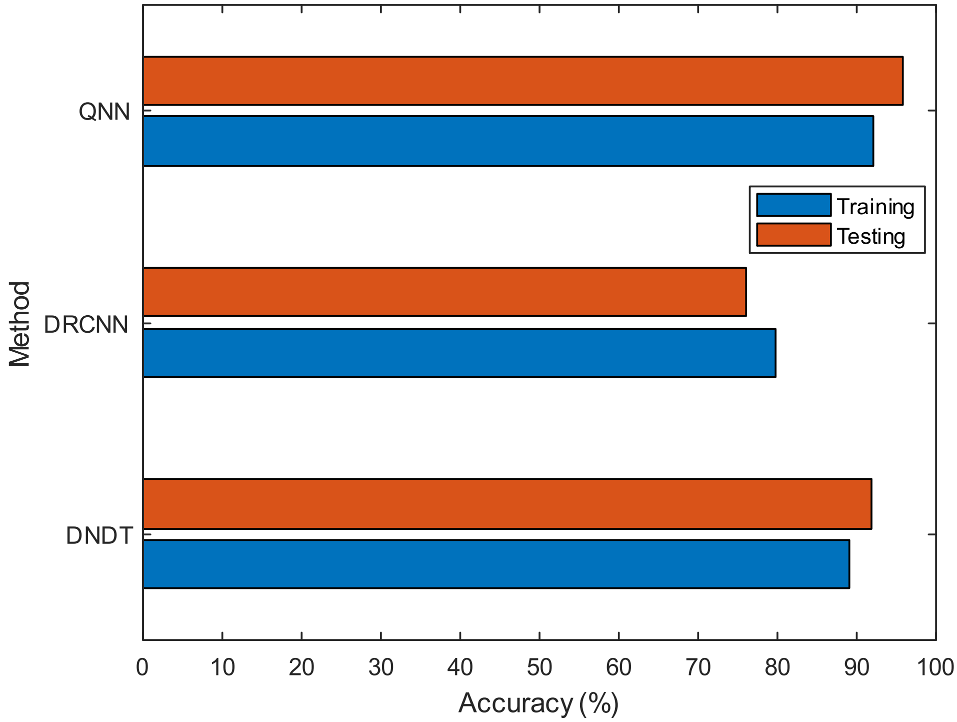

FIGURE 1 Results of accuracy evaluation: classification (%).

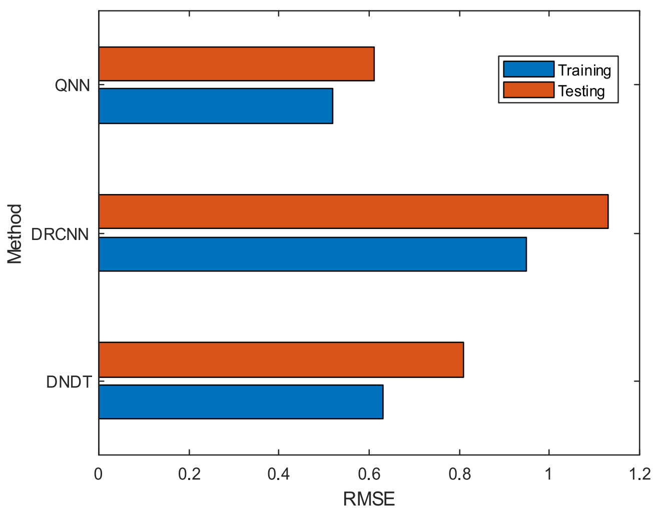

FIGURE 2 Results of accuracy evaluation: the root-mean-square error (RMSE).

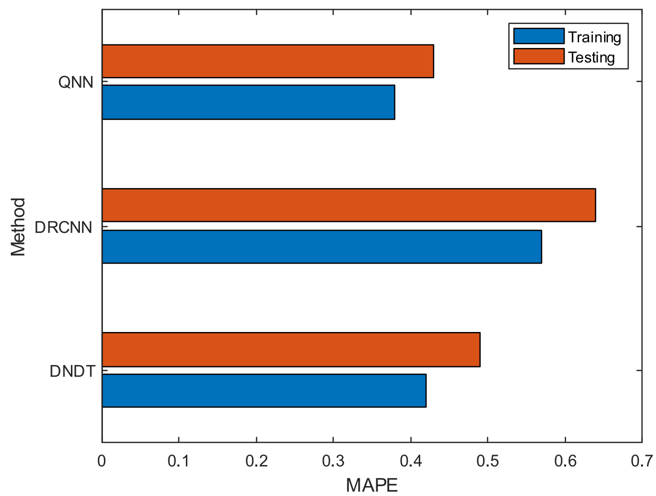

FIGURE 3 Results of accuracy evaluation: the mean absolute percentage error (MAPE).

shares. Chen et al. (2017) obtained a mean goodness of fit in their different estimated parameters of 30% using the OLS technique for their estimation. Gu, Kelly and Xiu (2020) achieved 67% accuracy using multilayer perceptron neural networks from S&P 500 data. Gu et al. (2021) obtained a goodness of fit of 57% using a conditional autoencoder for a sample S&P 500. Therefore, our results improve the estimate obtained by previous work on asset pricing models thanks to the use of neural network techniques that have allowed us to obtain high precision.

5 | CONCLUSION

In this study, we estimate a macro asset pricing (MAP) model for football clubs, and with the experience of the STOXX Europe Football index, we develop various types of risk in our model, such as long-term growth, long-term volatility, habitat and the residue level, which the latter appears in our results as persistent. The model is calculated with the DRCNN, DNDT and QNN methods. One of the benefits of the approach followed in this paper is the simplicity of modelling and decomposing the model factors with this MAP model.

Moreover, our results suggest that the price/dividend ratio rises for clubs with continuously good sporting results, particularly when clubs have won a title, which produces a consistently growing price/dividend ratio owing to the greater revenue generation of the club, as well as a higher attractiveness of investors in the club's shares. Fans of football clubs respond positively or negatively to their club's results. The purchase or sale of players to enhance the competitiveness of each team is an additional event that may cause considerable variation. Such a scenario provokes a strong reaction from both fans and investors, as the quality of the football team could improve or deteriorate and thus the value of the shares could change.

The results obtained have allowed us to detect a balance between the different risk levels, although the higher share is represented by the residual component, which accounts for 40% of the variance of the price-dividend ratio. Also, long-term and habitat risks represent an important influence on the valuation of the asset, although with smaller participation than the residual. Despite this, these two risks are more important than those obtained in previous studies to study market volatilities. The importance of the fluctuations, as observed with the significance of the residual factor, shows the impact of volatility with information not observed in the financial asset studied, but it is shown in a lower value than previous works, that is, this financial asset about football clubs has a more certain and reliable estimate than other assets other than the market. In previous literature, the residual parameter moves closely with asset prices but is not related to real economic growth and volatility. In our case, the innovations produced in the habit component have relative importance in the price of the asset, and in the same way, this behaviour is repeated in the factor included in excess consumption.

For its part, the accuracy results in the estimation of the MAP model with the proposed neural network techniques show that the QNN methodology obtains superior precision with training and testing data. Closely followed is DNDT, which is shown to be the best alternative to the quantum network. In the last place, concerning precision is DRCNN, which although it is the most widely used computational method in estimating financial models, presents difficulties in approaching the ability to hit the other methodologies presented.

The results of this study can guide academics and professionals interested in asset pricing in the possibility of using neural networks, specifically DNDT and QNN to estimate valuation models with a great capacity for success. Furthermore, although the application of the valuation model used in this study shows the behaviour of the financial assets of football clubs listed on the STOXX Europe Football stock index, the conclusions obtained can also be extended to football clubs listed on other stock indices. This becomes more important not only for academics but mainly for football club interest groups since the price of football clubs has always been a little predictable and this uncertainty is increasing in the current crisis of COVID-19, which has hit the football industry hard.

In conclusion, our model prepares investors in the football industry for the event of unexpected crises in the future, such as the sudden shock induced by COVID-19. This scenario revealed the fragility of business models in the global sports industry. Our model of estimation of a MAP for football clubs helps sports managers to face a pressing need to develop long-term strategies to survive in the time of crisis. Further research in this field would be the expansion of our model based on data from other football clubs in other regions of the world or different sports disciplines.

CONFLICT OF INTEREST STATEMENT

The authors declare that there is no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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APPENDIX A: STOXX EUROPE FOOTBALL INDEX

Parken Sport & Entertainment	Denmark
AGF	Denmark
Brondby if B	Denmark
Aalborg Boldspilklub	Denmark
Olympique Lyonnais	France
Borussia Dortmund	Germany
Juventus	Italy
AS Roma	Italy
SS Lazio	Italy
AFC Ajax	Netherlands
Ruch Chorzow	Poland
Sport Lisboa e Benfica	Portugal
Sporting de Portugal	Portugal
Futebol Clube do Oporto	Portugal
Teteks ad Tetovo	Republic of Macedonia
AIK Football	Sweden
Galatasaray	Turkey
Trabzonspor Sportif Yatir	Turkey
Fenerbahce Sportif Hizmet	Turkey
Besiktas	Turkey
Manchester United	United Kingdom
Celtic	United Kingdom