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Portfolio performance of European target prices

Joana Almeida Raquel M. Gaspar *

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Abstract

This paper explores the performance of actively managed portfolios constructed based on target price recommendations provided by analysts. We propose two methods for constructing portfolios using Bloomberg's 12-month target price consensus, which we use as a signal to buy or sell assets.

Using a sample of 50 European stocks over a 15-year period (2004-2019), we compare the performance of target price-based portfolios to traditional alternatives such as a naive homogeneous portfolio and the Eurostoxx 50 index, as well as to passive portfolios based on mean recommendations. We also examine the mean-variance efficiency of these portfolios and find that they all exhibit similar levels of efficiency, with theoretical tangent portfolios vastly outperforming all others.

Our results indicate that target price-based portfolios show performance very close to that of the naive homogeneous portfolio. Even the passive "mean" portfolios, which require pre-knowledge of targets for the entire investment period, are unable to outperform the naive portfolio.

We also investigate the impact of rebalancing on portfolio performance and find that it does pay off in the long run (over an 8-year investment period), but that the frequency of rebalancing matters. Rebalancing only once a year is as detrimental to performance as not rebalancing at all. However, it is unclear whether the transaction costs associated with frequent rebalancing would offset any relative outperformance.

Overall, our study contributes to the literature on portfolio management by showing the potential benefits and limitations of using target price recommendations to construct portfolios, and highlighting the importance of carefully considering rebalancing strategies in order to achieve optimal performance.

KEYWORDS: Target prices, portfolio performance, mean-variance theory

JEL CODES: G11, G02.

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1 Introduction

=> My Intro

Currently, millions of shares are traded daily on world markets. Investors who buy and sell shares wonder if they are trading at the right/fair prices.

Defenders of market efficiency would claim market prices are "fair", by definition, and that there is no added value to stock picking. Still, financial markets are full of financial analysts that keep analysing stocks and providing buy/hold/sell recommendations, suggesting it is possible to "beat" the market by investing according to their advise. These analysis typically also provide so-called "price targets". According to Bilinski et al. (2013) "a target price forecast reflects the analyst's estimate of the firm's stock price level in 12 months, providing easy to interpret, direct investment advice".

Nowadays, price targets determined by financial analysts are available to investors via platforms such as Bloomberg or even Yahoo Finance and can, therefore, be used for defining investment strategies. Although price targets may vary from analyst to analyst, depending on the models they use and parameter estimations, one can rely on general statistics also provided by financial data platforms.

In this study we use Bloomberg's *12–month consensus target prices* for 50 of the highest capitalisation European stocks, over the past 15 years, and look on how they may be used to build active portfolios.

This issue is virtually not addressed in the literature. One exception is Barber et al. (2001) who focus on the profitability of investment strategies based upon target prices. Their database, however, is not based upon target prices but recommendation ratings instead (between 1, reflecting a strong buy, and 5, a strong sell).

This study is, to the best of our knowledge, the first to consider a large amount of European stocks and the direct use of target price in portfolio construction.

Concretely, we propose ways to use the resulting price spreads (difference between the current price and the target price) in the construction of active portfolios, and test the relative performance of such portfolios. To the best of our knowledge this is the first attempt to understand how useful target prices may be in a portfolio context.

The remaining of the text is organised as follows. Section 2 contextualises our study within the existing literature and discusses its contribution. Section 3 presents the data and methodology. In Section 4 we present and discuss the results. Finally, Section 5 summarises the main findings and present some ideas about future research.

=> Chat GPT Intro without REFs

Financial markets are an integral part of modern economies, where millions of shares are traded daily. The question of whether these market prices are fair has been the subject of much debate. Supporters of market efficiency argue that prices are inherently fair, and that there is no added value to stock picking. However, despite this view, financial analysts continue to provide buy/hold/sell recommendations and set price targets for individual stocks.

Price targets are easy-to-interpret and direct investment advice, as they reflect an analyst's estimate of the stock's price level in the future. Platforms such as Bloomberg and Yahoo Finance make these targets readily available to investors. Although these price targets may vary from analyst to analyst, general consensus statistics are available from financial data platforms.

In this study, we explore the use of Bloomberg's 12-month consensus target prices for 50 high capitalisation European stocks over the past 15 years. Our goal is to investigate how these targets may be used to construct active portfolios, an issue that has been largely unexplored in the literature. We propose two ways to use the resulting price spreads (the difference between the current price and the target price) to construct actively managed portfolios based on analysts' recommendations.

To the best of our knowledge, this is the first attempt to understand the usefulness of target prices in a portfolio context using a large sample of European stocks. We compare the performance of active portfolios constructed using target prices with that of standard alternatives, such as the naive homogeneous portfolio or the Eurostoxx 50 index. We also consider passive portfolios using "mean" recommendations over the investment period.

Our results shed light on the relative performance and mean-variance efficiency of these portfolios over the 15-year period. We find that, excluding theoretical tangent portfolios that outperform all others, the use of 12-month consensus target prices in active portfolio building results in performance comparable to that of the naive homogeneous portfolio. Additionally, we examine the impact of portfolio rebalancing on long-term performance and find that infrequent rebalancing is as bad as no rebalancing at all.

The rest of the paper is structured as follows: Section 2 contextualizes the study within the existing literature and discusses its contribution. Section 3 describes the data and methodology used in this study. Section 4 presents and discusses our results, and Section 5 summarizes the main findings and provides ideas for future research.

=> Chat GPT Intro with REFs

Currently, millions of shares are traded daily on world markets. Investors who buy and sell shares wonder if they are trading at the right/fair prices. Defenders of market efficiency would claim market prices are "fair," by definition, and that there is no added value to stock picking (e.g., **?**). Still, financial markets are full of financial analysts that keep analyzing stocks and providing buy/hold/sell recommendations, suggesting it is possible to "beat" the market by investing according to their advice. These analyses typically also provide so-called "price targets." According to Bilinski et al. (2013), "a target price forecast reflects the analyst's estimate of the firm's stock price level in 12 months, providing easy to interpret, direct investment advice."

Nowadays, price targets determined by financial analysts are available to investors via platforms such as Bloomberg or even Yahoo Finance and can, therefore, be used for defining investment strategies. Although price targets may vary from analyst to analyst, depending on the models they use and parameter estimations, one can rely on general statistics also provided by financial data platforms.

In this study, we use Bloomberg's *12–month consensus target prices* for 50 of the highest capitalization European stocks, over the past 15 years, and look on how they may be used to build active portfolios. This issue is virtually not addressed in the literature. An exception is Barber et al. (2001) who focus on the profitability of investment strategies based upon target prices. Their database, however, is not based upon target prices but recommendation ratings instead (between 1, reflecting a strong buy, and 5, a strong sell).

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The remaining of the text is organized as follows. Section 2 contextualizes our study within the existing literature and discusses its contribution. Section 3 presents the data and methodology. In Section 4 we present and discuss the results. Finally, Section 5 summarizes the main findings and presents some ideas about future research.

2 Literature Review

The discussion about whether or not price targets can be used to "beat" the market is related to the much older but on-going debate about passive *versus* active portfolio management, or even the more general discussion about the market efficiency. See Fama (1965), Fama et al. (1969), Barr Rosenberg and Lanstein (1984), Sharpe (1991), Admati and Pfleiderer (1997), Sorensen et al. (1998), Malkiel (2003), Shukla (2004), French (2008), Vermorken et al. (2013) or Cao et al. (2017), or Elton et al. (2019), to mention just a few over time.

Although the literature about market efficiency presents mixed evidence depending on concrete markets, asset classes and/or forms of efficiency under analysis (see, for instance, Dimson and Mussavian (1998) overview), there seems to be an agreement that, in particular for large capitalisation stocks, markets are supposed to be at least semi-strong efficient. That is, one should not be able to trade profitably on the basis of publicly available information, such as analysts' recommendations and target prices. Nonetheless, research departments of brokerage houses spend large sums of money on security analysis – with particular emphasis on large capitalisation stocks – presumably because these firms and their clients believe its use can generate superior returns (Barber et al., 2001), suggesting markets may not be that efficient.

Besides the non-efficiency argument, it could also be that target prices act in financial markets as self-fulfilling prophecies. See, for instance, the overviews of Krishna (1971) and Zulaika (2007). A self-fulfilling prophecy is an event that is caused only by the preceding prediction or expectation that it was going to occur. If extremely large numbers of people base trading decisions on the same indicators, thereby using the same information to take their positions, this pushes the market in the predicted direction. The self-fulfilling prophecy argument as been mostly used in studies about financial bubbles (Garber, 1989), market cycles (Farmer Roger, 1999) or panics (Calomiris and Mason, 1997), but also to justify some industry (theoretically odd) trading practices, such as technical analysis (Menkhoff, 1997; Oberlechner, 2001; Reitz, 2006) and momentum (Jordan, 2014), for instance. Most analysts determining price targets work at high status entities such as consulting firms and investment banks. It turns out that the reputation of these entities ultimately could significantly influence the behaviour of investors, in our view, supporting the self-fulling argument.

The possibility that there could exist profitable investment strategies based on the publicly available recommendations of security analysts is suggested by the findings of Stickel (1995) and Womack (1996), who show that favourable (unfavorable) changes in individual analysts' recommendations are accompanied by positive (negative) returns at the time of their announcement. Our paper's perspective, however, is different from that of Stickel and Womack. Their primary goal is to measure the average price reaction to changes in individual analysts' recommendations; therefore, they take an analyst and event-time perspective. As in Barber et al. (2001), here we take a more hands-on investor-oriented perspective. Differently from Barber et al. (2001), we take a portfolio approach using a fixed set of assets for the entire time-span under analysis.

3 Data & Methodology

3.1 Data

This study focuses on 50 major European companies. From all the constituents of EURO STOXX 50 index during our15 years sample, we chose the 50 companies that stayed the longest in the index.

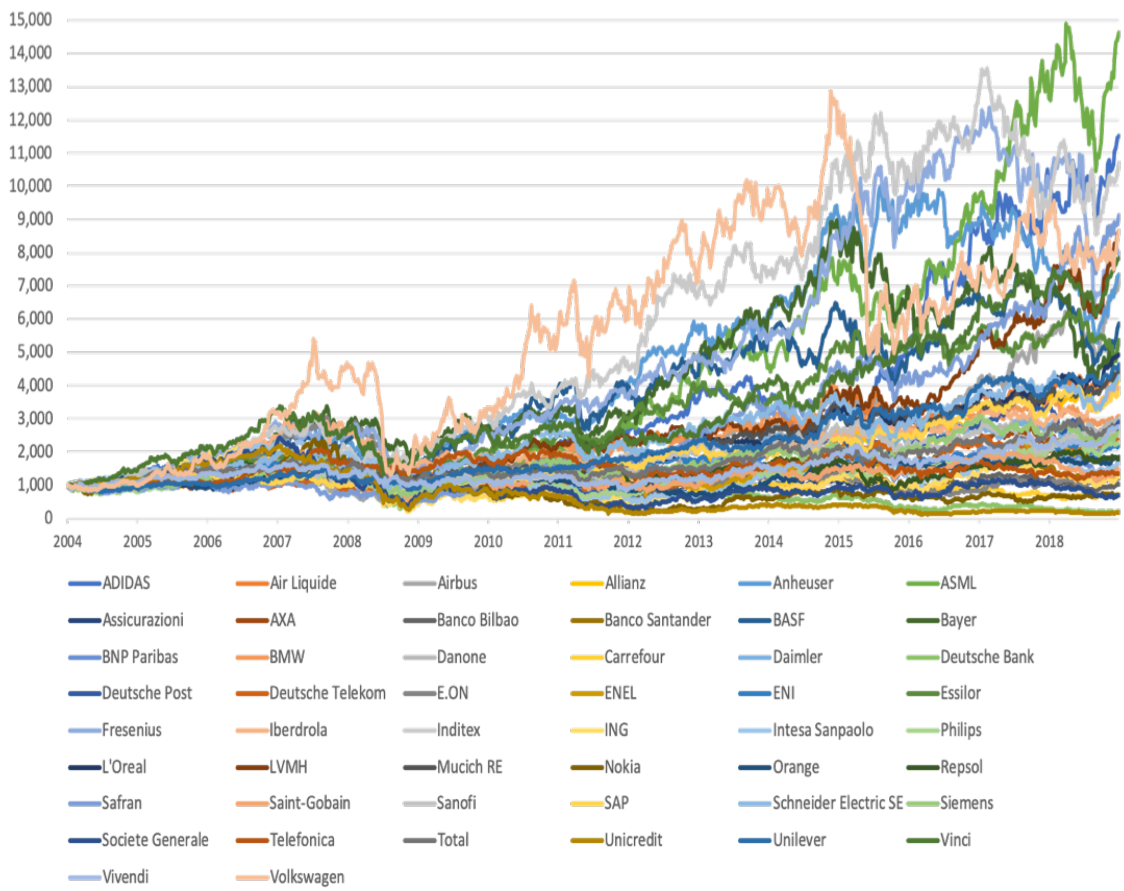
Concretely, we look at the companies listed in Table 1.

Table 1: List of European stocks under analysis (by alphabetic order)

Adidas	BASF	E.ON	L'Oreal	Schneider Electric SE
Air Liquide	Bayer	ENEL	LVMH	Siemens
Airbus	BNP Paribas	ENI	Mucich RE	Societe Generale
Allianz	BMW	Essilor	Nokia	Telefonica
Anheuser	Danone	Fresenius	Orange	Total
ASML	Carrefour	Iberdrola	Repsol	Unicredit
Assicurazioni	Daimler	Inditex	Safran	Unilever
AXA Deutsche	Bank	ING	Saint-Gobain	Vinci
Banco Bilbao	Deutsche Post	Intesa Sanpaolo	Sanofi	Vivendi
Banco Santander	Deutsche Telekom	Philips	SAP	Volkswagen

From Table 1 it is clear we do not focus in any particular country or sector, as the listed companies belong to a variety of countries and all sort of sectors, from Air Fright & Logistics; Airspace & Defense; Automobile manufactures; Chemicals; Construction & Engineering; Consumer durables & Apparel; Diversified chemicals; Diversified banks; Electric Components & Equipment; Electric Utilities; Food Products; Food, beverage & Tobacco; Health Care Equipments; Industrial Conglomerates; Integrated Oil & Gas; Integrated Telecommunication Services; Movies & Entertainment; Multi-line Insurance; Personal Products; Pharmaceuticals; Real State; Reinsurance; Retailing; Semiconductors, Software; Technology Hardware & Equipment; to Hypermarkets, supermarkets, convenience stores, cash & carry, and e-commerce. For each of the companies under analysis we collected weekly (close) prices and the so-called Bloomberg 12-month consensus target prices, from 2004-04-27 until 2019-04-23, providing us with a total of 78,300 observations (783 observations for each variable and stock).

Figure 1: Evolution of individual asset investments



Although the focus of this study is *portfolio* performance, Figure 1 shows what would have been the evolution of opting to invest the full amount in only one of our 50 stocks. Table 2 also presents some descriptive statistics on the individual stock returns. Besides the data on individual stocks, we have also collected weekly values of EURO STOXX 50 total return Index.

Table 2: Descriptive statistics of individual stock returns & Eurostoxx 50 TR

	$\bar{R}$	σ	SR		$\bar{R}$	σ	SR
Adidas	20.06%	27.49%	0.5690	Iberdrola	12.13%	24.63%	0.3131
Air Liquide	11.84%	19.86%	0.3737	Inditex	19.11%	25.75%	0.5705
Airbus	18.44%	32.71%	0.4285	ING	12.02%	45.93%	0.1656
Allianz	14.22%	30.73%	0.3189	Intesa Sanpaolo	10.97%	39.32%	0.1666
Anheuser	16.80%	26.21%	0.4724	Philips	9.25%	27.44%	0.1762
ASML	22.27%	29.73%	0.6004	L'Oreal	12.60%	19.86%	0.4119
Assicurazioni	5.32%	26.83%	0.0336	LVMH	17.62%	25.49%	0.5179
AXA	13.28%	37.63%	0.2356	Mucich RE	12.39%	22.08%	0.3610
Banco Bilbao	5.90%	34.10%	0.0433	Nokia	4.62%	37.55%	0.0053
Banco Santander	7.37%	32.76%	0.0901	Orange	6.41%	22.52%	0.0884
BASF	15.53%	27.80%	0.3996	Repsol	8.38%	29.43%	0.1347
Bayer	13.58%	27.58%	0.3321	Safran	19.12%	29.69%	0.4953
BNP Paribas	10.20%	36.55%	0.1583	Saint-Gobain	7.80%	32.54%	0.1039
BMW	12.31%	31.24%	0.2526	Sanofi	8.26%	20.99%	0.1828
Danone	9.25%	19.43%	0.2488	SAP	11.80%	24.07%	0.3068
Carrefour	1.15%	26.06%	-0.1256	Schneider E.SE	13.70%	28.38%	0.3272
Daimler	12.08%	34.57%	0.2217	Siemens	10.70%	29.32%	0.2142
Deutsche Bank	-2.32%	41.84%	-0.1611	Societe Generale	7.17%	43.90%	0.0627
Deutsche Post	11.08%	28.23%	0.2360	Telefonica	4.56%	22.75%	0.0060
Deutsche Telek.	7.95%	21.39%	0.1650	Total	9.24%	21.99%	0.2190
E.ON	5.17%	28.52%	0.0265	Unicredit	0.37%	49.22%	-0.0823
ENEL	8.87%	23.29%	0.1912	Unilever	11.90%	18.52%	0.4040
ENI	8.09%	24.01%	0.1530	Vinci	17.07%	26.09%	0.4849
Essilor	13.22%	20.23%	0.4349	Vivendi	9.27%	22.59%	0.2146
Fresenius	17.07%	25.37%	0.4986	Volkswagen	21.59%	37.40%	0.4592
Eurostoxx 50 TR	9.94%	16.60%	0.3327				

Descriptive statistics based on annualised values of weekly stock returns over a 15 year period (2004-04-27 until 2019-04-23). The last column presents Sharpe (1966) ratios determined using a riskless rate $R_f = 4.481\%$ (the 15–year zero–coupon yield rate determined by the European Central Bank for the initial investment date 2004-04-27).

3.2 Setup

We compare three different types of portfolios:

- Homogeneous portfolio,
- Active portfolios, built based upon analysts' recommendations,
- Mean-variance (theoretical) tangent portfolios (with and without short-selling),

and use the total return EURO STOXX 50 index itself, as benchmark.

The key idea here is to consider an initial investment of 1,000 euros and to mimic the evolution of the above mentioned portfolios, during your entire sample period of 15 years, considering also a variety of possible portfolio rebalancing schemes:

- full rebalance, which in our case means weekly rebalance,
- monthly rebalance,
- semi-annual rebalance,
- annual rebalance, or
- no rebalance.

3.2.1 Homogeneous portfolio

Not much need to be said about the **homogeneous portfolio** (H) as, by definition, that is the portfolio assigning equal weights to all assets, also known as the $1/N$ portfolio. For the 50 stocks in analysis we, thus, have $w_i^H = 1/50 = 2\%$. Since the seminal work of DeMiguel et al. (2007) it is common practice to consider the homogeneous portfolio as minimal requirement in portfolio construction, as it is as passive and naive as it can get.

3.2.2 Active recommendations–based portfolios

There may be several ways for building portfolios based upon analysts' recommendations. Here we define and use the notions of absolute and relative spreads.

Let us define as the *absolute analysts spread* for company i at date t – denoting it as $spread^a_{it}$ – as the difference between the 12-month target price and the current market price,

$$spread^a_{it} = P^*_{it} P_{it} \ . \tag{1}$$

where P^*_{it} denotes the Bloomberg consensus target price at time t for firm i, and P_{it} is the market observed price for the same time and firm.

Analysts' spreads can be interpreted as how much, in absolute terms (say, euros), analysts expect a particular stock to go up (for positive spreads) or to go down (for negative spreads), within the next year.

Considering a portfolio of N stocks, an investor wishing to maximize absolute gains based upon targets prices should invest in a portfolio with the following weights,

$$w_{it}^{\text{AAP}} = \frac{spread^a_{it}}{\displaystyle\sum_{i=1}^{N} spread^a_{it}} \ , \tag{2}$$

which, by definition, always add up to 1. Let us call this the **absolute active portfolio** (AAP).

Alternatively, one could maximize relative gains by building an **relative active portfolio** (RAP), with weights

$$w_{it}^{\text{RAP}} = \frac{spread^r_{it}}{\displaystyle\sum_{i=1}^{N} spread^r_{it}} \ , \tag{3}$$

where the relative spreads, $spread^r_{it}$ are simply the ratio between the absolute spread and the current markets price,

$$spread^r_{it} = \frac{spread^a_{it}}{P_{it}} \ . \tag{4}$$

Note that, by construction, we may get negative weights (shortselling positions) whenever target prices are below current market prices.

As spreads change constantly over time, both AAP and RAP are truly active portfolios. We call them simply as (absolute or relative) "active portfolios", instead of "active recommendations–based portfolios" because the alternative portfolios in this study – homogenous and tangent portfolios – are all passive. Figure 2 illustrates evolution of the AAP portfolio compositions, under the annual rebalancing scheme (for the full rebalancing scheme we would have 783 different compositions).

For pure comparativeness purposes, we also define the **mean absolute average portfolio** (MAAP) and the **mean relative average portfolio** (MRAP). These are passive portfolios, where for each stock we consider a fixed weight – the average weight based upon the 783 weekly weights one gets, under the full rebalancing scheme.

For those we have

$$w^{\text{MAAP}}_{it} = \frac{\sum_{t=1}^{T} spread^a_{it}}{\displaystyle\sum_{i=1}^{N}\sum_{t=1}^{T} spread^a_{it}} \ , \tag{5}$$

and

$$w^{\text{MRAP}}_{it} = \frac{\sum_{t=1}^{T} spread^r_{it}}{\displaystyle\sum_{i=1}^{N}\sum_{t=1}^{T} spread^r_{it}} \ , \tag{6}$$

where the absolute and relative spreads $spread^a_{it}$ and $spread^r_{it}$ are defined as in (1) and (4), respectively.

3.2.3 Mean-variance tangent portfolios

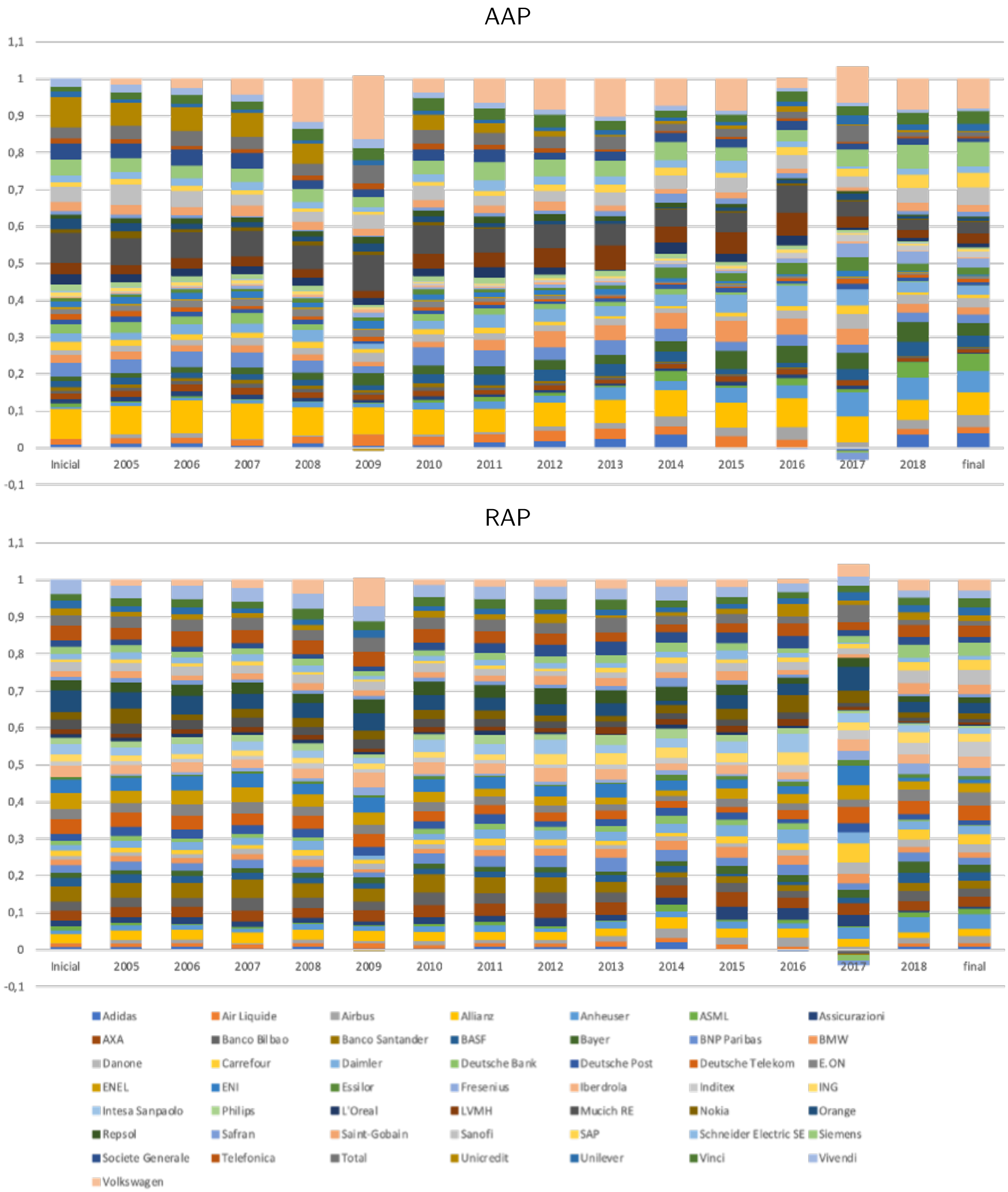
We use Markowitz (1952) mean-variance theory to determine the theoretical tangent portfolios, with and without shortselling, as well as the associated investments opportunity set (IOS) frontier.

Our portfolios are purely theoretical, as we consider as mean-variance inputs the in-sample estimates of expected returns and variance-covariance matrix[1]. Our purpose is simply to have a view on how far from the theoretical efficiency the other investments under analysis are.

For our sample, the mean-variance inputs – the vector of expected returns $(\bar{R})$ and the variance-covariance matrix (V) – can be found in the first column of Table 2 or inferred from the volatilities in the third column of Table 2 and the correlation Table A1 in the appendix. Besides the stock related data, described on Section 3.1, we have also used, as riskless rate, the 15–year zero-coupon yield rate

[1] In practice, estimations must naturally be out-of-sample, and the existence of estimation risk may lead to sub-optimal solutions. For further details on estimation risk and robust estimation of mean-variance inputs see, for instance Best and Grauer (1991), Fabozzi et al. (2007) and Fabozzi et al. (2007)

Figure 2: Evolution of the annually rebalanced AAP portfolio



at the initial investment date (2004-04-27) as determined by the European Central Bank[2]. So, in our computations, $R_f = 4.481\%$, which is the same value used to determine the 15-year individual investments Sharpe ratios in the last column of Table 2.

The hyperbola delimiting the IOS is easily determined by,

$$\sigma_i^2 = \frac{A\bar{R}_i^2 - 2B\bar{R}_i + C}{AC - B^2} \ , \tag{7}$$

where

$$A = \mathbb{1}'V^{-1}\mathbb{1} \ ,$$
$$B = \mathbb{1}'V^{-1}\bar{R} \ ,$$
$$C = \bar{R}'V^{-1}\bar{R} \ ,$$

are scalars based upon the matrix mean-variance inputs $\bar{R}$ and V and where $\mathbb{1}$ is a column vector of ones.

The weights of the portfolio with maximal Sharpe ratio – the so-called **tangent portfolio** (T) – can then be obtained as,

$$w_i^T = \frac{z_i}{\sum_{i=1}^{n} z_i} \tag{8}$$

where the z_i are the elements of the vector,

$$Z = V^{-1}\left[\bar{R} - R_f\mathbb{1}\right] \ .$$

The weights in equation (8) are not restricted in any sense, allowing for negative (shortselling) positions and possibly utopian extreme positions. It turns out, the composition of our tangent portfolio is not as extreme as it could be[3]. Still, following the common practice, we have also numerically determined the portfolio with maximal Sharpe ratio and no shortselling by imposing $w_i^{\text{TNS}} \geq 0$ for all i – **tangent portfolio withy no shortselling** (TNS).

Figure 3 gives a mean-variance representation of all previously mentioned portfolios, including the representation of investing in individual assets. Table 3 gives the actual weights determined to all portfolios. It is important to recall the homogeneous (H), tangent (T and TNS) and mean (MAAP and MRAP) portfolios are passive, so the weights reported are the ones used to rebalance the portfolio at the appropriate dates for each rebalancing scheme. That is not the case for the active recommendation based portfolios (AAP and RAP), which have different weights for all possible rebalancing dates and schemes. Having to opt for a concrete composition to use in Figure 3 and Table 3, we considered the initial compositions, which are the actual composition over time, only for the no rebalancing scheme. We note that the TNS portfolio requires investment in only 8 assets, which (not surprisingly) are the best performing ones (compare Sharpe ratios of individual assets in Table 2).

4 Results

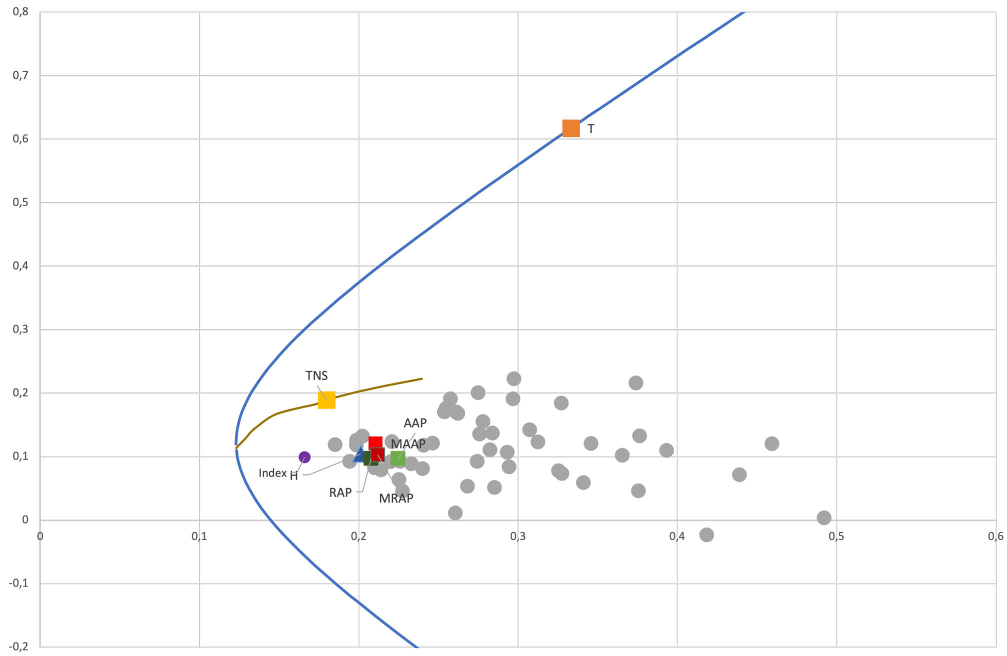
Our benchmark – the Eurostoxx TR index – over the sample presented:

[2] The ECB estimates daily zero-coupon yield curves for the euro area. The "riskless" yield curve is determined by only "AAA-rated" euro area central government bonds.

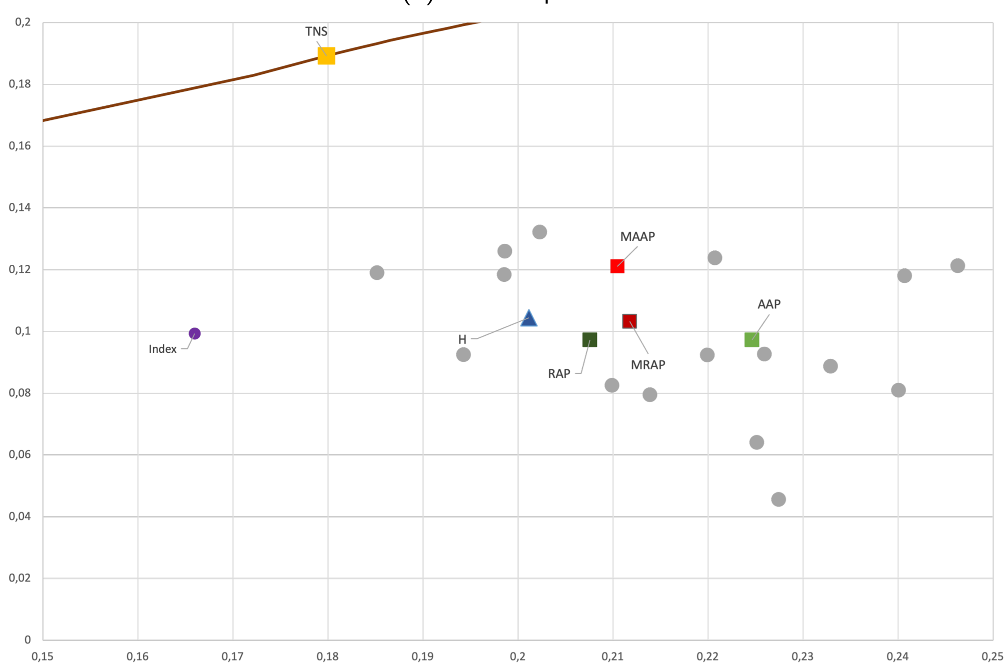
[3] From Table 3 one sees the tangent portfolio weights range from -63.72% to $+57.34\%$

Figure 3: Mean-variance Representation

(a) Full picture



(b) Zoomed picture



Mean-variance representation of: the investment opportunity set frontier assuming shortselling is allowed (the hyperbola $\sigma_i^2 = 0.3909\bar{R}_i^2 - 0.0956\bar{R}_i + 0.0210$ from equation (7), blue line) or not allowed (set of constrained hyperbolas); the individual assets (grey dots); the various portfolios – tangent portfolio (T, orange square), tangent portfolio with no shortselling (TNS, yellow square), homogeneous portfolio (H, blue triangle), absolute and relative active portfolios (AAP and RAP, light and dark green squares), average portfolios (MAAP and MRAP, light and dark red squares), and the TR index (purple). For the active portfolios (AAP and RAP) the representation is based upon initial compositions.

Table 3: Portfolio weights

	H	TNS	T	AAP*	RAP*	MAAP	MRAP
Adidas	2.00%	15.72%	30.38%	1.03%	0.85%	1.90%	0.95%
Air Liquide	2.00%	0.00%	-7.20%	1.48%	0.91%	1.98%	1.01%
Airbus	2.00%	0.00%	11.93%	0.17%	0.16%	1.57%	1.34%
Allianz	2.00%	0.00%	22.45%	8.11%	2.60%	6.93%	2.35%
Anheuser	2.00%	12.64%	25.09%	0.58%	0.89%	2.48%	1.63%
ASML	2.00%	20.18%	41.35%	0.84%	1.12%	0.97%	0.65%
Assicurazioni	2.00%	0.00%	-33.26%	1.19%	1.49%	0.85%	1.78%
AXA	2.00%	0.00%	19.17%	1.49%	2.63%	1.36%	2.94%
Banco Bilbao	2.00%	0.00%	-25.31%	0.84%	2.60%	0.63%	2.69%
Banco Santander	2.00%	0.00%	21.40%	0.82%	4.03%	0.57%	3.33%
BASF	2.00%	0.00%	41.19%	1.77%	2.30%	2.46%	1.76%
Bayer	2.00%	0.00%	10.46%	1.20%	1.38%	2.81%	1.56%
BNP Paribas	2.00%	0.00%	30.79%	3.66%	2.11%	3.41%	2.50%
BMW	2.00%	0.00%	0.28%	2.18%	1.44%	2.85%	1.78%
Danone	2.00%	0.00%	-28.12%	1.32%	0.93%	1.92%	1.34%
Carrefour	2.00%	0.00%	-40.27%	2.14%	1.51%	1.24%	1.64%
Daimler	2.00%	0.00%	-26.35%	2.29%	1.62%	2.99%	2.31%
Deutsche Bank	2.00%	0.00%	-56.05%	2.56%	1.06%	1.45%	1.15%
Deutsche Post	2.00%	0.00%	-0.99%	1.25%	1.92%	1.04%	1.99%
Deutsche Telekom	2.00%	0.00%	7.68%	1.58%	4.09%	0.81%	2.80%
E.ON	2.00%	0.00%	-25.77%	1.31%	2.62%	1.10%	2.25%
ENEL	2.00%	0.00%	-2.57%	0.57%	4.29%	0.31%	2.87%
ENI	2.00%	0.00%	-16.88%	1.60%	3.68%	1.32%	3.22%
Essilor	2.00%	8.41%	15.29%	0.76%	0.62%	1.68%	0.86%
Fresenius	2.00%	18.13%	16.76%	0.00%	0.00%	1.02%	1.06%
Iberdrola	2.00%	0.00%	37.79%	0.37%	3.02%	0.36%	2.50%
Inditex	2.00%	14.43%	35.26%	0.19%	1.20%	0.59%	1.31%
ING	2.00%	0.00%	-2.02%	1.11%	1.91%	0.70%	2.14%
Intesa Sanpaolo	2.00%	0.00%	40.90%	0.23%	2.75%	0.18%	2.67%
Philips	2.00%	0.00%	-38.14%	1.76%	1.84%	1.04%	1.61%
L'Oreal	2.00%	0.00%	7.68%	2.90%	0.97%	1.81%	0.64%
LVMH	2.00%	0.00%	18.51%	3.07%	1.25%	4.12%	1.31%
Mucich RE	2.00%	0.00%	25.20%	8.01%	2.66%	6.31%	2.01%
Nokia	2.00%	0.00%	-17.52%	0.95%	2.14%	0.51%	2.12%
Orange	2.00%	0.00%	3.03%	2.88%	5.89%	1.25%	3.48%
Repsol	2.00%	0.00%	-12.72%	1.24%	2.48%	1.31%	3.17%
Safran	2.00%	2.91%	15.05%	0.81%	0.97%	0.85%	0.97%
Saint-Gobain	2.00%	0.00%	-66.73%	2.44%	1.63%	2.13%	1.97%
Sanofi	2.00%	0.00%	-15.39%	4.30%	2.38%	3.45%	2.03%
SAP	2.00%	0.00%	6.84%	1.18%	0.72%	1.70%	1.11%
Schneider Electric SE	2.00%	0.00%	-2.48%	1.78%	1.66%	2.00%	1.54%
Siemens	2.00%	0.00%	-17.02%	4.34%	1.78%	4.23%	1.99%
Societe Generale	2.00%	0.00%	-7.70%	4.36%	1.78%	2.85%	2.28%
Telefonica	2.00%	0.00%	-43.15%	1.30%	3.88%	0.95%	3.17%
Total	2.00%	0.00%	15.87%	3.19%	2.86%	3.18%	3.06%
Unicredit	2.00%	0.00%	-12.36%	8.12%	1.87%	3.04%	1.94%
Unilever	2.00%	0.00%	17.40%	1.49%	2.16%	1.08%	1.52%
Vinci	2.00%	0.00%	57.34%	1.22%	1.78%	2.84%	2.41%
Vivendi	2.00%	0.00%	1.09%	2.02%	3.55%	1.45%	3.07%
Volkswagen	2.00%	7.57%	21.82%	0.00%	0.00%	6.43%	2.18%

Weights of the portfolios T, TNS, AAP, RAP, MAAP and MRAP, as described in Section 3.2. *Initial compositions of the active portfolios AAP and RAP.

(i) an annualised expected return $\bar{R} = 9.94\%$;
(ii) a volatility of $\sigma = 16.60\%$, and thus
(iii) an implicit Sharpe Ratio of $SR = 0.332$.

Table 4 reports similar statistics to all considered portfolios and rebalancing schemes.

The main conclusion seem to be that excluding the (theoretical) tangent portfolios, with a far better performance, all other portfolios present levels of performance that are comparable to the benchmark, that itself has a performance close to the homogeneous portfolio. It seems fair to say that the benchmark did not even "beat" the naive portfolio, during the 15-year period of our sample.

Looking at the performance of the portfolios that explicitly use analysts recommendations – AAP and RAP – they seem to perform marginally better than both the benchmark and the homogenous portfolio using the full rebalance scheme, but consistently worse for all other schemes.

Recalling the "average" portfolios – MAAP and MRAP – are built based upon the observation of all recommendations over the full sample period, their performance cannot the comparable directly with the other portfolios. Still, in relative terms we can conclude that mean absolute spreads seem to perform better than mean relative spreads (MAAP Sharpe ratios range from 0.360 to 0.365, while MRAP ratios range from 0.274 to 0.279).

Our results are robust across the various rebalancing schemes. Figure 4 reports the evolution of the various portfolios considering the two extreme rebalancing schemes – full rebalancing and no rebalancing. For all other rebalancing schemes the evolution is in between. It is particular interesting to notice the extreme performance of the in-sample tangent portfolios (with or without shortselling allowed). All other portfolios, including the ones based upon mean target spreads over the entire sample period, present much lower performance.

Figure 5 compares all the rebalancing schemes for the homogenous (H) and for the two active portfolios AAP and RAP.

Looking across rebalancing schemes, both for the theoretical tangent portfolios and all other, the main conclusions are:

- Overall, performance increases with frequency of rebalancing.
- Full (i.e. weekly) rebalancing allows to reach the theoretical MVT statistics.
- Anual rebalancing does as bad as no rebalancing at all over the 15-year period.
- The frequency of rebalance does not seem to matter so much, when each asset has only a relatively small weight.

The last statement is possibly the less evident, but we note performance seems to be rather stable across rebalancing schemes for the H, MAAP and MRAP portfolios, which are passive investments that assign relatively small weight to each asset (recall Table 3).

Figures A1 and A2, in the appendix, also corroborate that the frequency of rebalancing matters most when the weight in individual assets is not too small.

5 Conclusion

As far as we know this is the first study to propose concrete ways to construct ative portfolios based upon "consensus" target prices that, nowadays, can be considered public information and used when making investment decisions.

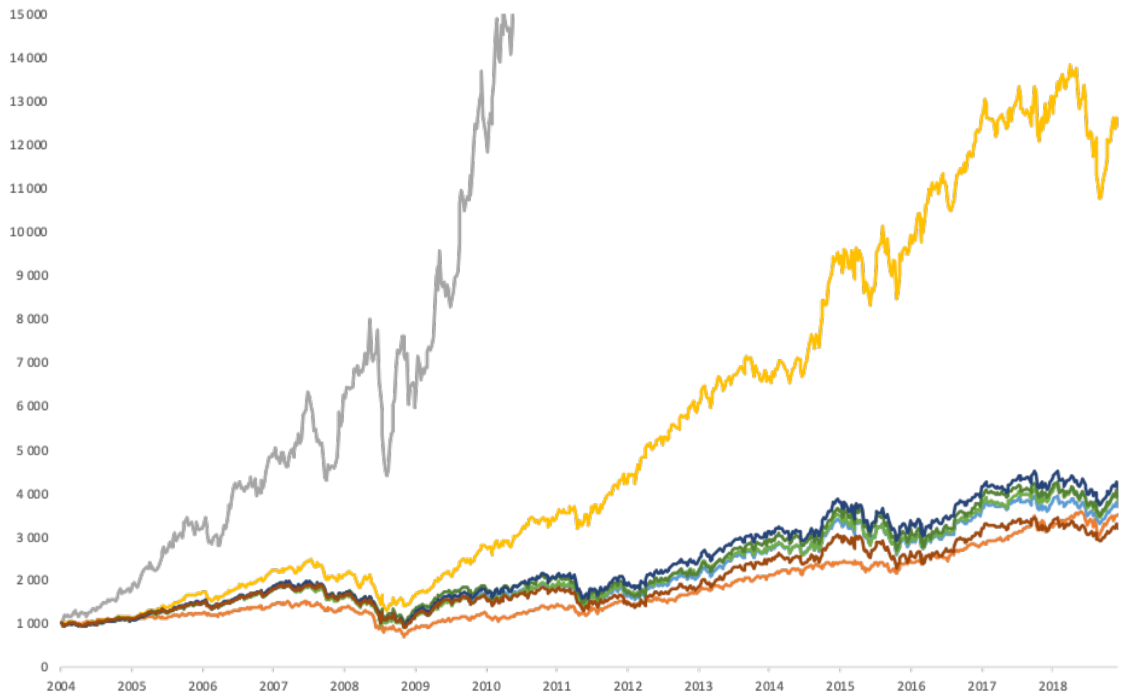
Table 4: Portfolio performance analysis

	MVT	Full	Monthly	Semi-annual	Annual	No
			H			
$\bar{R}$	11.14%	11.14%	10.92%	10.58%	10.90%	10.90%
σ	20.45%	20.46%	20.39%	20.20%	19.01%	19.01%
SR	0.328	0.328	0.319	0.305	0.341	0.341
			T			
$\bar{R}$	61.75%	61.75%	60.19%	56.53%	24.95%	24.95%
σ	33.31%	33.33%	33.19%	31.11%	20.77%	20.77%
SR	1.721	1.720	1.681	1.675	0.989	0.989
			TNS			
$\bar{R}$	18.93%	18.93%	18.58%	18.20%	17.00%	17.00%
σ	17.99%	18.00%	17.97%	17.99%	18.06%	18.06%
SR	0.807	0.806	0.788	0.766	0.697	0.697
			AAP			
$\bar{R}$	n.a.	11.86%	11.21%	9.97%	9.60%	9.60%
σ	n.a.	21.44%	21.32%	21.30%	20.21%	20.21%
SR	n.a.	0.347	0.318	0.261	0.256	0.256
			RAP			
$\bar{R}$	n.a.	12.01%	11.21%	9.94%	9.22%	9.22%
σ	n.a .	22.22%	22.01%	21.64%	19.40%	19.4%
SR	n.a.	0.342	0.309	0.255	0.247	0.247
			MAAP			
$\bar{R}$	12.11%	12.11%	11.88%	11.52%	11.69%	11.69%
σ	21.05%	21.06%	20.98%	20.80%	20.18%	20.18%
SR	0.365	0.365	0.356	0.341	0.360	0.360
			MRAP			
$\bar{R}$	10.33%	10.33%	10.13%	9.79%	9.80%	9.80%
σ	21.18%	21.19%	21.11%	20.89%	19.68%	19.68%
SR	0.279	0.279	0.270	0.257	0.274	0.274

Performance of the portfolios H. T. TNS. AAP. RAP. MAAP and MRAP. as described in Section 3.2.

Figure 4: Portfolio Evolution

(a) Full Rebalancing



(b) No rebalancing

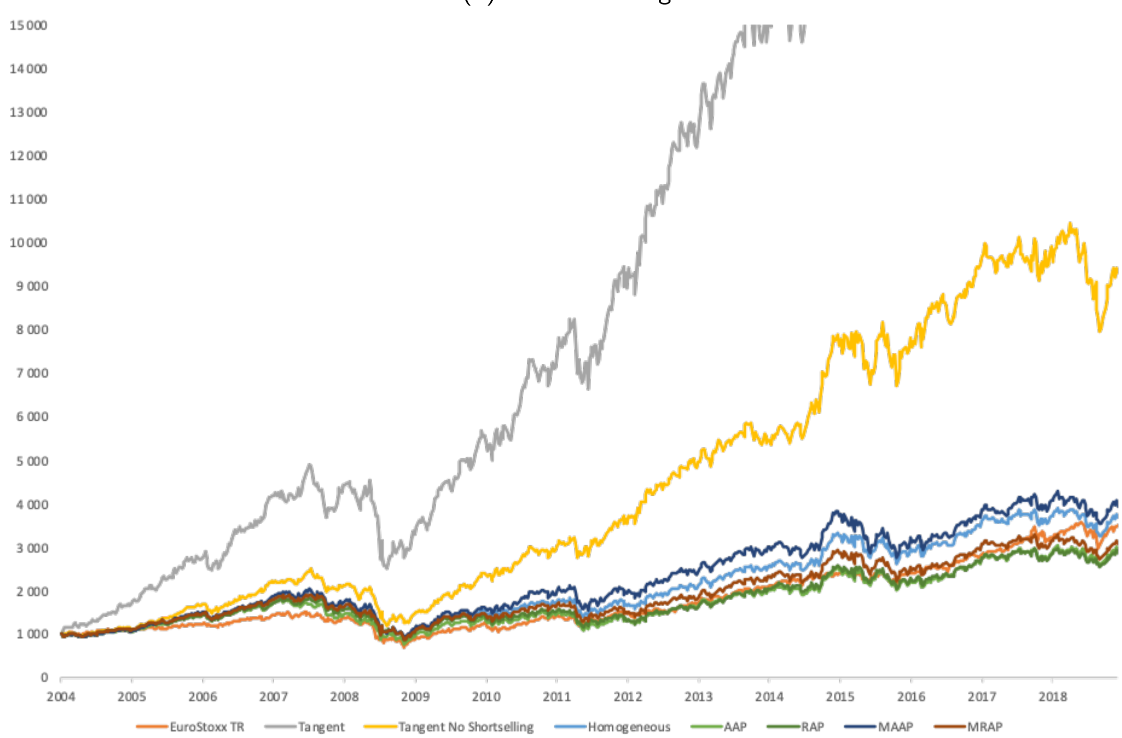


Figure 5: Rebalancing Schemes

Homogeneous

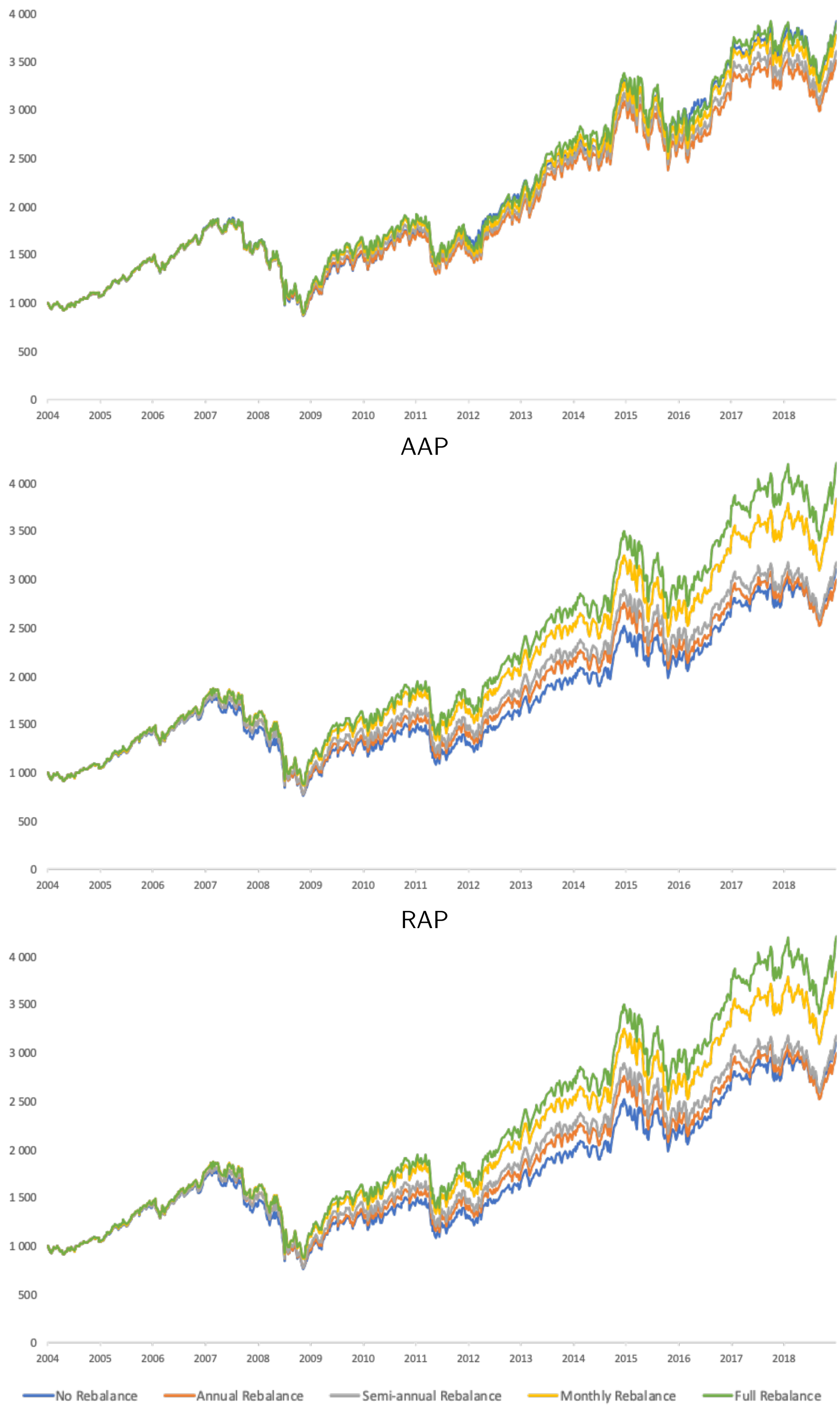
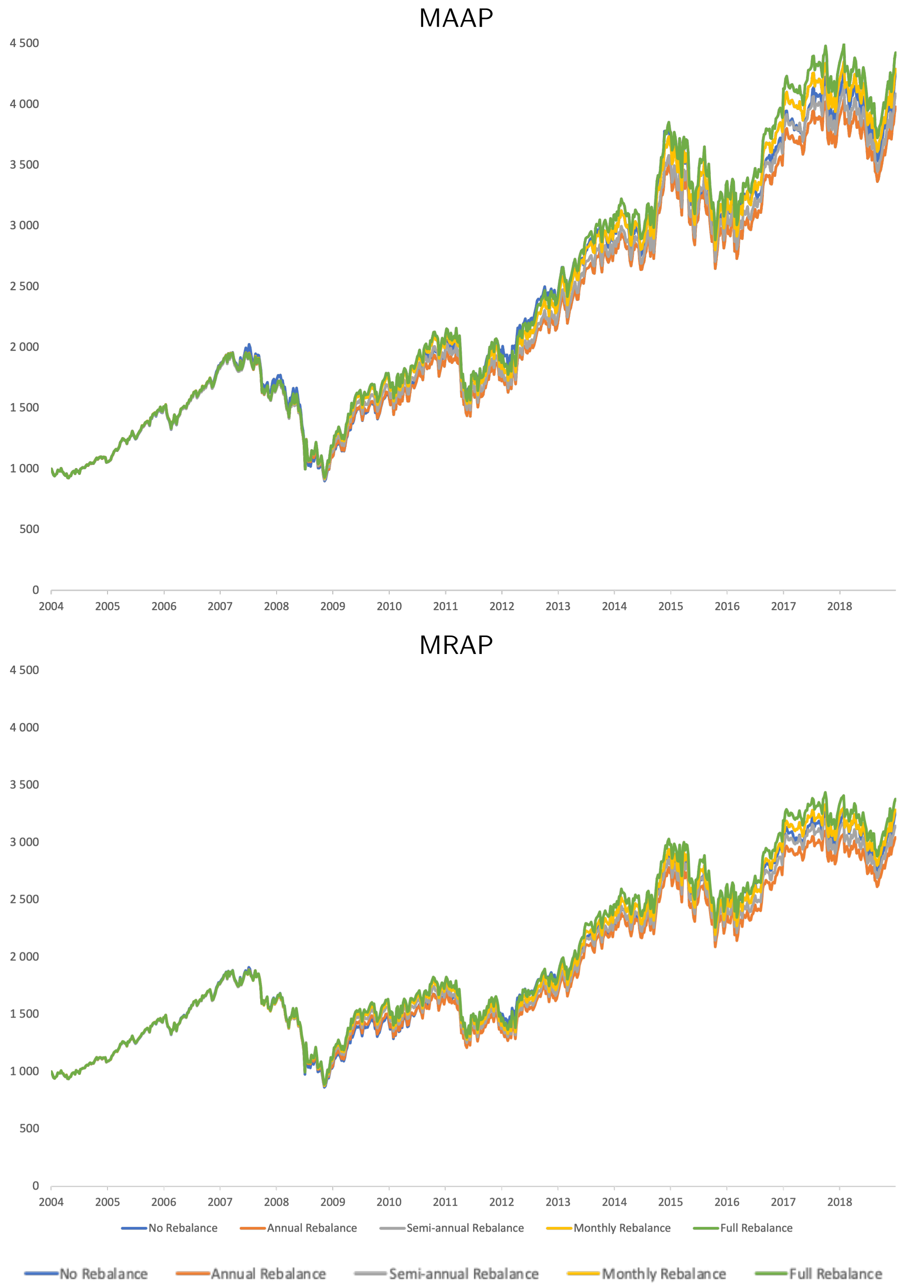


Figure 5 continues =>

Figure 5: Rebalancing Schemes (cont.)



We propose two concrete active portfolios – AAP and RAP – based upon absolute spreads and relative spreads, respectively. Our results show the performance of these active strategies do not seem do beat that of Eurostoxx TR, nor, in fact, the one of the naive homogeneous portfolio, H.

We also consider the mean-variance passive tangent portfolios T and TNS (with and without short-selling allowed) and build two passive portfolios based upon the average target price recommendations MAAP and MRAP. All these portfolios are based upon the full sample information, in terms of expected returns, variances and covariances (mean-variance inputs), as well as in terms of average recommendations, so they should be interpreted as "theoretical" and understood in that context.

Still, using them we are able to show that for the long-term investment period under analysis – 15 years, from 2004 to 2019 – all portfolios based upon target prices are far way from efficient frontiers, even when we consider the no-shortselling (much constrained) frontier. In fact in terms of efficiency they do not "beat" the Eurostoxx TR, nor the naive portfolio H.

A side product of our analysis are the impact of different rebalancing schemes in the performance of portfolios. Frequency seems to matter, although not so much for the AAP, RAP, MAAP, MRAP and H portfolios that, by construction, tend to be invested in relatively small amount of all assets. The patterns of weight evolutions depending on rebalancing schemes in the other (mean-variance) portfolios is worth a deeper look at, in future studies.

In terms of the main limitations, the first is that we look only to one very long-term investment period of 15 years. Also our sample includes the great financial crisis of 2008-2010, which may be biasing the results. Still, it is worth recalling this is a *comparative* study and that all portfolios experienced the exact same conditions. It would be interesting to check if the results presented extend to other samples, in other markets and periods, or smaller investment periods. Finally, it would also be interesting if the relative increased performance of more frequent rebalancing schemes is enough to cover the additional transaction costs.

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Appendix

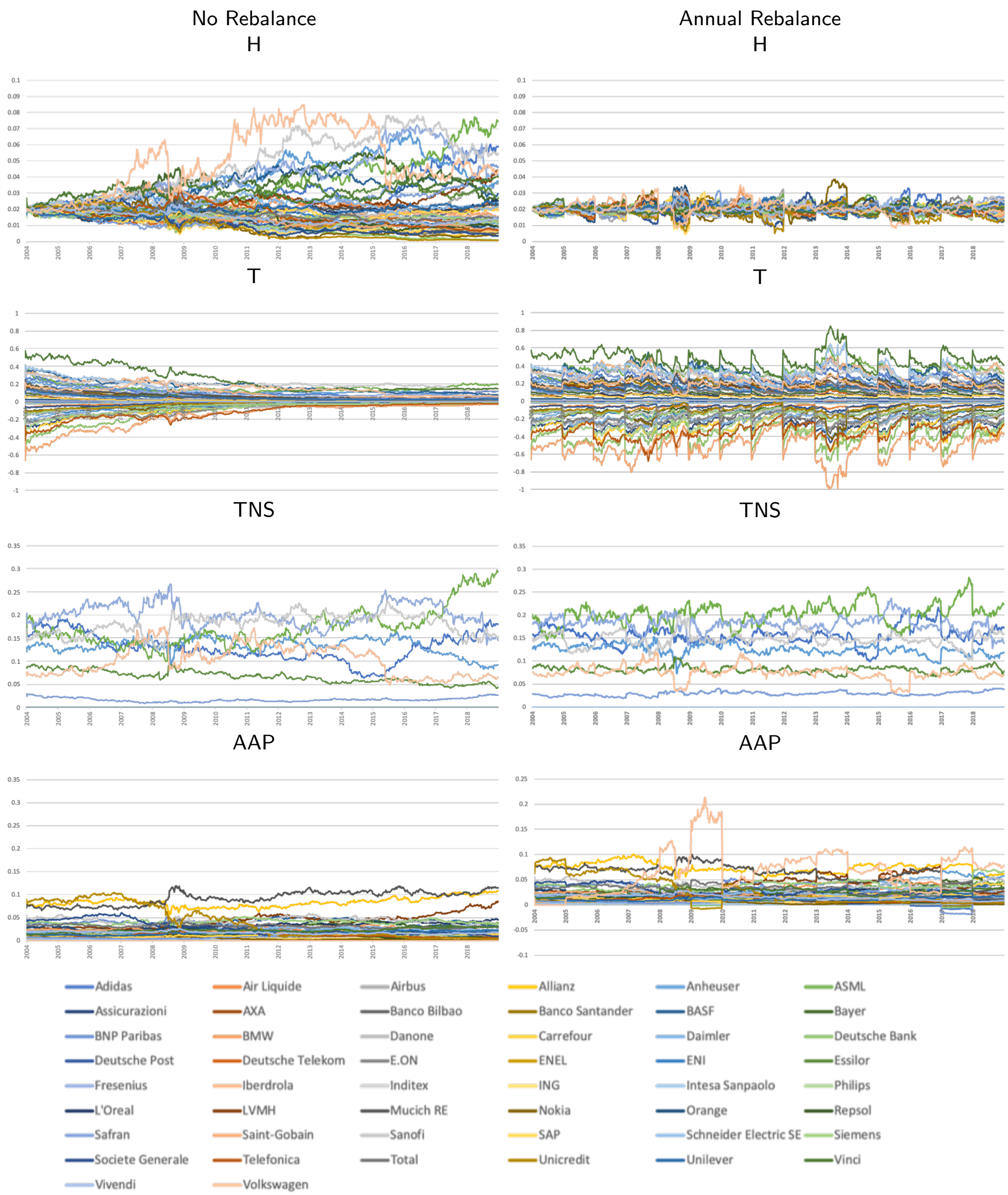
Table A1: Return correlation matrix

	Adidas	Air Liquide	Airbus	Allianz	Anheuser	ASML	Assicurazioni	AXA	B. Bilbao	B.Santander	BASF	Bayer	BNP Paribas	BMW	Danone	Carrefour	Daimler
Adidas	1,00																
Air Liquide	0,51	1,00															
Airbus	0,38	0,48	1,00														
Allianz	0,58	0,64	0,43	1,00													
Anheuser	0,34	0,40	0,31	0,37	1,00												
ASML	0,37	0,46	0,48	0,43	0,29	1,00											
Assicurazioni	0,41	0,54	0,35	0,63	0,29	0,37	1,00										
AXA	0,54	0,63	0,45	0,86	0,32	0,42	0,70	1,00									
B. Bilbao	0,45	0,55	0,39	0,71	0,33	0,40	0,71	0,75	1,00								
B.Santander	0,45	0,56	0,40	0,72	0,36	0,41	0,70	0,74	0,92	1,00							
BASF	0,58	0,74	0,48	0,75	0,42	0,48	0,55	0,69	0,64	0,63	1,00						
Bayer	0,46	0,59	0,38	0,52	0,34	0,43	0,47	0,50	0,48	0,48	0,62	1,00					
BNP Paribas	0,44	0,51	0,38	0,70	0,28	0,39	0,64	0,75	0,75	0,76	0,59	0,46	1,00				
BMW	0,55	0,63	0,48	0,64	0,39	0,46	0,49	0,65	0,56	0,57	0,73	0,52	0,57	1,00			
Danone	0,38	0,49	0,38	0,37	0,41	0,32	0,36	0,36	0,35	0,37	0,42	0,45	0,34	0,39	1,00		
Carrefour	0,34	0,43	0,36	0,42	0,28	0,35	0,46	0,47	0,47	0,45	0,42	0,34	0,50	0,41	0,40	1,00	
Daimler	0,59	0,65	0,53	0,70	0,37	0,50	0,51	0,68	0,60	0,59	0,76	0,53	0,54	0,82	0,39	0,43	1,00
Deutsche B.	0,52	0,56	0,39	0,78	0,32	0,40	0,61	0,76	0,72	0,72	0,70	0,49	0,74	0,64	0,32	0,41	0,65
Deutsche P.	0,53	0,59	0,43	0,68	0,35	0,41	0,52	0,65	0,60	0,59	0,69	0,52	0,51	0,61	0,35	0,37	0,66
Deutsche T.	0,37	0,47	0,37	0,48	0,30	0,36	0,45	0,43	0,44	0,45	0,47	0,47	0,40	0,41	0,38	0,38	0,43
E.ON	0,44	0,52	0,36	0,58	0,33	0,34	0,52	0,54	0,57	0,56	0,62	0,51	0,45	0,47	0,36	0,39	0,52
ENEL	0,40	0,55	0,37	0,52	0,31	0,33	0,66	0,58	0,63	0,60	0,55	0,45	0,52	0,44	0,41	0,45	0,50
ENI	0,47	0,61	0,46	0,57	0,37	0,42	0,63	0,59	0,61	0,60	0,66	0,55	0,55	0,55	0,42	0,46	0,57
Essilor	0,29	0,44	0,37	0,28	0,36	0,31	0,32	0,31	0,29	0,29	0,37	0,37	0,29	0,31	0,40	0,36	0,30
Fresenius	0,30	0,35	0,31	0,31	0,26	0,31	0,30	0,28	0,24	0,23	0,37	0,38	0,24	0,26	0,30	0,25	0,31
Iberdrola	0,42	0,56	0,35	0,60	0,34	0,37	0,61	0,60	0,69	0,67	0,58	0,45	0,51	0,47	0,41	0,43	0,52
Inditex	0,48	0,48	0,39	0,52	0,35	0,41	0,47	0,51	0,52	0,52	0,47	0,40	0,46	0,46	0,42	0,42	0,49
ING	0,52	0,60	0,40	0,79	0,36	0,39	0,65	0,82	0,76	0,74	0,71	0,51	0,72	0,61	0,29	0,42	0,65
Int. Sanpaolo	0,43	0,51	0,36	0,70	0,30	0,36	0,74	0,76	0,79	0,77	0,61	0,46	0,72	0,53	0,31	0,44	0,57
Philips	0,51	0,58	0,51	0,64	0,45	0,57	0,50	0,63	0,60	0,58	0,65	0,55	0,58	0,59	0,42	0,44	0,63
L'Oreal	0,43	0,58	0,39	0,48	0,39	0,42	0,41	0,46	0,46	0,44	0,53	0,49	0,39	0,46	0,62	0,45	0,49
LVMH	0,58	0,65	0,53	0,62	0,37	0,52	0,48	0,61	0,52	0,52	0,65	0,53	0,54	0,65	0,48	0,45	0,68
Mucich RE	0,48	0,57	0,41	0,78	0,34	0,41	0,60	0,72	0,60	0,60	0,65	0,50	0,60	0,57	0,37	0,41	0,61
Nokia	0,29	0,34	0,30	0,39	0,22	0,38	0,36	0,40	0,38	0,39	0,37	0,34	0,37	0,39	0,27	0,31	0,40
Orange	0,30	0,45	0,31	0,44	0,26	0,30	0,47	0,42	0,45	0,45	0,39	0,41	0,39	0,36	0,40	0,39	0,38
Repsol	0,45	0,58	0,39	0,59	0,32	0,40	0,59	0,59	0,68	0,69	0,63	0,50	0,59	0,55	0,37	0,40	0,57
Safran	0,43	0,53	0,59	0,47	0,26	0,46	0,38	0,50	0,42	0,40	0,53	0,44	0,42	0,54	0,36	0,31	0,57
Saint-Gobain	0,57	0,63	0,53	0,72	0,33	0,53	0,59	0,76	0,66	0,65	0,71	0,53	0,67	0,69	0,42	0,47	0,74
Sanofi	0,27	0,45	0,37	0,37	0,33	0,34	0,39	0,37	0,36	0,37	0,39	0,47	0,34	0,39	0,41	0,38	0,37
SAP	0,49	0,57	0,39	0,57	0,32	0,45	0,42	0,53	0,44	0,42	0,58	0,48	0,43	0,54	0,42	0,34	0,61
Schneider E	0,53	0,67	0,52	0,64	0,36	0,48	0,56	0,66	0,60	0,59	0,69	0,52	0,60	0,65	0,45	0,46	0,69
Siemens	0,58	0,65	0,49	0,73	0,35	0,51	0,54	0,68	0,63	0,61	0,76	0,55	0,55	0,67	0,41	0,40	0,72
Soc.Generale	0,45	0,48	0,34	0,72	0,36	0,36	0,66	0,76	0,76	0,76	0,60	0,43	0,83	0,55	0,28	0,45	0,55
Telefonica	0,40	0,58	0,38	0,60	0,34	0,37	0,62	0,58	0,69	0,71	0,55	0,50	0,54	0,50	0,43	0,43	0,52
Total	0,47	0,66	0,47	0,55	0,36	0,44	0,56	0,56	0,58	0,58	0,67	0,57	0,55	0,56	0,46	0,46	0,58
Unicredit	0,40	0,48	0,35	0,63	0,23	0,31	0,68	0,72	0,75	0,73	0,56	0,44	0,71	0,50	0,26	0,42	0,53
Unilever	0,41	0,50	0,35	0,37	0,42	0,36	0,36	0,35	0,37	0,37	0,43	0,43	0,30	0,37	0,64	0,38	0,38
Vinci	0,54	0,62	0,47	0,63	0,30	0,44	0,55	0,66	0,61	0,57	0,65	0,46	0,57	0,59	0,39	0,45	0,67
Vivendi	0,40	0,55	0,42	0,55	0,25	0,41	0,54	0,56	0,53	0,52	0,52	0,47	0,49	0,46	0,41	0,42	0,51
Volkswagen	0,36	0,38	0,30	0,41	0,25	0,35	0,38	0,42	0,39	0,39	0,46	0,37	0,38	0,56	0,30	0,29	0,54

	Deutsche B.	Deutsche P.	Deutsche T.	E.ON	ENEL	ENI	Essilor	Fresenius	Iberdrola	Inditex	ING	Int. Sanpaolo	Philips	L'Oreal	LVMH	Munich RE	Nokia
Deutsche B.	1,00																
Deutsche P.	0,61	1,00															
Deutsche T.	0,42	0,47	1,00														
E.ON	0,54	0,55	0,49	1,00													
ENEL	0,48	0,50	0,48	0,61	1,00												
ENI	0,55	0,56	0,46	0,60	0,63	1,00											
Essilor	0,29	0,24	0,30	0,29	0,34	0,35	1,00										
Fresenius	0,26	0,29	0,30	0,31	0,28	0,33	0,35	1,00									
Iberdrola	0,52	0,53	0,46	0,61	0,68	0,57	0,31	0,28	1,00								
Inditex	0,44	0,47	0,37	0,39	0,44	0,47	0,35	0,29	0,47	1,00							
ING	0,75	0,66	0,38	0,55	0,57	0,57	0,30	0,25	0,59	0,49	1,00						
Int. Sanpaolo	0,72	0,58	0,41	0,54	0,65	0,59	0,23	0,21	0,60	0,46	0,75	1,00					
Philips	0,60	0,57	0,46	0,52	0,48	0,55	0,35	0,36	0,50	0,50	0,64	0,55	1,00				
L'Oreal	0,40	0,48	0,45	0,43	0,47	0,47	0,42	0,31	0,50	0,48	0,41	0,40	0,52	1,00			
LVMH	0,56	0,54	0,40	0,46	0,46	0,56	0,41	0,32	0,46	0,55	0,57	0,50	0,62	0,62	1,00		
Mucich RE	0,63	0,56	0,47	0,50	0,48	0,54	0,31	0,32	0,54	0,47	0,65	0,58	0,60	0,46	0,55	1,00	
Nokia	0,36	0,34	0,29	0,32	0,33	0,35	0,16	0,16	0,39	0,37	0,38	0,34	0,38	0,35	0,39	0,32	1,00
Orange	0,37	0,39	0,68	0,42	0,51	0,42	0,29	0,24	0,49	0,36	0,36	0,45	0,41	0,46	0,41	0,42	0,36
Repsol	0,55	0,56	0,43	0,57	0,54	0,73	0,28	0,25	0,62	0,47	0,57	0,58	0,52	0,44	0,53	0,50	0,38
Safran	0,43	0,47	0,33	0,36	0,38	0,46	0,33	0,34	0,38	0,41	0,48	0,38	0,55	0,45	0,54	0,44	0,33
Saint-Gobain	0,68	0,64	0,44	0,50	0,56	0,59	0,32	0,28	0,56	0,54	0,71	0,66	0,66	0,51	0,69	0,62	0,40
Sanofi	0,31	0,34	0,46	0,37	0,39	0,45	0,36	0,31	0,37	0,34	0,31	0,33	0,43	0,44	0,40	0,37	0,26
SAP	0,52	0,47	0,37	0,43	0,41	0,51	0,25	0,31	0,42	0,43	0,50	0,45	0,55	0,47	0,58	0,50	0,33
Schneider E	0,59	0,58	0,40	0,47	0,54	0,58	0,36	0,32	0,52	0,56	0,64	0,57	0,64	0,53	0,68	0,57	0,39
Siemens	0,67	0,67	0,47	0,58	0,53	0,61	0,29	0,35	0,57	0,52	0,65	0,59	0,69	0,52	0,68	0,61	0,40
Soc.Generale	0,75	0,55	0,40	0,51	0,53	0,55	0,27	0,22	0,56	0,46	0,77	0,76	0,59	0,35	0,50	0,62	0,34
Telefonica	0,54	0,53	0,59	0,54	0,58	0,58	0,32	0,28	0,67	0,49	0,53	0,59	0,50	0,49	0,49	0,56	0,36
Total	0,54	0,54	0,47	0,58	0,59	0,66	0,38	0,33	0,55	0,44	0,52	0,53	0,56	0,51	0,60	0,52	0,36
Unicredit	0,70	0,53	0,37	0,47	0,59	0,55	0,24	0,19	0,53	0,40	0,75	0,82	0,52	0,35	0,44	0,51	0,32
Unilever	0,31	0,38	0,41	0,40	0,40	0,46	0,37	0,30	0,39	0,41	0,32	0,30	0,46	0,62	0,47	0,37	0,26
Vinci	0,58	0,58	0,42	0,51	0,60	0,59	0,33	0,29	0,58	0,51	0,61	0,60	0,58	0,49	0,63	0,54	0,39
Vivendi	0,49	0,48	0,48	0,47	0,53	0,51	0,32	0,31	0,50	0,44	0,49	0,51	0,53	0,48	0,52	0,51	0,33
Volkswagen	0,40	0,40	0,27	0,32	0,33	0,36	0,18	0,20	0,35	0,38	0,40	0,38	0,40	0,37	0,47	0,36	0,32

	Orange	Repsol	Safran	Saint-Gobain	Sanofi	SAP	Schneider E	Siemens	Soc.Generale	Telefonica	Total	Unicredit	Unilever	Vinci	Vivendi	Volkswagen
Orange	1,00															
Repsol	0,39	1,00														
Safran	0,28	0,45	1,00													
Saint-Gobain	0,42	0,56	0,55	1,00												
Sanofi	0,38	0,36	0,33	0,35	1,00											
SAP	0,35	0,43	0,44	0,58	0,34	1,00										
Schneider E	0,38	0,58	0,56	0,76	0,37	0,57	1,00									
Siemens	0,42	0,59	0,54	0,73	0,37	0,61	0,68	1,00								
Soc.Generale	0,38	0,56	0,36	0,64	0,32	0,41	0,56	0,57	1,00							
Telefonica	0,67	0,65	0,37	0,55	0,38	0,44	0,51	0,55	0,54	1,00						
Total	0,44	0,73	0,45	0,59	0,46	0,51	0,61	0,63	0,52	0,57	1,00					
Unicredit	0,39	0,51	0,39	0,62	0,26	0,39	0,52	0,54	0,74	0,54	0,48	1,00				
Unilever	0,38	0,40	0,39	0,36	0,50	0,39	0,39	0,40	0,27	0,43	0,46	0,26	1,00			
Vinci	0,44	0,53	0,50	0,76	0,33	0,53	0,69	0,65	0,55	0,52	0,59	0,55	0,37	1,00		
Vivendi	0,51	0,46	0,44	0,57	0,44	0,44	0,55	0,55	0,47	0,55	0,51	0,46	0,42	0,57	1,00	
Volkswagen	0,25	0,41	0,39	0,44	0,23	0,38	0,48	0,44	0,38	0,36	0,34	0,37	0,26	0,41	0,35	1,00

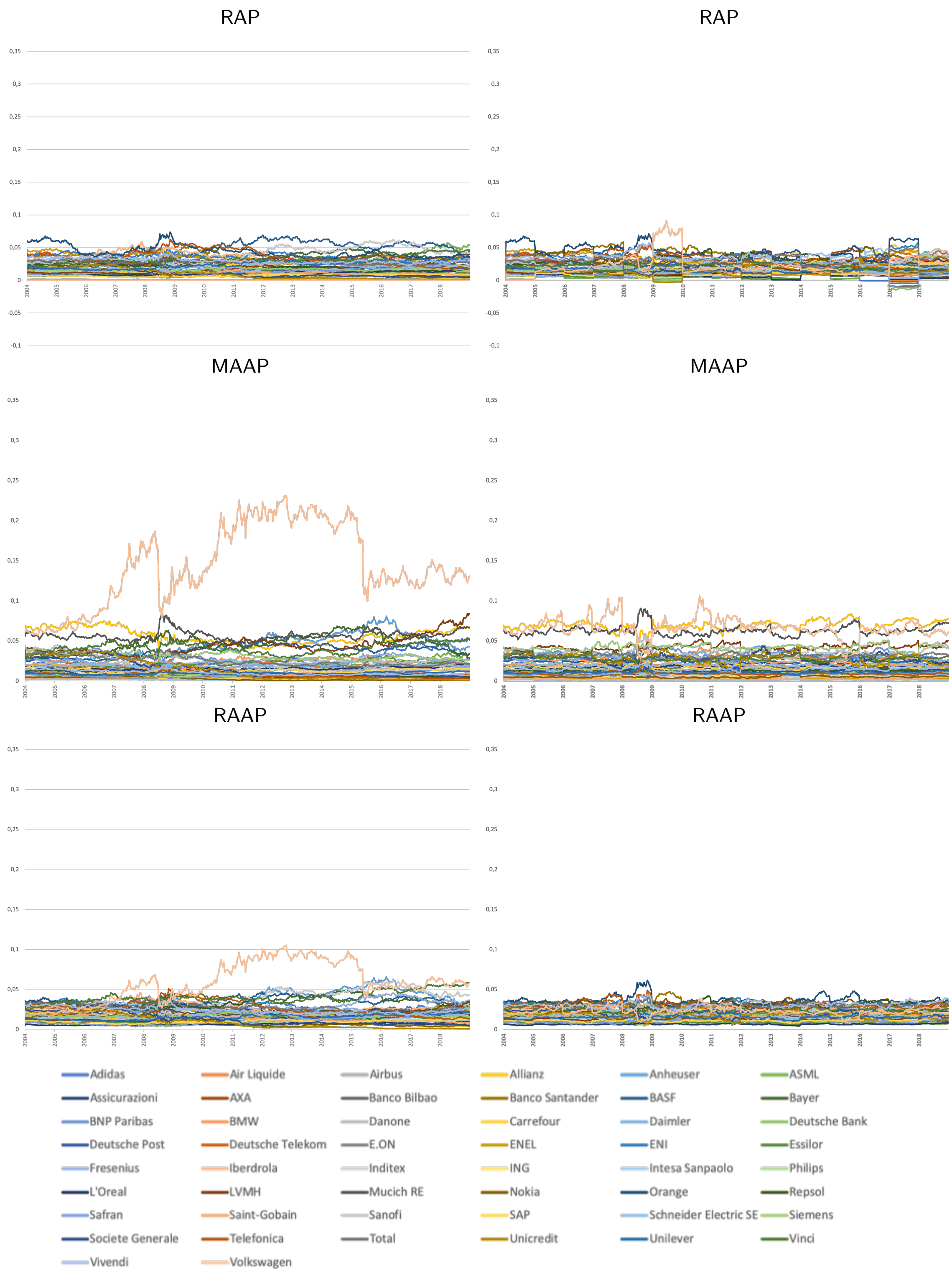
Figure A1: Portfolio weights evolution: no rebalance *versus* annual rebalance



Actual evolution of weights when no rebalance (left) or annual rebalance (right) is considered for the portfolios: H, T, TNS, AAP, RAP, MAAP and MRAP. Vertical scales differ.

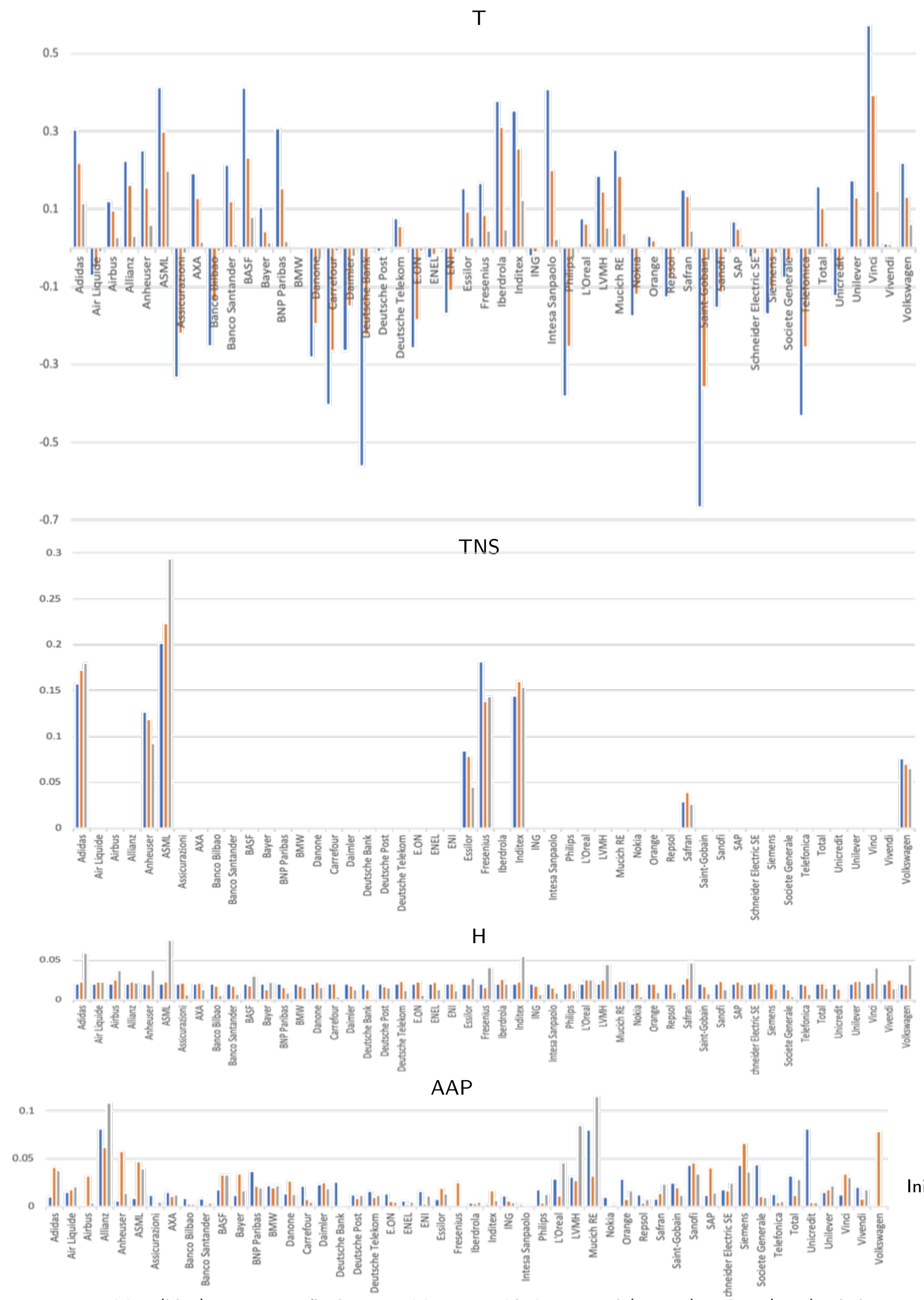
Figure A1 continues =>

Figure A1: (Cont.) Portfolio weights evolution: no rebalance *versus* annual rebalance



Actual evolution of weights when no rebalance (left) or annual rebalance (right) is considered for the portfolios: H, T, TNS, AAP, RAP, MAAP and MRAP. Vertical scales differ.

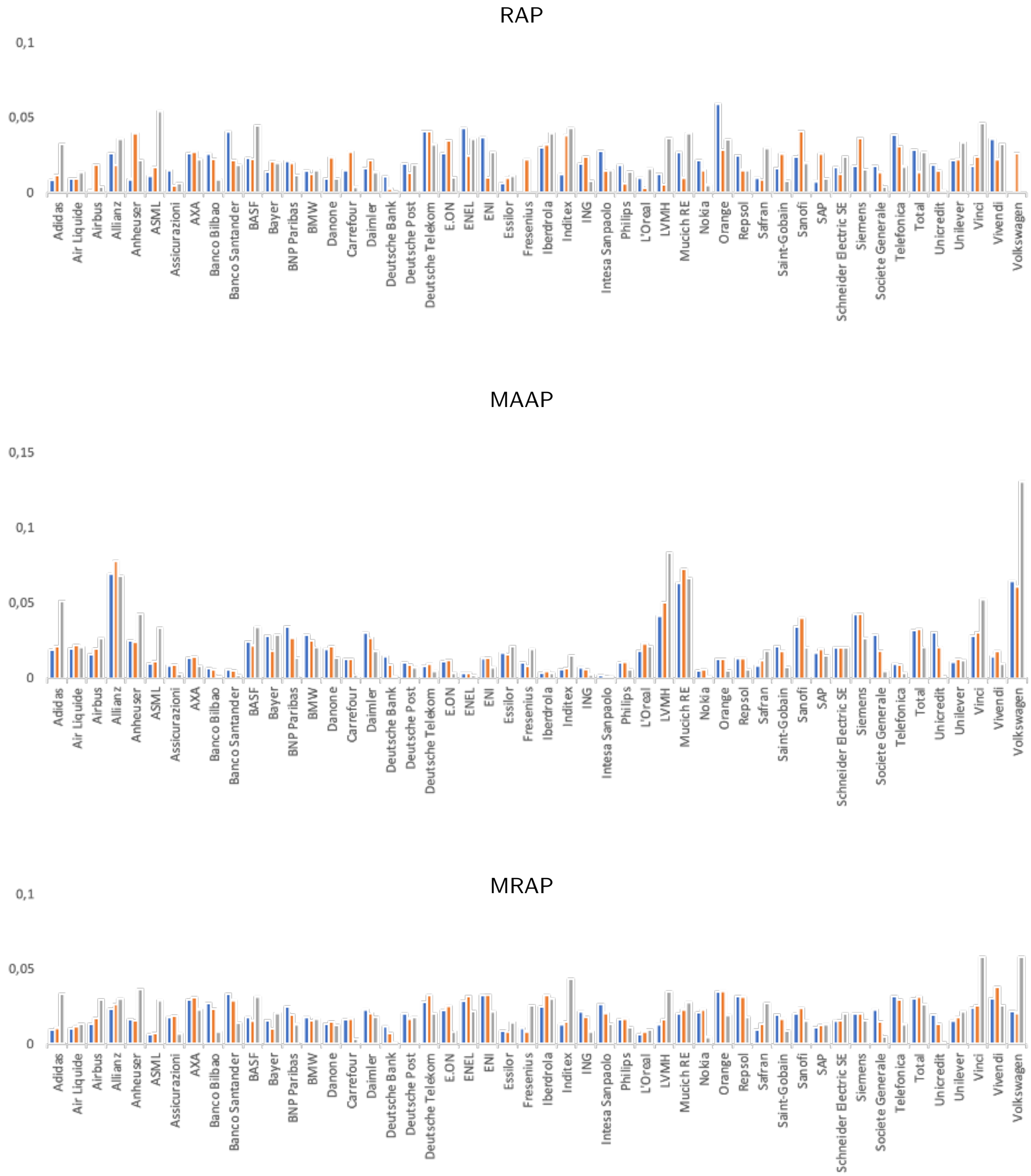
Figure A2: Initial *versus* final compositions: influence of rebalancing schemes



Initial composition (blue) *versus* two final compositions, considering annual (orange) and no (grey) rebalance.

Figure A2 continues =>

Figure A1: (Cont.) Initial *versus* final compositions: influence of rebalancing schemes



Initial composition (blue) *versus* two final compositions, considering annual (orange) and no (grey) rebalance.