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ARTICLE

Ten Years After the 2008 Crisis: Has Risk Aversion Won?

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ABSTRACT

The aim of this paper is to investigate the performance of low-volatility portfolio strategies representing risk aversion after the 2008 global financial crisis. Five investment portfolios were built by taking into consideration the weight distribution criteria defined by the inverse of the standard deviation of assets, the natural logarithm and exponential of these values, as well as the minimum variance and tangent portfolios, based on the S&P 500 futures index, dollar futures index, US government long-term bond (10-year Treasury Bond) and gold futures. The design of the strategies used both twelve- and thirty-month rolling windows for the standard deviation and conditional volatility estimates. Mean return of portfolio, risk through standard deviation, Sharpe index, and risk-adjusted return were calculated for evaluation purposes. Results have evidenced that, together, risk-based portfolios using 12-month rolling window or conditional volatility were superior to the tangent portfolio, as well as that the minimum variance portfolio was competitive to other alternatives. The main contribution of the current study lies in the fact that risk aversion was relevant to portfolios' performance in the post-crisis period.

KEYWORDS

Financial Crises, Portfolios, Risk Aversion, Decision-Making

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1. INTRODUCTION

The financial crisis that emerged in late 2007 disrupted the theoretical paradigms that substantiated the economic policies of recent years. This crisis forced theorists and managers to question and doubt the free market ideology (Cassidy, 2011). The traditional way macroeconomists explain economic fluctuations has mostly ignored the important role played by risk aversion in the process to help better understand business cycles.

This study takes into consideration both the evidence-based theory and studies about the cycle of financial crises defended by Zanalda (2015), Keynes (1936), Schumpeter (1934), Fisher (1933) and Minsky (1986, 1992). It also takes into account studies conducted by Kindleberger and Aliber (2011) and Dünhaupt et al. (2016), who investigated financial crises, and whose conclusions were in compliance with the crisis cycle theory. However, this paper goes beyond these theorists, because we herein advocate that investors' non-rational behavior, political interference, information asymmetry and credit systems' unreliability were relevant factors for the 2008 subprime crisis. According to the aforementioned authors, the policies associated with economy stagnation, wage squeeze, and wealth concentration in the hands of few destabilizes the economy and generates financial crises.

Risk aversion plays a key role in the process to better understand the behavior of different economic periods, mainly those of a economic recession. Individual preferences are often complex and influenced by a whole variety of economic, political, human, or even cultural factors, which have promoted changes in macroeconomic and financial theories that have acknowledged the fundamental role played by risk aversion in economic cycles and evidenced the countercyclical association between risk preferences and economic period (Díaz & Esparcia, 2019).

The aim of the current study was to analyze the performance of low volatility portfolios in the post-subprime crisis period. More than 10 years after the crisis that has affected several economies worldwide, it is worth investigating whether risk aversion - which is reflected in weight allocation in investment portfolios based on low volatility strategies - provided gains to investors.

Accordingly, the performance of five different portfolios was investigated. The first three portfolios used the inverse of standard deviation as weight distribution criterion (ratio strategy), as well as the natural logarithm and exponential of these values (natural logarithm and exponential weight strategies, respectively). The last two portfolios represented the minimum variance portfolio (MVP) and the tangent portfolio (TP), based on the Modern Portfolio Theory (MPT) developed by Markowitz (1952). Twelve- and thirty-month rolling windows, as well as conditional volatility estimates based on information deriving from the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, were used for this purpose.

Four globally-known assets were selected as the financial assets to build the portfolios, namely: the S&P 500 futures index, wherein S&P 500 is the main American stock market indicator; dollar index futures (dollar index), which is a futures contract representing the US dollar variation relative to a basket of global currencies; the long-term bond (10 years) issued by the US treasury, which represents the fixed income class and the safest investment; and gold futures contract (gold) based on the price offset for one ounce of gold – it is a traditional commodity in the financial market.

The herein reported results have suggested that, collectively, the construction of portfolios based on risks by using a standard deviation with a 12-month window, or conditional volatility, performed better than the tangent portfolio during the analyzed post-subprime crisis period. In addition, they have indicated the competitiveness of the minimum variance portfolio, which is widely adopted in the literature, in comparison to other proposals. Findings associated with the 30-month window point towards an initially significant risk-adjusted return that did not remain in the robustness test. Furthermore, there were portfolios outperforming the Sharpe ratio of individual assets. Altogether, risk aversion in decision-making, as investment, was beneficial for investors.

Thus, the current study makes at least three clear contributions, namely: i) it provides evidence favoring low volatility portfolios, whose results showed their better performance in comparison to that of benchmarks themselves, which corroborates the study by Blitz and Van Vliet (2007), who addressed the potential of this strategy type; ii) it addresses the post-crisis period, which enabled identifying whether risk aversion was relevant to portfolios' performance; iii) it brings useful conclusions for investors' decision-making processes, since risk aversion is an easy-to-implement strategy.

2. THEORETICAL FRAMEWORK

2.1. Crisis – Global financial crises

Amaral (2009) points out that crises are historically permanent. According to the aforementioned author, financial crises have been around for many years or even for several centuries - the first recorded crisis dates back to 1618. Indebtedness – which is the very core of any financial crisis - is one of the oldest financial management strategies practiced since Babylon (Fergusson, 2009). Banking institutions started their activities to manage public and private debt funds and, since then, the subsequent crises have always derived from banks' participation in them. Indebtedness can be summarized as social strategy used to overcome the frustration posed by material limitations for goals' achievement (Amaral, 2009).

Several capitalist crises were created by the credit-expansion alternating movement and by the subsequent credit contraction and they were listed by Kindleberger and Aliber (2011), whose report started in the Kipper- und Wipperzeit crisis, in the Holy Roman Empire; and followed the 1636-1637 "tulip mania", in the Netherlands; the Mississippi and South Sea Companies' bubbles, in 1719-1720; the Japanese crisis, in the 1990s; the Asian crisis, in 1997-1999; the Scandinavian crises, in early 1990s; the dotcom crisis in the early 21st century; and the 2008 global financial crisis (GFC).

According to Minsky (1986), financial systems are unstable, weak, and prone to crisis due to instable credit supply, which is in compliance with his financial instability hypothesis. According to Zanalda (2015), world economy setbacks have been having strong impact on Stock Exchanges, as well as affecting the lives of millions of investors. These setbacks, such as financial crises, have affected investors' behavior, since sometimes they push these professionals away from the financial market and sometimes they bring them closer to it – this behavior either evidences investors' trust in the financial market or lack of it. According to Kindleberger and Aliber (2011), investors' non-rational behavior, poor political management, information asymmetry, and credit systems' unreliability have contributed to the emergence of financial crises.

Financial crises are often associated with negative effects on financial markets. However, Vieito et al. (2016) concluded that the 2008 global financial crisis (GFC) had some positive impact on G7 indices (Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States). Overall, GFC resulted in more efficient and mature markets, and it confirmed that crises can also have positive impact on equity markets. The study by Vieito et al. (2016) provided relevant information for investors and market regulators, since it has evidenced that post-crisis investors often invest in the most stable assets, as well as in safer fundamentals, in order to reduce both volatility and systemic risk – this behavior shows risk aversion after the global financial crisis.

Theorists focus on studies aimed at determining, understanding, and simplifying the way individuals make decisions that have impact on markets. To do so, it is essential to analyze factors substantiating individuals' choices within decision-making processes, since it can open new windows for better meeting financial market investors' expectations.

2.2. Decision-making process

Decision-making takes place through multiple processes emerging on the continuum between the rational and the non-rational (Foucault, 1994; Machado, 2006). Immersed in a collectively constructed social-historical context, individuals live based on given dynamics that comprise their human dimensions (physical, emotional, cognitive, and spiritual structures), as well as the collective/social group they are part of. This interaction between individual and social aspects enables people to produce typifications, to build their preferences, to give meaning to everyday life, to develop values and attitudes, and to make decisions. It all results from interactions taking place in multiple realities that are both learned and shared through socialization processes (Berger & Luckman, 1978).

Financial theories have failed to explain crises taking place in stock markets, as well as to understand the reasons why markets crash. These disruptions or anomalies emerge from time to time in the form of stock market bubbles capable of triggering financial crises, market overreaction or underreaction, momentum, and reversals. Based on this paradigm, behavioral finance started to evolve as an attempt to provide behavioral explanations for these anomalies (Kapoor & Prosad, 2017). This behavioral topic in finance takes two different aspects as objects of study, namely: individual investors and the whole financial market. Psychosocial features, such as gender, age, cognitive abilities, skills, moral values, and knowledge, affect the decisions made by both individuals and groups (Nofsinger & Varma, 2014), a fact that leads to cognitive and emotional biases that, in their turn, can lead to judgment errors and to poor choices.

The contemporary financial market environment knows no borders or barriers, and it becomes unregulated and volatile because it is based on individual projects with collective effects (Castells et al., 2013). Markets merge and significantly influence the daily lives of different cultures worldwide. From this perspective, this large organizational environment - which encompasses peculiar beliefs, routines, and rituals that identify it as cultural life, with its own identity - becomes dangerous due to the weakness of a globalized and interdependent network (Morgan, 2006).

According to Taffler and Tucket (2016) and Darren Duxbury et al. (2020), basically, financial markets are social environments where individuals engage with one another to set asset prices that reflect opinions and expectations about the future. This factor makes the environment inherently unpredictable and unknowable, and it generates emotional responses at both neurological and psychological level - these emotions mainly comprise anxiety, which leads to stress. Making investments depends on making judgments about the availability of information to solve two different uncertainty orders, namely: the one caused by unavoidable information asymmetries at decision-making time and the one determined by the fact that the future is unknown and susceptible to unexpected events.

The investment process means investors' engagement in a necessarily ambivalent emotional attachment (whether unconsciously, or not) to something that can easily let them down. According to Forgas and Tan (2013), negative feelings can be linked to greater social concern and to a given sense of justice, whereas positive emotions can be associated with selfishness and with the expectation of one's own interests.

Psychological prejudices/concepts are evidenced in individuals' behavior based on which they can make suboptimal decisions. These decisions, on a large scale, are known as market anomalies and they can lead to market disruptions. Because these anomalies have devastating effects on individual financial health, as well as on the financial health of the entire economy, they must be avoided.

2.3. Risk aversion

According to Bazerman (1994) and Kahneman et al. (1982), uncertainty lies on the absolute lack of any indication of likelihood to estimate the expected value of a given event. Risk is the measure of uncertainty enabling estimates on the likelihood of expected events. The likely behaviors towards risk comprise risk aversion - when the decision is made for the lowest risk - and risk propensity – when a decision is made for the alternative showing the greatest expected benefit, even if it is the one with the highest risk. Decision is always made for the alternative which shows the lowest expected risk and the greatest benefit. In other words, the alternative showing the greatest expected benefit is always the chosen one, whenever different alternatives present the same risk; whereas the one with the lowest risk is always chosen, whenever different alternatives present the same expected benefit.

The study conducted by psychologists Amos Tversky and Daniel Kahneman has introduced the concept of Prospect Theory for the analysis of decision-making under risk (Kahneman & Tversky, 1979). The value function in the Prospect Theory replaces the utility function in the Expected Utility Theory, which estimates the "value" placed by individuals on their gains or losses. The aforementioned function shows that some gains or losses are felt at higher intensity than others. Moreover, sometimes the pain associated with a given loss is stronger than the happiness about an equivalent amount of gain. This phenomenon is known as loss aversion since one's losses are greater than its gains. The Prospect theory has three main propositions (Kahneman & Tversky, 1979): according to the first one, individuals do not show a standard risk attitude, a fact that gives the value function an S shape, i.e., concave for gains and convex for losses. The second proposition suggests that individuals shall calculate the value of the likely gain based on a reference point, which is often the *status quo* or current wealth level, deciding their gain or loss, from a given perspective. The third proposition advocates that losses are greater than gains (loss aversion). This trend is observed in all individuals, since the desire to avoid losses is much greater than to seek gains. This theory is seen as seminal work in behavioral finance, and it forms the underlying basis of biases such as loss aversion, framing, and the disposition effect.

The incidence of errors and biases of thinking result from suppressing the logic that favors the establishment of a vicious circle, since, oftentimes, results of judgments based on simplifying rules are satisfactory for individuals, a fact that enables the use of frequent mental shortcuts and, therefore, turns mistakes and biases into a constant factor. Cognitive failures have a strong impact on the stock market—representativeness, availability, and anchoring heuristics account for overreactions and under-reactions in this market. Over-optimism and pessimism are the most common emotional biases accounting for volatility in trading volume and for speculative bubbles (Prosad et al., 2015).

According to Loewenstein et al. (2001), individuals interact with risk perspective in two different ways: by cognitively assessing risk and by emotionally reacting to it. Thus, cognition and emotion are interrelated, since cognitive assessments generate emotions that, in their turn, affect cognitive assessments. Baker and Ricciardi (2014) have pointed out that expert and mature investors know that success depends on their ability to control emotions and to overcome prejudices. This ability helps them to avoid typical overconfidence-related mistakes made by new investors. Based on the conclusion by Byder et al. (2019), female and less experienced self-employed investors show significant reaction after a given critical event.

2.4. Low Volatility Portfolios

The study by Markowitz (1952) has substantiated the Modern Portfolio Theory (MPT), which introduced the mean-variance approach and emphasized the important role played by diversification in getting efficient portfolios. Thus, based on investors' rationality assumption, these individuals pursue portfolios that present the best return-risk ratio, i.e., there will be no other portfolio with lower risk for a given expected return level or, similarly, there will be no portfolio capable of generating higher return for a given risk level - these combinations are represented in the efficient frontier developed by the aforementioned author. Therefore, this is one of the major tradeoffs investors are involved in, since Markowitz (1952) was the first to advocate for the positive association between expected return and risk.

However, in practical terms, mean-variance makes it difficult to estimate expected returns and covariance matrix (Demiguel & Nogales, 2009). Thus, the literature has investigated different strategies used to build portfolios by taking into consideration the ones focusing on minimizing risks (minimum variance portfolio), whose weight estimation process does not depend on expected returns or do not use optimization.

Accordingly, Jagannathan and Ma (2003) analyzed the restriction to short selling in portfolio weights and pointed out that there is not much to be lost by ignoring the average when there is no additional information about the mean population to be taken into consideration, due to estimation errors. Their findings have evidenced that the global minimum variance portfolio presented better out-of-sample performance than the mean-variance portfolio.

Haugen and Baker (1991) used a population comprising 1,000 high market capitalization stocks in the United States, from 1972 to 1989, to build a minimum variance portfolio with restrictions on the allocation of weights in assets and industries, in order to enable diversification without short sales. Results recorded for out-of-sample performance have shown that this portfolio is advantageous for investors, since it generates higher returns and lower risk than the Wilshire 5000 index, which was highlighted by the authors as the broadest weighted by market capitalization of stocks in the United States.

Clarke et al. (2006) extended these analyses from January 1968 to December 2005. They focused on minimum variance portfolios for 1,000 stocks presenting the highest market capitalizations in the United States, and estimated the covariance matrix based on asymptotic principal components, based on Connor and Korajczyk (1988), as well as used the shrinkage model by Ledoit and Wolf (2003). Their analyses have confirmed the results reported by Haugen and Baker (1991).

Blitz and Van Vliet (2007) assessed the performance of low volatility portfolios defined from assets' ordering by deciles based on their historical volatility. Thus, as previously highlighted by these authors, this formulation has only taken into consideration diagonal elements of the covariance matrix, in contrast to the study by Clarke et al. (2006), which was based on the minimum variance portfolio. They used the period from December 1985 to January 2006, all FTSE World Development Index assets, and monthly portfolios based on assets' division into deciles by taking into account the previous 3 years of volatility and equally weighted weights. Their analysis has shown that these portfolios generated higher risk-adjusted return than those built with higher-variability assets. The aforementioned authors named these findings as the 'volatility effect', which was not only observed in the United States, but also in Europe and Japan. Furthermore, this effect was not captured through size, value, and momentum strategies.

Moreover, Blitz et al. (2013) focused on investigating the return/risk association in emerging markets dealing with assets linked to the S&P/IFC Investable Emerging Markets Index, from December 1988 to December 2010. The aforementioned authors have stated that the 'volatility effect' is not specific to the United States, Europe, and Japan, according to the previous study, but that it is also evident in emerging countries. In addition, Blitz et al. (2013) performed additional analyses by controlling size, value and timing effects, in a subgroup that only comprises 50% of the largest stocks in the sample, at portfolio holding periods of up to 5 years, and their results remained unchanged.

Samsonescu et al. (2016) presented initial evidence of the out-of-sample performance of low volatility portfolios in Brazil, from 2003 to 2013. They observed higher absolute return and Sharpe ratio in comparison to Ibovespa's behavior, as well as better performance in low market periods, as evidenced by the 2008 financial crisis. However, this outcome was reversed in high market periods. Overall, period-based results reported by these authors have evidenced the low volatility portfolio with a higher Sharpe ratio in 9 of the 11 analyzed years, a fact that reinforced its relevance.

3. METHODOLOGICAL PROCEDURES

3.1. Data

The herein selected study period went from January 2009 to May 2020; it totaled 137 observations (L = 137) performed on a monthly basis, at the time window right after the subprime crisis' height, with the closing of the Lehman Brothers bank on September 15, 2008. This day was acknowledged by the specialized media as one of the worst days in the history of the global financial markets. Information about assets selected in the current study is publicly available online and widely known. S&P 500 futures index, dollar futures index (dollar index), 10-year US Treasury bond (T-Bond 10Y) and gold futures contract (gold) were collected at the Investing website (https://www.investing.com/). It was also necessary to collect the return of both the risk-free asset and the market portfolio for the American capital market, in order to perform the analyses – this information was extracted from Kenneth French's website[1].

Indices recorded for the first two assets reflected how futures market participants perceived the behavior of the main US stock market indicator (S&P 500), as well as the dollar price against other global currencies. On the other hand, the third financial asset refers to yield on long-term bonds (10 years) issued by the US treasury, based on variations in its market price (mark-to-market); therefore, it is a fixed-income instrument. The fourth financial asset is featured as a commodity; it was selected due to investors' perception about it as a store-of-value asset, and for diversification purposes. Therefore, all these assets capture different dimensions (varying versus fixed income) in the financial market, as well as enable different risk exposure levels; thus, they are attractive options for investors' portfolios, depending on their risk aversion profile, mainly in the post-subprime crisis period.

3.2. Building Portfolios and Performance Indicators

These data were used to estimate the weights of each asset in the portfolio, based on five strategies and their derivations. The first three strategies were applied in compliance with the proposal developed by Blitz and Van Vliet (2007) who used global portfolios, depending on assets' standard deviation, based on Equation 1:

$$w_i = \frac{\frac{1}{\sigma_i}}{\sum_{i=1}^{N} \frac{1}{\sigma_i}} \tag{1}$$

Wherein, w_i represents the weight of asset i; σ_i is the standard deviation of asset i; and N is the number of assets in the portfolio (four). Thus, the first one was the so-called ratio strategy, and it was calculated through Equation 1. The following two strategies were the natural logarithm and exponential strategies that, as their names suggest, were based on the natural logarithm of the 1/σ_i values and on their exponential, respectively.

Three specifications were used to obtain the standard deviation of the adopted strategies: the first two specifications refer to the rolling window scheme, according to which, the last 12 or 30 observation months ($T = 12$ ou $T = 30$) were used to obtain the standard deviation of the series, and as weighting scheme. For instance, when T = 12, the weights of the assets in a given strategy were defined based on using the returns recorded from January to December 2009 to build the portfolio for January 2010; the third specification was based on conditional volatility, it took into consideration the Generalized Autoregressive Conditional Heteroskedasticity – GARCH (p, q) model developed by Bollerslev (1986), which is an extension of Engle's (1982) Autoregressive Conditional Heteroskedastic (ARCH) process. It was done by taking a lag for the p and q terms, which represented the lag of the conditional variance and the squared error, respectively.

In details, firstly, GARCH (1,1) was adopted for each series based on using all available observations ($L = 137$) and it provided the weighting (coefficients) to be assigned the conveyed information. Initial volatility estimate calculated based on the first 12-return observations, as well as the model's coefficients were adopted to estimate the conditional volatility for the next period. Accordingly, the conditional volatility of each moment was found and it enabled making the estimate for the following month. Thus, the first set of weights was defined in late December 2009, based on the conditional volatility estimated for the following period; it was done in order to build the portfolio for January 2010, and so on.

Figure 1 helps to better visualize assets' weight allocation behavior (response) based on a volatility increase. It was elaborated based on the scheme of a rolling window of 12 observations used to calculate the standard deviation. This figure shows that the exponential strategy significantly favors less volatile assets by giving them greater relative weight in the portfolio.

The fourth strategy is the minimum variance portfolio (MVP), which is on the efficient frontier and whose weights result from the optimization problem described in Equation 2:

$$\underset{w}{min}\, w'\hat{\Sigma}w \tag{2}$$

$$\text{subjected to } \sum_{i=1}^{N} w_i = 1$$

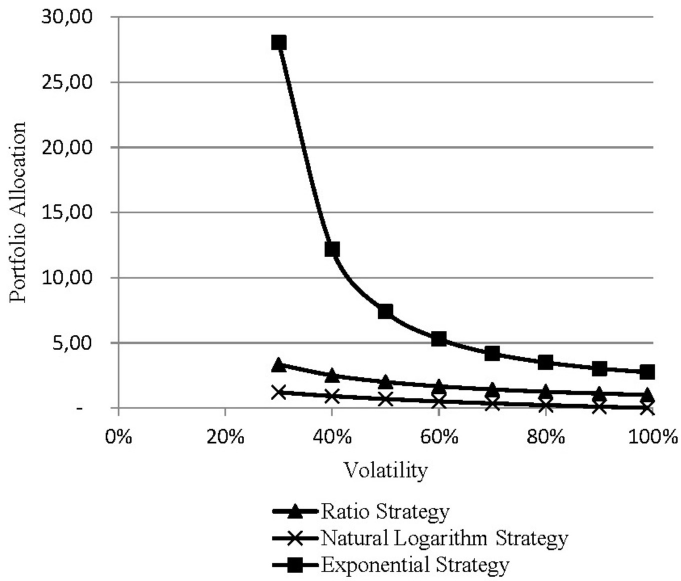

Figure 1. Variability of Assets' Returns and Reflections on Weights.
Source: Elaborated by the authors (2022)

Wherein, $\hat{\Sigma}$ is the sample covariance matrix. Thus, it is a special case of the mean variance portfolio by Markowitz (1952), with infinite risk aversion coefficient and risk premium (excess return in comparison to the return of a risk-free asset) equal to zero. According to Clarke et al. (2006), MVP is a portfolio on the efficient frontier presenting the unique property of having weights that do not depend on the assets' expected return, as it occurs in all other portfolios in it.

Finally, the last strategy is another portfolio of interest in the efficient frontier, namely: tangent portfolio (TP). TP is the best combination of risky assets and it presents the highest Sharpe ratio (the ratio between the portfolio's excess return and its standard deviation). This portfolio requires providing asset returns as input. The weights for this portfolio are described in Equation 3:

$$w = \widehat{\Sigma^{-1}}\left(\hat{\mu} - r_f\right) \tag{3}$$

$$\text{subjected to } \sum_{i=1}^{N} w_i = 1$$

Wherein, $\hat{\mu}$ is the mean of risky assets and r_f is the return on the risk-free asset. The 12-month rolling window (T = 12) was used to estimate the information necessary to compute both MVP and TP. An alternative version of the process to build MVP and TP weights was based on the GARCH (1,1) model, which, in its turn, used conditional volatility estimates for the following period of each series previously obtained, as well as the 12 last observations of returns to calculate the correlation between assets, in order to find the sample covariance matrix and to determine weights. Again, the first set of weights was herein defined at late December 2009 to build the January 2010 portfolio.

Thus, the weights found for each period t, for each of the strategies and for their derivations, generated the portfolio return in t+1. Hence, in order to evaluate the performance of each portfolio p, we obtained the mean return ($\hat{\mu}_p$), the standard deviation ($\hat{\sigma}_p$), the Sharpe ratio (IS_p) and the risk-adjusted return (α_p) based on the estimate substantiated by the Capital Asset Pricing Model (CAPM), which was independently developed by Sharpe (1964), Lintner (1965) and Mossin (1966). The aforementioned indicators were defined as follows:

$$\hat{\mu}_p = \frac{1}{L-T}\sum_{t=T}^{L-1} w_t' R_{t+1} \tag{4}$$

$$\hat{\sigma}_p = \sqrt{\frac{1}{L-T-1}\sum_{t=T}^{L-1}\left(w_t' R_{t+1} - \hat{\mu}_p\right)^2} \tag{5}$$

$$IS_p = \frac{\hat{\mu}_p - r_f}{\hat{\sigma}_p} \tag{6}$$

$$w_t' R_{t+1} - r_{f,t+1} = \alpha_p + \beta_p\left(r_{m,t+1} - r_{f,t+1}\right) + \varepsilon_{p,t+1} \tag{7}$$

Wherein, $w_t' R_{t+1}$ is portfolio return at $t+1$, $r_{f,t+1}$ is return on the risk-free asset in the same portfolio period, $t+1$; $r_{m,t+1}$ is the return on the market portfolio, also at $t+1$; α_p and β_p are the intercept and the sensitivity of the evaluated portfolio return in comparison to variations in the market portfolio, respectively; $\varepsilon_{p,t+1}$ is the model error term. The other variables were previously defined. The Sharpe ratio represents the reward per unit of risk, based on the standard deviation. On the other hand, the intercept in the CAPM model must be null. However, whenever it is positive (negative) and statistically significant, it indicates return on the asset/portfolio above (below) the expected one, given the risk level and, consequently, value generation (loss). This metric, also known as Jensen's alpha (1968), is widely used for investment evaluation purposes. Standard errors using the Newey-West (1987) procedure were adopted whenever autocorrelation or heteroscedasticity issues were identified in the estimated regressions.

4. RESULTS AND DISCUSSION

Table 1 initially presents the comparisons of individual assets in terms of mean monthly return, risk measured based on standard deviation and Sharpe ratio based on data from January 2010, which represents the first month portfolios are built for, based on weights recorded through the investigated strategies (except for those that used 30 observations for the rolling window). It was possible observing a tradeoff between return and historical risk, because the S&P 500 futures index recorded the highest return rate (0.890%), the second highest volatility rate (4.020%), and the highest Sharpe ratio (0.210). However, this index was also the one recording the worst minimum return (-12.920%), i.e., the most severe drop among the analyzed assets.

On the other hand, it is worth emphasizing the higher Sharpe ratio recorded for T-Bond 10Y's yield against both the dollar and gold futures indices (0.106 versus 0.075 and 0.097, respectively). It means that, during the investigated period, the long-term bond issued by the US treasury generated reward-risk ratio better than that of dollar and gold trading in the futures markets. Table 2 presents the Pearson's correlation matrix to help better understanding these assets.

Table 1
Descriptive Statistics of Individual Assets

Indicators	S&P 500 Futures Index	Dollar Futures Index	T-Bond 10Y	Gold Futures
Mean return	0.890	0.204	0.268	0.491
Standard deviation	4.020	2.134	2.109	4.587
Sharpe Index	0.210	0.075	0.106	0.097
Minimum Return	-12.920	-5.360	-5.383	-12.120

Note: Values were expressed in percentage, except for the Sharpe ratio. Data cover the period from January 2010 to May 2020.
Source: Elaborated by the authors (2022)

Table 2
Correlation Matrix

Correlation	S&P 500 Futures Index	Dollar Futures Index	T-Bond 10Y	Gold Futures
S&P 500 Futures Index	1.000	-0.412	-0.485	0.078
Dollar Futures Index		1.000	0.204	-0.333
T-Bond 10Y			1.000	0.258
Gold Futures				1.000

Note: Data cover the period from January 2010 to May 2020.
Source: Elaborated by the authors (2022)

The S&P 500 futures index return has shown moderate negative correlation to both the dollar futures index and the T-Bond 10Y (-0.412 and -0.485, respectively). These aspects were quite relevant for the aims of the current study since they showed diversification-associated benefits for investors due to portfolio risk reduction. Furthermore, dollar index futures and gold futures recorded weak negative correlation (-0.333), and it also helped reducing volatility in the portfolio construction process. Table 3 shows the performance of all five proposed portfolios and their alternatives for the post-subprime crisis period in terms of mean return, standard deviation, Sharpe ratio, minimum return and risk-adjusted return, which is based on the CAPM model.

Findings reported for portfolios comprising the 12-month window estimates, as well as those based on conditional volatility, have suggested that the natural logarithm strategy presented the highest mean returns (0.45% for 12m and GARCH). However, if one takes into consideration the reward-risk Sharpe ratio, it is possible seeing that the minimum variance portfolio based on the GARCH scheme (GARCH MVP) was the one recording the best result (0.364); it was followed by the GARCH and MVP ratio strategies, which presented similar behavior (0.347 and 0.345, respectively). It is worth emphasizing that, overall, the MVP strategy was the one recording the lowest worst losses in minimum return (-2.235% and -2.614% for MVP and GARCH MVP, respectively).

On the other hand, the exponential 12-m and GARCH strategies were the ones presenting the lowest, although positive, Sharpe ratio performance (close to 0.10), and both strategies recorded sharp minimum returns (-5.382% and -4.348%, respectively), a fact that placed them only behind TP, which recorded the worst loss (-6.287%). However, if one takes into consideration the risk-adjusted return metric based on the CAPM model, it is possible observing that the exponential

12-m and GARCH strategies added more value, and they were followed by both the 12-m and GARCH ratio strategies and by MVP.

Table 3
Performance of Weight Allocation Strategies

Indicators / Strategies	Mean Return	Standard Deviation	SI	Minimum	CAPM Alfa
12-m ratio	0.421	1.138	0.331	-3.055	0.339***
30-m ratio	0.391	1.154	0.295	-3.135	0.272**
GARCH ratio	0.420	1.083	0.347	-3.266	0.310***
12-m natural logarithm	0.452	1.322	0.309	-3.925	0.292**
30-m natural logarithm	0.411	1.356	0.266	-3.915	0.224*
GARCH natural logarithm	0.451	1.320	0.308	-4.006	0.282**
12-m exponential	0.250	2.100	0.098	-5.382	0.453***
30-m exponential	0.241	1.941	0.098	-5.373	0.358
GARCH exponential	0.238	2.000	0.097	-4.348	0.405**
MVP	0.419	1.084	0.345	-2.235	0.295***
GARCH MVP	0.430	1.063	0.364	-2.614	0.291***
TP	0.430	1.650	0.234	-6.287	0.137
GARCH TP	0.435	1.390	0.281	-3.591	0.176*

Note: Table 3 presents the performance of weight allocation strategies in terms of mean return, standard deviation, Sharpe ratio (IS), minimum return (Minimum) and risk-adjusted return (Alpha) based on the CAPM model of the proposed strategies and on their alternatives. Ratio, natural logarithm and exponential refer to strategies holding these very same names at the time to compute the weights through Equation 1, whereas MVP is the minimum variance portfolio and TP is the tangent portfolio. Moreover, 12m and 30m are the 12- and 30-month rolling window schemes used to calculate the standard deviation. GARCH is the weighting scheme based on the conditional volatility estimated for the following period, based on information deriving from a GARCH (1,1) model. Values were expressed in percentage, except for the Sharpe ratio. ***, ** and * represent statistical significance at 1%, 5% and 10%, respectively.
Source: Elaborated by the authors (2022)

On the other hand, the risk-adjusted return of these portfolios was identified as robust when the five-factor asset pricing model by Fama and French (2015) was adopted; besides the market risk premium, this model uses the following risk factors: size, book-to-market ratio, profitability and investment. The results, which were not presented here for brevity[2] purposes, pointed out that, despite the change in produced alphas' ranking, these very same portfolios, in addition to the GARCH MVP one, were the ones retaining value at 5% significance level, at least. Most specifically, exponential GARCH and 12-m, GARCH MVP and MVP, and GARCH and 12-m ratio portfolios have generated values whose alphas ranged from 0.455% to 0.225%.

Finally, with respect to portfolios built based on the 30-month window, it was possible seeing that the 30-m exponential strategy recorded low Sharpe ratio (close to 0.10) and worse negative variation (-5.373%), as well as that it did not generate significant risk-adjusted return when the CAPM model was used. In addition, based on the five-factor model by Fama and French (2015), it was overall possible to see that none of the strategies using this window size has generated value, i.e., they did not generate positive and statistically significant alpha.

These results have evidenced that the process to build risk-based portfolios (standard deviation with 12-month window and conditional volatility) performed better than the tangent portfolio – which requires asset return estimates as input – and that the widely spread minimum variance portfolio is competitive to alternative portfolio construction processes. In addition, if one compares these findings to data available in Table 1, which presents the behavior of individual assets, it is possible to see gains from building portfolios aimed at reducing the exposure to the volatility of its components, for instance, a Sharpe ratio of more than 1.5 times higher than the one recorded for the S&P 500 futures index alone, which was the asset presenting the highest indicator.

5. CONCLUDING REMARKS

The economic crisis in the North American real estate market reached the world in 2008 and became an international financial crisis with global effects. It caused financial and economic discomfort by emphasizing the weakness of the economic system, lack of efficient regulation, and the risks of the globalized financial market, besides raising serious doubts about whether the capitalist economic model would be able to maintain a sustainable financial market.

Thus, more than 10 years after the crisis that flooded other economies worldwide, it was perceived as opportune to reason about whether risk aversion - reflected in the allocation of weights in investment portfolios based on low volatility strategies - brought gains for investors. Therefore, the current study has analyzed the performance of portfolio strategies based on investors' risk aversion in the post-subprime crisis period. It was done based on using four globally known assets, namely: S&P 500 futures index, dollar futures index, US government long-term bond (10 years) and gold futures contract. With respect to the overall performance metrics, results have shown that risk-based portfolios built based on the 12-month rolling window or conditional volatility performed better than the tangent portfolio, as well as that the widely spread minimum variance portfolio was competitive to other alternatives.

Risk aversion plays an important role in the process of understanding agents' behavior in different economic periods, mainly in times of economic recession. Individual preferences are as complex as human behavior, since they are influenced by economic, political, human, and even cultural factors. This parameter amplifies the response of the most relevant macroeconomic variables to uncertainty shocks and, in short, it is the conciliation point that enables relating finance, macroeconomics, and uncertainty. Anxiety motivated by uncertainty is associated with disruptions in emotional and decision-making processes. Consequently, anxious individuals often make decisions that help them to avoid losses.

Emotional responses at neuropsychological level, mostly the anxiety-related ones, can be observed when the environment is interpreted as unpredictable due to instability perceived by individuals, a fact that can lead to stress, when this anxiety is not properly controlled through emotion regulation strategies. Investment activities depend on making judgments to solve uncertainties about information asymmetries and about the probability of having unexpected events taking place. Emotional regulation is a coping mechanism that can be elaborated in a problematic or adaptive manner. The problematic manner is evident when risk asset investors run away, similarly to the herd effect. Adopting other strategies, such as avoiding risk, enables adaptively regulating emotions, and it can reduce emotions' intensity and exacerbation.

Results corroborated studies that pointed out that investors mostly invested in stable assets and in safer fundamentals after the financial crisis, a fact that evidenced risk aversion after this event. Thus, the answer to the title of the current article is: Yes, risk aversion has won!

Finally, the present study had some limitations, such as the selection of the four assets used to build the portfolios. Therefore, we recommend future studies to use a broader set of stocks, as well as to compare the investigated portfolios to the global ones. Moreover, it would be interesting to compare the performance of the adopted strategies to that of equally weighted portfolio, which does not require optimization and that just distribute the same weight to the assets. This feature makes the equally weighted portfolio easy to be implemented by investors, besides presenting mixed evidence about its advantage, as shown in the literature.

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NOTES

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[2] Available upon request to the authors.

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EMMFT: Project's concept and management, conclusion and final review of the manuscript. **CMSR:** Methodology writing and empirical analysis. **PMR:** Literature review and empirical analysis of results. **BPF:** Methodology concepts, development and writing, as well as final review of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest capable of hindering the publication of the current article.

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