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ORIGINAL ARTICLE

Capital asset pricing model in Portugal: Evidence from fractal regressions

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Abstract We examine risk profiles of the Portuguese stock market index component stocks using a novel approach to the classical capital asset pricing model (CAPM). Specifically, we estimate the CAPM via fractal regressions that allow studying the marginal effects at selected scales. In this way, we can reveal whether the risk is perceived differently by market participants with different investment horizons. Apart from the analysis itself, we provide new statistical insights into the issue of separating and comparing the scale-specific effects with statistical validity. We find several stocks deviating from an expected risk perception homogeneity across investment horizons. This is true for both analysed periods, i.e. before and after the global financial crisis. There are also several stocks that changed their relationship to the market portfolio in between, which has strong implications for possible portfolio construction. The proposed methodology is not limited to financial topics but can be used in any discipline where the scale-specific marginal effects might be of interest.

Keywords Capital asset pricing model · Detrended cross-correlation analysis · Detrending moving-average cross-correlation analysis · Fractal regressions · Portugal

JEL codes C19 · G12

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1 Introduction

The capital asset pricing model (CAPM), developed independently in the work by Sharpe (1964), Lintner (1965) and Mossin (1966), is one of the most famous and influential models of financial economics, regardless of its limitations. The CAPM serves as a valuation technique for financial assets, building on the idea of market equilibrium and implied asset prices. Building on a detailed theory, a linear relationship between asset returns and market returns is found. As such, this linear relationship has usually been estimated using standard econometric techniques, specifically the (ordinary) least squares (OLS) regression. The model assumes, in line with the modern financial economics theory, that the risk associated with holding an asset is perceived in the same way by each economic agent. However, the current stream of literature leans more strongly towards heterogeneity of economic agents and thus also a different perception of risk (Brock and Hommes 1998). We contribute to this perspective by inspecting the heterogeneity of such risk perception via the CAPM estimated through two novel estimation methods based on fractal analysis.

Developed by Kristoufek (2015, 2016), the regression frameworks based on detrended fluctuation analysis and detrending moving average allow studying relationships between variables at different scales. In the context of financial time series, the effects for different investment horizons can be distinguished, e.g. a difference between the effect for short-term and long-term investors. In addition, the methods have been shown to be robust regarding several statistical phenomena generally connected to financial time series, such as fat tails and long-range dependence (Kristoufek 2014a, b). We closely follow the current study of Kristoufek (2018) which introduces the fractal regression into the CAPM environment and specifically focuses on the Dow Jones Industrial index component stocks. In our study, we take a similar path and analyse the risk structure of the Portuguese stock market by combining the CAPM and fractal regressions to see whether the results are comparable for a less developed stock market. The Portuguese stock market was valued at about 48,909 million euros in 2016, an increase of more than 12% on the previous year. Economically, the country is recovering from both the global financial and sovereign debt crises, with evidence of economic growth. As Portugal has been hit by these crises in the last decade, we are also interested in the changes in this risk structure with respect to Portugal's specific economic performance.

The remainder of the paper is organized as follows. Section 2 presents a theoretical background of the CAPM framework and a literature review of its important applications. Section 3 covers the fractal regressions methodology. Section 4 describes the analysed dataset and Section 5 presents the results of our analysis. Section 6 concludes. We find several stocks deviating from an expected (or assumed) risk perception homogeneity across investment horizons. This is true for both analysed periods, i.e. before and after the global financial crisis. Several stocks changed their relationship to the market portfolio in between, which has strong implications for possible portfolio construction. We also contribute to discussion of the statistical inference of the methods used as well as methods focusing on estimation of parameters at different scales in general.

2 Capital asset pricing model: Theory and some evidence

2.1 Theoretical framework

The capital asset pricing model (CAPM) is one of the building blocks of modern financial economics relating risk and return on equilibrium markets with rational agents. The model was developed in the 1960s (in three independent papers by Sharpe 1964, Lintner 1965 and Mossin 1966), building on Markowitz's modern portfolio theory (Markowitz 1952). Theory around the model leads to a relationship between individual assets and a respective aggregate market in a form of

$$E(R_{it}) = R_{ft} + \beta_i\left(E\left(R_{mt} - R_{ft}\right)\right) \tag{1}$$

where $E(.)$ is the expectations operator, R_i is a return of asset i, R_f is a risk-free rate, and R_m a market return (all referring to the respective time period t). The model assumptions imply an equilibrium relationship between an asset return and the whole market (after correcting for the risk-free rate). Conveniently, the β parameter can be expressed as a ratio of covariance between the asset and market return, and market return variance:

$$\beta_i = \rho_{im}\frac{\sigma_i}{\sigma_m} = \frac{cov(R_{it}, R_{mt})}{R_{mt}} \tag{2}$$

with being the correlation between the returns of an individual asset and the market, the standard deviation of the return of an asset i, and is the standard deviation of the market return. Note that Eq. (2) directly corresponds to the OLS estimator of a simple linear regression. The relationship can be rewritten as a standard regression model, specifically as

$$R_{it} - R_{ft} = \alpha_i + \beta_i\left(R_{mt} - R_{ft}\right) + u_{it} \tag{3}$$

with u_i as the error term and α_i as a deviation from the equilibrium return. The α parameter is expected to be equal to zero for the equilibrium situation and as such, can be used to make investment decisions – $\alpha > 0$ suggests overpricing of an asset and $\alpha < 0$ suggests underpricing. From the asset riskiness viewpoint, the β parameter is essential. The existence of a negative β is rare as well as counterintuitive, because it suggests that assets move against the market. If $0 < \beta < 1$, a given asset moves in the same direction as the market but with lower volatility, i.e., with lower risk. Such assets are considered as defensive ones. An asset with $\beta = 1$ copies the market, while if it has $\beta > 1$, it moves in the same direction as the market but with higher volatility and such assets are considered aggressive.

2.2 Brief literature review

There have been several extensions of the original CAPM. Ibbotson and Sinquefield (1976) find that stock returns are better explained when other variables (namely the company size and its book to market ratio) are added to the model. Some authors dispute the use of indices as adequate measures of market portfolio (see, for example, Roll 1977). Banz (1981) states that small and large firms have different degrees of risk.

Authors like Adedokun and Olakojo (2012) and Hasan et al. (2013), although using different samples, find evidence against CAPM validity.

After the continuous CAPM tests, and based on the strict assumptions, some adjustments were made to the model. The early work of Merton (1973) considers intertemporal beta. Following this idea, Breeden (1979) adds information about consumption to the model. Recent work, such as Tsuji (2017), uses this idea. Some authors have considered the information of market indicators like the price to earnings ratio, the debt to equity ratio or the book to market ratio to be important in the expected stock returns definition (see, for example, Basu 1977; or Fama and French 1993, among others). The use of networks is another example of newer methodologies to analyse the CAPM (see, for example, Squartini et al. 2017). But it is still possible to find studies encouraging the use of the original model (see, for example, Guermat 2014).

The model has been used in different contexts, countries and samples. Jensen (1968) presents one of the first empirical studies, using information from the NYSE, between 1931 and 1965, arguing in favour of CAPM validity. Other applications with the NYSE were made, for example, by Fama and MacBeth (1973). Numerous studies focus on other international markets, e.g. Switzerland (Isakov 1999), Australia (Haque and Mackay 2016), European emerging markets (Zhang and Wihlborg 2005), Greece (Michailidis et al. 2006) and Turkey (Köseoğlu and Mercangöz 2013).

The CAPM literature focusing on the Portuguese stock market is scarce, although it is possible to find some examples. Alves (2013) compares the CAPM with the Fama and French (1993) model, which includes different factors in explaining stock returns. Khudoykulov et al. (2015) present the analysis of CAPM for 8 different stocks of 5 countries, including Portugal. They conclude that CAPM is not adequate for the stocks under analysis. However, using just part of the stocks for each country, monthly data and regression analysis could determine such results. This highlights the importance of focusing on different methodologies as well as larger datasets.[1]

2.3 From homogeneity to heterogeneity

Some CAPM criticisms and the history of the last decade have shown both theorists and practitioners that market participants perceive assets' behaviour differently. In fact, there are different types of investors, with different trading strategies and different investment horizons. The basis of the CAPM is that agents perceive asset-specific and market risks similarly in the same logic as in the efficient market hypothesis framework (Fama 1970, 1991). Agents distinguishable by their specific investment horizon are the basis of some competing theories, most markedly the fractal market hypothesis (Peters 1991, 1994).

In this line, the CAPM considers all agents to be homogeneous with a common investment horizon (Vasicek and McQuown 1972). Nevertheless, facts suggest otherwise. Specifically for investment horizons, there are specific agent types, ranging from algorithmic and noise trading (with very short horizons in a span of second fractions) to pension funds (with long investment horizons of several years or even decades). Using the proposed

[1] It is also possible to find other studies of Portuguese stocks. For example, Alpalhão and Alves (2005) use a specific model to analyse how the Portuguese market behaves in relation to its risk exposure, concluding that the market has higher risk exposure than other European ones. Curto et al. (2003) and Ferreira and Dionísio (2014) analyse the existence of dependence in some stock markets, including the Portuguese one. Lobão and Azeredo (2018) investigate the momentum effect and value-growth effect in the Portuguese stock market.

methodology allows us to examine whether an asset can be seen in a different perspective, in the CAPM sense, because it can distinguish between short-term and long-term investors. More details about the methods are given in the following section.

3 Fractal regressions

We use the regression framework proposed by Kristoufek (2015), based on two fractal methods originating outside mainstream economics and finance – the detrended fluctuation analysis (DFA) and the detrending moving average (DMA) (Peng et al. 1994; Vandewalle and Ausloos 1998; Alessio et al. 2002). An important feature of these methods is their robustness to persistence, short-range correlations and partially to heavy tails as well (Barunik and Kristoufek 2010), which is very convenient for examining financial time series. Both methods build on an idea of Zebende (2011) who combined DFA and its bivariate generalisation DCCA (Podobnik and Stanley 2008) into a measure of correlation for a specific scale, which can in turn be interpreted as an investment horizon in financial terms. Kristoufek (2014a, b) extends the same idea to the DMA-based correlation coefficient based on the detrending moving-average cross-correlation analysis (DMCA) (Arianos and Carbone 2009; He and Chen 2011).

Kristoufek (2015, 2016) closes the gap between correlations and regression coefficients and introduces regression frameworks based on DFA/DCCA and DMA/DMCA. The estimators deliver estimates of the effects for different scales while keeping desirable properties of the original methods. The methods keep the same logic as the ordinary least squares (OLS) estimator. As the bivariate OLS estimator can be seen as a ratio of covariance between the series and their respective standard deviations, the DFA/DCCA and DMA/DMCA scale-specific covariance and variance can be used for rewriting the estimator as

$$\hat{\beta}^{DFA}(S) = \frac{F^2_{XY,DFA}(S)}{F^2_{X,DFA}(S)}, \quad \hat{\beta}^{DMA}(S) = \frac{F^2_{XY,DMA}(\lambda)}{F^2_{X,DMA}(\lambda)} \tag{4}$$

where $F^2_{X,DFA}(S)$, $F^2_{XY,DFA}(S)$, $F^2_{X,DMA}(\lambda)$, $F^2_{XY,DMA}(\lambda)$ are fluctuation functions parallel to scale-specific (with scales s and λ for DFA and DMA, respectively) covariance and variance functions for DFA/DCCA and DMA/DMCA procedures, respectively. The new βs here are interpreted as scale-specific effects between the independent and dependent variables (in our case the excess market return and excess asset return, respectively). More details about the methodologies and the theory can be found in the original papers of Kristoufek (2015, 2016) and the recent study by Ferreira and Kristoufek (2017).

An essential issue when studying the relationships between variables for different scales is their statistical inference. To be able to interpret our results with statistical validity, we construct a scale-dependent distribution of the estimators with respect to the null hypothesis of no scale dependence. Specifically, we estimate the CAPM model as given in Eq. 3 using the standard OLS procedure to obtain the estimates of α and β as well as the residuals of the regression. The residuals are then reconstructed using the methodology of Theiler et al. (1992), which constructs series with the same spectrum as the original using the randomised phases of the Fourier coefficients as well as the same empirical distribution. The reconstructed residuals thus have the same linear serial correlation structure as the original ones as well as the same distributional properties. These are then used, together with the estimated coefficients α and β, to reconstruct the asset returns series. This procedure is repeated 333 times for each stock in both analysed periods and the scale-dependent critical values (confidence intervals around the null hypothesis of no heterogeneity across scales) are constructed as the 2.5th and 97.5th quantiles to obtain the critical values for the 95% confidence level. The procedure is described in detail in Kristoufek (2018).

4 Dataset description

We study the main Portuguese stock index, PSI-20, and its current components. At the moment, the PSI-20 index comprises 18 stocks, which have different starting dates of trading in that index. As we preferred a longer time window to allow us to analyse eventual differences among the periods before and after the global financial crisis, we decided to recover data from January 2003. The last retrieved observation was from 6 September 2017. We split our sample into two sub-samples: the period before the crisis, from the beginning of the sample to the end of 2006 (a total of 1043 observations), and the period from the beginning of the crisis until the end of the analysed period (2788 observations).

For the first sub-period, we retrieved information for 12 firms: BCP, Corticeira Amorim, EDP, Ibersol, Jerónimo Martins, Mota Engil, Navigator, NOS, Novabase, Pharol, Semapa and Sonae SGPS. In the second sub-period, we added two stocks – Altri and Galp.

For the stocks and the market rate (the PSI-20 index), we use the logarithmic returns. For the risk-free rate needed for the CAPM estimation, we used the Portuguese benchmark 10-year bond. This is an annual interest rate in percentage points. As we use daily stock and index data, it is necessary to transform the interest rate in daily yields. Considering a 250-day trading year, the (compounded) daily yields are given by

$$R_f = \left(1 + \frac{AY}{100}\right)^{1/250} - 1 \tag{5}$$

with AY being the annual yield in percentage points.

5 Results and discussion

As previously stated, we estimate the CAPM for part of the PSI-20 components, between 2003 and 2017, allowing for a comparison of the periods before and after the crisis. We use the DCCA and DMCA-based regressions for a different range of scales: between 10 and 500 trading days in the case of DCCA and between 11 and 501 for DMCA. We construct corresponding confidence intervals with the objective of analysing the behaviour of the estimated β for different scales, according to the procedures referred in Section 3.

Results are presented for the pre-crisis (Fig. 1) and post-crisis (Fig. 2) periods, with the DCCA estimations on the left and the results of DMCA on the right. The red line identifies the estimated scale-specific βs, while the shaded area identifies the confidence intervals. We keep the same notation and logic of statistical testing as in Kristoufek (2018) so that the red lines outside the shaded area imply that the estimated parameters vary across scales with statistical power. Contrarily, if the estimations are inside the calculated confidence intervals, the simple OLS estimation should be enough to capture CAPM, i.e., investors do not make any distinction between different investment horizons. This hypothesis, in line with the efficient markets, differs from the possibility of the fractal market hypothesis validity, which states that investors have different investment horizons, which would be shown by the red lines outside the shaded area.

In general, the results are qualitatively similar for both methods, although the DMCA-based regressions are much smoother than the DCCA estimates, which is in line with previous work comparing the methods (see, for example, Kristoufek 2014a, b, 2018 or Ferreira and Kristoufek 2017). Across the different time scales, the confidence intervals are wider for higher time scales, justified by effectively fewer observations for higher scales.

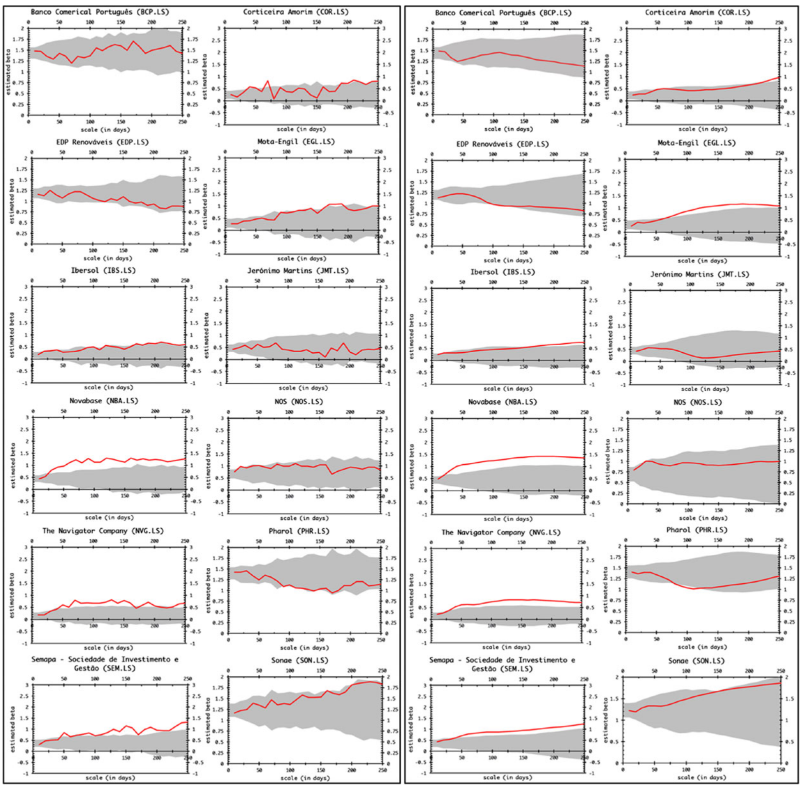

Fig. 1 Scale-specific estimates of the CAPM β parameter, for the pre-crisis period. In the left panel, the results for the DCCA-based regression (scales between 10 and 500, with a step of 10) are shown; in the right panel the results for the DMCA-based regression (scales between 11 and 501, due to central moving averages) are shown. Red lines represent the estimates and the shaded area represents the 95% confidence intervals around the null hypothesis. The confidence values are based on 333 surrogate series

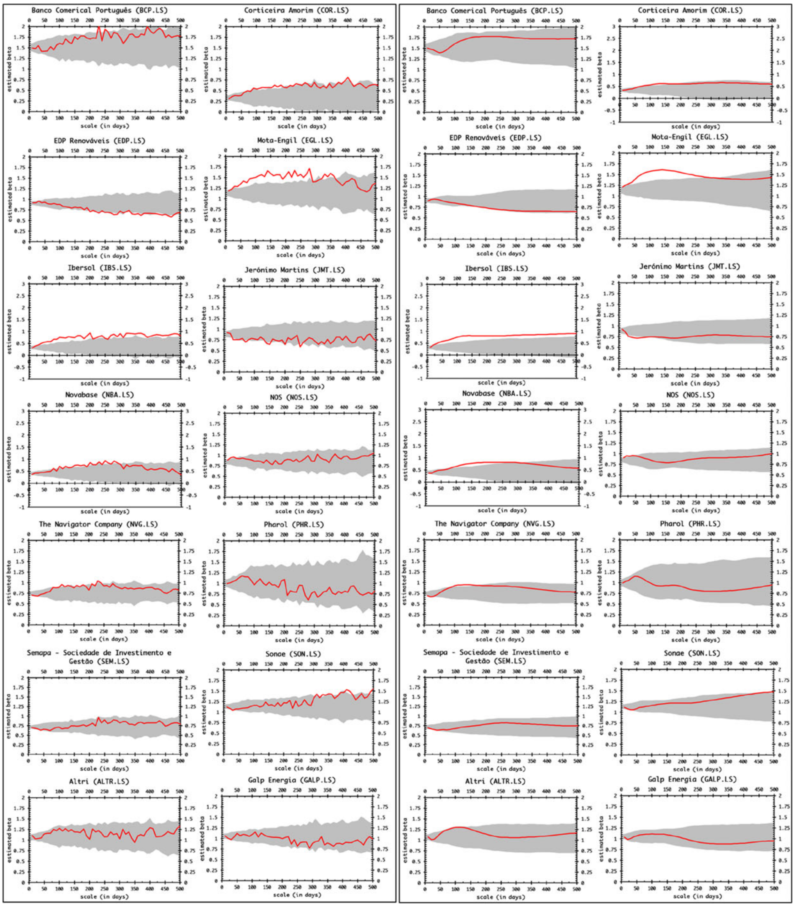

Fig. 2 Scale-specific estimates of the CAPM β parameter, for the period after the beginning of the crisis. In the left panel, the results for the DCCA-based regression (scales between 10 and 500, with a step of 10) are shown; in the right panel the results for the DMCA-based regression (scales between 11 and 501, due to central moving averages) are shown. Red lines represent the estimates and the shaded area represents the 95% confidence intervals around the null hypothesis. The confidence values are based on 333 surrogate series

Considering the pre-crisis period, stocks with different patterns are found: aggressive stocks like BCP, Novabase (although defensive in very short scales) and Pharol (in medium scales, it follows the market); market stocks like EDP Renováveis (although a little aggressive for short scales) and NOS; defensive stocks like Corticeira Amorim, Ibersol, Jerónimo Martins and Navigator. Mota Engil and Semapa show mixed results, being defensive in short time scales and aggressive in higher time scales.

Our results identify variability for practically all the studied titles. Furthermore, the results show statistically significant scale-dependence of β in some cases, when the estimated parameter is compared with the confidence intervals. Most of the stocks behave with the red curve within the confidence interval shaded area, meaning that CAPM for those shares could be studied with a single global β parameter. The exceptions are Mota Engil (clearer in the case of the DMCA regression), Ibersol (for higher time scales), Novabase, Navigator and Semapa.

Mota Engil is a strongly defensive stock at short scales and behaves like the market at higher ones, being a strong candidate for long-term risk diversification in a portfolio. Ibersol and Navigator are also defensive at short scales but come closer to the market dynamics for higher scales. Novabase and Semapa come from being defensive to being aggressive with an increasing investment horizon.

After the crisis, the following patterns are found: aggressive stocks in the case of BCP, MotaEngil, Sonae and Altri; NOS, Pharol and Galp as market stocks; CorticeiraAmorim, EDP Renováveis, Ibersol, Jerónimo Martins, Novabase, Navigator and Semapa could be considered defensive stocks.

Note that some changes occurred between the two sub-periods: Novabase passed from an aggressive stock to a defensive one; Pharol from an aggressive stock to a market follower; EDP Renováveis from market to defensive; and MotaEngil and Semapa had mixed results in the pre-crisis period, but in the post-crisis, the former became aggressive and the latter defensive.

Considering the comparison between the estimations and the confidence intervals, in the second sub-period, there are less statistically significant scale-dependent βs: MotaEngil, Ibersol and Novabase in medium scales are the only examples. Curiously, all of them also had this pattern in the first sub-period.

Overall, the results are very interesting. Several stocks show statistically significant deviations from an expected (or assumed) risk perception homogeneity across investment horizons. This is true for both analysed periods, i.e. before and after the global financial crisis. There are also several stocks that changed their relationship with the market portfolio in between, which has strong implications for possible portfolio construction. In addition, we have shown that treating the potential heterogeneity of market participants with a proper statistical approach prevents us from revealing too much heterogeneity, as simply looking at the scale-dependent estimates would yield many more stocks with possible heterogeneity in risk perception. The methodology we present here can be used when studying any bivariate relationship where the interest lies in different effects across scales, which is not limited to economics and finance.

6 Concluding remarks

The CAPM framework provides a method of pricing financial assets assuming the state of market equilibrium. According to the original idea, there is a linear relationship between asset returns and market returns which can be easily estimated using the standard OLS regression. Such an approach can be limiting, and in addition to other theoretical issues of the model, it led to frequent criticism of CAPM, but the framework has remained popular. In this paper, we contribute to the current stream of CAPM literature by using two novel estimation methods based on fractal analysis which allows distinguishing between different investors' behaviour, and here specifically the perception of risk implied by CAPM.

Applying these techniques to the Portuguese stock market, comparing the pre and post-crisis periods, we identified both aggressive and defensive stocks as well as market-following stocks. Interestingly, there is only one stock (BCP) that had higher risk than the market in both periods. Some stocks could be considered as defensive investiments (Corticeira Amorim, Ibersol, Jerónimo Martins and Navigator), while NOS is in line with the market in both periods.

The methodologies used could also detect possible scale-dependence of the β parameter, which would imply different perception of risk for different investor classes with respect to their investment horizon. While for most stocks the use of a single β parameter is sufficient, there are exceptions, showing that the use of different scales is relevant (in the case of MotaEngil, Ibersol, Novabase, Navigator and Semapa). The results for these stocks imply that risk perception is not homogeneous across investment horizons as the original CAPM states. Regarding the limitations of CAPM, the risk perception heterogeneity implies there is no single market portfolio that would be ideal for all investors – investors with a specific dominant investment horizon have a specific optimal market portfolio, and this portfolio structure and portfolio weights differ with respect to the investment horizon.

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