

How do elderly consumption patterns, personality traits and Covid-19 pandemic shock influence their investment risk profiles across Europe?

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**HOW DO ELDERLY CONSUMPTION PATTERNS,
PERSONALITY TRAITS AND COVID-19 PANDEMIC
SHOCK INFLUENCE THEIR INVESTMENT RISK
PROFILES ACROSS EUROPE?**

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Table of Contents

ACKNOWLEDGEMENTS.....	2
TABLE OF CONTENTS.....	3
LIST OF ABBREVIATIONS.....	7
INTRODUCTION.....	8
1 LITERATURE REVIEW AND STUDY SCOPING	10
1.1 FOUNDATIONAL THEORIES.....	10
1.1.1 TRADITIONAL FINANCE AND RATIONALITY	10
1.1.2 BEHAVIORAL FINANCE AND IRRATIONALITY	11
1.2 PREVIOUS EMPIRICAL STUDIES.....	13
1.2.1 CONSUMPTION PATTERNS AND RISK PROPENSITY	13
1.2.2 PERSONALITY TRAITS AND RISK PROPENSITY	15
1.2.3 CRISES SHOCKS AND RISK PROPENSITY.....	16
1.2.4 INDIVIDUALS’ PERSONAL CHARACTERISTICS AND RISK PROPENSITY	17
1.3 IDENTIFIED GAPS IN EXISTING LITERATURE	19
1.4 CONTRIBUTION TO THE RESEARCH FIELD	19
2 DATA AND VARIABLES.....	20
2.1 DATABASE	20
2.2 DATA.....	20
2.3 VARIABLES.....	20
2.3.1 TARGET VARIABLE: INVESTMENT RISK PROFILES	21
2.3.2 INDEPENDENT VARIABLES: CONSUMPTION PATTERNS.....	23
2.3.3 INDEPENDENT VARIABLES: PERSONALITY TRAITS	26

2.3.4	INDEPENDENT VARIABLE: COVID-19 PANDEMIC SHOCK.....	27
2.3.5	CONTROL VARIABLES: PERSONAL SOCIODEMOGRAPHIC CHARACTERISTICS.....	27
2.3.6	CONTROL VARIABLES: PERSONAL HEALTH CHARACTERISTICS	29
2.4	SUMMARY STATISTICS	30
2.4.1	RISK SEEKER INVESTMENT PROFILE.....	30
2.4.2	RISK DIVERSIFIER – DYNAMIC INVESTMENT PROFILE.....	31
2.4.3	RISK DIVERSIFIER – PERFECTLY INVESTMENT PROFILE	31
2.4.4	RISK DIVERSIFIER – DEFENSIVE INVESTMENT PROFILE.....	32
2.4.5	DEFENSIVE INVESTMENT PROFILE	32
2.4.6	RISK AVERSE INVESTMENT PROFILE	32
2.4.7	TABLES OF SUMMARY STATISTICS	34
3	METHODOLOGY.....	36
3.1	TREATMENT OF MULTICOLLINEARITY.....	36
3.1.1	CORRELATION ANALYSIS	36
3.1.2	VARIANCE INFLATION FACTOR	36
3.2	RANDOM-EFFECTS PROBIT REGRESSION FOR PANEL DATA	37
3.3	FIXED-EFFECTS MULTINOMIAL LOGIT REGRESSION FOR PANEL DATA.....	38
4	RESULTS & DISCUSSION.....	39
4.1.1	TABLES OF RANDOM-EFFECTS PROBIT REGRESSION (PANEL DATA) RESULTS	40
4.2	ELDERLY, CONSUMPTION PATTERNS AND INVESTMENT RISK PROFILES.....	46
4.2.1	ELDERLY RISKY CONSUMPTION AND THEIR INVESTMENT RISK PROFILES	46
4.2.2	ELDERLY HEALTHY CONSUMPTION AND THEIR INVESTMENT RISK PROFILES.....	46
4.2.3	ELDERLY CONSUMPTION PATTERNS AND THEIR INVESTMENT RISK PROFILES	47
4.3	ELDERLY, PERSONALITY TRAITS AND INVESTMENT RISK PROFILES	47
4.3.1	ELDERLY <i>EXTRAVERSION</i> TRAIT AND THEIR INVESTMENT RISK PROFILES	47

4.3.2	ELDERLY <i>OPENNESS</i> TRAIT AND THEIR INVESTMENT RISK PROFILES	48
4.3.3	ELDERLY <i>CONSCIENTIOUSNESS</i> TRAIT AND THEIR INVESTMENT RISK PROFILES	49
4.3.4	ELDERLY <i>AGREEABLENESS</i> TRAIT AND THEIR INVESTMENT RISK PROFILES	49
4.3.5	ELDERLY <i>NEUROTICISM</i> TRAIT AND THEIR INVESTMENT RISK PROFILES.....	50
4.3.6	ELDERLY PERSONALITY TRAITS AND THEIR INVESTMENT RISK PROFILES.....	51
4.4	ELDERLY, COVID-19 PANDEMIC SHOCK AND INVESTMENT RISK PROFILES.....	51
4.5	ELDERLY, PERSONAL CHARACTERISTICS AND INVESTMENT RISK PROFILES	53
4.5.1	ELDERLY AGE AND THEIR INVESTMENT RISK PROFILES.....	53
4.5.2	ELDERLY GENDER AND THEIR INVESTMENT RISK PROFILES	53
4.5.3	ELDERLY RELATIONSHIP STATUS AND THEIR INVESTMENT RISK PROFILES	53
4.5.4	ELDERLY EDUCATION LEVEL AND THEIR INVESTMENT RISK PROFILES	54
4.5.5	ELDERLY EMPLOYMENT STATUS AND THEIR INVESTMENT RISK PROFILES.....	54
4.5.6	ELDERLY COUNTRY OF ORIGIN AND THEIR INVESTMENT RISK PROFILES	55
4.5.7	ELDERLY HEALTH STATUS AND THEIR INVESTMENT RISK PROFILES	55
4.6	HETEROGENEITY TESTING PER INVESTMENT RISK PROFILES.....	56
4.6.1	RISK SEEKER PROFILE HETEROGENEITY TESTING	56
4.6.2	RISK DIVERSIFIER – DYNAMIC PROFILE HETEROGENEITY TESTING	57
4.6.3	RISK DIVERSIFIER – PERFECT PROFILE HETEROGENEITY TESTING	58
4.6.4	RISK DIVERSIFIER – DEFENSIVE PROFILE HETEROGENEITY TESTING	59
4.6.5	RISK AVERSE PROFILE HETEROGENEITY TESTING.....	60
4.7	LIMITS OF OUR STUDY.....	62
4.7.1	DATABASE AND SAMPLE LIMITATIONS	62
4.7.2	METHODOLOGY LIMITATIONS.....	62
4.7.3	PATHWAYS FOR FUTURES RESEARCH.....	62
	CONCLUSION.....	64

APPENDICES 65

BIBLIOGRAPHY 92

EXECUTIVE SUMMARY 105

List of Abbreviations

- APT Arbitrage Pricing Theory
- BMI Body Mass Index
- CAPM Capital Asset Pricing Model
- CC Central European group of countries
- EC Eastern European group of countries
- ECB European Central Bank
- EMH Efficient Market Hypothesis
- EUT Expected Utility Theory
- ISCED International Standard Classification of Education
- MPT Modern Portfolio Theory
- NC Northern European group of countries
- SC Southern European group of countries
- SHARE Survey of Health, Ageing and Retirement in Europe
- VIF Variance Inflation Factor

INTRODUCTION

During the Dutch Golden Age, in the 1630s, tulips, once an exotic flower, triggered a frenzy that swept the Netherlands when a single flower could reach a price greater than ten times the annual salary of a skilled artisan. At that time, the possession of a tulip was a symbol of richness, making its sales literally explode and pushing investors to eagerly chase any of the existing bulbs in the market. The price of tulips evidently reached extraordinary heights, driven by speculation and irrational exuberance of investors. However, as quickly as prices had risen, they collapsed when investors realized they were spending astronomical sums only on short-lived and fragile flowers. It was the first speculative bubble, known as “Tulipomania”. This historical episode illustrates the profound impact of human psychology on financial decision making, laying the foundations for what have been the conceptual framework of our study, behavioral finance (Kapoor & Prosad, 2017).

While traditional financial theories postulate that investors are entirely rational and markets perfectly efficient, behavioral finance dig into the psychological factors and cognitive biases that often underpin irrational investors behaviors (Veni & Kandregula, 2020). This research field aims at understanding how emotions and irrational thinking can lead to market anomalies such as speculative bubbles which are frequently observed in financial markets (Kapoor & Prosad, 2017).

One of the motivations for writing this study was inspired by a similar paper that explored behavioral finance from an original angle. Brunen (2019) examined the effect of *moral licensing* in Socially Responsible Investing and its interaction with behavioral biases. *Moral licensing* refers to the phenomenon according to which individuals justify risky behaviors by relying on their previous actions, that they perceive as morally positive. She found that investors who had already engaged in Socially Responsible Investments felt entitled to take greater risks in other areas (Brunen, 2019). This observation really sparked our interest and provided a good basis for a further investigation into how psychological mechanisms might influence broader financial decision making.

We decided, based on discussions with our supervisor and resources available, to focus our work on examining the potential influence of consumption patterns — both risky and healthy — alongside the Big Five personality traits (*extraversion, openness, conscientiousness, agreeableness* and *neuroticism*) and the impact of the Covid-19 pandemic shock on the investment risk profiles of the elderly across Europe.

For our study, we used the secondary data from the *Survey of Health, Ageing and Retirement in Europe* (hereafter referred to as "SHARE"). The longitudinal nature of the data enabled us to analyze periods both pre- (2019 to early 2020) and post-Covid-19 (2022) pandemic for each individual. We also added sociodemographic and health status control variables to ensure a comprehensive analysis. Once our primary dataset established, we employed two statistical methods: (1) a series of random-effects probit regression models and (2) a fixed-effects multinomial logit regression model.

The first one aimed at incrementally testing the different independent variables for each of the six dummies investment risk profiles (i.e. *risk seeker, risk diversifier* — whether *dynamic, perfect* or *defensive* — *defensive* and *risk averse*). With the second the goal at determining whether there had been a change in risk profiles, using a categorical variable representing these six profiles, as a result of the Covid-19 pandemic shock.

The primary objectives of our study were centered around testing the following hypotheses derived from existing literature (see the next section “Literature review and Study Scoping”) concerning the investment risk profiles of elderly across Europe:

- Firstly, whether the elderly consumption patterns consistently and significantly influenced their investment risk profiles. Specifically, it was assumed that elderly individuals who engaged in risky behaviors, such as consuming alcohol or smoking, were more likely to have riskier investment profiles. Conversely, those who adopted healthier lifestyle behaviors, including regular consumption of fruits, vegetables, dairy products, meat and engaging in regular physical activity, were expected to exhibit less risky investment profiles.
- Secondly, as regards personality traits, whether the elderly with high levels of *extraversion* would have high risk tolerant profiles, while those with higher levels of *openness* and *conscientiousness* were expected to have moderate risky investment profiles. Furthermore, we assumed that elderly with high levels of *agreeableness* tended to have less risky investment profiles, whereas those with high levels of *neuroticism* were more likely to exhibit risk free behaviors.
- Thirdly, whether the Covid-19 pandemic influenced the investment behaviors of the elderly. The hypothesis was that the pandemic had prompted elderly to invest in less risky assets, thereby adopting less risky investment profiles leading to a change from their initial profile.
- Finally, whether personal sociodemographic and health characteristics had any role in shaping investment risk profiles of the elderly.

Following the introduction, the first chapter provides a comprehensive literature review for the scoping of our study. It starts by examining foundational theories, including traditional finance and rationality of investors, as well as behavioral finance and its focus on their discovered irrationality. It then sketches out an overview of previous empirical studies and our hypothesis on consumption patterns, personality traits, crisis shocks and their respective influences on elderly risk profiles. The chapter concludes by identifying gaps in the existing literature and outlines our study contribution to the research field.

The second chapter digs into the data and variables used in our study. It describes the database and data sources and introduces the key variables, including the target variable (investment risk profiles), the independent variables (consumption patterns, personality traits and the Covid-19 pandemic) as well as the control variables related to personal sociodemographic and health characteristics. This chapter also presents summary statistics for each investment profile analyzed.

The third chapter focuses on the methodology employed in our study and discusses the treatment of multicollinearity through correlation analysis and variance inflation factor assessments. This chapter then details the two statistical models applied to test our hypothesis.

The fourth and last chapter touches on the results and discussion. It opens with an in-depth analysis of the relationships between the elderly consumption patterns, personality traits, Covid-19 pandemic shock and their investment risk profiles. It then examines the role of personal characteristics and conducts heterogeneity tests for five major investment risk profiles.

Our study then concludes with an assessment of its limitations and paves the way for future research opportunities.

1 LITERATURE REVIEW AND STUDY SCOPING

1.1 Foundational Theories

1.1.1 Traditional finance and rationality

Traditional finance has evolved through several key major theories and concepts, each providing a new perspective on how financial markets would operate, how investors would make decisions and how risks and returns would be evaluated based on the primary assumption that investors are purely rational (Veni & Kandregula, 2020). The following paragraphs only outline these major theories, but we thought important to properly grasp them first to introduce those that followed in their wake and focused on the behavioral aspects of risk perception.

In 1844, John Stuart Mill, a British philosopher and economist, introduced the concept of the *Economic Man* or *Homo Economicus*. This theoretical model proposed that individuals would act rationally, seeking to maximize their personal satisfaction (Chen & Potters, 2021). According to Mill, the Economic Man would be a rational being, capable of making logical and reflected decisions by weighting costs and benefits to achieve maximum satisfaction (Bee & Desmarais-Tremblay, 2022) under three conditions: complete information, self-interest and perfect logic (Veni & Kandregula, 2020). This basis economic decision-making model was the first introduction of economic rationality and cost-benefit analysis (Kapoor & Prosad, 2017).

In 1738, Daniel Bernoulli proposed the *Expected Utility Theory* (hereafter referred to as “EUT”) but which was only formalized in 1954. He introduced the idea of the “diminishing marginal utility”, according to which each additional unit of wealth would provide less satisfaction (Samuelson, 1977). The EUT postulates that individuals would make decisions in order to maximizing their expected utility (Friedman & Savage, 1952) but under uncertainty as all information available would never be fully known (Dimand & Dimand, 1995).

In 1944, John Von Neumann and Oskar Morgenstern published *Theory of Games and Economic Behavior* making the EUT applicable (Dimand & Dimand, 1995) by introducing four axioms that underpin it (*completeness, transitivity, continuity and independence*). An individual adhering to these rational behavior axioms would act in a way that maximizes its gain in risky circumstances and confronted with several options (Von Neumann & Morgenstern, 1944). In this EUT, the first classification of individuals based on their choices concerning risk was established (Zhang et al., 2014). Individuals unwilling to take risks were categorized as “risk averse”, those with a neutral stance towards risk were termed “risk neutral” and those showing an appetite for risks were identified as “risk takers” (Veni & Kandregula, 2020). This classification would help to understand and predict how different types of individuals would behave in various financial scenarios.

In 1952, Harry Markowitz revolutionized traditional finance theories with his *Modern Portfolio Theory* (hereafter referred to as “MPT”) assuming that all investors would be risk averse and always seek to minimize the risk taken while maximizing their return (Veni & Kandregula, 2020). He highlighted the concept of diversification to reduce uncertainty and suggested that diversifying assets would decrease the total risk of a portfolio, expressed as variance of the portfolio return (Elbannan, 2014), because of the correlations between those assets (Markowitz, 1991). As a matter of fact, MPT introduced the idea of the efficient frontier, which denoted the best asset pairings that would minimize risk for a given projected return or maximize return for a given level of risk (Markowitz, 1952).

Jack Treynor (1961), William Sharpe (1964), John Lintner (1965) and, independently, Jan Mossin (1966) developed the *Capital Asset Pricing Model* (hereafter referred to as “CAPM”). This model underlined the distinction between systematic risk, inherent to the market and not diversifiable and specific risk, unique to an asset. This model helped pricing an individual asset (Veni & Kandregula, 2020) as in the CAPM, systematic risk is quantified by the beta, which would represent its sensitivity to market movements (Elbannan, 2014). CAPM is still widely used in the literature for determining the expected return of an asset based on its beta (Veni & Kandregula, 2020).

In 1970, Eugene Fama formalized the *Efficient Market Hypothesis* (referred to as “EMH”) which postulates that financial asset prices would reflect all available information on the market, making it impossible to consistently achieve superior returns without additional risk. This model integrates the concept of informational efficiency in financial markets and stated that all markets would be efficient (Fama, 1970).

In 1976 Stephen Ross introduced the *Arbitrage Pricing Theory* (hereafter referred to as “APT”) as a response to some limitations of the CAPM. APT focuses on how rational traders would exploit mispriced securities created by irrational traders. Unlike the CAPM, which relies on a single market risk factor, the APT considers that asset returns would be influenced by multiple sources of systematic risks (betas). As arbitrage would correct mispricing, the prices of securities would more accurately reflect all available information, leading to a more efficient allocation of capital in the market (Ross, 1976).

1.1.2 Behavioral finance and irrationality

Behavioral finance emerged as a subfield challenging traditional assumptions of market rationality as introduced in the previous section. Unlike traditional theories that assume investors would act entirely rationally and markets would be perfectly efficient, behavioral finance explores market anomalies and irrational behaviors of investors which would lead, for instance, to underreaction, overreaction or speculative bubbles (Kapoor & Prosad, 2017) regularly observed in markets. These mechanisms would arise because people tend to think and act emotionally rather purely rationally (Veni & Kandregula, 2020). This section aims at introducing the fundamental concepts of behavioral finance, examining how cognitive biases would impact financial decisions and, ultimately, markets.

1.1.2.1 Heuristics

The three first Heuristics, one of the keys first concepts in this discipline, were introduced in 1974 by Amos Tversky and Daniel Kahneman. These Heuristics would be mental shortcuts used by individuals to simplify their decision-making process when facing uncertainty (Veni & Kandregula, 2020).

With the first Heuristic *representativeness*, individuals would evaluate the likelihood of an event by comparing it to an existing archetype. When estimating this likelihood, individuals would typically neglect other relevant statistical information by focusing on how much an event would match previous events they are acquainted with (Tversky & Kahneman, 1974). Waweru et al. (2008) highlighted that these biased individuals would tend to prefer assets that have performed well in the past and dislike those that have poorly performed. This type of reactions would ultimately lead to overreaction (Bondt & Thaler, 1985), as decisions are made precipitously and without prior and proper study of the market based on actual facts (Ferdinand, 2023).

According to the second Heuristic *availability*, individuals would estimate the likelihood of an event by considering how readily past similar examples are remembered. Something would be sometimes thought to be more common or likely if it can immediately be recalled (Tversky & Kahneman, 1974). Veni and Kandregula (2020) underlined that individuals would be used to rely on information coming from close friends or family members rather than from unknown people. They would also prefer to invest in national known assets rather than in international unfamiliar ones, even if they would get lower returns (Veni & Kandregula, 2020).

The third Heuristic *adjustment and anchoring* would imply a subsequent revision of an initial value (Tversky & Kahneman, 1974). Individuals would tend to place more importance on the first piece of information they received when deciding. Subsequently, even if that initial information turns to be unfounded (Lai, 2023), they would continue basing their conclusion on it. For example, an individual exhibiting this type of heuristic behavior buys an asset at a given purchased price. This price would then serve as an anchor and the individual would not sell the asset unless its price would be above the purchase price, regardless of whether this decision would negatively impact its portfolio strategy (Matsumoto et al., 2013).

1.1.2.2 *Prospect theory*

Prospect theory, developed by Daniel Kahneman and Amos Tversky later in 1979, introduced a more realistic decision-making model that accounted for individuals' irrational behaviors. It offered a critique of the EUT, proposing an alternative that would better explain how individuals actually make choices under risk when facing uncertainty (Kahneman & Tversky, 1979).

According to this theory, individuals would evaluate outcomes in relation to a reference point, often the status quo or an initial expectation (Kahneman & Tversky, 1979). From this reference point, individuals would generally be more sensitive to losses than to gains, a phenomenon known as *Loss Aversion*. The perceived loss would have a stronger emotional impact than a gain of the same size. This would manifest a behavior, known as the "disposition effect", according to which investors would hesitate to sell assets with a loss, hoping that prices will rebound (Summers & Duxbury, 2007). The theory postulates that the value function would be concave for gains and convex and steeper for losses. This S-shaped value function would explain why people tend to avoid risks when it comes to gains but seek risks when trying to avoid losses (Kahneman & Tversky, 1979).

Beside these two theories, there are many other theories and concepts that make up behavioral finance as a new discipline. However, for the purpose of our study, we decided to present only an outline of fundamental theories of traditional and behavioral finance. This approach provides the necessary framework for how various factors influence investment behaviors and, hence, risk profiles.

1.2 Previous Empirical Studies

This section, which digs into empirical studies, examines the relationship between external factors and individuals' risk tolerance.

1.2.1 Consumption patterns and risk propensity

1.2.1.1 *Risky consumption patterns and risk seeking*

The consumption of tobacco and alcohol documented in the existing literature would be associated with certain risky behaviors. Wittgens et al. (2022) investigated the underlying mechanisms linking alcohol use to other risky behaviors. They demonstrated how psychological factors such as stress feeling as well as sensation seeking and impulsivity (Peretti-Watel et al., 2013), would be frequently exacerbated by the consumption of tobacco and alcohol and could lead to questionable decisions in various aspects of life (Wittgens et al., 2022).

Mudryj et al. (2019) also showed that risky behaviors, such as drinking or smoking, would be frequently accompanied by other harmful habits such as poor sleep hygiene, a lack of healthy eating habits (eating fruits and vegetables on regularly basis) or physical activity, all indicating a general risk taking way of life (Mudryj et al., 2019).

For younger people, the consumption of alcohol and tobacco would also be frequently accompanied with hazardous sexual behaviors such as having several partners at the same time or engaging in repeated unprotected relations (Cho & Yang, 2023; Choudhry et al., 2014), showing that risky behaviors would not occur in isolation; they would be frequently interconnected, forming a network of risk taking (Connell et al., 2009; Kipping et al., 2012). Furthermore, when beginning in the adolescence, the likelihood of these risky behaviors influencing the risk profile for the individual's future life would be high (Griffin et al., 2019).

From this trend one could believe that risky consumption extends to financial behaviors, such as in investment decisions-making.

1.2.1.2 *Healthy consumption patterns and risk aversion*

Healthy lifestyle behaviors, such as balanced eating and regular physical activity, would be frequently associated with better physical and mental health. Ding et al. (2015), among others, investigated risk behaviors related to lifestyle, emphasizing the need of a healthy diet and regular physical activity in maintaining good health. Such discipline and awareness of the long-term consequences could also result in more cautious way of taking decisions (Ding et al., 2015).

Selivanova and Cramm (2014) and Wong et al. (2023) went one step further by investigating the relationship between physical activity, healthy lifestyle behaviors and health outcomes. They observed that physically active individuals with a balanced diet would have better mental and cognitive health (Li et al., 2024; Serra et al., 2020), which could impact their judgment and decision-making.

Moreover, individuals' emotional responses would also be influenced by their way of life. De Rezende et al. (2014) discussed the influence of sedentary versus physical activity on mental health outcomes. A lack of physical activity would lead to diseases like dementia, resulting in a higher mortality rate among sedentary people. On the other hand, individuals who would combine regular physical activity with a healthy diet would tend to have a better life balance (Lacombe et al., 2019) and less stress (Wong et al., 2023), both of which could positively influence their decision as they would be less prone to rush and make risky choices (Peretti-Watel et al., 2013).

The benefits of a healthy diet extend well beyond their physical and mental effects. This would have a significant influence on mental health, making people who would eat healthy more satisfied with their lives, encouraging social interaction and networking (Sowa et al., 2016). In contrast, unhealthy eating habits could promote negative emotions such as isolation for instance (Schrempft et al., 2019). Moreover, Ford et al., (2011) demonstrated that low risk lifestyle behaviors would be associated with a significant reduction in mortality from all causes.

By analogy, one could believe that individuals who engage in healthy behaviors in their daily lives also take a wise approach as regards their financial decisions.

1.2.1.3 Influence of consumption patterns on risk profiles hypothesis

Despite the absence of specific studies on the influence of smoking and alcohol consumption on investment decisions, other studies on behavioral mechanisms suggest a general tendency towards risk taking, when individuals consume risky products, which could be extended to financial decisions.

Similarly, existing literature suggests a general tendency of healthy individuals for cautiousness with regard to risk, which could be extended to their financial decisions as well.

Therefore, one could believe that individuals who engaged in a risky or a healthy behavior in their daily consumption also take a consistent approach as regards their financial decisions.

Hypothesis 1 (H1): *Elderly consumption patterns significantly influence consistently their investment risk profiles. In particular, among our sample:*

- ***H1a:*** *Elderly who consume alcohol or smoke in a risky manner are significantly more likely to have riskier investment risk profiles.*
- ***H1b:*** *Elderly adopting healthy lifestyle behaviors, such as regular consumption of fruits, vegetables, dairy products, meat and regular physical activity, are significantly more likely to have less risky investment profiles.*

1.2.2 Personality traits and risk propensity

As seen in the previous sections, behavioral finance is based on the fact that investors would make their decisions more emotionally than rationally. Therefore, it seemed relevant to examine which personality traits would shape risk tolerance, as does frequently the *Big Five Theory*, a growing topic of interest in behavioral finance. This theory postulates that each individual possesses five main personality traits, to varying degrees, making personality unique (Novikova, 2013). These five traits are *extraversion* indicating sociability, energy and assertiveness, *openness* referring to imagination, curiosity and openness to new experiences, *conscientiousness* reflecting organization, responsibility and diligence, *agreeableness* corresponding to empathy, pleasantness and cooperativeness and finally *neuroticism* expressing negative feeling such as anxiety, stress or anger (Raad & Mlacic, 2015).

1.2.2.1 Extraversion and risk seeking

Individuals considered risk takers would often exhibit high levels of *extraversion*. Sahinidis et al. (2020) and Joseph and Zhang (2021) showed that *extraverted* individuals would be more inclined to seek thrills (Nicholson et al., 2005) and demonstrate optimism (Lai, 2019), which could drive them to engage in riskier investments.

1.2.2.2 Openness, conscientiousness and risk diversifying

Individuals considered as moderate risk takers would often exhibit high levels of *openness* and *conscientiousness*. Researches by Lai (2019) and Wang et al. (2016) highlighted that individuals with high level of *openness* would tend to diversify their portfolios and explore new investment opportunities, corresponding to a moderate risk tolerance. Moreover, Yadav and Narayanan (2021) indicated that individuals with high level of *conscientiousness* would be more prone to biases even though they would generally tend to take fewer risks when getting older (Isidore & Arun, 2021). These methodical individuals would also be excessive risk takers if they have confidence in their thorough analyses and well-structured plans, offering them a biased vision of risks (Yadav & Narayanan, 2021).

1.2.2.3 Agreeableness, neuroticism and risk aversion

On the other side, individuals considered as less likely to be high or moderate risk takers would often exhibit high levels of *agreeableness* and *neuroticism*. Ahmad and Maochun (2019) showed that highly developed *agreeableness* trait highly developed, would make individuals prefer prudent financial behaviors, avoiding high financial risks to maintain harmonious relationships and avoid conflicts. This tendency to seek security and stability would be reinforced by stressful events such as crises (Ahmad & Maochun, 2019).

De Bortoli et al. (2019) added that individuals with high scores of *neuroticism* would prefer less risky investments (Oehler et al., 2018) due to their tendency to avoid stressful and uncertain situations. Additionally, these risk averse individuals (Oehler & Wedlich, 2018) would exhibit biased behaviors that soften their risk aversion when it comes to losses (De Bortoli et al., 2019).

1.2.2.4 Influence of personality traits on risk profiles hypothesis

Based on the aforementioned research that showed the effect of the Big Five personality traits on individuals risk perception, one could believe that highly developed *extraversion* trait is associated with high risk takers, highly developed *openness* and *conscientiousness* is with moderate willingness to take risk and high levels of *agreeableness* and *neuroticism* with low and risk free seekers.

Hypothesis 2 (H2): *Elderly personality traits significantly influence their investment risk profiles. In particular, among our sample:*

- ***H2a:*** *Elderly with high level of extraversion have significantly high risky investment profiles.*
- ***H2b:*** *Elderly with high level of openness have significantly moderate risky investment profiles.*
- ***H2c:*** *Elderly with high level of conscientiousness have significantly moderate risky investment profiles.*
- ***H2d:*** *Elderly with high level of agreeableness have significantly low risky investment profiles.*
- ***H2e:*** *Elderly with high level of neuroticism have significantly risk free investment profiles.*

1.2.3 Crises shocks and risk propensity

Crises, either economic, health related or financial, would significantly impact individual behaviors, particularly in terms of risk perception and decision-making. Indeed, Cori et al. (2020) and Li et al. (2020) analyzed how risk perception evolved during the Covid-19 pandemic and how it influenced individual behaviors. They demonstrated that the uncertainty and severity of the infection would strongly influence negative emotions such as fear and anxiety, having an effect on daily decisions and creating more vulnerability among individuals (Millroth & Frey, 2021), resulting in a drop of risk tolerance (Heo et al., 2021).

This fear, and hence the perception of risk that each person has, would be influenced by factors other than rationality (Manzoor et al., 2023). These factors, such as knowledge, direct perception of the threat or even confidence in a remedy or government actions (Zivi et al., 2023), would either have increased or decreased fear (Cori et al., 2020). Individuals showing higher levels of anxiety or a negative opinion towards government measures would have a lower risk profile. During a health crisis, individuals would have a general tendency to reduce their willingness to take risks in a wide range of situations, including in investment decisions (Dita et al., 2023). This reduction would be attributable to the increased sense of risks and uncertainty about the economic future (Zivi et al., 2023).

In addition, the effects of crises on mental health seemed to be important and were addressed by Dettmann et al. (2022) who highlighted also the increase in anxiety and depression levels during the Covid-19 pandemic. These mental disorders directly would have affected risk perception and decision-making behaviors. Lockdowns experienced by persons would have had a strong impact on depression and it was observed that this social isolation would have increased uncertainty and exacerbated mental health problems (Probst et al., 2020).

Regarding financial decision-making, Dita et al. (2023) investigated how Covid-19 pandemic would have altered investment behaviors. They noted that increased uncertainty would have led to greater risk aversion among many investors, thus confirming the tendency towards a more risk averse perception. The study also highlighted biased behaviors that investors would have exhibited during periods of uncertainty, such as loss aversion (Kahneman & Tversky, 1979). This bias was assessed being predominant during the pandemic leading investors to avoid risky investments even if it had meant forgoing potential returns (Dita et al., 2023).

Regarding the socio-economic impacts of the Covid-19 on household financial behaviors, Martin et al. (2020) conducted a study revealing that loss of income and economic uncertainty would have led many households to reduce their spending and increase their savings as a precautionary measure. This trend was attributed to several key factors. Firstly, uncertainty about the duration and severity of the pandemic would have driven households to adopt a more conservative approach toward financial management, prioritizing short-term financial stability during the crisis (Vu et al., 2021). Secondly, concerns about job stability and future economic prospects would have encouraged households to increase their precautionary savings to prepare for unforeseen contingencies (Martin et al., 2020).

1.2.3.1 Influence of Covid-19 shock on risk profiles hypothesis

Based on the above mentioned studies on the influence of a global crisis on investors' risk profiles, one could believe that the impact of Covid-19 pandemic made investors more risk averse, thereby changing their risk tolerance profiles.

Hypothesis 3 (H3): Covid-19 pandemic shock pushed significantly elderly to change their investment risk profiles.

1.2.4 Individuals' personal characteristics and risk propensity

The fact that many factors would influence investors' risk profiles has become a common given, be their decision-making in daily activities, personality traits or external factors such as a global crisis. Sociodemographic and health personal characteristics would also be elements potentially shaping a risk profile.

1.2.4.1 Age and risk propensity

Research showed that older investors would be less inclined to take financial risks. Brooks et al. (2018) and Saivas and Lokhande (2022) demonstrated that this increased risk aversion in elderly would be due to a shorter investment horizon, an increased need for financial security (Malik & Sharma, 2024) and would likely reduce cognitive abilities (Brooks et al., 2018).

1.2.4.2 Gender and risk propensity

In addition to the influence of age, the gender would also imply significant differences in risk perception and tolerance. Alsharawy et al. (2021), Barasinska et al. (2009) and Thanki (2015), among others, showed that women would tend to have higher risk aversion and greater fear during financial crises, while men would tend to have a higher appetite for risk. Desmoulins-Lebeault et al. (2022) justified this biologically by studying the influence of hormones such as testosterone, present at higher levels in men, on risk taking. They stated that this hormone would have a direct relationship with risk seeking behavior, pushing men with more testosterone to seek more risk than women with less of this hormone. They noted that women with high cortisol levels, a hormone related to stress (Katsu & Baker, 2021), would also be inclined to seek risk (Desmoulins-Lebeault et al., 2022).

1.2.4.3 Relationship status and risk propensity

This gender dynamic would also be reflected in the risk taking stance of individuals with stability in their personal relationships. Abdellaoui et al. (2013) showed that women in couples would tend to be more conservative in their investment choices due to the need for consensus and risk sharing dynamics. Thanki (2015) confirmed this trend of risk aversion for married individuals compared to single ones, as partnering with someone would entail responsibilities that could reduce risk tolerance in investments (Thanki, 2015).

1.2.4.4 Education and risk propensity

Education would also play a crucial role in risk tolerance. Hastings and Mitchell (2020), Muhammad Khurram Shehzad and Qaisar Ali (2019) and Outreville (2015), among others, noted that individuals with higher education levels and better financial literacy, i.e. understanding and knowledge of the global and fundamental principles of finance (Hastings & Mitchell, 2020), would be less risk averse (Outreville, 2015). This could result in a more well diversified portfolio (Muhammad Khurram Shehzad & Qaisar Ali, 2019) and more effective financial decisions (Fong et al., 2021).

1.2.4.5 Employment status and risk propensity

Lippi et al. (2022) added that employment status would also influence risk tolerance. Individuals with stable employment would be more inclined to take financial risks compared to those with precarious or no employment status. This observation seemed to be in line with the idea that perceived security, be it financial or employment-related, would play a role in the willingness to take risks (Lippi et al., 2022).

1.2.4.6 Health status and risk propensity

Addoum et al. (2017), found that better perceived health status and increased social activity would as well be factors that increase the likelihood of holding risky assets. Households with better perceived health would be more inclined to take financial risks (Vu et al., 2021).

1.2.4.7 Influence of sociodemographic and health characteristics on risk profiles hypothesis

Based on the above mentioned studies on the influence of a personal characteristics (i.e. sociodemographic and health) on investors' risk profiles, one could believe that:

Hypothesis 4 (H4): Sociodemographic and health personal characteristics significantly influence financial investments risk profiles of the elderly in Europe. In particular, among our sample:

- ***H4a:*** Over seventy, individuals have significantly less risky profiles.
- ***H4b:*** Men have significantly riskier profiles and women less risky profiles.
- ***H4c:*** Individuals in couples have significantly less risky profiles.
- ***H4d:*** Individuals with the highest education levels have significantly riskier profiles.
- ***H4e:*** Employed or self-employed individuals have significantly riskier profiles.

- **H4f:** *Individuals with a good health status have significantly riskier profiles.*

1.3 Identified Gaps in Existing Literature

The field of traditional and behavioral finance extensively studied factors influencing investment decisions and risk profiles of investors. However, we identified several gaps in understanding how the elderly consumption patterns, personality traits and the impact of the Covid-19 pandemic shock influenced their investment risk profiles across Europe.

Firstly, although previous studies documented general consumption patterns and associated risk behaviors, there was a substantial lack of research directly linking these consumption patterns to investment risk profiles of the elderly. So far, existing studies have tended to focus on individuals and their behaviors in other situation than financial decisions, leaving a gap on how the elderly consumption behaviors impacted their financial decisions.

Secondly, while personality traits were studied concerning risk behaviors, there was also a notable gap in research focusing on how these traits specifically impacted the investment decisions of the elderly. Existing studies have tended to generalize the influence of personality on financial behavior without digging into how these traits interacted with age-related factors shaping risk profiles of the elderly.

Finally, crises such as the Covid-19 pandemic also introduced new dynamics in risk perception and investment behavior, but there was little research on how this health crisis altered the investment risk profiles of the elderly.

1.4 Contribution to the Research Field

Our study aims at filling the previous identified gaps in the literature by providing a comprehensive analysis of how elderly consumption patterns, personality traits and the Covid-19 pandemic shock influenced their investment risk profiles across Europe.

By exploring the interaction between risky and healthy consumption behaviors of the elderly and their corresponding investment decisions, our study investigates whether regular consumption of alcohol or tobacco among the elderly have been consistent with a greater risk tolerance to invest in riskier assets, whereas healthy consumption habits have been consistent with a greater risk aversion regarding the same risky assets.

By focusing on personality traits as measured by the Big Five model, our study outlines how these traits would have specifically affected the investment risk profiles of the elderly, shaping their strategies.

By analyzing changes during and after the Covid-19 pandemic, our study provides insights into behavioral adjustments induced by global crises. Principally, how the Covid-19 pandemic reshaped the risk tolerance and investment behaviors of the elderly.

Our study therefore contributes to the field of behavioral finance and risk management by providing a deeper understanding of factors influencing investment risk profiles of the elderly.

2 DATA AND VARIABLES

2.1 Database

Addressing the study objectives required the recourse to a robust and comprehensive data source across Europe. Using secondary data on a larger scale was deemed more appropriate to obtain a sufficiently large sample of respondents, the reason why the external SHARE database was exploited throughout the study process.

SHARE is a comprehensive database that compiles responses from over 140,000 individuals aged 50 and above. The database contains data from all member states of the European Union, providing a meaningful overview of varied national situations (Survey of Health, Ageing and Retirement in Europe, n.d.).

Detailed information on various aspects of people's lives, including health, social, economic and environmental factors, is collected by SHARE during multiple periods of time, known as waves. Those waves extend over more than two decades and, therefore, provide a valuable longitudinal perspective allowing for the analysis of trends and developments over time. This database is widely recognized as a valuable resource in research as it has already grounded more than 3,000 scientific publications (Survey of Health, Ageing and Retirement in Europe, n.d.).

2.2 Data

The objective of our study is to explore the relationship between individuals' risk profiles, by examining their portfolio allocation, their consumption behavior and their personality traits during two periods of time, pre- and post-Covid-19 pandemic. The data used for this purpose were obtained from the questionnaires available in SHARE, as explained above.

The initial step involved sorting and cleaning the data to create a dedicated sample. One of the challenges encountered from the outset was dealing with many missing values. The period under this study was marked by significant disruptions in the collection of data as a result of Covid-19 pandemic worldwide lockdowns (Probst et al., 2020). Fortunately, SHARE provides files for each study period that were already imputed using complex methods for estimating missing values. Whenever possible, data were sourced directly from these imputed documents. This is the case for data used to create variables such as the healthy consumption, personality traits and various demographic variables. The process to create them is explained in detail in the next section "Variables".

To represent the time horizon corresponding to the impact of Covid-19 pandemic, our sample was organized by retaining individuals who responded from 2019 onwards, thus focusing on the most recent waves of data available. There were nine waves in total, with the first dating back from 2004. For the purposes of this study, the pre- and post-Covid-19 pandemic periods were chosen to evaluate its impact using panel data. This corresponds to waves eight and nine, covering the years 2019 to early 2020 and year 2022, respectively. With this constraint, our sample was composed of 3,933 individuals who responded in both periods which made 7,866 observations over time.

2.3 Variables

For our study, we decided to create dummy and categorical variables. Also, since this study is based on a temporal shock, we applied a longitudinal approach, which means studying the same individuals over time. Each variable is listed and defined synoptically in Table 1 (see Appendix A).

To illustrate the dependent and independent variables, raw and imputed data from SHARE were converted into key variables to be tested in our models: risk profiles in investment decisions, risky consumption and healthy consumption behavior and personality traits to study the relation and the consistency of risk profiles of individuals over time.

2.3.1 Target variable: investment risk profiles

The dependent or target variable in our models, referred to as *risk profiles*, was obtained based on the portfolio distribution into six distinct categories of financial assets. Assets were categorized according to the level of risk they entailed for the individuals (Delen Private Bank, 2020).

- *Very risky assets*: This category comprises the allocation in stocks, considered having the highest level of risk due to the volatility and potential for high returns or significant losses associated with stock investments.
- *Diversified risky assets*: This category comprises the allocation in mutual funds with a fully or a majority of stocks picking. Mutual funds in stocks generally carry a moderate level of risk compared to direct stock investments.
- *Diversified assets*: This category comprises the allocation in mutual funds with an equality of stocks and bonds picking. Mutual funds with a balanced composition generally carry a moderate level of risk.
- *Diversified less risky assets*: This category comprises the allocation in mutual funds with a fully, or a majority of, bonds picking. Mutual funds in bonds generally carry a moderately higher level of risk compared to direct bonds investments which usually give a certain return at the end of the time horizon.
- *Less risky assets*: This category comprises the allocation in bonds, typically viewed as less risky than stocks and mutual funds because they offer fixed interest payments and the refund of principal upon maturity.
- *Risk free assets*: This category comprises money held on bank and savings accounts.

After this first classification and the calculation of proportions to determine the global portfolio allocation of each individual, the primary category within each portfolio was identified. This could be achieved straightforwardly, as there was systematically one of these six categories being predominant for each individual. The SHARE database, as its name indicates, focuses mainly on health and demographic data of the population. Consequently, our sample was predominantly composed of individuals who, due to health factors, demographic constraints, a lack of necessary knowledge or other factors not developed in our study, were unable to engage in complex investment strategies. Thus, for the sake of simplicity, we only considered the asset with the largest share in the portfolio to define the risk profile. This approach eased the analysis while still ensuring clarity for the categorization of risk profiles.

Risk profiles were split into the following six sub-profiles according to the same level of risk they entailed for the individuals, as previous seen for assets categorization (Delen Private Bank, 2020):

- The portfolio of the *risk seeker* is primarily composed of stock investments, entailing the most aggressive and high risk strategy, therefore focusing mainly on very risky assets, stocks. Those individuals are willing to accept significant volatility and potential losses in exchange for the possibility of substantial gains. The risk seeker's portfolio reflects a strong appetite for risk, prioritizing potential capital appreciation over stability and income.
- The *risk diversifier* invests primarily in mutual funds, known for providing a significant level of diversification, especially for retail investors who generally lack the means to invest directly in a sufficiently diversified package of stocks and bonds.

This profile is further divided into three distinct categories to capture the varying levels of risk taken by the individuals when they invest in mutual funds:

- The *diversifier - dynamic* primarily invests in mutual funds that focus on the stock market, in diversified risky assets. This allows for diversification across the stocks market, reducing the risk associated with individual stock investments.
 - The *diversifier - perfect* invests in mutual funds with an equal split between stocks and bonds. This balanced approach aims at achieving a perfect balance between risk and return, leveraging the higher potential income of stocks while mitigating risk through the stability of bonds.
 - The *diversifier - defensive* invests in mutual funds that focus mainly on the bonds market, in the diversified less risky assets. It seeks to minimize risk and get higher income by spreading investments across a range of bonds, benefiting from the relative safety and steady income provided by bond investments while still maintaining some level of diversification within its portfolio.
- The *defensive* primarily invests in individual bonds, less risky assets, prioritizing stability and consistent returns over high risk, high reward opportunities.
 - The *risk averse* does not invest in risky assets, ensuring the stability and security of its financial resources. As previously mentioned, not investing is not solely a matter of choice due to high-risk aversion, it can also be a necessity due to factors other than the unwillingness to invest. For the sake of simplicity and completeness of our models, it was considered that risk averse individuals are risk averse by choice not to invest in risky assets, exclusively as a result of risk aversion (i.e. any other external reasons affecting this choice were excluded).

When observing the variations in risk profiles pre- and post-Covid-19 pandemic in the following Table 2 showing their respective distribution within the sample, we note some variations. These latter suggest adjustments in investment behaviors that could have been influenced by external factors. This prompted us to explore further the potential causes of these changes to better understand their underlying dynamics.

Table 2: Risk profiles over Covid-19 pandemic

Risk profiles categorial	(1) 2019-2020 period: PRE Covid-19 (Wave 8)		(2) 2022 period: POST Covid-19 (Wave 9)		(3) Variation from Wave 8 to 9 [(Wave9 – Wave8)/Wave8]
	Freq.	Percent	Freq.	Percent	Δ Risk profiles
Risk seeker	293	7.45%	292	7.42%	- 0.003
Risk diversifier - dynamic	151	3.84%	167	4.25%	+ 0.106
Risk diversifier - perfectly	362	9.20%	336	8.54%	- 0.072
Risk diversifier - defensive	67	1.70%	58	1.47%	- 0.134
Defensive	50	1.27%	48	1.22%	- 0.040
Risk averse	3,010	76.54%	3,032	77.09%	+ 0.007
Total	3,933	100.00%	3,933	100.00%	

Note: Done based on « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 8 » & « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 9 ». (2024). Data sets: DOI: 10.6103/SHARE.w8.900 & DOI: 10.6103/SHARE.w9.900.

2.3.2 Independent variables: consumption patterns

This study also tries to understand the relationship that could exist between individuals' consumption patterns and their profile in investment decisions. In this context, consumption patterns were represented through two types of consumption: the risky consumption and the healthy consumption, the first one being based on the consumption of alcohol and tobacco (through different types of smoking) and the second on the consumption of healthy food and physical activities habits.

2.3.2.1 Risky consumption

To analyze individuals' daily risky consumption habits, data describing drinking habits in the SHARE database were selected. First, a dummy indicating whether individuals have consumed alcohol in the last seven days, enabled the distinction between regular and occasional drinkers. Then, a quantitative variable measuring the total number of alcoholic drinks consumed by individuals in the last seven days allowed the identification of risky drinking levels, classifying individuals according to their risk associated with alcohol consumption. In short, individuals were first sorted based on whether they consumed alcohol or not and this consumption was then quantified to incorporate risk thresholds in their alcohol consumption.

Using thresholds defined by previous studies (Paille et al., 2015), individuals that showed an emerging or a confirmed problematic alcohol consumption were considered in our study as risky drinkers. Emerging problematic drinking was defined as nine to fourteen drinks per week for women and fourteen to twenty-one drinks per week for men, while confirmed problematic drinking was defined as being over these two thresholds.

Another dummy *alcohol risk* was created to represent this risk associated with alcohol consumption. Individuals with a consumption below the previous thresholds were assigned the value zero, indicating they did not show an emerging or confirmed problematic consumption of alcohol, while those above these thresholds were assigned the value one (Paille et al., 2015).

To further enhance the risk profile regarding daily risky consumption habits, a dummy *smokers* representing the smoking status was included. This latter indicated tobacco consumption among participants, giving the value zero when an individual did not smoke and the value one, when its smoked. Quantifying the number of cigarettes or other forms of smoking was deemed unnecessary as literature indicated that even light or intermittent smoking would already present significant health risks (Underner & Peiffer, 2010).

After having created the two previous dummies, the final independent dummy *risky consumption* was added. The value one was assigned to this dummy for indicating risky consumption if the individual either smoked or drank. No specific risk quantification was established for consumption because the goal was to identify whether an individual exhibited any risky consumption behavior. Therefore, even if an individual only smoked or only drank, it was considered a risky consumption, equivalent to engaging in both behaviors in parallel.

Looking at the below Table 3, we observe that the share of individuals engaging in risky consumption behaviors slightly decreased from one period to another. This prompted us to explore further the potential causes of these changes to better understand their underlying dynamics.

Table 3: Risky consumption over Covid-19 pandemic

	(1) 2019-2020 period: PRE Covid-19 (Wave 8)		(2) 2022 period: POST Covid-19 (Wave 9)		(3) Variation from Wave 8 to 9 [(Wave9 – Wave8)/Wave8]
Risky consumption dummy	Freq.	Percent	Freq.	Percent	Δ Risky consumption
0	3,277	83.32%	3,319	84.39%	+0.013
1	656	16.68%	614	15.61%	-0.064
Total	3,933	100.00%	3,933	100.00%	

Note: Done based on « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 8 » & « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 9 ». (2024). Data sets: DOI: 10.6103/SHARE.w8.900 & DOI: 10.6103/SHARE.w9.900.

2.3.2.2 *Healthy consumption*

We created the dummy *healthy consumption* representing another aspect of individuals consumption patterns, the daily healthy consumption. This dummy indicated whether individuals engaged in regular physical activities of any kind, including basic sports as well as whether they moved frequently during the day for housework or physical work. Moreover, their good eating habits, such as consumption of fruits, vegetables, dairy products and meat, were also considered. This dummy took the value one if the individual did sport and ate good products mentioned above. It took the value zero if at least one of these habits was not followed on a regular basis.

Healthy consumption was developed independently and not assumed to be the opposite of the risky consumption, as an individual may not have engaged in risky behaviors like smoking or drinking but may have still not maintained a healthy lifestyle.

Based on the data included in the following Table 4, we observe that the share of individuals having engaged in healthy consumption behaviors increased from one period to another. This prompted us to explore further the potential causes of these changes to better understand their underlying dynamics.

Table 4: Healthy consumption over Covid-19 pandemic

	(1) 2019-2020 period: PRE Covid-19 (Wave 8)		(2) 2022 period: POST Covid-19 (Wave 9)		(3) Variation from Wave 8 to 9 [(Wave9 – Wave8)/Wave8]
Healthy consumption dummy	Freq.	Percent	Freq.	Percent	Δ Healthy consumption
0	3,358	85.38%	3,195	81.24%	-0.049
1	575	14.62%	738	18.76%	+0.283
Total	3,933	100.00%	3,933	100.00%	

Note: Done based on « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 8 » & « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 9 ». (2024). Data sets: DOI: 10.6103/SHARE.w8.900 & DOI: 10.6103/SHARE.w9.900.

The combined variations appearing in Table 3 and Table 4 above suggested shifts in consumption patterns that may have been influenced by factors other than the simple passage of time, prompting further investigation. Together with these healthy and risky consumption classifications, the risk appetite or aversion could be analyzed for determining whether the same individuals were consistent while adopting a healthy diet, potentially indicating risk aversion or neglecting their health (i.e. engaged in excessive drinking and/or smoked) suggesting a tendency to take risks.

In the Table 5 below, cross tabulating the two types of consumption, we can already observe that some individuals exhibited irrational behavior due to inconsistencies in their consumption patterns. For instance, 5,469 observations were neither risky nor healthy over the two periods. Additionally, there were 186 observations where individuals were both risky and healthy simultaneously. This indicates, as seen in previous section “Literature Review and Study Scoping”, that individuals did not always make rational decisions. It was therefore interesting to examine whether both type of consumptions influenced their investment decision profiles.

Table 5: Cross-tabulation of risky consumption and healthy consumption dummies

Risky consumption dummy	Healthy consumption dummy		
	0	1	Total
0	5,469	1,127	6,596
1	1,084	186	1,270
Total	6,553	1,313	7,866

Note: Done based on « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 8 » & « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 9 ». (2024). Data sets: DOI: 10.6103/SHARE.w8.900 & DOI: 10.6103/SHARE.w9.900.

2.3.3 Independent variables: personality traits

The personality of individuals was represented through their self-reported level of each of the Big Five Model traits. In the SHARE raw questionnaire, to evaluate each trait, their level was assessed as follows:

- *Extraversion* based on self-perception as not being a reserved person and as someone outgoing and sociable.
- *Openness* based on self-perception as someone who has artistic interests and has an active imagination.
- *Conscientiousness* based on self-perception as someone who does not tend to be lazy and does a thorough job.
- *Agreeableness* based on self-perception as someone generally trusting and not finding fault with others.
- *Neuroticism* based on self-perception as someone who is not much relaxed, does not handle stress well and gets nervous easily.

In the imputed file on SHARE, we accessed variables that were created based on their answers to the previous different questions and that represented the assessment of individuals' level of each trait on a scale ranging from one to five. The levels were defined as follows: one, "Not at all"; two, "Not that much"; three, "Neutral"; four, "Little"; five, "High".

Using these responses, five dummies were created for each personality trait. A trait took the value one when the score was greater than or equal to four (i.e., "High" or "Little" in SHARE first categorization), for *extraversion*, *agreeableness*, *conscientiousness* and *openness* and less than or equal to two for *neuroticism* (i.e. "Not at all" or "Not that much" in SHARE first categorization), as this trait captures emotional stability and positive emotions (Soto, 2015). The value zero was assigned to each trait in all other cases.

For the scope of our study, we chose to examine the risk reactions of each personality trait independently to simplify the analysis and ensure clarity. This approach avoids the complexity of interactions between traits, making it easier to identify the specific influence of each of them on risk investment profiles.

According to the below Table 6, the analysis of personality traits pre- and post-Covid-19 shows minimal changes among individuals, with *agreeableness* being the most adopted traits among our sample.

Table 6: Personality description over Covid-19 pandemic

	<i>Extraversion dummy</i>					<i>Openness dummy</i>					<i>Conscientiousness dummy</i>				
	(1) 2019-2020 period: PRE Covid-19 (Wave 8)		(2) 2022 period: POST Covid-19 (Wave 9)		(3) Variation from Wave 8 to 9 [(Wave9 – Wave8)/Wave8]	(1) 2019-2020 period: PRE Covid-19 (Wave 8)		(2) 2022 period: POST Covid-19 (Wave 9)		(3) Variation from Wave 8 to 9 [(Wave9 – Wave8)/Wave8]	(1) 2019-2020 period: PRE Covid-19 (Wave 8)		(2) 2022 period: POST Covid-19 (Wave 9)		(3) Variation from Wave 8 to 9 [(Wave9 – Wave8)/Wave8]
	Freq.	Percent	Freq.	Percent	Δ Extraversion	Freq.	Percent	Freq.	Percent	Δ Openness	Freq.	Percent	Freq.	Percent	Δ Consc.
0	2,364	60.11%	2,370	60.26%	0.003	2,706	68.80%	2,704	68.75%	-0.001	1,073	27.28%	1,063	27.03%	-0.009
1	1,569	39.89%	1,563	39.74%	-0.004	1,227	31.20%	1,229	31.25%	0.002	2,860	72.72%	2,870	72.97%	0.003
Total	3,933	100.00%	3,933	100.00%		3,933	100.00%	3,933	100.00%		3,933	100.00%	3,933	100.00%	

	<i>Agreeableness dummy</i>					<i>Neuroticism dummy</i>				
	(1) 2019-2020 period: PRE Covid-19 (Wave 8)		(2) 2022 period: POST Covid-19 (Wave 9)		(3) Variation from Wave 8 to 9 [(Wave9 – Wave8)/Wave8]	(1) 2019-2020 period: PRE Covid-19 (Wave 8)		(2) 2022 period: POST Covid-19 (Wave 9)		(3) Variation from Wave 8 to 9 [(Wave9 – Wave8)/Wave8]
	Freq.	Percent	Freq.	Percent	Δ Agreeableness	Freq.	Percent	Freq.	Percent	Δ Neuroticism
0	1,833	46.61%	1,825	46.40%	-0.004	2,288	58.17%	2,292	58.28%	0.002
1	2,100	53.39%	2,108	53.60%	0.004	1,645	41.83%	1,641	41.72%	-0.002
Total	3,933	100.00%	3,933	100.00%		3,933	100.00%	3,933	100.00%	

Note: Done based on « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 8 » & « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 9 ». (2024). Data sets: DOI: 10.6103/SHARE.w8.900 & DOI: 10.6103/SHARE.w9.900.

2.3.4 Independent variable: Covid-19 pandemic shock

To represent the Covid-19 pandemic shock and clearly distinguish between the pre- and post-periods across the two waves, a dummy variable *post-Covid* was created. This variable took the value zero for the pre-Covid-19 period and the value one for the post-Covid-19 period.

2.3.5 Control variables: personal sociodemographic characteristics

In exploring how the elderly consumption patterns, personality traits and the Covid-19 pandemic influenced investment decisions across Europe, it was essential to control the personal sociodemographic characteristics of our sample.

2.3.5.1 Country

The first variable is the *country* which specifies from where the participants originated. Our sample included individuals from eleven European countries and we therefore decided to regroup them into four geographical regions.

In Table 7 (see Appendix A), we can observe the sample distribution across these four regions. The *Northern European group* (NC) (*country* categorial variable took value one), consisting of Sweden and Denmark accounted for 21.6%. The *Central European group* (CC) (*country* categorial variable took value two), including Austria, Germany, France, Switzerland and Belgium constituted the largest segment representing 42.3% of the sample. *Eastern Europe* (EC) (*country* categorial variable took value three), composed solely of Poland accounted for 6.3% while *Southern Europe* (SC) (*country* categorial variable took value four), including Spain, Italy and Greece made up 29.8% of the sample in each period.

2.3.5.2 Age

Age is another variable chosen for representing the age distribution within the sample. Initially, age data was collected as a continuous variable measured in years within SHARE. For the purpose of our study, we converted it into a categorial variable to facilitate analysis, which took the value one for “Under 60”, two for “Between 60 and 69” and three for “Over 70”.

This categorial age distribution, also represented in Table 7 (see Appendix A), revealed that the majority of the sample consisted in individuals aged over 70 with an increase from a period to another in all geographical regions.

As multicollinearity was created with this categorization (see next section “Methodology”), we added a dummy which took the value one for individuals over 70 and the value zero under this age. The initial age categorization was only applied for the basic sample description of Table 7 (see Appendix A) to illustrate the overall trend, whereas the added dummy was used in all other analysis of our study.

2.3.5.3 Gender

Another critical piece of information about the population is the *gender* dummy which took the value one for female and zero for male. Table 7 (see Appendix A) shows a slight male dominance in both periods and across regions.

2.3.5.4 Relationship status

The dummy *relationship status* indicates whether individuals were in a couple relationship status or in single one. It took the value one for couple situation and zero for single situation. Table 7 (see Appendix A) indicates that the majority of the sample were in couple in both periods and across all regions, with a slight decrease from a period to the other.

2.3.5.5 Educational level

The *education level* variable indicates the highest level of education reached by the individuals. Initially, this variable was an imputed variable indicating the number of years of schooling completed. For our study, the data was categorized into three distinct levels of education. This categorization was based on the *International Standard Classification of Education* (hereafter referred to as “ISCED”) by SHARE.

The variable took the value one for “Low”, two for “Medium” and three for “High” educational level. These levels are described as follows (United Nations Educational, Scientific and Cultural Organization, 2006):

- *Low educational level* corresponds to pre-primary education (Level 0 of ISCED 1997), primary education or first stage of basic education (Level 1 of ISCED 1997) and lower secondary or second stage of basic education (Level 2 of ISCED 1997).
- *Medium educational level* includes upper secondary education (Level 3 of ISCED 1997) and post-secondary non-tertiary education (Level 4 of ISCED 1997).
- *High educational level* encompasses the first stage of tertiary education (Level 5 of ISCED 1997) and the second stage of tertiary education (Level 6 of ISCED 1997).

The education level distribution shows different tendencies across regions, as observed in Table 7 (see Appendix A). We note that Northern regions were mostly composed of high educated individuals while Southern countries mostly had lower educated individuals. The two other regions were composed of medium educated individuals. These tendencies remained unchanged from a region to another in post-Covid-19 period.

2.3.5.6 *Employment status*

Lastly, the *employment status* indicates the job situation of the participants and took the value one for “Retirement”, two for “Employment or Self-employment”, three for “Unemployment”, four for “Permanently Sick”, five for “Homemaker” and six for “Other”, also shown in Table 7 (see Appendix A). The data reveals that retirement was the most prevalent status, with a noticeable increase from one period to another in line with the evolution of the average age of our sample.

2.3.6 Control variables: personal health characteristics

When controlling the effects of the previous personal sociodemographic variables, we also considered worthwhile incorporating an analysis of the personal health characteristics of our sample.

2.3.6.1 *Number of chronic diseases*

The first health characteristic is the *number of chronic diseases* variable. This variable records the number of chronic diseases individuals had experienced at the time of the interview. It took the value one for “None”, two for “One to two” and three for “Three or more” chronic diseases.

In Table 8 (available in Appendix A), we see a general tendency of individuals suffering from one or two chronic diseases for Northern, Central and Southern regions and three or more for Eastern countries. We can also observe that this situation remained similar from one period the another with a shift from one or two diseases to three or more.

2.3.6.2 Body mass index

The *Body Mass Index* (hereafter referred to as “BMI”) variable is another important health indicator included in our study. BMI was calculated by SHARE in the imputed file directly based on the height and weight of individuals. This variable took the value of one if an individual was “Underweight”, two with a “Normal” corpulence, three if “Overweight” and four if in “Obesity” state (Lebiedowska et al., 2021).

As reported in Table 8 (see Appendix A), normal weight individuals were most common in Northern and Central Europe while overweight individuals were most prevalent in Southern and Eastern regions. This distribution remained the same from a period to the other.

As for the age dummy explained previously, multicollinearity was also created with this first BMI categorization (see section “Methodology”). We added another dummy which took the value one if individuals were in an alarming weight situation (i.e. underweight, overweight or in obesity status) and the value zero if they had a normal corpulence. The initial BMI categorization was only applied for the basic sample description of Table 8 (see Appendix A) to illustrate the overall trend, whereas the added dummy was used in all other analysis of our study.

2.3.6.3 Self-perceived health status

Lastly, the *Self-Perceived Health Status* variable captures individuals’ subjective assessment of their health. This variable, directly categorized by SHARE, took the value one for “Excellent” health perception, two for “Very Good”, three for “Good”, four for “Fair” and five for “Poor”. As Table 8 shows, a similar good health perception was noted across all regions and for both periods.

2.4 Summary Statistics

The tables below provides the descriptive profiles according to our independent variables, control variables and the periods pre- (Table 9) and post- (Table 10) Covid-19 pandemic. Each variable is listed and defined synoptically in Table 1 (see Appendix A). In these summary statistics tables, we applied Chi-square tests of independence since all these variables are dummies and categorical (Jmp Statistical Discovery, 2024). This test aimed at examining the potential dependencies that may have existed between our risk profiles and explanatory variables independently.

The purpose of this section is to describe the potential association independently between each categorical variable and the various investment profiles. We do not yet consider the complexity of interactions that are addressed with our models in the subsequent sections.

2.4.1 Risk seeker investment profile

Individuals with a *risk seeker* profile would exhibit a high tolerance for risk and tend to engage in risky behaviors. Our sample was composed of 293 risk seekers pre- and 292 post-Covid-19 pandemic, a relatively stable profile.

Before the Covid-19 pandemic, their consumption patterns were not significantly different from other profiles. However, after the pandemic, both risky and healthy consumption increased and became significant at a low level of 10%. This suggest that the pandemic might have influenced a portion of these individuals to adopt more risky consumption behaviors and/or healthier dietary habits, prompting further analysis.

Personality traits dummies such as *extraversion* and *neuroticism* were highly significant both pre- and post-Covid-19. This indicates, as their means were higher or close to half, that risk seekers would be typically sociable, energetic, assertive and emotionally unstable.

The profile also shows a significant dominance of females, with stable significant influences from other sociodemographic and health characteristics.

2.4.2 Risk diversifier – dynamic investment profile

Risk diversifiers – dynamic individuals would be risk tolerant who tend to diversify their portfolio while investing. As profile, they would usually show a medium high risk appetite. We observe a shift from other profiles to this one after pandemic, as it grew from 151 to 167 individuals post-Covid-19 (an increase of 10%). It is therefore suggested that the Covid-19 pandemic might have had a significant positive impact on this profile.

This profile had non-significant risky consumption patterns before the pandemic and this trend continued after, indicating that risky consumption did not significantly impact this profile. However, healthy consumption, which was non-significant pre-pandemic, became significant and increased post-pandemic, suggesting a notable shift towards healthier eating habits.

Examining personality traits dummies, *extraversion* was significant before the pandemic, however, this latter lost its significance after the pandemic, suggesting that these characteristics became less influential. Conversely, *conscientiousness* gained significance post-pandemic, highlighting an increased importance of characteristics like organization, responsibility and diligence in managing risks dynamically, with its mean closed to one. *Neuroticism* remained significant in both periods and even increased, underscoring persistent emotional instability within this profile as its mean was above half. These findings suggest that risk diversifiers - dynamic would be usually characterized by structure, reliability and commitment as well as tendency for dominance of negative emotions.

This profile tended to be predominantly held by women. Demographic factors such as country of origin, education level, job situation and health status consistently showed significant impacts, highlighting stable influences on this profile, prompting further analysis.

2.4.3 Risk diversifier – perfectly investment profile

Risk diversifier – perfectly individuals would be those with a balanced diversification strategy in their investment decisions, considered as medium risk in their investment risk profiles. We observe a decrease of about 7% from one period to the other, moving from 362 to 336 individuals having this strategy and profile.

Individuals with a *risk diversifier - perfectly* profile exhibited significant healthy consumption both before and after the pandemic. However, the extent of their healthy eating habits decreased post-pandemic. This indicates a consistent but slightly diminished emphasis on maintaining a healthy diet over time.

Personality traits such as *extraversion* were significant before the pandemic, suggesting that sociability, energy and assertiveness had a moderate influence on this profile. Indeed, the mean was lower than half, which indicates that individuals with fewer of these traits were predominant. Post-pandemic, *extraversion* remained significant but decreased, indicating that these traits were even less pronounced among this profile. *Neuroticism* maintained its stability and significance in both periods.

For this profile, the mean was also below half, indicating that the majority held low levels of *neuroticism*, which meant having emotional stability.

Moreover, this profile was predominantly held by males and by individuals in a relationship before the pandemic but shifted to being significantly dominated by females and over 70 individuals after the pandemic. Other socioeconomic and health status remained stable and significant in both periods, indicating that these factors too had influence on these profiles, prompting further analysis.

2.4.4 Risk diversifier – defensive investment profile

Risk diversifier - defensive profile would be composed of individuals choosing a relatively low risk diversification strategy in their investment decisions, considered as medium low risk profile. We also observe a shift from this profile to the others, from 67 to 58 individuals.

For them, consumption patterns did not show significant effects before or after the Covid-19 pandemic. This suggests that individuals within this profile did not exhibit distinct differences in their risky or healthy consumption behaviors compared to other profiles, regardless of the pandemic's impact.

In terms of personality, before the pandemic, *extraversion* and *openness* were significant. However, their respective means were below half, indicating that individuals in this profile predominantly had lower levels of these two traits. After the pandemic, these latter were no longer significant, suggesting an end of their influence. *Neuroticism*, with a mean above half, was significant both before and after the pandemic, although it slightly decreased post-in the second period. This suggests that emotional instability remained an important trait for this diversified defensive profile, although slightly less pronounced after the pandemic.

Demographically, this profile was predominantly held by males before the pandemic but shifted to a predominance of females after the pandemic. Additionally, age became a significant factor post-pandemic, with over 70 individuals being more prevalent in this profile. In both periods, country of origin and education level remained stable and significant for *risk Diversifier – defensive* profile, prompting further analysis.

2.4.5 Defensive investment profile

The *defensive* profile, being the one with the fewest individuals in our sample, 50 pre-Covid-19 to 48 post-Covid-19, would be individuals showing the less willingness to take risk in their investment decisions. They were considered as having a low risk profile (while still investing).

Defensive profile showed a possible relationship with the trait of *openness*. This trait was very low among defensive individuals and remained consistently so after the pandemic, with the tendency to further decrease, prompting further analysis.

2.4.6 Risk averse investment profile

Risk averse profile was the biggest profiles, with 3,010 individuals pre- and 3,032 post-Covid-19 pandemic. In this category individuals would not invest for several reasons as explained in the previous section “Target Variables”.

The *risk averse* profiles demonstrated significant healthy consumption both before and after the pandemic, with an increase observed in the second period. This suggests a stable but growing preference for healthy eating.

In terms of personality, *extraversion* was low and significant in both periods, with an increase noted post-pandemic and means below half, indicating that these individuals generally possessed lower levels for such a cautious profile. Similarly, *openness* was significant in both periods, showing an increase post-pandemic but still staying below half, indicating a general tendency towards lower *openness*. *Neuroticism* remained also significantly low both before and after the pandemic, reflecting persistent emotional stability.

Gender was consistently significant, initially male-dominated but shifted to a female dominance post-pandemic. Moreover, before the pandemic, individuals in this profile tended to be single and this tendency became non-significant after the pandemic. Other factors such as socioeconomic and health status remained stable and significant in both periods, indicating enduring influences, prompting further analysis.

2.4.7 Tables of summary statistics

Table 9: Summary statistics for pre-Covid-19 pandemic period, wave 8

Wave 8 (2019-2020): Pre-Covid19 N= 3,933

	Risk seeker N = 293			RD - dynamic N = 151			RD - perfectly N = 362		
	Mean	(SD)	p-value	Mean	(SD)	p-value	Mean	(SD)	p-value
Risky consumption	0.191	(0.394)	0.245	0.209	(0.410)	0.686	0.179	(0.384)	0.406
Healthy consumption	0.116	(0.321)	0.129	0.075	(0.265)	0.986	0.146	(0.354)	0.001***
<i>Extraversion</i>	0.539	(0.499)	0.000***	0.567	(0.499)	0.012**	0.497	(0.502)	0.000***
<i>Openness</i>	0.362	(0.481)	0.056	0.478	(0.496)	0.291	0.351	(0.478)	0.628
<i>Conscientiousness</i>	0.727	(0.445)	0.993	0.701	(0.461)	0.205	0.754	(0.431)	0.227
<i>Agreeableness</i>	0.543	(0.499)	0.756	0.569	(0.497)	0.371	0.569	(0.496)	0.160
<i>Neuroticism</i>	0.587	(0.493)	0.000***	0.552	(0.501)	0.005**	0.491	(0.501)	0.000***
Age	0.730	(0.445)	0.032**	0.687	(0.467)	0.623	0.656	(0.479)	0.814
Gender	0.570	(0.495)	0.000***	0.552	(0.501)	0.001***	0.492	(0.501)	0.038**
Couple	0.610	(0.490)	0.519	0.507	(0.504)	0.809	0.622	(0.486)	0.003**
Country	1.480	(0.653)	0.000***	1.790	(0.862)	0.000***	1.701	(0.781)	0.000***
Education	2.190	(0.760)	0.000***	2.210	(0.770)	0.000***	2.320	(0.743)	0.002**
Job situation	1.270	(0.921)	0.004**	1.240	(0.818)	0.000***	1.210	(0.686)	0.219
Chronic diseases	2.050	(0.719)	0.002**	2.060	(0.625)	0.645	2.080	(0.673)	0.014**
BMI	0.590	(0.495)	0.181	0.540	(0.503)	0.293	0.560	(0.498)	0.000***
Health status	2.740	(1.073)	0.000***	2.790	(1.038)	0.001***	2.770	(1.021)	0.135

Wave 8 (following)

	RD – defensive N = 67			Defensive N= 50			Risk averse N = 3,010		
	Mean	(SD)	p-value	Mean	(SD)	p-value	Mean	(SD)	p-value
Risky consumption	0.182	(0.387)	0.350	0.160	(0.370)	0.897	0.161	(0.368)	0.085
Healthy consumption	0.086	(0.280)	0.094	0.120	(0.328)	0.598	0.158	(0.365)	0.000***
<i>Extraversion</i>	0.488	(0.501)	0.005**	0.380	(0.490)	0.783	0.366	(0.482)	0.000***
<i>Openness</i>	0.323	(0.468)	0.003**	0.440	(0.501)	0.049*	0.298	(0.457)	0.001***
<i>Conscientiousness</i>	0.727	(0.446)	0.634	0.760	(0.431)	0.600	0.726	(0.446)	0.812
<i>Agreeableness</i>	0.569	(0.496)	0.351	0.540	(0.503)	0.931	0.528	(0.499)	0.195
<i>Neuroticism</i>	0.530	(0.501)	0.025**	0.480	(0.505)	0.373	0.378	(0.485)	0.000***
Age	0.679	(0.467)	0.825	0.720	(0.454)	0.485	0.668	(0.471)	0.130
Gender	0.494	(0.502)	0.062*	0.500	(0.505)	0.391	0.411	(0.492)	0.000***
Couple	0.561	(0.497)	0.809	0.580	(0.499)	0.444	0.646	(0.478)	0.001***
Country	1.690	(0.721)	0.000***	2.520	(1.216)	0.638	2.680	(1.114)	0.000***
Education	2.160	(0.764)	0.000***	2.020	(0.742)	0.195	1.773	(0.766)	0.000***
Job situation	1.210	(0.706)	0.219	1.340	(0.982)	0.702	1.620	(1.385)	0.000***
Chronic diseases	2.130	(0.696)	0.111	2.080	(0.674)	0.320	2.210	(0.681)	0.000***
BMI	0.560	(0.498)	0.142	0.560	(0.501)	0.351	0.640	(0.484)	0.000***
Health status	2.740	(0.970)	0.663	2.980	(1.059)	0.135	3.200	(0.975)	0.000***

Note: The p-values presented in this table were derived from Chi-square tests of independence conducted for each variable across different risk profiles.

Significance levels are indicated by stars: *p < 0.05, **p < 0.01, ***p < 0.001.

Done based on « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 8 » & « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 9 ». (2024). Data sets: DOI: 10.6103/SHARE.w8.900 & DOI: 10.6103/SHARE.w9.900.

Table 10: Summary statistics for post-Covid-19 pandemic period, wave 9

Wave 9 (2022): Post-Covid19 N= 3,933

	Risk seeker N = 292			RD- dynamic N = 167			RD - perfectly N = 336		
	Mean	(SD)	p-value	Mean	(SD)	p-value	Mean	(SD)	p-value
Risky consumption	0.205	(0.405)	0.016*	0.121	(0.329)	0.523	0.174	(0.380)	0.475
Healthy consumption	0.137	(0.344)	0.021*	0.103	(0.307)	0.007**	0.108	(0.311)	0.000***
Extraversion	0.486	(0.501)	0.001***	0.500	(0.504)	0.217	0.443	(0.498)	0.000***
Openness	0.342	(0.475)	0.251	0.414	(0.497)	0.515	0.335	(0.474)	0.999
Conscientiousness	0.702	(0.458)	0.269	0.707	(0.459)	0.005**	0.635	(0.483)	0.207
Agreeableness	0.599	(0.491)	0.024*	0.655	(0.479)	0.384	0.569	(0.497)	0.561
Neuroticism	0.599	(0.491)	0.000***	0.586	(0.497)	0.048*	0.491	(0.501)	0.001***
Age	0.795	(0.405)	0.564	0.655	(0.479)	0.068	0.838	(0.369)	0.032*
Gender	0.575	(0.495)	0.000***	0.621	(0.489)	0.005**	0.545	(0.499)	0.001***
Couple	0.586	(0.493)	0.401	0.586	(0.497)	0.386	0.641	(0.481)	0.143
Country	1.541	(0.724)	0.000***	1.966	(1.008)	0.000***	1.581	(0.714)	0.000***
Education	2.243	(0.741)	0.000***	2.293	(0.726)	0.000***	2.234	(0.744)	0.000***
Job situation	1.178	(0.705)	0.000***	1.155	(0.834)	0.037*	1.198	(0.746)	0.000***
Chronic diseases	2.127	(0.674)	0.037*	2.207	(0.585)	0.166	2.126	(0.678)	0.026*
BMI	0.572	(0.496)	0.166	0.534	(0.503)	0.151	0.557	(0.498)	0.047*
Health status	2.692	(0.999)	0.000***	3.000	(0.838)	0.000***	2.701	(1.009)	0.000***

Wave 9 (following)

	RD – defensive N = 58			Defensive N= 48			Risk averse N = 3,032		
	Mean	(SD)	p-value	Mean	(SD)	p-value	Mean	(SD)	p-value
Risky consumption	0.170	(0.376)	0.454	0.104	(0.309)	0.318	0.150	(0.358)	0.070
Healthy consumption	0.110	(0.314)	0.098	0.104	(0.309)	0.136	0.208	(0.406)	0.000***
Extraversion	0.494	(0.501)	0.108	0.396	(0.494)	0.982	0.374	(0.484)	0.000***
Openness	0.313	(0.464)	0.094	0.479	(0.505)	0.012*	0.304	(0.460)	0.030*
Conscientiousness	0.759	(0.428)	0.693	0.792	(0.410)	0.331	0.734	(0.442)	0.286
Agreeableness	0.521	(0.500)	0.067	0.479	(0.505)	0.427	0.528	(0.499)	0.079
Neuroticism	0.506	(0.501)	0.009**	0.479	(0.505)	0.381	0.382	(0.486)	0.000***
Age	0.827	(0.378)	0.019*	0.833	(0.377)	0.378	0.773	(0.419)	0.026*
Gender	0.524	(0.500)	0.005**	0.458	(0.504)	0.798	0.408	(0.492)	0.000***
Couple	0.571	(0.496)	0.724	0.542	(0.504)	0.338	0.615	(0.487)	0.152
Country	1.735	(0.756)	0.007**	2.271	(1.144)	0.261	2.667	(1.115)	0.000***
Education	2.196	(0.767)	0.000***	2.021	(0.758)	0.291	1.770	(0.766)	0.000***
Job situation	1.161	(0.707)	0.242	1.313	(0.993)	0.812	1.543	(1.347)	0.000***
Chronic diseases	2.125	(0.697)	0.108	2.083	(0.613)	0.112	2.247	(0.681)	0.000***
BMI	0.560	(0.497)	0.235	0.583	(0.498)	0.703	0.624	(0.484)	0.001***
Health status	2.735	(0.970)	0.318	2.938	(0.976)	0.305	3.213	(0.979)	0.000***

Note: The p-values presented in this table are derived from chi-square tests of independence conducted for each variable across different risk profiles.

Significance levels are indicated by stars: *p < 0.05, **p < 0.01, ***p < 0.001.

Done based on « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 8 » & « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 9». (2024). Data sets: DOI: 10.6103/SHARE.w8.900 & DOI: 10.6103/SHARE.w9.900.

We can observe that there were relationships within each profile. However, no definitive conclusions could be drawn from only these basic observations. After this initial understanding of the composition of each profile, these relationships are analyzed in a more complex manner, considering the interactions and multiple influencing factors, in the following section “Methodology”.

3 METHODOLOGY

As a reminder, the purpose of this study is to investigate how the elderly consumption patterns, personality traits and the Covid-19 pandemic shock influenced their investment risk profiles. These complex relationships were examined using two statistical models to determine causality and understand the factors influencing investment decisions among this particular population.

To explore the relationship between independent variables and investment risk profiles given the longitudinal nature of the data, (1) a series of random-effects probit regression models and (2) a fixed-effects multinomial logit regression models are conducted.

3.1 Treatment of Multicollinearity

Prior to the main analysis, the first step was to test whether our main variables were multicollinear. Multicollinearity arises when variables in a regression model are strongly linked, resulting in incorrect and unstable regression coefficient estimations. It was important to detect and address multicollinearity upfront to ensure the validity of the models results (Anesthesiol, 2019).

3.1.1 Correlation analysis

We first generated the correlation matrix of the dependent and independent variables for both waves eight (Table 11, see Appendix B) and nine (Table 12, see Appendix B), corresponding to pre- and post-Covid-19 periods. Correlation analysis is a foundational step for understanding the relationships between variables within a dataset as it provides insights into how variables moved together, which could, in turn identify patterns and potential multicollinearity issues.

One of the most interesting observations from both correlation matrices is the absence of extremely high or low correlation coefficients, with no value exceeding 0.8 or falling below -0.8. This absence suggests that while there were relationships between variables, none were strong enough to indicate direct dependence. This lack of extremely high correlations implies a lower risk of multicollinearity (Anesthesiol, 2019).

Moreover, these correlation matrixes give a first insight on moderate correlations observed, which suggested that each variable contributed independently to the investment risk profiles, without any single variable dominating the influence. This allows for a more nuanced understanding of how various factors collectively shaped investment behaviors and highlights the importance of a deeper empirical research.

3.1.2 Variance inflation factor

Although the above correlation analysis suggested a low risk of multicollinearity, it was still essential to conduct formal tests such as the *Variance Inflation Factor* (hereafter referred to “VIF”) to confirm this result (Anesthesiol, 2019). In our initial analysis (Table 13, see Appendix B), the VIF test indicated severe multicollinearity issues for the age and BMI variables when treated as categorical variables, i.e. both VIF above 10 (Anesthesiol, 2019). To address this, we converted these variables into dummies based on relevant thresholds (see section “Variables” or Table 1 in Appendix A).

After having considered the new dummies, the updated VIF test did not result anymore in multicollinearity issues i.e. all VIFs were largely under 10 (Table 14, see Appendix B).

3.2 Random-effects Probit Regression for Panel data

The initial phase of the main analysis employed a series of probit regressions for panel data to examine the relationship between the dependent variable (investment risk profiles) and the independent variables (consumption patterns, personality traits and other control variables). Each variable is listed and defined synoptically in Table 1 (see Appendix A).

Incremental random-effects probit models were used to begin the analysis. The models started with simpler version and we then incrementally added our variables in order to observe changes in the coefficients. This stepwise approach helped understanding the individual and combined effects of the variables on the dependent variable. The probit model was suitable for binary dependent variable and could handle the panel structure of the data (Gibbons & Hedeker, 1994). Moreover, the use of a random-effects model in this study allowed for capturing the complexity of panel data while considering the non-observed effects specific of each individual (Stata.com, n.d.).

We created the four following models:

- **Model 1:** Base model with sociodemographic and health characteristics to control:

$$P(\text{Risk_Profiles}_{it} = 1) = \phi(\beta_0 + \beta_1 X_{it} + \varepsilon_{it})$$

- **Model 2:** Addition of consumption patterns:

$$P(\text{Risk_Profiles}_{it} = 1) = \phi(\beta_0 + \beta_1 X_{it} + \beta_2 C_{it} + \varepsilon_{it})$$

- **Model 3:** Inclusion of personality traits:

$$P(\text{Risk_Profiles}_{it} = 1) = \phi(\beta_0 + \beta_1 X_{it} + \beta_2 C_{it} + \beta_3 P_{it} + \varepsilon_{it})$$

- **Model 4:** To investigate the impact of the Covid-19 pandemic, we included terms of interaction of post-Covid-19 dummy with our consumption and personality dummies:

$$P(\text{Risk_Profiles}_{it} = 1) = \phi(\beta_0 + \beta_1 X_{it} + \beta_2 C_{it} + \beta_3 P_{it} + \beta_4 (C_{it} \times \text{Post_Covid19}_t) + (\beta_5 P_{it} \times \text{Post_Covid19}_t) + \varepsilon_{it})$$

With,

$P(\text{Risk_Profiles}_{it} = 1)$ being the probability that individual i at time t was in the corresponding risk profile;

X_{it} being the vector of individuals' personal characteristics (sociodemographic and health);

C_{it} being the vector of individuals' consumption patterns (healthy and risky);

P_{it} being the vector of individuals' personality traits (*extraversion, openness, conscientiousness, agreeableness and neuroticism*);

Post_Covid19 being the dummy corresponding to post Covid-19 period (wave 9).

3.3 Fixed-effects Multinomial Logit Regression for Panel data

To complement the analysis, we used a fixed-effects multinomial logit regression for panel data (Liu, 2016). This method allowed evaluating the impact of the Covid-19 pandemic on different risk profiles by comparing changes in profiles within the same individuals before and after the pandemic.

The fixed-effects multinomial logit model was justified for the following reasons: it allowed for intra-individual comparisons, which is crucial for observing behavioral changes within the same individuals over different periods. Additionally, the multinomial approach was suitable for dependent categorical variables with more than two categories, such as the various investment risk profiles when using the categorical variables instead of six dummies (see Table 1, Appendix A for variables synoptic description) (Liu, 2016). This allowed us checking whether Covid-19 pandemic caused a change in risk profiles.

The second model equation is specified as follows:

$$\Pr(Risk_Profiles_{it} = l) = 1 + \frac{\exp(\alpha_k + \beta_{1k}PostCovid19_t)}{\sum_{l=1}^k \exp(\alpha_l + \beta_{1l}PostCovid19_t)}$$

With,

$\Pr(Risk_Profiles_{it} = l)$ being the probability that individual i at time t was in risk profile l ;

k being the initial risk profile and l the post-Covid-19 risk profile;

$PostCovid19_t$ being the dummy corresponding to post Covid-19 period (wave 9).

4 RESULTS & DISCUSSION

The initial model, tested in an incremental approach, is a random-effects probit regression for panel data analysis used to understand the relationship that potentially existed between consumption patterns, personality traits, Covid-19 pandemic and each risk profile. The results are fully available in Tables 15 to 20 (see Appendix C) while a summary of the significant coefficients for each profile is available in the next section “Tables of random-effects probit regression (panel data) results” (Tables 21 to 26).

All six tables of results follow the same methodology, based on four increments where the basic model (Model 1) includes the relationships with the sociodemographic and health personal control variables. The second model (Model 2) adds the two consumption pattern variables, the third one (Model 3) the five personality traits and finally the fourth one (Model 4) includes the interactions of the latter independent variables with the post-Covid-19 pandemic period.

The second model, the fixed-effect multinomial logit regression for panel data, is used to understand the Covid-19 pandemic impact on risk profiles. The related results are available in Table 27, in the corresponding section.

4.1.1 Tables of random-effects probit regression (panel data) results

Table 21: Summary of significant random-effects probit regression (panel data) results for RISK SEEKER¹

Variables	<u>Model 1</u>	<u>Model 2</u>	<u>Model 3</u>	<u>Model 4</u>
Gender: Female	0.4624*** (0.1051)	0.4632*** (0.1055)	0.4413*** (0.1065)	0.4475*** (0.1079)
Country region: Central	-1.0888*** (0.1172)	-1.0921*** (0.1173)	-1.1156*** (0.1233)	-1.1317*** (0.1252)
Country region: Eastern	-2.7390*** (0.4145)	-2.7469*** (0.4148)	-2.7575*** (0.4189)	-2.7970*** (0.4252)
Country region: Southern	-2.5088*** (0.2264)	-2.5053*** (0.2263)	-2.4868*** (0.2291)	-2.5200*** (0.2329)
Education level: Medium	0.3319*** (0.1277)	0.3297*** (0.1279)	0.2810** (0.1283)	0.2872** (0.1299)
Education level: High	0.4875*** (0.1333)	0.4792*** (0.1339)	0.4339*** (0.1344)	0.4418*** (0.1361)
Health status: Poor	-0.4470* (0.2456)	-0.4273* (0.2465)	-0.3731 (0.2474)	-0.3493 (0.2501)
Personality: <i>Openness</i>	-	-	0.1892* (0.1044)	0.2063 (0.1258)
Personality: <i>Agreeableness</i>	-	-	-0.1993* (0.1021)	-0.3534*** (0.1242)
Personality: <i>Neuroticism</i>	-	-	0.2143** (0.1016)	0.1932 (0.1227)
<i>Extraversion</i> * post Covid-19	-	-	-	-0.2640** (0.1341)
<i>Agreeableness</i> * post Covid-19	-	-	-	0.2999** (0.1362)
Observations	7,778	7,778	7,778	7,778
Pseudo R ²	0.211	0.211	0.215	0.217

Note: Significance levels are indicated by stars: *p < 0.05, **p < 0.01, ***p < 0.001.

Coefficients are first written and standard errors are in parentheses.

Pseudo R² = 1 - $\frac{\text{Log Likelihood entire model}}{\text{Log Likelihood Iteration 0}}$ (Veall & Zimmermann, 1994).

Although Pseudo R² values are small, they increase progressively, indicating that the model increasingly explains the variability in the data.

The results of random-effects probit regression (panel data) for this profile are fully available in Table 15.

Done based on « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 8 » & « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 9 ». (2024). Data sets: DOI: 10.6103/SHARE.w8.900 & DOI: 10.6103/SHARE.w9.900.

¹ This Table 21 was only used for simplicity in the core text to have an overview of the significant relations directly. These results took in account all of the interactions with independent and control variables as the equation (see "Methodology" section) indicated.

Table 22: Summary of significant random-effects probit regression (panel data) results for RISK DIVERSIFIER - DYNAMIC²

Variables	Model 1	Model 2	Model 3	Model 4
Gender: Female	0.2969*** (0.0931)	0.3015*** (0.0933)	0.2919*** (0.0938)	0.2918*** (0.0942)
Country region: Central	-0.4420*** (0.0964)	-0.4445*** (0.0964)	-0.4352*** (0.1004)	-0.4380*** (0.1008)
Country region: Eastern	-2.0480*** (0.4745)	-2.0544*** (0.4748)	-2.0884*** (0.4812)	-2.1018*** (0.4855)
Country region: Southern	-1.3839*** (0.1814)	-1.3833*** (0.1813)	-1.3741*** (0.1834)	-1.3771*** (0.1844)
Education level: Medium	0.2973*** (0.1170)	0.2977*** (0.1170)	0.2924*** (0.1170)	0.2934*** (0.1174)
Education level: High	0.5167*** (0.1209)	0.5175*** (0.1210)	0.5088*** (0.1212)	0.5077*** (0.1217)
Job: Permanently Sick	0.7525* (0.3880)	0.7695** (0.3892)	0.7792** (0.3877)	0.7715** (0.3896)
Health status: Fair	-0.3054* (0.1614)	-0.2999* (0.1614)	-0.3396** (0.1628)	-0.3370** (0.1636)
Health status: Poor	-0.4843** (0.2384)	-0.4663* (0.2395)	-0.5041** (0.2405)	-0.4957** (0.2421)
Personality: <i>Conscientiousness</i>	-	-	-0.2499*** (0.0946)	-0.1641 (0.1240)
Observations	7,840	7,840	7,840	7,840
Pseudo R ²	0.131	0.131	0.134	0.136

Note: Significance levels are indicated by stars: *p < 0.05, **p < 0.01, ***p < 0.001.

Coefficients are first written and standard errors are in parentheses.

Pseudo R² = 1 - $\frac{\text{Log Likelihood entire model}}{\text{Log Likelihood Iteration 0}}$ (Veall & Zimmermann, 1994).

Although Pseudo R² values are small, they increase progressively, indicating that the model increasingly explains the variability in the data.

The results of random-effects probit regression (panel data) for this profile are fully available in Table 16.

Done based on « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 8 » & « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 9 ». (2024). Data sets: DOI: 10.6103/SHARE.w8.900 & DOI: 10.6103/SHARE.w9.900.

² This Table 22 was only used for simplicity in the core text to have an overview of the significant relations directly. These results took in account all of the interactions with independent and control variables as the equation (see "Methodology" section) indicated.

Table 23: Summary of significant random-effects probit regression (panel data) results for RISK DIVERSIFIER - PERFECT³

Variables	Model 1	Model 2	Model 3	Model 4
Gender: Female	0.2627*** (0.0877)	0.2659*** (0.0875)	0.2498*** (0.0881)	0.2502*** (0.0885)
Relationship status: Couple	-0.1649* (0.0863)	-0.1711** (0.0861)	-0.1813** (0.0864)	-0.1800** (0.0868)
Country region: Central	-0.3721*** (0.0925)	-0.3751*** (0.0922)	-0.3720*** (0.0968)	-0.3746*** (0.0972)
Country region: Eastern	-2.9466*** (0.5596)	-2.9498*** (0.5577)	-2.9636*** (0.5565)	-2.9721*** (0.5573)
Country region: Southern	-1.6352*** (0.1617)	-1.6227*** (0.1608)	-1.6017*** (0.1634)	-1.6099*** (0.1642)
Education level: Medium	0.2138** (0.1046)	0.2103** (0.1043)	0.1946* (0.1044)	0.1945* (0.1049)
Education level: High	0.3877*** (0.1099)	0.3809*** (0.1097)	0.3874*** (0.1102)	0.3889*** (0.1107)
Job: Employed/self-employed	-0.3672** (0.1741)	-0.3635** (0.1734)	-0.3501** (0.1730)	-0.3559** (0.1737)
Health status: Fair	-0.3571** (0.1512)	-0.3409** (0.1510)	-0.3249** (0.1520)	-0.3419** (0.1528)
Health status: Poor	-0.4661** (0.2150)	-0.4164* (0.2157)	-0.3979* (0.2165)	-0.4275** (0.2181)
Consumption: Healthy	-	-0.2242** (0.1084)	-0.2278** (0.1084)	-0.3273** (0.1545)
Personality: Agreeableness	-	-	-0.1888** (0.0849)	-0.0946 (0.1027)
Observations	7,840	7,840	7,840	7,840
Pseudo R ²	0.173	0.174	0.176	0.178

Note: Significance levels are indicated by stars: *p < 0.05, **p < 0.01, ***p < 0.001.

Coefficients are first written and standard errors are in parentheses.

Pseudo R² = 1 - $\frac{\text{Log Likelihood entire model}}{\text{Log Likelihood Iteration 0}}$ (Veall & Zimmermann, 1994).

Although Pseudo R² values are small, they increase progressively, indicating that the model increasingly explains the variability in the data.

The results of random-effects probit regression (panel data) for this profile are fully available in Table 17.

Done based on « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 8 » & « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 9 ». (2024). Data sets: DOI: 10.6103/SHARE.w8.900 & DOI: 10.6103/SHARE.w9.900.

³ This Table 23 was only used for simplicity in the core text to have an overview of the significant relations directly. These results took in account all of the interactions with independent and control variables as the equation (see "Methodology" section) indicated.

Table 24: Summary of significant random-effects probit regression (panel data) results for RISK DIVERSIFIER - DEFENSIVE⁴

Variables	Model 1	Model 2	Model 3	Model 4
Age: Older (+ 70 years old)	-0.2626* (0.1336)	-0.2535* (0.1341)	-0.2437* (0.1341)	-0.2429* (0.1375)
Gender: Female	0.3998*** (0.1317)	0.4116*** (0.1325)	0.4212*** (0.1347)	0.4324*** (0.1387)
Relationship status: Couple	-0.2824** (0.1285)	-0.2942** (0.1290)	-0.2650** (0.1296)	-0.2796** (0.1333)
Country region: Central	-0.2938** (0.1366)	-0.3002** (0.1368)	-0.3229** (0.1444)	-0.3292** (0.1482)
Country region: Eastern	-1.0127*** (0.3950)	-1.0364*** (0.3964)	-0.9875*** (0.3995)	-1.0218*** (0.4136)
Country region: Southern	-0.6736*** (0.2037)	-0.6700*** (0.2035)	-0.6389*** (0.2106)	-0.6510*** (0.2163)
Education level: Medium	0.3003* (0.1621)	0.3023* (0.1622)	0.2559 (0.1626)	0.2646 (0.1669)
Education level: High	0.4979*** (0.1683)	0.5003*** (0.1689)	0.4330*** (0.1691)	0.4495*** (0.1738)
Consumption: Healthy	-	-0.2904 (0.1841)	-0.3142* (0.1855)	-0.4114 (0.2713)
Personality: <i>Extraversion</i>	-	-	0.2209* (0.1239)	0.3431** (0.1622)
Personality: <i>Openness</i>	-	-	0.2973** (0.1272)	0.3769** (0.1626)
Personality: <i>Agreeableness</i>	-	-	-0.0827 (0.1241)	-0.3214** (0.1640)
<i>Agreeableness</i> * post Covid-19	-	-	-	0.5109** (0.2183)
Observations	7,752	7,752	7,752	7,752
Pseudo R ²	0.166	0.168	0.172	0.174

Note: Significance levels are indicated by stars: *p < 0.05, **p < 0.01, ***p < 0.001.

Coefficients are first written and standard errors are in parentheses.

Pseudo R² = 1 - $\frac{\text{Log Likelihood entire model}}{\text{Log Likelihood Iteration 0}}$ (Veall & Zimmermann, 1994).

Although Pseudo R² values are small, they increase progressively, indicating that the model increasingly explains the variability in the data.

The results of random-effects probit regression (panel data) for this profile are fully available in Table 18.

Done based on « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 8 » & « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 9 ». (2024). Data sets: DOI: 10.6103/SHARE.w8.900 & DOI: 10.6103/SHARE.w9.900.

⁴ This Table 24 was only used for simplicity in the core text to have an overview of the significant relations directly. These results took in account all of the interactions with independent and control variables as the equation (see "Methodology" section) indicated.

Table 25: Summary of significant random-effects probit regression (panel data) results for DEFENSIVE⁵

Variables	Model 1	Model 2	Model 3	Model 4
Age: Older (+ 70 years old)	0.3599* (0.2067)	0.3577* (0.2067)	0.3749* (0.2077)	0.3742* (0.2101)
Education level: Medium	0.4492** (0.2079)	0.4472** (0.2074)	0.3885* (0.2061)	0.3912* (0.2085)
Personality: <i>Openness</i>	-	-	0.4319** (0.1734)	0.3709* (0.2132)
Observations	7,644	7,644	7,644	7,644
Pseudo R^2	0.164	0.165	0.167	0.169

Note: Significance levels are indicated by stars: *p < 0.05, **p < 0.01, ***p < 0.001.

Coefficients are first written and standard errors are in parentheses.

Pseudo $R^2 = 1 - \frac{\text{Log Likelihood entire model}}{\text{Log Likelihood Iteration 0}}$ (Veall & Zimmermann, 1994).

Although Pseudo R^2 values are small, they increase progressively, indicating that the model increasingly explains the variability in the data.

The results of random-effects probit regression (panel data) for this profile are fully available in Table 19.

Done based on « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 8 » & « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 9 ». (2024). Data sets: DOI: 10.6103/SHARE.w8.900 & DOI: 10.6103/SHARE.w9.900.

⁵ This Table 25 was only used for simplicity in the core text to have an overview of the significant relations directly. These results took in account all of the interactions with independent and control variables as the equation (see "Methodology" section) indicated.

Table 26: Summary of significant random-effects probit regression (panel data) results for RISK AVERSE⁶

Variables	Model 1	Model 2	Model 3	Model 4
Age: Older (+ 70 years old)	-0.1710 (0.1047)	-0.1844 (0.1048)	-0.1782 (0.1049)	-0.1856* (0.1057)
Gender: Female	-0.7646*** (0.1146)	-0.7694*** (0.1145)	-0.7333*** (0.1151)	-0.7395*** (0.1160)
Relationship status: Couple	0.2035* (0.1074)	0.2139** (0.1072)	0.2027* (0.1077)	0.2013* (0.1085)
Country region: Central	1.4301*** (0.1312)	1.4334*** (0.1308)	1.4620*** (0.1367)	1.4743*** (0.1378)
Country region: Eastern	4.5840*** (0.4523)	4.5933*** (0.4496)	4.6152*** (0.4517)	4.6513*** (0.4572)
Country region: Southern	3.3485*** (0.2130)	3.3344*** (0.2123)	3.3039*** (0.2161)	3.3328*** (0.2183)
Education level: Medium	-0.6486*** (0.1322)	-0.6431*** (0.1319)	-0.5837*** (0.1320)	-0.5895*** (0.1330)
Education level: High	-1.0707*** (0.1442)	-1.0597*** (0.1439)	-1.0067*** (0.1442)	-1.0166*** (0.1454)
Job: Unemployed	1.8315 (0.9370)	1.8446** (0.9373)	1.8070* (0.9327)	1.8126* (0.9431)
Health status: Fair	0.4787*** (0.1636)	0.4700*** (0.1635)	0.4247** (0.1645)	0.4232** (0.1658)
Health status: Poor	0.6279*** (0.2224)	0.5781*** (0.2228)	0.5275** (0.2238)	0.5193** (0.2254)
Consumption: Healthy	-	0.3013*** (0.1101)	0.3079*** (0.1103)	0.3587** (0.1536)
Personality: <i>Extraversion</i>	-	-	-0.1471 (0.1076)	-0.2758** (0.1215)
Personality: <i>Openness</i>	-	-	-0.2043* (0.1109)	-0.2574** (0.1249)
Personality: <i>Agreeableness</i>	-	-	0.3527*** (0.1081)	0.4225*** (0.1225)
Personality: <i>Neuroticism</i>	-	-	-0.3298*** (0.1082)	-0.3772*** (0.1222)
Extraversion * post Covid-19	-	-	-	0.2602** (0.1109)
Observations	7,866	7,866	7,866	7,866
Pseudo R^2	0.188	0.189	0.190	0.191

Note: Significance levels are indicated by stars: *p < 0.05, **p < 0.01, ***p < 0.001.

⁶ This Table 26 was only used for simplicity in the core text to have an overview of the significant relations directly. These results took in account all of the interactions with independent and control variables as the equation (see "Methodology" section) indicated.

Coefficients are first written and standard errors are in parentheses.

Pseudo $R^2 = 1 - \frac{\text{Log Likelihood entire model}}{\text{Log Likelihood Iteration 0}}$ (Veall & Zimmermann, 1994).

Although Pseudo R^2 values are small, they increase progressively, indicating that the model increasingly explains the variability in the data.

The results of random-effects probit regression (panel data) for this profile are fully available in Table 20.

Done based on « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 8 » & « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 9 ». (2024). Data sets: DOI: 10.6103/SHARE.w8.900 & DOI: 10.6103/SHARE.w9.900.

4.2 Elderly, Consumption Patterns and Investment Risk Profiles

Our study's primary objective is to explore the potential relationship between individuals' investment behaviors, which delineates their risk profiles and their consumption patterns. To this end, consumption is analyzed by incorporating from the first incrementation (Model 2) these individuals' choices in distinct aspects of their lives, characterized by risky and healthy behaviors.

4.2.1 Elderly risky consumption and their investment risk profiles

The first consumption patterns studied focused on risky consumption, examining whether individuals who drank and/or smoked alarmingly were consistent as regard their investment strategy.

Although the literature is sparse on the direct connection between risky consumption and investment risk profiles, it suggests general trends regarding individuals' willingness to take risks in other aspects of their lives, such as smoking or drinking alarmingly. It also clearly indicated that risky behaviors would not occur in isolation (Connell et al., 2009; Kipping et al., 2012) but could impact various aspects of life (Wittgens et al., 2022).

Hence, it was suggested through Hypothesis 1a that elderly individuals who consumed alcohol alarmingly - defined as above fourteen drinks per week for women and twenty-one for men - and/or smoked regularly, would also be likely, if consistent, to exhibit the same risk taking tendency in their investment strategies (Allard, 2009; Paille et al., 2015). Consequently, they would tend to have a profile of *risk seeker* or *risk diversifier - dynamic*, meaning they would invest the majority of their portfolio in the riskier assets such as individual stocks or through investment funds.

None of the incremented models (Model 2, 3 and 4) show significant relationships between any profiles and the dummy risky consumption of alcohol and/or tobacco.

Consequently, we rejected Hypothesis 1a, which assumed that individuals were consistent by maintaining the same risky profile in their consumption of harmful products as in their investment decisions.

4.2.2 Elderly healthy consumption and their investment risk profiles

The second consumption patterns studied focused on healthy consumption, examining whether individuals who regularly consumed fruits, vegetables, dairy products and meat as well as regularly engaged in physical activities were consistent as regard their investment strategy.

The literature indeed suggests that, similarly to risky consumption, daily healthy behavior could also be reflected in other aspects of life. This would be explained by the fact that healthy eating and physical activities would lead to better overall hygiene, resulting in improved mental health and cognitive abilities (Li et al., 2024; Serra et al., 2020). This enhanced mental capacity would partly be due to reduced stress levels associated with a better quality of life (Wong et al., 2023), which would positively influence decision-making processes. As a result, individuals would be less likely to make impulsive, poorly thought-out decisions and would be more likely to take less risks (Peretti-Watel et al., 2013).

Building upon these premises, we assumed with Hypothesis 1b that elderly individuals who exhibit healthy behaviors in their eating and regular physical activities would rationally maintain a similarly cautious profile in their investment decisions, thus being less risk tolerant or risk averse. This cautious approach would be translated into investing in less risky assets, such as bonds, either individually or through diversified mutual funds. It could also involve not investing at all (i.e. keeping their money on risk free bank or savings accounts).

As from all incremented models (Model 2, 3 and 4) for the *risk diversifier – perfect* and *risk averse* profile, the coefficients of the dummy healthy consumption are significant, negative and positive, respectively. This indicates that the more cautious investors tended to be, the healthier they would be in their daily consumption patterns. While moderate risky investors would tend to be less healthy.

Therefore, we confirmed Hypothesis 1b according to which a healthy lifestyle, reflected through healthy eating and regular physical activity, would positively influence the likelihood of being risk averse, aligning with the existing literature.

4.2.3 Elderly consumption patterns and their investment risk profiles

While risky consumption patterns would not appear to significantly influence investment risk profiles among the elderly, healthy consumption behaviors would be positively associated with more risk averse investment strategies, confirming partially Hypothesis 1 on the consumption patterns influence.

4.3 Elderly, Personality Traits and Investment Risk Profiles

4.3.1 Elderly *extraversion* trait and their investment risk profiles

The first trait based on the Big Five model examined in our study on the potential existence of a relationship between an individual's personality and their investment risk profile was *extraversion*. As a reminder, this trait encompasses levels of sociability, energy and assertiveness (Raad & Mlacic, 2015).

The literature teaches us that individuals with a high tolerance for risk would be those with high levels of *extraversion* in their personality (Joseph & Zhang, 2021; Sahinidis et al., 2020). This would be because individuals with this strong personality trait would tend to seek intense sensations (Nicholson et al., 2005) and therefore seek out risk.

Based on this premise, we assumed, with Hypothesis 2a, that individuals with high levels of *extraversion* in their personality would be those who seek risk, which would also be reflected in having a *risk seeker* profile in their investment strategy, looking for riskier assets such as stocks.

As from the incremented Model 3, in opposition to the existing literature, our findings indicate a more nuanced relationship between this trait, when being at high level, compared to low (reference category), and investment risk profiles. In particular we found:

- A significant positive impact for the *risk diversifier - defensive* profile for all incremented probit models. This suggests that individuals in this profile, who typically adopt a more cautious approach towards risk diversification, might have exhibited high characteristics of *extraversion*, as compared to low ones.
- That the *risk averse* profile is negatively significant for this trait in the last incremented probit model (Model 4) indicating that individuals with high *extraversion* would be less likely to be risk averse, as compared to low ones. Moreover, the interaction term with the post-Covid-19 dummy shows that the pandemic significantly would have influenced extraverted individuals to become more risk averse, as the coefficient is positive.
- That Covid-19 pandemic would also have influenced extraverted individuals to be less risk seeker in the last incremented probit model, as the interaction term shows a negative significant relationship.

On this basis, we rejected Hypothesis 2a assuming that a high level compared to a low ones of *extraversion* would be associated with a greater propensity to take risks. Indeed, our findings from our elderly sample indicate, on the contrary, a tendency for this trait at high level to diversify cautiously, predominantly into bonds through mutual funds. This trait at high level would still have encouraged investment, as it is negatively associated with the risk free profile and this latter is even more pronounced post-Covid-19 pandemic.

4.3.2 Elderly *openness* trait and their investment risk profiles

The second trait based on the Big Five model examined in our study was *openness*. This trait, when highly present in an individual's personality, would be characterized by a propensity for discovering new experiences, marked by curiosity, imagination and empathy (Raad & Mlacic, 2015).

Similarly to *extraversion*, *openness* is characterized in the literature by a profile with a tolerance for risk. However, this trait is less strongly associated with high risk taking than *extraversion*. *Openness* is typically linked to moderate risk tolerance, with individuals seeking diversified risk (Lai, 2019; Wang et al., 2016).

We therefore assumed with Hypothesis 2b that individuals with high levels of *openness* in their personality would be those who seek moderate risk. In the context of our study, this would be reflected in the *risk diversifier* (either *dynamic*, *perfectly* or *defensive*) profile, with a preference for assets providing good diversification, such as mutual funds.

As from the incremented Model 3, the results indicate:

- That *risk diversifier – defensive* and *defensive* profiles are significantly and positively impacted by high levels of *openness*, as compared to low ones (reference category). This suggests that individuals with higher *openness* compared to low ones would be more likely to adopt these profiles.

- That the *risk averse* profile shows a significant negative coefficient, suggests that individuals with higher levels of *openness*, as compared to low ones, would be less likely to adopt a *risk averse* profile.

This finding aligns with the notion from existing literature indicating individuals who have a high level of *openness* would tend to have moderately risky investment strategies. However, it is important to note that the significance level for *defensive* profile is at 10%, indicating a need for cautious interpretation, as it could have been influenced by sampling variability or other external factors.

Therefore, we confirmed the Hypothesis 2b that higher levels of *openness* would positively influence the likelihood of adopting *risk diversifier – defensive* profile while negatively impacting the likelihood of a *risk averse* profile. The findings from our elderly sample are in line with the existing literature indicating that individuals with high level of this trait compared to low ones would tend to diversify, by mainly investing in bonds through mutual funds. Additionally, we can infer that this trait would also still promote investment activity, given its negative association with the *risk averse* profile.

4.3.3 Elderly *conscientiousness* trait and their investment risk profiles

The third personality trait considered in our study was *conscientiousness*, which, with a high score, reflects tendencies towards organization, responsibility and diligence (Raad & Mlacic, 2015).

As the literature states, this trait would have a stronger tendency towards biased behaviors concerning risk (Isidore & Arun, 2021). Indeed, individuals with high *conscientiousness* would generally tend to take fewer risks as they get older. However, they would also become risk takers when they have strong confidence in their analysis (Yadav & Narayanan, 2021).

Therefore, we assumed with Hypothesis 2c, the possibility that individuals with high *conscientiousness* would exhibit moderate risk tendencies due to our older sample population. In the context of our study, this would be reflected in profiles such as *risk diversifier* (either *dynamic*, *perfect* or *defensive*), with a moderate risk compared to other profiles due to diversification.

In the results of incremented Model 3, a negative relationship is identified for individuals having a high level of *conscientiousness*, as compared to low ones (reference category) with the *risk diversifier - dynamic* profile. However, this trend disappeared once interaction terms were incremented in Model 4.

As a result, we rejected hypothesis 2c which suggested that individuals with a high level of *conscientiousness* would be significantly associated with a moderate risk profile.

4.3.4 Elderly *agreeableness* trait and their investment risk profiles

The fourth trait examined in this theory was *agreeableness*, which is associated with high levels of empathy, pleasantness and cooperativeness (Raad & Mlacic, 2015).

The literature suggests that individuals with this calm and serene trait, who tend to avoid conflict in favor of maintaining harmonious relationships (Ahmad & Maochun, 2019), would be more likely to reflect these characteristics in their investment decisions.

In our study, we assumed with Hypothesis 2d, that a high level of *agreeableness* would be reflected in low risk profiles, such as *defensive* or *risk averse* ones. When considering having a high level of *agreeableness*, as compared to a low one (reference category), we found the following:

- As from the incremented Model 3, we observe a negative relationship between *agreeableness* and the *risk seeker* profile. Additionally, the interaction between this trait and the post-Covid-19 dummy variable is also significant but positive.
- A similar trend, only for the incremented Model 4, is noted for the *risk diversifier – defensive* profile, with a negative coefficient for *agreeableness* standalone and positive for the interaction term. On the other hand, for the *risk diversifier – perfect* profile, a significant negative coefficient is noticed but it was only for the incremented Model 3, with this trend disappearing once interaction terms were incremented in Model 4.
- For the *risk averse* profile, there is a positive relationship with *agreeableness* for both incremented models.

All of these findings suggest that individuals exhibiting a high level of *agreeableness*, as compared to a low one, would be more likely to shy away from higher risk investments, this behavior being exacerbated by the Covid-19 pandemic (they instead showed preference for risk free assets).

We therefore confirmed Hypothesis 2d as our results are in line with existing literature suggesting that individuals with higher *agreeableness* would be associated with more conservative investment profiles.

4.3.5 Elderly *neuroticism* trait and their investment risk profiles

The last trait in the Big Five Model examined in our study was *neuroticism*, which at high levels encompasses negative emotions such as anxiety, stress and anger (Raad & Mlacic, 2015).

Existing literature on the relationship between high levels of *neuroticism* and willingness to take risks suggests that individuals who score high on this trait — meaning they would be more sensitive to negative emotions — would tend to take fewer risks (Oehler et al., 2018) in order to avoid situations that could potentially increase their stress levels (De Bortoli et al., 2019).

In our study, we assumed with Hypothesis 2e whether a high level of *neuroticism* would be reflected in risk free profiles, such *risk averse* profile. When considering having a high level of *neuroticism*, as compared to a low one (reference category), we found the following:

- A significant positive coefficient is noticed for *risk seeker* profile but it was only for the incremented Model 3, with this trend disappearing once interaction terms were incremented in Model 4.
- A significant negative relationship with the *risk averse* profile in both incremented Model 3 and 4. This suggests that individuals who score higher on this trait would be less likely to adopt a *risk averse* investment profile. This is somewhat counterintuitive because one would have expected, with regard to existing literature, individuals with higher levels of *neuroticism* to prefer safer, less risky investment strategies due to their sensitivity to potential losses (De Bortoli et al., 2019). However, the negative coefficient indicates the opposite—that these individuals may either not have engaged in risk averse behaviors as strongly as expected or may have been inclined to take on more risk despite their emotional predispositions.

These findings suggest that while *neuroticism* involved a predisposition to negative emotions, it would not have necessarily been translated into conservative financial behavior. Instead, the elderly might have reacted differently under stress. We therefore rejected Hypothesis 2e suggesting individuals with high level of this *neuroticism* would have *risk averse* profile.

4.3.6 Elderly personality traits and their investment risk profiles

Our analysis of the Big Five personality traits—*extraversion*, *openness*, *conscientiousness*, *agreeableness* and *neuroticism*—revealed nuanced relationships with the investment risk profiles of the elderly. While existing literature often associates certain traits with specific risk taking behaviors, our findings indicate that these relationships were more complex among this specific population.

- *Extraversion*, typically linked to risk seeking behavior, would instead be associated with more cautious investment strategies, particularly in the post-Covid-19 period.
- *Openness*, often connected to a moderate tolerance for risk, would be associated with a tendency toward diversified, yet still conservative, investment profiles.
- *Conscientiousness*, which we assumed being linked to lower risk profiles, did not show significant relationship in our models, leading to the rejection of the idea that this trait would influence investment behavior in our sample.
- *Agreeableness*, characterized by a preference for harmony and avoidance of conflict, would indeed be associated with less risky investment profiles, confirming the hypothesis that individuals with high *agreeableness* would tend to favor safer investment options.
- *Neuroticism*, contrary to expectations, would negatively be associated with the *risk averse* profile, suggesting that the elderly with higher levels of this trait would not have necessarily engaged in the risk free investment behavior, typically expected from those, prone to negative emotions.

While the majority of Big Five personality traits would influence investment risk profiles among the elderly, their impact would be moderated by various factors, confirming partially Hypothesis 2 on the personality traits influence.

4.4 Elderly, Covid-19 pandemic shock and Investment Risk Profiles

One of our study objectives is also to assess whether the Covid-19 pandemic impacted the evolution of investment risk profiles among the elderly. Additionally, through the use of interaction terms, we explored whether the Covid-19 pandemic had any effect on independent variables such as consumption patterns and personality traits (see Tables 15 to 20, Appendix C or summary Tables 21 to 26, at the end of this chapter).

Our initial random-effects probit panel models suggested that the Covid-19 pandemic might have had an impact on two personality traits: *extraversion* and *agreeableness*, as discussed in the previous section on personality traits.

Regarding the potential impact of the pandemic on the target variable of our study - investment risk profiles - the literature suggests that global crises could be accompanied by uncertainty (Millroth & Frey, 2021) and fear (Cori et al., 2020), emotions that would likely be associated with greater risk aversion (Heo et al., 2021). This increase in risk aversion could be explained by several factors, such as the vulnerability associated with these emotions (Millroth & Frey, 2021), trust in government-proposed solutions (Zivi et al., 2023), cognitive decline due to isolation and confinement-related issues like depression (Probst et al., 2020) and the need for precaution by limiting expenditures (Martin et al., 2020). All of these factors might have contributed to increased risk aversion among investors during the Covid-19 period, potentially leading to biased behaviors such as loss aversion (Dita et al., 2023).

This is the reason why we tested, through Hypothesis 3, whether the investment profiles of the elderly in our sample might have been impacted by the Covid-19 pandemic. To this end, we conducted a fixed-effect multinomial logit regression in panel data to determine whether this dummy might have caused elderly to change their investment risk profiles.

Our results included in Table 27 below, demonstrate that none of the coefficients for the post-Covid-19 variable across the various risk profiles are statistically significant. This finding challenge the initial assumption that the Covid-19 pandemic, characterized by widespread uncertainty and economic volatility, might have driven elderly to reassess and adjust their investment strategies.

However, the lack of significant change in our elderly sample suggests a certain resilience or consistency in their risk preferences, even when facing an unprecedented global crisis. It indicates that while the pandemic introduced many external stressors, these latter would not have had fundamentally altered the risk tolerance levels of the elderly in our sample.

In other words, our analysis suggests that the Covid-19 pandemic, despite its widespread effects on various aspects of life, would not have significantly influenced elderly investment risk profiles and we, therefore, rejected Hypothesis 3.

Overall, the Covid-19 pandemic would not have directly influenced investment risk profiles among the elderly but would have indirectly influenced them through some Big-Five model personality traits.

Table 27: Fixed-effects multinomial logit regression (panel data) results for risk profiles

Risk profiles (base: Risk averse)	Coefficient	Std. error	P-value
Risk seeker			
Post-Covid-19	-0.0524	(0.1282)	0.683
Risk diversifier - dynamic			
Post-Covid-19	0.0437	(0.1496)	0.770
Risk diversifier - perfectly			
Post-Covid-19	-0.1617	(0.1191)	0.175
Risk diversifier - defensive			
Post-Covid-19	-0.2391	(0.2101)	0.255
Defensive			
Post-Covid-19	-0.1067	(0.2398)	0.656
Observation		1,536	
N		768	

Note: Significance levels are indicated by stars: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Coefficients are first written and standard errors are in parentheses.

Done based on « *Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 8* » & « *Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 9* ». (2024). Data sets: DOI: 10.6103/SHARE.w8.900 & DOI: 10.6103/SHARE.w9.900.

4.5 Elderly, Personal Characteristics and Investment Risk Profiles

4.5.1 Elderly age and their investment risk profiles

Regarding the age dummy, the literature suggests that when getting older, individuals would tend to take fewer risks (Brooks et al., 2018; Saivas & Lokhande, 2022), as assumed with Hypothesis 4a.

As from the incremented Model 1, our results, however, indicate that being over 70 are negatively significant for the *risk diversifier defensive* and *risk averse* (only in Model 4) profiles but positively significant for the *defensive* profile.

These findings suggest that individuals over 70 in our sample would be likely to adopt more conservative profile, typically associated with lower risk investment strategies. This implies that they would not become totally risk averse as they get older, but these individuals would be more willing to explore investment strategies involving the lowest degree of risk.

This finding confirmed Hypothesis 4a suggesting that older individuals are more inclined towards lower risk profiles. However, as this result are significant at the 10% level, it should be interpreted with care.

4.5.2 Elderly gender and their investment risk profiles

Concerning the gender dummy, the literature suggests that men would tend to have a higher risk tolerance, while women would generally exhibit greater risk aversion (Alsharawy et al., 2021; Barasinska et al., 2009; Thanki, 2015), as assumed with Hypothesis 4b.

As from the incremented Model 1, the results of our analysis suggest that elderly women, contrary to what might have been expected, would not be solely inclined towards conservative investment strategies. On the contrary, they would show a propensity to adopt high risk profiles (*risk seeker* profile) or diversification strategies (*risk diversifier*, whether *dynamic*, *defensive* or *perfect* profile) while, with a negative significant relation with *risk averse* profile, would be less inclined to be risk averse.

This indicates that elderly women would significantly be more likely to adopt high risk and diversified profiles. Therefore, the hypothesis that men would have higher risk profiles and women lower risk profiles, Hypothesis 4b, was rejected.

4.5.3 Elderly relationship status and their investment risk profiles

Regarding the relationship status dummy, the literature suggests that single individuals would be more likely to have a higher risk tolerance, while those in a couple would tend to be more risk averse (Thanki, 2015), as assumed with Hypothesis 4c.

As from the incremented Model 1, our results indicate that being in a couple would be associated with a lower likelihood of adopting *risk diversifier - perfect* and *risk diversifier -* profiles, as they show a negatively significant impact. This suggests that individuals in a relationship would be more cautious and prefer less diversified and more conservative investment strategies, likely due to considering the preferences and needs of both partners, which would favor financial stability over diversification.

This tendency is further confirmed by the *risk averse* profile, where the couple dummy is positively significant. However, since this last tendency is significant at the 10% level, it should be interpreted with care.

Therefore, the hypothesis 4c suggesting that individuals in a couple would have lower risk profiles, was confirmed.

4.5.4 Elderly education level and their investment risk profiles

Education level, as highlighted by existing literature, would tend to positively impact risk tolerance (Muhammad Khurram Shehzad & Qaisar Ali, 2019; Outreville, 2015). Indeed, individuals with higher financial literacy and educational attainment would be more likely to exhibit greater risk tolerance (Hastings & Mitchell, 2020), as assumed with Hypothesis 4d.

As from the incremented Model 1, our results confirm that education would play a crucial role in an individual's ability to understand and manage financial risks. Better educated, either medium nor high, individuals, as compared to low ones (reference category) would be more likely to invest with different level of risk, corresponding to a positive relation with all five profiles *risk seeker*, *risk diversifier* (either *dynamic*, *perfect* or *defensive*) and *defensive*, while those with lower education levels would tend to prefer risk free investment strategies.

Therefore, Hypothesis 4d suggesting that individuals with higher education levels, as compared to low one, would have riskier profiles was confirmed.

4.5.5 Elderly employment status and their investment risk profiles

Regarding the current employment status of individuals, the literature suggests that having a stable job could make individuals more inclined to take risks (Lippi et al., 2022), as assumed with Hypothesis 4e.

As from the incremented Model 1, our results indicate that employed or self-employed individuals, as compared to retired ones (reference category), would be less likely with a significant negative coefficient to adopt risk diversified - perfect strategies, possibly due to their continuous income sources.

Non-employed individuals, on the other hand, would seem more inclined to seek stability, as they are positively associate with a *risk averse* profile while those permanent sick would look after risk diversified - dynamic strategies.

Therefore, Hypothesis 4e suggesting that employed or self-employed individuals, as compared to retired ones, would have higher risk profiles was rejected.

4.5.6 Elderly country of origin and their investment risk profiles

In our study, we adopted an exploratory approach to examine the relationships between the regions of origin of individuals and their risk profiles. We did not formulate specific hypotheses based on existing literature because no relevant prior research was identified. Instead, our model tested directly the presence and statistical significance of these potential relationships.

As from the incremented Model 1, our results reveal some trends, such as the preference of elderly individuals from the Central, Eastern and Southern regions, compared to Northern region (reference category), for risk free investment strategies, like the *risk averse* profile and a lower inclination, with negative significant coefficients, to adopt investment strategies leading to variate level of risk like the *risk seeker* and *risk diversifier* (either *dynamic*, *perfect* or *defensive*) profile.

Although these relationships were not predicted by specific hypotheses, they emerged from our data analysis. Therefore, we accepted the results of our model as an indication of potential trends, while remaining aware that these relationships would still need to be confirmed by additional studies.

4.5.7 Elderly health status and their investment risk profiles

With regard to the personal characteristics representative of the individual's health situation, the literature indicates that a good health status would generally goes hand in hand with a greater tendency to take risks (Addoum et al., 2017; Vu et al., 2021), as assumed with Hypothesis 4f.

As from the incremented Model 1, the impacts of BMI and number of known chronic diseases on investment risk profiles are minimal. Across all risk profiles, the coefficients are not significant, indicating that being in an alarming BMI state (either too low or too high) compared to having a normal weight (reference category) would not have significantly influenced individuals' investment risk profiles.

Being sick compared to being in good health (reference category), with no known chronic diseases, would not have significantly influenced risk profiles in their investment decisions neither. This suggests that BMI and known chronic diseases would not have played a critical role in determining the risk tolerance or aversion in investment decisions among the elderly.

In contrast, the analysis of self-reported health status reveals a more nuanced impact on investment risk profiles. For *risk seeker*, *risk diversifier - defensive* and *defensive* profiles, the coefficients across all health statuses are not significant, indicating that self-reported health status would not have significantly affected the likelihood of adopting these risk profiles. However, we should note that when the model was simpler, such as models 1 and 2, feeling in a poor health condition, would indicate a lower tendency to have a high tolerance, but this conclusion becomes less likely for both incremented models 3 and 4.

Conversely, *risk diversifier – dynamic* and *risk diversifier - perfect* profiles have negative and significant coefficients, indicating a decreased likelihood of adopting a dynamic nor perfect diversification strategy among those with fair and poorer health condition.

Moreover, *risk averse* profile with positive and significant coefficients, indicate a higher likelihood of risk aversion among individuals reporting fair or poor health, highlighting that poorer health status would be associated with a greater tendency towards risk averse investment behaviors.

We therefore confirmed Hypothesis 4f according to which individuals with poor health conditions would have less risky profiles.

4.6 Heterogeneity Testing per Investment Risk Profiles

In this section, we analyze the results of the heterogeneity tests for various profiles, excluding the *defensive* profile (as previous models did not yield significant results). We focus on examining the estimated coefficients for different covariates such as gender, country regions and education level, as these factors were highly significant across all five profiles studied. The results are summarized in the tables below (Tables 28 to 32), which present the associations between these covariates and various dimensions of consumption patterns and personality traits. These results are compared with the estimated coefficients without specific conditions included in the last lines of each Table (from random-effect probit regression for panel data Model 4), to assess the heterogeneity of the effects.

4.6.1 Risk seeker profile heterogeneity testing

The results in Table 28 below show a notable variation in the associations of our main independent variables and the tendency to be a risk seeker depending on different personal characteristics such as gender, country regions and education level, suggesting heterogeneity among our elderly sample.

Firstly, when observing risky consumption, the incremented Model 4 shows a negative non-significant relationship. However, when considering individuals with a low education level, this relationship becomes much more negative and significant. This indicates that for less-educated individuals, risky consumption behaviors would strongly be associated with a decreased tendency to be a risk seeker which differed from the global model.

When looking at healthy consumption, the incremented Model 4 also shows a negative coefficient which is not significant, suggesting a negative but non-robust relationship between healthy behavior and high risk taking. However, for men, this relationship becomes significantly more negative, indicating that men with healthy behaviors would be significantly less likely to engage in high risk taking profile compared to the general trend. A similar result is observed in the Central regions, where the relationship is also significantly negative but at a lower level.

For the dimension of *extraversion*, the incremented Model 4 shows a coefficient which is not significant either, implying that there is no relationship between *extraversion* and high risk taking profile across the entire sample. However, among those with a medium education level, this relationship becomes significant suggesting that *extraversion* would be a more important risk factor in this subgroup compared to the general population.

For the dimension of *openness*, the incremented Model 4 indicates a coefficient not significant suggesting no relationship on the whole sample between *openness* trait and high risk taking profile. However, for individuals with a low level of education, this relationship becomes significant implying that in this subgroup, a higher level of *openness* would be associated with an increased tendency to take risks compared to the general trend.

Finally for risk seekers when regarding *agreeableness*, we notice that incremented Model 4 coefficient is highly negatively significant indicating that overall, more agreeable individuals would tend to have a significantly reduced tendency to take risks. This result is even more pronounced among women, in the Central regions and for medium educated individuals. This suggests marked heterogeneity, with the effect of *agreeableness* on the tendency to be a risk seekers being stronger among those three control variables.

Table 28: Heterogeneity test for risk seeker profile

Risk seeker profile								
Covariables		Risky consumption	Healthy consumption	Extraversion	Openness	Conscientiousness	Agreeableness	Neuroticism
Gender	Male	-0.146 (0.218)	-0.558** (0.281)	0.200 (0.164)	0.265 (0.166)	-0.190 (0.178)	-0.225 (0.169)	-0.146 (0.218)
	Female	-0.073 (0.197)	0.097 (0.233)	0.260 (0.182)	0.154 (0.193)	0.277 (0.205)	-0.455** (0.185)	-0.073 (0.197)
Country regions	Northern	-0.196 (0.209)	0.028 (0.237)	0.136 (0.181)	0.183 (0.201)	-0.100 (0.189)	-0.186 (0.192)	-0.196 (0.209)
	Central	-0.047 (0.225)	-0.558* (0.310)	0.118 (0.189)	0.191 (0.187)	0.234 (0.226)	-0.628*** (0.195)	-0.047 (0.225)
	Eastern	No estimations because too little observations (only Poland)						
	Southern	-0.306 (0.740)	0.575 (0.620)	0.961 (0.628)	0.584 (0.536)	-0.347 (0.600)	0.114 (0.516)	-0.306 (0.740)
Education level	Low	-1.100** (0.529)	-0.551 (0.400)	0.239 (0.264)	0.562* (0.291)	0.081 (0.299)	-0.175 (0.276)	0.220 (0.267)
	Medium	0.149 (0.233)	0.207 (0.265)	0.564** (0.212)	0.021 (0.215)	-0.090 (0.230)	-0.583*** (0.215)	0.236 (0.212)
	High	-0.014 (0.214)	-0.447 (0.311)	-0.061 (0.195)	0.301 (0.195)	0.145 (0.214)	-0.275 (0.195)	0.148 (0.192)
All		-0.108 (0.145)	-0.172 (0.172)	0.217 (0.122)	0.206 (0.126)	0.016 (0.134)	-0.353*** (0.124)	0.193 (0.123)

Note: Significance levels are indicated by stars: *p < 0.05, **p < 0.01, ***p < 0.001.

Coefficients are first written and standard errors are in parentheses.

Done based on « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 8 » & « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 9 ». (2024). Data sets: DOI: 10.6103/SHARE.w8.900 & DOI: 10.6103/SHARE.w9.900.

4.6.2 Risk diversifier – dynamic profile heterogeneity testing

The results for the *risk diversifier – dynamic* profile included in Table 29 below, show less marked associations between our main independent variables and the tendency to diversify high risks depending on the same control variables as for the first profile. Moreover, it is crucial to approach these findings with care as all incremented Model 4 results are not statistically significant, which suggest that the observed relationships may not have been consistent or robust across the population.

For risky consumption, the incremented Model 4 shows a non-significant coefficient indicating no strong overall relationship between risky consumption and this profile. However, this relationship becomes positive and significant among individuals with a low level of education, suggesting that less-educated individuals who engage in risky consumption would have a slightly higher tendency to diversify their risky assets, resulting in our study to a *risk diversifier – dynamic* profile.

Regarding *agreeableness*, while the global coefficient is non-significant either, there is a significant and negative association in the Southern region. This finding implies that in the Southern region, more agreeable individuals would be less inclined to diversify risks.

However, for both of these significant findings, previous tendencies should again be interpreted with care due to the low level of significance and the fact that the results from the global model are not significant at all.

Table 29: Heterogeneity test for risk diversifier – dynamic profile

Risk diversifier – dynamic profile								
Covariables		Risky consumption	Healthy consumption	Extraversion	Openness	Conscientiousness	Agreeableness	Neuroticism
Gender	Male	-0.301 (0.258)	-0.067 (0.277)	0.111 (0.181)	-0.035 (0.185)	-0.241 (0.194)	-0.265 (0.188)	0.056 (0.182)
	Female	-0.005 (0.176)	0.184 (0.200)	0.023 (0.153)	0.051 (0.160)	-0.114 (0.164)	0.039 (0.154)	-0.008 (0.153)
Country regions	Northern	-0.026 (0.220)	-0.018 (0.256)	0.144 (0.187)	0.089 (0.205)	-0.285 (0.189)	-0.033 (0.199)	-0.091 (0.183)
	Central	-0.149 (0.205)	0.187 (0.224)	0.035 (0.159)	0.034 (0.160)	-0.229 (0.176)	0.056 (0.159)	-0.089 (0.159)
	Eastern	No estimations because too little observations (only Poland)						
	Southern	-0.575 (1.504)	0.407 (1.554)	0.229 (1.129)	0.907 (1.122)	2.123 (1.876)	-2.234* (1.239)	1.024 (1.111)
Education level	Low	0.581* (0.343)	-0.157 (0.409)	0.397 (0.293)	0.043 (0.330)	-0.306 (0.298)	-0.262 (0.296)	0.172 (0.285)
	Medium	-0.104 (0.228)	-0.020 (0.257)	-0.251 (0.184)	0.098 (0.186)	-0.229 (0.176)	-0.143 (0.181)	-0.141 (0.182)
	High	-0.326 (0.242)	0.279 (0.275)	0.258 (0.197)	-0.161 (0.197)	-0.313 (0.209)	0.012 (0.200)	0.181 (0.197)
All		-0.092 (0.144)	0.068 (0.161)	0.065 (0.116)	0.017 (0.120)	-0.164 (0.124)	-0.074 (0.117)	0.048 (0.116)

Note: Significance levels are indicated by stars: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Coefficients are first written and standard errors are in parentheses.

Done based on « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 8 » & « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 9 ». (2024). Data sets: DOI: 10.6103/SHARE.w8.900 & DOI: 10.6103/SHARE.w9.900.

4.6.3 Risk diversifier – perfect profile heterogeneity testing

The results for the *risk diversifier – perfect* profile included in Table 30 below show variations in the associations between our main independent variables and the tendency to diversify perfectly according to personal characteristics such as gender, country regions and education level suggesting heterogeneity among our elderly sample.

Looking at healthy consumption, the incremented Model 4 shows a significant negative coefficient suggesting that, overall, individuals who engaged in healthy consumption behaviors would be less likely to diversify their risks perfectly. This negative association is more pronounced among men, with a coefficient of significantly negative coefficient indicating that men with healthy consumption habits would be less inclined to diversify risks perfectly compared to the general trend. A similar pattern is observed in the Central regions and among individuals with a medium level of education, where negative associations are also significant.

Openness shows a non-significant incremented Model 4 coefficient suggesting no strong relationship with perfect risk diversification profile. However, in the Southern region, this relationship becomes significantly positive indicating that individuals who were more open would be more likely to perfectly diversify risks in this region, while in the Central regions, with a significant negative one, they would tend not to diversify risks perfectly compared to the general trend.

In contrast, for *neuroticism*, the incremented Model 4 coefficient is not significant. However, among men, this relationship becomes significantly positive suggesting that neurotic men would be more likely to diversify risks compared to others. This finding is also positively significant for individuals from Southern regions and also with a low level of education implying that more neurotic individuals in this regions or educational group would have a higher propensity to diversify risks perfectly.

Table 30: Heterogeneity test for risk diversifier – perfect profile

Risk diversifier – perfect profile								
Covariables		Risky consumption	Healthy consumption	Extraversion	Openness	Conscientiousness	Agreeableness	Neuroticism
Gender	Male	0.121 (0.194)	-0.517** (0.244)	0.086 (0.149)	-0.123 (0.154)	0.091 (0.170)	-0.016 (0.153)	0.305** (0.150)
	Female	-0.039 (0.163)	-0.166 (0.203)	0.035 (0.144)	-0.032 (0.151)	0.074 (0.157)	-0.159 (0.142)	0.001 (0.143)
Country regions	Northern	-0.129 (0.179)	-0.299 (0.218)	0.042 (0.148)	-0.081 (0.168)	0.207 (0.159)	0.036 (0.161)	-0.023 (0.149)
	Central	0.175 (0.187)	-0.407* (0.245)	0.121 (0.158)	-0.281* (0.159)	-0.047 (0.182)	-0.224 (0.156)	0.182 (0.158)
	Eastern	No estimations because too little observations (only Poland)						
	Southern	-0.355 (0.458)	-0.152 (0.422)	0.068 (0.295)	0.716** (0.290)	0.303 (0.374)	0.072 (0.286)	0.548* (0.296)
Education level	Low	-0.101 (0.281)	-0.441 (0.301)	-0.095 (0.190)	0.113 (0.208)	-0.035 (0.210)	-0.154 (0.192)	0.429** (0.190)
	Medium	-0.096 (0.208)	-0.618** (0.279)	0.100 (0.171)	-0.104 (0.176)	0.070 (0.193)	-0.005 (0.170)	0.159 (0.172)
	High	0.183 (0.197)	0.044 (0.255)	0.280 (0.182)	-0.258 (0.183)	0.165 (0.201)	-0.083 (0.183)	-0.068 (0.181)
All		0.006 (0.124)	-0.327** (0.154)	0.071 (0.102)	-0.080 (0.106)	0.067 (0.114)	-0.095 (0.103)	0.156 (0.102)

Note: Significance levels are indicated by stars: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Coefficients are first written and standard errors are in parentheses.

Done based on « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 8 » & « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 9 ». (2024). Data sets: DOI: 10.6103/SHARE.w8.900 & DOI: 10.6103/SHARE.w9.900.

4.6.4 Risk diversifier – defensive profile heterogeneity testing

The results for this fourth profile included in Table 31 below reveal several significant associations between our main independent variables and the tendency to diversify risks defensively under specific conditions, suggesting heterogeneity among our elderly sample.

For the *extraversion* trait, the incremented Model 4 shows a significant positive coefficient suggesting that individuals with higher levels of *extraversion* would be more likely to diversify their risks defensively. This relationship is even stronger among men, with a significant positive relation, indicating that extraverted men would be significantly more inclined to adopt defensive risk diversification strategies.

Similarly, positive associations are significant for individuals with medium and high levels of education suggesting that more educated extraverted individuals would tend to adopt this strategy.

For *openness*, the incremented Model 4 coefficient is also significant indicating that individuals with high levels of this traits would be more likely to engage in defensive risk diversification. This effect is similarly significant among men and those with medium levels of education. In the Southern region this relationship is also highly strong, although this result needs to be handled with care due to the small sample size in that region. This suggests that men with higher *openness*, those with a medium level of education or individuals from the Southern region would be more inclined to exhibit this profile.

In contrast, *agreeableness* shows a significant negative incremented Model 4 coefficient, suggesting that more agreeable individuals would be less likely to diversify risks defensively. This effect is more pronounced among women and in the Central regions, with both negative significant coefficients, indicating that *agreeableness* would play a critical role in reducing the likelihood of defensive risk diversification in these subgroups.

Table 31: Heterogeneity test for risk diversifier – defensive profile

Risk diversifier – defensive profile								
Covariables		Risky consumption	Healthy consumption	Extraversion	Openness	Conscientiousness	Agreeableness	Neuroticism
Gender	Male	0.145 (0.300)	-0.125 (0.380)	0.653** (0.268)	0.591** (0.252)	-0.045 (0.263)	-0.208 (0.253)	0.082 (0.245)
	Female	-0.185 (0.273)	-0.686 (0.426)	0.116 (0.231)	0.220 (0.239)	-0.049 (0.248)	-0.451* (0.235)	0.229 (0.233)
Country regions	Northern	-0.314 (0.317)	-0.226 (0.353)	0.238 (0.244)	0.210 (0.251)	-0.178 (0.236)	-0.228 (0.247)	0.062 (0.241)
	Central	0.015 (0.316)	-1.060 (0.644)	0.438 (0.279)	0.254 (0.270)	-0.015 (0.314)	-0.665** (0.299)	0.112 (0.272)
	Eastern	No estimations because too little observations (only Poland)						
	Southern	4.073 (2.313)	-0.453 (2.735)	3.847 (2.480)	6.935** (3.091)	1.839 (3.387)	-0.717 (2.273)	-1.007 (2.439)
Education level	Low	0.034 (0.610)	-0.870 (0.882)	-0.061 (0.447)	0.660 (0.507)	-0.304 (0.480)	-0.283 (0.444)	0.202 (0.453)
	Medium	-0.020 (0.326)	-0.229 (0.465)	0.486* (0.292)	0.529* (0.290)	0.010 (0.316)	-0.209 (0.284)	0.167 (0.285)
	High	-0.231 (0.339)	-0.625 (0.515)	0.612** (0.307)	0.208 (0.283)	-0.127 (0.303)	-0.488 (0.300)	0.091 (0.287)
All		-0.029 (0.192)	-0.411 (0.271)	0.343** (0.162)	0.377** (0.163)	-0.089 (0.173)	-0.321** (0.164)	0.146 (0.162)

Note: Significance levels are indicated by stars: *p < 0.05, **p < 0.01, ***p < 0.001.

Coefficients are first written and standard errors are in parentheses.

Done based on « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 8 » & « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 9 ». (2024). Data sets: DOI: 10.6103/SHARE.w8.900 & DOI: 10.6103/SHARE.w9.900.

4.6.5 Risk averse profile heterogeneity testing

The results for the last profile, *risk averse* included in Table 32 below, reveal several of the most significant associations between personality traits, consumption behaviors and the tendency to avoid risks under specific conditions, suggesting heterogeneity among our elderly sample.

Starting with healthy consumption, the incremented Model 4 shows a significant positive coefficient suggesting that individuals who engaged in healthy consumption behaviors would be more likely to adopt a *risk averse* profile. This relationship is particularly strong among men, in the Northern and also in Central regions and among individuals with a low level of education. This indicates that these groups would be more inclined to avoid risks when maintaining healthy consumption habits.

For *Extraversion*, incremented Model 4 displays a significant negative coefficient suggesting that individuals with higher levels of this trait would be less likely to exhibit a *risk averse* profile. This tendency is even more pronounced among men and those with medium and high levels of education. This indicates that these groups would be less inclined to avoid risks in their investment decisions while having a high level of *extraversion* trait.

When examining *openness*, the global coefficient is significantly negative indicating that more open individuals would be less likely to be risk averse. This trend is particularly strong in the Southern region and for individuals with a low level of education, suggesting that open individuals with these characteristics would be willing to take risks when investing.

For *conscientiousness*, while the incremented Model 4 coefficient is not significant, there is a significant negative association in the Southern region. This suggests that individuals in the Southern region who were more conscientious would be less likely to adopt a *risk averse* profile.

Agreeableness also shows a significant positive coefficient in the global model, suggesting that more agreeable individuals would be more likely to adopt a *risk averse* profile. This effect is particularly evident among both genders, in the Central regions and among those with a medium and a high level of education. This means that individuals with a level of *agreeableness* exhibiting these personal characteristics would be more inclined to be risk averse.

For *neuroticism*, the incremented Model 4 coefficient is significantly negative indicating that individuals with higher levels of *neuroticism* would be less likely to be risk averse. This relationship is particularly strong among men, in the Southern and Northern regions and among those with a low and high level of education.

The observed heterogeneity across different demographic groups among majority of risk profiles highlights the complexity of risk profiles and underlines the importance of considering individual differences when analyzing the impact of consumption patterns, personality traits on elderly investment risk profiles.

Table 32: Heterogeneity test for risk averse profile

Risk averse profile								
Covariables		Risky consumption	Healthy consumption	Extraversion	Openness	Conscientiousness	Agreeableness	Neuroticism
Gender	Male	0.054 (0.201)	0.650*** (0.225)	-0.339** (0.161)	-0.233 (0.162)	0.145 (0.178)	0.345** (0.164)	-0.462*** (0.163)
	Female	0.079 (0.184)	0.077 (0.219)	-0.216 (0.187)	-0.295 (0.196)	-0.254 (0.206)	0.474*** (0.187)	-0.211 (0.187)
Country regions	Northern	0.378 (0.234)	0.427* (0.259)	-0.366 (0.226)	-0.214 (0.255)	0.154 (0.238)	0.390 (0.244)	-0.381* (0.229)
	Central	-0.011 (0.193)	0.564** (0.236)	-0.200 (0.172)	0.012 (0.171)	0.013 (0.200)	0.558*** (0.171)	-0.260 (0.174)
	Eastern	No estimations because too little observations (only Poland)						
	Southern	-0.238 (0.354)	-0.436 (0.357)	-0.284 (0.301)	-1.210*** (0.322)	-0.734* (0.382)	0.121 (0.286)	-0.729** (0.304)
Education level	Low	-0.090 (0.282)	0.571** (0.288)	-0.067 (0.217)	-0.550** (0.234)	0.089 (0.239)	0.268 (0.220)	-0.659*** (0.221)
	Medium	-0.048 (0.225)	0.331 (0.254)	-0.346* (0.208)	-0.272 (0.213)	-0.153 (0.233)	0.556*** (0.210)	-0.247 (0.210)
	High	0.262 (0.226)	0.306 (0.286)	-0.518** (0.230)	0.022 (0.226)	0.044 (0.246)	0.425* (0.227)	-0.377** (0.122)
All		0.089 (0.134)	0.359** (0.154)	-0.276** (0.122)	-0.257** (0.125)	-0.013 (0.134)	0.423*** (0.123)	-0.377*** (0.122)

Note: Significance levels are indicated by stars: *p < 0.05, **p < 0.01, ***p < 0.001.

Coefficients are first written and standard errors are in parentheses.

Done based on « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 8 » & « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 9 ». (2024). Data sets: DOI: 10.6103/SHARE.w8.900 & DOI: 10.6103/SHARE.w9.900.

4.7 Limits of our Study

Our study presents several potential limitations that could have impacted its robustness and the extrapolation of its findings.

4.7.1 Database and sample limitations

The SHARE database is, as its name suggests, primarily focused on the acquisition of health and demographic data. While it includes monetary data, they are not the main focus of these questionnaires, so it should be kept in mind that the information may not be complete nor an accurate representation of reality for the entire elderly population.

The sample size of 3,933 individuals, while substantial, might still be considered too small to fully capture the diversity and complexity of the population under study. With such a limited sample, there is a greater risk that the results may be influenced by outliers, which could skew the overall findings.

The extrapolation of the findings could also be limited due to the focus on the elderly in Europe. While this focus provides valuable insights, the results might not be applicable to younger populations or those outside Europe. Moreover, the sociodemographic and health characteristics of the elderly in Europe could restrict the applicability of the conclusions to other demographics or regions.

Additionally, our study control of personal health characteristics might be limited by the simplified measures used, such as the number of chronic diseases or BMI. These indicators may not fully capture the complexity of an individual's health status. Other relevant factors, not considered in this study, could also lead to omit important influences on the investment behaviors of the elderly.

4.7.2 Methodology limitations

The issue of missing data could also be an important limitation of our study. Although imputation methods are used by SHARE to estimate missing values, this process might introduce inaccuracies, potentially affecting the validity of our conclusions.

Methodologically, the cross-sectional nature of our study, despite using longitudinal data, might still face limitations in establishing causality between variables. The temporal sequence of waves may not perfectly cover this aspect, leading to possible misinterpretations of cause-and-effect relationships.

Additionally, the simplification of our primary variables, such as risk profiles, consumption patterns and personality traits into categorical or dummies, could result in a loss of nuance, failing to fully grasp the variability and complexity of these traits or behaviors. This could lead to oversimplified conclusions that do not account for the nuanced ways in which individuals' behaviors and traits interact with their investment profiles.

4.7.3 Pathways for futures research

Given the results of our study, several pathways for further research have emerged, which could deepen the understanding of the relationships between risk profiles, consumption patterns, personality traits and the impact of external shocks like the Covid-19 pandemic.

One key area for future exploration could be to investigate why the expected relationships between risky consumption or *conscientiousness* traits and investment risk profiles did not materialize. It would be worthwhile to explore whether our findings are specific to elderly sample or whether they reflect broader trends, potentially requiring more nuanced measures of risky consumption behaviors or *conscientiousness* trait.

Similarly, the unexpected results concerning *extraversion* and *neuroticism* have prompted further investigation. Contrary to the literature, our study found that risk diversifier - defensive, rather than risk seekers, had higher levels of *extraversion*, while risk averse did not display elevated levels of *neuroticism*. Future research could delve into these surprising findings by examining whether these traits influence investment behaviors differently across age groups or in different economic contexts.

Another path for further research lies in the analysis of the Covid-19 pandemic influence. Although the study did not find direct evidence linking the pandemic to changes in risk profiles, there are indications of indirect effects on personality traits like *extraversion* and *agreeableness*. Future studies could employ longitudinal methods to track changes in these traits over time and assess how they interact with external shocks to influence financial behaviors.

Our findings regarding sociodemographic variables such as age, gender, relationship status, education, employment status and health status are in line with existing literature in some areas but diverge in others, particularly concerning gender and employment status. Contrary to previous studies, our research found that women would be more inclined to take risks and those with stable employment would be less likely to engage in risky investments. Future research could investigate these discrepancies, perhaps by examining how gender and/or employment stability interact with other factors.

Our study findings on regional differences, though exploratory, suggest that cultural and economic contexts would significantly have impacted investment behaviors. Further research could also compare how these factors influence risk profiles in regions or countries other than these within the scope of our study.

Finally, the study brought to light significant heterogeneity across gender, regions and education level, indicating that sociodemographic personal characteristics could have played a crucial role in shaping investment behaviors. Understanding this heterogeneity could be essential for developing a comprehensive understanding of investment decisions making across diverse populations.

CONCLUSION

The problematic of our study, within the theme of behavioral finance, was to examine how consumption behaviors — both risky and healthy — the Big Five personality traits and the Covid-19 pandemic shock influenced investment risk profiles of elderly across Europe.

Contrary to what might have been expected, we found no significant link between risky consumption behaviors, such as alcohol use or smoking and the likelihood of adopting riskier investment profiles. However, a healthy lifestyle would indeed be consistent and associated with more risk averse investment behaviors, indicating that elderly individuals who prioritized their health would tend to reflect it in being more risk averse in their financial decisions.

In terms of personality traits, our findings challenged some established views. While *extraversion* would be often linked to high risk tolerant behavior, we found that individuals with high levels of this trait would be more likely to exhibit a defensive diversification strategy rather than taking on high risks. *Openness*, as anticipated, was also associated with moderate risk willingness, in line with existing literature. We found no clear connection between *conscientiousness* and any of our specific investment profiles. However, *agreeableness* was strongly linked to risk aversion, confirming the expectation that more agreeable individuals would tend to be more cautious investors. Finally, higher levels of *neuroticism* were not common among risk averse individuals, suggesting that those with greater emotional instability might have been less likely to avoid risk than previously thought.

Regarding the impact of the Covid-19 pandemic, our analysis did not find conclusive evidence that the crisis led elderly to shift towards other investment risk profile. Although there were some interactions identified between the pandemic and certain personality traits like *extraversion* and *agreeableness*, the overall effect of the Covid-19 pandemic on altering investment risk profiles was not significant.

These results require further work to be confirmed with more statistical confidence and obviously represent a drop in the ocean of the behavioral finance research field. This latter, despite its recent and growing recognition, still remains largely uncharted territories. But its effects seem to be increasingly relevant in today's volatile markets. This was again observed, while still drafting this thesis, on Monday August the 5th 2024 when the Nikkei 225 in Tokyo plummeted by 12.4%, the deepest fall ever recorded in one day for this index. The cause of this new “Black Monday” (which recovered largely in the following days)? Probably another overreaction of global investors. Indeed, analysts in the United States had forecasted a probable recession following the release of alarming July unemployment figures (Leparmentier, 2024), which were exacerbated by the Federal Reserve's delayed response in lowering their interest rates. According to them, this could potentially lead to an economic slowdown in the United States, which, in turn, triggered a worldwide markets drop (*Courrier International*, 2024).

This event underscores the profound impact that investor psychology and behavior can have on financial systems. It serves as a reminder of the power of emotions and cognitive biases in driving financial decisions - a core focus of behavioral finance. As the world becomes increasingly interconnected and markets more susceptible to collective actions, how can behavioral finance research be leveraged to foster greater market stability and prevent such precipitous declines in the future?

APPENDICES

Appendix A: Data and Variables description

Table 1: Variables summary

<u>Target Variable</u>		<u>Measure</u>
<i>Risk Profile</i>	○ Risk seeker	Dummy variable equals to one for individual whose portfolio is primarily composed of <u>stock investments</u> . It can also be a sub-category of “ <i>Risk profiles</i> ” coded as 1 for <i>risk seeker</i> .
	○ Risk diversifier – dynamic	Dummy variable equals to one for individual whose portfolio is primarily composed of <u>mutual fund with a majority of stock investments</u> . It can also be a sub-category of “ <i>Risk profiles</i> ” coded as 2 for <i>risk diversifier - dynamic</i> .
	○ Risk diversifier – perfectly	Dummy variable equals to one for individual whose portfolio is primarily composed of <u>mutual fund with a 50/50 strategy</u> of stocks and bonds investments. It can also be a sub-category of “ <i>Risk profiles</i> ” coded as 5 for <i>risk diversifier - perfect</i> .
	○ Risk diversifier – defensive	Dummy variable equals to one for individual whose portfolio is primarily composed of <u>mutual fund with a majority of bonds investments</u> . It can also be a sub-category of “ <i>Risk profiles</i> ” coded as 3 for <i>risk diversifier - defensive</i> .
	○ Defensive	Dummy variable equals to one for individual whose portfolio is primarily composed of <u>bonds investments</u> . It can also be a sub-category of “ <i>Risk profiles</i> ” coded as 4 for <i>defensive</i> .
	○ Risk averse	Dummy variable equals to one for individual who do <u>not invest in risky assets</u> . It can also be a sub-category of “ <i>Risk profiles</i> ” coded as 6 for <i>risk averse</i> .
<u>Independent Variables</u>		<u>Measure</u>
<i>Consumption</i>	○ Risky consumption	<u>Dummy variable</u> equals to one if individuals either smokes or drinks in an alarming way.

<p><i>Personality</i></p>	<ul style="list-style-type: none"> ○ Healthy consumption ○ <i>Extraversion</i> ○ <i>Openness</i> ○ <i>Conscientiousness</i> ○ <i>Agreeableness</i> ○ <i>Neuroticism</i> 	<p><u>Dummy variable</u> equals to one whether individuals engage in regular physical activity and maintain good eating habits, such as consuming fruits, vegetables, dairy products and meat.</p> <p><u>Dummy variable</u> equals to one if <i>extraversion</i> is high (≥ 4), indicating a high level of sociability and outgoingness.</p> <p><u>Dummy variable</u> equals to one if <i>openness</i> is high (≥ 4), indicating a high level of creativity and openness to new experiences.</p> <p><u>Dummy variable</u> equals to one if <i>conscientiousness</i> is high (≥ 4), indicating a high level of organization and reliability.</p> <p><u>Dummy variable</u> equals to one if <i>agreeableness</i> is high (≥ 4), indicating a high level of friendliness and cooperation.</p> <p><u>Dummy variable</u> equals to one if <i>neuroticism</i> is low (≤ 2), indicating a low level of emotional instability and anxiety.</p>
<p><u>Control Variables</u></p>		<p><u>Measure</u></p>
<p><i>Sociodemographic personal traits</i></p>	<ul style="list-style-type: none"> ○ Country of origin ○ Age ○ Older individuals ○ Gender ○ Relationship status 	<p><u>Categorical variable</u> coded into four geographical regions: 1 = Northern Europe (Sweden, Denmark). 2 = Central Europe (Austria, Germany, France, Switzerland, Belgium). 3 = Eastern Europe (Poland). 4 = Southern Europe (Spain, Italy, Greece).</p> <p><u>Categorical variable</u> coded into three groups to representant the age distribution of the population: 1 = People under 60 years old. 2 = People between 60 and 69 years old. 3 = People over 70 years old.</p> <p><u>Dummy variable</u> equals to one if individuals are aged above 70 and zero if they are younger (dummy used to avoid multicollinearity)</p> <p><u>Dummy variable</u> equals to one if individuals are female and zero if they are male.</p> <p><u>Dummy variable</u> equals to one if individuals are in couple and zero if they are single.</p>

	○ Educational level	<u>Categorical variable</u> coded into three groups to representant the maximum educational individuals reached: 1 = Low level. 2 = Medium level. 3 = High level.
	○ Employment status	<u>Categorical variable</u> coded into six groups to representant the current employment status of individuals: 1 = Retirement. 2 = Employed or Self-employed. 3 = Unemployed. 4 = Permantly sick. 5 = Homemaker. 6 = Other.
<i>Health personal characteristics</i>	○ Number of chronic diseases known	<u>Categorical variable</u> coded into three groups to representant the number of current known chronic diseases individuals suffer from: 1 = None. 2 = One or Two chronic diseases. 3 = Three or more chronic diseases.
	○ Body Mass Index (BMI)	<u>Categorical variable</u> coded into four groups to indicates the BMI of participants, calculated based on their height and weight: 1 = Underweight. 2 = Normal weight. 3 = Overweight. 4 = Obesity.
	○ Alarming BMI	<u>Dummy variable</u> equals to one if individuals have an alarming body mass index such as be underweighted, overweighted or obese and zero if they have a normal BMI. (dummy used to avoid multicollinearity)
	○ Self-perceived health status	<u>Categorical variable</u> coded into five groups to captures participants subjective assessment of their health: 1 = Excellent. 2 = Very Good. 3 = Good. 4 = Fair. 5 = Poor.

Table 7: Sample description of sociodemographic characteristics based on Europe regions distribution

	(1) 2019-2020 period: PRE-Covid-19 (Wave 8)					(2) 2022 period: POST-Covid-19 (Wave 9)				
	NC	CC	EC	SC	Total (Pre- Covid)	NC	CC	EC	SC	Total (Post-Covid)
Age groups										
Under 60	9 (1.1%)	16 (1.0%)	1 (0.4%)	16 (1.4%)	42 (1.1%)	6 (0.7%)	11 (0.7%)	0 (0.0%)	6 (0.5%)	23 (0.6%)
60-69	260 (30.6%)	513 (30.9%)	120 (48.2%)	347 (29.6%)	1,240 (31.5%)	165 (19.4%)	335 (20.2%)	80 (32.1%)	258 (22.0%)	838 (21.3%)
Over 70	582 (68.4%)	1,133 (68.2%)	128 (51.4%)	808 (69.0%)	2,651 (67.4%)	680 (79.9%)	1,316 (79.2%)	169 (67.9%)	907 (77.5%)	3,072 (78.1%)
Gender										
Male	466 (54.8%)	919 (55.3%)	146 (58.6%)	671 (57.3%)	2,202 (56.0%)	466 (54.8%)	919 (55.3%)	146 (58.6%)	671 (57.3%)	2,202 (56.0%)
Female	385 (45.2%)	743 (44.7%)	103 (41.4%)	500 (42.7%)	1,731 (44.0%)	385 (45.2%)	743 (44.7%)	103 (41.4%)	500 (42.7%)	1,731 (44.0%)
Relationship status										
No	373 (43.8%)	674 (40.6%)	70 (28.1%)	331 (28.3%)	1,448 (36.8%)	385 (45.2%)	701 (42.2%)	78 (31.3%)	375 (32.0%)	1,539 (39.1%)
Yes	478 (56.2%)	988 (59.4%)	179 (71.9%)	840 (71.7%)	2,485 (63.2%)	466 (54.8%)	961 (57.8%)	171 (68.7%)	796 (68.0%)	2,394 (60.9%)
Level of education										
Low	192 (22.6%)	473 (28.5%)	57 (22.9%)	775 (66.2%)	1,497 (38.1%)	192 (22.6%)	473 (28.5%)	57 (22.9%)	773 (66.0%)	1,495 (38.0%)
Medium	310 (36.4%)	715 (43.0%)	164 (65.9%)	257 (21.9%)	1,446 (36.8%)	310 (36.4%)	714 (43.0%)	164 (65.9%)	258 (22.0%)	1,446 (36.8%)
High	349 (41.0%)	474 (28.5%)	28 (11.2%)	139 (11.9%)	990 (25.2%)	349 (41.0%)	475 (28.6%)	28 (11.2%)	140 (12.0%)	992 (25.2%)
Current job situation										
Retired	730 (85.8%)	1,484 (89.3%)	219 (88.0%)	775 (66.2%)	3,208 (81.6%)	775 (91.1%)	1,552 (93.4%)	239 (96.0%)	805 (68.7%)	3,371 (85.7%)
Employed or self-employed	93 (10.9%)	93 (5.6%)	8 (3.2%)	64 (5.5%)	258 (6.6%)	57 (6.7%)	56 (3.4%)	3 (1.2%)	30 (2.6%)	146 (3.7%)
Unemployed	2 (0.2%)	6 (0.4%)	1 (0.4%)	11 (0.9%)	20 (0.5%)	1 (0.1%)	2 (0.1%)	0 (0.0%)	3 (0.3%)	6 (0.2%)
Permanently sick	8 (0.9%)	7 (0.4%)	13 (5.2%)	21 (1.8%)	49 (1.2%)	8 (0.9%)	2 (0.1%)	3 (1.2%)	26 (2.2%)	39 (1.0%)
Homemaker	3 (0.4%)	63 (3.8%)	1 (0.4%)	274 (23.4%)	341 (8.7%)	1 (0.1%)	48 (2.9%)	1 (0.4%)	270 (23.1%)	320 (8.1%)
Other	15 (1.8%)	9 (0.5%)	7 (2.8%)	26 (2.2%)	57 (1.4%)	9 (1.1%)	2 (0.1%)	3 (1.2%)	37 (3.2%)	51 (1.3%)
N	851 (21.6%)	1,662(42.3%)	249 (6.3%)	1,171 (29.8%)	3,933 (100.0%)	851 (21.6%)	1,662 (42.3%)	249 (6.3%)	1,171(29.8)	3,933 (100.0%)

Note: NC = Northern Countries; CC = Central Countries; EC= Eastern Countries; SC= Southern Countries.

Done based on « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 8 » & « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 9». (2024). Data sets: DOI: 10.6103/SHARE.w8.900 & DOI: 10.6103/SHARE.w9.900.

Table 8: Sample description of health characteristics based on Europe regions distribution

(1) 2019-2020 period: **PRE-Covid-19** (Wave 8)

(2) 2022 period: **POST-Covid-19** (Wave 9)

	NC	CC	EC	SC	Total (Pre- Covid)	NC	CC	EC	SC	Total (Post-Covid)
Number of chronic diseases										
None	178 (20.9%)	274 (16.5%)	25 (10.0%)	161 (13.7%)	638 (16.2%)	146 (17.2%)	268 (16.1%)	29 (11.6%)	132 (11.3%)	575 (14.6%)
1 or 2	440 (51.7%)	853 (51.3%)	95 (38.2%)	575 (49.1%)	1,963 (49.9%)	441 (51.8%)	815 (49.0%)	99 (39.8%)	562 (48.0%)	1,917 (48.7%)
3+	233 (27.4%)	535 (32.2%)	129 (51.8%)	435 (37.1%)	1,332 (33.9%)	264 (31.0%)	579 (34.8%)	121 (48.6%)	477 (40.7%)	1,441 (36.6%)
BMI groups										
Underweight	15 (1.8%)	21 (1.3%)	1 (0.4%)	4 (0.3%)	41 (1.0%)	21 (2.5%)	28 (1.7%)	2 (0.8%)	7 (0.6%)	58 (1.5%)
Normal weight	377 (44.3%)	691 (41.6%)	64 (25.7%)	349 (29.8%)	1,481 (37.7%)	380 (44.7%)	707 (42.5%)	68 (27.3%)	379 (32.4%)	1,534 (39.0%)
Overweight	303 (35.6%)	603 (36.3%)	98 (39.4%)	510 (43.6%)	1,514 (38.5%)	300 (35.3%)	606 (36.5%)	94 (37.8%)	505 (43.1%)	1,505 (38.3%)
Obesity	156 (18.3%)	347 (20.9%)	86 (34.5%)	308 (26.3%)	897 (22.8%)	150 (17.6%)	321 (19.3%)	85 (34.1%)	280 (23.9%)	836 (21.3%)
Self-perceived health status										
Excellent	122 (14.3%)	95 (5.7%)	1 (0.4%)	28 (2.4%)	246 (6.3%)	127 (14.9%)	90 (5.4%)	2 (0.8%)	21 (1.8%)	240 (6.1%)
Very good	266 (31.3%)	331 (19.9%)	18 (7.2%)	151 (12.9%)	766 (19.5%)	242 (28.4%)	331 (19.9%)	18 (7.2%)	163 (13.9%)	754 (19.2%)
Good	255 (30.0%)	749 (45.1%)	110 (44.2%)	452 (38.6%)	1,566 (39.8%)	283 (33.3%)	749 (45.1%)	113 (45.4%)	448 (38.3%)	1,593 (40.5%)
Fair	170 (20.0%)	392 (23.6%)	90 (36.1%)	415 (35.4%)	1,067 (27.1%)	166 (19.5%)	389 (23.4%)	79 (31.7%)	410 (35.0%)	1,044 (26.5%)
Poor	38 (4.5%)	95 (5.7%)	30 (12.0%)	125 (10.7%)	288 (7.3%)	33 (3.9%)	103 (6.2%)	37 (14.9%)	129 (11.0%)	302 (7.7%)
N	851 (21.6%)	1,662(42.3%)	249 (6.3%)	1,171(29.8%)	3,933 (100.0%)	851 (21.6%)	1,662(42.3%)	249 (6.3%)	1,171(29.8%)	3,933 (100.0%)

Note: NC = Northern Countries; CC = Central Countries; EC= Eastern Countries; SC= Southern Countries. Done based on « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 8 » & « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 9». (2024). Data sets: DOI: 10.6103/SHARE.w8.900 & DOI: 10.6103/SHARE.w9.900.

Appendix B: Methodology

Table 11: Correlation coefficients of variables (wave 8: pre-Covid-19 period)

	Risk Profile	Healthy consumption	Risky consumption	<i>Extraversion</i>	<i>Agreeableness</i>	<i>Conscientiousness</i>	<i>Openness</i>	<i>Neuroticism</i>	Age	Gender	Couple	Country regions	Education	Employment status	Chronic status	BMI	Self-perceived health status
Risk profile	1.00																
Healthy consumption	0.04	1.00															
Risky consumption	-0.02	-0.01	1.00														
<i>Extraversion</i>	-0.11	0.02	0.03	1.00													
<i>Agreeableness</i>	-0.01	0.00	-0.04	0.12	1.00												
<i>Conscientiousness</i>	0.01	-0.06	-0.03	0.08	0.08	1.00											
<i>Openness</i>	-0.05	-0.03	-0.02	0.09	-0.01	0.05	1.00										
<i>Neuroticism</i>	-0.13	-0.02	0.04	0.15	0.17	0.07	0.07	1.00									
Age	-0.03	0.09	-0.10	-0.01	0.01	0.00	-0.02	0.02	1.00								
Gender	-0.11	-0.02	0.10	-0.02	-0.04	-0.01	-0.03	0.11	0.06	1.00							
Couple	0.03	-0.06	0.00	-0.02	-0.06	0.05	-0.01	-0.05	-0.16	0.25	1.00						
Country regions	0.33	0.07	-0.07	-0.21	-0.12	-0.01	-0.07	-0.2	-0.01	-0.02	0.13	1.00					
Education	-0.20	-0.10	0.10	0.05	-0.02	0.01	0.13	0.08	-0.10	0.10	0.01	-0.35	1.00				
Employment status	0.10	0.08	-0.06	-0.05	0.02	-0.01	-0.03	-0.09	-0.16	-0.26	0.04	0.3	-0.18	1.00			
Chronic Diseases	0.07	0.09	-0.03	-0.03	-0.05	-0.08	-0.03	-0.09	0.16	-0.04	-0.05	0.10	-0.09	0.03	1.00		
BMI	0.06	0.03	-0.03	0.03	-0.02	-0.07	-0.05	-0.03	-0.03	0.07	0.05	0.13	-0.13	0.06	0.20	1.00	
Self-perceived health status	0.16	0.19	-0.03	-0.12	-0.07	-0.09	-0.09	-0.18	0.14	-0.06	-0.03	0.26	-0.21	0.08	0.40	0.15	1.00

Done based on « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 8 » & « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 9 ». (2024). Data sets: DOI: 10.6103/SHARE.w8.900 & DOI: 10.6103/SHARE.w9.900.

Table 12: Correlation coefficients of variables (wave 9: post-Covid-19 period)

	Risk profile	Healthy consumption	Risky consumption	Extraversion	Agreeableness	Conscientiousness	Openness	Neuroticism	Age	Gender	Couple	Country regions	Education	Employment status	Chronic status	BMI	Self-perceived health status
Risk Profile	1.00																
Healthy consumption	0.08	1.00															
Risky consumption	-0.04	-0.03	1.00														
Extraversion	-0.07	-0.01	0.04	1.00													
Agreeableness	-0.04	0.02	-0.02	0.12	1.00												
Conscientiousness	0.03	-0.05	-0.03	0.08	0.08	1.00											
Openness	-0.03	-0.05	-0.02	0.09	0.00	0.05	1.00										
Neuroticism	-0.13	-0.02	0.05	0.15	0.17	0.07	0.07	1.00									
Age	-0.02	0.10	-0.09	0.00	-0.01	-0.02	-0.03	0.03	1.00								
Gender	-0.11	-0.04	0.07	-0.03	-0.04	-0.01	-0.03	0.11	0.07	1.00							
Couple	0.01	-0.05	-0.01	-0.02	-0.06	0.06	-0.01	-0.04	-0.17	0.27	1.00						
Country regions	0.33	0.12	-0.07	-0.22	-0.11	0.00	-0.07	-0.20	-0.03	-0.02	0.11	1.00					
Education	-0.21	-0.14	0.10	0.06	-0.02	0.00	0.13	0.08	-0.08	0.10	0.02	-0.35	1.00				
Employment status	0.10	0.09	-0.06	-0.03	0.02	-0.01	-0.04	-0.08	-0.12	-0.26	0.02	0.34	-0.20	1.00			
Chronic diseases	0.06	0.08	-0.07	-0.03	-0.03	-0.06	-0.02	-0.07	0.16	-0.01	-0.06	0.09	-0.09	0.02	1.00		
BMI	0.05	0.04	-0.04	0.04	-0.02	-0.07	-0.04	-0.04	-0.01	0.06	0.05	0.12	-0.11	0.05	0.19	1.00	
Self-perceived health status	0.17	0.23	-0.04	-0.12	-0.10	-0.08	-0.08	-0.18	0.10	-0.06	-0.04	0.26	-0.22	0.11	0.37	0.16	1.00

Done based on « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 8 » & « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 9 ». (2024). Data sets: DOI: 10.6103/SHARE.w8.900 & DOI: 10.6103/SHARE.w9.900.

Table 13: First variance inflation factor analysis

Variables	VIF
Healthy consumption	1.10
Risky consumption	1.04
<i>Extraversion</i>	1.10
<i>Agreeableness</i>	1.11
<i>Conscientiousness</i>	1.05
<i>Openness</i>	1.07
<i>Neuroticism</i>	1.13
Age (Between 60 and 70)	25.96
Age (Over 70)	27.08
BMI (Normal)	19.71
BMI (Overweight)	19.91
BMI (Obesity)	14.8
Gender	1.26
Relationship status	1.16
Country (Central)	1.94
Country (Eastern)	1.41
Country (Southern)	2.33
Education (Medium level)	1.46
Education (High level)	1.52
Job (Employed or self-employed)	1.19
Job (Unemployed)	1.03
Job (Permantely sick)	1.05
Job (Homemaker)	1.29
Job (Other)	1.03
Chronic diseases (One or two)	2.30
Chronic diseases (Three or more)	2.59
Self-perceived health status (Very Good)	3.41
Self-perceived health status (Good)	4.94
Self-perceived health status (Fair)	4.58
Self-perceived health status (Poor)	2.42

Done based on « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 8 » & « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 9». (2024). Data sets: DOI: 10.6103/SHARE.w8.900 & DOI: 10.6103/SHARE.w9.900.

Table 14: Second variance inflation factor analysis with new updated dummies (in bold)

Variables	VIF
Healthy consumption	1.10
Risky consumption	1.04
<i>Extraversion</i>	1.10
<i>Agreeableness</i>	1.10
<i>Conscientiousness</i>	1.04
<i>Openness</i>	1.07
<i>Neuroticism</i>	1.13
Older individuals (Over 70)	1.22
Alarming BMI (Underweight or overweight or obesity)	1.07
Gender	1.24
Relationship status	1.16
Country (Central)	1.94
Country (Eastern)	1.41
Country (Southern)	2.33
Education (Medium level)	1.46
Education (High level)	1.52
Job (Employed or self-employed)	1.14
Job (Unemployed)	1.02
Job (Permantely sick)	1.05
Job (Homemaker)	1.28
Job (Other)	1.03
Chronic diseases (One or two)	2.29
Chronic diseases (Three or more)	2.57
Self-perceived health status (Very Good)	3.41
Self-perceived health status (Good)	4.94
Self-perceived health status (Fair)	4.58
Self-perceived health status (Poor)	2.42

Done based on « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 8 » & « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 9». (2024). Data sets: DOI: 10.6103/SHARE.w8.900 & DOI: 10.6103/SHARE.w9.900.

Appendix C: Results

Table 15: Random-effects probit regression (panel data) for RISK SEEKER profile

Variables	<u>Model 1</u>	<u>Model 2</u>	<u>Model 3</u>	<u>Model 4</u>
Post Covid-19 dummy	-0.0148 (0.0654)	-0.0113 (0.0655)	-0.0089 (0.0655)	-0.0039 (0.1685)
Age: Older (+ 70 years old)	0.1015 (0.1083)	0.1098 (0.1086)	0.1078 (0.1086)	0.1090 (0.1098)
Gender: Female	0.4624*** (0.1051)	0.4632*** (0.1055)	0.4413*** (0.1065)	0.4475*** (0.1079)
Relationship status: Couple	-0.0029 (0.1033)	-0.0063 (0.1034)	0.0055 (0.1040)	0.0067 (0.1052)
Country region: Central	-1.0888*** (0.1172)	-1.0921*** (0.1173)	-1.1156*** (0.1233)	-1.1317*** (0.1252)
Country region: Eastern	-2.7390*** (0.4145)	-2.7469*** (0.4148)	-2.7575*** (0.4189)	-2.7970*** (0.4252)
Country region: Southern	-2.5088*** (0.2264)	-2.5053*** (0.2263)	-2.4868*** (0.2291)	-2.5200*** (0.2329)
Education level: Medium	0.3319*** (0.1277)	0.3297*** (0.1279)	0.2810** (0.1283)	0.2872** (0.1299)
Education level: High	0.4875*** (0.1333)	0.4792*** (0.1339)	0.4339*** (0.1344)	0.4418*** (0.1361)
Job: Employed/self-employed	-0.1587 (0.1843)	-0.1568 (0.1842)	-0.1507 (0.1839)	-0.1381 (0.1858)
Job: Unemployed	-0.0499 (0.8020)	-0.0672 (0.8052)	-0.0360 (0.8043)	-0.0619 (0.8207)
Job: Permanently sick	-	-	-	-

Table 15: Random-effects probit regression (panel data) for RISK SEEKER profile

Job: Homemaker	0.2534 (0.2500)	0.2599 (0.2502)	0.2691 (0.2506)	0.2706 (0.2540)
Job: Other	-0.4052 (0.4389)	-0.4041 (0.4388)	-0.3802 (0.4369)	-0.4105 (0.4453)
BMI: Alarming situation	0.0473 (0.0934)	0.0468 (0.0934)	0.0336 (0.0936)	0.0372 (0.0948)
Chronic diseases: 1-2 diseases	-0.0844 (0.1129)	-0.0825 (0.1129)	-0.0777 (0.1131)	-0.0734 (0.1143)
Chronic diseases: 3+ diseases	-0.1614 (0.1326)	-0.1603 (0.1327)	-0.1569 (0.1328)	-0.1674 (0.1344)
Health status: Very good	-0.1253 (0.1467)	-0.1327 (0.1468)	-0.1209 (0.1470)	-0.1141 (0.1490)
Health status: Good	-0.2193 (0.1506)	-0.2225 (0.1506)	-0.1926 (0.1513)	-0.1835 (0.1533)
Health status: Fair	-0.2346 (0.1669)	-0.2322 (0.1668)	-0.1883 (0.1684)	-0.1741 (0.1707)
Health status: Poor	-0.4470* (0.2456)	-0.4273* (0.2465)	-0.3731 (0.2474)	-0.3493 (0.2501)
Consumption: Risky	-	0.0309 (0.1122)	0.0201 (0.1127)	-0.1076 (0.1446)
Consumption: Healthy	-	-0.1413 (0.1214)	-0.1521 (0.1217)	-0.1724 (0.1721)
Personality: <i>Extraversion</i>	-	-	0.0852 (0.1003)	0.2172 (0.1218)
Personality: <i>Openness</i>	-	-	0.1892* (0.1044)	0.2063 (0.1258)

Table 15: Random-effects probit regression (panel data) for RISK SEEKER profile

Personality: <i>Conscientiousness</i>	-	-	-0.0610 (0.1097)	0.0157 (0.1343)
Personality: <i>Agreeableness</i>	-	-	-0.1993* (0.1021)	-0.3534*** (0.1242)
Personality: <i>Neuroticism</i>	-	-	0.2143** (0.1016)	0.1932 (0.1227)
Risky consumption * post Covid-19	-	-	-	0.2463 (0.1761)
Healthy consumption * post Covid-19	-	-	-	0.0335 (0.2182)
<i>Extraversion</i> * post Covid-19	-	-	-	-0.2640** (0.1341)
<i>Openness</i> * post Covid-19	-	-	-	-0.0293 (0.1372)
<i>Conscientiousness</i> * post Covid-19	-	-	-	-0.1525 (0.1472)
<i>Agreeableness</i> * post Covid-19	-	-	-	0.2999** (0.1362)
<i>Neuroticism</i> * post Covid-19	-	-	-	0.0473 (0.1338)
Observations	7,778	7,778	7,778	7,778
Pseudo R^2	0.211	0.211	0.215	0.217

Note: ***p<0.01, **p<0.05, *p<0.1 Coefficients are first written and standard errors are in parentheses.

Done based on « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 8 » & « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 9 ». (2024). Data sets: DOI: 10.6103/SHARE.w8.900 & DOI: 10.6103/SHARE.w9.900.

Pseudo $R^2 = 1 - \frac{\text{Log Likelihood entire model}}{\text{Log Likelihood Iteration 0}}$ (Vcall & Zimmermann, 1994). Although Pseudo R^2 values are small, they increase progressively, indicating that the model increasingly explains the variability in the data.

Table 16: Random-effects probit (panel data) regression for RISK DIVERSIFIER - DYNAMIC profile

Variables	Model 1	Model 2	Model 3	Model 4
Post Covid-19 dummy	0.0560 (0.0704)	0.0561 (0.0704)	0.0556 (0.0703)	0.2832 (0.1700)
Age: Older (+ 70 years old)	0.1255 (0.1031)	0.1269 (0.1034)	0.1222 (0.1030)	0.1263 (0.1035)
Gender: Female	0.2969*** (0.0931)	0.3015*** (0.0933)	0.2919*** (0.0938)	0.2918*** (0.0942)
Relationship status: Couple	0.0301 (0.0922)	0.0261 (0.0923)	0.0411 (0.0926)	0.0426 (0.0930)
Country region: Central	-0.4420*** (0.0964)	-0.4445*** (0.0964)	-0.4352*** (0.1004)	-0.4380*** (0.1008)
Country region: Eastern	-2.0480*** (0.4745)	-2.0544*** (0.4748)	-2.0884*** (0.4812)	-2.1018*** (0.4855)
Country region: Southern	-1.3839*** (0.1814)	-1.3833*** (0.1813)	-1.3741*** (0.1834)	-1.3771*** (0.1844)
Education level: Medium	0.2973*** (0.1170)	0.2977*** (0.1170)	0.2924*** (0.1170)	0.2934*** (0.1174)
Education level: High	0.5167*** (0.1209)	0.5175*** (0.1210)	0.5088*** (0.1212)	0.5077*** (0.1217)
Job: Employed/self-employed	0.2023 (0.1690)	0.2066 (0.1689)	0.1984 (0.1683)	0.2029 (0.1695)
Job: Unemployed	(empty)	(empty)	(empty)	(empty)
Job: Permanently sick	0.7525* (0.3880)	0.7695** (0.3892)	0.7792** (0.3877)	0.7715** (0.3896)

Table 16: Random-effects probit (panel data) regression for RISK DIVERSIFIER - DYNAMIC profile

Job: Homemaker	-0.1879 (0.2827)	-0.1869 (0.2826)	-0.1962 (0.2826)	-0.1971 (0.2840)
Job: Other	-0.0472 (0.4394)	-0.0438 (0.4385)	-0.0398 (0.4349)	-0.0404 (0.4382)
BMI: Alarming situation	0.0066 (0.0860)	0.0083 (0.0859)	-0.0052 (0.0860)	-0.0045 (0.0864)
Chronic diseases: 1-2 diseases	0.0659 (0.1138)	0.0669 (0.1138)	0.0612 (0.1136)	0.0612 (0.1140)
Chronic diseases: 3+ diseases	0.0913 (0.1304)	0.0914 (0.1304)	0.0807 (0.1300)	0.0776 (0.1305)
Health status: Very good	-0.1848 (0.1447)	-0.1852 (0.1446)	-0.1982 (0.1443)	-0.1952 (0.1450)
Health status: Good	-0.1240 (0.1432)	-0.1239 (0.1431)	-0.1466 (0.1436)	-0.1418 (0.1440)
Health status: Fair	-0.3054* (0.1614)	-0.2999* (0.1614)	-0.3396** (0.1628)	-0.3370** (0.1636)
Health status: Poor	-0.4843** (0.2384)	-0.4663* (0.2395)	-0.5041** (0.2405)	-0.4957** (0.2421)
Consumption: Risky	-	-0.0552 (0.1072)	-0.0680 (0.1075)	-0.0923 (0.1442)
Consumption: Healthy	-	-0.0716 (0.1180)	-0.0751 (0.1177)	0.0679 (0.1605)
Personality: <i>Extraversion</i>	-	-	-0.0079 (0.0895)	0.0648 (0.1159)
Personality: <i>Openness</i>	-	-	0.0190 (0.0926)	0.0166 (0.1204)

Table 16: Random-effects probit (panel data) regression for RISK DIVERSIFIER - DYNAMIC profile

Personality: <i>Conscientiousness</i>	-	-	-0.2499*** (0.0946)	-0.1641 (0.1240)
Personality: <i>Agreeableness</i>	-	-	-0.0514 (0.0898)	-0.0743 (0.1174)
Personality: <i>Neuroticism</i>	-	-	-0.0053 (0.0891)	0.0478 (0.1160)
Risky consumption * post Covid-19	-	-	-	0.0522 (0.1889)
Healthy consumption * post Covid-19	-	-	-	-0.2833 (0.2202)
<i>Extraversion</i> * post Covid-19	-	-	-	-0.1438 (0.1435)
<i>Openness</i> * post Covid-19	-	-	-	0.0052 (0.1479)
<i>Conscientiousness</i> * post Covid-19	-	-	-	-0.1624 (0.1505)
<i>Agreeableness</i> * post Covid-19	-	-	-	0.0454 (0.1452)
<i>Neuroticism</i> * post Covid-19	-	-	-	-0.1025 (0.1428)
Observations	7,840	7,840	7,840	7,840
Pseudo R^2	0.131	0.131	0.134	0.136

Note: ***p<0.01, **p<0.05, *p<0.1 Coefficients are first written and standard errors are in parentheses.

Done based on « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 8 » & « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 9 ». (2024). Data sets: DOI: 10.6103/SHARE.w8.900 & DOI: 10.6103/SHARE.w9.900.

Pseudo $R^2 = 1 - \frac{\text{Log Likelihood entire model}}{\text{Log Likelihood Iteration 0}}$ (Vcall & Zimmermann, 1994). Although Pseudo R^2 values are small, they increase progressively, indicating that the model increasingly explains the variability in the data.

Table 17: Random-effects probit regression (panel data) for RISK DIVERSIFIER - PERFECT profile

Variables	<u>Model 1</u>	<u>Model 2</u>	<u>Model 3</u>	<u>Model 4</u>
Post Covid-19 dummy	-0.0898 (0.0577)	-0.0854 (0.0576)	-0.0843 (0.0576)	0.0189 (0.1487)
Age: Older (+ 70 years old)	0.0325 (0.0913)	0.0426 (0.0913)	0.0348 (0.0912)	0.0374 (0.0916)
Gender: Female	0.2627*** (0.0877)	0.2659*** (0.0875)	0.2498*** (0.0881)	0.2502*** (0.0885)
Relationship status: Couple	-0.1649* (0.0863)	-0.1711** (0.0861)	-0.1813** (0.0864)	-0.1800** (0.0868)
Country region: Central	-0.3721*** (0.0925)	-0.3751*** (0.0922)	-0.3720*** (0.0968)	-0.3746*** (0.0972)
Country region: Eastern	-2.9466*** (0.5596)	-2.9498*** (0.5577)	-2.9636*** (0.5565)	-2.9721*** (0.5573)
Country region: Southern	-1.6352*** (0.1617)	-1.6227*** (0.1608)	-1.6017*** (0.1634)	-1.6099*** (0.1642)
Education level: Medium	0.2138** (0.1046)	0.2103** (0.1043)	0.1946* (0.1044)	0.1945* (0.1049)
Education level: High	0.3877*** (0.1099)	0.3809*** (0.1097)	0.3874*** (0.1102)	0.3889*** (0.1107)
Job: Employed/self-employed	-0.3672** (0.1741)	-0.3635** (0.1734)	-0.3501** (0.1730)	-0.3559** (0.1737)
Job: Unemployed	(empty)	(empty)	(empty)	(empty)
Job: Permanently sick	-0.1264 (0.4645)	-0.1069 (0.4671)	-0.1160 (0.4672)	-0.1275 (0.4702)

Table 17: Random-effects probit regression (panel data) for RISK DIVERSIFIER - PERFECT profile

Job: Homemaker	-0.2191 (0.2193)	-0.2067 (0.2188)	-0.2118 (0.2189)	-0.2215 (0.2207)
Job: Other	0.1984 (0.3183)	0.2117 (0.3172)	0.2233 (0.3153)	0.2144 (0.3182)
BMI: Alarming situation	-0.1136 (0.0791)	-0.1113 (0.0788)	-0.1170 (0.0791)	-0.1170 (0.0794)
Chronic diseases: 1-2 diseases	0.0042 (0.0981)	0.0055 (0.0979)	0.0144 (0.0977)	0.0130 (0.0982)
Chronic diseases: 3+ diseases	-0.0250 (0.1144)	-0.0261 (0.1141)	-0.0213 (0.1139)	-0.0196 (0.1144)
Health status: Very good	0.1191 (0.1330)	0.1154 (0.1328)	0.1193 (0.1328)	0.1055 (0.1334)
Health status: Good	-0.0220 (0.1352)	-0.0198 (0.1348)	-0.0110 (0.1353)	-0.0219 (0.1359)
Health status: Fair	-0.3571** (0.1512)	-0.3409** (0.1510)	-0.3249** (0.1520)	-0.3419** (0.1528)
Health status: Poor	-0.4661** (0.2150)	-0.4164* (0.2157)	-0.3979* (0.2165)	-0.4275** (0.2181)
Consumption: Risky	-	0.0055 (0.0978)	-0.0107 (0.0979)	0.0059 (0.1236)
Consumption: Healthy	-	-0.2242** (0.1084)	-0.2278** (0.1084)	-0.3273** (0.1545)
Personality: <i>Extraversion</i>	-	-	0.0975 (0.0844)	0.0711 (0.1020)
Personality: <i>Openness</i>	-	-	-0.1045 (0.0880)	-0.0798 (0.1062)

Table 17: Random-effects probit regression (panel data) for RISK DIVERSIFIER - PERFECT profile

Personality: <i>Conscientiousness</i>	-	-	0.0900 (0.0940)	0.0671 (0.1140)
Personality: <i>Agreeableness</i>	-	-	-0.1888** (0.0849)	-0.0946 (0.1027)
Personality: <i>Neuroticism</i>	-	-	0.1024 (0.0845)	0.1562 (0.1021)
Risky consumption * post Covid-19	-	-	-	-0.0259 (0.1567)
Healthy consumption * post Covid-19	-	-	-	0.1924 (0.1968)
<i>Extraversion</i> * post Covid-19	-	-	-	0.0557 (0.1167)
<i>Openness</i> * post Covid-19	-	-	-	-0.0523 (0.1216)
<i>Conscientiousness</i> * post Covid-19	-	-	-	0.0469 (0.1312)
<i>Agreeableness</i> * post Covid-19	-	-	-	-0.1960 (0.1177)
<i>Neuroticism</i> * post Covid-19	-	-	-	-0.1135 (0.1168)
Observations	7,840	7,840	7,840	7,840
Pseudo R^2	0.173	0.174	0.176	0.178

Note: ***p<0.01, **p<0.05, *p<0.1 Coefficients are first written and standard errors are in parentheses.

Done based on « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 8 » & « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 9 ». (2024). Data sets: DOI: 10.6103/SHARE.w8.900 & DOI: 10.6103/SHARE.w9.900.

Pseudo $R^2 = 1 - \frac{\text{Log Likelihood entire model}}{\text{Log Likelihood Iteration 0}}$ (Vcall & Zimmermann, 1994). Although Pseudo R^2 values are small, they increase progressively, indicating that the model increasingly explains the variability in the data.

Table 18: Random-effects panel probit regression for RISK DIVERSIFIER - DEFENSIVE profile

Variables	<u>Model 1</u>	<u>Model 2</u>	<u>Model 3</u>	<u>Model 4</u>
Post Covid-19 dummy	-0.0793 (0.1003)	-0.0780 (0.1005)	-0.0772 (0.1008)	-0.1387 (0.2611)
Age: Older (+ 70 years old)	-0.2626* (0.1336)	-0.2535* (0.1341)	-0.2437* (0.1341)	-0.2429* (0.1375)
Gender: Female	0.3998*** (0.1317)	0.4116*** (0.1325)	0.4212*** (0.1347)	0.4324*** (0.1387)
Relationship status: Couple	-0.2824** (0.1285)	-0.2942** (0.1290)	-0.2650** (0.1296)	-0.2796** (0.1333)
Country region: Central	-0.2938** (0.1366)	-0.3002** (0.1368)	-0.3229** (0.1444)	-0.3292** (0.1482)
Country region: Eastern	-1.0127*** (0.3950)	-1.0364*** (0.3964)	-0.9875*** (0.3995)	-1.0218*** (0.4136)
Country region: Southern	-0.6736*** (0.2037)	-0.6700*** (0.2035)	-0.6389*** (0.2106)	-0.6510*** (0.2163)
Education level: Medium	0.3003* (0.1621)	0.3023* (0.1622)	0.2559 (0.1626)	0.2646 (0.1669)
Education level: High	0.4979*** (0.1683)	0.5003*** (0.1689)	0.4330*** (0.1691)	0.4495*** (0.1738)
Job: Employed/self-employed	-0.1982 (0.2517)	-0.1936 (0.2519)	-0.2148 (0.2538)	-0.2074 (0.2595)
Job: Unemployed	(empty)	(empty)	(empty)	(empty)
Job: Permanently sick	(empty)	(empty)	(empty)	(empty)

Table 18: Random-effects panel probit regression for RISK DIVERSIFIER - DEFENSIVE profile

Job: Homemaker	-0.3292 (0.3849)	-0.3160 (0.3840)	-0.2990 (0.3857)	-0.2937 (0.3938)
Job: Other	0.2376 (0.4452)	0.2464 (0.4442)	0.2527 (0.4500)	0.2701 (0.4570)
BMI: Alarming situation	-0.1198 (0.1184)	-0.1207 (0.1184)	-0.1494 (0.1196)	-0.1549 (0.1225)
Chronic diseases: 1-2 diseases	0.2519 (0.1676)	0.2553 (0.1680)	0.2435 (0.1684)	0.2398 (0.1722)
Chronic diseases: 3+ diseases	0.0250 (0.1951)	0.0233 (0.1955)	0.0131 (0.1957)	-0.0007 (0.2004)
Health status: Very good	-0.0315 (0.2278)	-0.0399 (0.2280)	-0.0056 (0.2297)	0.0160 (0.2355)
Health status: Good	0.1197 (0.2217)	0.1129 (0.2215)	0.1915 (0.2245)	0.2113 (0.2305)
Health status: Fair	0.0699 (0.2422)	0.0884 (0.2421)	0.1796 (0.2463)	0.2000 (0.2531)
Health status: Poor	-0.0140 (0.3322)	0.0516 (0.3337)	0.1609 (0.3373)	0.2071 (0.3460)
Consumption: Risky	-	-0.1096 (0.1505)	-0.1125 (0.1508)	-0.0293 (0.1925)
Consumption: Healthy	-	-0.2904 (0.1841)	-0.3142* (0.1855)	-0.4114 (0.2713)
Personality: <i>Extraversion</i>	-	-	0.2209* (0.1239)	0.3431** (0.1622)
Personality: <i>Openness</i>	-	-	0.2973** (0.1272)	0.3769** (0.1626)

Table 18: Random-effects panel probit regression for RISK DIVERSIFIER - DEFENSIVE profile

Personality: <i>Conscientiousness</i>	-	-	-0.1062 (0.1325)	-0.0890 (0.1725)
Personality: <i>Agreeableness</i>	-	-	-0.0827 (0.1241)	-0.3214** (0.1640)
Personality: <i>Neuroticism</i>	-	-	0.1541 (0.1243)	0.1458 (0.1615)
Risky consumption * post Covid-19	-	-	-	-0.2421 (0.2856)
Healthy consumption * post Covid-19	-	-	-	0.1496 (0.3564)
<i>Extraversion</i> * post Covid-19	-	-	-	-0.2447 (0.2086)
<i>Openness</i> * post Covid-19	-	-	-	-0.1532 (0.2079)
<i>Conscientiousness</i> * post Covid-19	-	-	-	-0.0490 (0.2257)
<i>Agreeableness</i> * post Covid-19	-	-	-	0.5109** (0.2183)
<i>Neuroticism</i> * post Covid-19	-	-	-	0.0398 (0.2106)
Observations	7,752	7,752	7,752	7,752
Pseudo R^2	0.166	0.168	0.172	0.174

Note: ***p<0.01, **p<0.05, *p<0.1 Coefficients are first written and standard errors are in parentheses.

Done based on « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 8 » & « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 9 ». (2024). Data sets: DOI: 10.6103/SHARE.w8.900 & DOI: 10.6103/SHARE.w9.900.

Pseudo $R^2 = 1 - \frac{\text{Log Likelihood entire model}}{\text{Log Likelihood Iteration 0}}$ (Vcall & Zimmermann, 1994). Although Pseudo R^2 values are small, they increase progressively, indicating that the model increasingly explains the variability in the data.

Table 19: Random-effects probit (panel data) regression for DEFENSIVE profile

Variables	<u>Model 1</u>	<u>Model 2</u>	<u>Model 3</u>	<u>Model 4</u>
Post Covid-19 dummy	-0.0525 (0.1240)	-0.0449 (0.1240)	-0.0471 (0.1240)	-0.0297 (0.3073)
Age: Older (+ 70 years old)	0.3599* (0.2067)	0.3577* (0.2067)	0.3749* (0.2077)	0.3742* (0.2101)
Gender: Female	0.1701 (0.1748)	0.1798 (0.1746)	0.1874 (0.1751)	0.1899 (0.1771)
Relationship status: Couple	-0.2426 (0.1723)	-0.2504 (0.1720)	-0.2705 (0.1728)	-0.2805 (0.1752)
Country region: Central	-0.1174 (0.2056)	-0.1348 (0.2051)	-0.2746 (0.2145)	-0.2781 (0.2166)
Country region: Eastern	-0.6361 (0.4984)	-0.6684 (0.4983)	-0.7608 (0.5049)	-0.7642 (0.5091)
Country region: Southern	0.2106 (0.2397)	0.2105 (0.2382)	0.1352 (0.2459)	0.1392 (0.2480)
Education level: Medium	0.4492** (0.2079)	0.4472** (0.2074)	0.3885* (0.2061)	0.3912* (0.2085)
Education level: High	0.3225 (0.2292)	0.3237 (0.2285)	0.2520 (0.2275)	0.2559 (0.2296)
Job: Employed/self-employed	0.4591 (0.3207)	0.4550 (0.3198)	0.4625 (0.3196)	0.4696 (0.3226)
Job: Unemployed	(empty)	(empty)	(empty)	(empty)
Job: Permanently sick	(empty)	(empty)	(empty)	(empty)

Table 19: Random-effects probit (panel data) regression for DEFENSIVE profile

Job: Homemaker	-0.0344 (0.3140)	-0.0374 (0.3146)	-0.0448 (0.3161)	-0.0265 (0.3175)
Job: Other	(empty)	(empty)	(empty)	(empty)
BMI: Alarming situation	-0.0049 (0.1587)	-0.0082 (0.1581)	0.0012 (0.1586)	0.0045 (0.1601)
Chronic diseases: 1-2 diseases	0.0624 (0.2040)	0.0614 (0.2035)	0.0585 (0.2037)	0.0549 (0.2056)
Chronic diseases: 3+ diseases	-0.3050 (0.2479)	-0.3088 (0.2476)	-0.3075 (0.2477)	-0.3126 (0.2500)
Health status: Very good	0.0315 (0.2989)	0.0223 (0.2977)	0.0057 (0.2962)	-0.0035 (0.2989)
Health status: Good	-0.0250 (0.2965)	-0.0267 (0.2948)	-0.0221 (0.2935)	-0.0268 (0.2959)
Health status: Fair	-0.1725 (0.3248)	-0.1553 (0.3235)	-0.1450 (0.3237)	-0.1647 (0.3275)
Health status: Poor	0.1773 (0.3902)	0.2443 (0.3925)	0.2548 (0.3942)	0.2448 (0.3985)
Consumption: Risky	-	-0.1635 (0.2106)	-0.1639 (0.2120)	-0.0301 (0.2642)
Consumption: Healthy	-	-0.2712 (0.2186)	-0.2680 (0.2187)	-0.1562 (0.3001)
Personality: <i>Extraversion</i>	-	-	-0.0731 (0.1692)	-0.0821 (0.2117)
Personality: <i>Openness</i>	-	-	0.4319** (0.1734)	0.3709* (0.2132)

Table 19: Random-effects probit (panel data) regression for DEFENSIVE profile

Personality: <i>Conscientiousness</i>	-	-	0.1535 (0.1881)	0.0952 (0.2345)
Personality: <i>Agreeableness</i>	-	-	-0.2080 (0.1665)	-0.1004 (0.2068)
Personality: <i>Neuroticism</i>	-	-	0.0449 (0.1653)	0.0381 (0.2079)
Risky consumption * post Covid-19	-	-	-	-0.3136 (0.3817)
Healthy consumption * post Covid-19	-	-	-	-0.2378 (0.4064)
<i>Extraversion</i> * post Covid-19	-	-	-	0.0191 (0.2588)
<i>Openness</i> * post Covid-19	-	-	-	0.1335 (0.2522)
<i>Conscientiousness</i> * post Covid-19	-	-	-	0.1273 (0.2970)
<i>Agreeableness</i> * post Covid-19	-	-	-	-0.2268 (0.2566)
<i>Neuroticism</i> * post Covid-19	-	-	-	0.0144 (0.2552)
Observations	7,644	7,644	7,644	7,644
Pseudo R ²	0.164	0.165	0.167	0.169

Note: ***p<0.01, **p<0.05, *p<0.1 Coefficients are first written and standard errors are in parentheses.

Done based on « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 8 » & « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 9 ». (2024). Data sets: DOI: 10.6103/SHARE.w8.900 & DOI: 10.6103/SHARE.w9.900.

Pseudo R² = 1 - $\frac{\text{Log Likelihood entire model}}{\text{Log Likelihood Iteration 0}}$ (Vcall & Zimmermann, 1994). Although Pseudo R² values are small, they increase progressively, indicating that the model increasingly explains the variability in the data.

Table 20: Random-effects probit (panel data) regression for RISK AVERSE profile

Variables	Model 1	Model 2	Model 3	Model 4
Post Covid-19 dummy	0.0874 (0.0545)	0.0786 (0.0546)	0.0765 (0.0546)	-0.1231 (0.1375)
Age: Older (+ 70 years old)	-0.1710 (0.1047)	-0.1844 (0.1048)	-0.1782 (0.1049)	-0.1856* (0.1057)
Gender: Female	-0.7646*** (0.1146)	-0.7694*** (0.1145)	-0.7333*** (0.1151)	-0.7395*** (0.1160)
Relationship status: Couple	0.2035* (0.1074)	0.2139** (0.1072)	0.2027* (0.1077)	0.2013* (0.1085)
Country region: Central	1.4301*** (0.1312)	1.4334*** (0.1308)	1.4620*** (0.1367)	1.4743*** (0.1378)
Country region: Eastern	4.5840*** (0.4523)	4.5933*** (0.4496)	4.6152*** (0.4517)	4.6513*** (0.4572)
Country region: Southern	3.3485*** (0.2130)	3.3344*** (0.2123)	3.3039*** (0.2161)	3.3328*** (0.2183)
Education level: Medium	-0.6486*** (0.1322)	-0.6431*** (0.1319)	-0.5837*** (0.1320)	-0.5895*** (0.1330)
Education level: High	-1.0707*** (0.1442)	-1.0597*** (0.1439)	-1.0067*** (0.1442)	-1.0166*** (0.1454)
Job: Employed/self-employed	0.1700 (0.1837)	0.1648 (0.1833)	0.1583 (0.1836)	0.1528 (0.1854)
Job: Unemployed	1.8315 (0.9370)	1.8446** (0.9373)	1.8070* (0.9327)	1.8126* (0.9431)
Job: Permanently sick	0.3419 (0.5070)	0.3139 (0.5090)	0.2778 (0.5076)	0.3069 (0.5123)

Table 20: Random-effects probit (panel data) regression for RISK AVERSE profile

Job: Homemaker	-0.0391 (0.2213)	-0.0558 (0.2211)	-0.0561 (0.2214)	-0.0695 (0.2234)
Job: Other	0.1021 (0.3565)	0.0831 (0.3542)	0.0701 (0.3533)	0.0529 (0.3561)
BMI: Alarming situation	0.1114 (0.0923)	0.1100 (0.0921)	0.1226 (0.0924)	0.1184 (0.0930)
Chronic diseases: 1-2 diseases	-0.0994 (0.1071)	-0.0986 (0.1070)	-0.1030 (0.1071)	-0.1066 (0.1077)
Chronic diseases: 3+ diseases	0.0710 (0.1261)	0.0723 (0.1260)	0.0662 (0.1260)	0.0711 (0.1269)
Health status: Very good	0.0787 (0.1458)	0.0886 (0.1457)	0.0746 (0.1459)	0.0743 (0.1471)
Health status: Good	0.1972 (0.1501)	0.2024 (0.1499)	0.1704 (0.1504)	0.1716 (0.1516)
Health status: Fair	0.4787*** (0.1636)	0.4700*** (0.1635)	0.4247** (0.1645)	0.4232** (0.1658)
Health status: Poor	0.6279*** (0.2224)	0.5781*** (0.2228)	0.5275** (0.2238)	0.5193** (0.2254)
Consumption: Risky	-	0.0299 (0.1105)	0.0470 (0.1108)	0.0892 (0.1338)
Consumption: Healthy	-	0.3013*** (0.1101)	0.3079*** (0.1103)	0.3587** (0.1536)
Personality: <i>Extraversion</i>	-	-	-0.1471 (0.1076)	-0.2758** (0.1215)
Personality: <i>Openness</i>	-	-	-0.2043* (0.1109)	-0.2574** (0.1249)

Table 20: Random-effects probit (panel data) regression for RISK AVERSE profile

Personality: <i>Conscientiousness</i>	-	-	0.0577 (0.1182)	-0.0134 (0.1343)
Personality: <i>Agreeableness</i>	-	-	0.3527*** (0.1081)	0.4225*** (0.1225)
Personality: <i>Neuroticism</i>	-	-	-0.3298*** (0.1082)	-0.3772*** (0.1222)
Risky consumption * post Covid-19	-	-	-	-0.0983 (0.1511)
Healthy consumption * post Covid-19	-	-	-	-0.0900 (0.1866)
<i>Extraversion</i> * post Covid-19	-	-	-	0.2602** (0.1109)
<i>Openness</i> * post Covid-19	-	-	-	-0.1329 (0.1110)
<i>Conscientiousness</i> * post Covid-19	-	-	-	0.1408 (0.1221)
<i>Agreeableness</i> * post Covid-19	-	-	-	0.1049 (0.1124)
<i>Neuroticism</i> * post Covid-19	-	-	-	0.0908 (0.1103)
Observations	7,866	7,866	7,866	7,866
Pseudo R^2	0.188	0.189	0.190	0.191

Note: ***p<0.01, **p<0.05, *p<0.1 Coefficients are first written and standard errors are in parentheses.

Done based on « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 8 » & « Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 9 ». (2024). Data sets: DOI: 10.6103/SHARE.w8.900 & DOI: 10.6103/SHARE.w9.900.

Pseudo $R^2 = 1 - \frac{\text{Log Likelihood entire model}}{\text{Log Likelihood Iteration 0}}$ (Vcall & Zimmermann, 1994). Although Pseudo R^2 values are small, they increase progressively, indicating that the model increasingly explains the variability in the data.

BIBLIOGRAPHY

Disclaimer: Use of ChatGPT

As part of this work, some sections, including Stata coding, creation of tables layout and some phrase reformulation, were carried out with the help of ChatGPT, a language model developed by OpenAI.

It is important to note that:

- All information, including coding, table layout and reformulations provided by ChatGPT, were systematically carefully verified and validated to ensure its accuracy and relevance in the context of this work.
- As the author of this work, I assume full responsibility for the generated content and its integration into the final document. The suggestions provided by ChatGPT were used critically and adapted to the specific requirement of this work.

Charlotte Ylieff Counhaye.

Abdellaoui, M., l'Haridon, O., & Paraschiv, C. (2013). Individual vs. couple behavior: An experimental investigation of risk preferences. *Theory and Decision*, 75(2), 175–191.

<https://doi.org/10.1007/s11238-012-9322-7>

Addoum, J. M., Korniotis, G., & Kumar, A. (2017). Stature, Obesity, and Portfolio Choice. *Management Science*, 63(10), 3393–3413. <https://doi.org/10.1287/mnsc.2016.2508>

Ahmad, M., & Maochun, Z. (2019). Personality Traits and Investor Decisions. *Asian Journal of Economics, Finance and Management*, 19–34.

Allard, F. (2009). *Vos patients sur l'alcool ! 44*.

Alsharawy, A., Spoon, R., Smith, A., & Ball, S. (2021). Gender Differences in Fear and Risk Perception During the COVID-19 Pandemic. *Frontiers in Psychology*, 12.

<https://doi.org/10.3389/fpsyg.2021.689467>

Anesthesiol, K. J. (2019, December). *Multicollinearity and misleading statistical results—PMC*.

<https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6900425/>

- Barasinska, N., Badunenko, O., & Schäfer, D. (2009). Risk Attitudes and Investment Decisions across European Countries—Are Women More Conservative Investors than Men? *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.1342731>
- Bernoulli, D. (1954). Exposition of a New Theory on the Measurement of Risk. *Econometrica*, 22(1), 23–36. <https://doi.org/10.2307/1909829>
- Bondt, W. F. M. D., & Thaler, R. (1985). Does the Stock Market Overreact? *The Journal of Finance*, 40(3), 793. <https://doi.org/10.2307/2327804>
- Brooks, C., Sangiorgi, I., Hillenbrand, C., & Money, K. (2018). Why are older investors less willing to take financial risks? *International Review of Financial Analysis*, 56, 52–72. <https://doi.org/10.1016/j.irfa.2017.12.008>
- Brunen, A.-C. (2019). *Moral Licensing and Socially Responsible Investment Decisions* (SSRN Scholarly Paper 3440186). <https://doi.org/10.2139/ssrn.3440186>
- Cho, H.-S., & Yang, Y. (2023). Relationship Between Alcohol Consumption and Risky Sexual Behaviors Among Adolescents and Young Adults: A Meta-Analysis. *International Journal of Public Health*, 68, 1605669. <https://doi.org/10.3389/ijph.2023.1605669>
- Choudhry, V., Agardh, A., Stafström, M., & Östergren, P.-O. (2014). Patterns of alcohol consumption and risky sexual behavior: A cross-sectional study among Ugandan university students. *BMC Public Health*, 14(1), 128. <https://doi.org/10.1186/1471-2458-14-128>
- Connell, C. M., Gilreath, T. D., & Hansen, N. B. (2009). A multiprocess latent class analysis of the co-occurrence of substance use and sexual risk behavior among adolescents. *Journal of Studies on Alcohol and Drugs*, 70(6), 943–951. <https://doi.org/10.15288/jsad.2009.70.943>
- Cori, L., Bianchi, F., Cadum, E., & Anthonj, C. (2020). Risk Perception and COVID-19. *International Journal of Environmental Research and Public Health*, 17(9), Article 9. <https://doi.org/10.3390/ijerph17093114>

- De Bortoli, D., da Costa, J., Goulart, M., & Campara, J. (2019). Personality traits and investor profile analysis: A behavioral finance study. *PloS One*, 14(3), e0214062–e0214062. <https://doi.org/10.1371/journal.pone.0214062>
- de Rezende, L. F. M., Rey-López, J. P., Matsudo, V. K. R., & do Carmo Luiz, O. (2014). Sedentary behavior and health outcomes among older adults: A systematic review. *BMC Public Health*, 14, 333. <https://doi.org/10.1186/1471-2458-14-333>
- Delen Private Bank. (2020). *Brochure à propos des risques des principaux instruments financiers*. https://blog.delen.bank/hubfs/-/media/juridische-info/Informatiebrochure_FR.pdf?hsLang=fr-be
- Desmoulin-Lebeault, F., Gajewski, J.-F., & Meunier, L. (2022). The Impacts of Incentive Contracts and Hormones on Risk Taking. *Finance, Prépublication*, 1–34. <https://doi.org/10.3917/fina.pr.008>
- Dettmann, L. M., Adams, S., & Taylor, G. (2022). Investigating the prevalence of anxiety and depression during the first COVID-19 lockdown in the United Kingdom: Systematic review and meta-analyses. *British Journal of Clinical Psychology*, 61(3), 757–780. <https://doi.org/10.1111/bjc.12360>
- Dimand, R. W., & Dimand, M. A. (1995). Von Neumann and Morgenstern in Historical Perspective / Von Neumann et Morgenstern dans le contexte historique. *Revue d'économie Politique*, 105(4), 539–557.
- Ding, D., Rogers, K., van der Ploeg, H., Stamatakis, E., & Bauman, A. E. (2015, December 8). *Traditional and Emerging Lifestyle Risk Behaviors and All-Cause Mortality in Middle-Aged and Older Adults: Evidence from a Large Population-Based Australian Cohort* | *PLOS Medicine*. <https://journals.plos.org/plosmedicine/article?id=10.1371/journal.pmed.1001917>
- Dita, R. D. R. T., Heryana, T., & Basuki, T. I. (2023). Investment Decision-Making Behavior in the Era of Covid-19: An Analysis on the Basis of Mental Accounting, Loss Aversion Bias, and Risk

- Tolerance. *HOLISTICA – Journal of Business and Public Administration*, 14(2), 33–42.
<https://doi.org/10.2478/hjbpa-2023-0014>
- Elbannan, M. A. (2014). The Capital Asset Pricing Model: An Overview of the Theory. *International Journal of Economics and Finance*, 7(1), p216. <https://doi.org/10.5539/ijef.v7n1p216>
- Fama, E. (1970). *Efficient Capital Markets: A Review of Theory and Empirical Work on JSTOR*.
<https://www.jstor.org/stable/2325486?seq=33>
- Ferdinand, D. Y. Y. (2023). *Overconfidence Heuristic-Driven Bias in Investment Decision-Making: Mediating Effects of Risk Perception and Moderating Effects of Asymmetry Information*.
- Fong, J. H., Koh, B. S. K., Mitchell, O. S., & Rohwedder, S. (2021). Financial literacy and financial decision-making at older ages. *Pacific-Basin Finance Journal*, 65, 101481.
<https://doi.org/10.1016/j.pacfin.2020.101481>
- Ford, E. S., Zhao, G., Tsai, J., & Li, C. (2011, October). *Low-Risk Lifestyle Behaviors and All-Cause Mortality: Findings From the National Health and Nutrition Examination Survey III Mortality Study—PMC*. <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3222361/>
- Friedman, M., & Savage, L. J. (1952). The Expected-Utility Hypothesis and the Measurability of Utility. *Journal of Political Economy*, 60(6), 463–474.
- Gibbons, R. D., & Hedeker, D. (1994). Application of random-effects probit regression models. *Journal of Consulting and Clinical Psychology*, 62(2), 285–296. <https://doi.org/10.1037/0022-006X.62.2.285>
- Griffin, K. W., Lowe, S. R., Botvin, C., & Acevedo, B. P. (2019, April 25). *Patterns of adolescent tobacco and alcohol use as predictors of illicit and prescription drug abuse in minority young adults—PMC*. <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6559855/>
- Hastings, J., & Mitchell, O. S. (2020). How financial literacy and impatience shape retirement wealth and investment behaviors. *Journal of Pension Economics & Finance*, 19(1), 1–20.
<https://doi.org/10.1017/S1474747218000227>

- Heo, W., Rabbani, A., & Grable, J. E. (2021). An Evaluation of the Effect of the COVID-19 Pandemic on the Risk Tolerance of Financial Decision Makers. *Finance Research Letters*, 41, 101842. <https://doi.org/10.1016/j.frl.2020.101842>
- Isidore, R., & Arun, C. J. (2021). RISK PROFILING OF SECONDARY EQUITY INVESTORS FROM THE CHENNAI CITY OF INDIA BASED ON THE BIG FIVE PERSONALITY MODEL. *Copernican Journal of Finance & Accounting*, 10(4), Article 4. <https://doi.org/10.12775/CJFA.2021.014>
- James Chen & Charles Potters. (2021, July 31). *What Is Homo Economicus? Definition, Meaning, and Origins*. Investopedia. <https://www.investopedia.com/terms/h/homoeconomicus.asp>
- Jmp Statistical Discovery. (2024). *Test du khi-deux d'indépendance*. https://www.jmp.com/fr_fr/statistics-knowledge-portal/chi-square-test/chi-square-test-of-independence.html
- Joseph, E. D., & Zhang, D. C. (2021). Personality Profile of Risk-Takers. *Journal of Individual Differences*, 42(4), 194–203. <https://doi.org/10.1027/1614-0001/a000346>
- Kahneman, D., & Tversky, A. (1979). *Prospect Theory: An Analysis of Decision under Risk* on JSTOR. <https://www.jstor.org/stable/1914185?seq=27>
- Kapoor, S., & Prosad, J. M. (2017). Behavioural Finance: A Review. *Procedia Computer Science*, 122, 50–54. <https://doi.org/10.1016/j.procs.2017.11.340>
- Katsu, Y., & Baker, M. E. (2021). Subchapter 123D - Cortisol. In H. Ando, K. Ukena, & S. Nagata (Eds.), *Handbook of Hormones (Second Edition)* (pp. 947–949). Academic Press. <https://doi.org/10.1016/B978-0-12-820649-2.00261-8>
- Kipping, R. R., Campbell, R. M., MacArthur, G. J., Gunnell, D. J., & Hickman, M. (2012). Multiple risk behaviour in adolescence. *Journal of Public Health*, 34(suppl 1), i1–i2. <https://doi.org/10.1093/pubmed/fdr122>
- Lacombe, J., Armstrong, M. E. G., Wright, F. L., & Foster, C. (2019). The impact of physical activity and an additional behavioural risk factor on cardiovascular disease, cancer and all-cause mortality:

- A systematic review. *BMC Public Health*, 19(1), 900. <https://doi.org/10.1186/s12889-019-7030-8>
- Lai, C.-P. (2019). Personality Traits and Stock Investment of Individuals. *Sustainability*, 11(19), Article 19. <https://doi.org/10.3390/su11195474>
- Lai, X. (2023). *View of Anchoring and Adjustment Heuristic in behavioral finance*. <https://madison-proceedings.com/index.php/aemr/article/view/1723/1712>
- Le 5 août 2024, “lundi noir” à la Bourse de Tokyo. (2024, August 5). *Courrier International*. https://www.courrierinternational.com/article/le-5-aout-2024-lundi-noir-a-la-bourse-de-tokyo_220908
- Lebiedowska, A., Hartman-Petrycka, M., & Błońska-Fajfrowska, B. (2021). How reliable is BMI? Bioimpedance analysis of body composition in underweight, normal weight, overweight, and obese women. *Irish Journal of Medical Science (1971 -)*, 190(3), 993–998. <https://doi.org/10.1007/s11845-020-02403-3>
- Leparmentier, A. (2024, August 6). Les Bourses redoutent une récession et plongent. *Le Monde.fr*. https://www.lemonde.fr/economie/article/2024/08/05/les-bourses-redoutent-une-recession-et-plongent_6268577_3234.html
- Li, H., Zheng, Y., Li, Q., & Wang, M. (2024). Cognitive Function, Healthy Lifestyle, and All-Cause Mortality among Chinese Older Adults: A Longitudinal Prospective Study. *Nutrients*, 16(9), 1297. <https://doi.org/10.3390/nu16091297>
- Lintner, J. (1965). The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets. *The Review of Economics and Statistics*, 47(1), 13–37. <https://doi.org/10.2307/1924119>
- Lippi, A., Rossi, S., & Soana, M. G. (2022). Status quo bias and risk tolerance in asset allocation decision-making. *Journal of Neuroscience, Psychology, and Economics*, 15(4), 195–209. <https://doi.org/10.1037/npe0000166>

- Liu, X. (2016). *Multinomial Logit Model—An overview*.
<https://www.sciencedirect.com/topics/mathematics/multinomial-logit-model>
- Malik, P., & Sharma, S. (2024). *INDIVIDUAL INVESTORS' FINANCIAL RISK APPETITE AND DEMOGRAPHIC ATTRIBUTES: AN EMPIRICAL STUDY*.
- Manzoor, A., Jan, A., Shafi, M., Ashraf Parry, M., & Mir, T. (2023). Role of perceived COVID-19 disruption, personality traits and risk perception in determining the investment behavior of retail investors: A hybrid regression-neural network approach. *Journal of Economic and Administrative Sciences, ahead-of-print(ahead-of-print)*. <https://doi.org/10.1108/JEAS-01-2023-0026>
- Markowitz, H. (1952). Portfolio Selection. *The Journal of Finance*, 7(1), 77–91.
<https://doi.org/10.2307/2975974>
- Markowitz, H. M. (1991). Foundations of Portfolio Theory. *The Journal of Finance*, 46(2), 469–477.
<https://doi.org/10.2307/2328831>
- Martin, A., Markhvida, M., Hallegatte, S., & Walsh, B. (2020). Socio-Economic Impacts of COVID-19 on Household Consumption and Poverty. *Economics of Disasters and Climate Change*, 4(3), 453–479. <https://doi.org/10.1007/s41885-020-00070-3>
- Matsumoto, A. S., Fernandes, J. L. B., Ferreira, I., & Chagas, P. C. (2013, November 24). *Behavioral Finance: A Study of Affect Heuristic and Anchoring in Decision Making of Individual Investors by Alberto S. Matsumoto, Jose L. B. Fernandes, Israel Ferreira, Paulo César Chagas: SSRN*.
https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2359180
- Michele Bee & Maxime Desmarais-Tremblay. (2022, September 19). *THE BIRTH OF HOMO ŒCONOMICUS: THE METHODOLOGICAL DEBATE ON THE ECONOMIC AGENT FROM J. S. MILL TO V. PARETO* | *Journal of the History of Economic Thought* | Cambridge Core.
<https://www.cambridge.org/core/journals/journal-of-the-history-of-economic->

thought/article/birth-of-homo-oeconomicus-the-methodological-debate-on-the-economic-agent-from-j-s-mill-to-v-pareto/0B1260BA2526657C3811A4773BDD4645

Millroth, P., & Frey, R. (2021). Fear and anxiety in the face of COVID-19: Negative dispositions towards risk and uncertainty as vulnerability factors. *Journal of Anxiety Disorders*, *83*, 102454. <https://doi.org/10.1016/j.janxdis.2021.102454>

Mossin, J. (1966). Equilibrium in a Capital Asset Market. *Econometrica*, *34*(4), 768–783. <https://doi.org/10.2307/1910098>

Mudryj, A. N., Riediger, N. D., & Bombak, A. E. (2019). The relationships between health-related behaviours in the Canadian adult population. *BMC Public Health*, *19*(1), 1359. <https://doi.org/10.1186/s12889-019-7674-4>

Muhammad Khurram Shehzad, N., & Qaisar Ali, M. (2019, June). *Financial Attitude and Investment Decision Making—Moderating Role of Financial Literacy*. <https://www.proquest.com/openview/c795d95c4c29533d3e91c30fb899ebac/1?pq-origsite=gscholar&cbl=2050138>

Nicholson, N., Soane, E., Fenton-O’Creevy, M., & Willman, P. (2005). Personality and domain-specific risk taking. *Journal of Risk Research*, *8*(2), 157–176. <https://doi.org/10.1080/1366987032000123856>

Novikova, I. A. (2013). Big Five (The Five-Factor Model and The Five-Factor Theory). In K. D. Keith (Ed.), *The Encyclopedia of Cross-Cultural Psychology* (1st ed., pp. 136–138). Wiley. <https://doi.org/10.1002/9781118339893.wbeccp054>

Oehler, A., & Wedlich, F. (2018). The relationship of extraversion and neuroticism with risk attitude, risk perception, and return expectations. *Journal of Neuroscience, Psychology, and Economics*, *11*(2), 63–92. <https://doi.org/10.1037/npe0000088>

- Oehler, A., Wendt, S., Wedlich, F., & Horn, M. (2018). Investors' Personality Influences Investment Decisions: Experimental Evidence on Extraversion and Neuroticism. *The Journal of Behavioral Finance*, 19(1), 30–48. <https://doi.org/10.1080/15427560.2017.1366495>
- Outreville, J. F. (2015). The Relationship Between Relative Risk Aversion and the Level of Education: A Survey and Implications for the Demand for Life Insurance. *Journal of Economic Surveys*, 29(1), 97–111. <https://doi.org/10.1111/joes.12050>
- Paille, F., Aubin, H.-J., Gillet, C., & Rigaud, A. (2015). *Mésusage de l'alcool dépistage, diagnostic et traitement*. <https://www.charentes.synlab.fr/Media/PDF/BIOPAJ/BIOPAJ-Mesusage-de-lalcool.pdf>
- Peretti-Watel, P., L'Haridon, O., & Seror, V. (2013). Time preferences, socioeconomic status and smokers' behaviour, attitudes and risk awareness. *The European Journal of Public Health*, 23(5), 783–788. <https://doi.org/10.1093/eurpub/cks189>
- Probst, T., Budimir, S., & Pieh, C. (2020). Depression in and after COVID-19 lockdown in Austria and the role of stress and loneliness in lockdown: A longitudinal study. *Journal of Affective Disorders*, 277, 962–963. <https://doi.org/10.1016/j.jad.2020.09.047>
- Raad, B., & Mlacic, B. (2015). Big Five Factor Model, Theory and Structure. *International Encyclopedia of the Social & Behavioral Sciences* (pp. 559–566). <https://doi.org/10.1016/B978-0-08-097086-8.25066-6>
- Ross, S. (1976). *The arbitrage theory of capital asset pricing*—ScienceDirect. <https://www.sciencedirect.com/science/article/abs/pii/0022053176900466>
- Sahinidis, A. G., Tsaknis, P. A., Gkika, E., & Stavroulakis, D. (2020). The Influence of the Big Five Personality Traits and Risk Aversion on Entrepreneurial Intention. In A. Kavoura, E. Kefallonitis, & P. Theodoridis (Eds.), *Strategic Innovative Marketing and Tourism* (pp. 215–224). Springer International Publishing. https://doi.org/10.1007/978-3-030-36126-6_24

- Saivas, R., & Lokhande, M. (2022, June 20). *Influence of risk propensity, behavioural biases and demographic factors on equity investors' risk perception | Emerald Insight*.
<https://www.emerald.com/insight/content/doi/10.1108/AJEB-06-2021-0074/full/html>
- Samuelson, P. A. (1977). St. Petersburg Paradoxes: Defanged, Dissected, and Historically Described. *Journal of Economic Literature*, 15(1), 24–55.
- Schrempft, S., Jackowska, M., Hamer, M., & Steptoe, A. (2019). Associations between social isolation, loneliness, and objective physical activity in older men and women. *BMC Public Health*, 19(1), 74. <https://doi.org/10.1186/s12889-019-6424-y>
- Selivanova, A., & Cramm, J. M. (2014). The relationship between healthy behaviors and health outcomes among older adults in Russia. *BMC Public Health*, 14(1), 1183. <https://doi.org/10.1186/1471-2458-14-1183>
- Serra, M. C., Dondero, K. R., Larkins, D., Burns, A., & Addison, O. (2020). Healthy Lifestyle and Cognition: Interaction between Diet and Physical Activity. *Current Nutrition Reports*, 9(2), 64–74. <https://doi.org/10.1007/s13668-020-00306-4>
- SHARE-ERIC (2024). Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 8. Release version: 9.0.0. *SHARE-ERIC*. Data set. DOI: 10.6103/SHARE.w8.900
- SHARE-ERIC (2024). Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 9. Release version: 9.0.0. *SHARE-ERIC*. Data set. DOI: 10.6103/SHARE.w9.900
- Sharpe, W. (1964). *CAPITAL ASSET PRICES: A THEORY OF MARKET EQUILIBRIUM UNDER CONDITIONS OF RISK**—Sharpe—1964—*The Journal of Finance*—Wiley Online Library. <https://onlinelibrary.wiley.com/doi/10.1111/j.1540-6261.1964.tb02865.x>
- Soto, C. J. (2015). Is Happiness Good for Your Personality? Concurrent and Prospective Relations of the Big Five With Subjective Well-Being. *Journal of Personality*, 83(1), 45–55. <https://doi.org/10.1111/jopy.12081>

- Sowa, A., Tobiasz-Adamczyk, B., Topór-Mądry, R., Poscia, A., & Ignazio la Milia, D. (2016, September 5). *Predictors of healthy ageing: Public health policy targets* | *BMC Health Services Research* | Full Text. <https://bmchealthservres.biomedcentral.com/articles/10.1186/s12913-016-1520-5>
- Stata.com. (n.d.). *Random-effects and population-averaged probit models (xtprobit)*. Retrieved 4 August 2024, from <https://www.stata.com/manuals13/xtxtprobit.pdf>
- Summers, B., & Duxbury, D. (2007, November 27). *Unraveling the Disposition Effect: The Role of Prospect Theory and Emotions* by Barbara Summers, Darren Duxbury: SSRN. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1026915
- Survey of Health, Ageing and Retirement in Europe. (n.d.). *Data Archive* | *ControlConstructSchemes*. <https://www.share-datadocutool.org/control-construct-schemes/view/159>. Consulted on 18 June 2024.
- Survey of Health, Ageing and Retirement in Europe. (n.d.). *FAQs & support*. <https://share-eric.eu/data/faqs-support>. Consulted on 19 June 2024.
- Survey of Health, Ageing and Retirement in Europe. (n.d.). *Impact. SHARE-ERIC*. <https://share-eric.eu/impact>. Consulted on 17 June 2024.
- Thanki, H. (2015). Risk Tolerance Dependent on What? Demographics or Personality Type: Findings from an Empirical Research. *Journal of Marketing and Consumer Research*, 6(0), 48.
- Treynor, J. L. (1961). *Market Value, Time, and Risk* (SSRN Scholarly Paper 2600356). <https://doi.org/10.2139/ssrn.2600356>
- Tversky, A., & Kahneman, D. (1974). *Judgment under Uncertainty: Heuristics and Biases*. 185.
- Underner, M., & Peiffer, G. (2010). Petits fumeurs et fumeurs intermittents. *Revue Des Maladies Respiratoires*, 27(10), 1150–1163. <https://doi.org/10.1016/j.rmr.2010.10.003>
- United Nations Educational, Scientific and Cultural Organization. (2006). *International Standard Classification of Education (ISCED) 1997*.

https://uis.unesco.org/sites/default/files/documents/international-standard-classification-of-education-1997-en_0.pdf

- Veall, M. R., & Zimmermann, K. F. (1994). *Evaluating Pseudo-R²'s for binary probit models* | *Quality & Quantity*. <https://link.springer.com/article/10.1007/BF01102759>
- Veni, P., & Kandregula, R. (2020). *EVOLUTION OF BEHAVIORAL FINANCE*. 5(3).
- Von Neumann, J., & Morgenstern, O. (1944). *Theory Of Games And Economic Behavior*. <http://archive.org/details/in.ernet.dli.2015.215284>
- Vu, T.-H.-P., Li, C.-S., & Liu, C.-C. (2021). Effects of the financial crisis on household financial risky assets holdings: Empirical evidence from Europe. *International Review of Economics & Finance*, 71, 342–358. <https://doi.org/10.1016/j.iref.2020.09.009>
- Wang, C. M., Xu, B. B., Zhang, S. J., & Chen, Y. Q. (2016). Influence of personality and risk propensity on risk perception of Chinese construction project managers. *International Journal of Project Management*, 34(7), 1294–1304. <https://doi.org/10.1016/j.ijproman.2016.07.004>
- Waweru, N. M., Munyoki, E., & Uliana, E. (2008, July 7). *The effects of behavioural factors in investment decision-making: A survey of institutional investors operating at the Nairobi Stock Exchange* | *International Journal of Business and Emerging Markets*. <https://www.inderscienceonline.com/doi/abs/10.1504/IJBEM.2008.019243>
- Wittgens, C., Muehlhan, M., Kräplin, A., Wolff, M., & Trautmann, S. (2022). Underlying mechanisms in the relationship between stress and alcohol consumption in regular and risky drinkers (MESA): Methods and design of a randomized laboratory study. *BMC Psychology*, 10(1), 233. <https://doi.org/10.1186/s40359-022-00942-1>
- Wong, M. Y. C., Ou, K., Chung, P. K., Chui, K. Y. K., & Zhang, C. (2023). The relationship between physical activity, physical health, and mental health among older Chinese adults: A scoping review. *Frontiers in Public Health*, 10. <https://doi.org/10.3389/fpubh.2022.914548>

- Yadav, A., & Narayanan, G. B. (2021). DO PERSONALITY TRAITS PREDICT BIASEDNESS WHILE MAKING INVESTMENT DECISIONS? *International Journal of Accounting & Finance Review*, 6(1), 19–33.
<https://doi.org/10.46281/ijafr.v6i1.939>
- Zhang, R., Brennan, T. J., & Lo, A. W. (2014). *The origin of risk aversion* (Vol. 111).
<https://www.jstor.org/stable/43278784?refreqid=fastly-default%3A6c76d5a44891a118d827294d6f0f85bd>
- Zivi, P., Sdoia, S., Alfonsi, V., Gorgoni, M., Mari, E., Quagliari, A., De Gennaro, L., Giannini, A. M., & Ferlazzo, F. (2023). Decision-Making and Risk-Propensity Changes during and after the COVID-19 Pandemic Lockdown. *Brain Sciences*, 13(5), Article 5.
<https://doi.org/10.3390/brainsci13050793>

EXECUTIVE SUMMARY

This study, as a contribution to the behavioral finance research field, aimed at understanding how risky consumption behaviors (i.e. smoking and/or alarming drinking) and healthy consumption patterns (i.e. daily consumption of fruits, vegetables, meat and dairy products, along with regular physical activities), the big Five personality traits (*extraversion*, *openness*, *conscientiousness*, *agreeableness* and *neuroticism*) and the Covid-19 pandemic shock influenced the investment risk profiles (*risk seeker*, *dynamic or perfect or defensive risk diversifier*, *defensive* and *risk averse*) of the elderly across eleven European countries, while taking into account the effect of personal sociodemographic and health characteristics.

Using secondary data from SHARE, the study focused on both pre- (2019 to early 2020) and post-Covid-19 pandemic (2022) periods. This longitudinal study employed a methodology that first applied a series of four incremental random-effects probit panel regressions to analyze the relationships between these independent variables and each of the six investment profiles independently. Then, to assess whether the Covid-19 pandemic had a causal effect on potential changes in these profiles, we used a fixed-effects multinomial logit panel regression.

The initial panel regression models showed that, for our sample of elderly, risky consumption behaviors would not have had a significant relationship with any investment risk profiles. However, the literature suggests that risky behaviors would tend to be interconnected and are often found in other aspects of life (Mudryj et al., 2019; among others). This would also be true for healthy consumption behaviors (Peretti-Watel et al., 2013; among others). Our study confirmed the latter, that elderly who maintained healthy daily consumption habits would be risk averse.

The same models showed that among the five personality traits, *extraversion*, which is typically associated with a greater propensity for risk taking (Sahinidis et al., 2020; among others), was correlated in our study to cautious risk diversification, indicating a moderately low level of risk. The trait of *openness* is also associated in literature with risk taking but in a more moderate way (Lai, 2019; Wang et al., 2016). Our study similarly found that a high level of *openness* would correspond to cautious diversification, resulting in a moderate level of risk. The third trait, *conscientiousness*, is generally associated with moderate risk taking and could sometimes lead towards both risk seeking and risk averse behaviors (Isidore & Arun, 2021; Yadav & Narayanan, 2021). However, our study did not find a significant relationship between *conscientiousness* and risk profiles in our sample. The fourth trait, *agreeableness*, is typically associated with risk aversion at high levels (Ahmad & Maochun, 2019) and our findings were in line with this, showing that a high level of *agreeableness* would be linked to risk aversion. Finally, the trait of *neuroticism*, at high levels, is generally associated with risk aversion (De Bortoli et al., 2019; Oehler & Wedlich, 2018). However, our study found a negative influence of high *neuroticism* on risk aversion, suggesting a tendency towards risk seeking rather than risk avoidance, although our model did not specify the exact level of risk.

Regarding the Covid-19 pandemic shock, although the literature suggests that a crisis bringing uncertainty would typically lead to increased risk aversion (Heo et al., 2021; among others), our multinomial logit panel model did not show any significant influence on the evolution of the investment profiles of the elderly from a period to the other. However, we found an indirect effect of Covid-19 pandemic on the personality traits of *extraversion* and *agreeableness*, which in turn would have impacted their influence on these investment profiles.

Words count = 24,345