Vega-Gámez and Alonso-González
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How likely is it to beat the target at different investment horizons: an approach using compositional data in strategic portfolios

Fernando Vega-Gámez[1,2] and Pablo J. Alonso-González[1*]

*Correspondence: pablo.alonsog@uah.es

[1] Economics Department, Universidad de Alcalá, Plaza de La Victoria 2, 28802 Alcalá de Henares, Madrid, Spain
[2] EDM Gestión SGIIC, Partner-Director, Paseo de la Castellana 78, 28046 Madrid, Spain

Abstract

Strategic portfolios are asset combinations designed to achieve investor objectives. A unique feature of these investments is that portfolios must be rebalanced periodically to maintain the initially established structure. This paper introduces a methodology to estimate the probability of not exceeding a specific profitability target with this type of portfolio to determine if this kind of build portfolio makes obtaining certain profitability targets easy. Portfolios with a specific distribution of fixed-income and equity securities were randomly replicated and their performance was studied over different time horizons. Daily data from 2004 to 2021 was used. Since the sum of all asset weights invariably equals the unit, the original data were transformed using the compositional data methodology. With these transformed data, the probabilities were estimated for each analyzed portfolio. The study also performed a sensitivity analysis of the estimated probabilities, modifying the weight of specific assets in the portfolio.

Keywords: Compositional data, Investment horizons, Logit models, Probability, Strategic portfolios

Introduction

Since Markowitz (1952) devised his modern portfolio theory, portfolio construction theory has typically focused on the expected return and the risk a given investor is willing to accept. Several authors have persisted in formulating more or less elaborated models that invariably focused on these two components (Konno and Yamazaki 1991, Black and Litterman 1992, Tsao 2010, Greco et al. 2013, and Filippi et al. 2020, among others); however, a third often-overlooked element is crucial when building a portfolio: the investment horizon. It is essential to remember that Markowitz's conventional analysis of investment optimization using the mean–variance model fails to consider the time horizon. Later, however, Merton (1969), Samuelson (1994), Bodie (1995), Thorley (1995), Merrill and Thorley (1996), and Lenoir and Tuchschmid (2001) reflected on the importance of including the time horizon in any investment project.

In theory, it is possible to determine the composition of a portfolio and, therefore, what its expected return and risk would be given a specific investment horizon. As

Barberis (2000) indicated, in the interest of efficiency, long-term investors must invest differently than they would in the short term, allocating more weight to equities. Moreover, using appropriate models allows the various investment targets to fit into specific time horizons. Eychenne et al. (2011) and Jacquier and Polson (2011) constructed efficient portfolios based on long-term expectations using a Bayesian approach, while Saputra and Safitri (2022) applied data from a long series of past returns in the Monte Carlo simulation. Gomes and Michaelides (2005) and Arwall et al. (2007) use the investor life cycle model.

In these approaches, time is a given, not a variable to be determined; however, it should also be possible to study which time horizon would meet a specific target based on the makeup of a given portfolio. In this paradigm, it would be essential to establish the investor's objective, which can be set in terms of risk and return. More recently, time has been studied using wavelets, an extension of spectral and cross-spectral analysis used to decompose a time series within the time–frequency space. In finance, frequency relates to the period of cycles into which a time series can be decomposed. This information can be used to analyze the risk related to an investor's time horizon (Mestre 2023). Gençay et al. (2003, 2005) were the first to use it in finance, specifically in the Capital Asset Pricing Model (CAPM). They obtained different values of betas depending on the investment horizon considered, suggesting that the risk profile is frequency-dependent. This line of research includes papers by Mestre and Terraza (2019), NcNevin and Mix (2018), Sakemoto (2020), Alexandris and Hasan (2020) and Mestre (2021) can be included in this line of research.

In financial theory, investors are generally disinclined to experience losses (Geambasu et al. 2013). Research shows that investors are interested in making a minimum return and that anything less is considered a loss (Tsai and Wang 2012). Klos et al. (2005) suggested that informing investors about the aggregate distribution of returns helps them make better investment decisions. This paper will examine this approach in-depth, which involves determining the horizon over which an investor should hold a strategic portfolio of assets to achieve a specific target return at the end of the time interval chosen for the investment. Naturally, the answer must be rendered in probability and based on the investor's risk profile, a key element. Wavelets assess temporal risk dynamics, whereas this paper focuses on obtaining a probability distribution of returns over the investment horizons considered. To carry out the analysis, we must establish some guidelines for creating the portfolios to be considered. Thousands of randomly generated strategic portfolios under certain conditions were studied, with 50% of assets invested in fixed income (government debt and corporate bonds) and the remainder in equities. Five share indices represent this division as securities representing different world markets: Spain's IBEX-35 as the domestic market and indices corresponding to the European, US, Japanese, and emerging markets. For a more detailed explanation, see Sect. "Data used". For efficiency, assets of varying natures have been used (Brinson et al. 1991 and Rau 2013). Regarding the number of assets considered, we followed the proposal of Grinold and Messe (2000) have been followed.

The study was conducted using different time horizons. The probabilities of not exceeding a given profitability threshold have been estimated for each horizon. The study considered the weight of each asset included in the strategically created portfolios.

As explained in Sect. "Methodological aspects", this kind of portfolio is featured by the fact that the weight of each asset is constant during the whole investment horizon. This constraint is critical for the modeling of the results. In all cases, the sum of the weights is equal to unity, making it impossible to use an econometric model that incorporates an intercept; therefore, the probabilities sought were estimated using the compositional data methodology (Aitchison 1982). As explained in more detail in Sect. "Methodological aspects", this approach requires the transformation of the data in such a way as to reduce the dimension of the dataset by one unit. This way, the transformed series allows conventional models to obtain the desired estimates. Finally, we undo the transformation for explanatory purposes to obtain the betas associated with each asset initially included in the portfolios. A compositional data approach is common in fields like material physics (Tanimoto and Rehren 2008) and geochemistry (Tolosana-Delgado and von Eynatten 2010); however, few studies apply this methodology in areas such as economics or finance. Even so, it is possible to research on marketing applications (Joueid and Coenders 2018), specific economic sectors (Grifoll et al 2019, Coenders and Ferrer-Rosell 2020 or Ferrer-Rosell et al 2022), financial performance (Creixans-Tenas et al. 2019 or Fiori and Porro 2023), financial ratios (Linares-Mustarós et al. 2022) or life expectancy estimates (Kjærgaard et al. 2020). Belles-Sampera et al. (2016) apply this methodology to study capital allocation for a one-year horizon, while Boonen et al. (2019) apply it to the risk allocation problem in a dynamic context. By applying this approach, our paper aims to estimate the probability that a strategic investment portfolio fails to achieve a stated target return. The study was completed by examining the impact that modifying the weight of each risk asset would have on the probability of incurring losses. This analysis used Random Forest (Breiman 2001), generalized linear logit models, and compositional data analysis.

The rest of the article is structured as follows. Sect. "Methodological aspects" addresses the configuration of strategic portfolios and explains the methodology used to estimate a given portfolio's probability of loss considering all the assets at once (compositional data). Sect. "Data used" explains the data applied and the process followed to generate the portfolios, while Sect. "Results" details the analysis results with transformed and original data. Finally, Sect. "Conclusions" presents the main conclusions.

Methodological aspects

This section explains the process of compiling the analyzed portfolios and the methodology used to estimate the probability that the investment will not exceed the established profitability target.

Typically, the study of investment portfolio construction considers two factors: i) specific information about the assets (return, volatility, correlation between them), and ii) investor preference, meaning their attitude toward risk vis-à-vis the expected returns. As mentioned, a third element, the investment horizon, is often overlooked. Strategic and tactical securities allocation concepts emerge in a dynamic context of selecting optimal portfolios. Both would be within integrated asset allocation or a combination of assets that maximizes the investor's decision rule at a given time, considering their risk tolerance and the forecast of expected returns, volatility, and correlations (Sharpe 1987). Sharpe (1987) suggested that strategic allocation refers to long-term investment policy, while tactical allocation permits deviation from long-term decisions when short-term and long-term predictions diverge (Lederman and Klein 1994). Xiong et al. (2010) indicated that the return sensitivity of a static asset allocation can be represented by a beta similar to that of the CAPM model. Since their study has a time dimension, this beta would capture the sensitivity of the excess return of this asset allocation to the excess return relative to a given investment policy's market return. Therefore, the static asset allocation represents the evolution of the markets defined by the combination of benchmark indices representative of the asset classes that ensure (in their correct weighting) the achievement of objectives. Once defined, an investor's strategic portfolio should not change unless the targets or their expected degree of fulfillment change. Consequently, the strategic portfolio is a long-term static portfolio.

Regarding the makeup of the analyzed portfolios, this project studied what are known as strategic asset portfolios. Strategic asset allocation (SAA) typically entails longer time horizons (more than 5 years) and is based on expectations considering long-term risk, returns, and the correlations between them. SAA involves an asset allocation policy wherein a target weight is set for each asset in the portfolio, permitting some slight variations (Lumholdt 2018). The portfolio is rebalanced periodically to maintain the investment objectives established at the outset; these revisions are usually conducted one or more times a year. Following Arnott and Lovell (1992) and Goodsall and Plaxo (1996), rebalances were done at the end of each calendar quarter.

The strategic portfolio is linked to long-term investment decisions; if the set of investment opportunities varies over time and the variables that determine the investment show elevated autocorrelation, these decisions differ from those associated with short-term investments (Hoevenaars et al. 2008). Eychenne et al. (2011) indicated that SAA should be the manifestation of the long-term decisions for a given economic scenario based on the stationary risk premia hypothesis.

One important aspect of configuring a strategic portfolio lies in the assets selected. To create a portfolio that meets the investor's objectives—specifically Spain in this case—fixed-income assets were represented by two highly-rated bond indices for both government and private debt. Regarding equities, in addition to the world's main indices in the US, Europe, Japan, and emerging markets, the Spanish equity index was included to represent local investment, comply with the diversification proposed by Grinold and Messe (2000), and reach efficiency.

After defining the selected procedure for choosing a given portfolio's dynamics, we assess the probability that investing in these portfolios will obtain a result below the established profitability target. Recall that the analyzed portfolios are characterized by the following:

- They consist of two large categories (fixed income and equities) that must have the same weight throughout the investment (in our case, 50% each).
- Fixed income comprises two assets—government debt and corporate bonds—such that if the weight of one is w%, then the weight of the other is 50%–w%.
- The equities category consists of five assets, which must also have a total weight of 50%.

We assume that fixed-income assets account for 50% of the portfolio, which is a concrete application for illustrative purposes. Portfolios with similar allocations are relatively common in day-to-day wealth management practice.

While an econometric model (a logit, for example) can be used to estimate these probabilities based on the weight of the various portfolios analyzed, this approach is not possible because the data used as explanatory variables are weights over a total, and the sum of all is always the unit. In this case, the analysis of constant-sum data involves considerable statistical challenges, which are often not adequately addressed. Therefore, this paper proposes using compositional data analysis, the standard method for solving the same problem of constant-sum data in chemical, biological, or geological analysis (Joueid and Coenders 2018). For this reason, the compositional data technique (Aitchinson, 1982; Aitchinson, 1986) has been used. This technique replaces the original data in D dimensions with a new D—1 dimension set equal to the input set (Barceló-Vidal, 2000; Billheimer et al. 2001; Pawlowsky-Glahn and Egozcue 2001). The literature has several transformations (Pawlowsky-Glahn and Egozcue 2006; Greenacre 2018; Filzmoser et al. 2018); a simple way to perform the transformation is the one described in Pawlowsky-Glahn and Egozcue (2006). Starting from an original data set, $\mathbf{x} \in \mathbb{R}^D$, we perform the isometric log-ratio transformation (*ilr*) to obtain $\mathbf{x}^* \in \mathbb{R}^{D-1}$ where:

$$x_k^* = \frac{1}{\sqrt{k(k+1)}} \ln \left(\frac{x_{k+1}^k}{\prod_{j=1}^{k} x_j} \right) = \frac{1}{\sqrt{k(k+1)}} \left(k \ln x_{k+1} - \sum_{j=1}^{k} \ln x_i \right) \quad / \quad k = 1, \ldots, D—1 \tag{1}$$

It can be expressed in a matrix form as:

$$\mathbf{x}^* = \mathbf{V} \ln (\mathbf{x}) \quad / \quad \mathbf{V} = \mathbf{AB} \tag{2}$$

where **A** is a matrix of order $(D—1) \times (D - 1)$ defined as follows:

$$A = diag\left\{ \frac{1}{\sqrt{k(k+1)}} \right\} \quad / \quad k = 1, \ldots, D-1 \tag{3}$$

B is a matrix of order $(D—1) \times D$ defined as follows:

$$B_{ij} = \begin{cases} -1 & i \geq j \\ i & i+1 = 1 \\ 0 & otherwise \end{cases} \tag{4}$$

x is the vector with the values of the input variables. In our case, **x** reflects the weights of each asset in each portfolio. This project uses the R compositions library (Van der Boogaart et al. 2021), the results of which are the same as those of the transformation described above.

Data used

The strategic portfolios used in this study comprise seven different assets—two are fixed income, and the rest are equity assets. The weight of both categories is 50%, and seven indices represent the seven assets. All information was extracted from the

Bloomberg database between 31/12/2003 and 31/12/2021. This period includes two major market crises: the global financial crisis in 2008 and the crisis triggered by the COVID-19 pandemic in 2020. Data are available upon request.

The two fixed-income indices used were:

- The Bloomberg Barclays series Euro Government 1-3Y Bond index indicates government debt. It collects information on bonds maturing within one and three years, issued by the governments of 15 Eurozone countries.
- ICE BofAML 1-3Y is an indicator of corporate bonds maturing within one and three years. ICE Data Services, a member of the Bank of America Merrill Lynch financial group, compiled the set.

The indices used for equities include all the financial rights associated with equity investment, such as dividends and non-contributed capital increases. They are net indices; that is, they are discounting tax withholdings. The indices selected are (identification codes in parentheses) as follows:

- IBEX-35 NR (SPA) is the Spanish stock market's main benchmark index. It is compiled by Bolsas y Mercados Españoles and includes Spain's 35 most liquid listed companies.
- MSCI Europe NR (EUR) is the most representative index of European equities. It pulls data from 447 companies in 15 countries and covers approximately 85% of European market capitalization. It is hedged with monthly forwards for all currency exposure (other than the euro) to eliminate currency risk.
- S&P 500 NR (USA) is a US equities index based on the market cap of 500 companies listed on the NYSE and the NASDAQ.
- Nikkei 225 NR (JAP) is the Japanese market's most representative equity index, consisting of 225 companies listed on the Tokyo Stock Exchange.
- MSCI Emerging Markets Index TR (EME) is the most representative emerging markets equity index, comprising roughly 1,200 companies listed on various markets in 26 countries. The MXEF Index, denominated in euros because of the different currencies it includes, has been taken from Bloomberg. Due to the non-existence of a net return in this specific instance, the total return index was used. This approach incorporates all investor rights on a gross basis or without considering tax withholdings (though the difference is insignificant in this case).

As the study takes the European investor's point of view, all the returns must be referred to as an investment in euros; therefore, exchange rates must be used to express the indices in the European currency. These rates have been obtained from the European Central Bank each day.

Now that the indices used have been defined, we explain how the strategic portfolios are selected and created. Ideally, we assume that each asset has a weight between 0 and 50%, the weight its category occupies in the portfolio. Furthermore, increments of 1% in the fixed-income indices and 2% in the stake of each equity asset were considered to achieve greater atomization. This approach provided 2,601 fixed-income combinations and more than 11.8 million equity combinations. Now, two conditions must be imposed. The first one is that the sum of the weightings must equal 100%. With this restriction, the number of possible combinations narrows to more than 1.2 million possible portfolios. The second constraint is that all the weights must have a positive value. This limitation reduces the possible portfolios to almost 521,000, from which 1,000 were randomly selected to use in the calculation process. Finally, the last element is related to the returns obtained from government debt securities issued by the Spanish treasury with varying maturities. The information corresponds to the internal rate of return (IRR) on securities traded in cash with a residual life equal to the horizons considered (1–15 years), taken from the last session of each year and posted in the daily bulletins of the government debt market (published by the Bank of Spain until April 2018) and in the daily AIAF bulletin (after April 2018).

Results

As mentioned in the introduction, this project aims to assess how investment duration may affect the profitability of strategic portfolios. This objective will be expressed in probability and estimated for portfolios with a specific makeup (50% fixed income, 50% equities, considering the assets listed in Sect. "Data used"). Five possible annual return targets were set:

- Zero return: Compatible with no loss in the portfolio's nominal value;
- Positive compound return: 3%, 4%, and 5% annually;
- Lastly, the annual return at a certain time horizon was estimated by investing in government debt issued by the Spanish treasury.

The probability of not incurring a loss at the end of a certain investment horizon was estimated in the zero-return scenario; therefore, in this case, the probability of not exceeding the 0% threshold has been assessed without analyzing the portfolio makeup in detail. This type of analysis was also replicated in the other four cases. Finally, regarding the comparison to government debt yields, the following aspects were considered:

- We only considered debt issued by the Spanish treasury at maturities that range from one to 30 years, depending on the year considered.
- Calculating the return obtained at a certain maturity in a specific year is based on the reinvestment of coupons obtained from previous investments at residual maturities. For example, to obtain the overall return obtained at a horizon of 10 years, an investment in securities with that maturity at a given IRR and a coupon rate is made at time t_0. The coupons collected the following year would then be reinvested for a 9-year term at the current IRR for that maturity in t_0+1. In t_0+2, coupons are collected for investments made in t_0 and t_0+1, which are then reinvested over 8 years at the current IRR for that term in t_0+2, and so on. Overall, the investment is equal to creating a synthetic zero-coupon bond with a given horizon, used to calculate the return obtained at the maturity considered.

- When no securities exist with the desired term, we must estimate their return using exponential interpolation between the upper and lower limits nearest the horizon considered. This is achieved by applying the following expression:

$$\hat{r}_t = r_{t-1}\left(\frac{r_{t_U}}{r_{t_L}}\right)^{\frac{1}{t_U - t_L}} \tag{5}$$

where the subscripts L and U refer to lower and upper limits, respectively.

Investment horizons from 1 to 15 years (inclusive) were considered; however, for simplicity, only the results for 1, 5, 10, and 15 years will be shown in detail. Table 1 illustrates the probability of not exceeding the established probability targets in the five horizons mentioned. This table is merely descriptive; the probabilities included were obtained as the quotient of the randomly generated strategic portfolios that do not exceed the desired profitability threshold and the total number of cases.

Returns were calculated for periods ending in 2021 at the latest; thus, it was only possible to calculate 15-year horizons from investments initiated in 2006 (only three cases: 2004, 2005, and 2006). Therefore, the average probability was calculated from 3,000 results (1,000 portfolios $\times$ 3 starting years). Similarly, the average probabilities for the remaining horizons were calculated for all investments that—initiated in at least 2004 and with an established duration of H years—began at the latest in 2020, 2016, and 2011 for the 1-, 5-, and 10-year horizons, respectively. For the case where $r = 0\%$, the probability of incurring losses is zero for any horizon beyond seven years; hence, this scenario was not included in the calculations. That would then be the minimum interval for a 50–50 portfolio to avoid incurring losses with a unit probability. Considering the results in Table 1, whether the chosen sample size is appropriate could be questioned. The results of Table 1 were reproduced for selections of 500 to 1,000 portfolios in increments of 100. For illustrative purposes, Table 2 presents the empirical probabilities for the 500 and 1,000 portfolio cases for the horizons and scenarios considered in Table 1.

The probabilities shown in Table 1 are averages obtained from considering 1,000 random portfolios, each with a different makeup, invested at different times (from 2004 onward). Therefore, assuming that markets fluctuate over time and that

Table 1 Empirical probability of not exceeding targets

		H = 1	H = 5	H = 10	H = 15
$r = 0\%$	prob	0.2558	0.1218	0.0000	0.0000
	acc.r	0.00%	0.00%	0.00%	0.00%
$r = 3\%$	prob	0.4242	0.4504	0.2489	0.0500
	acc.r	3.00%	15.93%	34.39%	55.80%
$r = 4\%$	prob	0.4687	0.5400	0.3893	0.7550
	acc.r	4.00%	21.67%	48.02%	80.09%
$r = 5\%$	prob	0.5135	0.6351	0.8478	0.9900
	acc.r	5.00%	27.63%	62.89%	107.89%
$r = $ IRR	prob	0.4168	0.5245	0.4070	0.3900
	acc.r	2.82%	19.76%	49.03%	69.94%

acc.r = accumulated return; prob = probability; IRR = Internal Rate of Return of Treasury Bonds

Source: Compiled by the authors

Table 2 Sensitivity of empirical probability to sample sizes

	Size	H = 1	H = 5	H = 10	H = 15
r = 0%	500	0.2532	0.1198	0.0000	0.0000
	1,000	0.2558	0.1218	0.0000	0.0000
r = 3%	500	0.4235	0.4466	0.2460	0.0433
	1,000	0.4242	0.4504	0.2489	0.0500
r = 4%	500	0.4674	0.5397	0.3888	0.7493
	1,000	0.4687	0.5400	0.3893	0.7550
r = 5%	500	0.5113	0.6352	0.8455	0.9880
	1,000	0.5135	0.6351	0.8478	0.9900
r = IRR	500	0.4166	0.5226	0.4048	0.3827
	1,000	0.4168	0.5245	0.4070	0.3900

Source: Compiled by the authors

investors cannot control these fluctuations, a strategic portfolio's makeup might affect the probability of not exceeding the established profitability targets. To examine this effect, we used a logit model with a dependent dichotomous variable to determine if the profitability target would be exceeded for a given portfolio over a given time horizon. The explanatory variables are the weights of each asset within the portfolio. Since the sum of these weights is always the unit, the model could not be estimated; therefore, we must apply a variable transformation according to the compositional data methodology (Aitchinson, 1982), as explained in Sect. "Data used". The estimation model is:

$$\ln\left(\frac{p}{1-p}\right)_{ih}^{s} = \hat{\beta}_0^s + \sum_{k=1}^{6} \hat{\beta}_k^s x_{kih}^{*} \tag{6}$$

where the subscripts i and h refer to the random portfolio and the time horizon, respectively; the superscript s refers to the scenario considered. We estimated 60 regressions with all possible combinations of scope and scenario (15 horizons $\times$ 4 different scenarios). Because these estimates correspond to regressions with transformed variables, these variables do not have any direct financial interpretation; rather, they are instruments applied to determine the estimated probability of not exceeding the proposed profitability target. For example, suppose a portfolio with the following proportions: 25% and 10% in each of the fixed-income and equity assets considered, respectively, meaning $x = (1/4, 1/4, 1/10, 1/10, 1/10, 1/10, 1/10)$. In this case, taking into the transformation described in Sect. "Data used", the vector of transformed variables, $\mathbf{x}^*$, is:

$\mathbf{x}^* = (0, -0.748, -0.529, -0.410, -0.335, -0.282)$.

By applying these transformed variables to the estimated logit model for a specific profitability target and investment horizon, the desired probability of not exceeding the profitability threshold at a given time horizon can be obtained by calculating $\exp\left\{X\hat{\beta}\right\} \Big/ \left(1+\exp\left\{X\hat{\beta}\right\}\right)$ or $1 \Big/ \left(1+\exp\left\{X\hat{\beta}\right\}\right)$ to determine the probability of exceeding that target at that horizon. The calculations were performed for the 1000 randomly generated portfolios, calculating the estimated probability for each. The statistics in Table 3 represent the estimated probabilities for time horizons of 1, 5, 10, and 15 years and the profitability targets considered.

Table 3 Statistical summary for estimated probabilities

	r = 3%				*r* = 4%			
	H = 1	**H = 5**	**H = 10**	**H = 15**	**H = 1**	**H = 5**	**H = 10**	**H = 15**
Minimum	0.3438	0.2817	0.1718	0.0000	0.3961	0.5014	0.1600	0.0007
Q1	0.3977	0.4111	0.2253	0.0000	0.4463	0.5276	0.2950	0.6083
Q2	0.4237	0.4480	0.2480	0.0002	0.4699	0.5406	0.3855	0.9527
Q3	0.4498	0.4925	0.2719	0.0089	0.4916	0.5530	0.4803	0.9971
Maximum	0.5170	0.5859	0.3277	0.9936	0.5451	0.5832	0.7314	1.0000
Average	0.4242	0.4504	0.2489	0.0500	0.4687	0.5400	0.3893	0.7550
s.d	0.0352	0.0575	0.0326	0.1559	0.0307	0.0168	0.1203	0.3354
	r = 5%				*r* = IRR			
	H = 1	**H = 5**	**H = 10**	**H = 15**	**H = 1**	**H = 5**	**H = 10**	**H = 15**
Minimum	0.4432	0.4658	0.4783	0.2014	0.3323	0.4655	0.1680	0.0102
Q1	0.4941	0.5865	0.7902	0.9998	0.3890	0.5126	0.3116	0.1605
Q2	0.5152	0.6401	0.8757	1.0000	0.4159	0.5242	0.4048	0.3437
Q3	0.5326	0.6846	0.9275	1.0000	0.4434	0.5384	0.4995	0.5993
Maximum	0.5894	0.8016	0.9812	1.0000	0.5152	0.5634	0.7427	0.9124
Average	0.5135	0.6351	0.8477	0.9900	0.4168	0.5245	0.4070	0.3900
s.d	0.0271	0.0692	0.1039	0.0552	0.0367	0.0186	0.1222	0.2616

s.d. = standard deviation

Source: Authors' elaboration

Q1 to Q3 refer to quartiles 1 to 3. These results correspond to this work's first aim: determining the probability of not exceeding a specific profitability target given a certain investment horizon. The next objective aims to assess the impact that investing more or less in a specific asset has on achieving the first objective. In other words, knowing which of the assets included has a greater influence in explaining the estimated probabilities of not exceeding a certain target return over a specific time horizon is desired. We focused on equity assets using three different methodologies to conduct this analysis. First, the weight of an asset's stake in a portfolio was assessed using the relative importance indicator in a Random Forest (Breiman 2001). The next approach used to analyze the influence of each variable on the results is based on the compositional data methodology. Finally, the impact of investing more or less in a given asset is assessed using logit models. Concerning the application of random forest, the objective is to determine the relative importance of each variable in explaining the results following the approach explained in Breiman (2001). To this end, 500 trees for each asset, scenario, and horizon were estimated using the randomForest R library (Liaw and Wiener 2002). The application of the algorithm tries to explain the probability of not exceeding a certain target return over a particular time horizon. The explanatory variables used by the algorithm have been the weights of each of the assets considered in each one of the portfolios. The process was conducted using original data. Results were obtained after determining the basic parameters of each triad (asset, scenario, and horizon). Table 4 shows the results by asset and profitability target for horizons of 1, 5, 10, and 15 years.

The results suggest that the two assets with the largest impact (in bold) on explaining the estimated probabilities correspond to Spanish and US equities. The relative importance indicator only reflects the impact of each variable on the quality of the random

Table 4 Relative importance of each asset according to horizon and profitability target (figures in %)

	r **= 3%**				***r*** **= 4%**			
	H = 1	**H = 5**	**H = 10**	**H = 15**	**H = 1**	**H = 5**	**H = 10**	**H = 15**
TB	1.2%	1.9%	0.7%	2.1%	0.8%	0.5%	1.0%	1.2%
CB	1.2%	2.0%	0.6%	1.9%	0.8%	0.5%	1.0%	1.3%
SPA	**52.6%**	3.2%	35.3%	**60.3%**	**62.2%**	**64.0%**	**70.4%**	10.7%
EUR	2.4%	4.7%	1.4%	1.9%	2.2%	2.5%	2.4%	2.0%
USA	39.3%	**73.2%**	**59.1%**	28.1%	31.3%	28.8%	20.3%	**80.9%**
JAP	1.1%	7.8%	1.3%	2.6%	1.1%	2.3%	1.7%	2.2%
EME	2.1%	7.2%	1.8%	3.1%	1.5%	1.5%	3.2%	1.6%
	r **= 5%**				***r*** **= IRR**			
	H = 1	**H = 5**	**H = 10**	**H = 15**	**H = 1**	**H = 5**	**H = 10**	**H = 15**
TB	4.3%	0.8%	1.3%	2.8%	1.3%	2.7%	1.0%	0.8%
CB	4.3%	0.8%	1.3%	3.1%	1.3%	2.6%	1.1%	0.7%
SPA	**63.4%**	**63.1%**	**47.9%**	4.7%	**52.6%**	4.9%	**68.3%**	19.2%
EUR	12.4%	10.3%	5.0%	2.4%	2.3%	2.2%	2.4%	1.7%
USA	9.9%	3.1%	41.1%	**81.2%**	39.8%	**78.1%**	23.3%	**75.4%**
JAP	2.4%	11.4%	1.6%	2.8%	1.1%	3.1%	1.7%	1.0%
EME	3.3%	10.5%	1.8%	3.0%	1.6%	6.4%	2.1%	1.2%

TB = Treasury bonds; CB = Corporate bonds

Source: Authors' elaboration

forest adjustment. In other words, it only collects whether the incidence of each variable is large or small, but not whether it contributes to raising the estimated probabilities.

As indicated above, the compositional data methodology allows us to investigate which variables have the most significant impact and in what sense. To this end, we back-transformed the beta coefficients in the 60 regressions estimated in (6); thus, the results can be interpreted concerning the original data, i.e., the five market indices. If we substitute (1) for (6) and operate on it, we can obtain the logit as a function of the estimated betas and the original variables. The resulting expression can be written as follows:

$$\ln\left(\frac{p}{1-p}\right)_{ih} = \hat{\beta}_0^{sh} + \hat{\beta}_{-0}^{sh'}\mathbf{M}\ln(x_i) \tag{7}$$

where $\hat{\beta}_0^{sh}$ = intercept of the regression for scenario s and time horizon h. $\hat{\beta}_{-0}^{sh'}$ = transposed vector of the estimated betas (without considering the intercept) for each transformed variable in scenario s and time horizon h. $\mathbf{M}$ = matrix of order $(D—1) \times D$ defined as follows:

$$\mathbf{M}_{ij} = \begin{cases} -\frac{1}{\sqrt{i(i+1)}} & i \geq j \\ \frac{i}{\sqrt{i(i+1)}} & i+1=j \\ 0 & otherwise \end{cases} \tag{8}$$

Finally, $ln(x_i)$ is the natural logarithm of each of the original values of the variables considered, i.e., the portfolio weight of each asset. As Coenders and Pawlowsky-Glahn (2020) indicated, the combinations of the betas, given by $\hat{\beta}_{-0}^{sh'}\mathbf{M}$, would indicate the impact of each variable. For illustrative purposes, Table 5 shows the maximum and minimum betas for the 1-, 5-, 10- and 15-year horizons in the four scenarios considered.

The results indicate that, in general, the two assets that have the most significant impact on performance are the Spanish and US indices. Moreover, the direction is always identical; the worst performances are linked to increasing the share of the Spanish index in the portfolio. In contrast, the best performances are linked to increasing the share of the US index. This pattern is reinforced in the long term because no possible differences exist with the described pattern. For example, for a five-year horizon and a target return of 3%, the worst performance would correspond to the emerging market index, not the Spanish one.

Finally, the impact of investing more or less in a given asset has been assessed without considering the rest of them. A set of logit models was used to quantify the influence of each asset. They all have the same dependent dichotomous variable in the compositional data models. The explanatory variables are also dichotomous and associated with the weight of each asset in the portfolio. The estimation model is:

$$\ln\left(\frac{p}{1-p}\right)_i = \hat{\beta}_1 + \hat{\beta}_2 I2_i + \hat{\beta}_3 I3_i + \hat{\beta}_4 I4_i \tag{9}$$

where the subscript i refers to the *i-th* portfolio; variables *I2*, *I3*, and *I4* have the value of one if the weight of the asset is situated within the intervals (0.125, 0.25), (0.25, 0.375) or (0.375, 0.50), respectively. For each asset, 60 regressions were estimated (4 targets × 15 different horizons). Because the first tranche is used as a reference, the betas associated with each of the remaining tranches include the differential effect of these, framed in an interval different from the first. Therefore, the probabilities of not exceeding a certain profitability target in a specific time horizon are obtained as $\exp\left\{\hat{\beta}_1\right\}\Big/\left(1+\exp\left\{\hat{\beta}_1\right\}\right)$ if the weight of a specific asset does not exceed 12.5% and $\exp\left\{\hat{\beta}_1+\hat{\beta}_i\right\}\Big/\left(1+\exp\left\{\hat{\beta}_1+\hat{\beta}_i\right\}\right)$ if the weight of the asset is situated in the i-th interval, where $i = 2, 3, 4$. Table 6 shows the estimated probabilities of not exceeding the profitability targets by intervals for each target and horizon considered.

Table 5 Minimum and maximum beta (from the compositional data analysis)

	H = 1	H = 5	H = 10	H = 15	H = 1	H = 5	H = 10	H = 15
	***r* = 3%**				***r* = 4%**			
Min β	− 0.1113	− 0.1063	− 0.1334	− 4.7961	− 0.1105	− 0.0605	− 0.4867	− 1.6191
Index	SPA	EME	SPA	SPA	SPA	SPA	SPA	SPA
Max β	0.1159	0.2151	0.1485	2.9715	0.0859	0.0455	0.3144	4.0690
Index	USA	USA	USA	USA	USA	USA	USA	USA
	***r* = 4%**				***r* = IRR**			
Min β	− 0.1124	− 0.2646	− 0.6385	− 1.7711	− 0.1155	− 0.0353	− 0.4764	− 0.8416
Index	SPA	SPA	SPA	SPA	SPA	EME	SPA	SPA
Max β	0.0362	0.1333	0.6602	5.0845	0.1227	0.0653	0.3391	1.3863
Index	EUR	JAP	USA	USA	USA	USA	USA	USA

Source: Authors' elaboration.

Table 6 Estimated probabilities of not exceeding profitability targets

		H = 1 *r* **= 3%**	**H = 5**	**H = 10**	**H = 15**	**H = 1** *r* **= 4%**	**H = 5**	**H = 10**	**H = 15**
SPA	I1	0.4093	0.4399	0.2281	0.0049	0.4476	0.5251	0.3133	0.6568
	I2	0.4611	0.4488	0.2616	0.1930	0.5044	0.5612	0.5294	0.8812
	I3	0.4855	0.4122	0.4403	0.5124	0.5171	0.6315	0.7015	0.9851
	I4	0.4866	0.5035	0.7045	0.6667	0.5401	0.6713	0.7500	1.0000
EUR	I1	0.4291	0.4456	0.2603	0.1042	0.4708	0.5402	0.4029	0.7310
	I2	0.4249	0.4318	0.2480	0.0745	0.4567	0.5503	0.3877	0.7439
	I3	0.4278	0.4238	0.2364	0.0364	0.4706	0.5385	0.3727	0.7879
	I4	0.4353	0.4308	0.2500	0.0000	0.4706	0.5692	0.4000	0.8667
USA	I1	0.4465	0.4742	0.2791	0.1283	0.4809	0.5553	0.4394	0.9340
	I2	0.3887	0.3701	0.2317	0.0000	0.4550	0.5334	0.2989	0.2972
	I3	0.3529	0.3035	0.0955	0.0000	0.3583	0.4448	0.2568	0.0121
	I4	0.3529	0.3077	0.0000	0.0000	0.3529	0.3916	0.2500	0.0000
JAP	I1	0.4271	0.4246	0.2571	0.1051	0.4655	0.5450	0.4117	0.6895
	I2	0.4293	0.4696	0.2544	0.0760	0.4716	0.5378	0.3810	0.8099
	I3	0.4277	0.4879	0.2500	0.0476	0.4714	0.5385	0.3339	0.9143
	I4	0.4498	0.5204	0.2500	0.0000	0.4637	0.5385	0.3088	1.0000
EME	I1	0.4277	0.4257	0.2557	0.1034	0.4676	0.5460	0.4134	0.6937
	I2	0.4274	0.4656	0.2580	0.0803	0.4663	0.5357	0.3780	0.8112
	I3	0.4304	0.4921	0.2500	0.0423	0.4669	0.5372	0.3175	0.8783
	I4	0.4545	0.5245	0.2500	0.0000	0.4706	0.5385	0.3182	1.0000
		H = 1 *r* **= 5%**	**H = 5**	**H = 10**	**H = 15**	**H = 1** *r* **= IRR**	**H = 5**	**H = 10**	**H = 15**
SPA	I1	0.4891	0.5883	0.7806	0.9783	0.4004	0.5127	0.3296	0.3022
	I2	0.5413	0.7066	0.9266	1.0000	0.4515	0.5269	0.5491	0.5452
	I3	0.5566	0.7979	0.9907	1.0000	0.4811	0.5442	0.7164	0.7214
	I4	0.5882	0.8531	0.9773	1.0000	0.4866	0.6224	0.7614	0.9091
EUR	I1	0.5134	0.6262	0.8238	0.9803	0.4204	0.5187	0.4198	0.3943
	I2	0.4962	0.6485	0.8501	0.9959	0.4173	0.5235	0.4045	0.3889
	I3	0.4888	0.6685	0.8636	1.0000	0.4182	0.5147	0.3909	0.4545
	I4	0.4706	0.7077	0.9000	1.0000	0.4000	0.4923	0.4250	0.5333
USA	I1	0.5174	0.6443	0.8807	1.0000	0.4378	0.5349	0.4590	0.5383
	I2	0.5119	0.6197	0.7518	1.0000	0.3785	0.5065	0.3125	0.0393
	I3	0.3925	0.5818	0.5864	0.8000	0.3508	0.4056	0.2568	0.0000
	I4	0.3529	0.5385	0.4886	0.6667	0.3476	0.3287	0.2500	0.0000
JAP	I1	0.5061	0.6546	0.8367	0.9791	0.4187	0.5134	0.4266	0.3757
	I2	0.5173	0.6039	0.8339	0.9985	0.4198	0.5310	0.4030	0.4327
	I3	0.5000	0.5604	0.7982	1.0000	0.4218	0.5374	0.3536	0.4571
	I4	0.4706	0.5385	0.8088	1.0000	0.4325	0.5385	0.3309	0.5294
EME	I1	0.5075	0.6539	0.8360	0.9798	0.4192	0.5153	0.4306	0.3781
	I2	0.5124	0.6064	0.8368	0.9960	0.4193	0.5258	0.3936	0.4311
	I3	0.4939	0.5531	0.7857	1.0000	0.4174	0.5372	0.3353	0.4233
	I4	0.4813	0.5385	0.8182	1.0000	0.4492	0.5385	0.3523	0.6364

Source: Authors' elaboration

Although the analysis only considers a particular asset's effects, we can draw some conclusions. Generally, regarding the investment in the Spanish stock market, it can be seen that the longer the investment horizon, the more likely the profitability target will not be exceeded; the same pattern appears as the weight of the investment in the asset increases. Conversely, the performance of the investment in US equities is radically different; the longer the horizon, the lower the probability of not exceeding the set target, except in the most demanding case ($r=5\%$). Furthermore, the greater the weight of the portfolio invested in this asset, the lower the probability of not exceeding the set targets, whatever they may be. Regarding the remaining assets, the conclusions drawn from Table 4 are not as apparent as those for the US equities case; thus, the longer the term, the greater the probability of not exceeding the targets, except in the most favorable case ($r=3\%$). As regards the effects of greater or lesser asset weights in the portfolios, greater weight is not necessarily accompanied by a greater probability of exceeding the investment targets, except in strong concentrations over very long durations. Finally, analyzing the results obtained when the profitability target is reached by Spanish government debt indicates that the greater the concentration in an asset over a longer investment horizon, the greater the probability of not exceeding the return offered by debt. This behavior is widespread, except for the US stock market, which is the opposite.

Conclusions

This paper analyzed the potential relationship between exceeding a given profitability threshold and investment horizon. This analysis used a specific type of portfolio (equal proportions fixed income and equity securities) and considered a specific set of assets from each class. The estimated probabilities of not exceeding a specific return were obtained considering that investments are carried out in changing environments. The proposed method considers that the data used are the weights of each asset in the portfolio, and together, they total one unit. This rationale led us to use the compositional data methodology. This approach transforms the original variables so the problem's dimension is reduced to a single unit, and it also permits the use of conventional statistical tools, like a logit model.

The most relevant aspect of this project is not the results but the methodological approach to the analysis. The results are contingent upon the data and the portfolio design applied. For the specific case examined in this paper, the results suggest that, as expected, the probability of not exceeding certain profitability thresholds depends on the investment horizon and the portfolio makeup. The study shows that the longer the duration, the lower the probability of not recovering the invested value, indicating that the probability of incurring losses on an investment depends on the time horizon. One preliminary result to consider if the goal is not to lose value is that losses occur with a probability close to one for investment horizons of at least seven years.

Considering the results of the relative importance indicator, the assets with the most significant influence on results are investments in the Spanish and US stock markets. Logit models were used to qualify this statement further. Thus, for cases in which a demanding profitability target is imposed, such as those with an annual return of 5%, the probability of not exceeding that target rises with the horizon considered; however, it falls as the weight of the investment increases. A couple of clear conclusions can be drawn from this. The first is that US stock market investments must be present in medium- and long-term investments, and the greater this presence, the greater the probability of exceeding the pre-set targets. In contrast, the investment performance in the domestic market suggests that its stake in the portfolio should be much smaller. The results indicate that the weight of the investment in this market would hinder the estimated probability of not exceeding the targets.

This research analyzed the performance of the portfolios with different profitability targets and can offer several ways to move forward in the future. The analysis for two fixed-income and equity weight distributions could be replicated, making it possible to re-estimate the probabilities analyzed for portfolios that incorporate assets other than the two considered (fixed income and equities), such as high-yield bonds or alternative assets. As this paper focused on the sensitivity to profitability targets, future studies could examine different risk targets or some metric that combines risk and return, such as the Sharpe ratio. It might also be interesting to delve into the results that different local equity indices yield; for example, this study could be extended to Spanish equities or extrapolated to other markets to determine the actual effects of home bias on strategic portfolio makeup. Finally, in any of the cited instances, it seems reasonable to estimate the value of the weight of each asset to achieve an optimal portfolio.

Abbreviations

CAPM	Capital asset pricing model
CB	Corporate bonds
SAA	Strategic asset allocation
TB	Treasury bonds
US	United States

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Author contributions
Conceptualization: FVG, PJAG. Methodology: FVG, PJAG. Software: FVG, PJAG. Validation: PJAG. Formal analysis: FVG. Investigation: FVG, PJAG. Resources: Data Curation: FVG, PJAG. Writing – original draft: FVG, PJAG. Writing – review & editing: FVG, PJAG. Visualization: Supervision: PJAG. Project administration: PJAG. Funding acquisition: PJAG.

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Availability of data and materials
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Declarations

Competing interests
The authors declare that they have no competing interests.

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