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Empirical Paper

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Market-moving events and their role in portfolio optimization of generations X, Y, and Z

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Abstract: We examine how generations X, Y, and Z might react to market-moving events over short- and long-term horizons to maintain an optimal balance among risk, return, and investor preferences. To analyze various portfolio variants, we use data on selected global assets and several types of economic and non-economic events for 2000-2021H1, applying the mean-variance optimization procedure. According to our results, in optimal portfolios, fixed-income assets dominate and are the main driver of portfolio adjustments. Portfolios with short-term horizons with less risk-averse investors and those for generation Z are the most reactive to analyzed types of events. None of the events *per se* creates an extraordinary opportunity to increase returns. However, expansionary monetary policy generates the greatest potential for incremental returns. Our findings provide practical implications for investors on how to adjust their portfolios in response to significant market events.

Keywords: market events, risk aversion, portfolio management, portfolio vulnerability
JEL Classification: F21, G11, G15

"*The only constant in life is change*" (Heraclitus).

1 Introduction

Investors attempt to find a balance between maximizing return and minimizing risk, given their preferences and constraints. This problem was pioneered in a seminal study by Markowitz [1952] and Sharpe [1963, 1966] who created modern portfolio selection theory. In practice, portfolio optimization is a complex multi-objective and multistage decision-based investment problem. Thus, decisions about the selection of portfolio assets have since been assisted by, for example, arbitrage pricing theory or postmodern portfolio theory. However, hard facts and simulations alone do not constitute the basis for investors' decisions. Behavioral aspects also play a significant role, including reactions to various events. This study aims to assess how investors from various generations (X, Y, and Z) might adjust their portfolio composition in reaction to important economic and non-economic market-moving events.

Our study combines the analyses of the impact of news spillovers on portfolio optimization with the investment preferences of generations X, Y, and Z. In contrast to other studies on investment patterns from a life-cycle perspective, we do not use microdata from surveys as a data source. Our data sources cover

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market data and various market events. Additionally, we *ex ante* assume certain investment preferences for generations X, Y, and Z based on a literature review and expert judgment, diverging from assessing the buy-and-hold strategy, which dominates in most studies. In turn, we study the portfolio selection problem in the context of real-life events that may shape asset allocation decisions, both strategic and tactical. The dynamic strategy applied in this study is closer to genuine market conditions faced by an investor. Exploring dynamic portfolio adjustments has become even more relevant, given the severe impact that the COVID-19 pandemic has had on financial markets since 2020 [for a review see, e.g., Berger and Demirgüç-Kunt, 2021]. Crises like this have been found to materially increase return and volatility transmission, causing market spillovers [Choudhry and Jayasekera, 2014; Huber et al., 2021] and thus creating further motivation to explore effective methods to adjust investment portfolios to such events.

As observed, many theoretical models on portfolio optimization in the literature are tested only on limited financial market data (e.g., only using data from a single country). Instead, we use daily financial market data covering two decades (2000-2021H1) for 7 major asset types and 11 types of events (financial and non-financial) to analyze several portfolio variants. A similar methodological approach was adopted by Ahmed et al. [2020], who first identified the extent of spillovers from the major sectors of the US economy and then used these measures at the industry level to guide international investments, concluding that diversification opportunities are prevalent in low-spillover countries and sectors.

Our contribution to the literature consists of the analysis of optimal event-driven portfolios of generations X, Y, and Z and provides practical guidelines for how investors from different generations might react to a given type of event. In that context, we also assess the existence of 'reaction schemes' to particular types of events that could enhance portfolio returns. The results highlight several important findings. The long-term investment perspective is characterized by a visibly smaller frequency of shifts in the portfolio structure, while in the short term, greater variability in portfolios is observed, especially for younger generations. Optimal portfolios across generations tend to be dominated by fixed-income instruments, and gold plays a significant role in the long-term portfolios of generations X and Y. The impact of Bitcoin on portfolio results is mixed. Regarding events, those originating in the US are more important for shifts in the portfolio's structure. Furthermore, economic events exhibit greater potential for enhancing portfolio incremental returns (than non-economic ones), especially expansionary monetary policy events.

The remainder of the article is organized as follows. In the next section, we present a review of the literature leading to the identification of research gaps. We review the two streams of the literature relevant to our study: In the first stream, we account for life-cycle investing and intergenerational differences in consumption and investor behavior, and in the second stream, we address the research on portfolio optimization and diversification. Section 3 describes the data sources and explains the details of the methodology. Section 4 presents and discusses the results. Finally, Section 5 offers conclusions.

2 Literature review

2.1 Life-cycle investing and generations

In many studies on life-cycle investing, assets have been divided into risk-free and risky assets. For example, Cohn et al. [1975] and Morin and Suarez [1983] divided different financial and non-financial asset categories into "risky" or "marketable risky" (stocks, mutual funds, derivatives, non-residential real estate) and "risk-free" (treasuries, savings accounts, personal residence, and personal property). In this study, we focus particularly on financial assets and do not include real estate in the portfolio analysis since there are no daily market prices for these types of assets.[1] As Cohn et al. [1975] underscore, it is difficult to find

1 Moreover, these assets rely on appraisal-based valuations; thus, their measures of price volatility are not directly comparable to those of financial assets. As a result, optimization procedures might inappropriately overweight this type of asset relative to financial ones. For similar reasons, we do not account for human capital, which additionally should be assessed using individual or household features.

a “riskless” asset because even treasuries – often regarded as such – are still risky, although with low-risk characteristics. Therefore, all assets in our portfolios are treated as “risky” to some extent. Moreover, since we do not use surveys as a data source, riskless assets, such as saving accounts or deposits, are not included; thus, the overall wealth of the investor is not considered. Because new investment opportunities have emerged on the market in recent decades, we go beyond traditional asset classes, such as bonds and stocks, adding a representative of crypto assets – Bitcoin – due to its popularity [Bouri et al., 2017; Guesmi et al., 2019; Shahzad et al., 2019] as an emerging asset class.

Individuals save for various reasons, including precautionary and life-cycle motives [for a comprehensive review, see, e.g., Browning and Lusardi, 1996]. In recent years, the discussion on individuals’ savings preferences (e.g., residential property, deposits, and stocks) from a life-cycle perspective has lost vigor. Ando and Modigliani [1963], based on the pioneering work of Modigliani and Brumberg [1954], emphasized the long-term stability and cyclical variability of the ratio of savings to income while allowing individuals to maintain similar standards of living throughout the life cycle. As their income sources and patterns, as well as risk aversion, change over the life cycle, maintaining similar living standards might thus require shifting the volume and structure of their portfolios. Decreasing risk aversion (usually proxied by the share of risky assets) has been associated with significantly increasing wealth [e.g., Cohn et al., 1975; Riley and Chow, 1992; Wang and Hanna,1997] and with age [Riley and Chow, 1992; DaSilva et al., 2019]. With respect to age, the optimal asset portfolios [see Horneff et al., 2009] should include a large proportion of shares for young investors, which exhibit a downward trend as age increases. In particular, Blake et al. [2014] suggested a high initial share of equities and then a gradual switch to debt instruments as one approaches retirement in the accumulation phase. These studies have not accounted for emerging crypto assets.

In recent years, discussions of differences among generations X, Y, and Z from various perspectives have emerged in many streams of research; however, such discussions have not been particularly popular in the field of finance. Generations are defined based on their year of birth (X – born between 1965 and 1979; Y – 1980-1994, also called “millennials”; and Z – 1995 +). Their overall sociodemographic features have been presented by, e.g., Betz [2019]. All of these generations represent different lifestyles, life-work balances, and education and different scopes and scales of the use of technologies, which are very important from an investment perspective, that is, response time and 24/7 access to trading [e.g., Betz, 2019; Bank of America, 2020]. Generations Y and Z are called “digital natives” [see Betz, 2019]. In particular, generation Z has grown up in a technologically advanced era with easy access to information and its diffusion; they are supposed to be very open to using innovative financial services and types of assets, especially if these instruments are available through mobile applications or online platforms. Therefore, generations Y and Z are more likely to invest in crypto assets [e.g., Fisch et al., 2021], which makes them different from generation X.

Against this background, we identified a research gap related to the lack of studies investigating the investment preferences of various generations. As we rely on market data, instead of microdata from consumer surveys, we do not reflect the actual portfolios of assets, but we predefined their structure to run consecutive simulations.

2.2 Portfolio optimization and diversification

The literature on portfolio optimization is extensive [for a review, see, e.g., Kolm et al., 2014; Kalayci et al., 2019]. Based on the extant literature, we apply the mean-variance optimization (MVO) procedure and quantify risk based on the actual volatility of portfolio assets. However, the debate in the literature focuses on comparing the performance of various asset allocation methods. A seminal study by DeMiguel et al. [2009] provides evidence that naive allocation – where investors allocate their investment capital evenly across a few different asset classes, without accounting for the individual characteristics of each asset class – mostly outperforms various mean-variance strategies. This may be because the gain from optimal diversification is more than offset by estimation error. Recent studies on longer data find that mean-variance models might be superior to the naive approach for asset allocation, which is primarily because estimation errors are lower for asset classes than for individual assets. Furthermore, in-depth studies show that the basic Bayes-Stein framework cannot offer better out-of-sample performance [Board and Sutcliffe, 1994], but the generalized version, enhanced with the use of machine learning, can offer better out-of-sample performance than the 1/N strategy [Gounopoulos et al., 2022], which is also true for sophisticated portfolio techniques that control for estimation errors.

Achieving portfolio diversification effects requires adding or removing a particular asset class to or from a portfolio. Most research has focused on diversification effects with portfolios consisting of only several components, while we cover seven global asset classes. While there is no single optimal selection of assets, several studies have offered useful guidelines. Ciner et al. [2013] confirmed that the bond market continues to play its traditional role as a hedge for the equity market. Both Khalfaoui et al. [2015] and Khalfaoui et al. [2019] found that investors should hold less stocks than crude oil, with the optimal portfolio weight for oil being close to 20%. This finding was confirmed by many other studies, for example, Belhassine and Karamti [2021], Mensi et al. [2021b], and Kartsonakis-Mademlis and Dritsakis [2021], which provided evidence that indices are good hedges for oil and that oil assets reduce portfolio risk. Moreover, many researchers have also argued that including gold in a portfolio adds to diversification effects since gold acts as a safe haven during turbulent periods [Alkhazali and Zoubi, 2020; Zhang et al., 2021].

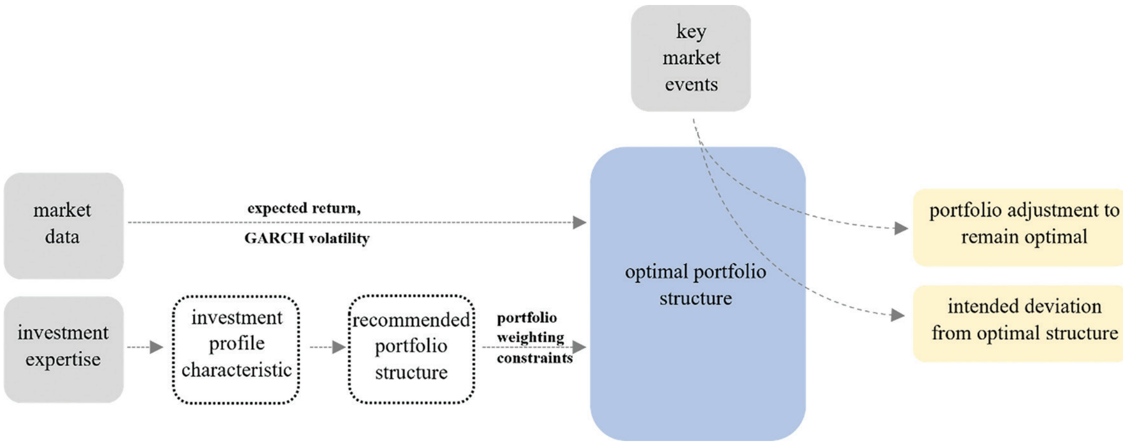
Furthermore, in recent years, there has been a proliferation of studies examining the diversification effects of cryptocurrencies, especially Bitcoin. Cryptocurrencies can be incorporated into financial portfolios to provide effective risk management and for optimal dynamic hedging purposes [Hsu et al., 2021]. Nevertheless, there is no fixed consensus on whether Bitcoin can serve investors as a portfolio diversifier, a hedge, or a safe haven [Bakry et al., 2021]. Dyhrberg [2016], Guesmi et al. [2019], and Mensi et al. [2021a] proved that hedging strategies involving Bitcoin considerably reduce a portfolio's risk relative to a portfolio without it. Including Bitcoin in the portfolio generates substantially higher risk-adjusted returns [Platanakis and Urquhart, 2020]. Huang et al. [2022] show that during uncertain economic environments, such as the post-COVID-19 period, cryptocurrencies provide the same diversification benefits as in more-stable environments. However, Bitcoin's diversification benefits for investors are counterbalanced by its high volatility [Damianov and Elsayed, 2020] and might be viable mainly for investors with short investment horizons [Corbet et al., 2018] or for risk-seeking investors in non-crisis times [Bakry et al., 2021]. Thus, Damianov and Elsayed [2020] found that Bitcoin's optimal weight in a minimum variance portfolio is only approximately 1%, while Eisl et al. [2015] suggested 2%–8%. Overall, the safe haven and hedging roles of Bitcoin, gold, and commodities are time varying and differ across horizons and stock market indices [Bouri et al., 2017; Shahzad et al., 2019].

Against this background, we identified a research gap related to the lack of studies showing the portfolio optimization of different generations. The aim of this study is to reduce this gap and stimulate further academic discussion.

All in all, the identified research gaps regarding the investment preferences and the approach to portfolio optimization of various generations (X, Y, and Z) allowed us to formulate the purpose of our investigation, that is, to assess how investors from various generations might adjust their portfolio composition in reaction to important economic and non-economic market-moving events.

3 Data and methodology

Our methodological approach relies on three types of information: market pricing, investment expertise, and market-relevant events. The first two are included in the initial stages, when we assess the optimal structure of investment portfolio. Then, since we recognize the importance of key market events, we study two ways in which the investor might adjust portfolio elements – one assuming that he/she wants to keep the portfolio optimal and the second introducing an intended deviation from the optimal state with the aim of earning an event-specific incremental return. Since we study a relatively long time span, our approach should make it possible to evaluate whether any 'patterns' – which are generally appropriate for a given type of event – already exist. The broad picture of our approach is presented in Scheme 1, while the details are described in the following section.



Scheme 1. Research methodology concept.

3.1 Selection of assets

Due to the large number of asset types available in global markets, the set of assets selected in particular studies varies significantly [see, e.g., Aït-Sahalia and Xiu, 2016; Tiwari et al., 2018; Kurka, 2019; Le et al., 2021], and there is no widely accepted standard set of assets included in the portfolio. We assume that our investors have access to global markets and prefer highly liquid instruments either of global nature or from developed countries. Such an assumption may be particularly important in the context of this study as some events may lead to liquidity constraints and thus an inability to adjust the investment portfolio. Therefore, American and European stock and T-bond markets are the focus, complemented by global assets, such as gold, Bitcoin, and – in some scenarios – oil as an important type of commodity. Thus, we allow an investor to construct a portfolio using the following assets: the S&P 500 index, the EuroStoxx 600 index, 10-year US and German government bonds, gold, Bitcoin, and Brent crude (a major benchmark for oil prices). Both selected stock market indices account for a significant market capitalization in the US and Europe (approximately 75% in 2021) and thus may be treated as representative of these two markets. In the US and the largest economy in Europe, that is, Germany, T-Bonds and gold are regarded as safe-haven assets [e.g., Tachibana, 2022; Ugoliniet al., 2023], reducing the volatilities of the portfolio. Additionally, gold and crude oil provide a hedge against inflation. Bitcoin, being rather speculative in nature, although called "digital gold" [Selmi et al., 2022], represents the largest capitalization of all cryptocurrencies. Moreover, we treat the chosen asset classes as 'layers' within which a further selection of specific instruments, which meet certain characteristics, can be introduced. Therefore, the effects of the events analyzed should be understood as those that affect the particular asset class as a whole in a certain way.

Geographically, in turn, the choice is limited to developed markets in Europe and the US, which is constrained both by the location of the events analyzed and by concentration characteristics [e.g., for equities, Europe and the US represent approximately 60% of the global market, Kuvshinov and Zimmermann, 2022]. As government bonds and equities account for around two-thirds of the global market portfolio [Doeswijk et al., 2014], in our study, we use two representatives of these markets, instead of one. Market price data for financial instruments are sourced from Bloomberg.

This choice of different asset classes allows us to include the diverse investor preferences of each generation (see Figure 1). Moreover, since different asset classes should, by definition, exhibit relatively low or opposite correlations [due to internal homogeneity and external heterogeneity; see Kritzman, 1999], such a selection of assets should allow portfolio diversification effects to be achieved. In the long term, correlations between our selected assets are low overall and conform to this approach (a correlation table is available in Appendix 1). We are aware that a relatively small number of assets in a portfolio may raise some concerns about limited diversification benefits. Nevertheless, there is still a body of literature suggesting that a small number of assets is indeed sufficient to achieve a significant diversification effect – for example, approximately 7–10 [e.g., Barber and Odean, 2000; Stotz and Wei, 2014] or 6 for active equity

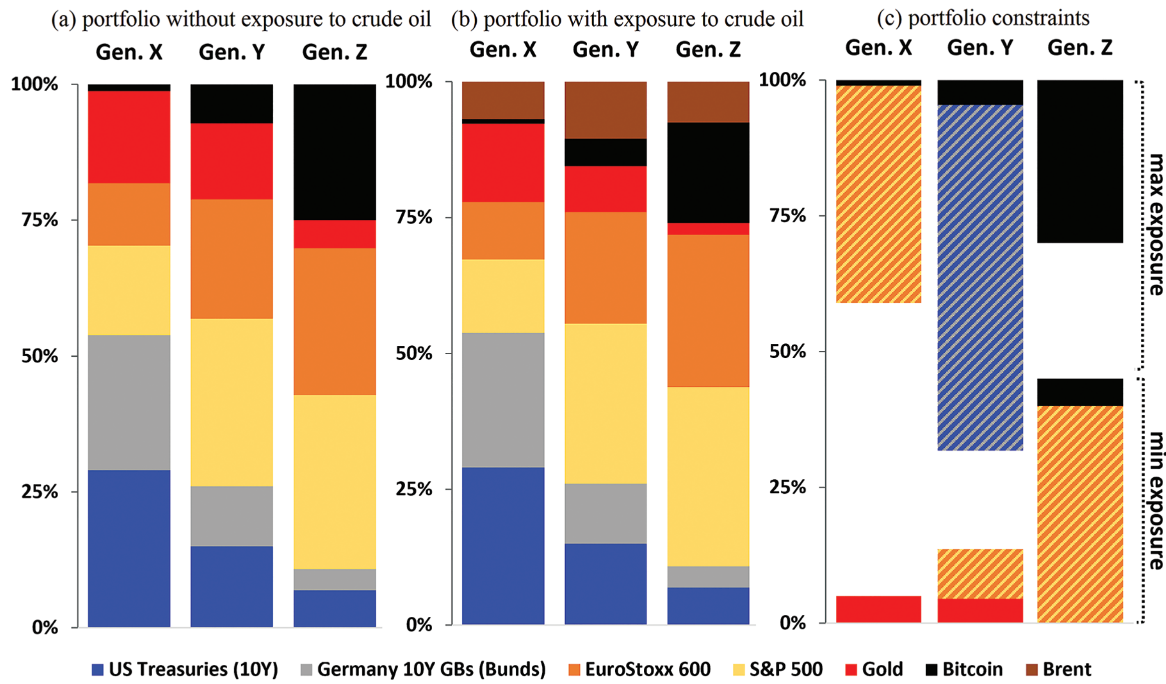


Figure 1. Portfolios dedicated to generations X, Y, and Z. (A) Portfolio without exposure to crude oil. (B) Portfolio with exposure to crude oil. (C) Portfolio constraints.
Note: Portfolio exposures presented in panels (A) and (B) refer to the averages, while the formulated constraints rely additionally on the dispersion of the proposed structures; in panel (C), the columns starting from the bottom denote the constraint applied to the minimum share of the given asset, the columns starting from the top indicate the maximum share of the asset, and the striped columns denote constraints on an aggregate exposure to two assets, with no distinction between European and US assets.
Source: own work.

funds included in the funds-of-funds portfolio [Brands and Gallagher, 2005]. This benefit comes with a smaller number of assets, especially when these assets belong to different classes. In effect, the global minimum variance portfolio is considered to be constructed from different sets of 10 assets [Green and Hollifield, 1992]. Obviously, these numbers are determined by a number of factors, including the specifics of the markets, the interrelations between them or current conditions. Nonetheless, limiting the number of asset classes to 7 also makes it easier to identify and understand the relationships. Still, the selected assets give the investor exposure to a number of factors, including economic growth, inflation, interest rates, credit risk, or – albeit indirectly – market uncertainty.

We do not include alternative investments among the assets available for portfolio optimization for several reasons. The valuation of alternative investments is often problematic, which limits their liquidity and thus dynamic portfolio diversification potential on a daily basis. Furthermore, alternative investments constitute a heterogeneous group of assets, their intrinsic value is often tied to the regional market, and they are not easily understood by a typical investor. Consequently, they are much less likely to be included in the portfolio of a "typical" investor from generation X, Y, or Z.

3.2 Construction of portfolios appropriate for generations

To simulate the optimal portfolios of investors from different generations, we first define these generations by formulating allocation constraints. Such constraints are necessary to construct a portfolio suitable for a particular type of investor – in our case belonging to different generations. We define them using the extant literature [e.g., Eisl et al., 2015; Damianov and Elsayed, 2020] and experts' judgment. We contacted 10 market practitioners (6 of whom responded), including Certified Financial Analysts (CFA),[2] with

2 We would like to thank: Krzysztof Borowski, Piotr Bujko, Monika Czerwonka, Paweł Dolegacz, Adam Drozdowski andRafał Tuzimek

questions about a portfolio structure that they would suggest as adequate for different investor types. This helped us validate our ideas on the portfolio structures. Each respondent provided us with suggested portfolio structures for three generations. Based on the literature review, methodological constraints for the optimization procedure, and expert judgment, we obtained the following *average* structure of dedicated portfolios for generation X, Y and Z investors (please see Figure 1; detailed data are available in Appendix 2).

The aforementioned portfolio structures reflect some specific characteristics that should be mitigated in our methodology. Specifically, they present a snapshot of a portfolio that is adequate at a given point in time, thus reflecting both the market environment and the preferences and abilities of the generation observed at this point. Moreover, they indicate a fixed portfolio structure over time, which requires frequent rebalancing (to keep the structure stable) and does not allow for temporal adjustments in response to, for example, important events (each adjustment requires an expert assessment). Nevertheless, it also provides some general relations that are worth emphasizing. First, a dominant portion of the portfolios of all generations (amounting to approximately three-quarters) is represented by exposure to two asset classes – fixed income and equity. Thus, when shifting across generations, the majority of adjustment occurs within these asset classes. Second, fixed income is a preferable asset for generation X, while equities are preferable for generations Y and Z. Third, generation X should not be exposed to Bitcoin but to gold instead, while Bitcoin is favored by generation Z, instead of gold. Fourth, exposure to crude oil does not reduce exposure to major assets (fixed income, equities) but is introduced at the expense of gold (gen X) or Bitcoin (gen Z). Importantly, both constraints and optimization adopt the perspective of an asset-only approach in search of the optimal portfolio. We therefore focus solely on the asset side of the investor's balance sheet and do not model liabilities or goals, which in practice may also have an impact on asset selection and portfolio constraints.

We consider these relations and address them in the form of allocation constraints in our optimization procedure (see Scheme 1). We treat portfolio structures reported by respondents as a reference point for formulating constraints on the portfolio weights. In other words, we use the structure only to tilt the portfolio toward the preferences of each generation and to distinguish them from others. We also want to allow for flexibility and enable the application to past data; therefore, we formulate these constraints only for some of the assets with respect to their minimum or maximum shares in the portfolio (see Figure 1C) while addressing all of the major relations stated before.

For example, we do not assume that generation Z holds Bitcoin as a significant part of their portfolio, as might be suggested by Figure 1A). Instead, we assume that the proportion of Bitcoin in the portfolio cannot be greater than approximately 25%, while the minimum share cannot be lower than 5% (Figure 1C). These limits not only are based on expert judgment but also follow the literature [e.g., Eisl et al., 2015; Damianov and Elsayed, 2020]. Importantly, the constraints imposed must still apply to the group of investors characterized by different perceptions of risk. In particular, the upper-limit constraint is particularly binding for an investor with above-average risk tolerance, while an investor with above-average risk aversion would probably hold a much lower proportion of the portfolio in Bitcoin, despite their generational perceptions. Therefore, a significant part of the portfolio is allocated to Bitcoin only in the case of a specific investor (generation Z with above-average risk tolerance), which in our study is perceived as an investor with the highest possible risk tolerance for whom the risk associated with, for example, equities is not sufficient or, more precisely, that the reward for this risk is too low.

3.3 Optimization procedure

From a formal perspective, we implement a classical MVO procedure. Despite the well-known shortcomings of the model, MVO is often the starting point for making asset allocation decisions. Obviously, the literature offers a range of possible alternatives – from more-sophisticated approaches, including machine learning [which take into consideration higher moments of risk than volatility; see, e.g., DeMiguel et al., 2009] to simpler alternatives (such as the naïve portfolio diversification rule).

In this study, however, while recognizing the drawbacks, we also acknowledge the advantages of MVO. Most notably, it is a simple and easy-to-implement approach that has been widely used in finance for many years. This opens up the possibility of a broad comparison with other results in the literature, a possibility that is not impaired by, for example, the implementation of more-sophisticated and less-popular methods. Most notably, it allows for the identification of not only economic and but also methodological drivers of results. Nevertheless, MVO is flexible enough to be adapted to different investment objectives and constraints and can be combined with other techniques. Ultimately, we prefer to begin with a simple method to more precisely identify possible relations. At the same time, we attempt to minimize the model's shortcomings, first by selecting assets whose valuations do not include many hard-to-control premiums (e.g., liquidity or extensive credit risk), which need to be managed by higher moments of the return distributions and, second, by our approach to the expected returns.

Our objective is to identify the optimal portfolio on the efficient frontier according to specified criteria. Obviously, this frontier will differ depending on how the risk-free asset is considered. Although we consider long-term government bonds, we do not perceive them as a completely risk-free asset; in fact, we include them in the optimization process. Moreover, we do not allow short selling to mitigate the MVO tendency to produce extreme portfolios combining extreme shorts with extremely long portfolios and to keep the frontier less vulnerable to new information. Therefore, asset weights in the portfolio are described as $w \in W$, where $W := \{w \in \mathbb{R}^N | w'1 = 1\}$. Given the mean ($\mu_p$) and variance $\left(\sigma_P^2\right)$ of the portfolio, the mean-variance efficient portfolio maximizes quadratic utility for a selected level of risk tolerance (λ)[3]:

$$w\left(\lambda\right) := \max_{w \in W} \mu_P - \frac{1}{2\lambda}\sigma_P^2 = \max_{w \in W} w'\mu - \frac{1}{2\lambda} w'\Sigma w \tag{1}$$

where X ∈ R N is a vector of asset returns with mean μ and positive-definite covariance matrix Σ.

Defining $Q := \Sigma^{-1} - \left(1'\Sigma^{-1}1\right)^{-1} \Sigma^{-1}11'\Sigma^{-1}$, w($\lambda$) has the solution w($\lambda$) = $w_{GMV} + \lambda Q\mu$, where $w_{GMV} := \frac{\Sigma^{-1}1}{1'\Sigma^{-1}1}$, and Σ denotes the positive-definite covariance matrix. With respect to the above, $\lambda = 0$ corresponds to the global minimum-variance (GMV) portfolio, while $\lambda = \infty$ corresponds to the maximum mean return portfolio. Empirically, most investors' risk aversion is consistent, with λ between 1 and 10, and $\lambda = 4$ can represent a moderately risk-averse investor [Ang, 2014]. Therefore, in our study, we introduce two levels of that parameter: above-average risk aversion ($\lambda = 2$) and below-average risk aversion ($\lambda = 7$). Importantly, in our study, we assume that these parameter values are common to investors of all generations. We do not impose different risk tolerance levels for different generations as we believe that in a 'conservative' generation, there may be individuals with a higher risk tolerance, and vice versa. Furthermore, to the best of our knowledge, the literature has not defined lambda parameters with reference to investors belonging to different generations.

One of the most important inputs in MVO is the vector of expected returns, partly because of the model's significant sensitivity to estimation errors of the input parameters [see, e.g., Kan and Zhou, 2007; Kuhn et al., 2009]. Simultaneously, the literature confirms that the accurate estimation of expected returns is difficult and sensitive to the chosen methodology and, particularly, that historical returns are confirmed to be a poor predictor of expected returns [e.g., Ledoit and Wolf, 2003]. The selection of assets for analysis mentioned previously gives us the comfort of deriving the market perspective of expected returns, rather than relying on estimates. Since for all assets – except Bitcoin – an investor can easily access the range of derivative financial instruments, instead of attempting to improve the quality of moment estimates, this study uses forward-looking moments of return distributions that can be derived from option pricing. The market probability distribution derived at a given point in time is, in our view, a good proxy for market expectations at a given horizon. In this approach, we follow Martin [2017] and do not rely on the assumption of any particular return distribution. By introducing such an approach to expected returns, we believe we

3 The risk aversion coefficient (λ) characterizes the investor's risk-return trade-off; in this context, it is the rate at which an investor will forgo expected return for less variance.

can control the typically high sensitivity of the composition of efficient portfolios to estimates of expected returns and overcome the drawbacks of the MVO technique as a relatively simple method.

With respect to the expected return of Bitcoin, which can be seen as a specific case of the aforementioned approach, we mirror the approach of Foley et al. [2022] and share the range of characteristics obtained. In particular, the expected return of Bitcoin is several times higher than, for example, that of the stock market, which was at its highest in early 2018 and has gradually declined in recent years. In particular, this is in line with the general perception of Bitcoin as a high-risk asset that should be rewarded accordingly. However, derivative markets for Bitcoin were not developed during its early years of operation. Therefore, for the analysis of investment portfolio structure in the years of 2012–2017, we assumed that the expected returns of Bitcoin in this specific period are proxied by its historical performance. For the remaining sample, as for other financial instruments, the expected returns are implied from the derivatives. We consider the potential risks outlined earlier and associated with this approach to be relatively mitigated as we allow only a small portion of the portfolio to be allocated to Bitcoin.

Since we believe that the interrelations across assets and their risk-to-return characteristics evolve over time, we rely on a dynamic approach to find an optimal portfolio structure. To do so, we estimate the model presented previously in a rolling window for two investment perspectives. We consider a short-term portfolio, in which the decision-making process considers only the last three years and a long-term portfolio formulated based on the last 10 years. Additionally, given that the assets included in this study are relatively widely available at low cost, we assumed the transaction cost to be fixed and to account for 0.1%. Such an approach simply indicates higher transaction costs for more-diversified and/or more-frequently adjusted portfolios. In our opinion, a more in-depth approach to transaction costs – additionally considering, for example, liquidity differentiation across asset classes – falls beyond the scope of this study.

3.4 Assessing the impact of events on portfolios

The main objective of this study, in fact, is not to propose a perfect portfolio structure for the aforementioned investors. Instead, we assess whether short-term events can affect the strategic portfolio structure. On the one hand, such a structure should, by definition, be based on at least a medium-term perspective of the market and thus not be affected by short-term episodes. On the other hand, if events are significant enough, they may be reflected in asset characteristics – such as expected return or volatility – and hence in the structure of the optimal portfolio. The literature tends to independently examine whether the events in question can affect the expected return, the volatility of the assets, or the interrelations between them. In this study, however, we want to consider their 'combined' effect, assessed from the perspective of holdings in the optimal portfolio. Such a combined effect may indicate that although a specific event affects both the expected return and risk of an asset, the overall effect on the portfolio may be negligible. Therefore, we attempt to analyze whether the magnitude or direction of these adjustments was common within the category of events. In our view, this may be useful since it allows us to identify which categories of events may affect financial markets only in the short term (around the time of their occurrence) and may have longer-term consequences as a result of the rebalancing of investment portfolios that they trigger. In addition, it enables verifying to what extent the portfolio – in order to remain optimal – is affected by a specific category of undivorceable risk that arises purely from unpredictable events.

As stated before, given the estimated portfolio weights, we attempt to assess whether their evolutions might arise from events. To capture this possibility, we specify a regression model for asset weights in the portfolio ($\mathrm{w_i}$) in which we control the overall market risk:

$$q_\tau\left(\mathrm{w_i}|\Omega_\mathrm{t}\right)=\alpha_\tau+\beta_\tau D_t+\gamma_\tau \mathrm{RISK_t} \tag{2}$$

where $q_\tau(\cdot)$ is the conditional quantile function evaluated at the τth quantile, Ω_t is the information set available at time t, and α_τ, β_τ, and γ_τ are the parameters to be estimated at the τth quantile. The dummy variable D_t takes the value of 1 during the periods corresponding to the events and 0 otherwise. The variable

$RISK_t$ should be viewed as a measure of overall market systematic risk and is constructed using a statistical technique, principal component analysis (PCA), with aims to reduce the idiosyncratic nature of a set of measures and capture only the common element of market risk. Specifically, the $RISK_t$ measure is the first component (of a set of components extracted from the PCA) for a group of indicators describing investor sentiment in stock markets (VIX index), currency markets (JPM G7 implied volatility index), and bond markets (MOVE index), as well as the overall economic uncertainty (TED spread), global market liquidity squeeze (USD basis swap premium), and credit risk (US IG-HY spread). Therefore, the RISK variable allows us to control for widely understood market risk separately from the volatility risk specific to the asset category that was already introduced into the optimization procedure. The outcome of this part of the analysis is presented in Section 4.2.

To assess the impact of events on the optimal portfolio structure, we use the further refined and updated event database from Iwanicz-Drozdowska et al. [2021]. The database covers more than 300 individual events classified on a daily basis from January 1, 2000, to June 30, 2021. In contrast to the original version, we organized events into 11 categories (by, e.g., merging the monetary policy categories). We included (separately for the US and Euroarea) restrictive and expansive monetary policy,[4] prudential policy in the banking sector,[5] and major problems of multinational banks.[6] Non-economic events are classified into key geopolitical events of international importance, major terrorist attacks, and information about the outbreak and spread of a virus.[7] We believe that this approach covers the main types of potential market-moving events and allows us to generate findings, rather than analyzing each event separately. Of course, each may differ to some extent, but within one category, they share a number of similarities – including, most importantly, their nature and channels of potential impact.

As a next step, finally, we investigate whether an investor can enhance the portfolio return (with respect to the optimal return) by introducing tactical overweighting in reaction to the events. The motivation behind this approach is as follows. Since the events analyzed can be interpreted as having short-term, rather than structural, effects, they may not be reflected in the estimates of expected returns and hence in the optimal portfolio structure. However, an investor may wish to capitalize on such events. Thus, we simulate a decision-making process that allows us to overweight one selected asset on the day of the event occurrence (while proportionally decreasing the weighting of other assets in the portfolio).

This tactical deviation is introduced with the rule-based approach, that is, a general rule that applies in a similar way to all assets and events analyzed. Specifically, assuming that, on the day before an event occurred, the share of asset *i* in the portfolio amounted to w_i (in percent terms), the investor reacts to the event by increasing the allocation to that asset by $\sqrt{w_i}$. Theoretically, such reaction scaling leaves space for tactical overweighting ranging from 1 percentage point (when the original share was close to 1%) to 10 percentage points (if the portfolio consists of a single asset). It is a simple rule, but it ensures that the decision to deviate is strictly linked to the initial structure of the portfolio. This is particularly important because the initial structure represents the strategic view of the investor and is constructed with the aim of being consistent with the investment profile and risk tolerance characteristics. Therefore, as a tactical deviation, the investors cannot completely rebalance their portfolio structure but must remain within the strategic view. In addition, a strict rule reduces emotionally driven decisions. In this sense, the proposed rule helps maintain long-term goals and avoid impulsive decisions. This may be particularly important in the context of this study as we intend to analyze a number of market events. These events, in fact, may cause or contribute to market instability and volatility, and the temptation to profit from them can lead to the portfolio being shaped by emotional biases. In this context, a simple rule reduces this risk. As a result, short-term market fluctuations are introduced into the portfolio in a consistent manner. Ultimately, we are

4 This category consists of changes in interest rates by the central bank, an increase or decrease in the scale and scope of QE, and the launch of liquidity support programs by the central bank, including swaps.

5 This category includes significant changes in micro- and macro-prudential tools, key milestones in postcrisis regulation in banking and stress test results.

6 This category covers major problems, scandals and defaults of international banks and announcements of bank support schemes using public funds.

7 The binary database is available as an online appendix and coded as “1” for the given day on which an event occurred.

not suggesting that the aforementioned rule is the best way to react to various events, and most likely it is not. Rather, the purpose of this exercise is to test whether a one-size-fits-all reaction function can benefit the investor who reacts when a particular event occurs.

The simulation is conducted separately for each analyzed asset. This means that if we have five assets in the portfolio, we allow the investor to make five independent decisions to overweight each asset. The aim is to compare and contrast all the possible outcomes and identify the asset that benefits the investor the most. More importantly, the aim is to see whether the similar response to each type of event produces a similar outcome and whether a pattern that worked once can be repeated. The findings of this exercise are reported in Section 4.3.

4 Empirical findings

The investor's response to events can be introduced into the portfolio in a twofold manner. On the one hand, a specific event could trigger an evolution of return-risk characteristics between asset classes (Section 4.1); thus, it can be introduced at the level of the optimal portfolio structure (Section 4.2). On the other hand, it could affect expectations of future market perceptions and thus calls for a tactical deviation from the optimal portfolio (Section 4.3). In this study, we present all of these aspects.

As an introductory step, we assessed the vulnerability of selected portfolio assets to the occurrence of a given type of event in the database over the period of 2000–2021H1. For each type of asset, we examined whether the volatility (i.e., standard deviation) and returns close to the event date differed markedly from their historical values. We accounted for reactions at both the short- and long-term horizons. As a result, the heatmap (see Table 1) provides the average direction of strong reactions of given asset indices to the event types. Overall, the events have a relatively smaller impact on the volatility of asset indices, while they influence asset returns to a larger extent. S&P 500, 10Y Bunds, and gold are among the most vulnerable asset types that respond to many types of events. For example, we find that European Central Bank (ECB) monetary policy decisions negatively impact returns from the S&P 500, while problems in the banking sector rattle the gold market, as do geopolitical events.

Table 1. Heatmap of events' impacts on returns from asset classes (2000–2021H1)

	Eurostoxx 600	S&P500	Gold	Bitcoin	Brent	DE 10Y	US 10Y
Restrictive monetary policy (EA)							
Expansive monetary policy (EA)							
Prudential policy (EA)							
Bank problems (EA)							
Restrictive monetary policy (US)							
Expansive monetary policy (US)							
Prudential policy (US)							
Bank problems (US)							
Geopolitical events							
Terrorist attacks							
Virus							

Note: Heatmap presents the change in average asset returns in the short term, that is, during the period with a high probability that it does not include the impacts of other factors that should be proxied. Therefore, we included time windows of –/+5, –/+21, and –/+63 days before and after the day when an event of a given type occurred; red indicates an average decrease in returns, while green denotes an average increase in returns.

Source: own work.

For Federal Reserve (Fed) quantitative easing (QE) announcements, Corbet et al. [2019] suggested that they caused material stock market volatility as well. We additionally confirm the findings of Markoulis and Katsikides [2020] and Iwanicz-Drozdowska et al. [2021] that terror attacks and virus-related events impact the returns of the largest number of asset indices. Harjoto et al. [2021] and Okorie and Lin [2021] showed that COVID-19 pandemic events generated negative shocks to equity markets, which was also confirmed in our study.

4.1 Evolution of the optimal portfolio structure

In the first step, a broad picture of the portfolio structure – that is, an outcome of rolling estimation given exogenous constraints – should be provided. Such an approach results in a dynamic structure for this portfolio that can be analyzed from several perspectives – across investment horizons, generations, and risk tolerances and with respect to the significance of asset exposure (see Figure 2). It should be noted that the evolution of the portfolio structure might not be associated with a particular event, but rather reflects the broad environment that affects market pricing. Therefore, an assessment of portfolio evolution that arises around particular events is undertaken in the following section.

First, addressing the investment horizon, we confirm that the long-term perspective (Figure 2B) is characterized by a visibly smaller frequency of shifts in the portfolio structure. Over this horizon, a similar asset composition of a portfolio persists for years, while in the short term, it evolves many times even during a single year (Figure 2A). This process results – to some extent – from our assumptions, that is, the length of the observation window, which is considered when the investor decides on the adjustment of the portfolio structure. However, a greater tendency of short-term portfolios toward rapid and frequent shifts is not an obvious characteristic since it is evidenced only in the most recent

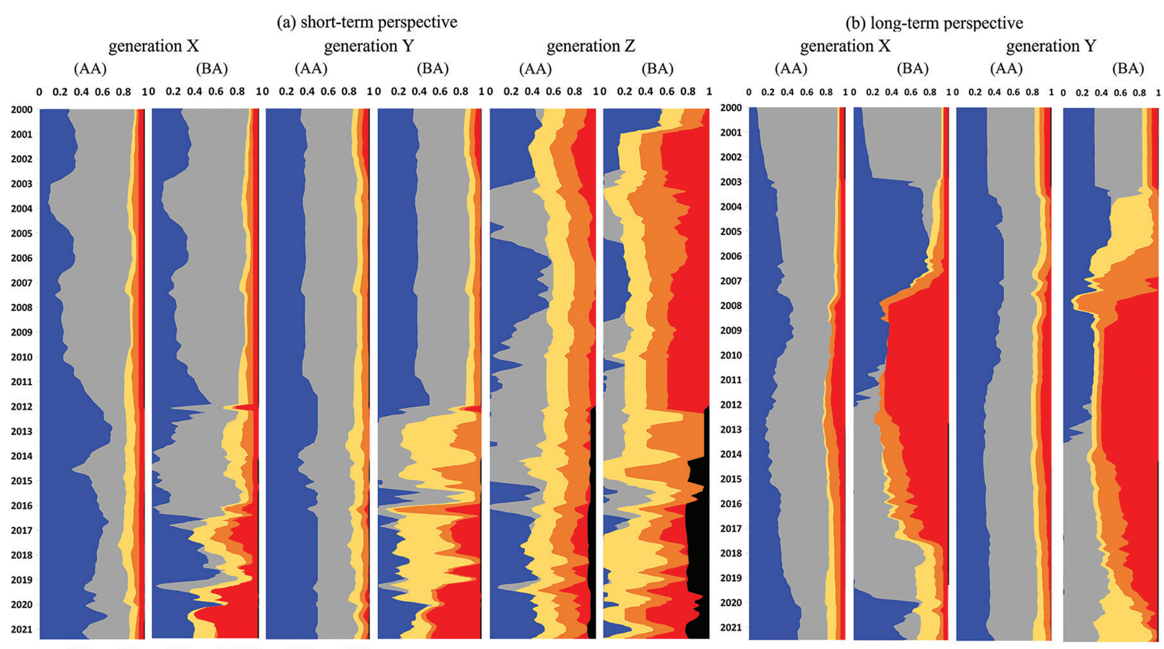


Figure 2. Evolution of the optimal portfolio structure over time, generations, and investment horizons.
Note: The graph shows the evolution of the optimal portfolio structures over time. Each structure is estimated independently at a given point in time. The evolution is implemented using a rolling-window estimation that reflects the investment horizon. We consider the short-term portfolio to have a 3-year perspective, while the long-term portfolio has a 10-year perspective. Generations reflect the portfolio constraints discussed 3.2. Above-average risk aversion refers to $\lambda = 2$, while below-average risk indicates $\lambda = 7$.
Source: own work. AA – above-average risk aversion; BA – below-average risk aversion; BTC – Bitcoin; DE – DE 10Y Bunds; SPX – S&P500 stock index; STOXX – Eurostoxx 600 stock index; UST – US 10Y Treasuries; XAU – gold.

years. In particular, until 2012, the implied structure of the short-term portfolio was characterized by significantly greater stability, which was evidenced for all generations and both risk tolerance levels. We believe that this structure might be the result of the start of the sovereign debt crisis in several Euroarea (EA) countries, which rattled financial markets thereafter (and, e.g., increased demand for safe assets such as 10Y Bunds). In this way, we confirm the findings of Bratis et al. [2020] that financial spillovers strengthened in the postcrisis period.

Second, regarding the differences between generations, at the short-term investment horizon, variability in the portfolio structure intensifies as the generation becomes younger. Therefore, the frequency of portfolio adjustment does not solely arise from the length of horizons considered in the decision process (as might be supposed when comparing short- and long-term horizons) but also results from the investment preferences and risk tolerance of a given generation. In summary, the portfolio structure is more stable in the case of (i) a long-term investment horizon (in contrast to a more-volatile short-term horizon); (ii) older generations (as opposed to younger ones); and (iii) portfolios with greater risk aversion (than risk-seeking ones).

Third, the younger the generation is and/or as the risk aversion relaxes, a broader range of asset classes is introduced into the portfolio with a significant share. On the one hand, the investor seeks returns and thus introduces assets with greater return-generating characteristics into the portfolio at the cost of higher portfolio volatility. On the other hand, however, this broader range of asset classes allows investors to benefit from diversification effects, which might be particularly important given the diverse impacts of particular event types on the risk-to-return ratio for different asset classes. Therefore, although the risk-averse portfolios with "safe assets" might experience lower volatility, they might also expose an investor to the concentration of event risk. In this light, more-diversified portfolios might compensate for event risk through diversification effects. Nevertheless, diversification benefits are likely to be lower during periods of financial market stress [Ming-Yuan, 2007; Bratis et al., 2020].

Fourth, with respect to exposure to particular asset classes, in the majority of optimal portfolios, fixed income instruments dominate, most notably before 2012 (see Figure 2). Thus, this dominant asset class transmits impulses to the portfolio and reflects investors' perceptions of the past environment, and it acts as a hedge for the equity market [Ciner et al., 2013]. Therefore, it is simultaneously expected to be the class that will reflect the reaction to a variety of events the most. Since equities were *ex ante* allocated a relatively small share (even for the above-average risk tolerance portfolio), they are the most likely source of improvement in portfolio returns. Bitcoin's share, in turn, is driven to a great extent by the constraints. The optimization procedure suggests allocating a prominent share of portfolios to this asset class, despite its substantial volatility. This share in the majority of the analyzed period is then limited by exogenous constraints. Thus, our results subscribe to the mixed impact of Bitcoin on portfolio volatility or its returns [Dyhrberg, 2016; Guesmi et al., 2019; Damianov and Elsayed, 2020; Bakry et al., 2021].

Against this background, gold plays a significant role, particularly in long-term portfolios. At this investment horizon, exposure to gold becomes significant for all analyzed generations (in some periods accounting for even half of the portfolio), while most of the short-term portfolios allocate only a meagre share to it. The post-global financial crisis (GFC) environment resulted in short-term portfolios being skewed toward equity exposure and long-term portfolios toward gold. Moreover, the short- and long-term perspectives introduce gold in different periods. Interestingly, portfolios with above-average risk aversion – for both investment horizons – do not allow for any significant exposure to gold. This aversion is evidenced even regardless of gold being recognized as a safe haven asset under some circumstances [in line with the results of Baur and McDermott, 2016; Nguyen et al., 2016; Alkhazali and Zoubi, 2020; Zhang et al., 2021]. According to our analysis, gold as a commodity – albeit a specific one – is characterized by greater price volatility than particularly fixed income. Since our optimization procedure employs this measure as a main risk component, it penalizes the allocation toward gold for an investor who is characterized by above-average risk aversion, that is, below-average volatility. The role of this characteristic in the optimization procedure was particularly strengthened by the market environment, namely, the medium-term underperformance of gold since 2011.

4.2 Adjustments in the optimal portfolio structure

Next, we assess the extent to which events drive the evolution of the optimal portfolio structure. Hence, we analyze shifts in the optimal portfolios of different generations in response to economic and non-economic events from short- and long-term perspectives.

From a short-term perspective (Figure 3A), the youngest generation might be more reactive to events to maintain the optimal portfolio structure. For more risk-averse investors from generations X and Y, reactions to various events focus mainly on slight shifts in exposure to treasuries, regardless of the type of event, while generation Z is expected to introduce more adjustments. The increased focus on US treasuries can be attributed to the role that prudential measures play in the economy, that is, they show the implied risk reduction in the financial industry through, for example, deleveraging. The most significant changes in the portfolio structure for generation Z are also induced by restrictive monetary policy measures (in the US and Eurozone) and the EA's prudential events and defaults.

From a short-term perspective but for less risk-tolerant investors (i.e., below-average risk aversion; see Figure 3, bottom-left panel), the optimal portfolios require more adjustments in response to various events than in the case of more risk-averse investors. As in the previous case, the portfolios of generation Z are the most reactive; thus, we comment on them.

From the short-term perspective, the most significant (±10 p.p.) shifts in the portfolios of generation Z are mostly caused by two non-economic events (terror and virus) and prudential and monetary policy events (mostly in the US). These non-economic events cause a shift from US stocks to European stocks.

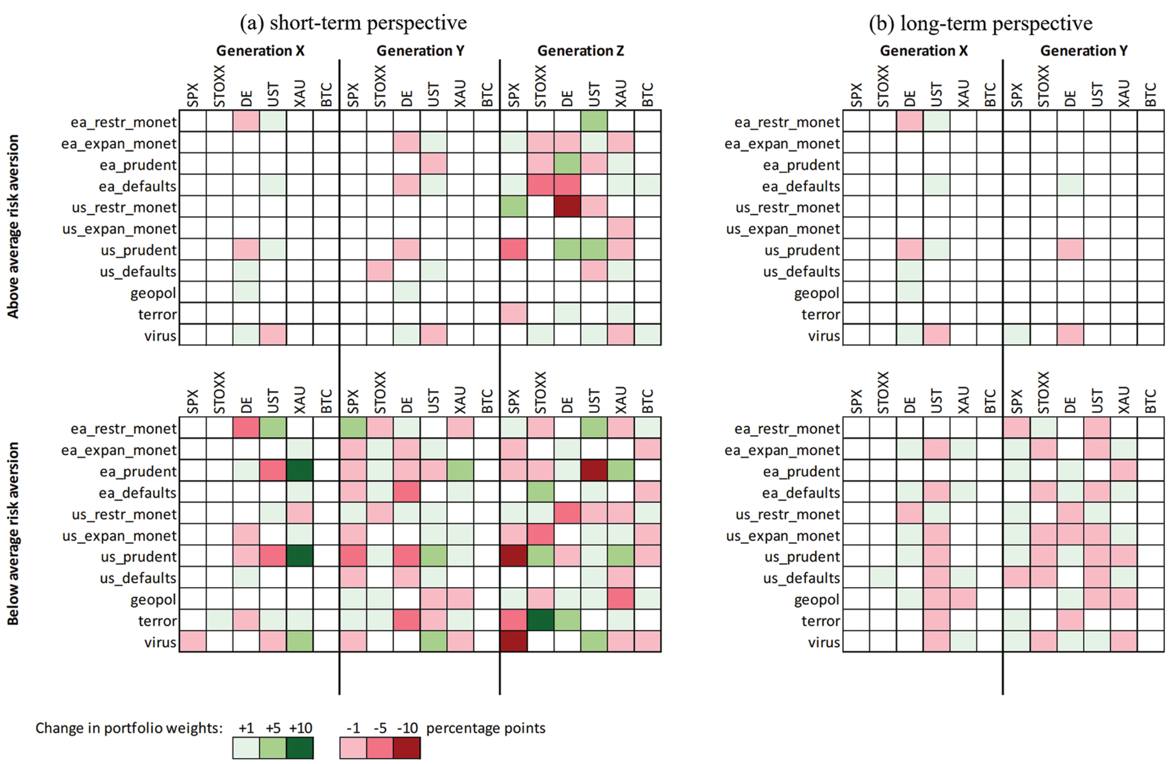


Figure 3. Average change in the optimal portfolio structure in response to the selected events. (A) short-term perspective. (B) long-term perspective.

Note: The graph presents the average change in the optimal portfolio structure due to the occurrence of events belonging to each particular category and reports the results of the regression presented in Section 3.4. The averages of statistically significant relations only (with at least a 5% level of significance). Above-average risk aversion refers to $\lambda = 2$, while below-average risk indicates $\lambda = 7$.

Source: own work. BTC – Bitcoin; DE – DE 10Y Bunds; SPX – S&P500 stock index; STOXX – Eurostoxx 600 stock index; UST – US 10Y Treasuries; XAU – gold.

The impact of prudential events reduces the share of US stocks in return for increased exposure to gold. Moreover, EA prudential actions result in a decrease in US treasuries. Regarding monetary policy measures, for US events, portfolio adjustments are focused on the European market (decreasing stakes), while restrictive policy in the EA shifts portfolios to higher exposures to US treasuries. In this context, the portfolios of generations X and Y are less reactive. In general, while generation Y might shift its portfolio structure to a lesser degree (±5 p.p.) than generation Z, for generation X, only a few events result in significant changes. For treasuries, shifts in generation Y's portfolios should follow economic events, US prudential steps, and EA defaults.

From a long-term perspective (Figure 3B), we consider generations X and Y since, for generation Z, the investment perspective is too short. Generation Z includes investors born typically in early 2000s; thus, their investment activities would have started much later than in case of generations X and Y. Accordingly, given the fact that our sample ends on 2021H1, practical investment experience of generation X is likely no more than several years, which cannot be considered as a long-term perspective on par with generations X and Y. In the case of more risk-averse investors, one can observe only slight shifts in treasuries, confirming that from a long-term perspective, the given event types are of lower importance.

This presentation relied on an *average* reaction to a specific type of event. Importantly, however, a relatively high level of ambiguity of each selected event within a category was observed. For the sake of consistency, we present here results and comments only for more risky investors from generation X (Figure 4). The remaining results are presented in Appendixes 3 (short-term) and 4 (long-term).

Although for Euro Stoxx and Bitcoin, the changes are rather concentrated (approximately ±1–5 p.p.), this is not the case for other assets, the reactions of which to events can differ significantly (by more than ±10 p.p.). A question arises: Which of the events causes the most significant changes? For example, the outbreak of the COVID-19 pandemic shifted portfolios toward gold. Terrorist attacks in Europe (Nice and Berlin in 2016 and London and Manchester in 2017) resulted in other shifts. Among geopolitical events, the most striking are social unrest in Turkey (June 2013) and presidential elections in the US (November 2016). They resulted in shifts between German and US treasuries.

Regarding economic events, the bailout measures approved for Banca Monte dei Paschi di Siena, for example, coincided with expansionary US policy measures, resulting in significant shifts between German (increase) and US treasuries (decrease). Individual events could result in a significant change in the portfolio structure, although, on average, they range between ±10 p.p.

Overall, in the short run, events originating in the US are more important for shifts in the portfolios. Events from the Eurozone cause a change in investors' interest in US assets and gold.

This exercise led us to two key findings: (i) For the majority of event categories, the response of the optimal portfolio structure is rather muted, in particular for long-term portfolios; (ii) a relatively high level of ambiguity was observed for each selected event within a category.

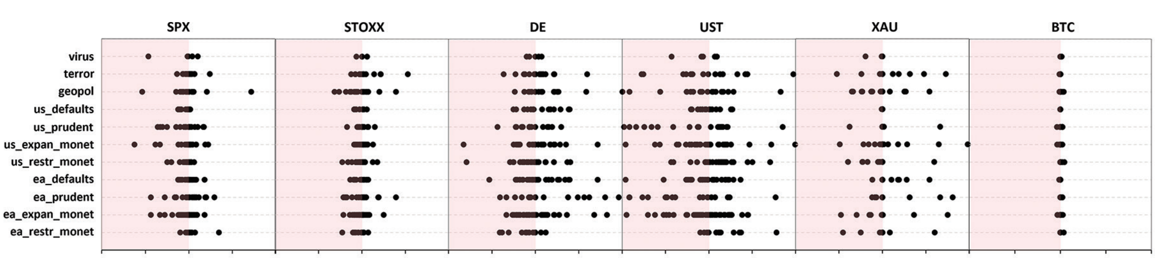


Figure 4. Change in the optimal portfolio structure in response to selected events – the case of the investment portfolio of generation X with below-average risk aversion.
Note: The graph presents the change in the optimal portfolio structure due to the occurrence of each particular event belonging to each particular category. Every dot represents the estimated result of the regression presented in Section 3.4. for each event. The numbers on the horizontal axis indicate the strength of this effect, that is, the percentage-point change in the share of the particular asset in the optimal portfolio.
Source: own work. BTC – Bitcoin; DE – DE 10Y Bunds; SPX – S&P500 stock index; STOXX – Eurostoxx 600 stock index; UST – US 10Y Treasuries; XAU – gold.

These findings are, in our view, consistent with a general characteristic of most of the events mentioned. As these events are not structural in nature, their market effects tend to diminish relatively quickly. Therefore, they may not have a significant impact on the estimates of asset characteristics (such as expected return or covariance). For equities, estimates of expected returns can be affected to a greater extent by, for example, earnings data [Lamont, 1998], investments [Cochrane, 1991], or aggregate consumption or wealth [Lettau and Ludvigson, 2002]. The common element of these factors is that they capture at least the medium term, whereas the range of events we are analyzing is more short term in nature. Therefore, their natural characteristic is that they tend to diminish sooner or later. The events may not be expected to change the perception of expected return or covariance, or the impact may not be worth acting upon. However, even if the events do not affect the expected return, they are reflected in the pricing through the abnormal returns.

4.3 Tactical deviation from an optimal portfolio structure

The purpose of this section is to analyze a general rule for the event category that is purely exogenous in terms of the magnitude of portfolio weighting adjustments. The analysis presented in this section is intended to give the reader an idea of how such a rule (by deviating from the optimal state) has actually worked in the past. The aim is to be able to select an asset class to overweight when a particular event occurs, regardless of whether the event affects expected return estimates.

This step of the analysis is intended to assess whether a deviation from the optimal portfolio, based on the exogenous decisions of an investor, can bring an additional return to the portfolio or – in other words – whether the investor is able to capitalize on the short-term nature of the events. Therefore, we simulated a reaction to an event independent of the estimated optimal portfolio structure and assessed whether it could bring an additional return to the portfolio over that implied by the optimal portfolio. The simulation assumes that the investor chooses one specific asset class and overweights its share in the portfolio when a specific event occurs. Which asset type to select in reaction to which type of events is evaluated through the incremental return that the portfolio should earn in comparison to the optimal structure discussed previously.

This part of the analysis provides additional insights, which are presented in a complex way in Figure 5. Their interpretation can be summarized using a simple example: the red triangle within the EA restrictive monetary policy in the top left-hand panel of Figure 5. The interpretation of this point can be formulated as follows: "*The decision to overweight gold in response to a restrictive monetary policy decision adds ~1 p.p. of additional annual return to the portfolio of the generation X investor, who is characterised by above-average risk aversion.*"

Considering the broad picture, we found that, first, an exogenous change in exposure in response to a specific event could affect the return profile across all of the generations and for both the short- and long-term perspectives (see Figure 5). In other words, the reactions to all categories of events can bring an additional return to a portfolio; however, an inappropriate selection of assets might also result in incremental loss in the portfolio across all categories. This outcome in particular means that none of the events creates an extraordinary opportunity to generate profit, regardless of the asset selected for the portfolio.

Second, the return-generating ability of a selected portfolio adjustment generally seems to be consistent across many original portfolios. Most notably, as long as the structure of the portfolio remains within a given investment style, the exogenous decision to overweight one selected asset seems to benefit the portfolios across types and investment horizons.

Third, the incremental portfolio returns are relatively moderate since they usually do not exceed ±4 percentage points. With a decrease in risk aversion (hence an increase in risk tolerance), the additional gain/loss in response to an event usually increases. Most notably, different types of events call for different adjustments to the portfolio structure to generate incremental gain. Thus, the selection of an asset that should be overweighted in comparison to the optimal portfolio should rely on the type of event at hand.

Nevertheless, comparing this step with the previous one (Section 4.2), exogenous portfolio adjustments reduce the ambiguity of the reactions to events within each category. As stated previously, the optimal portfolio in some cases requires different responses for similar events in each category. This step, however,

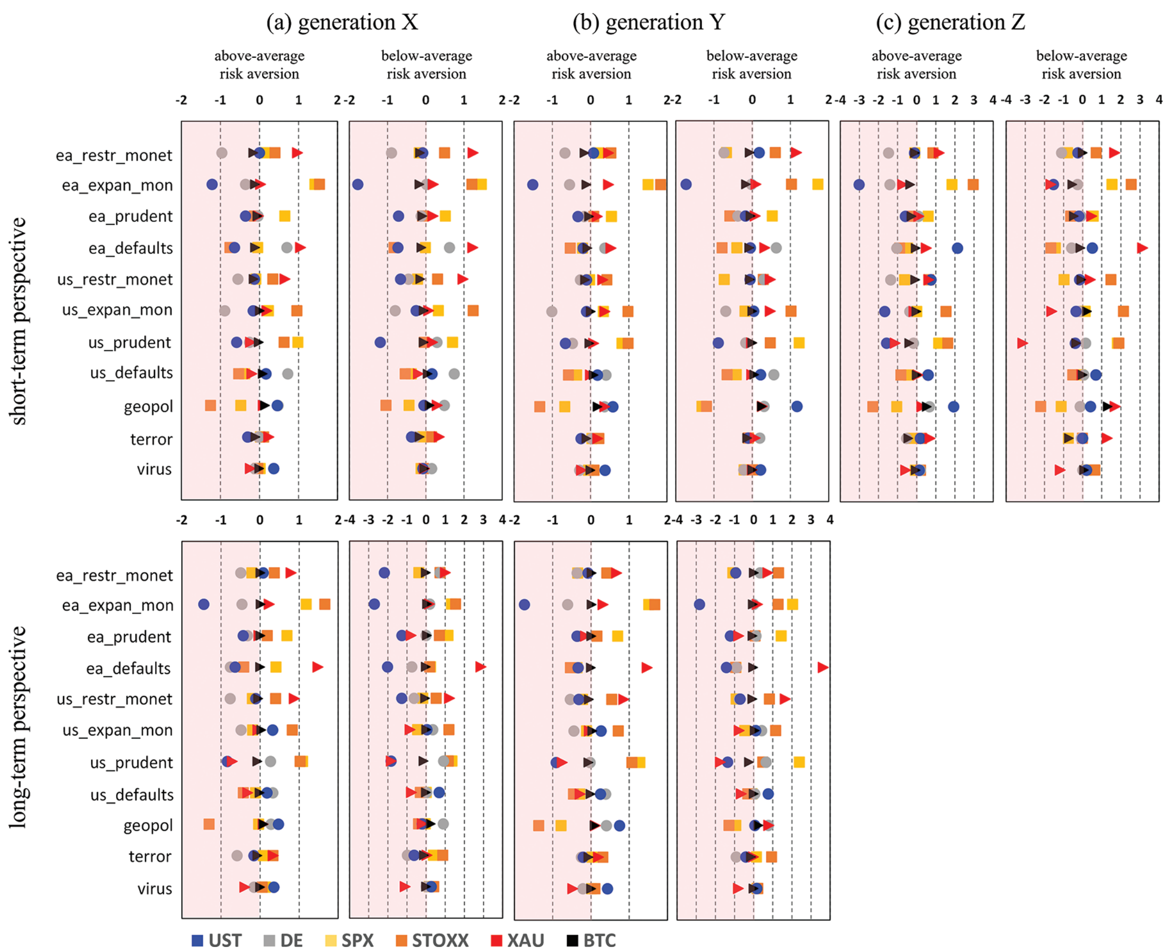


Figure 5. Incremental annual return due to the change in exposure in response to events. The horizontal axis reports the size of the incremental returns. The incremental return refers to the additional return that the portfolio should generate over the investment horizon (i.e., in the short or long term) relative to the portfolio with the optimal structure. Each symbol refers to an incremental return which can be generated by overweighting one selected asset on the day of the event occurrence by the root of its original weighting (see the methodology section for details). For an interpretation example, consider the red triangle within the EA restrictive monetary policy in the top left-hand panel – the decision to overweight gold in response to restrictive monetary policy decision adds on average ~1 p.p. of additional annual return to the short-term portfolio of a generation X investor characterized by above-average risk aversion.
Source: own work. BTC – Bitcoin. DE – DE 10Y Bunds; SPX – S&P500 stock index; STOXX – Eurostoxx 600 stock index; UST – US 10Y Treasuries; XAU – gold.

assumes that within each group of events, investors' reaction is fully coherent. Such decision-making "comfort", in fact, results in incremental returns being relatively muted.

We find that expansionary monetary policy generates the greatest potential for incremental returns across all of the analyzed events and for all investor profiles. This finding is likely a consequence of significant global spillovers caused by monetary policy decisions [Georgiadis, 2016; Georgiadis and Gräb, 2016]. The return is typically introduced into the portfolio by overweighting the equity market. In the case of defensive portfolios (i.e., those for above-average risk aversion), this additional exposure to equity is relatively small since the portfolio must be kept consistent with the investor's profile. However, the incremental return over the optimal portfolio that such an action generates is relatively comparable to that originating from a similar action undertaken in the aggressive portfolios (which by definition need a greater change in equity exposure).

In response to the restrictive monetary policy shock, rising exposure to gold usually brings the greatest incremental return for all types of investors. Moreover, as in the previous case, equities can also be perceived as enhancing portfolio returns in restrictive monetary policy environments, although to a relatively smaller extent. This finding might seem to be counterintuitive since restrictive monetary policy results in rising real interest rates and should exert downward pressure on gold (as demand for inflation hedge weakens) and equities (throughout higher marginal cost of market funding). In line with this expectation, we confirm that the optimal portfolio reacts by lowering exposure to these two assets in a restrictive monetary policy environment (see, e.g., Figure 4). In this section, however, we find that reversing this action throughout a tactical deviation from the optimal portfolio can, in fact, enhance the portfolio return. Empirical studies have confirmed that the relation of gold and interest rates is strong only in the recessionary phase [e.g., Apergis et al., 2019] and that gold loses its inflation hedging characteristics during periods of low inflation [Zhu et al., 2018], which is the case for the period in our study. In this context, we claim that restrictive monetary policy can be seen as an opportunity to build up exposure to gold without introducing drawdown risk into the portfolio. Obviously, this outcome might be only a period-specific effect since expansionary monetary policy significantly dominated our sample; thus, the effects of restrictive monetary action might be understated.

Given this scenario, the return that arises from the fixed-income part of the portfolio and its adjustment to events should also be analyzed with respect to the role of the investment horizon. Since the market reaction to events is usually relatively short- to medium-lived, an investor in the fixed-income market remains in the space when the pricing effect of interest rate changes outweighs the cash flow effect. Therefore, the short-term portfolio usually generates a loss while increasing exposure to the fixed-income market in response to restrictive monetary policy. However, our study confirms that as the horizon changes from a short to long term or as risk aversion decreases, the incremental loss also originates from increased exposure to fixed income in response to expansionary monetary policy. Notably, the aforementioned findings for monetary policy events are comparable for both the US and EA in terms of structure. When considering the incremental size of return/loss due to the action, however, it is greater in the latter case. This finding might not necessarily mean that the monetary policy of the ECB has a greater impact on markets and thus affects the analyzed portfolios to a greater extent. This outcome might partly arise from US monetary policy being accorded greater consideration at the level of the optimal portfolio. Consequently, the tactical deviation from this structure does not result in significant incremental returns.

Addressing the second subset of economic events – namely, the micro- and macroprudential policies, as well as defaults – we find that their return-generating ability calls for a comparable response to that of expansionary and restrictive monetary policy, respectively. Specifically, to generate incremental returns in response to a prudential action – similar to expansionary monetary policy – the equity market should be overweighted in the portfolio. Moreover, this view is consistent for the short- and long-term investment horizons. However, at both horizons, such an action in response to US prudential events enhances portfolio returns to a greater extent than in the case of responses to EA prudential events. When considering default, return enhancement characteristics can be introduced by overweighting gold, particularly over the long-term investment horizon (EA market) or fixed income (US market). Unlike the prudential action, the response to default episodes allows us to enhance portfolio returns to a greater extent when originating from the EA market.

In contrast to this, both the incremental gains and losses that arise due to the reaction to non-economic events are relatively small compared to economic ones. In particular, increased exposure to fixed income and/or gold protects against the effects of geopolitical events since these assets add some incremental return to the portfolio, while overweighting equities results in a loss for all investor types. The smallest incremental return in this case can arise from the investment approach itself. First, an optimal portfolio should mitigate the return effect of such types of events; second, the market reaction to them, particularly that of major asset classes, could be relatively short-lived with a strong tendency to be reversed, which is derivative of the minor and short-lived impacts that terror attacks, for example, exert on the stock market [Markoulis and Katsikides, 2020]. As a result, the overall value added in such an environment is meagre.

The perspectives of incremental returns due to changes in asset exposure for short- and long-term portfolios share a range of similarities. However, the introduction of crude oil into the portfolio (see the results in Appendix 5) starts to significantly differentiate the incremental returns of these two types of investing. Such a strong differentiation was not evidenced earlier, that is, for a comparable portfolio structure that did not include this commodity. From the short-term perspective, the presence of crude oil in the portfolio significantly reduces the return opportunity that can be generated due to the reaction to events in most cases, with the strongest effect being observed in the portfolio of generation Y. In other words, if crude oil is introduced into the portfolio, overweighting any other asset class in response to events results in weaker incremental returns (generations X and Z) or even incremental losses (generation Y) compared with portfolios without this commodity. In certain cases, crude oil generates an opportunity to realize greater gains; however, this opportunity is relatively rare (evidenced only for two types of events, e.g., prudential action and US expansionary monetary policy). Therefore, crude oil can be perceived as an asset class that introduces more event risk than opportunities into the portfolio due to the reactions to some episodes. We thus concur with the findings of Raza et al. [2016] that oil volatilities have a negative impact on stock markets in both the short and long terms. However, we stand partly in contrast to Martín-Barragán et al. [2015], who showed the diversification benefits of oil in non-crisis times, and El Hedi Arouri et al. [2011], who argued that oil is a dynamic and valuable asset class that helps improve risk-adjusted performance.

5 Conclusions

We assessed how investors from various generations might adjust their portfolios in reaction to important market-moving events, using daily financial market data covering 2000-2021H1 for 7 major asset types and 11 types of events (financial and non-financial) in 10 portfolio variants. Since various events can generate market spillovers, we examined the process of portfolio selection and its optimization from a contagion perspective.

Overall, we confirm that the long-term investment perspective is characterized by a visibly smaller frequency of shifts in the portfolio structure. In the short term, greater variability in portfolios is observed, especially for younger generations. We find that events originating in the US are more important for shifts in the portfolios and that the events from the EA change investors' preferences toward US assets and gold. For younger generations and less risk-averse investors, a broader range of assets is introduced into their portfolios with significant shares. In optimal portfolios across generations, fixed-income instruments dominate, especially before 2012, when the sovereign debt crisis in the EA and an ultra-expansionary monetary policy environment started to shift investors' preferences away from fixed income. Nevertheless, fixed-income instruments act as a hedge for the equity market and transmit impulses into the portfolio in response to most events. Until 2012, the implied structure of the short-term portfolio was characterized by greater stability for all generations and both risk tolerance levels.

Importantly, gold plays a significant role in the long-term portfolios of generations X and Y; however, for more risk-averse investors over both investment horizons, exposure to gold is not significant, which could be attributed to its medium-term underperformance. We also find a mixed impact of Bitcoin, which is an important asset class for generation Z, on a portfolio's volatility or its returns.

We also find that a response to a given type of event might affect the return profiles across all generations and for both investment horizons. The proper reaction to all types of events could bring an additional return that increases with risk tolerance but remains relatively muted, while an inappropriate selection of assets could result in incremental loss. This finding means that none of the event types *per se* creates an extraordinary opportunity to increase returns, regardless of asset selection. The decision of which assets should be overweighted (commonly equities) in the portfolio should be based on the type of event. Our results also indicate that the introduction of Brent oil brings more risks than opportunities for all generations. Therefore, portfolios without Brent might be treated as more predictable.

We claim that economic events exhibit greater potential for enhancing portfolio incremental returns. The most attractive from a return perspective are expansionary monetary policy events (in the US and EA) for all investment profiles. They should result in an increased share of equities in portfolios. In the case of restrictive monetary policy events, the highest incremental return is offered by gold for all types of investors. Equities might also bring an additional return in this case but to a relatively smaller extent. Alongside monetary policy measures, fixed-income instruments could bring losses in the short (restrictive measures) and long terms and for more risky investors (expansionary measures). In the case of non-economic events, the potential for enhancing returns is limited. Higher exposure to fixed income and gold as safe havens reduces drawdowns in the case of geopolitical events as equity exposure brings losses.

This study is not free from limitations. First, we focused on seven highly liquid global asset classes, so our results provide guidelines for investors targeted at well-developed and highly liquid markets. Guidelines for investors oriented toward local markets require additional studies. Second, the investment profiles of investors from generations X, Y, and Z were based on the literature and experts' judgment. The identification of actual profiles of all generations would require conducting a global, representative, interdisciplinary study, which could be a direction for future research. Third, we did not explore behavioral aspects of the investment style of generation X vs. generations Y and Z, called "digital natives," whose reactions to various events could be prompter and more prone to herding due to the use of, for example, digital platforms. Finally, as in all asset allocation problems, past reactions to market events within an optimal portfolio might not be indicative of future results.

In terms of possible directions for further studies on the topic covered in this article, the increasing role of machine learning techniques in finance [see, among others, Rasekhschaffe and Jones, 2019; Doumpos, et al., 2022] – and in portfolio optimization problems – should be noted. Some studies have shown that machine learning techniques enable a more precise and probably more efficient identification of the impact of a series of events on market pricing with a higher frequency of data and outperform classic MVO [see Ban et al., 2018; Chen et al., 2021; Ma et al., 2021; Pinelis and Ruppert, 2022]. In the context of this study, it could also be useful to identify patterns of appropriate relationships to selected events using deep learning techniques and to contrast the results with those of our approach. From the perspective of the optimization problem, we also see scope for implementing these methods to address the problems of non-linearities across assets. Finally, as the expected return characteristics of asset classes remain crucial to estimate, machine learning techniques can be used to complement the estimation methods.

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Appendix

Appendix 1. Correlation matrix between daily returns of selected asset classes over the long term (2000-2021H1)

	Eurostoxx 600	S&P500	Gold	Bitcoin	Brent	DE 10Y	US 10Y
Eurostoxx 600	1						
S&P500	0.581	1					
Gold	−0.040	−0.028	1				
Bitcoin	0.064	0.045	0.039	1			
Oil	0.249	0.235	0.173	0.057	1		
DE 10Y	0.394	0.251	−0.129	−0.005	0.127	1	
US 10Y	0.303	0.398	−0.126	−0.001	0.153	0.553	1

Note: The correlations between daily returns on most asset classes refer to price correlations, excluding bonds for which we rely on yields instead of prices.
Source: own work.

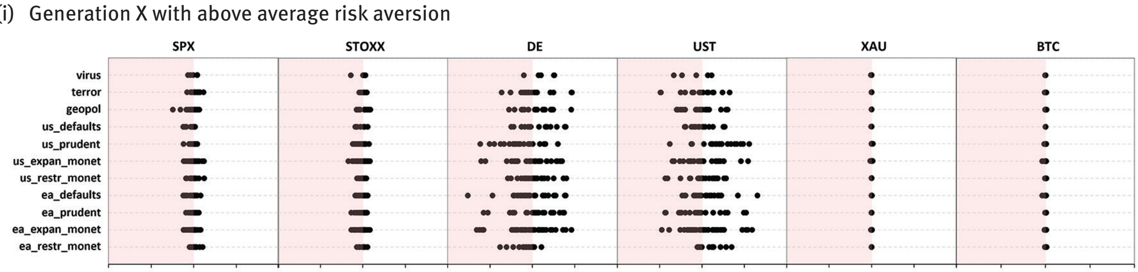
Appendix 2. Initial structure of portfolios of generation X, Y, Z based on mini-Delphi

	Type of asset	Gen. X	Gen. Y	Gen. Z
With Brent Crude Oil	Gold (%)	14.5	8.5	2.2
	Bitcoin (%)	0.8	5.0	18.5
	10Y Bunds (%)	24.8	11.0	3.9
	US Treasuries (10Y) (%)	29.0	15.0	6.9
	EuroStoxx 600 (%)	10.5	20.5	28.0
	S&P 500 (%)	13.5	29.5	33.0
	Brent (%)	6.9	10.5	7.5
Without Brent Crude Oil	Gold (%)	17.0	14.0	5.2
	Bitcoin (%)	1.2	7.2	25.0
	10Y Bunds (%)	24.8	11.0	3.9
	US Treasuries (10Y) (%)	29.0	15.0	6.9
	EuroStoxx 600 (%)	11.5	21.9	27.0
	S&P 500 (%)	16.5	30.9	32.0

Source: own work.

Appendix 3. Change in the optimal portfolio structure in response to selected events – short-term perspective

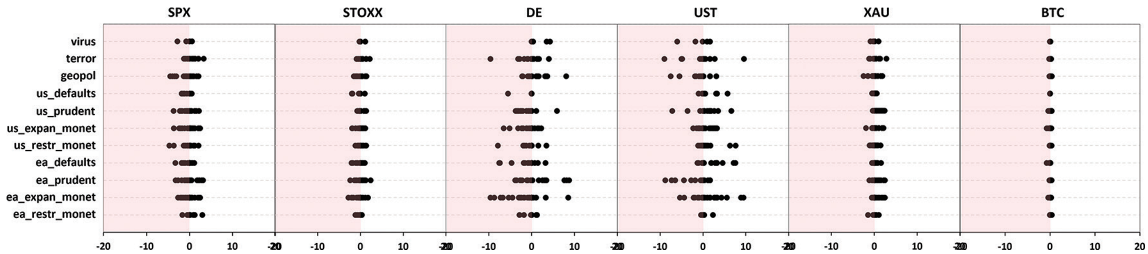
(i) Generation X with above average risk aversion



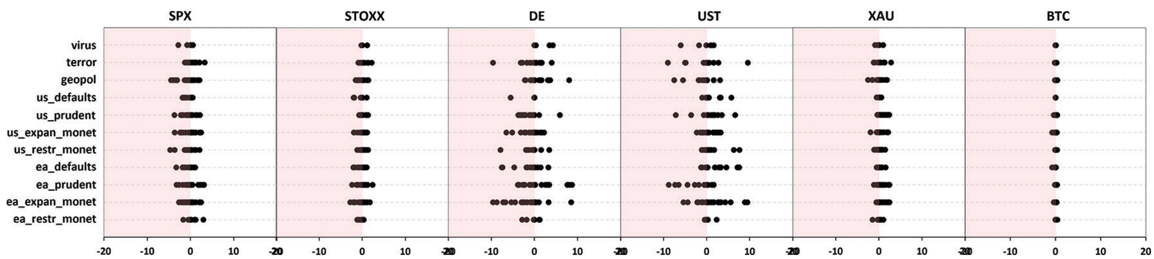
(*Continued*)

Continued

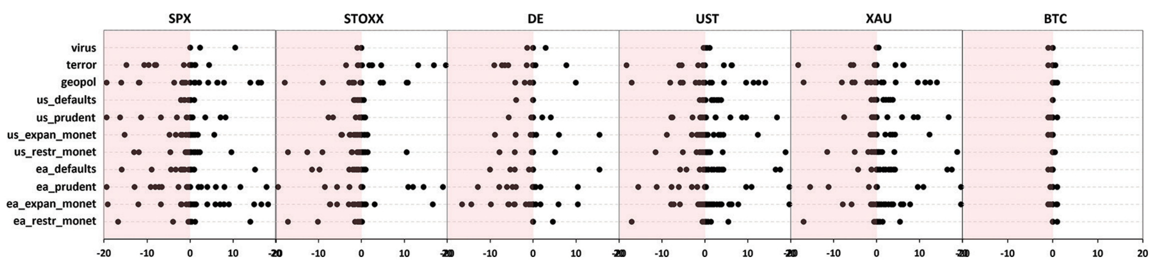
(ii) Generation X with below average risk aversion



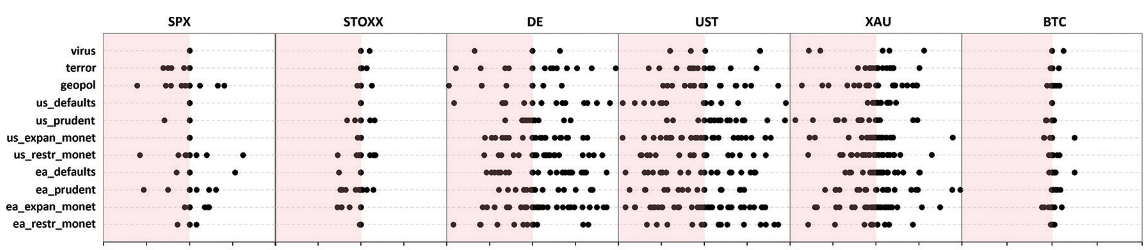
(iii) Generation Y with above-average risk aversion



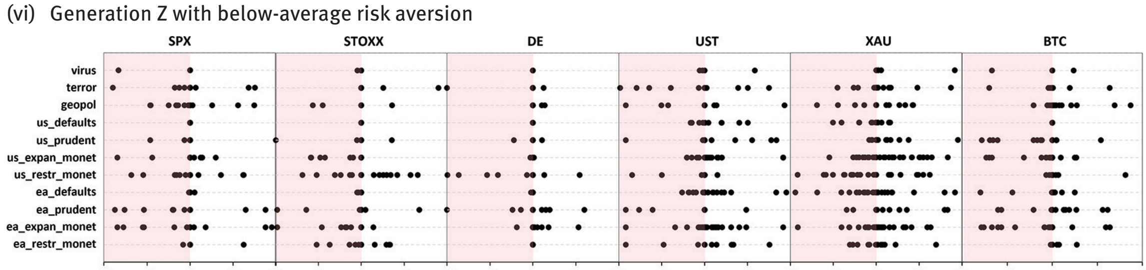
(iv) Generation Y with below-average risk aversion



(v) Generation Z with above-average risk aversion



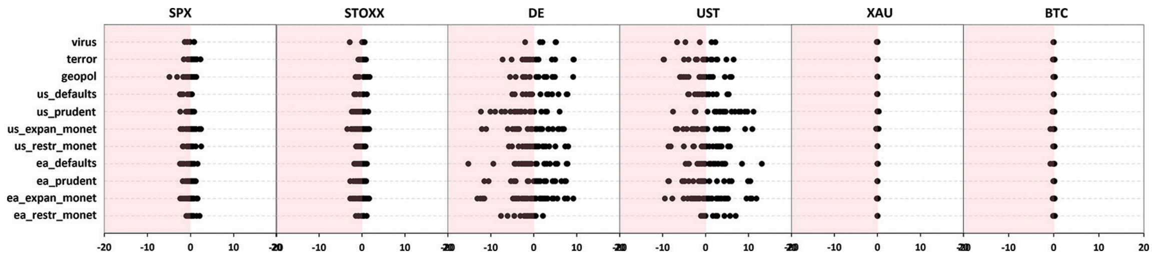
(vi) Generation Z with below-average risk aversion



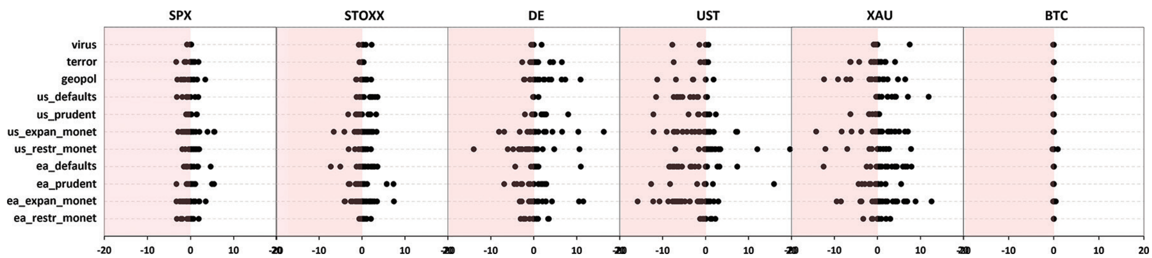
Source: own work.

Appendix 4. Change in the optimal portfolio structure in response to selected events – long-term perspective

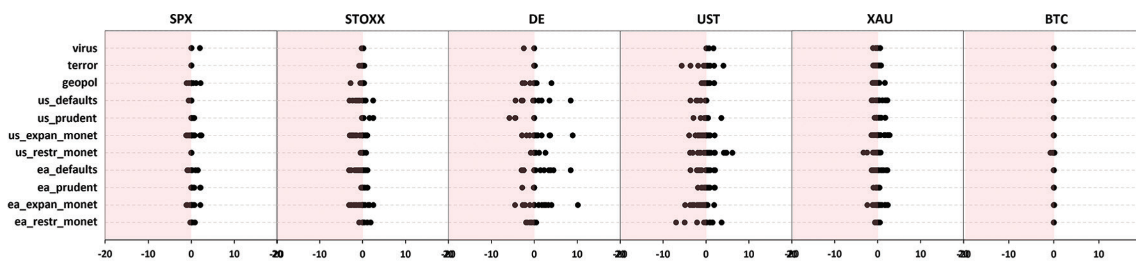
(i) Generation X with above-average risk aversion



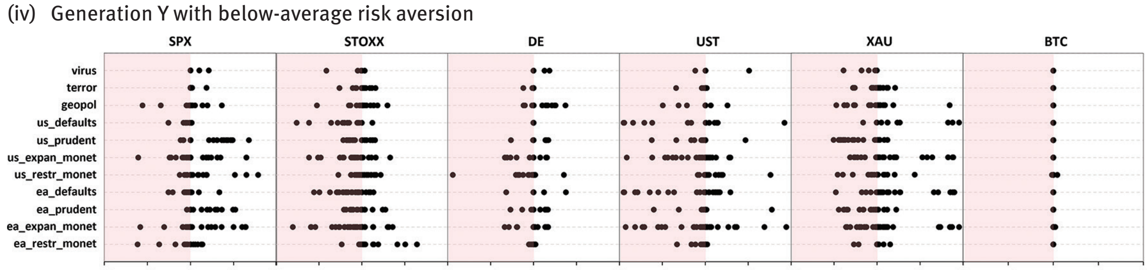
(ii) Generation X with below-average risk aversion



(iii) Generation Y with above-average risk aversion

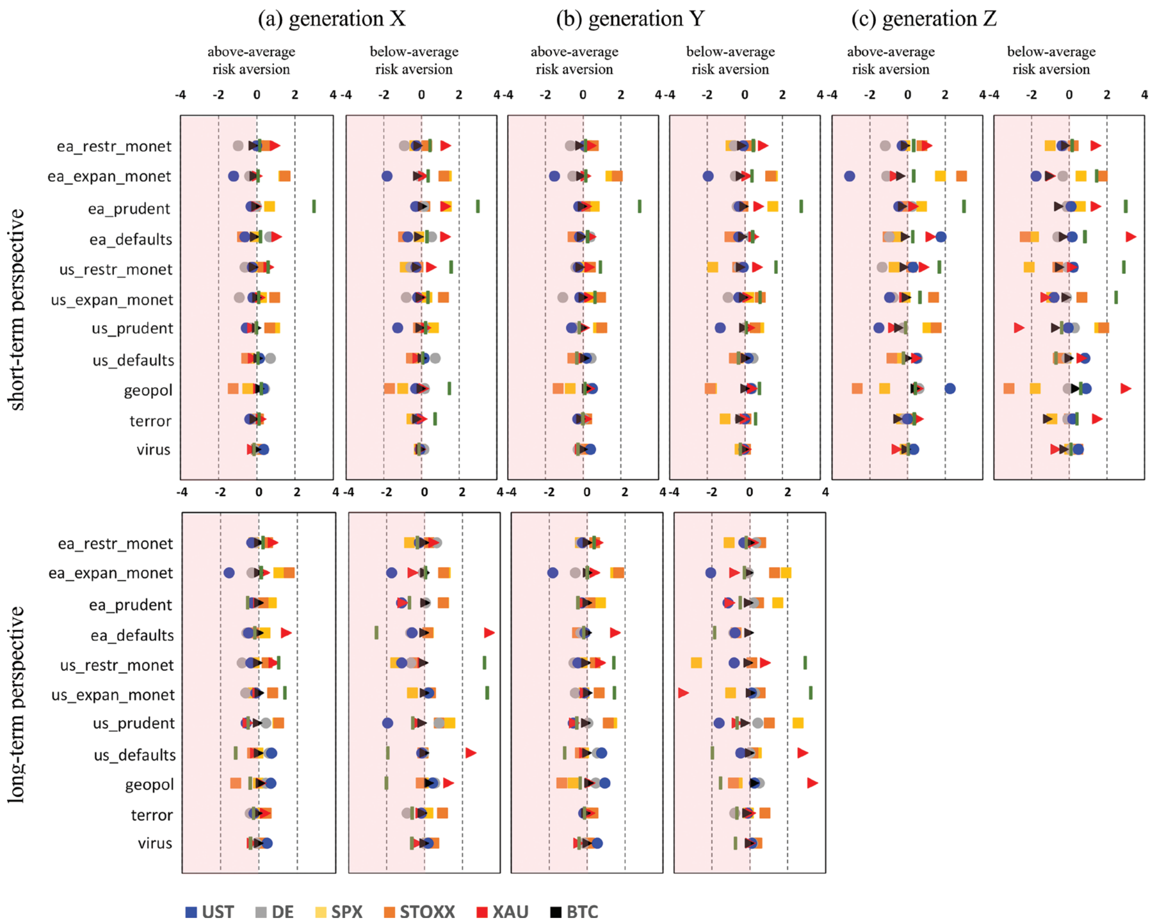


(iv) Generation Y with below-average risk aversion



Source: own work.

Appendix 5. The incremental annual return due to the change in exposure in response to events – a case of a portfolio with crude oil exposure



Note: UST – US 10Y Treasuries; DE – DE 10Y Bunds; SPX – S&P500 stock index; STOXX – Eurostoxx 600 stock index; XAU – gold; BTC – Bitcoin.

Each symbol refers to an incremental return over the optimal portfolio, which can be generated by overweighting one selected asset on the day of the event occurrence by the root of its original weighting (see the methodology section for details).

Source: own work.