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Finance comportementale des ménages et robo-advising

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General Introduction

General Introduction

In four empirical articles conducted across three years of study, my research examines the behavior of investors who save every month (Jones, 2024, Chapter 1), who make changes to their passive portfolios (Benoit et al., 2024, Chapter 2), who saved during the Covid-19 pandemic (Boulou-Reshef and Jones, 2024, Chapter 3), and who save on behalf of their children (Direr and Jones, 2024, Chapter 4). This general introduction has three parts. First, I will briefly outline then describe in technical detail each of three major trends which shape a growing fraction of the global assets under management and make up the intellectual context of the present work: household finance, behavioral finance, and the use robo-advisors. Next, I will thoroughly explain the general empirical methodology adopted and the unique robo-advisor database used throughout all four papers of this unified work. Lastly, I will provide overviews of each of my articles and link the contributions of this work back to the overall intellectual context in which this work takes place.

Nobel prize-winning economist Harry Markowitz (1952) outlined that an investor could construct a portfolio which maximizes an expected return for a given level of risk through diversification of non-perfectly correlated assets, inventing Modern Portfolio Theory (MPT). MPT largely replaced the naive diversification strategy that investors used prior to its invention. Extensions of MPT, such as the Capital Asset Pricing Model (CAPM) by Nobel prize-winning economist William Sharpe (1964) or the Three- or Five-Factor Model by Nobel prize-winning economist Eugene Fama and French (1992, 2015), are industry standards. Though there are three important limitations of MPT. First, expected returns and asset covariance are computed using historical data which cannot necessarily predict the future (Fama, 1965), a limitation which also affects the models which built upon MPT. Second, risk in finance is seen as probabilistic instead of structural, which means that potential risks with little or no historical data are routinely ignored (Taleb, 2007). Third, empirically investors deviate from constrained utility-maximizing strategies in many ways and for many reasons (Barberis and Thaler, 2003; Shiller, 2003). Despite these flaws, MPT and the other models which build upon it are how contemporary financial institutions practice diversification. This research contributes to the sub-field centered around the third limitation cited, a sub-field called behavioral finance.

Saving is common and the benefits of diversification are well-known, but building and especially maintaining a scientifically diversified portfolio that suits an investor's unique financial situation is difficult. Therefore, financial technologies have been invented to make diversification easier. Since at least 1924, investors have pooled their resources and delegated the task of managing a diversified investment portfolio, called a mutual fund (Farina et al., 1969). However, the fees associated with paying the manager and reimbursing their trades meant most mutual funds had below-average returns (Sharpe, 1966). Furthermore, mutual funds that outperformed in one year rarely maintained this streak in subsequent years (Carhart, 1997). This is predictable. In any given trade, the average return of the buyer and seller is slightly negative: one makes a profit and the other makes a loss, but they both pay transaction fees. If financial markets are efficient (Fama, 1970), an imperfect but plausible and widely-held view, the fact that few managers can reliably earn above-average returns after deducting transaction fees logically follows. To address this shortcoming with the typical mutual fund, Jack Bogle launched Vanguard in 1975 with a mutual fund called an "index fund," which gives up the chance of outperformance to guarantee average returns by tracking a broad stock market index such as the S&P 500 (Bogle, 1999). Further financial technologies improved on this model. Buying and selling shares of a mutual fund can be tricky, so Exchange Traded Funds (ETFs) were invented in 1989 to make trading index funds easier. Eventually, there were so many ETFs on the market that investors needed help choosing among them, so robo-advisors were invented in 2008 to give advice on and manage portfolios composed purely of ETFs (Fisch et al., 2019). This research focuses on robo-advisors, the last financial technology in this evolutionary line.

With each new simplifying technology, portfolio diversification becomes more accessible to and inclusive of diverse audiences (see Chatterjee, 2020). Whereas once only the wealthiest institutions and individuals could access sophisticated diversification, with ETFs and especially robo-advisors the financial and informational barriers to entry have been greatly reduced. Just as other technologies which have reduced the barriers to stock market participation have raised participation rates (Bogan, 2008), robo-advisors are bringing new entrants into financial markets as well (Reher and Sokolinski, 2019). The actions taken by these untrained, middle-class individuals are of great interest to governments, regulators, asset managers, financial markets, and academics exactly because they are so typical of the median person, a person who has either very little experience in finance or has not yet even entered financial markets. As more people enter the global middle class (Kochhar, 2015), as stock market participation rises across many countries (Campbell, 2006), and as more individuals' pensions are covered by defined contribution instead of defined benefit plans (Broadbent et al., 2006; Gomes et al., 2021), the number of household investors participating in the stock market will only grow. This research examines the increasingly common household investor.

Now to combine these three trends. Around the world, robo-advisors collect an unprecedented amount

of information about the demographic, financial, and psychological characteristics of millions of household investors and offers to those clients a distinct, simplified choice set of investments. It has never been easier to observe, compare, and study the behavior of retail investors. All of these three trends – household finance, behavioral finance, and the use of robo-advisors – are critical to understanding every one of the four papers included in this work.

Household finance

Popular household finance

There is a sizeable gap between popular and academic household finance, both in terms of schools of thought and of readership. Choi (2022) summarizes the bestsellers in popular finance, with some books selling tens of millions of copies. For contrast, the single most common number of citations for an academic paper is zero, and earning citations in the thousands is extremely rare (Redner, 1998). Suffice to say that the reach of popular finance is magnitudes larger than academic finance.

Yet popular work is often ignorant of or in direct conflict with research findings. Choi (2022) summarized that across eight dimensions, consensus popular and academic household finance agreed on just one. (Coincidentally, that sole dimension of agreement is to invest in passive index funds, e.g. with robo-advisors.) Chapter 1 of this thesis addresses head-on this tension between popular household finance and academic household finance by finding a dimension on which the advice differs – saving regularly – and observing how real households behave empirically.

To understand better this tension between the two related disciplines, take budgeting, for example. Popular household finance is obsessed with budgets. Budgets are mentioned in every popular household finance book, including the bestsellers like *The Millionaire Next Door* by Stanley and Danko (1996) and *I Will Teach You to Be Rich* by Sethi (2009). In this literature, everyone should have a budget which should follow certain rules, such as saving fifteen cents of every dollar or not spending more than a third of income on housing. On the other hand, academic household finance does not have any accepted theory of budgeting. Rational agents simply spend and save in whatever manner maximizes their lifetime utility, automatically and without fail. Spending too much or not saving enough are not problems that rational agents have.

As another example of a characteristically popular financial advice, Dave Ramsey (2013), author of the third bestselling book on the list by Choi (2022) *The Total Money Makeover*, advises his readers to use the "debt snowball" technique, in which debtors pay off their creditors in order of smallest to largest

balance instead of the more rational order of largest to smallest interest rate. Ramsey's rationale for the debt snowball is that achieving "quick wins" is important for maintaining the motivation to get out of debt. Meanwhile, traditional academic finance researchers would advise paying off debt by interest rate, because they assume that emotions do not affect financial decision-making and that motivation is a non-issue.

From where does this rift between popular and academic household finance originate? Most likely, the rift is explained by a difference in perspective and industry culture between popular authors and academic economists. Most of the popular finance authors come from business or industry backgrounds instead of academic or scientific backgrounds. And they work with regular people as paying clients, while academic economists work with other academic economists as scrutinizing referees. Popular authors cannot overestimate their clients' real capabilities while academic economists cannot assert without evidence that normal people cannot solve the problems that they can solve.

So where is the evidence? Why does academic household finance defend unintuitive stances such as individuals save as much as they need to save, their emotions do not affect their expenditures, and motivation is infinite? It comes down to this concept of "rationality." Rationality is a theoretical concept, important for building mathematical models which make predictions about aggregate behavior. In contrast to the empirical approach adopted in all four chapters of this thesis, academic household finance adopts a theoretical, rational approach.

Academic household finance

If popular household finance is pessimistic about the ordinary person's capabilities, academic household finance is optimistic. To avoid taking on debt, Dave Ramsey (2013) encourages his readers to rent until they have the money to buy their primary residence in cash because they cannot be trusted with debt. Meanwhile, Ando and Modigliani (1963) assume that people can solve lifetime consumption optimization problems or at least behave as if they have done so. These two perspectives have little in common.

While popular financial advisors work with regular humans, academic economists study *homo economicus*, a risk-adjusted, time-discounted expected utility optimizer with infinite time, perfect information, complete self-control, and no responsibilities beyond solving university-level math problems. These are the flawlessly rational agents of Rational Choice Theory, the dominant thought in economics, at least during the twentieth century. Our species of regular humans, *homo sapiens*, are not like this (see Thaler and Sunstein, 2021, for a detailed discussion). And economists accept this. At least, now they do (see Thaler, 2015, for a history of how the economics profession came to accept that Rational Choice Theory

may function better as a prescriptive than a descriptive tool). Economists define optimal behavior to have a standard against which to compare observed behavior. In the words of Richard Thaler (2015), a Nobel prize-winning economist who has dedicated much of his career to challenging academic household finance with empirical behavioral findings inconsistent with theory, "Without the rational framework, there are no anomalies from which we can detect misbehavior." As such, the major findings of academic household finance relevant to this work are the extent to which regular people deviate from rational people, presented in the form of "puzzles." Chapter 4 of this work includes several puzzles which cannot be explained within a rational framework, notably that parents invest for their children remarkably similarly to how they invest for themselves despite their children being in plausibly different financial situations.

Mehra and Prescott (1985) first defined the equity premium as a puzzle. The equity premium is that the historical returns for equity (stocks) have exceeded the historical returns for default-free debt (Treasury bills). Of course, rational agents will be somewhat risk-averse and so will demand higher compensation for higher risk. This is not the puzzle; the puzzle is the sheer *extent* to which equity is compensated, even over-compensated. Mehra and Prescott (1985) found that the coefficient of relative risk aversion needed to explain the history was absurd: for the math to work people must be willing to pay 49% of their wealth to avoid a 50-50 chance to lose 50% of their wealth. Even though many papers were published trying to rationalize this finding, Weil (1989) demonstrated that no plausible rational solution to the equity premium puzzle can be found, because any purely rational explanation would result in the following contradiction. An economy of rational individuals can have high levels of risk aversion or a low risk-free rate, but not both. Extremely risk-averse individuals will push up the risk-free rate to sustain smooth levels of inter-temporal consumption while the low risk-free rates observed historically imply that the real economy is filled with fairly risk-neutral individuals. In doing so, Weil (1989) named this contradictory puzzle: the risk-free rate puzzle.

If stock returns are inexplicably high and Treasury bill returns are inexplicably low, then one would expect that all households in an economy of rational agents would hold some equity. Indeed, this is an implication of MPT (Markowitz, 1952). But this is far from the case, and this incongruity is known as the stock market participation puzzle (Mankiw and Zeldes, 1991). Once again, no plausible rational explanation exists for the stock market participation puzzle (Haliassos and Bertaut, 1995). Stock market participation rates in the United States have doubled since the puzzle was first identified, but the current rate of around 50% participation is still far below 100%, and many other wealthy countries have participation rates near 0% (Campbell, 2006).

Since these three puzzles – the equity premium puzzle, the risk-free rate puzzle, and the stock market participation puzzle – cannot be solved within the rational framework, another framework must be adopted: a behavioral framework.

Behavioral finance

The influence of behavioral economics

If a premise leads only to implausible conclusions, then the premise is flawed. In an economy of rational agents, why are there so many paradoxes? The answer is simple: we are not in an economy of rational agents. This is the founding premise of behavioral economics. Just as finance does not exist without economics, behavioral finance does not exist without behavioral economics. Several key findings from behavioral economics demonstrate that we are not in an economy of rational agents.

Adam Smith (1759), often cited as the first economist, recognized that human beings do not make economic decisions purely based on money. But concerns about "God, Family, and Country" are hard to quantify and were gradually lost as Rational Choice Theory became more developed. In the modern era, Nobel prize-winning economist Herbert Simon (1955) first proposed limiting the omniscience of *homo economicus* with what he called "bounded rationality." Agents that are rational within bounds still optimize, but they are limited by imperfect information, time constraints, math ability, etc. Bounded rationality was not a direct attack on Rational Choice Theory, more of a gentle modification along behavioral lines.

Genuine attacks to Rational Choice Theory came from Nobel prize-winning economists Daniel Kahneman & Amos Tversky¹, who are originally psychologists. Unlike earlier periods of history in which "natural philosophers" (scientists) were expected to know about diverse fields such as astronomy, biology, and geometry, in the twentieth century academics were cloistered into faculties that rarely conversed with one another. As such, two irreconcilable perspectives of human behavior developed: economists believed people made perfectly rational economic decisions essentially all of the time, while psychologists did not believe people could make rational decisions even under the best of circumstances. Before their contact with the economics profession, Kahneman & Tversky did the routine work of psychologists documenting biases in human judgment (Tversky and Kahneman, 1974). Then they advanced an alternative to Rational Choice Theory that they called "Prospect Theory" (Kahneman and Tversky, 1979). In Rational Choice Theory, an individual's current level of wealth does not matter at all; agents treat gains and losses approximately equally and have stable risk preferences. In Prospect Theory, an individual's current level of wealth matters enormously; agents treat losses as more important than gains and are risk-averse to collect gains but risk-seeking to avoid losses. Unlike bounded rationality, Prospect Theory

¹Nobel prizes are not awarded post-mortem, and Amos Tversky unfortunately died quite early in his life. However, many in the field regard the prize being awarded to his long-time coauthor Daniel Kahneman as being essentially a prize for them both.

is impossible to reconcile with Rational Choice Theory. Contact between psychology and economics had been established; the behavioral economics revolution had begun.

For the psychologists Kahneman & Tversky this vision of the world in which humans made predictable mistakes was self-evident. Over time, the economics profession moved in this direction, collecting a long list of empirical evidence that humans do not behave as described in Rational Choice Theory. All four chapters of this work contribute to this empirical evidence collection in which real-world data is the most important. These findings include but are not limited to loss aversion, non-linear probability weighting, satisficing, anchoring, mental accounting, the availability and representativeness heuristics, the endowment and framing effects, the gambler and hot hand fallacies, and the recency, confirmation, and status quo biases (see Angner and Loewenstein, 2007, for a review). Chapter 3 of this work interrogates how these kind of emotions and biases could have potentially lead to irrational behavior among Yomoni's clients during the Covid-19 pandemic.

Before behavioral economics started gaining ground, Rational Choice Theory strongly influenced public policy in many countries. So the thinking went: expanding the choice set increases utility, and since rational agents are practically omniscient it does not matter if these choices are buried under mountains of paperwork or written in legalese, take hundreds of hours to learn or decades of self-discipline to implement. The switch from defined benefit to defined contribution retirement plans exemplifies this thinking. Under the defined benefit plan, the average person need not do anything besides hold a job, which they would likely do anyway; while under the defined contribution plan, the average person must make dozens or even hundreds of decisions about their retirement plan over the course of their lifetime. And yet, the rational model upon which these public policies were built had been thoroughly undermined by behavioral economists.

Enter nudging. In 2008, Nobel prize-winning economist Richard Thaler and distinguished legal scholar Cass Sunstein published *Nudge: Improving Decisions about Health, Wealth, and Happiness*. This book is built upon earlier work (e.g. Thaler and Benartzi, 2004), but it was the book that gave nudging its name and brought it into the public conversation. Nudging works as follows: since people who present others with choices must necessarily also decide the way in which these choices are presented, a well-meaning person can present these choices in such a way that makes it as easy as possible for the chooser to choose what is best for them despite their behavioral biases. For readers who have learned the version of English that Thaler and Sunstein speak, this is a libertarian paternalist choice architect nudging a Human (Thaler and Sunstein, 2021). Nudging has been enormously influential, inspiring most famously the Behavioral Insights Team (AKA the "nudge unit") in the UK government and hundreds of copycat organizations in governments and businesses globally. Yomoni implements nudges into their core investment offering, and Chapter 1 of this thesis suggests that unintended nudges may have lead to investors who save regularly

saving less, and what counter-nudges could be implemented to fix this problem.

These are the highlights of behavioral economics today. While this intellectual struggle between the rational and behavioral perspectives permeated all levels of economic research, from theory to natural and lab experiments, a key battleground was research about financial markets. The argument was thus: no one cares if college students act strangely when you give them university-branded mugs (Kahneman et al., 1990), a market of experienced professionals making decisions with billions of dollars on the line will behave rationally. Or will it?

Macro-level behavioral finance

Like with behavioral economics in general, history shows traces of the idea that financial markets can be affected by irrational phenomenon such as emotions. Arguably the first incidence of macro-level behavioral finance was labelling speculative bubbles as "manias" and financial crises as "panics."

Like Herbert Simon was a forerunner to behavioral economics, John Maynard Keynes (1936) wrote down a critical insight for macro-level behavioral finance with his metaphor of "beauty contests." Investors do not necessarily try to pick the stocks of the companies with the best fundamentals; if this is their strategy, then they may go bankrupt waiting for the stock price to go up (this is known as a "limit to arbitrage," see Barberis and Thaler, 2003). Investors try to pick the stocks of the companies that the *other* investors will all soon want to buy. It is not a company's competent board or consistent profits that makes the stock price go up, only demand for its stock. If everyone plays this beauty contest game, as indeed they should because their profits depend on it, then stock prices do not reflect anything besides what everyone thinks everyone else thinks.

Nobel prize-winning economist Robert Shiller wrote the first modern papers in macro-level behavioral finance. Shiller et al. (1981) demonstrated that average dividends are fairly stable while average stock prices (a formal claim to those future dividends) vary wildly. This has been called the "volatility puzzle." Furthermore, Shiller (1984) (re-)popularized the notion among academic economists that stock market movements are at least somewhat explainable simply by the "sentiment," "fashion," or "mood" that is in vogue among investors at any given moment, an idea he expanded upon in the book *Irrational Exuberance* (Shiller, 2000). De Bondt and Thaler (1985) followed up on Shiller's work by asking a heretical question: "Does the stock market overreact?" They found that stock market prices regress towards the mean – reliably, former winners later lose and former losers later win – which implies that these stocks valued at the extremes were mispriced. This was surprising, because rational agents operating in an efficient market in which prices reflect all available information would not ever reliably misprice stocks like this. Then Fama and French (1992, 1996, 2015) began to document that including criteria

such as small firm size and high book-to-market ratios (later also consistent profits and a firm-level conservative investment strategy) improves the predictive power of the CAPM. In other words, investors were considering supposedly irrelevant factors in their investment decisions, and this was having an effect on the whole market. This has been called the "predictability puzzle." Evidence was mounting that even if some intelligent and informed rational agents exist in financial markets, they may be outnumbered and outspent by the "noise traders."

The most convincing evidence that behavioral finance exists even at the macro-level came from stock market anomalies. Lamont and Thaler (2002) documented many anomalies that could not be true in an efficient financial market of rational agents, such as Shell stock and Royal Dutch stock having unrelated prices despite being twin shares. A year later, (Lamont and Thaler, 2003) detailed the Palm-3Com spin-off. The market was willing to pay substantially more for Palm stock than 3Com stock, despite 3Com *owning* Palm *and* having a number of other assets and revenue streams. If irrational agents are having such pernicious effects on macro-level prices, just what are they thinking and doing at the micro-level?

Micro-level behavioral finance

Micro-level behavioral finance seeks to document, understand, and explain investors' departures from traditional economic theory. It prioritizes empirical evidence over theory, exploits big data of investors' real world actions, and makes no excuses for bizarre behavior. This is the subfield under which all four chapters of this work can be categorized.

Can micro-founded models and micro-level evidence address the aforementioned macro-level behavioral finance puzzles? Two main explanations for the equity premium / risk-free rate puzzle have been advanced: Prospect Theory (Benartzi and Thaler, 1995; Barberis et al., 2001) and uncertainty aversion (Maenhout, 2004; Camerer and Weber, 1992). Furthermore, the stock market participation puzzle has several plausible explanations: narrow framing (Barberis et al., 2006), financial literacy (Van Rooij et al., 2011), trust in the stock market, (Guiso et al., 2008), and even IQ (Grinblatt et al., 2011). "Momentum," or the under- and over-reaction to news, could explain the volatility and predictability puzzles (Chan et al., 1996), though this would also seriously violate the efficient market hypothesis. Coincidentally, Chapter 2 of this thesis empirically documents a form of momentum: clients slowly and gradually increase the equity exposure in their portfolios, especially when the stock market is rising, but make more drastic changes when they do decide to reduce their equity exposure.

Yet micro-level behavioral finance has discovered puzzles of its own. "Portfolio choice" puzzles observe that individuals hold portfolios out of line with economic theory (Dimmock et al., 2016). The Rational Choice Theory is to diversify internationally across all assets in proportion to their market share

(Markowitz, 1952), or arguably even to short the domestic financial market because of one's home equity and human capital (Baxter and Jermann, 1995). But in reality, investors under-diversify (Benartzi and Thaler, 2001). Investors hold too much company stock (Benartzi, 2001) and home-country stock (French and Poterba, 1991), and trade excessively (Barber and Odean, 2000, 2001). In the micro-level behavioral finance research, one can hear echoes of popular household finance, with its insistence that regular people need simple rules to follow, and even then are likely to make mistakes.

So many more explanations have been offered and so many puzzles have been identified, but there is not space to address them here. It is remarkable how far behavioral finance has come as a field. Whereas puzzles were assumed not to exist under the classical model, finding and explaining puzzles using psychology has now become routine work of finance researchers. One could call this "psychological imperialism" (Lazear, 2000). Indeed, the four chapters in this thesis follow this "micro-level puzzle" way of thinking: investors who save every month save less overall (Jones, 2024, Chapter 1), investors display Prospect Theory-like behavior when adjusting their portfolio allocations (Benoit et al., 2024, Chapter 2), investors save less during major crises (Boulou-Reshef and Jones, 2024, Chapter 3), and investors save on behalf of their children as if they were saving for themselves (Direr and Jones, 2024, Chapter 4).

Though these micro-level puzzles were all found while studying the clients of a robo-advisor. Robo-advisors are a new technology and therefore an atypical environment in which to study investor behavior. Some explanation is in order.

Robo-advisors

How robo-advisors work

A brief description of the technical function of robo-advisors (also known as automated financial advisors) will be useful for understanding the rest of this work. D'Acunzio et al. (2019) define robo-advising as "the delivery and execution of financial advice through automated algorithms on digital platforms." Maume (2021) identifies two key functions of robo-advisors: giving personalized advice and managing a client's portfolio. All robo-advisors do the former, but not all do the latter. So, I will start with the former.

Robo-advisors can and have been used to give advice on many topics. So far, they have been used primarily to dispense investment advice. Searching "robo-advisor" on the internet will return all asset managers. However, robo-advice is a basic technology. Any kind of advice could be given algorithmically. One could imagine a robo-advisor that gives advice on adopting dog breeds. But, in this series of studies,

I concentrate on the traditional, investment-related robo-advisors.

First, a robo-advisor must decide what information will influence its advice to investors. Some information may be irrelevant, such as an investor's favorite color. Meanwhile, some information may be critical, such as an investor's risk preferences. Some information may be illegal to consider, such as an investor's gender. Meanwhile, some information may be illegal *not* to consider, such as an investor's financial literacy. Questions may be asked about a client's age, education, employment status, sector, income, investment horizon, initial deposit, financial wealth, retirement plans, financial literacy, investment experience, home ownership status, immediate family members, investment goal, preferred tax wrapper, outstanding debt, current savings, major life events, planned monthly contributions, and preferences about risk and ESG, local, real estate, and alternative investments. Once this set of questions is formalized, typically between ten and thirty questions, a robo-advisor asks its prospective clients for this information in the form of a survey. While nothing stops prospective clients from lying, they must answer truthfully in order to get advice that is relevant to their situation.

Next, a robo-advisor must decide *to what extent* each question will influence its advice. The most important information may have ten or even a hundred times the weight of the least important information. Take a prospective client's income, for example. To what extent should a person's income affect their portfolio's asset allocation? One robo-advisor may decide income is the most important factor in its advice, while another may think this information is almost completely irrelevant. Often the chosen weights are informed by academic research, though in some cases even the research is not clear on how important a given factor should be.

The factors and their weights combine into one long equation, the *algorithm*. The algorithm of a robo-advisor is a black box, often known only to few within an organization. While the factors in this algorithm are public knowledge due to the questions asked, the weights are trade secrets. After answering the survey, the prospective clients receive their algorithmically generated advice. This advice normally takes the form of an asset allocation, such as 60% stocks and 40% bonds, and may include advice about how much to save each month or when the client could reasonably retire.

For robo-advisors that only give personalized advice, the process stops here. However, robo-advisors that both give personalized advice and manage a client's portfolio are more common. The advice-only business model is difficult to monetize. Few people are willing to pay for advice before they receive it, because they do not know whether it will be good. Even fewer people are willing to pay for advice *after* they receive it, because now they already know it. Worst of all, the advice-only business model does not respond to many retail investors' true need: someone else to do this for them.

Enter the robo-advisor that also manages clients' accounts, which is the majority of robo-advisors. In this case, the personalized robo-advice functions as an advertisement or on-ramp for the asset manage-

ment. As asset managers, robo-advisors can and do invest in anything. At time of writing in 2024, most robo-advisors allow their clients to invest in REITs, gold, and cryptocurrencies. But the majority of assets in any robo-advisor portfolio are ETFs. ETFs are the bread and butter of robo-advisors because they have low fees, sometimes as low as three basis points (0.03%), and offer an easy path to diversification even with small amounts of capital. Indeed, Chapter 2 of this work zooms in on this "lazy" aspect of robo-advisors and asks why anyone who chooses this purely passive form of investment would ever go back and change their portfolio allocations.

Robo-advisors which manage accounts make money through fees, kickbacks, premium services, and loans. Most robo-advisors charge some percentage of the assets under management as a fee, similar to human financial advisors but a fraction of the cost. Yet, more and more robo-advisors are opting for a no-fee model, relying on less obvious ways of turning a profit. Some robo-advisors are attached to an asset manager that creates its own ETFs and thus can receive kickbacks for these fees, such as Fidelity Go recommending Fidelity ETFs. Some robo-advisors offer premium services for a monthly subscription fee or a higher percentage of assets under management, such as Merrill Guided Investing. Finally, some robo-advisors may require clients to hold some fraction of their portfolio as cash that the robo-advisor then loans out, which is the case for Schwab Intelligent Portfolios.

Of course, robo-advisors compete with each other based on the quality and pertinence of their advice. But robo-advisors also compete with each other on fees, services, amount of choice, and branding. Some robo-advisors attract clients with automatic dividend reinvestment, automated rebalancing, or tax loss harvesting, promising a completely hands-off experience for the investor, such as Betterment. Other robo-advisors intentionally do not offer these services to not overwhelm their potential clients, like Amundi's Robo-Advisor. Some robo-advisors are also brokers and give their clients access to a wider investment universe, such as Wealthfront, whereas other robo-advisors intentionally restrict their offerings to make it as simple as possible, such as SoFi Automated Investing. Finally, some robo-advisors try to appeal to niches, such as Ellevest for women investors, Goodvest for ESG investors, or Acorns for compulsive shoppers. Robo-advisors have come a long way since their invention in 2008, and there are now hundreds of robo-advisors appealing to every market segment imaginable.

Research about robo-advisors

Robo-advisors are a recent technology, but they have already attracted the attention of academic researchers (see Torno et al., 2021, for a systematic literature review). Broadly, this research can be divided into research about robo-advisors themselves, treated in this section, and research using robo-advisors' datasets to answer other questions, treated in the next section. While Chapters 1, 3, and 4 are

mainly research using robo-advisors' data, Chapter 2 of this work is indeed research *about* robo-advisors, posing the question of why someone would use a robo-advisor if they wish to actively manage their investments.

Robo-advisors can give financial advice to clients and manage their investment accounts. These are exactly the same services that human financial advisors perform. Human financial advisors and robo-advisors are substitutes. To this effect, Brenner and Meyll (2020) found that "using robo-advisors is associated with a 15.8 percentage point decrease in investors' likelihood to consult human financial advisors" after controls. Though they are not in direct competition with each other; often robo-advisors cater to a low-wealth market segment on whom human financial advisors could never turn a profit, and the persistence of human financial advisors among the high-wealth market segment attests to their continued demand (Jung et al., 2018). So-called "algorithm averse" individuals just prefer to have a human in the loop (Greig et al., 2023). Robo-advisors can also act as infinitely patient AI teachers, demonstrating to investors how to better diversify their portfolio without necessarily taking up the time of or replacing a human financial advisor (Loos et al., 2020). Furthermore, sometimes human financial advisors use robo-advisors to automate routine tasks, increase their productivity, or achieve greater consistency. This is called "hybrid" advising (Merkle, 2020). Hybrid advising can be offered by asset managers as a bridge between robo-advising and traditional financial advising for clients in the middle-wealth market segment – surpassing the minimum account balance for a robo-advisor but still not enough assets under management to warrant bespoke attention. Nevertheless, researchers have compared the two.

Many human financial advisors are credentialed, experienced, and scientific. But many are not. Certain flaws among human financial advisors have been well documented. To start, human financial advisors can advise their clients to hold portfolios that reflect their own portfolios (Foerster et al., 2017; Linnainmaa et al., 2021). This is not necessarily good advice. Not only is each client in need of different advice that fits their unique financial situation, in the words of Linnainmaa et al. (2021), human advisors can "trade frequently, chase returns, prefer expensive, actively managed funds, and underdiversify." Chalmers and Reuter (2020) found that the portfolios of clients who sought financial advice from brokers underperformed target date funds, in part because advisors steered clients towards higher fee products. Human advisors can steer their clients to high-fee, often self-serving financial instruments (Mullainathan et al., 2012). Mullainathan et al. (2012) also documented evidence of age and gender discrimination towards clients. Sharpe (1966) observed that the average mutual fund performed below the market average; half a century later, it is still the case that the average human financial advisor underperforms the market and sometimes even naive retail investors without advice (Hackethal et al., 2012; Chalmers and Reuter, 2020).

That human financial advisors can discriminate, respond to perverse incentives, and be overconfident

should not be too surprising, because these are human flaws. Robo-advisors do not have these problems. Though many human financial advisors are hard-working and honest, bad experiences do provide push factors to seek alternatives. Even when retail investors like and trust their financial advisor, they may seek a second opinion with robo-advisors (Zhang et al., 2021). Some users prefer robo-advisors because they are more accountable (Philippon, 2019), objective Jung et al. (2019), precise (Wexler and Oberlander, 2021), or convenient (Mesbah et al., 2019) than human financial advisors.

Research using robo-advisors' data

Naturally, robo-advising has been researched and compared with traditional financial advising, but can data from robo-advisors really be used to answer questions beyond this narrow specialty? In fact, it has already been done to find that reminder emails can increase investor attention (Bianchi and Briere, 2022), investor attention and investment performance are positively correlated (Gargano and Rossi, 2018), and goal-setting increases savings rates (Gargano and Rossi, 2023). Chapters 1, 3, and 4 of this work seek to understand how investors behave broadly, even outside of the context of robo-advisors. But because this question of whether research can use robo-advisors' data challenges every one of the four chapters in the present work, I address it here.

Of course, while research using robo-advisors addresses the limitations of other financial research with bigger and better datasets than previously accessible, this research is not without its own limitations. There are at least four general blind spots of research using robo-advisors: institutional investors who do not use robo-advisors, retail investors who do not use robo-advisors, the variability among different robo-advisors, and the ambiguity surrounding investors' activities outside of the robo-advisor.

One limitation of research using robo-advisors is that institutional investors do not use robo-advisors. For securities listed on the NYSE stock exchange, approximately 70% are owned by institutional investors, and these institutional investors also account for 98% of the trade volume (Griffin et al., 2003; Evans, 2009). Just one class of institutional investors, investment funds, control financial assets greater than some OECD countries' GDP, notably the United States, where this figure was 125% in 2020 (OECD, 2020). Institutional investors such as governments, banks, insurance agencies, and funds employ departments of highly specialized financial professionals. Institutional investors do not use robo-advisors, they *are* the advisors. Any research that does not study institutional investors cannot describe how financial markets behave in general.

A second limitation is that not every retail investor uses robo-advisors, either. On the surface level, robo-advisors are more likely to be adopted by those without a pre-existing relationship with a financial advisor, i.e. the younger and less wealthy investors (Fulk et al., 2018; Todd and Seay, 2020), though this

may change in the future as clients age and attitudes about robo-advisors change (Belanche et al., 2019). On a deeper level, the service that robo-advisors offer – advice in choosing among and management of ready-made ETF portfolios – will attract some investors and put off others. Those investors looking to day trade, use derivatives, construct their own portfolio, or get rich quick will not use robo-advisors. Any research that does not study active traders cannot describe how retail investors behave in general.

A third limitation is that every robo-advisor is different. Maume (2021) defines three types of robo-advisors based on the type of services they offer: generic robo-advice, personalized robo-advice, and robo-managed accounts; meanwhile D’Acunto and Rossi (2021) outline four dimensions along which robo-advisors differ: personalization, involvement, discretion, and human interaction. That is to say nothing of the fee structure, additional services, geographical distribution, and branding that may influence investors’ final choice of robo-advisor. Any research that studies only one robo-advisor cannot describe how investors use robo-advisors in general.

Finally, robo-advisors are limited in the extent to which they observe the financial activity of their investors beyond the use of their service. Not every client delegates their entire portfolio of liquid assets to one robo-advisor to manage. Most robo-advisors ask questions about their clients’ income and other financial assets to generate the advice, and while clients are incentivized to answer these questions truthfully in order to receive advice that is useful to their situation, this is nevertheless an imprecise measure. Robo-advisors operated by banks may have access to transaction data from clients’ checking accounts, but this does not necessarily reveal anything about other investment accounts held at other institutions. Tax records could help complete this information, but they are notoriously difficult to access for researchers (Chetty et al. (2014) had to undergo a competitive selection process, a background check, and fingerprinting to access IRS tax records). Beyond the practical concerns, there are also serious privacy and ethical concerns about prying into people’s financial lives to this extent.

Will we ever really know how the stock market works? It is true that robo-advisors are not the final answer to this question. Of course, it would be great if there was a database containing every person’s every transaction since birth, both legal and illegal. But this kind of data does not exist.

Limitations noted. Using more and better data than has ever been available before, research from robo-advisors helps answer how passive middle-class investors save. Middle-class investors do not control most of the assets in the stock market, but they are a huge and growing demographic. Some middle-class investors have the time and the will to be very active traders, but it is hard to imagine a future in which day traders are ever the majority of middle-class investors. Not every robo-advisor is identical, but most robo-advisors share the core business model of offering and managing an investment portfolio for their clients. Robo-advisors’ datasets are not complete, but the quantity of quality of their data far surpasses the limited self-report surveys or the aggregated macro data that finance researchers are accustomed to

using. To summarize, research using robo-advisors' data is not perfect, but it is one of the strongest tools for understanding the increasingly large group of middle-class investors spread across the world. And it is very good at identifying the kind of micro-level behavioral finance puzzles presented in the following four chapters.

The Yomoni database

How Yomoni works and the introductory questionnaire

The data in this unified work comes from the asset manager and robo-advisor Yomoni. The dataset spans the entire history of the company from its first transaction on August 25th, 2015 to the date upon which the data was scraped on April 10th, 2022. On that day, the company had 36,836 clients and €795.7 million in assets under management. Data include rich demographic and financial information about each client as well as their entire history of transactions with Yomoni.

As a growing business, Yomoni occasionally changes its offerings, but the following is all true at the time of data collection. Yomoni has no client-facing brick-and-mortar storefronts, so all investment accounts are opened online through their website. Being a completely B2C operation, a prospective retail investor client hears about Yomoni via an internet search, an advertisement, or word of mouth. Once at the Yomoni website, a prospective client fills out a questionnaire to receive robo-advice about which of Yomoni's ten investment portfolios is most suited for their financial situation (details about these portfolios in the next section). Only once the questionnaire is complete can the client then open an investment account managed by Yomoni, though they are free to ignore the advice if so desired.

The introductory questionnaire is 45 questions total split into two parts: 24 questions used to calculate the robo-advice, at which point the prospective client pauses to read and consider this advice, and then if the client wishes to invest in one of Yomoni's ten portfolios another 21 questions are posed to fulfill all regulatory requirements. The full questionnaire is included in the Online Appendix. Briefly, the questionnaire asks clients about their age, sex, residency, family, income, wealth, employment, financial literacy, risk tolerance, liquidity needs, and about their investment's goal, amount, horizon, and monthly contribution. The information about the client's identity is independently verified with a government-issued ID such as a passport. The other information is taken as given. The clients are incentivized to truthfully report at least approximate information in order to have a relevant investment recommendation. Regulations also require that clients update their responses to this questionnaire every 1-2 years, and Yomoni reminds the clients at regular intervals to do so.

Opening an account requires signing a contract online, providing a few supplemental documents such as a proof of address, and, in rare circumstances, calling with a customer service agent to confirm all the details. After a delay of a few business days on average, all of the formalities are complete and the investment account is officially opened. After this point, the typical client occasionally deposits money into their account, but rarely if ever changes their portfolio allocation (see Chapter 2), withdraws money, or closes their account (see Chapter 3). More complex operations such as options trading are not possible. The mean total value saved by an investor at Yomoni is €21,602 (SD = €62,208). The median total value saved is €7,273.

In the database, the data is organized in the following way: *families* are composed of one or more *individuals*, each of whom have one or more *accounts*, in which there are *transactions* and *changes to the account*, both which take place over time. This information is spread across multiple datasets, requiring truly *extensive* data cleaning to link transactions to accounts to individuals to families and to fold multiple accounts into one individual, separate open and closed accounts, distinguish between actual and prospective clients, sort the many categories of transactions into clear buckets, and take into account the evolution of the business over time. Additionally, the data requires security clearance to access and is fully anonymized by default; all families, individuals, and accounts are referred to exclusively with a hexadecimal tag. There is no sensitive information about any individual investor in the database; for example, addresses do not appear in the database, only zip codes. The default level of analysis used in this work is the individual-level, though Chapter 4 is interested in both individuals and families. Chapters 1 and 3 analyze transactions at the individual-level while Chapter 2 analyzes changes to the account at the account-level.

Portfolio compositions, risk profiles, and tax wrappers

When opening a new investment account with Yomoni, the prospective clients respond to an introductory questionnaire. During the account opening process, the data collected from the introductory questionnaire is fed into an algorithm, which recommends whichever one of the robo-advisor's ten available portfolio compositions ("risk profiles") is most adapted to the client's investment goals, individual characteristics, and financial situation. The exact function of the algorithm is proprietary information, but which variables affect the algorithm's recommendation and by how much are motivated by peer-reviewed academic research (Boulou-Reshef et al., 2022). For example, clients with shorter investment horizons are recommended portfolios with more bonds and fewer stocks. The ten available portfolios are called "risk profiles" because their composition changes based on exposure to market risk. The ten risk profiles are labelled from 1 to 10. Profile 1 is a portfolio composed of 100% Euro Funds (for which the

capital is guaranteed and the return is known in advance)², while profile 10 is a portfolio composed of 100% Stock ETFs. The pivotal profile is profile 6 (the strategic portfolio), with 50% invested in equities and 50% in bonds. The remaining eight risk profiles mix three types of financial instruments in the ratios described in Table 1.³ The profiles with increasing exposure to market risk are riskier by definition.

Table 1: **Portfolio composition and allocation.**

This table reports portfolio composition and allocation by asset classes for each risk profile.

Composition per risk profile (expressed in percentages)										
Risk Profiles	1	2	3	4	5	6	7	8	9	10
Euro Funds	100	70	60	40	20	0	0	0	0	0
Profile 6	0	30	40	60	80	100	80	60	40	0
Profile 10	0	0	0	0	0	0	20	40	60	100

Allocation by asset classes (expressed in percentages)										
Risk Profiles	1	2	3	4	5	6	7	8	9	10
Euro Funds	100	70	60	40	20	0	0	0	0	0
Bond ETFs	0	15	20	30	40	50	40	30	20	0
Stock ETFs	0	15	20	30	40	50	60	70	80	100

When savers select Yomoni as their asset manager, they make two choices with respect to their investment: a risk profile and a tax wrapper. The only other financial interaction a client can have with the robo-advisor besides deposits and withdrawals is changing their risk profile, even if the latter is not recommended by the asset manager. The risk profile should only change in response to a change in one's lifestyle, as captured by the responses in the profiling questionnaire. Chapters 2 and 4 analyze the risk profile in detail.

A tax wrapper (also known as a wrap account) consolidates investments in a tax efficient way. Yomoni offers four tax wrappers: (i) a standard tax-advantage investment account (*assurance-vie*, not to be confused with life insurance); (ii) a stock savings plan (*Plan Epargne Actions*); (iii) a defined contribution plan (*Plan Epargne Retraite*); and (iv) a generic securities account (*compte-titres*). Each type of tax wrapper impacts taxation on account closure differently. This taxation only concerns the capital gain realized. These four tax wrappers rely on the same benchmark index, also known as the strategic portfolio, to allocate the investment. While the selected risk profile from a given saver remains the same whatever the chosen tax wrapper, allocation and performance can differ significantly among the three tax wrappers in the following ways:

²Unique to France, "Euro Funds" (*Fonds en Euros*) are financial products which pay a guaranteed return with no risk of losing the initial capital. The inflation-adjusted returns of the Euro Funds were positive for the majority of the time period studied in this paper. Five of the ten risk profiles available to the clients in the sample, those which are least risky, include the zero-risk Euro Funds in their portfolios.

³Risk profile 1 is not available for new contracts as of September 10th, 2020, but contracts which selected this risk profile before this date continued unchanged. Meanwhile, risk profile 2 was changed on April 30th, 2021, when the distribution of financial instruments changed from 80-10-10 to 70-15-15. Contracts which had selected risk profile 2 were changed to the new distribution.

- Financial products eligible to stock savings plans are restricted to Exchange-Traded Funds (ETFs), and index funds. This constrained investment universe does not necessarily permit a perfect replication of the strategic portfolio.
- The insurer in charge of the standard tax-advantage investment account does not systematically have the necessary products (ETFs or index funds) in its investment universe.
- In stock savings plans, savers hold ETF units which, like equities, cannot be fraction. As a result, when the amount invested is low, some ETFs may be put aside because their value is too high. This is not the case with life insurance policies, where the insurer holds the shares, while the customer only has a synthetic, and therefore has only a fraction shares called the units of account (*Unité de Compte* in French).

After the client chooses their preferred tax wrapper, Yomoni's goal as a wealth manager is to maximize the performance of their managed accounts while staying within the asset allocations defined by the client's selected risk profile. The objective of the wealth management team is never to deviate from the mandate conferred to them by the client. In other words, the trades which the wealth management team may make must never alter the clients' investment portfolios so much so that an investor who chose the risk profile 6 finds themselves with an asset allocation more similar to that of the risk profile 7, for example. Chapter 2 focuses on these changes made to the risk profile.

The information provided in the questionnaire can be reasonably presumed to be approximately accurate. All of the information in the questionnaire is self-reported, but some fields require proof. Before signing a contract, a client must provide an identity card (*pièce d'identité*), a proof of address (*justificatif de domicile*), a mobile phone bill (*facture de téléphone mobile*), and bank account identification details (*relevé d'identité bancaire*). Additional paperwork must be provided when opening an account on behalf of a child, discussed in greater detail in Chapter 4, which is dedicated to the parent-child investment relationship. In contrast, no documents are requested to justify a client's financial situation, such as a pay stub or a tax form. The self-reports on financial details are thus approximate and not externally verified. That said, while proof is not required, prospective clients are nevertheless incentivized to provide correct information about their financial situation in order to receive relevant advice from the robo-advisor. Without providing at least approximate information, the advice received from the robo-advisor is practically useless.

The regulatory bodies AMF (*Autorité des marchés financiers*) and ACPR (*Autorité de Contrôle Prudentiel et de Résolution*) require the business to update each client's demographic information (KYC or "Know Your Customer") every 1-2 years. In compliance with this regulation, Yomoni regularly asks every client to update their information via a pop-up when they log into their online account. The mean

length of time that a client goes without updating their information is 318 days, or 0.87 years.

Scheduled and unscheduled deposits

With virtually any bank or asset manager, clients can make two types of deposits: unscheduled deposits and scheduled deposits. Unscheduled deposits can be done at any time for any amount, while scheduled deposits come with set intervals and amounts pledged in advance. At Yomoni, these two types of deposits are given different names in the transaction data, allowing them to be studied independently. If an investor decides to schedule deposits, they can do so either monthly or quarterly, though scheduling monthly is far more common. In this dataset, unscheduled deposits are larger than scheduled deposits in terms of value. The mean unscheduled deposit ($M = \text{€}3,409$, $SD = \text{€}20,071$) is fifteen times larger than the mean scheduled deposit ($M = \text{€}216$, $SD = \text{€}621$), $t(94,761) = 48.95$, $p < .001$. Meanwhile, the median unscheduled deposit ($\text{€}500$) is five times larger than the median scheduled deposit ($\text{€}100$). At Yomoni, there is a $\text{€}50$ minimum deposit value, which is identical for both scheduled and unscheduled deposits. However, the maximums are different – $\text{€}150,000$ per month for scheduled deposits and $\text{€}10,000,000$ for a single unscheduled deposit – though only 120 times total did clients deposit more than $\text{€}150,000$ in one month. During the data collection period, the minimum value with which an investor could open an account was $\text{€}300$.

At the time of data collection, the third question in the introductory questionnaire asked: "How much would you like to invest each month?" The question could be skipped and had a default response of $\text{€}0$. Many nudge-based A/B tests have been conducted internally on this question over the years (see Thaler and Sunstein (2021) for an explanation of nudges). Amusingly, I was randomly given one myself while writing Chapter 1. As of January 2024, the official question now reads: "How much would you like to invest each month? Investing money every month could make a big difference in a few years. 55% of our customers have made this choice and invest an average of $\text{€}200$ per month." Now, the prospective client cannot skip this question and there is no default response, although responding with $\text{€}0$ per month is still allowed. Anecdotally, the implementation of the social-proof, forced-response, and anchoring nudges has correlated with a gradual increase in the rate of making scheduled deposits by a few percentage points and the value of said deposits by a few euros on average. However, the results of these experiments are not discussed in this document. The introductory questionnaire takes some time, and the company prioritizes shortening the questionnaire as much as possible with brief questions that can be skipped. If the company added several sentences to the question and forced all clients to respond, it is only because the advantages outweighed the disadvantages in their view. To summarize, the amount an investor wants to invest each month is an *input* to the advice, not an *output* of the advice. While there is plenty of non-

personalized information about optimal savings rates posted publicly on the website, during the sign-up procedure prospective clients do not receive advice about how much money to save.

If a client does not set a scheduled deposit upon account opening, they can activate the option later within the online interface. Using the online interface is also the only way to activate the quarterly scheduled deposit option or to cancel one's scheduled deposits. Chapter 1 examines an unexpected consequence of this design, which is that the clients who use this feature to save end up saving less overall and therefore perhaps less than they would have saved without the option.

The representativeness of the Yomoni database

As mentioned previously, no two robo-advisors are exactly alike, and this is one manner in which they compete with each other. Furthermore, robo-advising is a specific financial service and not every investor uses one. As such, it is reasonable to question to what extent the Yomoni database is representative.

In reverse alphabetical order, French robo-advisors include Yomoni, Ramify, Nalo, Mon Petit Placement, Grisbee, Goodvest, Fundvisory, Fundshop, Birdee, Advize, and Amundi, and this is a non-exhaustive list. For a complete comparison, Rama (2022) compiled a report contrasting many of these robo-advisors along specific axes such as asset classes and tax wrappers available. As of 2024, Yomoni is the largest French robo-advisor, with over 50,000 users and €1 billion in assets under management.

When it comes to international competitors, regulatory barriers such as the Foreign Account Tax Compliance Act (FATCA) prevent French investors and even Americans living abroad from investing using several large American robo-advisors such as Betterment, Fidelity, and Wealthfront. However, there are still several American robo-advisors which overcome the regulatory barriers to compete in France for clients, including industry giants such as Vanguard and Charles Schwab. Though their clientele is usually considerably smaller, regulatory barriers pose fewer problems for robo-advisors headquartered in the EU, such as Curvo (Belgium), inbestMe and Indexa Capital (Spain), Mintos (Latvia), and Whitebox (Germany), though there are dozens of small robo-advisors with new ones launched every year. While Yomoni's approximately 50,000 users and €1 billion in assets under management is small compared to established international financial institutions, it is considerable in the European market which generally has lower rates of stock market participation than the United States (Campbell, 2006).

The Belgian robo-advisor Curvo posts detailed information about their service and even some aggregated data about their clientele directly onto their website. This uncommon data availability provides a rare opportunity to make a direct comparison between Yomoni's clientele and the users of another European robo-advisor. Curvo was founded in 2021, whereas Yomoni was founded in 2015. At time of writing in mid-2024, Curvo has around 1,300 clients and €6,500,000 in assets under management, which

means it is growing slower than Yomoni, which had about 7,000 clients three years after its launch and brought in nearly €6,000,000 in assets under management in the single month of January 2018 (see Table 3.2 on page 101). Curvo offers five portfolios instead of ten, but they are similarly arranged by market exposure and advised in accordance with the client's appetite for risk. Both companies' portfolios are 100% ETF-based, internationally diversified, automatically rebalanced, and ESG by default, and these portfolios do not include investments in real estate, crypto, or other alternative asset classes. Similar to Yomoni, the majority of Curvo's clients state that their motivation for investing is the vague and generic "make the most of my savings" while minorities state their motivation as "prepare for retirement," "buy a property," and "saving for my child(ren)," all of which motivate some of Yomoni's clients as well. About 70% of Curvo's clients make scheduled deposits compared to Yomoni's 50%, but the mean amount of these deposits is startlingly similar, with €205 for Curvo versus €216 for Yomoni. To summarize, there is some evidence to suggest that Yomoni's core business model and clientele are similar to other robo-advisors.

The question of representativeness can be posed another way: to what extent do Yomoni's clients reflect French investors? The OECD (2023) provides statistics which distinguish between French "new investors" (started investing in 2020 or later) and "traditional investors" (started investing before 2020), and these data can be compared to the descriptive statistics this research unearths about Yomoni investors. Table 2 summarizes the similarities and differences among Yomoni clients (90% of whom are French), French new investors, and French traditional investors. In short, investors with Yomoni are more similar to French new investors in some ways (younger, wealthier) and more similar to French traditional investors in others (more likely to be male, longer investment horizons), though the strategy of passive investment is still relatively unorthodox.

Table 2: **Comparison among Yomoni investors, French "new investors," and French "traditional investors" as defined by the OECD (2023).**

	Clients	French New Investors	French Traditional Investors
Sex	79% men	64% men	68% men
Age	33	36	51
Revenue	90% above 25k	75% above 30k	"above average"
Financial investments	168462 EUR	97435 EUR	68500 EUR
Real-estate investments	211925 EUR	-	-
ETF-holding rate	100%	11%	9%
Horizon, less than 10 years	46%	66%	37%
Horizon, more than 10 years	54%	13%	29%
Financial literacy*	97.5%	71%	-
Initial investment	8447 EUR	6743 EUR	-

For more detailed descriptive statistics about various cross sections of investors within the Yomoni

database, see Table 2.3 on 76 (Chapter 2) for investors who change their risk profiles, Table 3.4 on page 107 (Chapter 3) for investors who signed up between various dates, and Table 4.5 on page 145 (Chapter 4) for investors of different family statuses.

An ideal dataset – nationally representative, many decades, every transaction, complete demographic and financial information – does not exist for France. The Yomoni database has some advantages and some disadvantages which the reader should keep in mind. But there is evidence to suggest that Yomoni investors are remarkably similar to robo-advisor clients in other countries and at least not radically different from other investors in France.

Having established the necessary intellectual context, described the empirical approach, and detailed the Yomoni database, I will now provide brief overviews of each of the chapters included in this work and define how these articles contribute back to the research on household finance, behavioral finance, and the use robo-advisors.

Chapter 1: Poor Planning: Investors who Save Regularly Save Less Overall

Standard economic theory predicts rational economic agents will smooth consumption over their lifetime (Ando and Modigliani, 1963). In brief, lifetime consumption smoothing is accumulating debt during youth, paying off debt and saving during midlife, and dissaving during retirement. Rational agents will save how much they need to whenever they are able to. However, Choi (2022) remarks that all of the most popular personal finance books encourage their readers to save money every month, regardless of age and income. These financial advisors give out this advice with the intuition that this will increase their readers' savings. But does following this strategy – saving regularly every month instead of sporadically (or naively) actually increase savings? Put another way, does being a scheduler increase one's savings with respect to being a non-scheduler?

Perhaps not. Using a very simple t-test methodology, investors who scheduled deposits saved 32.6% (€8,630) less than investors who did not schedule deposits. The mean of these two groups was €21,602. However, a t-test does not exploit any of the additional investor-level data which is available with the Yomoni database, so a *ceteris paribus* linear regression which controls for these factors has the potential to reverse the trend seen in these surface-level statistics. But it does not. With this more sophisticated methodology, schedulers still saved 16.0% (€3,466) less than non-schedulers. Since the database has far more new clients who have had less time to accumulate savings, perhaps after several years the schedulers saved more. Still no. No annual cohort of schedulers saved statistically significantly more than non-schedulers, going all the way back to Yomoni's founding in 2015. Though these tests do not

exploit the Yomoni database’s time-series component. Perhaps a fixed effects regression, a much more sophisticated methodology which allows for controlling even unobserved variability by holding constant an individual over time, will reveal a positive effect during years that the individual was a scheduler versus a non-scheduler. In the end, no. Schedulers did not save significantly more during years in which they did schedule deposits as long as they continued to save sporadically. Multiple robustness tests and even changing the definition of “savings” to include different types of deposits always yielded the same core result: schedulers did not save significantly more than non-schedulers, and often saved significantly less.

Additionally, many factors such as an investor’s age, sex, number of children, income, wealth, investment horizon, ESG status, investment goal, and financial literacy were significantly related to an investor’s decision whether to make scheduled deposits and/or how much they eventually saved. While results about total savings were all found using the regression methodologies described above, results about whether an investor was likely to be a scheduler or not were found using a logistic regression. A logistic regression permits prediction of the outcome of a binary categorical variable, such as whether someone is a scheduler or not.

This study does not close the discussion about whether scheduling deposits really increases savings over time, but rather opens it. The popular advice does not work for every investor. The Yomoni database has enough limitations that it cannot provide a final answer. But it is clear that the received wisdom of scheduling deposits no matter who or when you are does not actually increase savings for every investor, at least over the medium term. More research must go into who needs or benefits from this advice.

Chapter 2: Managing a Lazy Investment: Being Actively Passive

Economists are interested in what factors theoretically and empirically determine an investor’s risk preferences (or their portfolio’s risk exposure), but these measurements are normally made only for the beginning of an investment. However, investors invest over time. Therefore, we can ask to what extent do the factors found to determine risk preferences/profile at Time t at the creation of an investment portfolio reflect or contradict the changes made to a portfolio at Time $t + 1$.

Robo-advisors are descended from a long lineage of financial instruments that seek to simplify the investment process and allow investors to step back and invest passively. Yomoni in particular is a robo-advisor with 100% ETF portfolios, putting several layers in between an investor and direct control over the assets in their portfolio. Both the inherently passive robo-advisor technology and their underlying investment philosophy, that portfolio changes should only be motivated by significant and unexpected changes in life circumstances, imply that portfolio changes should be infrequent. Yet, the Yomoni database

registers 9,250 changes for just 36,836 clients, and some clients change several times in a year. These clients are seemingly not using the robo-advisor as intended, making it a perfect environment to study whether the factors that influence changes to portfolio risk at creation have similar relationships for dynamic portfolios as the literature has found for static portfolios.

To understand why and how investors make changes to their robo-advisor portfolios, my coauthors and I study the 6,247 clients in the Yomoni database who made these 9,250 changes to their investment portfolios. Factors in the decision to change one's portfolio include macro-level market returns and volatility, which are suggestive of attempts to time the market. But factors also included micro-level financial variables such as portfolio age, return, volatility, value, ESG status, and goal, plus demographic variables such as investor age, sex, number of children, and risk preferences. These results suggest that an investor's decision to change their portfolio has many precedents outside those which Rational Choice Theory could explain. While many investors choose not to change their portfolios over long periods of time, taken together these results can be interpreted that investors are not uniformly following the robo-advisor's advice to change one's portfolio allocation only due to significant and unexpected changes in life circumstances.

To respond to our initial inquiry about to what extent the relationships these variables have to portfolios over time are either extensions or contradictions, these relationships were studied differentially for changes towards more or less market exposure. We adopt a multinomial logistic regression method. A multinomial logistic regression permits prediction of the outcome of a non-binary categorical variable, such as whether an investor adjusted their portfolio to have more, less, or equal market exposure. We use a K-Nearest Neighbor (KNN) matching algorithm common in data science to find demographically and financially similar "stayers" to the positive and negative "changers" so as not to bias these results with a qualitatively different subsample (e.g., a type of person who would never change their portfolio under any circumstances). By adopting this methodology, we find that the literature on static portfolio risk does not replicate perfectly to dynamic portfolios: for example, a replication for investor age but contradictions for investment horizon and investor income. As such, we cannot simply assume that, say, investors with a longer horizon will always keep the risky portfolio with which they may start.

Since investors show evidence suggestive of market timing, how these changes affected investors' returns are studied. A counterfactual test showed that on average accounts which adjusted their portfolio allocation outperformed identical hypothetical accounts in which no changes were made. This implies that investors were in fact able to time the market, at least somewhat. However, one could say that these gains have not yet been cashed out and so are only theoretical, so we ran the analysis again using a more constrained dataset including only realized gains (i.e., closed accounts). With this more restrictive dataset, the good market timing result did not replicate, as one might expect seeing as the literature

indicates that the average investor cannot time the market and loses large sums trying to do so.

Chapter 3: Good Old Lockdown: Household Investment Behavior during the Covid-19 Crisis

The Covid-19 pandemic was a monumental moment in history with major macroeconomic conditions and expectations about the future changing overnight in response to a plausibly exogenous variable, the spread of an unrelenting disease. Governments around the world reacted with mandatory lockdowns. The stock market also reacted, provoking the stock market crash of 2020. Yet the finance literature has so far not come to a consensus about how household investors behaved. Here again, there is a division between theory and empirics. Unless they believe the pandemic would continue for a decade, none of these shocks should matter in theory for retail investors with very long investment horizons such as those which make up a vast majority of the Yomoni database. My coauthor and I seek to establish empirically how these household investors in France responded to these shocks while they were happening.

To do so, we used a fixed effects regression similar to the one just described for Chapter 1. However, since an annual pulse is far too slow to measure behavior during the acute crises which lasted for weeks to months, we used a daily pulse for unscheduled deposits, which can take place any day, and a monthly pulse for scheduled deposits, which can only happen once a month.

Investors in this sample saved less during the stock market crash and lockdowns and less during the Covid period overall. When the stock market crash of 2020 and a Covid-19 lockdown coincided, there was a moderating effect as investors were not doubly panicked. However, the effects of the crises are differentiated for unscheduled deposits which reflect short-term reactions to these events versus scheduled deposits which provide an insight into how investors adjusted their plans for the future. To summarize, investors did not react in the same way to every crisis and did not react in the same way regarding scheduled and unscheduled deposits.

The fixed effects regression is designed for studying time variant variables such as whether a crisis is happening on a given day or not. One drawback of the fixed effects method is that variables that are time invariant (at least over the short run) like a person's sex or family structure cannot be studied. Therefore, we cannot get estimates for the questionnaire variables, which are measured upon contract creation, without also adopting another methodology to study the rich dataset of financial, demographic, and behavioral variables. Therefore, we use logistic regressions to study the likelihood of an investor making an (un)scheduled deposit and then linear regressions for studying this deposit's value.

Chapter 4: How Do Households Invest on Behalf of Their Children?: Evidence from a Robo-advisor

Governments, asset managers, and parents all want children to have savings made on their behalf. To make it easier, governments sponsor tax-incentive investment accounts such as the 529 account in the USA or the Livret Jeune in France, asset managers create and advertise investment accounts for children, and parents do open these such investment accounts on behalf of their children. Despite the practice being commonplace, little is known about how parents invest on behalf of their children. Rational Choice Theory predicts that being the agents to their children's principal, parents will invest perfectly considering the many ways in which the child's financial situation differs from theirs. But if the empirical evidence indicates that investors do not behave according to Rational Choice Theory for themselves, then it is unlikely that they do so when investing on behalf of their children.

The Yomoni database affords an opportunity to study these parent-child pairs, and once again it appears that real investors behave in ways that cannot be explained by Rational Choice Theory. It is not immediately clear *a priori* whether fathers would take care of their children's investment accounts, since indeed a household's investment accounts tend to be managed by the man of the family, or whether this task would be done by mothers, because it could be considered a form of childcare. This data shows that mostly fathers manage these accounts.

My coauthor and I identify two specific deviations from rationality. First, we document that fathers have a son preference, meaning that they open investment contracts more frequently for their sons than for their daughters. Since fathers make up a majority of the account managers, their son preference is enough to show up in the overall summary statistics. These results are found using a Pearson's chi-squared test, which is a standard tool in the psychology literature used to test for differences in groups sorted by categorical variables such as sex. Second, the risk profile of the children's investment portfolio is strongly correlated with their parent's risk profile, with parents often deviating from the robo-advisor's advice to have the same risk profile. In Rational Choice Theory, children's risk profiles are plausibly uncorrelated with those of their parents, because any inheritance is likely to come only much later in life and children's long-term personal financial situations have little in common with those of their parent's. One is a working adult with their education behind them and bills to pay in the short term, the other has up to eighteen years before they need to make their first financial decision larger than spending an allowance.

Research contributions

In summary, this thesis contributes to the literatures of behavioral finance, household finance, and the use of robo-advisors with a few surprising results. In Chapter 1, the investors who follow the consensus popular financial advice to save regularly are seen saving less overall than investors who save sporadically, which prompts us to rethink to what extent this advice should be universal. In Chapter 2, the results from the static portfolio risk literature are seen not to extend to dynamic portfolios in every case, which opens up questions about how investors who initially start with risky or conservative preferences may evolve over time. In Chapter 3, retail investor behavior during the Covid-19 pandemic is studied making a distinction between short- and long-term planning, which are notoriously difficult motivations to pick apart in standard datasets. In Chapter 4, rare information about whole family finances is exploited to learn about how investing behavior may (or may not) be passed from one generation to another. This work also contributes to an ongoing shift away from purely theory-driven papers and towards a mix of theory and empirical results in economics and finance. The four following papers question the traditional paradigm, answer big questions, and pave the way for future work.

Chapter 1

Chapter 1

Poor Planning: Investors who Save Regularly Save Less Overall

1.1 Introduction

Plans comfort us and keep us on track. Therefore, having a financial plan sounds like a good idea. However, a plan does not guarantee success. A bridge built perfectly to a bad blueprint will collapse, and scrupulously saving one dollar per year will still not pay for retirement. Following a bad plan could be worse than improvising.

Asset managers generally allow their clients to make scheduled and unscheduled deposits. Making scheduled deposits, a kind of financial plan, is extremely common. Choi (2022) states that the "consensus popular advice" is to save 10-15% of one's income each month regardless of age or income level, often before any other purchases are made. Readers may be familiar with popular adages to this effect such as "pay yourself first" or "spend after saving." Saving regularly is intuitive. But do those who follow this advice actually save more? Standard economic theory predicts that the distinction between regular and sporadic savers does not matter. Ando and Modigliani (1963) posit that rational individuals "smooth consumption," which is to say that they save to finance future spending in such a way to maintain a consistent rate of consumption, and the frequency of deposits does not impact this calculation. In other words, whether someone saves "regularly" or not is a purely psychological phenomenon. There are two competing theories. Are either of them right? What do the data say? In this paper, I analyze the clients of a robo-advisor and their transactions to observe the prevalence, stability, and demographics associated with making deposits, notably scheduled deposits. Then I observe how total savings differ between the regular and sporadic savers. To preview the main result: no, investors who schedule deposits are not necessarily saving more. In fact, they save less than those who do not schedule deposits.

The rest of this paper is formatted as follows. Section 1.2 explains the data and provides descriptive

statistics. Section 1.3 lists the econometric models used to study the data. Section 1.4 states the results of the analyses. Section 1.5 discusses the implications of the results. Finally, section 1.6 concludes.

1.2 Data

1.2.1 Source of the data

For a full explanation of the Yomoni database, please refer to the section "The Yomoni database" on page 178 of the general introduction. The questionnaire referenced in the following section is available in section 1.7 on page 50.

1.2.2 Scheduled and unscheduled deposits

The total value saved S (in euros) by each investor i over a given time period t (such as a month, a year, or the account's lifetime) can be found by summing their unscheduled deposits $D^{unsched}$, scheduled deposits D^{sched} , and initial deposit D^{init} used to open the account, then subtracting their withdrawals W .

$$S_{i,t} = (D_{i,t}^{unsched} + D_{i,t}^{sched} + D_{i,t}^{init}) - W_{i,t} \quad (1.1)$$

The mean total value saved by an investor at Yomoni is €21,602 (SD = €62,208). The median total value saved is €7,273. Additionally, the mean annual value saved by an investor at Yomoni is €7,489 (SD = €31,142). The median annual value saved is €1,200. Only 9% of the investors at Yomoni earn less than €25,000 per year, which means that the average client is not following the consensus popular financial advice of saving 10% of their income (at least, not by buying financial instruments at Yomoni).

1.2.3 Stability of scheduled and unscheduled deposits

Decisions which are identical in two consecutive time periods could be considered "stable" and may be used to predict how an investor might behave in a future period (Samuelson and Zeckhauser, 1988). Figure 1.1 illustrates the month-to-month stability with which investors at Yomoni make scheduled and unscheduled deposits, both in terms of propensity and value. "Propensity" is a binary variable for whether an investor made at least one deposit in a given month, while "value" is a continuous variable for the sum of their deposits in euros.¹ To reiterate, an investor is considered stable on a metric if they made the same decision this month as last month, regardless of whether that decision was to make a deposit or not.

¹Volume is condensed to propensity due to a low probability of an investor making more than one deposit in a month. In 79.6% of months in which an investor made at least one unscheduled deposit, they made exactly one unscheduled deposit. In 95.0% of months in which an investor made at least one scheduled deposit, they made exactly one scheduled deposit.

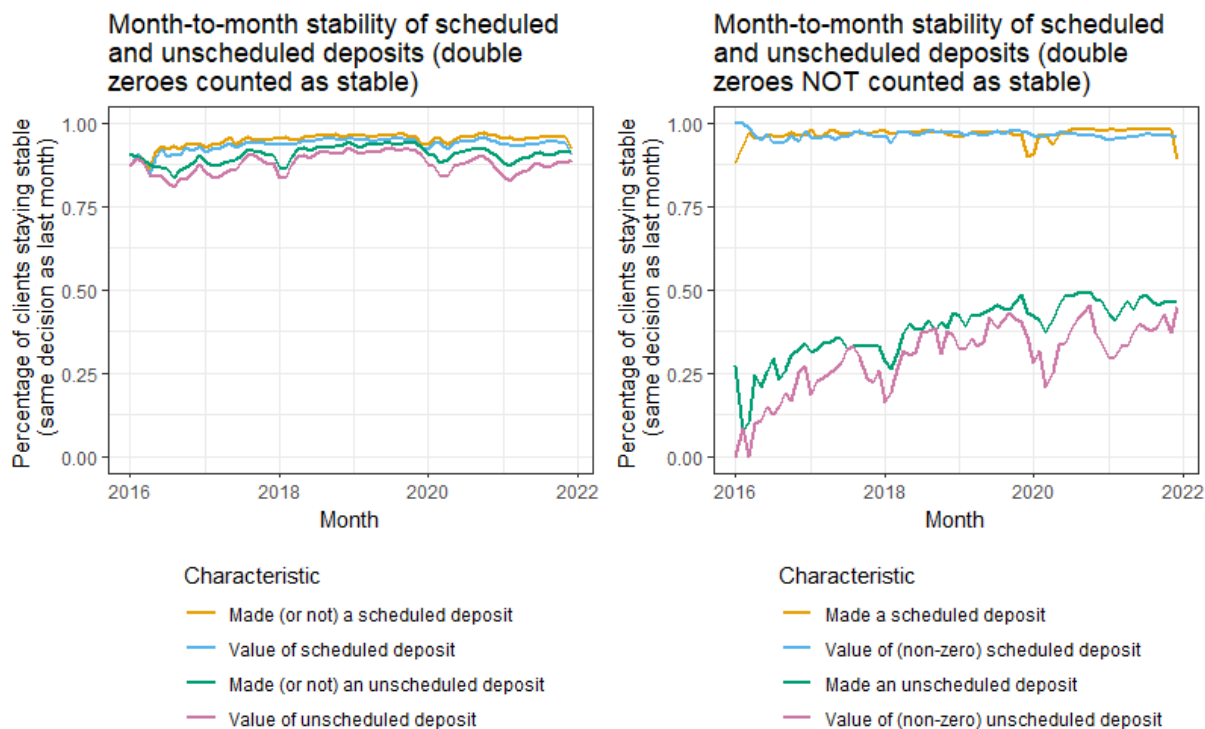


Figure 1.1: **Percentage of investors making the same decision as last month ("stability") with respect to four variables, including repeated months without any deposits as stable (left) or as not stable (right).**

On the left side of the figure, this includes all investors, including those who consistently do not make deposits. In case the reader wants to concentrate on only those investors who do make deposits, then on the right side of the figure, investors are considered stable only if they make deposits on consecutive months.² Additional descriptive statistics related to Figure 1.1 are provided in Table 1.1 (left) and Table 1.2 (right).

The left side of Figure 1.1 shows the percentage of investors who made the same decision as they made last month across four key questions: whether to make a scheduled deposit, what should be the value of that scheduled deposit, whether to make an unscheduled deposit, and what should be the value of that unscheduled deposit. The accompanying Table 1.1 provides descriptive statistics on this left half of the figure. One can interpret these findings as responding to the question, "How stable is the whole group of clients with respect to the decisions they make whether and how to invest?" The stability figures for propensity and value of (un)scheduled deposits are highly correlated with each other because when

²For transparency, August to December 2015 is not pictured in Figure 1.1 because of the single-digit sample size of early adopters. Likewise, January to March 2022 is not pictured because a change in the way that deposit data was recorded at Yomoni at the end of 2021 caused a large fraction of investors' scheduled deposits to be recorded in the incorrect month. The beginning of this change is visible in December 2021, at the far right of the graph, when scheduled deposits sharply drop. They continue to drop in January to around 70%. This change took place over several months, and the dataset does not return to normal before the last full month of the dataset in March 2022. These anomalous months are also excluded from the data analysis in Table 1.1 and Table 1.2.

an investor does not make a deposit one month, the value of their deposits is also necessarily unstable: it becomes zero. For this reason, the stability of deposits' value is also always less than the stability of deposits' propensity for as long as zero deposits are included. In case the reader wants to know the stability of deposits when only non-zero deposits are counted, this information is recorded on the right side of Figure 1.1 and in Table 1.2, explained shortly.

Each month, an average of 90.5% (SD = 0.025) of investors make stable decisions regarding whether to make an unscheduled deposit, and an average of 94.7% (SD = 0.021) of investors make stable decisions regarding whether to make a scheduled deposit. Decisions about scheduled deposits are more stable than decisions about unscheduled deposits, $t(138.6) = 11.11$, $p < .001$, though they are positively correlated, $r(70) = 0.51$, $p < .001$. However, a large fraction of this stability is driven by investors who make zero deposits, contributing zero euros – their consistent non-action counts as stability as well. Are these high stability figures being driven by a "silent majority" of investors who never make any deposits?

The right side of Figure 1.1 shows how the stability trends change when only decisions to make deposits in two or more consecutive months are considered stable. The accompanying Table 1.2 provides descriptive statistics on this half of the figure. This changes the precise question being asked. These findings respond to the question, "How stable are those investors who have made a deposit at least two months in a row?" An average of 38.1% (SD = 0.089) of these investors continue to make unscheduled deposits, and an average of 96.6% (SD = 0.020) of these investors continue to make scheduled deposits. With respect to the previous analysis, the stability decreased for unscheduled deposits, as one might expect when the do-nothings are excluded. However, the stability of scheduled deposits increased. This is because the previous analysis classified investors who made scheduled deposits at quarterly intervals as unstable when analyzed at the monthly level. But because investors who schedule their deposits quarterly never make scheduled deposits on two consecutive months, they are excluded from this analysis.

In other words, 3.4% of schedulers in any given month stopped making scheduled deposits. Of those investors who did not stop their scheduled deposit, 96.4% (SD = 0.011) made a scheduled deposit of the exact same value as last month's. The non-schedulers are less predictable. Of those investors who did not stop their unscheduled deposits, 29.8% (SD = 0.103) made an unscheduled deposit of the exact same value as last month's. This shows that the stability observed in the overall sample is not driven primarily by do-nothings: the schedulers are also stable. And scheduled deposits are significantly more stable than unscheduled deposits, $t(78.17) = 54.51$, $p < .001$.

1.2.4 Histories of scheduled and unscheduled deposits

Figure 1.2 describes the behavior of investors at Yomoni with respect to scheduled and unscheduled deposits in another way by analyzing the history of each individual investor. Every investor's history is

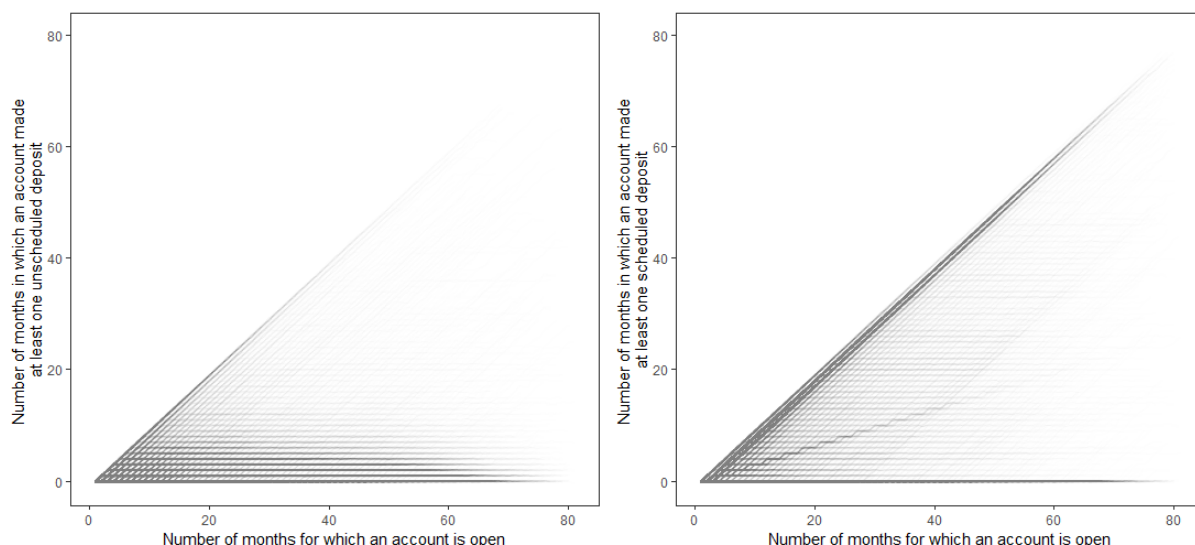


Figure 1.2: **Months of unscheduled (left) and scheduled (right) deposits by months an account is open.**

represented by a barely visible line that starts at zero and ends at the age of the account in months. Closed accounts do not age beyond the date at which they were closed. Each month, an investor has a binary choice: either to make at least one (un)scheduled deposit that month or not to do so. When an investor does not make at least one deposit, their account simply ages by one month. In this case, the line tracking an individual investor's behavior is horizontal. However, when an investor does make at least one deposit, their account ages by one month *and* they increase the number of months in which they made a deposit by one. In this case, the line tracking an individual investor's behavior is diagonal. When many investors' histories overlap, the line becomes thicker, darker, and easier to see. One can also read this figure as though each month had a frequency graph, with darker areas corresponding to higher frequencies.

When it comes to unscheduled deposits, Figure 1.2 shows that for each month, the most common behavior of investors is either near zero (the horizontal lines) or near the maximum (the diagonal lines). For example, at 20 months since the account was opened, the seven most frequent numbers of months in which an investor made an unscheduled deposit are zero months (7583), one (2762), two (1347), three (786), four (488), five (322), and nineteen (264). This habit of making an unscheduled deposit every month may last for up to several years, but it tends to peter out with enough time. At 60 months since the account was opened, all accounts are older (and thus fewer), but making fifty-nine unscheduled deposits is far rarer (8) than making zero (852), and no longer makes the top fifteen most common behaviors.

This can be directly compared with scheduled deposits. When it comes to scheduled deposits, Figure

1.2 shows that the three most common behaviors of investors at Yomoni are not scheduling (the horizontal line), scheduling monthly (the diagonal line), and scheduling quarterly (the stepped line). At 20 months since the account was opened, the seven most frequent numbers of months in which an investor made a scheduled deposit are zero months (6440), eighteen (3988), seventeen (1704), nineteen (436), sixteen (292), six (251, the quarterly option), and fifteen (217). Scheduled deposits often begin one or two months following the contract being opened due to a courtesy 30-day delay, which means that they cluster around the maximum. This is exactly the reverse of the unscheduled deposits. Making just a few scheduled deposits is relatively rare; instead, roughly half of the investors make none while the other half make one every month (or quarter). And the habit, whether an investor schedules or not, persists. At 60 months since the account was opened, the most frequent numbers of months in which an investor made a scheduled deposit are zero months (894), fifty-eight (261), fifty-seven (188), fifty-six (42), and thirty-three (36, the quarterly option).

Most savings plans were made when the contract was opened. These plans were made naively, i.e. in the absence of personalized financial advice. And, in general, investors have not revisited them since. The 2015-2022 period included a stock market crash, a global pandemic, a spike in both inflation and unemployment, several elections, and other turbulence that theoretically influences investor behavior (see Boulu-Reshef and Jones (2024) for a discussion on how the stock market crash and the Covid-19 pandemic affected investors at Yomoni). Over this multiyear period, some individual investors experienced life events, such as changes in jobs, salaries, or family composition, that also theoretically influence investor behavior. Yet, nearly all investors stuck with their savings plan.

1.2.5 Research Questions

There are those investors who make scheduled deposits (schedulers) and those who do not (non-schedulers), and these groups are relatively stable. This observation inspires two questions. What factors are related to whether an investor is a scheduler or a non-scheduler? And, do schedulers save more (or less) money?

Investors self-select into being (non-)schedulers, and there are many unobserved variables that could be affecting this decision. However, these groups are only *relatively* stable. There is a gray area between schedulers and non-schedulers: those investors who changed their scheduling behavior, i.e. the former (non-)schedulers. Analyzing this group of former (non-)schedulers can help answer whether it is scheduling deposits itself that causes a change in total value saved. Do former (non-)schedulers start saving more (or less) money when they change their behavior?

1.3 Methods

The question of what factors are related to whether an investor is a scheduler or a non-scheduler is treated with a logistic regression. The dependent variable in this regression is a binary dummy variable *Scheduler* that is equal to 1 if an investor i made at least one scheduled deposit since opening their account and equal to 0 if they never did so.³ A side-effect of this specification is that all schedulers made at least one deposit after the initial deposit, while many non-schedulers made zero deposits beyond the initial deposit, which gives a slight advantage to schedulers. The Q set of k independent variables comes from the introductory questionnaire used to generate the investor's robo-advice (see 1.7). Briefly, these factors are sex, age, investment horizon, ESG status, investment project, number of children, financial wealth, property assets, home ownership status, annual income, liquidity needs, risk preferences, and financial literacy. The investors are incentivized to answer these questions accurately in order to generate financial advice that is pertinent to their situation. The corresponding β for each of the k independent variables estimates the strength and direction of its relationship to the dependent variable. Finally, there is the intercept α and the error term ϵ .

$$\text{Scheduler}_i = \alpha + \beta_k Q_{k,i} + \epsilon_i \quad (1.2)$$

The relationship of these factors to the dependent variable are reported using average marginal effects (AME). A marginal effect is the percentage increase in the dependent variable when the value of an independent variable is increased by one unit. However, unit increases may not always have a linear relationship. Therefore, the average marginal effect takes the mean of the marginal effects, i.e., the mean of all one unit changes. That said, in many cases the independent variables of this regression are binary dummies, meaning that the "average" marginal effect is identical to the standard marginal effect of going from 0 to 1.

Next, the question of whether schedulers save more money is treated with a linear regression. The dependent variable in this regression is the total amount of money saved S (see Equation 3.1 for a specification) by each investor i . This time, the (non-)scheduler dummy variable *Scheduler* is used as an independent variable, with β_0 estimating the strength and direction of its relationship to *Scheduler* _{i} . To this is added the same Q set of k independent variables with β estimates from the previous regression, the intercept α , and the error term ϵ .

³Yomoni does not keep data on which investors are currently enrolled in scheduled deposits, whether they were at one point enrolled, for how long they were enrolled, etc. This information must be reconstructed somehow from the transaction data, which does specify whether a deposit was a scheduled or an unscheduled deposit. There are many possible operationalizations of the abstract concept "an investor who schedules deposits." The binary method used in this paper reflects a simple reality: the monthly and quarterly schedulers, the short- and long-term schedulers, the current and previous schedulers, the early- and late-adopter schedulers are all not non-schedulers, who never once even tried.

$$S_i = \alpha + \beta_0 \text{Scheduler}_i + \beta_k Q_{k,i} + \epsilon_i \quad (1.3)$$

Since the dependent variable in this regression is total savings in euros, the effects of each variable are also in euros.

Unfortunately, there is no way to observe the counterfactual, that being how much each investor would have saved in a hypothetical world in which they made the opposite choice to be a (non-)scheduler instead. However, studying those investors who started or stopped making scheduled deposits midway through data collection can offer insight. Thus, for the final model, the question of whether former (non-)schedulers start saving more (or less) money when they change their behavior is treated with a linear regression with individual fixed effects, in some ways similar to the previous Equation 1.3. This method is also sometimes referred to as time-series-cross-section (TSCS).

While the investors' transactions have hitherto been treated as cross-sectional data, they can also be analyzed as panel data, in which each investor i is observed across t time periods, calendar years in this case. A fixed effects model FE unites all the time-invariant heterogeneity across the investors i , including their intercept α , their Q set of k questionnaire variables, and their unobserved heterogeneity u , such that $FE_i = \alpha_i + Q_{k,i} + u_i$. Finally, the dummy variable *Scheduler* is time-variable in this specification, equal to 1 if an investor i made at least one scheduled deposit during a given t (a calendar year) and equal to 0 if they did not.

$$S_{i,t} = \beta_0 \text{Scheduler}_{i,t} + FE_i + \epsilon_{i,t} \quad (1.4)$$

Scheduler is the only time-variable factor (besides the error term) in this model. Like with the previous regression described in Equation 1.3, the effects of each variable are measured in euros.

1.4 Results

1.4.1 Factors which motivate scheduling deposits

Table 1.3 summarizes the results of the logistic regression described in Equation 1.2 concerning what factors influence the decision to make at least one scheduled deposit during the life of the account.⁴ Estimates are reported as average marginal effects (AME) to aide interpretation. Refer to Section 1.3 for an explanation of average marginal effects.

⁴Given the lag in scheduled deposits, investors who opened their accounts in 2022 may not have had enough time to make a scheduled deposit despite being signed up for them. As such, they are counted as non-schedulers, perhaps unfairly. Therefore, a robustness test was performed in which accounts created after December 31st, 2021, were excluded. Doing so reduced the number of investors observed to 30,226. The direction and significance of all variables remained stable.

The most influential factor in choosing whether to make scheduled deposits is income. With respect to the baseline condition of earning between €0 and €25,000, every income tranche significantly increases the probability of making scheduled deposits, and each one more than the last. Those earning €25,000 to €50,000 are 11.4% more likely to make scheduled deposits, those earning €50,000 to €100,000 are 13.9% more likely, those earning €100,000 to €150,000 are 17.6% more likely, and those earning more than €150,000 are 19.3% more likely. To contrast income with wealth, both financial wealth and property assets have near-zero effects while home ownership status is insignificant.

The second most influential factor in choosing whether to make scheduled deposits is the investment project. The investment project is the investor's stated motivation for opening the account. "Grow my savings" is not only the most generic motivation but also the most common, with 26,274 out of 36,836, or 71.3%, of clients choosing this option. As such, "Grow my savings" is used as the baseline to which the other motivations are compared. The 211 investors choosing "Finance my children's studies" are 19.2% more likely to make scheduled deposits, while the 4,155 investors choosing "Open an account for my child" are 15.7% *less* likely to make scheduled deposits. That accounts opened on behalf of one's children with two different motivations could elicit such different investment behavior is surprising, and this result builds on the results of Direr and Jones (2024) that investors' behavior with respect to opening accounts on behalf of their children is complicated and nuanced. Rounding out the remaining investment projects: investors selecting "Plan my retirement" are 11.4% more likely to make scheduled deposits, and those selecting "Prepare a major purchase" are 5.8% more likely, while those selecting "Bequeath an inheritance" and "Save in the event of hard times" are not significantly more or less likely.

The next most influential factors are age, investment horizon, and ESG status. For each additional year a client ages, they are 0.6% less likely to make scheduled deposits, while for each additional year of a client's investment horizon, they are 0.5% more likely to make scheduled deposits. Investors who chose ESG portfolios are 2.8% more likely to schedule deposits. Perhaps long-term thinking correlates with making scheduled deposits.

Lastly, liquidity needs and risk preferences may or may not have a relationship with scheduling deposits depending on the precise way they are measured, and financial literacy, sex, and number of children are not significantly related to scheduling deposits.

1.4.2 Do scheduled depositors save more money?

The investors who scheduled deposits did not save more money than the investors who did not schedule deposits. In fact, the schedulers saved much less. The mean scheduler (€17,875) saved significantly less money than the mean non-scheduler (€26,505), $t(23012.97) = -12.28$, $p < .001$. The median scheduler (€6,900) also saved less money overall than the median non-scheduler (€8,500). Likewise, the

mean scheduler (€5,962) saved significantly less money each year than the mean non-scheduler (€9,010), $t(81125.08) = -15.99$, $p < .001$. Even with the advantage of time, there is no subsample based on sign-up date in which schedulers save significantly more than non-schedulers.⁵ Finally, the linear regression described in Equation 1.3 shows that schedulers save €3,466 less overall than non-schedulers *ceteris paribus*. The results of this regression are reported in Table 1.4.⁶

Recall that the dummy variable *Scheduler* is equal to 1 if an investor i made at least one scheduled deposit since opening their account and equal to 0 if they never did so. This means that investors who make no deposits of any kind, scheduled or unscheduled, and who therefore necessarily contribute €0 after the initial deposit, are also non-schedulers. Allowing schedulers to have one "free" deposit like this gives them a structural advantage, so some readers may want a stricter comparison between schedulers who made at least one deposit and non-schedulers who made at least one deposit. In a robustness test of the prior result in which only the 29,722 investors who made at least one deposit of some kind are analyzed, schedulers saved €9,369 less than non-schedulers *ceteris paribus* ($p < .001$).

Recall also that the the total savings of the investor, S_i , is the sum of the scheduled, unscheduled, and initial deposits, minus the withdrawals. Some readers may be more interested in the savings rates of schedulers and non-schedulers after the initial deposit. This is the strictest test of whether the investors who follow the scheduled saving strategy outsave the investors who follow the sporadic saving strategy. Excluding the initial deposit, schedulers still saved €3,684 less than non-schedulers overall ($p < .001$) and €1,193 less *ceteris paribus* ($p < .05$). Repeating the methodology of the previous paragraph's robustness test in which only the 29,722 investors who made at least one deposit of some kind are analyzed, schedulers saved €9,139 less than non-schedulers *ceteris paribus* ($p < .001$).

However, investors can be compared both to other investors and to themselves over time. Most investors chose whether to schedule deposits at the beginning of their contract and never revisited this decision, but some investors did start or stop scheduling deposits. The fixed effects panel regression described in Equation 1.4 shows that investors who started or stopped scheduling deposits saved €3,247 more ($p < .001$) during years in which they scheduled deposits compared to those years in which they did not schedule deposits. The same robustness test from the previous paragraph can be applied here to see to what extent those who contribute €0 are driving the results. In fact, this effect is driven primarily by those years in which investors deposit nothing. When analyzing only those years in which at least one deposit of some kind is made, investors who started or stopped scheduling deposits did not save

⁵Seven subsamples spanning the complete range of dates in the panel were compared: clients who signed up on or before December 31st, 2021, 2020, 2019, 2018, 2017, 2016, or 2015. In none did schedulers save significantly more than non-schedulers.

⁶The same robustness test for the logistic regression was applied here, in which only accounts created up to December 31st, 2021 were used. The direction and significance of all variables remained stable, except for "Project: Open an account for my child," which became significant, $p = .02$. In this alternative specification, schedulers saved €4,226 less than non-schedulers.

significantly more (€427, $p = .49$) during years in which they scheduled deposits compared to those years in which they did not schedule deposits.⁷ In other words, investors saved more during years in which they scheduled deposits than years in which they did not save at all (something which is also true *a priori*), but they did not save more during years in which they scheduled deposits than years in which they continued saving, just without scheduling deposits.

1.4.3 Other factors motivating money saved

In addition to the main variable of interest *Scheduler*, Table 1.3 reports how the other factors influence the total amount of money an investor saved.

Similar to the logistic regression, the most important factor in explaining the total amount saved was income. Compared the baseline condition of earning between €0 and €25,000, every income tranche except €25,000 to €50,000 significantly increased the amount of money saved. Those earning €50,000 to €100,000 saved €3,835 more, those earning €100,000 to €150,000 saved €8,510 more, and those earning more than €150,000 saved €17,946 more. Wealth has a meaningful impact on amount saved, with each additional €10,000 in financial wealth (property assets) correlating with an additional €477 (€82) saved. Though home owners saved €4,536 less, presumably because they are not saving that capital which is tied up in the real estate. Conversely, the only investment project to significantly differ from the baseline in total amount saved was "Prepare a major purchase" (€9,509 more), presumably because these investors are saving in order to buy real estate.

The next most important factors in explaining the total amount saved were age, horizon, and the number of days for which the account was open. Each additional year of age corresponded to €410 more saved while each additional year of investment horizon corresponds to €278 less saved. In other words, young people (generally those with longer horizons) have less to save. But each day the account was open, the average investor saved €6, all other things being equal.

As discussed previously, *Scheduler* was associated with €3,466 less saving. Four other variables have relationships of around this size: ESG status, financial literacy, number of children, and sex. ESG status correlated with a significant drop in savings by €3,885. Meanwhile, each one of the three financial literacy questions answered correctly was associated with €1,291 more saved, summing to a €3,873 gap in savings between the most and the least financially literate. Each child was associated with €1,190 less saved,

⁷Since it can take up to two months for the first scheduled deposit to be withdrawn, some accounts which signed up for scheduled deposits and were opened in November or December may not have had any scheduled deposits for their first calendar year. As such, these clients would be listed as non-schedulers in their first calendar year but schedulers thereafter. Therefore, a robustness check was performed in which the first calendar year of clients who opened their account in November or December of that year was removed. The effect nearly doubled: investors who started or stopped scheduling deposits saved €5,791 more ($p < .001$) during years in which they scheduled deposits compared to those years in which they did not schedule deposits. But, once again, the effect of scheduling deposits became small (€106) and statistically insignificant ($p = .87$) after removing the years in which investors made zero deposits of any kind.

and men saved €2,345 more than women.

Lastly, like in the model explaining scheduled deposits, liquidity needs and risk preferences may or may not have a relationship with the total amount saved depending on the precise way these variables are measured.

1.5 Discussion

1.5.1 Summary of the main findings

Making a savings plan which includes scheduled monthly deposits is consensus popular financial advice Choi (2022). But, using this sample of 36,836 clients of an asset manager with a collective €795.7 million in assets under management and exploiting a panel of data from 2015-2022, no test showed that investors who scheduled deposits saved more than investors who did not schedule deposits. The logistic regression described in Equation 1.2 showed that making scheduled deposits is associated with high income, implying that investors do so if they have the means. Yet the linear regression described in Equation 1.3 showed that investors who schedule deposits save €3,466 less than non-schedulers, all else being equal ($p < .001$). Excluding the initial deposit such that only savings after account opening are considered, investors who scheduled deposits still saved €1,193 less than non-schedulers, all else being equal ($p < .05$). Even among the 1,507 clients who signed up before 2017, schedulers did not save more than non-schedulers, meaning that if schedulers ever save more money it would take more than six years to do so. A quick, back-of-the-napkin calculation indicates that Yomoni would increase its assets under management by about 10% if none of their clients scheduled deposits. Taken together, these results show that the importance of scheduling deposits found in the popular financial advice literature might be exaggerated. Monthly savings plans have heterogeneous effects on investors, and following a bad plan may be worse than improvising.

So, should the standard advice instead be to make no plan at all? Of course not. While non-schedulers save more overall, the results of the panel regression described in Equation 1.4 show that investors who start or stop scheduling deposits save €3,247 more when they do schedule deposits. This difference vanishes when non-depositors are excluded from the sample. In other words, this result is driven mainly by the fact that some investors make no deposits at all if they are not making scheduled deposits. While as a whole the investors in this sample continued to save with or without the scheduled deposits, the investors who only save with scheduled deposits clearly benefit from plans. These investors would save less without some kind of plan, even if it is sub-optimal.

How can a tool which appears to increase savings for the individual scheduler decrease savings for the group of schedulers? The answer lies in the low average saving rates of schedulers. Benartzi and Thaler

(2007) write that any new saver must answer three tough problems: whether to save, how much to save, and how to allocate their savings. Yomoni provides advice for two out of three of these problems. Recall that the third question in the introductory questionnaire asks: "How much would you like to invest each month?" Prospective clients do not receive advice about how much money to save. Instead, they state how much money they want to save, and this figure is simply taken at face value. As such, then investors could be underestimating the real extent to which they could (or need to) save.⁸

The lower savings rates of schedulers would not be a serious problem if investors did not revisit their savings plans so rarely. Samuelson and Zeckhauser (1988) first coined the term "status quo bias" to describe the inertia of individuals' retirement savings decisions. Once a decision was made, it was rarely if ever revisited. The median number of changes in their dataset's asset allocations over the lifetime was zero. Similarly, Cronqvist et al. (2018) found that the default portfolio allocation in Sweden's defined contribution Premium Pension Plan was a nudge that lasted "forever." In sixteen years, the median investor made just one trade. Studying this very dataset, Benoit et al. (2024) found that only 18.6% of investors made changes to their asset allocations after opening their account, and then the average number of adjustments over the lifetime of the account was just 1.4. To paraphrase these academics' findings, while the typical retail investor may or may not think about their holdings often, they commit to changing their holdings almost never. This means that decisions made at the beginning of a contract can last years or even decades. This paper extends these findings on stability in asset allocations to stability in (scheduled) deposits.

1.5.2 Why do schedulers save less?

The finding that investors who schedule deposits save less than investors who do not schedule deposits contradicts both economic theory and popular intuition, so an explanation is in order. Fortunately, some explanations can be ruled out with this dataset.

Schedulers do not save less because of an unfair specification on my part. Schedulers can make any kind of transaction and always make at least one deposit after the initial deposit, by construction. Meanwhile, non-schedulers cannot make scheduled deposits, and many make zero transactions after the initial deposit. This definition gives schedulers the maximum possible chance to save more, and yet, they still save less. In addition, several robustness tests using alternative specifications were performed (most detailed in the endnotes), and this counter-intuitive result always held or became stronger. For example, one of these robustness tests ruled out the possibility that schedulers save less because their

⁸Benartzi and Thaler (1999) note that it was "disturbing" how 58% of their sample spent "an hour or less" responding to one particularly difficult question: asset allocation. Twenty-five years later, Yomoni optimizes its introductory questionnaire such that the average prospective client finishes it in minutes, including the question on savings rate. How things have changed!

initial deposits are smaller.

Next, schedulers do not save less because they are poorer. The logistic regression shows that the likelihood of making scheduled deposits increases with income, so schedulers are actually richer. Furthermore, the linear regression on total savings controls for income. Additionally, schedulers do not save less because of a few extremely rich outliers. The median scheduler also saved less, which means that the entire distribution of savings for schedulers is closer to zero. Finally, schedulers do not save less because they are foolish. The logistic regression shows that financial literacy is not significantly related to the decision to schedule deposits.

However, some explanations cannot be ruled out by this dataset. Perhaps schedulers do not save more within the six years of data included here, but they would save more after ten, twenty, or thirty years. Though, if it is true that scheduling deposits takes a decade or more on average to break even with respect to an irregular strategy, then this will be an important caveat to the consensus popular financial advice. Perhaps non-schedulers adjust their unscheduled deposits in reaction to inflation or changes in income while schedulers do not react to these changes due to a status quo bias and a sense that they are already saving. If this is true, then the opposite long-term effect would be observed: schedulers would save stably less after ten, twenty, or thirty years. Perhaps schedulers have higher levels in some unobserved variable, such as impulsivity, which increases their odds to schedule deposits (due to desire to control their impulses) but decreases their total amount saved (due to uncontrolled spending), and if this unknown variable was controlled for in the regression then the observed relationship could disappear. If this is true, then there would be no relationship between scheduling deposits and total amount saved. Perhaps scheduling deposits simply has more heterogeneous effects than popularly assumed, and this strategy improves savings rates for some investors but not for those in this sample. If this is true, then a positive effect of saving regularly could still be observed for some types of investors even if it stops being consensus advice. And perhaps following the popular financial advice gives schedulers an unearned sense of financial security that makes them feel better but induces them to save less, an effect known as moral licensing (Blanken et al., 2015). If this is true, then the psychological benefit of saving regularly could be rationally traded off with the material benefit of other possible saving strategies. Clearly, there are many avenues of future research for understanding the advantages of and limits to saving regularly.

1.5.3 Increasing savings and assets under management

Rarely does one find a problem in which government, industry, and individuals are all on the same side. Increasing savings rates is one such problem. Governments want to alleviate pension burdens, industry wants more assets under management, and individuals often regret not saving enough (Choi et al., 2004; Börsch-Supan et al., 2023). What can be done?

Because so many investors are making their decisions once at the beginning and then rarely if ever revisiting them, but overloading investors with too many decisions may cause them to abandon their projects, special care should be given to this moment. I propose three promising avenues for future applied research.

First, asset managers may want to experiment with options that allow investors to delay the start of their scheduled deposits until several months in the future and to gradually increase their savings rate automatically. This may increase the savings of some investors who would have saved little (or nothing) due to short-term liquidity constraints and minimize the importance of possible savings rate underestimations. Thaler and Benartzi (2004) studied an automatic escalation scheme (aka "Save More Tomorrow" or "SMarT") in which employees could commit ahead of time to gradually increase their savings rate whenever they received a pay raise. The theory of this scheme is that since future consumption is already temporally discounted, rational agents are relatively less disincentivized to trade off future consumption than they are to trade off current consumption, for which they may feel loss aversion (Kahneman and Tversky, 1979). In other words, it hurts less to save future money. And it's true. The automatic escalation scheme had a high uptake rate, a low dropout rate, and was effective at increasing employee savings rates even over a decade later (Benartzi and Thaler, 2013). Due to this success, automatic escalation has been implemented in U.S. public policy: a provision in the Secure 2.0 Act makes automatic escalation of 1% per year the default in new 401(k) plans, starting in 2025. An asset manager could invite their clients to schedule later increased savings at whichever date wished – for example, in January, when many salaried employees receive a standard pay raise. Likewise, giving the investor the opportunity to pause their scheduled deposits may increase savings and assets under management long-term. A pause of one to six months allows the investor to replenish their checking account without resorting to the relatively final act of cancellation.

Second, asset managers often offer cash incentives to attract new clients, essentially paying them to use the service. These cash incentives can come in the form of a free deposit into a new account or upon an account reaching a certain age, lowered or zeroed out account management fees for a set period or within a set limit, etc. Along these lines, an asset manager could experiment with a "free trial" of scheduled deposits, in which a client gets one to three months of deposits free (or matched) in exchange for a commitment to finish the year with at least the specified savings rate. To take full advantage of this program, the investor would save the maximum amount that they could. Yet, the evidence suggests that the average retail investor will not revisit this decision; instead, they will simply adjust to their new consumption level. Alternatively, since the maximum match is another heuristic identified by investors, a maximum match which incentivizes high contributions could be used (Benartzi and Thaler, 2007). Insofar as this may increase savings and assets under management long-term with respect to a one-time

gift, incentivizing scheduled deposits may be a better method to dispense a sign-up bonus.

Finally, one last option for the asset manager worth an experiment would be to change the values investors may be using as anchors, such as the minimum or average deposits. Many investors at Yomoni set their scheduled deposit to the minimum transaction amount of €50, but they may not rely on the minimum deposit as a heuristic if the minimum was closer to zero (Benartzi and Thaler, 2007). Anyone could guess that saving one euro per month will never be enough, so an investor faced with this decision will not have an easy default. And if they nevertheless choose the minimum, withdrawing a single euro from the investor's bank account each month would be an innovative form of advertising. Likewise, investors may misinterpret the average scheduled deposit of €200 as being a satisfactory savings rate in their case, when €200 per month is not even 10% of the median income in France (€2,340 per month in 2023). Madrian and Shea (2001) showed that making the default retirement plan saving 3% of income in a money market account could increase enrollment overall while decreasing savings by people who would have otherwise chosen another option when prompted to choose. This famous warning looms large on the present study. Choosing a different (higher) figure as an anchor, notably a personalized one that depends on the investor's income and liquidity needs, could be a more powerful and useful signal.

1.6 Conclusion

Economists increasingly grapple with the implication that the average person is not a rational, consumption-smoothing, derivative-solving economist, and that the average person simply does not follow advice of this nature (Benartzi and Thaler, 2007; Choi, 2022). Policies and products intended for the average person should be designed for the average person.

This study showed that asking retail investors how much they *want* to save instead of advising them how much they *need* to save may unintentionally lead them to make decisions which reduce savings and assets under management in the long-term. It appears as though the average investor underestimates how much they must save, saves according to the uninformed plan they created, then rarely if ever revisits the issue. And this investor, who reliably follows a bad plan, saves less than an investor with no plan at all.

Table 1.1: Descriptive statistics of Figure 1.1, left (zeroes included)

(1) M = 0.905 SD = 0.025	(1) and (3) t(138.6) = -11.11*** r(70) = 0.51***	(3) M = 0.947 SD = 0.021
(1) and (2) t(136.13) = 5.94*** r(70) = 0.97***	(1) and (4) t(136.77) = -7.68*** r(70) = 0.62*** (2) and (3) t(126.29) = -16.02*** r(70) = 0.45***	(2) and (4) t(141.77) = 3.95*** r(70) = 0.98***
(2) M = 0.877 SD = 0.031	(2) and (4) t(123.47) = -13.07*** r(70) = 0.56***	(4) M = 0.934 SD = 0.020

¹ Stability of propensity to make an unscheduled deposit (zeroes included)² Stability of value of unscheduled deposits (zeroes included)³ Stability of propensity to make a scheduled deposit (zeroes included)⁴ Stability of value of scheduled deposits (zeroes included)

*** p < .001, ** p < .01, * p < .05

Table 1.2: Descriptive statistics of Figure 1.1, right (zeroes excluded)

(1) M = 0.381 SD = 0.089	(1) and (3) t(78.17) = -54.51*** r(70) = 0.24*	(3) M = 0.966 SD = 0.020
(1) and (2) t(138.98) = 5.18*** r(70) = 0.89***	(1) and (4) t(78.4) = -51.48*** r(70) = -0.01, ns (2) and (3) t(76.34) = -53.99*** r(70) = 0.31**	(2) and (4) t(112.28) = 0.54, ns r(70) = -0.22, ns
(2) M = 0.298 SD = 0.103	(2) and (4) t(72.71) = -54.55*** r(70) = 0.04, ns	(4) M = 0.964 SD = 0.011

¹ Stability of propensity to make an unscheduled deposit (zeroes excluded)² Stability of value of unscheduled deposits (zeroes excluded)³ Stability of propensity to make a scheduled deposit (zeroes excluded)⁴ Stability of value of scheduled deposits (zeroes excluded)

*** p < .001, ** p < .01, * p < .05

Table 1.3: **Logistic regression for scheduling deposits**

This table reports the average marginal effects (AME) of the factors which influence the decision to schedule deposits.

	AME	St.Err.	T.St.	P.Val.	Sig.
Intercept	0.339	0.023	14.952	0.000	***
Sex (Male)	0.009	0.007	1.419	0.156	
Number of children	0.005	0.003	1.452	0.146	
Age	-0.006	0.000	-21.148	0.000	***
Horizon	0.005	0.000	11.113	0.000	***
ESG	0.028	0.011	2.571	0.010	*
Project: Grow my savings	(ref.)				
Project: Prepare a major purchase	0.058	0.012	4.651	0.000	***
Project: Open an account for my child	-0.157	0.016	-9.801	0.000	***
Project: Save in the event of hard times	-0.008	0.028	-0.295	0.768	
Project: Finance my children's studies	0.192	0.028	6.794	0.000	***
Project: Plan my retirement	0.114	0.010	11.048	0.000	***
Project: Bequeath an inheritance	-0.004	0.019	-0.224	0.823	
Financial wealth (per 10,000 EUR)	-0.001	0.000	-9.467	0.000	***
Property assets (per 10,000 EUR)	0.000	0.000	-3.765	0.000	***
Home owner	0.012	0.007	1.683	0.092	
Annual income 0k to 25k	(ref.)				
Annual income 25k to 50k	0.114	0.010	11.215	0.000	***
Annual income 50k to 100k	0.139	0.010	13.335	0.000	***
Annual income 100k to 150k	0.176	0.011	16.718	0.000	***
Annual income more than 150k	0.193	0.012	16.245	0.000	***
Liquidity Q1 Two years	0.000	0.003	0.028	0.978	
Liquidity Q2 Half of deposit	-0.056	0.007	-7.879	0.000	***
Risk Q1 Five year gamble	0.012	0.004	2.774	0.005	**
Risk Q2 Ten year gamble	-0.051	0.004	-11.934	0.000	***
Risk Q3 Buy when market dips	-0.001	0.002	-0.618	0.537	
Risk Q4 Experienced losses	-0.016	0.003	-5.754	0.000	***
Knowledge Q1 - Q3 Correct	-0.004	0.004	-0.987	0.324	

*** p < .001, ** p < .01, * p < .05

Table 1.4: **Linear regression for total savings**

This table reports the estimates (in euros) that each factor has on the total amount saved.

	Est. €	St.Err.	T.St.	P.Val.	Sig.
Intercept	-733.24	2600.91	-0.282	0.778	
Scheduler	-3466.41	628.52	-5.515	0.000	***
Days account is open	5.92	0.57	10.352	0.000	***
Sex (Male)	2345.00	678.41	3.457	0.001	***
Number of children	-1190.46	368.56	-3.230	0.001	***
Age	410.01	33.45	12.258	0.000	***
Horizon	-278.15	54.30	-5.123	0.000	***
ESG	-3885.30	1023.95	-3.794	0.000	***
Project: Grow my savings	(ref.)				
Project: Prepare a major purchase	9509.07	1341.92	7.086	0.000	***
Project: Open an account for my child	-2941.45	1578.88	-1.863	0.062	
Project: Save in the event of hard times	4183.05	2807.19	1.490	0.136	
Project: Finance my children's studies	-2357.76	4005.31	-0.589	0.556	
Project: Plan my retirement	-1043.93	1233.84	-0.846	0.398	
Project: Bequeath an inheritance	1393.23	1977.73	0.704	0.481	
Financial wealth (per 10,000 EUR)	477.29	9.34	51.112	0.000	***
Property assets (per 10,000 EUR)	82.34	10.94	7.526	0.000	***
Home owner	-4535.73	760.81	-5.962	0.000	***
Annual income 0k to 25k	(ref.)				
Annual income 25k to 50k	567.10	1135.74	0.499	0.618	
Annual income 50k to 100k	3835.30	1158.23	3.311	0.001	***
Annual income 100k to 150k	8510.18	1380.42	6.165	0.000	***
Annual income more than 150k	17946.01	1737.56	10.328	0.000	***
Liquidity Q1 Two years	-100.24	371.15	-0.270	0.787	
Liquidity Q2 Half of deposit	-1686.22	804.64	-2.096	0.036	*
Risk Q1 Five year gamble	-905.78	499.40	-1.814	0.070	
Risk Q2 Ten year gamble	-123.85	486.99	-0.254	0.799	
Risk Q3 Buy when market dips	419.70	238.00	1.763	0.078	
Risk Q4 Experienced losses	-625.88	306.28	-2.044	0.041	*
Knowledge Q1 - Q3 Correct	1290.53	430.08	3.001	0.003	***

*** p < .001, ** p < .01, * p < .05

1.7 Descriptions of variables

Table A1: **List of covariates.**

This table describes all covariates used in the analysis. The first column reports the name of the explanatory variable, and the second column reports its meaning. Variable names with a * are used in the K-Nearest Neighbor matching algorithm (Chapter 2).

Variable name	Description
Know Your Customers	
Horizon*	"In how much time would you like to benefit from this investment?" Answer expressed in years, minimum of 2, maximum of 30.
Liquidity Q1 Two years*	"Could you need all the savings held with [Name of the company] within the next two years?" • (4) Certainly not. • (3) Likely not. • (2) Likely. • (1) Very likely.
Liquidity Q2 Half of deposit*	"Could you need half of your investment before [the number of years indicated in <i>Horizon</i>] years?" • (4) Certainly not. • (3) Likely not. • (2) Likely. • (1) Very likely.
Sex (male)*	0 if female, 1 if male.
Age*	Age expressed in years.
Number of children	"How many children do you have?" • (0) None. • (1) One child. • (2) Two children. • (3) Three or more.
Annual income*	"What is the annual pre-tax revenue of your household? Think of the entirety of your revenue: salaries, pensions..." • (1) Less than €25,000. • (2) From €25,000 to €50,000. • (3) From €50,000 to €100,000. • (4) From €100,000 to €150,000. • (5) More than €150,000.
Financial literacy*	Sum of the correct answers to the following three true-false questions: • "A high gain prospect implies a high risk of capital loss." (True.) • "An ETF is a fund for which the capital is guaranteed." (False.) • "By delegating the management of my portfolio to a management company, I renounce making any investment decisions myself on it." (True.)
Risk Q1 Experienced losses*	"Have you already endured losses on your financial investments?" • (1) No, I have not endured a loss on my financial investments. • (2) Yes, of 10% maximum. • (3) Yes, of 20% maximum. • (4) Yes, of more than 20%.

Risk Q2 Five-year gamble*	"What profit/loss ratio are you willing to accept by investing €10,000 over 5 years? There is no right or wrong answer. We ask this question to find out where you stand." • (4) Potential gain of €5,000 / Potential loss of €2,000. • (3) Potential gain of €2,000 / Potential loss of €1,000. • (2) Potential gain of €1,000 / Potential loss of €400. • (1) Potential gain of €500 / Potential loss of €0.
Risk Q3 Ten-year gamble*	"What profit/loss ratio are you willing to accept by investing over 10 years? Here again, we are looking to understand your attitude towards risk." • (1) With an expected final gain of 20%, but with a risk of loss of 5%. • (2) With an expected final gain of 30%, but with a risk of loss of 10%. • (3) With an expected final gain of 50%, but with a risk of loss of 15%. • (4) With an expected final gain of 70%, but with a risk of loss above 15%.
Risk Q4 Buy when market dips*	"If your investment loses 10% of its value in 3 months, what do you do? One last step, your behavior during a crisis allows us to define your profile." • (5) I reinvest to benefit from this opportunity. • (4) I wait without panicking. • (2) I sell a portion to limit my potential losses. • (1) I sell everything. • (3) I do not know.
Time between account opening and risk profile change	The difference between the date the client opened their account and the date the client changed their risk profile. Expressed in years.
Client did not select the recommended risk profile	0 if the client accepted the robo-advisor's risk profile recommendation, 1 if the client chose their own risk profile.
Risk profile prior to change	Value between 1 and 10.
Investment project:	"What is your investment project?" • Grow my savings. • Save in the event of hard times. • Prepare a major purchase. • Plan my retirement. • Bequeath an inheritance. • Open an account for my child.
Know Financial Environment	
CAC 40 return (of yesterday, last week, or last month)	The closing price of the CAC 40 index divided by its closing price for the previous period, multiplied by 100%. "Yesterday" corresponds to the previous trading day; "last week" corresponds to five trading days previous; "last month" corresponds to twenty-one trading days previous. Data from Bloomberg.
CAC 40 volatility (of yesterday, last week, or last month)	The standard deviation of the returns for the CAC 40 for the period, annualized by multiplying the standard deviation by $\sqrt{252}$. For the daily volatility, the high and low price of the index within the trading day is used. Data from Bloomberg.
MSCI return (of yesterday, last week, or last month)	The closing price of the MSCI World index divided by its closing price for the previous period, multiplied by 100%. "Yesterday" corresponds to the previous trading day; "last week" corresponds to five trading days previous; "last month" corresponds to twenty-one trading days previous. Data from Bloomberg.

MSCI volatility (of yesterday, last week, or last month)	The standard deviation of the returns for the MSCI World for the period, annualized by multiplying the standard deviation by $\sqrt{252}$. For the daily volatility, the high and low price of the index within the trading day is used. Data from Bloomberg.
Deposited or withdrew money	Amount of money expressed in thousand euros which was deposited into or withdrawn from the account the day before changing the risk profile.
Total value of the account	The amount of money in Euros in the account the day before changing the risk profile.
Modified Dietz performance	An estimation of the returns for an account calculated using the modified Dietz method, expressed as a percentage, from the opening of the account to the day before changing the risk profile.
Account volatility	The volatility of an individual account calculated with the daily performances using the modified Dietz method, from the opening of the account to the day before changing the risk profile. The variable is annualized by multiplying the standard deviation by $\sqrt{252}$.
Days with negative returns	The number of days from from the opening of the account to the day before changing the risk profile for which the modified Dietz performance of an account was negative (losses).
Days with positive returns	The number of days from from the opening of the account to the day before changing the risk profile for which the modified Dietz performance of an account was positive (gains).
From ESG to non-ESG	1 if the risk profile change coincides with a change from an ESG version of a risk profile to a non-ESG version of a different risk profile. 0 otherwise.
From non-ESG to ESG	1 if the risk profile change coincides with a change from a non-ESG version of a risk profile to an ESG version of a different risk profile. 0 otherwise.
First Covid-19 Lockdown	1 if the risk profile change occurred between March 17th, 2020 and May 10th, 2020 (included). 0 otherwise.
Second Covid-19 Lockdown	1 if the risk profile change occurred between October 30th, 2020 and November 27th, 2020 (included). 0 otherwise.
Third Covid-19 Lockdown	1 if the risk profile change occurred between April 3rd, 2021 and May 2nd, 2021 (included). 0 otherwise.

Chapter 2

Chapter 2

Managing a Lazy Investment: Being Actively Passive

Co-written with Sylvain Benoît and Jérémy Dudek

2.1 Introduction

Stock market participation continues to expand globally as households have more disposable income and financial technologies decrease barriers to investing. Where once all portfolios were actively managed, either by scarce and expensive financial advisors or by individuals themselves, passive portfolio management through financial products such as ETFs and services like robo-advisors have made active management just one of several strategies. However, while financial technologies have streamlined the investment process for individuals, they do not prevent clients from making changes to portfolios. While many investors set and forget their portfolios, others day trade ETFs or micromanage robo-portfolios. In a sense, this latter group of investors actively manages passive portfolios. In this paper, we exploit a novel dataset of robo-advisor clients who made changes to their portfolios to better understand why and how one manages an otherwise "lazy" investment. We interrogate whether there are demographic and investment-related correlates, whether market returns and volatility impact changes made, whether investors who made changes are influenced by one of several psychological biases, and whether in the end their changes resulted in higher returns due to market timing.

First, the risk literature indicates that demographic variables like age and investment-related variables like horizon impact risk in portfolio allocation both theoretically and empirically. Yet portfolios are not static; they are dynamic. Investors can change their minds and thus their allocations over time. However, the risk literature largely does not address the question of how demographic variables impact the tendency to change one's portfolio allocation to be more or less risky *after* the original allotment. Do higher risk

preferences in initial allocations imply a greater tendency to adjust one's portfolio? And if so, is this tendency only to adjust in the more risky direction, or in both directions? These are open questions.

Second, market conditions like average returns and volatility affect investors overall. However, it is not clear whether and to what extent these broad trends extend to retail investors, who make up a fraction of the market. Furthermore, it is not obvious whether or why long-term investors would be influenced by market fluctuations years before their investment comes to term. Do yesterday's market returns or volatility influence an average person's long-term savings plans?

Third, retail investors are not immune to psychological biases like recency bias and home bias in portfolio allocations. But it has not yet been interrogated how or to what extent these biases extend into a robo-advisory setting, where investors select among a menu of portfolio allocations instead of building a portfolio themselves. Does information further in the past (days, weeks, months) have a weaker relationship to investment decisions than more recent information? Do investors privilege national stock market information despite having portfolios which are international in scope and out of their direct control?

Fourth, research has shown that most investors who attempt to time the market underperform with respect to a passive, buy-and-hold strategy, because of overconfidence, transaction fees, under- or naive diversification, opportunity costs, and more (French, 2008; Odean, 1998; Barber and Odean, 2000). However, investors in a robo-advisory setting do not face these two latter problems. Robo-advisor portfolios are generally well-diversified, and because purchases are made shortly after sales, clients' capital is always fully mobilized. This leads to the question: is this enough to reverse the trend seen in the literature? Do robo-advisor clients who change their portfolio allocations underperform with respect to those who did not make any changes?

To briefly preview the results, demographic variables such as age, sex, number of children, financial literacy, risk attitudes, and liquidity needs – but not income – influence the decision to update one's initial portfolio allocation to be more or less risky. Whether a client followed the robo-advice given to them was also meaningful. Micro-level financial factors such as a contract's age, horizon, value, performance, volatility, initial allocation, "goal," and ESG status also influence this decision. In addition, macro-level financial factors such as market returns, market volatility, and the Covid-19 lockdowns affected how likely a client was to adjust their portfolio allocation. There was evidence for a recency bias but no evidence for a home bias. Finally, accounts which adjusted their portfolio allocation outperformed counterfactual accounts in which no change occurred. However, when the sample to only those accounts with realized returns (i.e., closed accounts), there was no statistically significant benefit to changing one's portfolio allocation.

The format of the paper is as follows. Section 2.2 reviews the literature on robo-advisors and explains

the functionality of the specific robo-advisor from which the data is sourced. Section 2.3 details the structure of the data exploited, the variables examined, and the results expected. Section 2.4 defines the method of analysis and describes the results received. Section 2.5 performs robustness tests to verify the validity of the approach. Section 2.6 studies whether portfolio changes led to higher returns, first in theory and then in practice. Section 2.7 concludes.

2.2 Literature Review and delegated management

2.2.1 Robo-advisors

For a full explanation of robo-advisors, please refer to the section "Robo-advisors" on page 172 of the general introduction.

2.2.2 Investment opportunities at Yomoni

For a full explanation of the Yomoni database, please refer to the section "The Yomoni database" on page 178 of the general introduction. The questionnaire referenced in the following section is available in section 1.7 on page 50.

2.3 Robo-Advising and data collection

2.3.1 Know Your Risk Profile

When opening a contract, clients can accept the risk profile recommendation or choose their own. Thereafter, the contract's risk profile never changes except if a client manually changes it. The robo-advisor keeps a record of every time any client manually changes their risk profile, including the previous and new risk profiles and the date of the change. At the end of the data collection period, most clients had not changed their risk profile since opening their contract. About half of the clients opened their contracts in the two years prior to the end of the data collection period, so the proportion is expected to grow as clients age and their lifestyles drift further from those which they had when opening their contracts. Nevertheless, the robo-advisor recorded 9,250 risk profile changes. Around 50% of risk profile changes were done by clients who changed only once, and over 90% of risk profile changes were done by clients who changed five times or fewer. Table 2.2 summarizes the number of investors who made each number of changes. Clients who make one or two risk profile changes may simply be learning their true risk tolerance after being personally exposed to market conditions, though learning does not explain why clients might make three or more risk profile changes within a relatively short time span. Learning in

discussed in greater detail in section 2.5.4.

Two different clients who increased their risk profiles, one from 2 to 3 and the other from 8 to 9, would both be categorized as changing their risk profile by a magnitude of 1. Likewise, two different clients who decreased their risk profiles, one from 4 to 1 and the other from 10 to 7, would both be categorized as changing their risk profile by a magnitude of -3. Figure 2.1 summarizes the magnitude of risk profile changes. Overall, it is an off-center, bell-shaped curve. Positive changes are more common than negative changes, and slight changes are much more common than extreme changes. The most common changes overall are slight positive changes (+1 and +2 with a total number of changes equal to 2537 and 1984, respectively), which correspond to relatively riskier and more aggressive portfolios. However, extreme changes are more often negative. For more detail, the exact number of profile changes of each magnitude, as well as the years in which they were made, are enumerated in Table 2.1. The robo-advisor attracted an exponentially growing clientele during the data collection period, so even though later clients had less time to adjust their profiles than early adopters, they still did so in large numbers. While we are still observing a change of risk profile of +9 in 2021 (17 changes) and 2022 (10 changes), the opposite is not observed anymore due to the fact that Profile 1 is not available anymore. Clients who did not change their risk profile are assigned a value of 0; these clients are explained in detail in section 2.4, which is dedicated to the empirical analysis. There is a total of 9,250 recorded changes and an equal number of zeroes, for a total of 18,500 observations in the data set.

2.3.2 Know Your Customers

After opening an investment account, the robo-advisor keeps track of all transactions related to the account. Some transactions are initiated by the client manually, such as deposits and withdrawals, while other transactions are initiated by the robo-advisor automatically, such as fee payment and portfolio rebalancing (to maintain the portfolio compositions reported in Table 1).

The baseline set of explanatory variables comes from the introductory questionnaire and is composed as follows: the variables *Horizon*, *Liquidity Q1 & Q2*, *Sex*, *Age*, *Number of children*, *Annual income*, *Financial literacy*, *Risk Q1 – Q4*, and the three variables concerning the *risk profile*. The six variables concerning the *investment project* also come from the introductory questionnaire. There is other information included in the introductory questionnaire, but these are the variables that we consider to be key control variables for the analysis. These covariates are described in 1.7 and their expected impact on the probability of making a change of risk profile is summarized in the list below. The following assumptions are based on previous literature on risk preferences, which may or may not extend to the decision to increase or decrease one's risk profile with respect to a previous allocation, but we will begin with this intuition.

- *Horizon.* The standard financial advice is to increase a portfolio's share of risky assets for longer investment horizons and decrease this share for shorter horizons (e.g. Samuelson, 1969; Merton, 1969; Bodie et al., 1992; Barberis, 2000).
- *Liquidity.* Insofar as financial shocks can demand an appreciable portion of an individual's investment capital, higher liquidity constraints classically lead to more conservative portfolios, and lower constraints to more aggressive portfolios (e.g. Gollier, 2002).
- *Sex.* Meta-analyses of the vast literature on sex and risk preferences have shown that men tend to be slightly more risk tolerant than women (Croson and Gneezy, 2009; Charness and Gneezy, 2012).
- *Age.* In general, older people are advised to have more conservative portfolios to have a more predictable withdrawal rate and to be less dependent on capital markets' swings, while younger people can smooth their consumption functions over longer periods of time and can thus take on more capital risk (Bakshi and Chen, 1994).
- *Number of children.* While there is not a broad consensus in the literature on the impact of children on financial risk tolerance, several studies have found that children and risk tolerance are inversely correlated (Love, 2010; Chaulk et al., 2003; Chattopadhyay and Dasgupta, 2015).
- *Annual income.* Empirically, individuals with high incomes hold portfolios with greater proportions of risky assets than individuals with low incomes (e.g. Arrondel et al. (2010); Van Rooij et al. (2011) and Conlin et al. (2015)).
- *Financial literacy.* Prior research indicates that individuals high in financial literacy are more likely to own stocks than the less financially literate (Van Rooij et al., 2011).
- *Risk preferences.* Loss aversion and attitudes towards risk are known to be correlated with participation in the stock market, with more risk-seeking individuals owning more stocks than more risk-averse individuals (e.g. Dimmock and Kouwenberg, 2010).
- *Investment project.* When opening their investment account for the first time, clients are asked what is their "investment project," i.e., their ultimate intention for the capital once the investment horizon is reached. Such a mental accounting is a common technique in practice to incentivize clients to accurately set their original level of risk. If this variable influences the original risk profile, as found by Boulu-Reshef et al. (2022), then the same risk-seeking or risk-averse patterns should be observed among the different investment projects.

2.3.3 Know Your Financial Environment

CAC 40 index. Investors often consider market conditions when making their decisions. To capture market conditions, we construct the variables *return* and *volatility*, which refer to the return and volatility for a given period (daily, weekly, or monthly) for the indicated market index (CAC 40 or MSCI World in the robustness check). All these data come from the Bloomberg database of historical stock prices. In the analysis, the daily CAC 40 return and volatility are used as the baseline cases with robustness tests for the others. In theory, the day-to-day fluctuations of the market should have no relationship with investors' decisions to increase or decrease the portfolio composition of their long-term investments. After all, the risk profile suggested by the robo-advisor is derived from a given client's investment goals, financial situation, demographics, and risk attitudes. These facts change slowly or not at all, and certainly do not change whether the market went up or down a percent yesterday. Furthermore, investors with the robo-advisor are not exposed to the CAC 40 index through their investment in practice. Therefore they should not respond to its evolution.

Portfolio Characteristics. Like with the general stock market conditions, portfolio characteristics such as account activity (deposits and withdrawals), value, performance, and volatility theoretically should have no relationship to the decision to increase or decrease one's risk profile. The risk profile suggested does not change unless the client's life circumstances change, and even if clients choose not to follow the recommendation, supposedly they are not altering their risk profile based on how well their portfolio has performed.

Environmental, Social, and Governance. Starting on May 19th, 2021, the robo-advisor began to offer new ESG versions of the ten risk profile portfolios. These ESG portfolios favor industries such as energy, medicine, and public transportation while excluding industries such as tobacco, munitions, and adult entertainment. Thereafter, clients could easily switch between an ESG and a non-ESG portfolio at any time with one click, and many clients did so. Only those clients who changed from non-ESG to ESG, or vice versa, and changed their risk profile at the same time are counted in the dataset as changers. For example, a client who changed from "non-ESG risk profile 7" to "ESG risk profile 7" would not be counted as a changer, but a client who changed from "non-ESG risk profile 7" to "ESG risk profile 3" would be counted as a changer. Theoretically, preferring to invest in companies that sell medicine over those that sell tobacco should have no relationship to the ratio of stocks to bonds in one's portfolio, so there is no reason to expect switching back and forth from ESG to non-ESG to be related to the client's risk profile.

Lockdown. France was under national Covid-19 lockdowns three times. The first lockdown started March 17th, 2020 and ended May 10th, 2020 (included). The second lockdown started October 30th,

2020 and ended November 27th, 2020. The third lockdown started April 3rd, 2021 and ended May 2nd, 2021. Three dummy variables, one for each lockdown, are introduced post-hoc into the dataset of risk profile changes to identify the changes which took place during these crises. The dummy variable is equal to 1 if the risk profile change occurred during the given crisis, 0 otherwise. A variable for each lockdown is preferred to one variable for all lockdowns because each crisis may have affected investors differently – particularly the first lockdown, which was unthinkable until it was declared. Unlike daily market fluctuations, account-specific details like value and performance, and the introduction of ESG portfolio alternatives, the declaration of a Covid-19 lockdown does suddenly and profoundly alter one’s life circumstances in such a way that a modification to one’s risk profile may be merited. However, the overall direction is not easily predictable, because it depends on the way in which the lockdowns affected a given individual. If a lockdown resulted in a sudden and unexpected loss of business or employment for a client, then one could expect them to decrease their risk profile. Whereas another client who could telework without interruption may see no reason to change their risk profile.

2.4 Empirical Analysis

The use of a multinomial logistic model instead of a standard linear regression model or binomial logistic model is motivated by three reasons. First, a linear model averages the effect of all one-unit changes across the spectrum of available choices, but there is a strong reason to suspect that stepping from -1 to +1 would have profoundly different results than stepping from 2 to 4, for example. Second, to control for selection bias, we matched projects with at least one risk profile change to similar contracts without changes. These matching contracts without changes have been assigned a value of 0 in Table 2.1. Binomial logistic regressions may be used to determine the probability of making a risk profile change, whatever its direction. However, covariates explaining changes in risk profile may have a differentiated impact for explaining the likelihood of an upward change and a downward change. Third, to limit the number of groups in the multinomial logistic model and to reduce the estimation bias due to the fact that some magnitude of changes are scarce (e.g., 77 changes with a magnitude of -9 and 83 changes with a magnitude of +9), changes must be grouped somehow. Grouping them by positive and negative risk profile changes is the least arbitrary grouping, since it corresponds to the simple marginal direction of a more or less risky portfolio allocation. For these three reasons, a multinomial logistic regression model with three groups is most apt. As such, the changes are grouped into a dependent variable with three levels: *Lower*, *Equal*, and *Higher*.¹

¹All changes which decreased the account’s risk profile (from -9 to -1) were assigned the dummy variable *Lower*. Likewise, all changes which increased the account’s risk profile (from 1 to 9) were assigned the dummy variable *Higher*. All non-changes were assigned the dummy variable *Equal*.

2.4.1 Framework

Matching Strategy. Each client who changed their risk profile at least once ("changers") was paired with a very similar control subject who did not change their risk profile ("stayers"). Potential matches for a given changer included only those stayers who opened their contract either the same day or within the previous week, so that both the changer and the stayer were exposed to very similar market conditions. From this subset of stayers who opened their contracts at a similar time as the changer, the single stayer who would serve as the matched pair control subject for the changer was found using a K-Nearest Neighbor algorithm.

In general, the K-Nearest Neighbors algorithm seeks to find a grouping (in this case, a pairing) for a data point which minimizes the sum of deviations between the data point and the group along the variables used for matching. Given $\mathbf{x}$ is a set of P covariates for an investor i , the KNN algorithm solves for the single investor $\neg i$ which satisfies this formula:

$$\min \text{DIST}(x_i, x_{\neg i}) = \sum_{p=1}^P |\mathbf{x}_{i,P} - \mathbf{x}_{\neg i,P}| \quad (2.1)$$

For example, if a K-Nearest Neighbor algorithm sought to match a 45-year-old individual with an identically aged individual, but no other 45-year-old people were available, the algorithm would attempt to match them with someone who was 44 or 46, and so on until a match is eventually found. If a variable is not a variable used for matching, then it has no influence on the algorithm. Since the variables in our dataset are all of different scales, they were normalized for the sake of matching. Normalizing variables is a process which assigns 0 to the minimum value in a scale and 1 to the maximum value in a scale.

The K-Nearest Neighbors algorithm employed here took into account both demographic and investment-related information with the goal of finding the stayer who was most similar to the changer across all these metrics.² At the beginning of the data collection period, clients were few, so an early changer may have had the choice of only one stayer. Two changers were removed from the dataset because they had zero potential stayers. However, by the end of the data collection period, clients had become many, so the changer and their matched stayer tend to be more similar. Table 2.3 provides descriptive statistics on changers and stayers. Consistent with the matching strategy, these two groups are quite similar to each other. A changer who changed multiple times, and who therefore appears multiple times in the dataset of risk profile changes, is always associated with the same stayer. This means that for the 9,250 changes in the dataset, there are also 9,250 non-changes. These stayers' non-changes are reported in Table 2.1 under the 0 column.

²The information used for matching in the K-Nearest Neighbors algorithm were the following variables: risk profile (at the beginning of the contract before any changes were made), horizon, sex, age, annual income, financial literacy, liquidity Q1 & Q2, and risk Q1 - Q4.

The investors in this dataset, 90% of whom are French, can be compared to the average French investor using data from the OECD (2023). Adopting the terminology of the OECD (2023) report, the investors in this dataset are in some ways more similar to "new retail investors," meaning those who have started investing since 2020, and in other ways more similar to "traditional retail investors," meaning those who had already been investing by 2020. On average, traditional retail investors in France are age 51, 68% of whom are male, 29% of whom have an investment horizon longer than ten years, 9% of whom hold ETFs. Meanwhile, new retail investors in France are age 36, 64% of whom are male, 13% of whom have an investment horizon longer than ten years, 11% of whom hold ETFs. Finally, the retail investors in our data-set are age 33, 79% of whom are male, 54% of whom have an investment horizon longer than ten years, and (due to the nature of investing with the robo-advisor) 100% of whom hold ETFs. For reference, the average French person has 68,500€ in financial (non-property) wealth and a median annual net income of 30,000€. New retail investors in France have 97,435€ in financial wealth and 75% of them earn above the median income, while investors in our dataset have 168,462€ in financial wealth and 90% of them earn above 25,000€. Their levels of financial literacy can be compared directly thanks to one knowledge question which is remarkably similar between the two datasets. The OECD (2023) survey asks the following true-false question, "When investments offer higher rates of return, they are likely to be riskier than investments offering lower rates of return," with 71% of new retail investors answering correctly. While the robo-advisor phrases the same true-false question in the following way, "A high gain prospect implies a high risk of capital loss," with 98% of investors in our dataset responding correctly. To summarize, in comparison with new French retail investors, the investors in our dataset have comparable ages and incomes. However, the investors in our dataset are much more wealthy and financially literate, much more likely to be males and ETF-holders, and have much longer investment horizons, which is more similar to traditional French retail investors.

Regression Strategy. The multinomial logit model can explain the change in risk profile of the investors making an upward change, downward change, or no change. The group membership probabilities of a given investor i can be solved for explicitly, and are given by:

$$\text{Prob}(y_i = k|\mathbf{x}) = \frac{\exp(x_i\beta^k)}{\sum_{j=1}^K \exp(x_i\beta^j)} = \frac{\exp(\beta_0^k + \beta_1^k x_{i,1} + \dots + \beta_P^k x_{i,P})}{\sum_{j=1}^K \exp(\beta_0^j + \beta_1^j x_{i,1} + \dots + \beta_P^j x_{i,P})} \quad (2.2)$$

for $j = \{Lower; Equal; Higher\}$, and where $\mathbf{x}$ is a set of P covariates. Here, $K = 3$ and the baseline category is *Equal*. The ratio of any two group membership probabilities is a log-linear function of $\mathbf{x}$, since we have:

$$\log \frac{\text{Prob}(y_i = j|\mathbf{x})}{\text{Prob}(y_i = k|\mathbf{x})} = (\beta_0^j - \beta_0^k) + (\beta_1^j - \beta_1^k) x_{i,1} + \dots + (\beta_P^j - \beta_P^k) x_{i,P} \quad (2.3)$$

for any j and k . When j is equal to the baseline category *Equal*, we set $\beta_p^{Equal} = 0$ for $p = 0, 1, \dots, P$, which is a convenient choice to ensure model identifiability. The unknown parameters β^{Lower} and β^{Higher} (when the modality *Equal* is the baseline category) are estimated by the maximum likelihood method.

2.4.2 Regression Results

Regression results from the multinomial model are reported from Tables 2.4 to 2.11. Each table reports estimated coefficients and standard errors (in parentheses) for the regressions explaining risk profile changes on a given set of explanatory variables. The dependent variable, y , is a multinomial variable with three modalities: *Lower*, *Equal*, and *Higher*, for which *Equal* is the reference level. This reference level is composed of accounts which do not change the risk profile of their investment accounts. Meanwhile, *Lower* captures all changes which decreased the risk profile of their investment account by any amount, such as from Level 6 to Level 4, and *Higher* captures all changes which increased the risk profile of their investment account by any amount, such as from Level 7 to Level 8. Thus, for a single regression, two columns are displayed: $y:Lower$ and $y:Higher$, to ease the reading and underline the potential differentiated impact of a covariate. A positive coefficient for an explanatory variable indicates that a positive change in the explanatory variable is associated with an increased likelihood to change the risk profile in the direction noted (*Lower/Higher*), whereas a negative coefficient indicates that a positive change in the explanatory variable is associated with a decreased likelihood to change the risk profile in that direction.

Baseline Regressions. In Table 2.4, under Column 1 are the results of the first baseline regression using only the questionnaire variables. This is the baseline set of covariates, which is consistently used in each regression. Under Column 2 are the results of the second baseline regression using both the questionnaire variables and the performance and volatility of the CAC 40.

From the first baseline regression, most of the explanatory variables from the baseline set have at least one estimated coefficient which is significant for explaining the likelihood of a downward or an upward risk profile change. The time horizon of a investment has a positive impact of the likelihood of making a change, in both directions, meaning that clients with investments close to term tend not to change their risk profile at all, while clients with longer investment horizons are more likely to change. Liquidity needs appear not to have a strong relationship with the likelihood to increase or decrease one's risk profile, with the exception that clients who are certain that they will not need their investment in the next two years are less likely to decrease their risk profile. With respect to female clients, male clients are more likely to increase and less likely to decrease their risk profiles. The signs for *Lower* and *Higher* are also inverted for the explanatory variable "Age," meaning that as a client ages they become more likely to decrease their risk profile and less likely to increase it. Each additional child decreases the likelihood to

increase one's risk profile, but does not change the likelihood to decrease one's risk profile. Surprisingly, income has no relationship with the odds of increasing or decreasing one's risk profile. As with children, high financial literacy is associated with a lower chance of increasing one's risk profile, but there is no relationship with decreasing one's risk profile. It is interesting that risk attitude variables do not necessarily have an inverted shape, such as "Experienced losses" and "Ten-year gamble". In the case of these two variables, clients with a greater appetite for risk have a positive and significant probability both to increase and to decrease their risk profile. In contrast, when the risk appetite of "Five-year gamble" drops, the probability of lowering risk profile decreases, which is counter-intuitive. The exact wording of these questions is reported in the Appendix 1.7. Nevertheless, when the risk appetite of "Five-year gamble" and "Buy when market dips" raises, the probability to increase risk profile remains significantly positive. Clients who opened their account longer ago and who make a change over their holding period are more likely to decrease their risk profile and less likely to increase their risk profile.³ Clients who did not initially follow the robo-advisor's recommendation and clients with higher risk profiles prior to the change were both stably more likely to decrease their risk profile and less likely to increase their risk profile. While the likelihood of making a downward (upward) change in one's risk profile is intrinsically higher (lower) for investors with a low (high) risk profile, the value of the risk profile prior the change is added as control. Their estimated coefficients are as expected, since a higher risk profile prior to change has a higher (lower) probability of making a downward (an upward) modification in risk profile. The signs mentioned here for each covariates with respect to downward or upward changes are stable throughout the analysis, even when adding additional explanatory variables.

The goal of the second baseline regression is to highlight that investors with Yomoni are affected by market conditions, even when both Yomoni and general financial literacy advise them to keep their risk profile through their investment period independent of market fluctuations. Profits and losses can only be truly evaluated at the investment's term. First, we assume that changers are more influenced by market events which immediately preceded the date of the risk profile change. Following this assumption, the daily CAC 40 return and volatility observed the day before the change are introduced in the set of covariates. The daily CAC 40 return of yesterday is significant and increases the likelihood to increase one's risk profile, but decrease the likelihood to reduce one's risk profile. It means that positive past returns tend to encourages savers to make upward changes; in other words, they want to take more risk. A similar result is drawn when we focus on downward changes, since the probability of observing such events is lower when past positive returns are observed. Conversely, a past negative market return increases the probability of making a downward adjustment of the risk profile. The daily CAC 40 volatility of yesterday is also significant and decreases the likelihood to increase one's risk profile, but increases the

³Compared to the others covariates, this result is not stable across tables.

likelihood to reduce one's risk profile. It means that a higher stock market volatility both discourages savers to make upward changes and encourages them to make downward changes, i.e., to reduce one's exposure to the stock market. These results are intuitive and confirms that savers care about stock market conditions even if their portfolios are not directly invested in the CAC 40 index or its components. Before running some robustness checks on the stock market conditions in Section 2.5 to confirm these findings, additional control variables are added to see whether the trends for daily CAC 40 return and volatility still hold for other periods and lags.

Investment Project. Table 2.5 reports how clients are more or less likely to change the risk profile of their investment according to their investment project. Different investment goals may impact the likelihood of changing one's risk profile. To study the impact of each type of investment project (six types are proposed in the questionnaire, see 1.7), the project "Grow my savings" is set as the reference category to which the others are compared. Its impact is captured by the intercept, and the interpretation of estimated coefficients from investment project dummies are all done with respect to this reference category.⁴ The five types of investment project besides "Grow my savings" have a significant additional impact on the likelihood of making an upward change in risk profile. While "Prepare a major purchase" increases the likelihood (with respect to the option "Grow my savings"), the other four decreases the likelihood, e.g., savers opening an account for their child have a lower probability to increase their risk profile. This last result adds information to the previous research using this dataset on how parents invest on behalf of their children (Direr and Jones, 2024). In contrast, the likelihood of reducing risk profile is only positively affected by the project "Prepare major purchase."

Portfolios Characteristics. Table 2.6 illustrates how different portfolio characteristics such as account activity, value, performance, and volatility are related to the decision to increase or decrease risk profile. Individual portfolio information competes and combines with general market information, providing a more granular perspective about how and to what investors react. Relatively higher account values correlate with higher chances both to increase and to decrease risk profile. Better performing accounts, as estimated using the modified Dietz method, have their risk profiles decreased less frequently and increased more frequently. Each additional day an account is open decreases the likelihood that its risk profile changes at all, and this relationship hold whether an account has a negative *or* a positive overall performance (though the relationship is more powerful for losses). In other words, both increases and decreases in risk profile are more likely to come earlier in a contract's lifespan. But the power of all of these effects is low in comparison to the power of account volatility. Risk profile changes are

⁴The investment project "Grow my savings" is the most frequently selected, with 15,154 observations out of 18,500 choosing this option. Besides setting this project as the reference in the regression, another way to avoid perfect collinearity would be to omit the intercept from the regression. However, by doing so, it would not be possible to identify the differentiated effect between the six types of investment project.

less likely to occur with more volatile accounts, and this relationship is more powerful than any other relationship documented. Finally, importantly, including the portfolio characteristics does not change the sign, significance, or interpretation of the coefficients for the CAC 40 return and volatility.

Environmental, Social, and Governance. Investment satisfying environmental, social, and governance (ESG) criterion are becoming ever more popular, with the number of clients selecting ESG investment growing over the period. Table 2.7 shows that investors were more likely to change their risk profile in any direction when switching from a non-ESG portfolio to an ESG portfolio, and less likely to change their risk profile in any direction when switching from an ESG portfolio to a non-ESG portfolio. For savers, it seems that ESG portfolios do not imply the same level of risk as standard portfolios.

Lockdown. Table 2.7 also reports how investors modified their risk profiles during the three Covid-19 lockdowns. Investors were consistently less likely to decrease their risk profiles during the lockdowns, though for the first lockdown this relationship is only marginally significant. In other words, investors did not react to the crises by decreasing their market exposure. Meanwhile, investors were more likely to increase their risk profiles only for the third lockdown. Since the third lockdown (April 3rd to May 2nd, 2021) coincided with rapidly expanding availability of Covid-19 vaccines, investors may have anticipated the end of Covid-19 restrictions and felt more optimistic or open to taking more risk during this period. In addition, they may have learned from the first lockdown, during which markets fell for only one month (from February 21st, 2020, to March 20th, 2020, the CAC 40 fell by 28%) before rebounding. The rebound may be explained by measures which boosted confidence in the financial market, such as the announcements of the European Central Banks in April 2020 to launch a series of non-targeted, emergency, longer-term refinancing operations which maintained liquidity, by the quick and expansive adoption of teleworking which maintained productivity, or by the French government's decision to maintain approximately 70% of the salary for workers taking technical leave which maintained consumer demand. In both regressions reported in Table 2.7, the significance and interpretation of the coefficients for the CAC 40 return and volatility and also for the other baseline covariates remain similar to previous tables.

2.5 Robustness Checks

To confirm previous results, we perform three robustness checks. First, we relax the myopia of the investors regarding the previous trading day, since financial events observed over the last week or month may have also influenced the likelihood of changing one's risk profile. In addition, to check for this recency bias, daily returns and volatilities observed one week and one month ago are added as control variables. Second, we replace the CAC 40 index with the MSCI World index. Although investors may be more affected by their domestic environment than the global environment, investors' portfolios with

the robo-advisor are better reflected by the MSCI World. This exercise can also test for the existence of a possible home bias. Third, a regression with all explanatory variables used in the analysis was run to check whether any results are subject to an omitted-variable bias which we could potentially control.

2.5.1 Recency Bias

Investors take general stock market conditions into account when making their investment decisions even if past returns do not predict future returns. For imputing future stock market performance using past data, an investor determines how much information to consider. Instead of taking into account only the previous day's return and volatility, Table 2.8 studies how the regressions change when these variables of the previous week and month are used. For returns, when each time period is tested individually, returns for the previous week and month follow the same trends as returns for the previous day, with the returns of the previous week being similarly powerful, while those of the previous month are notably less powerful. When all three time periods are tested together, the directions of the effects do not change, but only the past week's returns are statistically significant. Looking at the past week could be the right time interval to gauge the likelihood of a change when considering only returns. Meanwhile, for volatilities, when each time period is tested individually, the volatility for the previous day, week, and month all decrease the likelihood to raise one's risk profile. However, the relationship is not the same for lowering one's risk profile. Volatility from the previous day increases the likelihood to lower one's risk profile, but volatility from the previous month decreases the likelihood to lower one's risk profile, and volatility from the previous week is insignificant. In effect, the sign flips when going from daily to monthly volatilities. This interesting trend also holds when all three time periods are tested together. Thus, long-term (short-term) volatility tends to decrease (increase) the likelihood of lowering one's risk profile. Several frequencies are useful to gauge the non-linear effect of the volatility and its discrepancy regarding the likelihood of increasing or decreasing one's risk profile.

If one does go down this route of using past returns as indicative of future returns, then one day's worth of data would be a very small sample to extract information. Yet the results of the last coin flip reveal as much information about the results of the next toss as the results of any other prior flip. Likewise, any single day's worth of data about the stock market would be equally good at predicting the future as any other single day. However, if yesterday's returns and volatilities are more strongly correlated with a change in the risk profile, that would be evidence of a recency bias. Table 2.9 compares data from single days at various time lags to check for recency bias. For returns, when all three variables are tested separately, the results for the same day from the previous week are statistically significant and in the same directions as the trends for yesterday, but there are no statistically significant results for the same day from the previous month. This finding confirms that the previous week contains valuable information

from the investors' perspectives. However, when tested together, only the returns from yesterday are statistically significant. For volatilities, the results from the same day from the previous week are in the same directions as the trends for yesterday, though one drops out of statistical significance. Meanwhile, for the same day from the previous month, nothing is statistically significant, as with the returns. When day, week, and month are tested together, the volatility from yesterday is the most powerful and statistically significant. However, the volatility from the same day last week has a moderating effect for the probability to decrease one's risk profile.

2.5.2 Home Bias

The stock and bond ETFs which compose the available portfolios of Yomoni are themselves composed of global assets more accurately captured by the MSCI World index than the CAC 40 index. The CAC 40 is an index for French large-cap companies which may be particularly salient for French investors, though only a tiny fraction of the assets in the clients' real portfolios are invested in French companies. Meanwhile, the MSCI World is an index for large- and mid-cap companies across many developed markets, most notably the United States, and much more closely mirrors the asset distribution in the clients' real portfolios. Nevertheless, the CAC 40 and the MSCI World are highly correlated. In fact, they are so highly correlated that they cannot both be put in the same model due to multicollinearity.⁵ Table 2.10 performs a robustness test, substituting the CAC 40 for the MSCI World in the regression at various frequencies, to observe whether anything changes. The trends observed with the MSCI World are identical to those observed and described with the CAC 40.⁶ At the daily frequency, coefficient estimates have the same magnitude, whereas these magnitudes are large in absolute value at a weekly frequency. Results from the monthly frequency do not exhibit a clear pattern with respect to the estimated coefficients magnitude. Consequently, there is no evidence of a home bias to explain the likelihood of a change in one's risk profile. Savers may look at both CAC 40 and MSCI World, confirming that savers care about the global stock market environment. For simplicity and without loss of generality, we continue to use the CAC 40 variables in the rest of the analysis.

2.5.3 Omitted-Variable Bias

A step-by-step approach has been followed to present the empirical results, but one may wonder whether coefficient estimates remain stable when all covariates are used in the regression. Table 2.11 answers this question by combining all the explanatory variables studied in the aforementioned tables into one single table (with the exception of MSCI World variables to avoid multicollinearity, and the

⁵In our sample, CAC 40 and MSCI World are correlated at 75.10%, 87.07%, and 89.30% at the daily, weekly and monthly frequency, respectively.

⁶The signs associated with the baseline covariates are identical to those reported in Tables 2.4 and 2.8.

alternative lags used in Table 2.9). Though additional questions about employment, sector, and marital status are included in the questionnaire, these variables are not included in this final table.⁷ Patterns previously described remain broadly consistent, meaning that there is no omitted-variable bias. There are a few exceptions. Some significance levels are stronger, such as the Modified Dietz performance and the First Covid-19 lockdown. The first lockdown period has a significant and positive impact on the likelihood of reducing one's risk profile, which is more in line with the common expectation that savers decrease their risk profile to be less exposed to a downward trend in the stock market. Meanwhile, some covariates are less significant, such as sex, and others even lose their significance, such as financial literacy.

Results regarding market conditions captured by the CAC 40 index are still significant, confirming that the weekly past returns have greater impact compared to the other frequencies. Whatever the frequency, the impact is negative on the likelihood of a downward change in the risk profile, whereas the impact is positive on the likelihood of making an upward movement. In contrast, the volatility impact is stronger and significant at the higher frequency (daily), and the negative impact of the monthly past volatility on the likelihood of decreasing its risk profile remains true, meaning that a higher volatility over the last month counterbalances the impact of a higher volatility observed the day before. While the negative impact of the account volatility from the opening of an account to the day before the change is clearly stated, the consequence of the volatility observed on the financial market is ambivalent. On the one hand, one may say that the adage higher volatility means higher returns holds at the monthly frequency, since savers are more keen to increase their risk profiles (or at least not reduce them) to increase their likelihood of having higher return. On the other hand, an increase of the volatility in the short-run could be associated with the start of a period of turmoil, and so savers are more keen to reduce their risk-taking by lowering their risk profile, since the likelihood of making a downward (upward) change increases (decreases).

2.5.4 Learning

Are investors changing their risk profiles because they are simply learning their "true" risk preferences over time? Given the learning opportunities investors have prior to opening their account, this explanation seems unlikely. Investors can freely observe over a hundred years of past market trends and see that financial markets have both ups and downs. The introductory survey tests potential investors on their understanding that higher returns imply higher risk. What's more, investors can use the robo-advisor's forecasting tool to model the potential gains and losses of their specific investment associated with each

⁷These tables are available upon request; they are simply not reported. These variables have dozens of levels, of which nearly all were not statistically significant.

risk profile, which includes both optimistic and pessimistic forecasts. Therefore, investors should have a very good understanding of their "true" risk profile before making their initial investment. However, as Julius Caesar once wrote, experience is the best teacher. Perhaps retail investors need the shock of seeing their own portfolios increase or decrease in value to make these lessons concrete. What can our data say about learning?

Granted that our data is not capable of confirming what is truly happening in the heads of the investors, we can exploit data about how investors decide their initial investment to give us a clue. Figure 2.2 elucidates the general trend: the half of clients who do not accept the initial risk profile recommendation make fewer changes than the half of clients who do. In other words, to the extent that the investors are learning their true risk profile, they do so at the very beginning of the investment contract using the information and the forecasting tool that are available to them.

2.6 Is it worth it to change risk profile?

The identikit picture of investors making a change in their risk profile has been drawn in the previous sections. Additional descriptive statistics about the number of investors and the number of *Higher* and *Lower* changes they made are available in Table 2.2. Overall, *Higher* changes are more common than *Lower* changes. For example, 77.83% of investors who only make one change to their account make a *Higher* change, i.e., they rebalance their portfolio to be more aggressive. Yet, *Lower* changes are significantly larger in absolute value (-3.71) than *Higher* changes (2.38).⁸ In other words, while changes which increase one's risk profile (and thus market exposure) are more common, changes which decrease one's risk profile are more severe. For example, among those investors who made only one change to their portfolio, if this change increased their risk profile then the average increase was 2.17, whereas if this change decreased their risk profile then the average decrease was -3.56.

Savers' characteristics, type of investment project and stock market conditions are key to explain why savers change their risk profile. However, savers' expectations about the goal of such a change in risk profile must be discussed. While the results highlight that investors want to safeguard their investment from financial turmoils since lower past returns tend to increase the likelihood of reducing risk profile, one may wonder whether savers are able to time the market and enjoy upward trend in the stock financial market. In this section, two exercises are run to gauge the ability of changers to earn more money by being active in their portfolio management: the realized returns analysis, in which we constrain the dataset to the 540 closed accounts, and the counterfactual analysis, in which we also compare accounts open at the

⁸On average, the magnitude of *Lower* changes is equal to 3.71 with a standard deviation of 2.31, whereas the magnitude of *Higher* changes is equal to 2.38 with a standard deviation of 1.74. The Welch Two Sample t-test used to check the equality between the two coefficients is equal to 26.84 in absolute value corresponding to a p-value smaller than 1%.

end of the period. While each of these methodologies will be detailed in their respective sections, Figure 2.3 provides a clarifying visual summary.

2.6.1 A Counterfactual Analysis

To evaluate the ability of savers to earn more money by modifying their risk profile through time, a counterfactual is built for each of the 6,637 accounts (one client can hold multiple accounts) with at least one change in risk profile through the holding period. This counterfactual corresponds to the hypothetical value of the account if the selected risk profile since the opening of the account is kept constant until the closure or the end of the sample period (in April 2022). In these hypothetical accounts, the same deposits, withdrawals, and fees are applied. Next, the level of each counterfactual account is compared to the true level of its associated account. If the real account outperforms the hypothetical account, then actively managing the passive account was worth it. In other words, we are verifying whether the managed account outperforms its counterfactual account in which there was no modification of the risk profile.

Figure 2.4 summarizes this information through time by counting at a daily basis the percentage of investment accounts which changed their risk profile at least once (reprofiling accounts) and with a higher balance than they would have without adjustment of their risk profile (counterfactual accounts). When the percentage is larger than 50%, on average reprofiling accounts outperform their associated counterfactual accounts.⁹ Over the period, reprofiling accounts tend to outperform their associated counterfactual accounts, and by a significant fraction. Indeed, shaded areas show periods in which there is a significant gain or loss associated to reprofiling accounts. The range of this percentage goes from 29.38% to 76.94% in March 25, 2018, and January 23, 2018, respectively. While this ratio is highly volatile at the beginning of the period, its volatility shrinks through time. In addition, this percentage exhibits an upward trend starting at the end of March, 2020, and ending at the end of 2021. This rise is concomitant to an appreciation of the CAC 40 of 38.42% over this period.¹⁰ In others words, reprofiling accounts which changed their risk profile to a higher risk profile during this period enjoyed a higher return than what they otherwise would have had when maintaining their risk profile.

Figure 2.4 shows that on average changers earned more money than they would have without modifying their risk profile, suggesting that these investors were able to time the market. However, these gains are only hypothetical, since most of the changers still have their account open at the end of the sample period. To realize the returns, the account would need to be closed.

⁹This performance does not consider the relative level of risk taken by the managed account when modifying its risk profile.

¹⁰Over the full studied period, the correlation between the CAC 40 index and the percentage of reprofiling accounts with a higher balance than their counterfactual accounts is equal to 65.98%.

2.6.2 A Study based on Realized Returns

To investigate realized (as opposed to latent) profits and losses made by changers, a focus on reprofiling accounts with a date of closure before the end of the sample is done. Already a minority of accounts change their risk profile, and even fewer close their account. As such, only 540 reprofiling accounts for which the risk profile was only once modified could be included in this analysis. Among these 540 reprofiling accounts, 280 accounts have a balance at the closing date larger than the balance of their counterfactual account. This 51.85% of reprofiling accounts with a higher balance is not significantly different from 50%. Individual modified Dietz of both managed or counterfactual accounts is computed; on average the difference between these two returns is equal to 23 basis points. In other words, the average additional realized gain obtained by savers managing their risk profile is quite low. In addition, the t-statistic used to determine whether this amount is equal to zero leads to the non-rejection of this hypothesis. Thus, on average the realized gain observed in reprofiling accounts is not significantly different from zero.

Studying these closed reprofiling accounts highlights that hypothetical profits and losses are not systematically converted into realized additional returns. While Figure 2.4 shows that changers track the upward trend in financial market, their ability to react timely by lowering their risk profile in period of turmoils is not demonstrated. It is likely that only a weak proportion of changers have the ability to do so. In contrast, focusing on managed account which are closed may also damper the ability of the savers to time the market, by construction. Indeed, the closure of an account is not only determined by the investor's wish to protect their gains or to limit their losses, but also by outside factors such as an investor's liquidity needs.

2.7 Conclusion

Portfolios are dynamic objects which change throughout an investor's lifespan due to the various adjustments that he or she makes. The results of this paper show that the literature's findings on general risk preferences do not extend directly into tendencies to adjust portfolio composition to be more or less risky. It is more nuanced. Some risk-related variables map onto portfolio adjustment exactly as one would predict, such as investor age, for which older clients are more likely to decrease their risk and less likely to increase their risk with respect to younger clients. But other risk-related variables simply make changes more likely in any direction, such as investment horizon, for which accounts with longer investment horizons are both more likely to decrease their risk *and* more likely to increase their risk with respect to accounts with shorter investment horizons. Still other risk-related variables surprisingly have no relationship with portfolio adjustment at all, such as investor income. Further research should conceptualize portfolios as flexible over long periods of time and conduct tests as to what extent previous

findings on static portfolios (such as risk preferences) also apply to dynamic portfolios.

Recent market returns and volatility impact not just institutional and short-term investors. Our results show that the transient ups and downs of the market also influence the long-term portfolio allocations of retail investors. This result in particular has important implications for practitioners. Capital markets will continue to have their ups and downs. If a client wishes to make a significant change in their portfolio allocation, then instead of simply approving the change immediately, financial advisors might find it within their mandate to question whether this adjustment is motivated by a change in life circumstances and investment goals or merely by recent market turbulence. In the case of the latter, while not constraining their clients' options, financial advisors should be prepared to offer sound and goal-oriented investment advice to panicked or overzealous clients. Similarly, online platforms may see fit to remind clients of their long-term goals in periods of high market volatility.

Robo-advisors have been widely studied for their capacity to limit the influence of psychological biases in investment decisions, both those of advisors and those of clients. We find evidence that the clients in our sample showed a recency bias, but not a home bias. To the extent that eliminating psychological biases from decisions about portfolio allocations is a worthy goal, more research about how this can be done in practice is needed.

Typically, investors who make more trades fare worse than their less active peers due to transaction fees, inefficient capital allocations, etc. Our results did not confirm that investors who changed their portfolio allocations underperformed in terms of realized gains; but neither did they outperform. On the other hand, the counterfactual analysis, which compares each changer to a hypothetical self who stayed, indicated that accounts which did change their risk profile on average outperformed those accounts which did not. Taken together, these results are encouraging for the actively passive investors.

Stock market participation continues to rise throughout the world and passively managed financial technologies continue to attract new clients. The number of "actively passive" investors who manage their "lazy" investments will only grow. More research should study this new type of household investor. They may one day be the majority.

Table 2.2: **Summary statistics on the number of investors making risk profile changes.**

Number of investors who made 1, 2, 3, etc. changes and the mean magnitude in terms of risk profile of each of their changes. Changes which increase risk profile (*Higher*) are more common than changes which decrease risk profile (*Lower*). However, changes which decrease risk profile are larger in absolute value ($M = 3.71$, $SD = 2.31$) than changes which increase risk profile ($M = 2.38$, $SD = 1.75$), $t(4049.1) = -26.84$, $p < .001$.

Number of Changes	Number of Investors	Total Changes	<i>Higher</i> Changes	<i>Lower</i> Changes	Percent <i>Higher</i>	Percent <i>Lower</i>	Mean <i>Higher</i>	Mean <i>Lower</i>
1	4596	4596	3577	1019	77.83%	22.17%	2.17	-3.56
2	1070	2140	1463	677	68.36%	31.64%	2.55	-3.90
3	286	858	524	334	61.07%	38.93%	2.60	-3.73
4	144	576	353	223	61.28%	38.72%	2.88	-3.89
5	60	300	181	119	60.33%	39.67%	2.62	-3.82
6	31	186	117	69	62.90%	37.10%	2.74	-4.06
7	15	105	60	45	57.14%	42.86%	3.27	-4.27
8	16	128	80	48	62.50%	37.50%	2.75	-4.08
9	10	90	46	44	51.11%	48.89%	2.48	-2.75
10+	19	271	147	124	54.24%	45.76%	2.59	-3.13

2.8 Tables

Table 2.1: **Summary statistics on the number of risk profile changes.**

Number of risk profile changes by magnitude and by year. The 0 column corresponds to matched pair control subjects, i.e., clients who did not change their risk profile but are otherwise very similar to those clients who did.

Year	-9	-8	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7	8	9	Sum
2016		1	1	1	1	1	3	11	22	101	30	16	11	1		2				202
2017	3	1	1	8	6	12	9	30	35	481	126	150	52	21	14	2	8	1	2	962
2018	10	13	23	18	19	32	47	64	62	577	105	86	40	29	10	5	10	1	3	1154
2019	25	19	51	25	45	52	49	91	67	841	143	139	65	30	12	13	3	4	8	1682
2020	39	34	57	56	75	89	74	116	91	1995	447	378	183	114	71	49	58	21	43	3990
2021		62	32	66	73	94	113	159	149	3887	1347	948	365	201	122	57	47	35	17	7774
2022		34	14	40	49	58	81	97	92	1368	339	267	90	76	53	24	13	31	10	2736
Sum	77	164	179	214	268	338	376	568	518	9250	2537	1984	806	472	282	152	139	93	83	18500

Table 2.3: **Descriptive statistics on changers and stayers**

	Changers Mean	Changers SD	Stayers Mean	Stayers SD
Horizon	10.8606	6.4677	10.5406	5.3721
Liquidity Q1 Two years	3.3695	0.6242	3.4255	0.5546
Liquidity Q2 Half of deposit	3.0735	0.6434	3.1282	0.5724
Sex	0.7877	0.4089	0.7890	0.4080
Age at subscription	33.1823	14.0474	33.4335	14.0132
Number of children	0.7157	0.9736	0.8092	1.0069
Annual income	2.7167	1.0099	2.7608	0.9051
Financial literacy	2.5499	0.6546	2.5689	0.6417
Risk Q1 Five year gamble	1.9184	1.0853	1.8627	1.0450
Risk Q2 Ten year gamble	3.2913	0.8493	3.3583	0.7640
Risk Q3 Buy when market dips	2.7565	0.9949	2.8417	0.8994
Risk Q4 Experienced losses	4.1125	0.6491	4.1197	0.5321
Financial wealth	168462	410840	154791	349976
Property assets	211925	357432	212773	332532
Home owner	0.5267	0.4993	0.5673	0.4955
Initial deposit	8530	45240	7324	24778
RP Recommended	6.4545	2.0826	6.9625	1.8217
RP Selected	6.0866	2.2270	6.8777	2.0524

Table 2.4: **Baseline regressions.**

This table reports estimated coefficients and standard errors (in parentheses) from the multinomial logit model explaining both downward and upward risk profile changes (the absence of change is the reference modality, i.e. *Equal*) on two alternative sets of explanatory variables. The first regression is estimated with the baseline set of covariates, whereas variables related to the CAC 40 are added in the second regression. Explanatory variables are described in 1.7. ***, **, * indicate that the coefficient is statistically significant at the 1%, 5% and 10% confidence level, respectively.

	<i>Dependent variable: $y=\{Lower; Equal; Higher\}$</i>			
	(1)		(2)	
	y:Lower	y:Higher	y:Lower	y:Higher
CAC 40 daily return (yesterday)			-5.759*** (1.347)	4.305*** (1.373)
CAC 40 daily volatility (yesterday)			0.835*** (0.104)	-0.923*** (0.110)
Horizon	0.016*** (0.004)	0.044*** (0.003)	0.016*** (0.004)	0.044*** (0.003)
Liquidity Q1 Two years	-0.126** (0.049)	-0.018 (0.038)	-0.123** (0.050)	-0.018 (0.038)
Liquidity Q2 Half of deposit	-0.027 (0.046)	0.026 (0.035)	-0.023 (0.046)	0.019 (0.036)
Sex (male)	-0.159*** (0.057)	0.124*** (0.045)	-0.159*** (0.057)	0.122*** (0.045)
Age	0.012*** (0.002)	-0.007*** (0.001)	0.012*** (0.002)	-0.007*** (0.001)
Number of children	-0.031 (0.023)	-0.133*** (0.019)	-0.025 (0.023)	-0.134*** (0.019)
Annual income	0.0001 (0.025)	-0.020 (0.020)	-0.007 (0.025)	-0.017 (0.020)
Financial literacy	-0.045 (0.037)	-0.056** (0.028)	-0.039 (0.037)	-0.058** (0.028)
Risk Q1 Experienced losses	0.227*** (0.021)	0.076*** (0.018)	0.232*** (0.022)	0.075*** (0.018)
Risk Q2 Five-year gamble	-0.093** (0.038)	0.214*** (0.028)	-0.087** (0.038)	0.211*** (0.028)
Risk Q3 Ten-year gamble	0.078** (0.036)	0.324*** (0.027)	0.078** (0.036)	0.326*** (0.027)
Risk Q4 Buy when market dips	-0.056 (0.038)	0.129*** (0.030)	-0.054 (0.038)	0.127*** (0.031)
Time between account opening and risk profile change	0.078*** (0.017)	-0.037** (0.015)	0.072*** (0.017)	-0.031** (0.015)
Client did not select the recommended risk profile	0.234*** (0.046)	-0.091** (0.038)	0.234*** (0.047)	-0.091** (0.039)
Risk profile prior to change	0.034** (0.015)	-0.508*** (0.012)	0.036** (0.015)	-0.512*** (0.012)
Intercept	-1.605*** (0.225)	0.530*** (0.176)	-1.884*** (0.229)	0.761*** (0.179)
Observations	18,500		18,500	
Log Likelihood	-16,648.330		-16,495.620	

Table 2.5: **Investment project.**

This table reports estimated coefficients and standard errors (in parentheses) from the multinomial logit model explaining both downward and upward risk profile changes (the absence of change is the reference modality, i.e. *Equal*) on a set of explanatory variables with the baseline covariates, the CAC 40 variables and the type of investment project. The project "Grow my savings" is used as reference and is captured by the intercept. Explanatory variables are described in 1.7. ***, **, * indicate that the coefficient is statistically significant at the 1%, 5% and 10% confidence level, respectively.

	<i>Dependent variable:</i>	
	<i>y={Lower; Equal; Higher}</i>	
	y:Lower	y:Higher
Investment project:	0.083	-0.241***
Save in the event of hard times	(0.085)	(0.076)
Investment project:	0.572***	0.384***
Prepare a major purchase	(0.091)	(0.070)
Investment project:	-0.030	-0.572***
Open an account for my child	(0.111)	(0.091)
Investment project:	-0.063	-0.178**
Plan my retirement	(0.087)	(0.074)
Investment project:	-0.123	-0.684***
Bequeath an inheritance	(0.143)	(0.138)
CAC 40 daily return (yesterday)	-5.666***	4.300***
	(1.357)	(1.393)
CAC 40 daily volatility (yesterday)	0.826***	-0.930***
	(0.105)	(0.112)
Horizon	0.021***	0.052***
	(0.004)	(0.003)
Liquidity Q1 Two years	-0.112**	0.007
	(0.050)	(0.039)
Liquidity Q2 Half of deposit	-0.007	0.059
	(0.047)	(0.036)
Sex (male)	-0.176***	0.063
	(0.058)	(0.047)
Age	0.013***	-0.010***
	(0.002)	(0.002)
Number of children	-0.012	-0.079***
	(0.025)	(0.021)
Annual income	-0.008	-0.013
	(0.026)	(0.021)
Financial literacy	-0.032	-0.055*
	(0.037)	(0.028)
Risk Q1 Experienced losses	0.231***	0.095***
	(0.022)	(0.019)
Risk Q2 Five-year gamble	-0.088**	0.211***
	(0.038)	(0.029)
Risk Q3 Ten-year gamble	0.080**	0.317***
	(0.036)	(0.027)
Risk Q4 Buy when market dips	-0.050	0.114***
	(0.039)	(0.031)
Time between account opening and risk profile change	0.064***	-0.025
	(0.018)	(0.016)
Client did not select the recommended risk profile	0.233***	-0.083**
	(0.047)	(0.039)
Risk profile prior to change	0.034**	-0.516***
	(0.01569)	(0.01227)
Intercept	-2.089***	0.691***
	(0.236)	(0.186)
Observations	18,500	
Log Likelihood	-16,188.91	

Table 2.6: **Portfolio characteristics.**

This table reports estimated coefficients and standard errors (in parentheses) from the multinomial logit model explaining both downward and upward risk profile changes (the absence of change is the reference modality, i.e. *Equal*) on a set of explanatory variables with the baseline covariates, the CAC 40 variables and portfolio characteristics. Explanatory variables are described in 1.7. ***, **, * indicate that the coefficient is statistically significant at the 1%, 5% and 10% confidence level, respectively.

	Dependent variable:	
	y:Lower	y:Higher
Deposited or withdrew money	0.047 (0.047)	-0.018 (0.044)
Total value of the account	0.055*** (0.008)	0.058*** (0.007)
Modified Dietz performance	-0.496* (0.260)	0.726** (0.287)
Account volatility	-5.471*** (0.593)	-2.855*** (0.523)
Days with negative returns	-0.004*** (0.0003)	-0.003*** (0.0003)
Days with positive returns	-0.002*** (0.0003)	-0.002*** (0.0003)
CAC 40 daily return (yesterday)	-4.852*** (1.384)	4.995*** (1.393)
CAC 40 daily volatility (yesterday)	1.065*** (0.112)	-0.716*** (0.116)
Horizon	0.017*** (0.004)	0.045*** (0.003)
Liquidity Q1 Two years	-0.110** (0.050)	-0.012 (0.038)
Liquidity Q2 Half of deposit	-0.006 (0.047)	0.036 (0.036)
Sex (male)	-0.153*** (0.058)	0.130*** (0.046)
Age	0.009*** (0.002)	-0.009*** (0.001)
Number of children	-0.018 (0.024)	-0.129*** (0.020)
Annual income	-0.015 (0.026)	-0.031 (0.021)
Financial literacy	-0.026 (0.038)	-0.054* (0.028)
Risk Q1 Experienced losses	0.217*** (0.022)	0.066*** (0.019)
Risk Q2 Five-year gamble	-0.066* (0.039)	0.216*** (0.029)
Risk Q3 Ten-year gamble	0.094*** (0.036)	0.326*** (0.027)
Risk Q4 Buy when market dips	-0.030 (0.039)	0.134*** (0.031)
Time between account opening and risk profile change	1.158*** (0.086)	0.943*** (0.080)
Client did not select the recommended risk profile	0.232*** (0.047)	-0.096** (0.039)
Risk profile prior to change	0.124*** (0.017)	-0.468*** (0.013)
Intercept	-2.508*** (0.237)	0.529*** (0.184)
Observations	18,500	
Log Likelihood	-16,167.99	

Table 2.7: **ESG and Lockdown.**

This table reports estimated coefficients and standard errors (in parentheses) from the multinomial logit model explaining both downward and upward risk profile changes (the absence of change is the reference modality, i.e. *Equal*) on a set of explanatory variables with the baseline covariates, the CAC 40 variables, the decision to change to or from an ESG portfolio, and investor behavior during the three Covid-19 lockdowns in France. Explanatory variables are described in 1.7. ***, **, * indicate that the coefficient is statistically significant at the 1%, 5% and 10% confidence level, respectively.

	Dependent variable: $y=\{Lower; Equal; Higher\}$			
	(1)		(2)	
	y:Lower	y:Higher	y:Lower	y:Higher
From ESG to non-ESG	-1.778*** (0.198)	-1.699*** (0.181)		
From non-ESG to ESG	2.690*** (0.181)	2.595*** (0.171)		
First Covid-19 Lockdown			-0.239* (0.127)	0.043 (0.111)
Second Covid-19 Lockdown			-0.910*** (0.225)	0.020 (0.123)
Third Covid-19 Lockdown			-0.474*** (0.144)	0.201** (0.087)
CAC 40 daily return (yesterday)	-5.758*** (1.356)	4.314*** (1.385)	-4.677*** (1.395)	4.104*** (1.398)
CAC 40 daily volatility (yesterday)	0.880*** (0.105)	-0.896*** (0.111)	0.908*** (0.113)	-0.913*** (0.120)
Horizon	0.016*** (0.004)	0.044*** (0.003)	0.017*** (0.004)	0.044*** (0.003)
Liquidity Q1 Two years	-0.132*** (0.050)	-0.024 (0.038)	-0.123** (0.050)	-0.017 (0.038)
Liquidity Q2 Half of deposit	0.007 (0.047)	0.045 (0.036)	-0.019 (0.047)	0.018 (0.036)
Sex (male)	-0.114** (0.058)	0.169*** (0.046)	-0.156*** (0.057)	0.124*** (0.045)
Age	0.012*** (0.002)	-0.007*** (0.001)	0.012*** (0.002)	-0.007*** (0.001)
Number of children	-0.032 (0.024)	-0.140*** (0.020)	-0.025 (0.023)	-0.134*** (0.019)
Annual income	-0.001 (0.026)	-0.012 (0.020)	-0.009 (0.025)	-0.017 (0.020)
Financial literacy	-0.034 (0.037)	-0.053* (0.028)	-0.037 (0.037)	-0.058** (0.028)
Risk Q1 Experienced losses	0.237*** (0.022)	0.077*** (0.018)	0.233*** (0.022)	0.076*** (0.018)
Risk Q2 Five-year gamble	-0.080** (0.038)	0.212*** (0.029)	-0.085** (0.038)	0.211*** (0.028)
Risk Q3 Ten-year gamble	0.092** (0.036)	0.335*** (0.027)	0.076** (0.036)	0.327*** (0.027)
Risk Q4 Buy when market dips	-0.060 (0.039)	0.122*** (0.031)	-0.054 (0.038)	0.126*** (0.031)
Time between account opening and risk profile change	0.072*** (0.017)	-0.030** (0.015)	0.073*** (0.017)	-0.032** (0.015)
Client did not select the recommended risk profile	0.239*** (0.047)	-0.087** (0.039)	0.235*** (0.047)	-0.091** (0.039)
Risk profile prior to change	0.031** (0.016)	-0.516*** (0.012)	0.035** (0.015)	-0.512*** (0.012)
Intercept	-2.128*** (0.232)	0.550*** (0.181)	-1.882*** (0.230)	0.753*** (0.179)
Observations	18,500		18,500	
Log Likelihood	-16,204.66		-16,471.90	

Table 2.8: **Frequency variations.**

This table reports estimated coefficients and standard errors (in parentheses) from the multinomial logit model explaining both downward and upward risk profile changes (the absence of change is the reference modality, i.e. *Equal*) on a set of explanatory variables with the baseline covariates and the CAC 40 variables with varying periods of prior returns and volatilities which investors may take into account when making their investment decisions. Explanatory variables are described in 1.7. ***, **, * indicate that the coefficient is statistically significant at the 1%, 5% and 10% confidence level, respectively.

	Dependent variable: $y=\{Lower; Equal; Higher\}$					
	(1)		(2)		(3)	
	y:Lower	y:Higher	y:Lower	y:Higher	y:Lower	y:Higher
CAC 40 daily return (yesterday)					-0.704 (1.556)	1.266 (1.562)
CAC 40 weekly return (last week)	-6.653*** (0.643)	3.705*** (0.552)			-4.212*** (0.926)	2.988*** (0.742)
CAC 40 monthly return (last month)			-3.966*** (0.372)	1.878*** (0.307)	-0.980* (0.523)	0.232 (0.401)
CAC 40 daily volatility (yesterday)					0.515** (0.211)	-0.509*** (0.188)
CAC 40 weekly volatility (last week)	0.101 (0.168)	-0.867*** (0.137)			-0.082 (0.317)	-0.252 (0.255)
CAC 40 monthly volatility (last month)			-0.878*** (0.229)	-0.430** (0.168)	-0.741** (0.334)	-0.165 (0.257)
Horizon	0.017*** (0.004)	0.044*** (0.003)	0.017*** (0.004)	0.044*** (0.003)	0.017*** (0.004)	0.044*** (0.003)
Liquidity Q1 Two years	-0.120** (0.050)	-0.015 (0.038)	-0.123** (0.049)	-0.013 (0.038)	-0.119** (0.050)	-0.016 (0.038)
Liquidity Q2 Half of deposit	-0.023 (0.046)	0.016 (0.036)	-0.026 (0.046)	0.019 (0.036)	-0.025 (0.047)	0.015 (0.036)
Sex (male)	-0.164*** (0.057)	0.123*** (0.045)	-0.161*** (0.057)	0.125*** (0.045)	-0.163*** (0.057)	0.124*** (0.045)
Age	0.012*** (0.002)	-0.007*** (0.001)	0.012*** (0.002)	-0.007*** (0.001)	0.012*** (0.002)	-0.007*** (0.001)
Number of children	-0.025 (0.023)	-0.134*** (0.019)	-0.024 (0.023)	-0.135*** (0.019)	-0.024 (0.023)	-0.134*** (0.019)
Annual income	-0.006 (0.025)	-0.019 (0.020)	-0.006 (0.025)	-0.018 (0.020)	-0.009 (0.025)	-0.018 (0.020)
Financial literacy	-0.031 (0.037)	-0.060** (0.028)	-0.038 (0.037)	-0.058** (0.028)	-0.030 (0.037)	-0.061** (0.028)
Risk Q1 Experienced losses	0.232*** (0.022)	0.078*** (0.018)	0.231*** (0.022)	0.075*** (0.018)	0.234*** (0.022)	0.077*** (0.018)
Risk Q2 Five-year gamble	-0.090** (0.038)	0.211*** (0.028)	-0.088** (0.038)	0.211*** (0.028)	-0.088** (0.038)	0.210*** (0.028)
Risk Q3 Ten-year gamble	0.078** (0.036)	0.327*** (0.027)	0.078** (0.036)	0.329*** (0.027)	0.080** (0.036)	0.328*** (0.027)
Risk Q4 Buy when market dips	-0.048 (0.038)	0.126*** (0.031)	-0.046 (0.038)	0.125*** (0.031)	-0.047 (0.038)	0.125*** (0.031)
Time between account opening and risk profile change	0.073*** (0.017)	-0.030** (0.015)	0.079*** (0.017)	-0.034** (0.015)	0.074*** (0.017)	-0.030** (0.015)
Client did not select the recommended risk profile	0.232*** (0.047)	-0.091** (0.039)	0.232*** (0.047)	-0.094** (0.039)	0.232*** (0.047)	-0.091** (0.039)
Risk profile prior to change	0.036** (0.015)	-0.512*** (0.012)	0.035** (0.015)	-0.512*** (0.012)	0.036** (0.015)	-0.512*** (0.012)
Intercept	-1.768*** (0.229)	0.710*** (0.178)	-1.543*** (0.230)	0.627*** (0.179)	-1.725*** (0.232)	0.751*** (0.180)
Observations	18,500		18,500		18,500	
Log Likelihood	-16,460.39		-16,520.65		-16,444.31	

Table 2.9: **Lag variations.**

This table reports estimated coefficients and standard errors (in parentheses) from the multinomial logit model explaining both downward and upward risk profile changes (the absence of change is the reference modality, i.e. *Equal*) on a set of explanatory variables with the baseline covariates and the CAC 40 variables with prior returns and volatilities at various time lags which investors may take into account when making their investment decisions. Explanatory variables are described in 1.7. ***, **, * indicate that the coefficient is statistically significant at the 1%, 5% and 10% confidence level, respectively.

	Dependent variable: $y=\{Lower; Equal; Higher\}$					
	(1)		(2)		(3)	
	y:Lower	y:Higher	y:Lower	y:Higher	y:Lower	y:Higher
CAC 40 daily return (yesterday)					-4.785*** (1.393)	4.046*** (1.408)
CAC 40 daily return (this day last week)	-6.824*** (1.588)	3.701*** (1.349)			-2.659 (1.650)	1.689 (1.391)
CAC 40 daily return (this day last month)			-0.952 (1.830)	0.048 (1.421)	-1.060 (1.853)	0.057 (1.421)
CAC 40 daily volatility (yesterday)					0.997*** (0.134)	-0.931*** (0.138)
CAC 40 daily volatility (this day last week)	0.222* (0.133)	-0.465*** (0.115)			-0.403** (0.169)	0.056 (0.142)
CAC 40 daily volatility (this day last month)			-0.265* (0.152)	-0.170 (0.116)	-0.278* (0.155)	-0.024 (0.121)
Horizon	0.017*** (0.004)	0.044*** (0.003)	0.016*** (0.004)	0.044*** (0.003)	0.016*** (0.004)	0.044*** (0.003)
Liquidity Q1 Two years	-0.128*** (0.049)	-0.015 (0.038)	-0.126** (0.049)	-0.018 (0.038)	-0.121** (0.050)	-0.018 (0.038)
Liquidity Q2 Half of deposit	-0.024 (0.046)	0.022 (0.035)	-0.027 (0.046)	0.025 (0.035)	-0.024 (0.046)	0.018 (0.036)
Sex (male)	-0.161*** (0.057)	0.123*** (0.045)	-0.159*** (0.057)	0.124*** (0.045)	-0.162*** (0.057)	0.123*** (0.045)
Age	0.012*** (0.002)	-0.007*** (0.001)	0.012*** (0.002)	-0.007*** (0.001)	0.012*** (0.002)	-0.007*** (0.001)
Number of children	-0.030 (0.023)	-0.133*** (0.019)	-0.031 (0.023)	-0.132*** (0.019)	-0.025 (0.023)	-0.134*** (0.019)
Annual income	-0.001 (0.025)	-0.019 (0.020)	0.0001 (0.025)	-0.020 (0.020)	-0.008 (0.025)	-0.017 (0.020)
Financial literacy	-0.045 (0.037)	-0.054* (0.028)	-0.045 (0.037)	-0.056** (0.028)	-0.035 (0.037)	-0.058** (0.028)
Risk Q1 Experienced losses	0.228*** (0.022)	0.075*** (0.018)	0.226*** (0.022)	0.076*** (0.018)	0.233*** (0.022)	0.075*** (0.018)
Risk Q2 Five-year gamble	-0.092** (0.038)	0.213*** (0.028)	-0.092** (0.038)	0.214*** (0.028)	-0.087** (0.038)	0.211*** (0.028)
Risk Q3 Ten-year gamble	0.079** (0.036)	0.326*** (0.027)	0.079** (0.036)	0.325*** (0.027)	0.080** (0.036)	0.326*** (0.027)
Risk Q4 Buy when market dips	-0.055 (0.038)	0.129*** (0.031)	-0.055 (0.038)	0.130*** (0.030)	-0.052 (0.038)	0.127*** (0.031)
Time between account opening and risk profile change	0.078*** (0.017)	-0.035** (0.015)	0.079*** (0.017)	-0.037** (0.015)	0.072*** (0.017)	-0.031** (0.015)
Client did not select the recommended risk profile	0.232*** (0.046)	-0.092** (0.038)	0.235*** (0.046)	-0.091** (0.038)	0.236*** (0.047)	-0.091** (0.039)
Risk profile prior to change	0.035** (0.015)	-0.511*** (0.012)	0.034** (0.015)	-0.508*** (0.012)	0.036** (0.015)	-0.511*** (0.012)
Intercept	-1.683*** (0.227)	0.629*** (0.178)	-1.556*** (0.227)	0.561*** (0.178)	-1.806*** (0.230)	0.757*** (0.180)
Observations	18,500		18,500		18,500	
Log Likelihood	-16,609.45		-16,646.13		-16,486.90	

Table 2.10: **Frequency variations with MSCI.**

This table reports estimated coefficients and standard errors (in parentheses) from the multinomial logit model explaining both downward and upward risk profile changes (the absence of change is the reference modality, i.e. *Equal*) on a set of explanatory variables with the baseline covariates and the MCSI World variables with varying periods of prior returns and volatilities which investors may take into account when making their investment decisions. Explanatory variables are described in 1.7. ***, **, * indicate that the coefficient is statistically significant at the 1%, 5% and 10% confidence level, respectively.

	Dependent variable: $y=\{Lower; Equal; Higher\}$					
	(1)		(2)		(3)	
	y:Lower	y:Higher	y:Lower	y:Higher	y:Lower	y:Higher
MSCI World return (yesterday)	-4.513*** (1.572)	5.008*** (1.625)				
MSCI World return (last week)			-9.097*** (0.836)	4.702*** (0.700)		
MSCI World return (last month)					-4.664*** (0.473)	2.083*** (0.378)
MSCI World volatility (yesterday)	0.826*** (0.104)	-0.994*** (0.112)				
MSCI World volatility (last week)			-0.014 (0.169)	-0.958*** (0.158)		
MSCI World volatility (last month)					-0.626** (0.248)	-0.636*** (0.194)
Horizon	0.016*** (0.004)	0.044*** (0.003)	0.017*** (0.004)	0.044*** (0.003)	0.017*** (0.004)	0.044*** (0.003)
Liquidity Q1 Two years	-0.126** (0.049)	-0.016 (0.038)	-0.120** (0.050)	-0.018 (0.038)	-0.122** (0.049)	-0.014 (0.038)
Liquidity Q2 Half of deposit	-0.025 (0.046)	0.019 (0.036)	-0.020 (0.047)	0.018 (0.036)	-0.022 (0.046)	0.018 (0.036)
Sex (male)	-0.160*** (0.057)	0.123*** (0.045)	-0.158*** (0.057)	0.123*** (0.045)	-0.153*** (0.057)	0.122*** (0.045)
Age	0.012*** (0.002)	-0.007*** (0.001)	0.012*** (0.002)	-0.007*** (0.001)	0.012*** (0.002)	-0.007*** (0.001)
Number of children	-0.027 (0.023)	-0.134*** (0.019)	-0.027 (0.023)	-0.133*** (0.019)	-0.024 (0.023)	-0.135*** (0.019)
Annual income	-0.003 (0.025)	-0.019 (0.020)	-0.005 (0.025)	-0.018 (0.020)	-0.003 (0.025)	-0.019 (0.020)
Financial literacy	-0.041 (0.037)	-0.058** (0.028)	-0.028 (0.037)	-0.063** (0.028)	-0.042 (0.037)	-0.057** (0.028)
Risk Q1 Experienced losses	0.231*** (0.022)	0.076*** (0.018)	0.232*** (0.022)	0.076*** (0.018)	0.229*** (0.022)	0.076*** (0.018)
Risk Q2 Five-year gamble	-0.093** (0.038)	0.213*** (0.028)	-0.092** (0.038)	0.213*** (0.028)	-0.088** (0.038)	0.212*** (0.028)
Risk Q3 Ten-year gamble	0.079** (0.036)	0.325*** (0.027)	0.078** (0.036)	0.327*** (0.027)	0.076** (0.036)	0.328*** (0.027)
Risk Q4 Buy when market dips	-0.052 (0.038)	0.126*** (0.031)	-0.045 (0.038)	0.125*** (0.031)	-0.047 (0.038)	0.125*** (0.031)
Time between account opening and risk profile change	0.073*** (0.017)	-0.030** (0.015)	0.072*** (0.017)	-0.030** (0.015)	0.075*** (0.017)	-0.032** (0.015)
Client did not select the recommended risk profile	0.233*** (0.047)	-0.090** (0.039)	0.228*** (0.047)	-0.089** (0.039)	0.233*** (0.047)	-0.094** (0.039)
Risk profile prior to change	0.038** (0.015)	-0.512*** (0.012)	0.037** (0.015)	-0.512*** (0.012)	0.036** (0.015)	-0.512*** (0.012)
Intercept	-1.840*** (0.229)	0.743*** (0.178)	-1.786*** (0.229)	0.698*** (0.178)	-1.616*** (0.229)	0.638*** (0.179)
Observations	18,500		18,500		18,500	
Log Likelihood	-16,491.72		-16,441.36		-16,514.64	

Table 2.11: **Regression without omitted variables.**

This table reports estimated coefficients and standard errors (in parentheses) from the multinomial logit model explaining both downward and upward risk profile changes (the absence of change is the reference modality, i.e. *Equal*) on a set of explanatory variables with all covariates used in the empirical analysis provided in Section 2.4. Explanatory variables are described in 1.7. ***, **, * indicate that the coefficient is statistically significant at the 1%, 5% and 10% confidence level, respectively.

	<i>Dependent variable: $y=\{Lower; \underline{Equal}; Higher\}$</i>	
	y:Lower	y:Higher
CAC 40 daily return (yesterday)	-0.593*** (0.007)	0.943*** (0.006)
CAC 40 weekly return (last week)	-4.655*** (0.032)	2.978*** (0.048)
CAC 40 monthly return (last month)	-0.132** (0.058)	0.578*** (0.078)
CAC 40 daily volatility (yesterday)	0.762*** (0.114)	-0.339** (0.149)
CAC 40 weekly volatility (last week)	-0.090 (0.135)	-0.316* (0.172)
CAC 40 monthly volatility (last month)	-0.803*** (0.096)	0.094 (0.234)
Deposited or withdrew money	0.052 (0.046)	-0.017 (0.043)
Total value of the account	0.054*** (0.008)	0.057*** (0.007)
Modified Dietz performance	-0.660*** (0.009)	0.4415*** (0.006)
Account volatility	-4.576*** (0.020)	-2.980*** (0.033)
Days with negative returns	-0.004*** (0.0003)	-0.003*** (0.0003)
Days with positive returns	-0.002*** (0.0003)	-0.002*** (0.0003)
From ESG to non-ESG	-1.841*** (0.082)	-1.722*** (0.080)
From non-ESG to ESG	2.656*** (0.069)	2.562*** (0.072)
First Covid-19 Lockdown	0.517*** (0.118)	0.226* (0.107)
Second Covid-19 Lockdown	-0.350 (0.020)	-0.005 (0.116)
Third Covid-19 Lockdown	-0.370** (0.146)	0.292*** (0.08990)

Investment project:	0.088	−0.145*
Save in the event of hard times	(0.088)	(0.078)
Investment project:	0.473***	0.339***
Prepare a major purchase	(0.094)	(0.071)
Investment project:	−0.004	−0.586***
Open an account for my child	(0.115)	(0.093)
Investment project:	−0.002	−0.118
Plan my retirement	(0.089)	(0.076)
Investment project:	−0.181	−0.702***
Bequeath an inheritance	(0.148)	(0.141)
Horizon	0.021***	0.051***
	(0.005)	(0.003)
Liquidity Q1 Two years	−0.105**	0.008
	(0.049)	(0.038)
Liquidity Q2 Half of deposit	0.028	0.096***
	(0.048)	(0.037)
Sex (male)	−0.133**	0.1149**
	(0.059)	(0.047)
Age	0.011***	−0.013***
	(0.002)	(0.002)
Number of children	−0.015	−0.081***
	(0.025)	(0.021)
Annual income	−0.013	−0.020
	(0.025)	(0.021)
Financial literacy	−0.007	−0.047
	(0.037)	(0.028)
Risk Q1 Experienced losses	0.221***	0.091***
	(0.022)	(0.019)
Risk Q2 Five-year gamble	−0.063	0.215***
	(0.040)	(0.030)
Risk Q3 Ten-year gamble	0.105***	0.324***
	(0.037)	(0.027)
Risk Q4 Buy when market dips	−0.026	0.113***
	(0.034)	(0.028)
Time between account opening and risk profile change	1.155***	0.920***
	(0.086)	(0.081)
Client did not select the recommended risk profile	0.232***	−0.085**
	(0.048)	(0.040)
Risk profile prior to change	0.108***	−0.478***
	(0.017)	(0.013)
Intercept	−2.691***	0.264
	(0.241)	(0.193)
Observations	18,500	
Log Likelihood	−15,553.84	

2.9 Figures

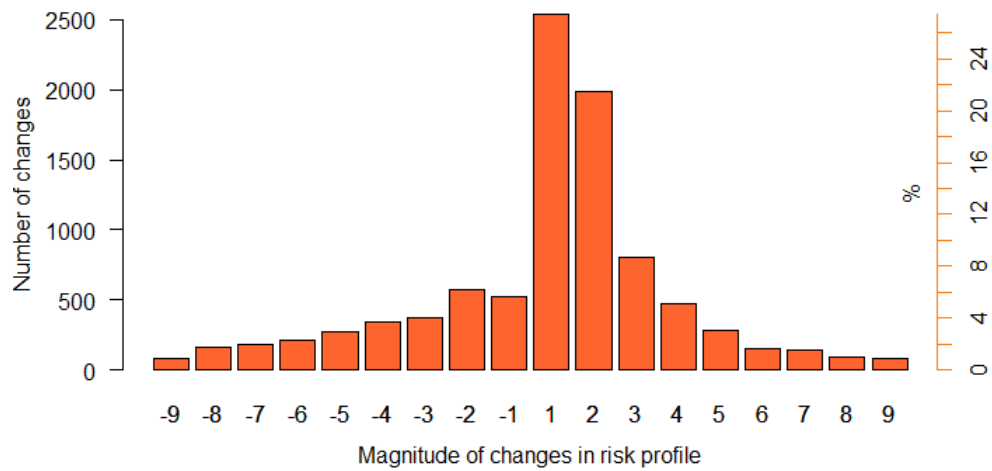


Figure 2.1: **Magnitude of changes in risk profile.**

This figure reports the frequency of each possible adjustment to a client's risk profile. Slight changes are more common than major changes, and positive changes are more common than negative changes.

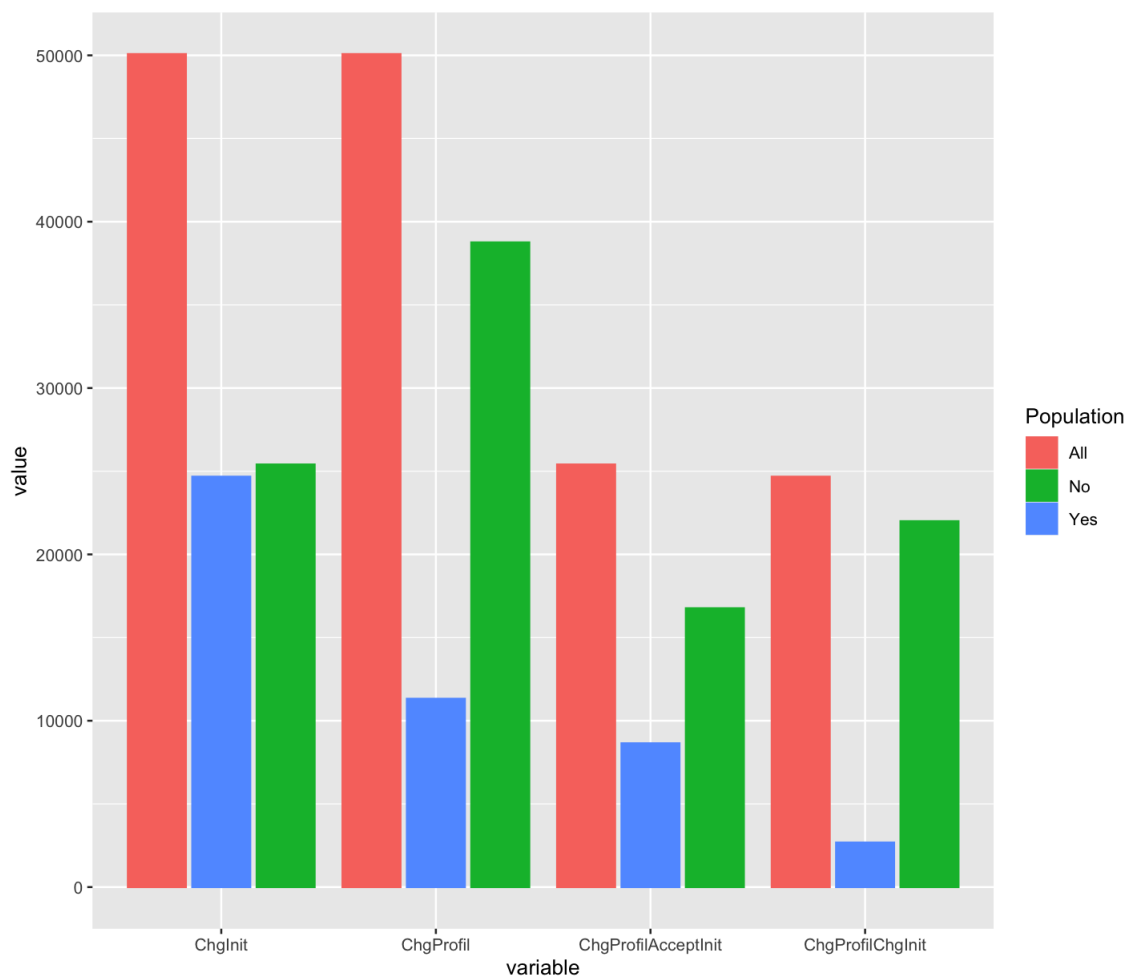


Figure 2.2: **Changers and stayers by whether they accepted the robo-advisor's initial risk profile recommendation.**

This figure provides some indication to what extent learning may have affected investors' decisions to change or not to change the risk profile of their investment. The leftmost set of three bars shows that out of around 50,000 contracts, approximately half accept the robo-advisor's initial risk profile recommendation whereas the other half do not. The center-left set of three bars shows that around one-fifth of these contracts later change their risk profile whereas four-fifths never do so. The center-right set of three bars shows that, among those who accepted the initial risk profile recommendation, about a third later change their risk profile while two-thirds never do so. Finally, the rightmost set of three bars shows that, among those who did not accept the initial risk profile recommendation, nearly all stay at that risk profile thereafter whereas few change thenceforth.

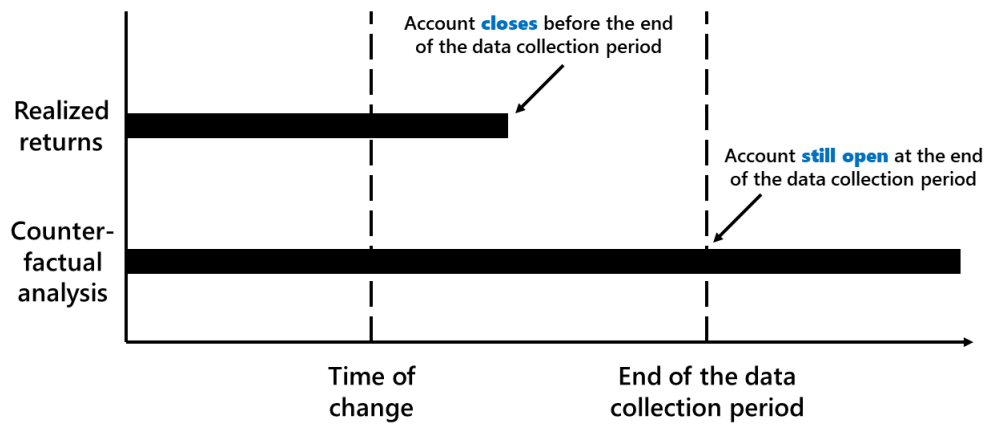


Figure 2.3: **Realized returns versus counterfactual analysis.**

This figure illustrates the sorting criteria by which an account is included in the data for the realized return analysis or the counterfactual analysis.

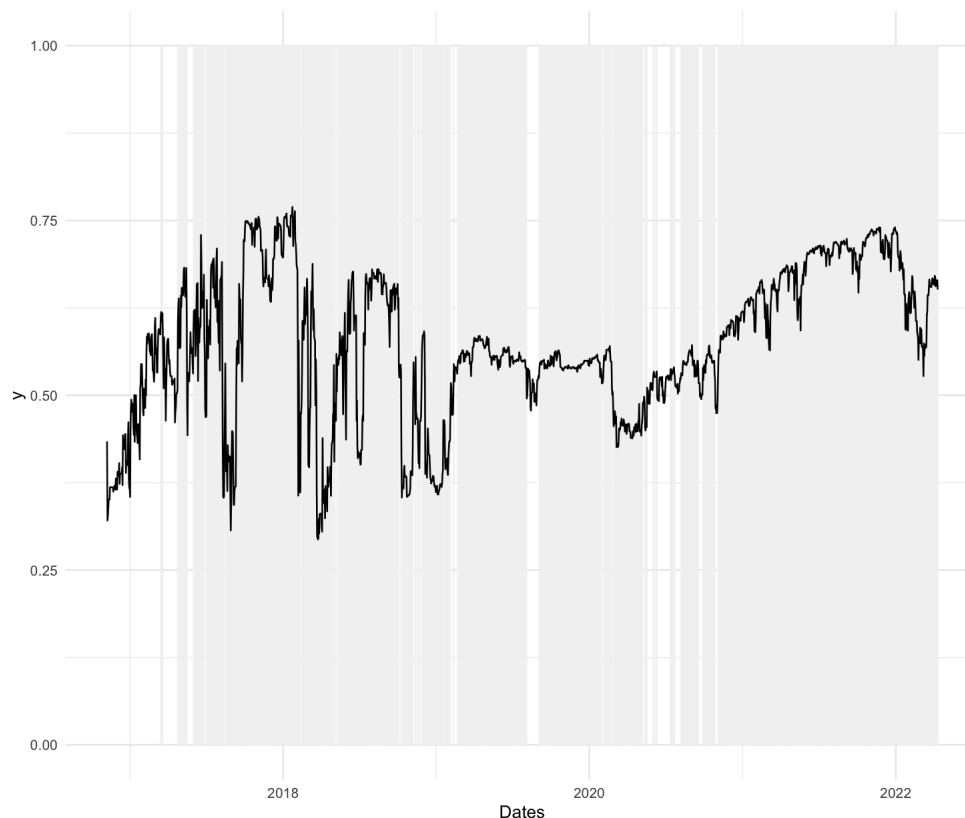


Figure 2.4: **Percentage of reprofiling accounts outperforming their counterfactual accounts.**

This figure shows the daily percentage of investment accounts which changed their risk profile at least once (reprofiling accounts) and with a higher balance than they would have without adjustment of their risk profile (counterfactual accounts). This percentage is calculated at a daily frequency and shows hypothetical (not realized) gains. The beginning of the time series starts when at least 50 investment accounts had changed their risk profile. The shaded areas report time periods in which a binomial test rejects the null hypothesis that the percentage of accounts which change their risk profile and outperforming (or underperforming) their counterfactual is equal to 50%.

2.10 Descriptions of variables

Chapter 3

Chapter 3

Good Old Lockdown: Household Investment Behavior during the Covid-19 Crisis

Co-written with Béatrice Boulu-Reshef

3.1 Introduction

Previous research has shown that during the pandemic, wealthier households saved while poorer households spent their savings. Allen and Rebillard (2021) report an increase in saving and wealth occurred at the top of the wealth distribution in the US during the Covid-19 pandemic. However, little is known about how those households which saved during the pandemic behaved at a granular level. The precise timing of these households' transactions can shed light on open research questions. Did households save as an immediate reaction to the stock market crash of 2020 or the Covid-19 lockdowns, or were households saving more because they had nothing to spend their money on (forced saving)? Did household savings increase just in the short-term, or did the crises affect investors' long-term financial planning? How did investors react to the double crisis of a stock market crash and a Covid-19 lockdown occurring at the same time? And are the individual variations in investors' decisions during the pandemic overall related to any variables such as risk preferences or financial literacy?

To respond to these questions, this paper studies the investment behavior during the Covid-19 pandemic of 6,857 retail investors who were clients of the leading robo-advisor in France by June 30th, 2018, using an individual-level fixed effects panel regression method. This subsample is selected in order to compare their behavior during the stock market crash of 2020 with the stock market correction of 2018.

Additionally, the investment behavior of a larger sample of 15,191 retail investors, which includes some who signed up during the pandemic, is studied in greater detail using linear and logistic regressions. The analyses report evidence from a rich dataset on households' investment behavior throughout the period, notably distinguishing between unscheduled deposits which reflect short-term reactions to these events versus scheduled deposits which provide an insight into how investors adjusted their plans for the future.

In a nutshell, with respect to normal times and controlling for the stock market level and volatility in an individual-level fixed effects model, our sample invested less per-person in terms of total value during the stock market crash of 2020 and during the first Covid-19 lockdown, but during the overlap of these two events there was a moderating effect such that the investors were not overreacting to an unprecedented double-crisis. Furthermore, this sample of investors saved less during "the Covid period" in France, as defined as February 2020 to June 2021. Results for the second and third lockdowns as well as the stock market correction of 2018 – the most similar events to which we can compare this result – showed similar though less extreme negative savings rates with respect to normal times. These results add nuance to the way retail investors react to crises, particularly the stock market crash and the Covid-19 lockdowns experienced in 2020-2021.

The paper is organized as follows. Section 3.2 reviews the relevant literature. Three studies are performed. Covered in section 3.3, Study 1 uses an individual fixed-effects panel regression model to study investors' overall behavior in terms of trade value. Section 3.3.1 outlines the methods of this analysis and section 3.3.2 shows its results. Covered in section 3.4, Study 2 extends the individual fixed-effects panel regression model to four ways of analyzing the different types of transactions. Like with Study 1, section 3.4.1 describes these different methods of interpreting the data while section 3.4.2 records the results of this more nuanced specification. Finally, since fixed-effects models do not estimate time-invariant variables, Study 3 (covered in section 3.5) estimates the relationships of these time-invariant variables to the four ways of analyzing the different types of transactions using linear and logistic regressions. Similarly, section 3.5.1 explains this alternative specification, and section 3.5.2 contains its results. Section 3.6 discusses the results of the three studies and puts them into context of each other. Section 3.7 concludes.

3.2 Literature Review

The Covid-19 pandemic brought about a unique set of economic challenges and characteristics that significantly impacted global economies. To cite only the major economic challenges, the Covid-19 pandemic led to unprecedented global economic disruption, sharp economic contraction, and massive government interventions and stimulus packages. Indeed, many countries experienced rapid economic contractions, with sharp declines in GDP. Baleyte et al. (2021) report that GDP fell by 6.6% in the euro area and

by 7.9% in France specifically, which concerns the data reported here. Sectors like tourism, retail, and entertainment were particularly hard-hit due to reduced consumer spending because of lockdowns and travel restrictions. To limit the social impact, governments implemented substantial fiscal stimulus and other economic measures to support businesses and individuals affected by the pandemic. This included direct payments, grants, loans, tax relief, and increased healthcare spending to stabilize the economy and to mitigate the financial impact on households and businesses. During this period, the French government enacted unprecedented and comprehensive fiscal plans and recovery measures which supported households and firms by preserving jobs and providing liquidity.

Over the pandemic, historic levels of government transfers boosted household income while household saving were forced by lockdown and social distancing. This led the personal saving rate to increase sharply. Aladangady et al. (2022) report that U.S. households accumulated about \$2.3 trillion in savings in 2020 and through the summer of 2021, which is "above and beyond what they would have saved if income and spending components had grown at recent, pre-pandemic trends." Guerrieri et al. (2022) find that the Covid-19 recession caused market income changes in the United States that were regressive in that large losses were more frequent than during the Great Recession and more concentrated at the bottom of the distribution. They document that progressive taxes and transfers, especially from expanded unemployment insurance benefits and stimulus checks, dramatically offset these declines. In Europe, Math (2021) reports that measures to support training, employment, and activity reduction accounted for over a quarter of the total measures taken in 2020 in the Eurozone. They were essential in keeping many businesses alive, as well as maintaining employment relationships and workers' incomes. Though the effects of these policies and of the pandemic overall are heterogeneous, with some studies finding that savings rates increased for the investing class but decreased for the working class.

3.3 Study 1: Individual-level fixed effects panel regression on total trade value, all transaction types

For a full explanation of the Yomoni database, please refer to the section "The Yomoni database" on page 178 of the general introduction. The questionnaire referenced in the following section is available in section 1.7 on page 50.

Study 2 focuses on the different transaction types while Study 3 investigates the demographic and financial variables measured in the questionnaire. In Study 1, these details will be set aside for the moment in order to get a global appreciation of how the investors behaved.

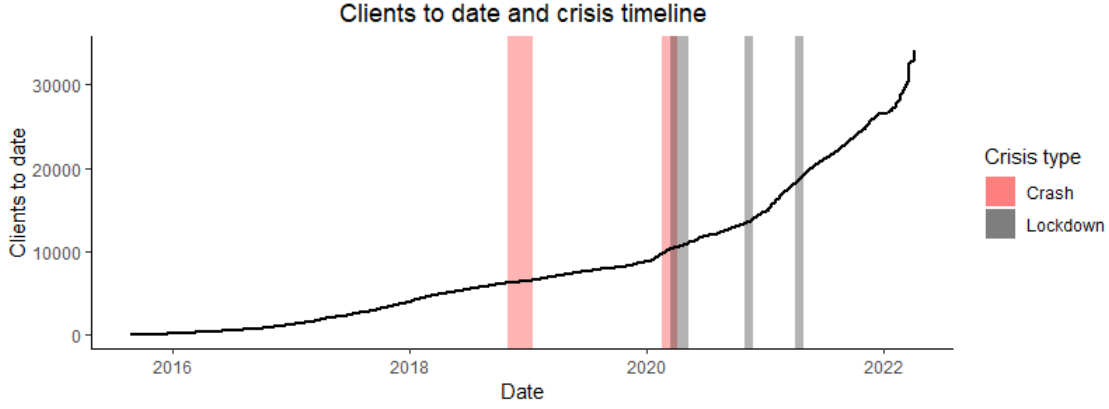


Figure 3.1: Robo-advisor clients by date

3.3.1 Methods

Figure 3.1 illustrates the exponential expansion of the robo-advisor's clientele throughout the period, which includes a stock market correction in 2018, a stock market crash in 2020, and three Covid-19 lockdowns. The clientele of the robo-advisor grew exponentially throughout the period despite the crises. Since each client is required to initiate at least one transaction (the initial subscription, which is often the largest single transaction a client ever does) and often engages in multiple transactions, the trade volume and trade value of transactions correlate with the size of the clientele. And since the aggregate account balances are constantly inflating in size and therefore obscuring the investors' behavior, the investors must be studied in stable cohorts.

The panel observes investors every day from the date at which they open their contract to the end of the data collection period (or until the end of their contract in the case that they terminate it early, which few do). In this circumstance, a panel model is preferable to a cross-sectional model because it takes into account the unobserved heterogeneities across investors. That leaves the question of whether to choose a fixed effects or a random effects model. Which one is econometrically most appropriate for these data can be determined with a Hausman test. The Hausman test rejected the null hypothesis, which is to say that the fixed effects model is more appropriate.

The independent variables in this regression are the stock market level and volatility (as instrumentalized by GSPC a.k.a. the S&P 500), and dummy variables for each of the stock market crashes and Covid-19 lockdowns. The dependent variable in this regression is the total value saved by the investors in euros. The total value saved S (in euros) by each investor i over a given time period t (in this case, a month) can be found by summing their unscheduled deposits $D^{unsched}$, scheduled deposits D^{sched} , and initial deposit D^{init} used to open the account, then subtracting their withdrawals W .

$$S_{i,t} = (D_{i,t}^{unsched} + D_{i,t}^{sched} + D_{i,t}^{init}) - W_{i,t} \quad (3.1)$$

Stock index returns and volatility. The returns and volatility of the S&P 500 (ticker GSPC) are also added as controls.¹ This data is sourced from Yahoo Finance historical stock returns. Prices at stock market opening are used. Volatility is calculated as the annualized intra-day volatility using the high and low of the index². For unscheduled deposits, which occur at a daily frequency, the S&P 500 (GSPC) variables are left as described. For scheduled deposits, which occur at monthly intervals, the average of the S&P 500 (GSPC) variables for the month is used.

Historical events. In France, the first Covid lockdown lasted from March 17th, 2020 to May 10th, 2020 and affected the whole country at the same time. The second lockdown lasted from October 30th, 2020 to November 27th, 2020 and also affected the whole country. The third lockdown started on different dates in different French departments, but eventually affected the whole country, with the national lockdown lasting from April 3rd, 2021 to May 2nd, 2021.³ The stock market crash of 2020 lasted from February 20th, 2020 to April 7th, 2020. There were not two crashes during the data collection period, but some other period of relative stock market volatility would be useful for comparison. The closest equivalent to a crash was a stock market correction in 2018, which lasted from October 30th, 2018 to January 16th, 2019.⁴

A dummy variable is constructed for each of the five historical events (the stock market correction of 2018, the stock market crash of 2020, and the three Covid-19 lockdowns) which is equal to 1 if an unscheduled deposit occurs during the historical event and 0 otherwise. Similarly to the adjustment made for monthly returns and volatilities, the average of these is taken for scheduled deposits, with the number of days in a month included in the crisis period divided by the total number of days in that month. Of course, other events were happening during these moments and in the personal lives of each client, so there is an unsolvable endogeneity problem. However, we do not believe that it is unrealistic to think that

¹While the robo-advisor is based in France, its portfolios are internationally diversified. Around 64% of its investments are US-based ETFs compared to only 19% Europe-based ETFs, of which France is only one country. For this reason, we choose to use the S&P 500 as the market index for reference. Using the same dataset, Benoit et al. (2023) found that the CAC 40 and MSCI World indices can also be used with no loss of generalization, since they happen to be highly correlated.

²The calculation follows this formula:

$$GSPC_{Volatility} = \sqrt{252} * \frac{P_{High} - P_{Low}}{P_{Low}}$$

³The third lockdown started on March 20th for the following departments: 02, 06, 27, 59, 60, 62, 75, 76, 77, 78, 80, 91, 92, 93, 94, 95; and on March 27th for the following departments: 10, 58, 69 (Vie-Publique, 2021). Unfortunately, how local restrictions affected the investors' behavior cannot be adequately studied in the French case because most restrictions were applied nationally. The third lockdown was phased in across different departments over a period of only two weeks, and the investors in this sample are too few in number and made too few trades to study this natural experiment.

⁴A stock market correction begins with a decline in the market cap of more than 10% but less than 20%, and ends when the market cap recovers 10% from its lowest point. In 2018, the S&P 500 peaked at 2936.76 on September 21st, 2018 and dropped below the 10% threshold on October 30th, 2018. The lowest point was 2363.12 on December 26th, 2018, a decline of 19.5% from the previous high. The correction ended on January 16th, 2019 when the S&P 500 rose above the 10% threshold to 2614.75.

an ongoing stock market crash might influence investors' portfolios or that nationwide lockdowns might influence clients' employment and financial situations. Since these major historical events are necessarily experienced by everyone in this sample, if they do have an average effect then this effect should be visible despite the unobserved local or personal events also occurring during these time periods.

The period of 2018-2021 in France saw three Covid lockdowns, two stock market corrections, and one moment in which a stock market correction and a Covid lockdown coincided, separated by short times of relative calm. In other words, it was a 2x2 natural experiment for comparing how investors behaved during these stock market corrections and Covid lockdowns. It is therefore possible to study investor behavior in a 2x2 matrix: during a stock market correction, during a Covid lockdown, during both, and during neither (the baseline situation). When regressing the transaction data, we implement a dummy variable for each of these five events – the stock market correction of 2018, the stock market crash of 2020, the first Covid-19 lockdown, the second Covid-19 lockdown, and the third Covid-19 lockdown – which is equal to 1 only if the transaction occurs during that event. During the lead-in to the third lockdown in which only some departments were affected, the dummy variable for the third lockdown is equal to 1 only for those transactions done by clients whose primary residence was located in one of the departments affected by the third lockdown. The interaction of the crash of 2020 and the first lockdown is studied by crossing these two dummy variables.

Because this paper is interested in how existing investors reacted to crises, new clients who signed up during a crisis are not included in the analysis. Therefore, in this study an individual-level fixed effects panel regression method is adopted, using the 6,857 clients who signed up on or before June 30th, 2018, a few months before the stock market correction of 2018.⁵

3.3.2 Results

The results of the individual-level fixed effects panel regression on total trade value across all transaction types is reported in Table 3.1. The leftmost model is extremely simple. Only one variable is included: a dummy variable that is equal to 1 if the month is between February 2020 and June 2021 (inclusive). This is to give the reader the broadest possible sense of how investors behaved during this period with respect to those months just before and after. The central model likewise adopts this telescopic perspective, but also considers overall stock market conditions. Finally, the rightmost model includes the main variables of interest, the historical events. While stock market volatility was the most influential variable included in the rightmost model, all the main variables of interest were statistically significant at the $p < .01$ level.

⁵The results replicate with alternative group specifications. For example, when using the 11,708 clients who signed up on or before December 31st, 2019, the stock market crash of 2018 cannot be observed, but the results for all subsequent crises are similar.

3.3. STUDY 1: INDIVIDUAL-LEVEL FIXED EFFECTS PANEL REGRESSION ON TOTAL TRADE VALUE, ALL TRANSACTION TYPES

Table 3.1: Individual-level fixed effects panel regression on total trade value across all transaction types

Dependent Variable:	Total value, monthly (SD)	Total value, monthly (SD)	Total value, monthly (SD)
<i>Variables</i>			
February 2020 - June 2021 ^a	-273.2*** (24.60)	-497.4*** (42.76)	
GSPC (per 100 points)		22.84*** (3.255)	11.07*** (2.965)
GSPC volatility		9,511.0*** (1,064.3)	12,794.2*** (1,484.4)
2018 stock market correction			-538.4*** (54.50)
2020 stock market crash			-1,149.4*** (145.1)
Crash of 2020 *			3,547.3*** (392.5)
First lockdown			-1,842.4*** (179.0)
Second Covid-19 lockdown			-509.9*** (62.43)
Third Covid-19 lockdown			-224.9*** (65.65)
<i>Fixed-effects</i>			
Individual-level	Yes	Yes	Yes
<i>Fit statistics</i>			
Observations	351,081	351,081	351,081
R ²	0.05460	0.05541	0.05517
Within R ²	0.00028	0.00114	0.00088

*Clustered (individual-level) standard-errors in parentheses. ***, **, * indicate that the coefficient is statistically significant at the 1%, 5% and 10% confidence level, respectively.*

^a *These results are robust adjusted by several months in any direction.*

To summarize the results, this sample of investors saved less during the overall February 2020 to June 2021 period and specifically saved less during the lockdowns and stock market crashes. For the moment in which the stock market crash of 2020 and the first Covid-19 lockdown overlapped, the interaction between these two crises had a moderating effect. Results for the second and third lockdowns as well as the stock market correction of 2018 – the most similar events to which we can compare this result – showed similar though less extreme negative savings rates with respect to normal times. Though the coefficient of determination (R^2) of this model is low, implying that these large macro-level events did not impact the average household's long-terms savings plans, at least not immediately.

3.4 Study 2: Individual-level fixed effects on different transactions types

There are certain limitations to Study 1 that motivate a more detailed analysis. Though there is a trade-off of moving from the big picture to more granular detail, it is possible to break the analysis into its constituent parts: individual transaction types and the value of transactions versus the propensity to make said transactions.

The nomenclature used in this paper is the following. First, we document deposits and withdrawals. Because clients can open any number of accounts and some have multiple accounts, in this paper, account creations and closures are classified as deposits and withdrawals, respectively. Deposits are the sum of "scheduled deposits" (*versements programmés*) and "unscheduled deposits" (*versements*). During the period considered, withdrawals were not able to be scheduled, so all withdrawals are unscheduled withdrawals. Scheduled deposits draw money directly from the client's linked bank account every month, automatically, on a predetermined date. The client decides the amount and the date of the scheduled deposit when it is first set up, but may change these details or cancel it entirely at any time. Unscheduled deposits are done on the initiative of the client and therefore tend to be much more sporadic.

Unscheduled deposits must be distinguished from scheduled deposits for two reasons: periodicity and disproportionality. Transactions can be studied only at the shortest periodicity for which data is available, which is daily for unscheduled deposits and monthly for scheduled deposits. However, unscheduled deposits are the majority of trade value but minority of trade volume for deposits, while scheduled deposits are the majority of trade volume but minority of trade value. The different periodicities and the disproportionality between the two types of deposits make it both difficult and less useful to predict trends for all deposits. For example, a change in all deposits' trade value for the month would be explicable almost entirely by a change in unscheduled deposits' trade value. Therefore, unscheduled deposits and scheduled deposits are studied independently.

Trade volume refers to the number of transactions, whereas trade value refers to the amount of money moved by the transactions. Trade volume *per se* can only be studied in aggregate, because individuals trade but rarely, so on the individual level trade volume is the propensity to make a trade. Transaction behavior is thus operationalized as trade volumes and trade values for deposits and withdrawals. We can also consider a propensity to make at least one transaction for trade volumes equal to or greater than one.

Basic statistics for trade volumes and trade values for deposits and withdrawals during the period of interest are included in Table 3.2.

Table 3.2 reports several key features. First, the volumes and values of all transaction types steadily

3.4. STUDY 2: INDIVIDUAL-LEVEL FIXED EFFECTS ON DIFFERENT TRANSACTIONS TYPES

Table 3.2: Trade volumes and trade values for deposits and withdrawals

Month	Unscheduled Deposits					Scheduled deposits					Withdrawals				
	Volume	Value	Avg. Value	% of Volume	% of Value	Volume	Value	Avg. Value	% of Volume	% of Value	Volume	Value	Avg. Value	% of Volume	% of Value*
2018-01	1366	5641945	4130	0.40	0.94	1974	355672	180	0.58	0.06	50	-198477	-3970	0.01	-0.03
2018-02	1027	3872459	3771	0.32	0.91	2092	379722	182	0.66	0.09	48	-341481	-7114	0.02	-0.08
2018-03	974	4473637	4593	0.29	0.92	2298	408793	178	0.69	0.08	64	-388652	-6073	0.02	-0.08
2018-04	822	3509311	4269	0.24	0.89	2481	437829	176	0.74	0.11	56	-226141	-4038	0.02	-0.06
2018-05	1051	3975094	3782	0.28	0.90	2643	453301	172	0.70	0.10	62	-620796	-10013	0.02	-0.14
2018-06	1018	2866940	2816	0.26	0.86	2770	469571	170	0.72	0.14	79	-402002	-5089	0.02	-0.12
2018-07	904	3274670	3622	0.23	0.87	2926	494804	169	0.75	0.13	63	-308185	-4892	0.02	-0.08
2018-08	1021	3655678	3580	0.25	0.88	3063	513836	168	0.74	0.12	64	-501720	-7839	0.02	-0.12
2018-09	926	2922204	3156	0.22	0.84	3180	536622	169	0.76	0.16	86	-527317	-6132	0.02	-0.15
2018-10	1163	4082118	3510	0.26	0.88	3291	556372	169	0.73	0.12	83	-600952	-7240	0.02	-0.13
2018-11	835	3081209	3690	0.19	0.85	3399	565097	166	0.79	0.15	89	-879993	-9888	0.02	-0.24
2018-12	859	2673996	3113	0.20	0.82	3436	573296	167	0.79	0.18	73	-1212132	-16605	0.02	-0.37
2019-01	1149	4066163	3539	0.24	0.88	3456	569145	165	0.73	0.12	119	-500247	-4204	0.03	-0.11
2019-02	1134	4011222	3537	0.24	0.88	3489	571304	164	0.74	0.12	86	-509645	-5926	0.02	-0.11
2019-03	1139	4768473	4187	0.23	0.89	3634	611333	168	0.74	0.11	116	-747595	-6445	0.02	-0.14
2019-04	1213	4627178	3815	0.24	0.87	3835	666831	174	0.75	0.13	96	-663047	-6907	0.02	-0.13
2019-05	1288	5699619	4425	0.24	0.89	3961	702494	177	0.74	0.11	129	-866109	-6714	0.02	-0.14
2019-06	1075	4355247	4051	0.20	0.86	4094	724961	177	0.78	0.14	91	-628737	-6909	0.02	-0.12
2019-07	1299	4757043	3662	0.23	0.87	4218	735614	174	0.75	0.13	111	-993369	-8949	0.02	-0.18
2019-08	1270	4851076	3820	0.22	0.87	4317	748757	173	0.76	0.13	88	-722222	-8207	0.02	-0.13
2019-09	1199	4230801	3529	0.21	0.84	4399	780061	177	0.77	0.16	101	-1315314	-13023	0.02	-0.26
2019-10	1381	5342347	3868	0.23	0.87	4484	794284	177	0.75	0.13	114	-827107	-7255	0.02	-0.13
2019-11	1531	6058519	3957	0.25	0.88	4624	822711	178	0.74	0.12	78	-856065	-10975	0.01	-0.12
2019-12	1799	6469124	3596	0.29	0.89	4383	778892	178	0.70	0.11	50	-1309755	-26195	0.01	-0.18
2020-01	2388	9260204	3878	0.36	0.93	4251	746585	176	0.63	0.07	62	-357196	-5761	0.01	-0.04
2020-02	2529	9947573	3933	0.36	0.92	4498	826702	184	0.63	0.08	74	-917308	-12396	0.01	-0.09
2020-03	3785	10186583	2691	0.44	0.92	4721	879242	186	0.55	0.08	141	-2509565	-17798	0.02	-0.23
2020-04	2963	7275784	2456	0.37	0.89	4927	909866	185	0.62	0.11	66	-701321	-10626	0.01	-0.09
2020-05	2734	5756532	2106	0.34	0.86	5283	975980	185	0.65	0.14	55	-250860	-4561	0.01	-0.04
2020-06	2976	7937297	2667	0.35	0.89	5580	1029326	184	0.65	0.11	67	-505975	-7552	0.01	-0.06
2020-07	2615	6037541	2309	0.30	0.85	5951	1104571	186	0.69	0.15	86	-725472	-8436	0.01	-0.10
2020-08	2618	7252475	2770	0.29	0.86	6334	1171459	185	0.70	0.14	71	-458508	-6458	0.01	-0.05
2020-09	2758	9084791	3294	0.29	0.88	6557	1220850	186	0.70	0.12	88	-651686	-7406	0.01	-0.06
2020-10	2707	6690786	2472	0.28	0.84	6732	1241508	184	0.71	0.16	70	-790976	-11300	0.01	-0.10
2020-11	3568	12703538	3560	0.33	0.91	7080	1314567	186	0.66	0.09	66	-797794	-12088	0.01	-0.06
2020-12	5472	23137920	4228	0.42	0.94	7378	1406032	191	0.57	0.06	72	-694881	-9651	0.01	-0.03
2021-01	5263	17434070	3313	0.40	0.92	7898	1562607	198	0.60	0.08	88	-863635	-9814	0.01	-0.05
2021-02	5443	22330376	4103	0.39	0.93	8410	1684248	200	0.60	0.07	73	-443534	-6076	0.01	-0.02
2021-03	5645	20941761	3710	0.38	0.92	9108	1829402	201	0.61	0.08	94	-1282549	-13644	0.01	-0.06
2021-04	5854	20696026	3535	0.37	0.91	9817	1984127	202	0.62	0.09	94	-784097	-8341	0.01	-0.03
2021-05	5411	17253817	3189	0.34	0.89	10417	2115145	203	0.65	0.11	96	-891962	-9291	0.01	-0.05
2021-06	5295	16723078	3158	0.32	0.88	11107	2273968	205	0.67	0.12	95	-771148	-8117	0.01	-0.04
2021-07	5708	19104500	3347	0.33	0.89	11666	2368703	203	0.67	0.11	73	-969266	-13278	0.00	-0.05
2021-08	6296	24829188	3944	0.34	0.91	12255	2481249	202	0.66	0.09	73	-1228523	-16829	0.00	-0.04
2021-09	6132	20443400	3334	0.32	0.89	12733	2603220	204	0.67	0.11	95	-1482007	-15600	0.01	-0.06
2021-10	5848	19899847	3403	0.30	0.88	13249	2666579	201	0.69	0.12	101	-2061827	-20414	0.01	-0.09

rose as the robo-advisor continued to attract new clients regardless of the uncertainty of the data collection period. This is a minor result in itself, since some traditional financial services, which primarily do business in person especially prior to the pandemic, struggled to grow or even maintain a positive balance sheet throughout the lockdowns and generally reduced physical presences. Second, while one would expect purchases and sales to roughly cancel each other out in the overall financial market as prices maintain an equilibrium, withdrawals from this robo-advisor account for 3% or less of all transactions each month in terms of trade volume and only 26% of the value of deposits at their height. In other words, few clients withdrew their capital from the robo-advisor during the data collection period. Third, unscheduled deposits on average account for 89% of the trade value of the deposits each month, but on average account for only 30% of the trade volume of all trades. This means that unscheduled deposits are far rarer than scheduled deposits, but, when done, they tend to move much larger amounts of money. Fourth, the coefficients of variations indicate that withdrawals ($CV = 0.49$) and unscheduled deposits ($CV = 0.16$) are far more variable than scheduled deposits ($CV = 0.07$). While withdrawals' and unscheduled deposits' average values fluctuated by thousands of euros each month, scheduled deposits' average values tended to be much lower throughout the entire period.

3.4.1 Methods

The individual-level fixed effects panel regression model described in section 3.3.1 can be repeated here, substituting a new set of dependent variables: propensity to make at least one unscheduled deposit, value of unscheduled deposits, propensity to make at least one scheduled deposit, and value of scheduled deposits.

Because propensity and value are different measures and scheduled and unscheduled deposits are different transaction types, *a priori* there is no reason to suspect that the relationships of the stock market crashes and Covid-19 lockdowns will be identical across all of these metrics.

3.4.2 Results

For unscheduled deposit propensity, investors more likely to make an unscheduled deposit during the crash of 2020 and the first lockdown, with the interaction between these events having a moderating effect. Investors were less likely to make an unscheduled deposit during the correction of 2018. There was not a statistically significant relationship between unscheduled deposit propensity and the second or third lockdowns.

For unscheduled deposit value, investors saved less with unscheduled deposits during the correction of 2018, the first lockdown, and the second lockdown. Investors saved more with unscheduled deposits

during the crash of 2020, though this is statistically significant only at the 10% level. The third lockdown and the interaction between the crash of 2020 and the first lockdown were statistically insignificant.

For scheduled deposit propensity, investors were more likely to make scheduled deposits during the correction of 2018 and less likely to make scheduled deposits during the crash of 2020. During the first and second lockdowns, investors were also less likely to make scheduled deposits, though there was no significant relationship with the third lockdown. The interaction between the crash of 2020 and the first lockdown had a moderating effect.

For scheduled deposit value, all five historical events were related to a statistically significant drop in savings. The interaction between the crash of 2020 and the first lockdown had a moderating effect.

Table 3.3: Individual-level fixed effects panel regression across all transaction types

Dependent Variables:	Unscheduled deposit propensity, daily (SD)	Unscheduled deposit value, daily (SD)	Scheduled deposit propensity, monthly (SD)	Scheduled deposit value, monthly (SD)
<i>Variables</i>				
GSPC (per 100 points)	$6.11 \times 10^{-5***}$ (1.26×10^{-5})	0.2183*** (0.0762)	-0.0010*** (0.0003)	2.271*** (0.1889)
GSPC volatility	0.0025*** (0.0003)	-0.4328 (2.076)	-0.2075*** (0.0439)	962.3*** (87.02)
2018 stock market correction	-0.0009*** (0.0001)	-4.050*** (1.183)	0.0522*** (0.0028)	-13.85*** (2.340)
2020 stock market crash	0.0020*** (0.0003)	3.776* (2.166)	-0.0994*** (0.0105)	-70.71*** (8.870)
Crash of 2020 *	-0.0015*** (0.0004)	0.1738 (2.741)	0.2120*** (0.0220)	179.8*** (19.56)
First Covid-19 lockdown	0.0007** (0.0003)	-3.556*** (1.220)	-0.0542*** (0.0062)	-105.6*** (10.05)
Second Covid-19 lockdown	-0.0003 (0.0002)	-4.460*** (1.369)	-0.0234*** (0.0035)	-24.90*** (3.284)
Third Covid-19 lockdown	0.0003 (0.0002)	-0.0396 (1.932)	-0.0038 (0.0025)	-16.28*** (2.841)
<i>Fixed-effects</i>				
Individual-level	Yes	Yes	Yes	Yes
<i>Fit statistics</i>				
Observations	7,391,476	7,391,476	351,081	351,081
R ²	0.03590	0.00293	0.40022	0.05154
Within R ²	0.00010	4.92×10^{-6}	0.00081	0.00012

Clustered (individual-level) standard-errors in parentheses.

***, **, * indicate that the coefficient is statistically significant at the 1%, 5% and 10% confidence level, respectively.

3.5 Study 3: Linear and logistic regressions on different transaction types

While the individual-level fixed effect panel regressions of Study 1 and Study 2 are strong and revealing due in part to the incorporation of unobserved heterogeneity across investors, a limitation is that they do not permit estimates of time-invariant variables such as those answered by the investors in the introductory questionnaire. A random effects model would give estimates, but as discussed in section 3.4.1, the results of a Hausman test indicated that a random effects model would not be econometrically appropriate with these data. Therefore, a random effects model may poorly estimate these time-invariant variables. As such, we face a trade-off between a model which gives the best possible estimations of the time-variant variables (crashes and lockdowns) and a model which gives the best possible estimations of the time-invariant variables (questionnaire data). This trade-off motivates Study 3, in which we adopt a different method to gain a deeper understanding of the time-invariant variables which may have had a relationship to investors' behavior during the crises.

Trade volume and trade value tend to grow month after month, if only due to the continuous entrance of new clients and their new capital. Therefore, dependent variables are averaged by the number of clients or the number of transactions within a given period. The analyses control for the size of the clientele by measuring trade volume and trade value on a per-client basis and observing whether the average volume and value shift over the period. However, this would still be insufficient to study clients' behavior, since new clients would be integrated into the analysis as soon as they arrived. Integrating these new clients would make it impossible to study whether changes in the key metrics are due to shifts in the average behavior of existing clients and not due to the behavior of the new arrivals. For those two reasons, stable subsets of clients are studied. The use of these different groups allows to carefully control for the impact of exposure to the various sanitary and economic shocks that characterize the period.

As a consequence, the clients were divided into three groups, depending on the date of their first contract opening and our main variable of interest which is the types and numbers of financial, economic, and sanitary disruptions they experienced. The three groups are composed as follows: Group 1 includes the 6,857 clients who signed up between August 2015 (the month in which the robo-advisor began operations) and June 30th, 2018. This is the same group of clients from the first two studies. Group 2 includes the 3,043 clients who signed up between July 1st, 2018 and June 30th, 2019. Group 3 includes the 5,291 clients who signed between July 1st, 2019 and June 30th, 2020. Since the group only becomes stable on the last day of the period, and otherwise suffers from the problems of ever-growing numbers of clients, analyses that require group stability can only begin once a group reaches its cut-off date. Group 1 is interesting in that their behavior from prior to the stock market correction of 2018 can be documented

and compared to their behavior during the stock market crash of 2020. Furthermore, this is the group for which the longest period of data is available, so group 1 has the most data per client. Group 2 can be thought of as a robustness test for group 1 for all time periods except for the stock market correction of 2018, and group 3 as a robustness test for groups 1 and 2. Groups are cut off a few months prior to their first crisis to observe how they behave in normal or pre-crisis circumstances.

Table 3.4 reports the characteristics of clients of the robo-advisor by group used for the analyses. There are substantial similarities among the groups. Between 72% and 80% are men. The average age at subscription is between 33 and 35. About two-thirds of them earn between 25,000€ and 100,000€ per year. On average, they have substantial property (230,000€) and financial assets (180,000€), and between 57% and 60% of them are homeowners. The average account is opened with around 5,000-8,000€ for a period of 10-12 years at risk profile 7 (see Boulu-Reshef et al. (2022) for more information on risk profiles). Liquidity needs, risk preferences, and financial literacy are similar across the three groups. However, there are also some differences among the groups to note. While men are a sizeable majority in all three groups, women become more common over time. Also, groups 2 and 3 have similar levels of wealth to each other, but around 60,000€ less capital than group 1. Nevertheless, groups 2 and 3 deposit larger amounts of money in their investment accounts with the robo-advisor and have progressively longer investment horizons. While it is interesting to observe the gradual shift in the clientele of the robo-advisor over time, these differences are small and not economically significant.

Table 3.4: Descriptive statistics of clients' characteristics by group

	Group 1		Group 2		Group 3	
	Mean	SD	Mean	SD	Mean	SD
N	6857		3043		5291	
Sex	0.80	0.40	0.77	0.42	0.72	0.45
Age	38.63	14.17	36.49	15.02	35.27	15.44
Age at subscription	34.09	14.09	33.41	15.05	33.24	15.42
Number of children	0.83	1.02	0.78	1.00	0.80	1.00
Annual income less than 25k	0.07	0.26	0.09	0.28	0.09	0.28
Annual income 25k to 50k	0.28	0.45	0.31	0.46	0.31	0.46
Annual income 50k to 100k	0.40	0.49	0.38	0.49	0.40	0.49
Annual income 100k to 150k	0.16	0.37	0.14	0.35	0.14	0.35
Annual income more than 150k	0.09	0.28	0.07	0.26	0.06	0.24
Home owner	0.60	0.49	0.57	0.49	0.57	0.49
Property assets	256735	381528	226812	356762	228189	363892
Financial wealth	197795	434552	166177	355252	160075	426375
Initial deposit	4852	11791	8117	24996	8103	22008
Horizon	10.1	5.91	11.14	6.34	11.91	6.46
Liquidity Q1 Two years	1.31	0.46	1.29	0.45	1.32	0.47
Liquidity Q2 Half of deposit	1.00	0.98	0.97	0.97	0.91	0.97
Risk Q1 Five year gamble	2.14	0.77	2.38	0.74	2.41	0.73
Risk Q2 Ten year gamble	2.06	0.81	1.95	0.78	2.00	0.78
Risk Q3 Buy when market dips	2.13	1.34	2.17	1.30	2.14	1.33
Risk Q4 Experienced losses	2.14	1.17	1.99	1.11	1.94	1.11
Knowledge Q1 Correct	0.97	0.18	0.97	0.18	0.98	0.15
Knowledge Q2 Correct	0.76	0.43	0.75	0.43	0.78	0.41
Knowledge Q3 Correct	0.71	0.46	0.72	0.45	0.74	0.44
RP Recommended	7.08	1.89	6.79	2.07	7.03	2.01
RP Selected	6.99	2.15	6.73	2.41	7.04	2.42

3.5.1 Methods

The dependent variables in the following set of four regressions are the same dependent variables used in Study 2: unscheduled deposit propensity, unscheduled deposit value, scheduled deposit propensity, and scheduled deposit value. Linear regressions are adopted to study (un)scheduled deposit value, while logistic regressions are adopted to study (un)scheduled deposit propensity. The independent variables will include the five historical events as controls as well as a comprehensive set of demographic, financial, and behavioral variables answered by the investors in the introductory questionnaire.

Questionnaire variables. The first part of the questionnaire focuses on clients' objectives and circumstances. It commences by inquiring about potential clients' investment goals, presenting a range of distinct options for consideration: increase savings, prepare a major purchase, bequeath an inheritance, plan their retirement, save in the event of hard times, prepare a real estate investment, or open an account for their child. The following questions request clients to state how much money they would like to deposit into their investment account, the amount they would like to transfer each month, their birth date, fiscal residence, how many children they have, their annual household income, if they own their primary residence, how much they pay for their mortgage/rent if they have one, the value of their property assets, their wealth, how much they can save each month, and the length of their investment horizon. The second part of the questionnaire deals with clients' risk/loss aversion, financial literacy, and liquidity needs. To summarize, the questionnaire contains information about clients' age, sex, residency, family, income, wealth, employment, financial literacy, risk tolerance, liquidity needs, and about their investment's goal, amount, horizon, and monthly contribution. These variables will be the majority of the control variables in the analysis. The phrasing of the questions is reported in Table 1.7.

Groups. Since the interest of Study 3 is not necessarily to study the historical events, the sample of investors studied can be expanded to include investors who signed up after June 30th, 2018. However, investors must still be grouped into cohorts because of the inflationary problems explained in section 3.3.1. As such, we define three groups. Group 1 includes the group of 6,857 investors who signed up on or before June 30th, 2018 that were studied in Studies 1 and 2. Group 2 includes the 3,043 investors who signed up between July 1st, 2018 and June 30th, 2019. Group 3 includes the 5,291 investors who signed up between July 1st, 2019 and June 30th, 2020.

For each of the following tables, the results for groups 1, 2, and 3 are reported side-by-side. The groups are non-overlapping, and subjects are independent. The four measures used here, scheduled deposits' propensity and average value and unscheduled deposits' propensity and average value, are four distinct investment behaviors. It is not anticipated that coefficients necessarily have similar powers and directions across these four different concepts. For example, a stock market downturn may induce investors to "buy

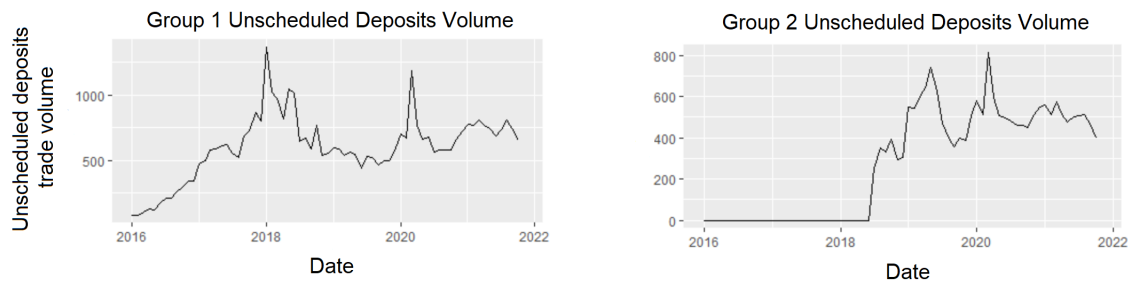


Figure 3.2: Month-to-month unscheduled deposits trade volume

low" with an unscheduled deposit in the moment with money that would have otherwise been used on future scheduled deposits.

Likewise, groups are not perfect replications of each other. Clients are grouped based on sign-up date and thus data availability. Grouping them along other criteria, such as income, would create unbalanced panels that could not be properly analyzed due to the client inflation problems detailed in section 3.3.1. Group 1 is the richest data, with the largest group of clients and the longest period of study. Yet since the four measures are not directly comparable to each other and relationships among variables may be unintuitive, groups 2 and 3 serve as a robustness test for all variables except for those historical periods which they did not experience. Though the characteristics and behaviors of the robo-advisor's clientele can and does change over time, because they are different people. If a relationship between the dependent variable and a factor is stable across all three groups, then it is not affected by these shifting but unobserved attitudes, and as such we consider it to be a robust result. To illustrate with an example, Figure 3.2 shows that for both groups 1 and 2 there was a spike in unscheduled deposits around March 2020; however, this cannot be verified for group 3 since they were not clients during this historical period. Phenomenon like this will be studied with all else being equal in the following regressions.

3.5.2 Results

Measures of commitment: Scheduled deposits

Table 3.5 reports the determinants of the propensity to make a scheduled deposit using a logistic regression and displaying the average marginal effects. The dependent variable is equal to 1 if the client made at least one scheduled deposit during the month, and 0 otherwise.

The primary determinant exerting the most substantial influence on the propensity to make a scheduled deposit is income, with an increasingly large positive effect associated with higher income tranches. Sorted from greatest to least cumulative impact, other positive determinants for the propensity to make a scheduled deposit are investment horizon, home ownership, and number of children. Meanwhile, nega-

tive determinants include stock market volatility, age, and liquidity needs. Property assets and financial wealth have a marginal negative relationship with the propensity to make a scheduled deposit. In other words, investors are more likely to make scheduled deposits when they have high income, their investment horizon is long, they own their homes, and they have more children, while investors are less likely to make scheduled deposits when the stock market is volatile, as they age, and if they need liquidity. The relationships of sex, financial literacy, and risk preferences and the overall stock market level are not consistent across the three groups for the propensity to make scheduled deposits.

3.5. STUDY 3: LINEAR AND LOGISTIC REGRESSIONS ON DIFFERENT TRANSACTION TYPES

Table 3.5: **Logistic regression - Clients' propensity to make a scheduled deposit (Average Marginal Effects), monthly**

***, **, * indicate that the coefficient is statistically significant at the 1%, 5% and 10% confidence level, respectively.

	Group 1 (N = 6857)			Group 2 (N = 3043)			Group 3 (N = 5291)		
	AME	St.Err.	Sig.	AME	St.Err.	Sig.	AME	St.Err.	Sig.
Intercept	0.1644	0.0493	***	0.4521	0.0897	***	-0.0115	0.1251	
GSPC (per 100 points)	-0.0202	0.0008	***	-0.0105	0.0015	***	0.0185	0.0022	***
GSPC volatility	-0.8114	0.0681	***	-0.6625	0.1247	***	0.2280	0.1739	
Sex (male)	0.0929	0.0106	***	0.0082	0.0173		-0.0408	0.0163	**
Age	-0.0126	0.0003	***	-0.0127	0.0006	***	-0.0175	0.0005	***
Number of children	0.0542	0.0046	***	0.0914	0.0081	***	0.0399	0.0083	***
Annual income 25k to 50k	0.6139	0.0204	***	0.5877	0.0295	***	0.3795	0.0282	***
Annual income 50k to 100k	0.9598	0.0201	***	0.7531	0.0297	***	0.4323	0.0284	***
Annual income 100k to 150k	1.1786	0.0219	***	0.8426	0.0342	***	0.6427	0.0333	***
Annual income more than 150k	1.2743	0.0250	***	1.0997	0.0412	***	0.6640	0.0414	***
Home owner	0.1114	0.0100	***	0.1425	0.0173	***	0.0484	0.0174	***
Property assets (per 10,000 EUR)	-0.0009	0.0001	***	-0.0014	0.0003	***	-0.0033	0.0003	***
Financial wealth (per 10,000 EUR)	-0.0027	0.0001	***	-0.0033	0.0003	***	-0.0005	0.0002	**
Horizon	0.0282	0.0007	***	0.0274	0.0012	***	0.0353	0.0012	***
Liquidity Q1 Two years	-0.0911	0.0051	***	-0.0343	0.0091	***	-0.0121	0.0090	
Liquidity Q2 Half of deposit	-0.2913	0.0108	***	-0.1407	0.0193	***	-0.3416	0.0189	***
Risk Q1 Five year gamble	0.0006	0.0058		0.1004	0.0129	***	0.1250	0.0128	***
Risk Q2 Ten year gamble	-0.0576	0.0055	***	-0.2614	0.0128	***	-0.3434	0.0126	***
Risk Q3 Buy when market dips	0.0185	0.0032	***	0.0409	0.0057	***	0.0179	0.0056	***
Risk Q4 Experienced losses	-0.0923	0.0040	***	-0.0348	0.0072	***	-0.0196	0.0071	***
Knowledge Q1 Correct	0.0604	0.0235	**	-0.4852	0.0415	***	-0.1463	0.0477	***
Knowledge Q2 Correct	-0.0628	0.0103	***	0.0424	0.0178	**	0.0012	0.0182	
Knowledge Q3 Correct	-0.0377	0.0093	***	0.1435	0.0165	***	0.0359	0.0165	**
Stock market correction of 2018	0.2495	0.0216	***						
Stock market crash of 2020	-0.4699	0.0842	***	-0.1658	0.1214				
Crash of 2020 * First lockdown	2.0039	0.2061	***	1.3125	0.3067	***			
First Covid-19 lockdown	-0.4896	0.0384	***	-0.3228	0.0568	***			
Second Covid-19 lockdown	-0.1196	0.0302	***	-0.0618	0.0431		0.0345	0.0337	
Third Covid-19 lockdown	-0.0049	0.0307		-0.0129	0.0439		0.0181	0.0337	
Log-likelihood	0.0397			0.0395			0.0458		

The average trade values of scheduled deposits is reported in Table 3.6. The estimates are in euros. However, the estimates reported are lower bounds of the true effects. Roughly half of the clients made a scheduled deposit in any given month while the other half did not. Put another way, the non-schedulers made a deposit of zero euros, and this considerably moderates the average estimates reported here. As a result of all of these zeroes being taken into account, both positive and negative estimates are less extreme than one would expect. To get closer to the effects of these variables observed just among the group of investors who do make scheduled deposits, the estimates could be doubled. This would roughly cancel out the influence of the half of the sample who are non-schedulers.

Once again, the primary determinant for the value of scheduled deposits is income, with higher income tranches depositing larger amounts. Other positive determinants for the propensity to make a scheduled deposit are sex and horizon. Age, property assets, and financial wealth have marginal positive impacts for the the value of scheduled deposits. Meanwhile, negative determinants include liquidity needs, home ownership, and number of children. In other words, investors' scheduled deposits scale with their incomes and investment horizons, and men make larger scheduled deposits than women. But investors make smaller scheduled deposits if they need liquidity, own their home, or have more children. Lastly, the relationships of risk preferences, financial literacy, and overall stock market volatility to the value of scheduled deposits are inconsistent or unclear.

3.5. STUDY 3: LINEAR AND LOGISTIC REGRESSIONS ON DIFFERENT TRANSACTION TYPES

Table 3.6: **Linear regression - Average monthly trade value of scheduled deposits, monthly**
 ***, **, * indicate that the coefficient is statistically significant at the 1%, 5% and 10% confidence level, respectively.

	Group 1 (N = 6857)			Group 2 (N = 3043)			Group 3 (N = 5291)		
	Est.	St.Err.	Sig.	Est.	St.Err.	Sig.	Est.	St.Err.	Sig.
Intercept	37.9869	4.8036	***	-9.9842	11.0693		-36.3793	17.5213	**
GSPC (per 100 points)	0.4910	0.0806	***	1.1480	0.1858	***	2.2653	0.3029	***
GSPC volatility	-15.2509	6.7924	**	-15.3660	15.4664		17.0609	24.3623	
Sex (male)	13.8509	1.0467	***	12.1284	2.1464	***	15.0775	2.2812	***
Age	0.2259	0.0325	***	0.8233	0.0670	***	0.7086	0.0725	***
Number of children	-5.2103	0.4593	***	-8.2309	1.0205	***	-2.0242	1.1608	*
Annual income 25k to 50k	18.2200	1.7340	***	29.4166	3.4195	***	34.8955	3.9020	***
Annual income 50k to 100k	47.7263	1.7216	***	57.3493	3.4616	***	63.5384	3.9271	***
Annual income 100k to 150k	81.7014	1.9367	***	93.5311	4.0564	***	96.7516	4.6158	***
Annual income more than 150k	131.2390	2.2783	***	210.8457	4.9339	***	185.0079	5.7398	***
Home owner	-15.4055	0.9953	***	-12.5814	2.1445	***	-51.3827	2.4185	***
Property assets (per 10,000 EUR)	0.1854	0.0143	***	-0.0669	0.0318	**	-0.0257	0.0364	
Financial wealth (per 10,000 EUR)	0.0913	0.0108	***	0.6384	0.0278	***	0.3441	0.0264	***
Horizon	1.0787	0.0738	***	0.6489	0.1475	***	1.1677	0.1635	***
Liquidity Q1 Two years	-6.7510	0.5147	***	-4.6913	1.1270	***	-5.7005	1.2623	***
Liquidity Q2 Half of deposit	-23.4845	1.0716	***	-15.4379	2.3963	***	-30.0731	2.6404	***
Risk Q1 Five year gamble	-5.5673	0.5798	***	7.4527	1.6054	***	8.2431	1.7874	***
Risk Q2 Ten year gamble	0.4516	0.5511		-6.5437	1.5887	***	-12.6590	1.7601	***
Risk Q3 Buy when market dips	-0.8239	0.3134	***	0.7723	0.7058		1.5536	0.7875	**
Risk Q4 Experienced losses	-4.8442	0.3904	***	-6.3906	0.8895	***	1.8687	0.9924	*
Knowledge Q1 Correct	5.7226	2.3295	**	-26.9615	5.1810	***	-3.6619	6.6758	
Knowledge Q2 Correct	-3.6972	1.0333	***	6.5779	2.1971	***	2.8538	2.5567	
Knowledge Q3 Correct	2.2241	0.9313	**	21.8851	2.0341	***	5.7121	2.3181	**
Stock market correction of 2018	9.0983	2.1947	***						
Stock market crash of 2020	-25.4546	8.1937	***	-6.6569	15.0147				
Crash of 2020 * First lockdown	78.3588	20.0980	***	53.0509	37.9701				
First Covid-19 lockdown	-13.2725	3.7324	***	-8.8540	7.0076				
Second Covid-19 lockdown	-4.7877	2.9393		-4.8519	5.3232		-0.7392	4.7213	
Third Covid-19 lockdown	0.0598	3.0078		1.9240	5.4326		0.4676	4.7310	
R-squared	0.0494			0.0525			0.0520		

Measures of one-time investments: Unscheduled deposits

Moving on, the propensity to make an unscheduled deposit is studied in Table 3.7. The dependent variable is equal to 1 if the client made at least one unscheduled deposit during the month, and 0 otherwise.

High levels of income are particularly predictive of making at least one unscheduled deposit on any given day, with financial literacy in second place. Maleness and stock market volatility are also positive correlates, while age has a marginal positive relationship. The only negative correlates observed for propensity to make unscheduled deposits are number of children and property assets, the latter of which is marginal. In other words, investors are more likely to make an unscheduled deposit when they have high incomes and high rates of financial literacy, when they are men, and when the stock market is volatile, and less likely if they have more children. Unrelated or inconsistent variables are stock market level, home ownership, financial wealth, investment horizon, liquidity needs, and risk preferences.

It is interesting to compare and contrast the results for the propensity to make an unscheduled deposit with those of the propensity to make a scheduled deposit. Some variables consistently increase the propensity, such as income, while others have a push-and-pull effect, such as the number of children. In other words, some variables simply increase the likelihood to invest in any manner (income) while other variables change one's investment strategy, at least in the short term (children).

3.5. STUDY 3: LINEAR AND LOGISTIC REGRESSIONS ON DIFFERENT TRANSACTION TYPES

Table 3.7: **Logistic regression - Clients' propensity to make an unscheduled deposit (Average Marginal Effects), daily**

***, **, * indicate that the coefficient is statistically significant at the 1%, 5% and 10% confidence level, respectively.

	Group 1 (N = 6857)			Group 2 (N = 3043)			Group 3 (N = 5291)		
	AME	St.Err.	Sig.	AME	St.Err.	Sig.	AME	St.Err.	Sig.
Intercept	-8.2374	0.0825	***	-7.1142	0.1168	***	-6.1024	0.1225	***
GSPC (per 100 points)	0.0161	0.0012	***	0.0069	0.0018	***	-0.0067	0.0020	***
GSPC volatility	0.4181	0.0488	***	0.1923	0.0652	***	0.2122	0.0827	**
Sex (male)	0.4020	0.0192	***	0.2147	0.0236	***	0.2071	0.0197	***
Age	0.0025	0.0005	***	0.0106	0.0007	***	0.0079	0.0006	***
Number of children	-0.2528	0.0077	***	-0.1618	0.0106	***	-0.1491	0.0097	***
Annual income 25k to 50k	0.2900	0.0343	***	0.2326	0.0377	***	0.4540	0.0340	***
Annual income 50k to 100k	0.7676	0.0332	***	0.4702	0.0376	***	0.4659	0.0342	***
Annual income 100k to 150k	0.9442	0.0353	***	0.6715	0.0422	***	0.7498	0.0383	***
Annual income more than 150k	0.7461	0.0404	***	0.7199	0.0499	***	0.4850	0.0495	***
Home owner	0.0378	0.0154	**	0.0669	0.0214	***	-0.2803	0.0192	***
Property assets (per 10,000 EUR)	-0.0026	0.0002	***	-0.0063	0.0004	***	-0.0020	0.0003	***
Financial wealth (per 10,000 EUR)	0.0013	0.0001	***	-0.0002	0.0003		-0.0003	0.0002	
Horizon	0.0209	0.0010	***	0.0072	0.0014	***	-0.0061	0.0013	***
Liquidity Q1 Two years	-0.0456	0.0080	***	-0.0964	0.0112	***	-0.0632	0.0102	***
Liquidity Q2 Half of deposit	0.0405	0.0162	**	-0.0630	0.0226	***	0.0860	0.0202	***
Risk Q1 Five year gamble	0.0627	0.0092	***	0.0529	0.0177	***	0.1280	0.0155	***
Risk Q2 Ten year gamble	0.1325	0.0088	***	0.3308	0.0161	***	0.1666	0.0142	***
Risk Q3 Buy when market dips	-0.0136	0.0047	***	-0.0717	0.0065	***	-0.0582	0.0059	***
Risk Q4 Experienced losses	-0.0865	0.0060	***	-0.0776	0.0086	***	-0.0446	0.0077	***
Knowledge Q1 Correct	-0.0319	0.0454		0.2491	0.0678	***	0.0539	0.0635	
Knowledge Q2 Correct	0.5403	0.0199	***	0.3881	0.0255	***	0.3260	0.0232	***
Knowledge Q3 Correct	0.5197	0.0169	***	0.1638	0.0214	***	0.2961	0.0201	***
Stock market correction of 2018	0.0551	0.0290	*						
Stock market crash of 2020	0.3952	0.0439	***	0.4285	0.0538	***			
Crash of 2020 * First lockdown	-0.2965	0.0642	***	-0.3096	0.0743	***			
First Covid-19 lockdown	0.2227	0.0380	***	0.2640	0.0443	***			
Second Covid-19 lockdown	-0.0081	0.0416		0.0288	0.0480		-0.0168	0.0337	
Third Covid-19 lockdown	0.0610	0.0419		-0.0254	0.0520		0.0877	0.0343	**
Log-likelihood	0.0248			0.0230			0.0180		

Finally, Table 3.8 examines the average trade values of unscheduled deposits. Like with the value of scheduled deposits, the estimates are in euros. However, these estimates suffer from the same problem as that which was described for scheduled deposits, in that considering a large number of zeroes from the investors who did not make an unscheduled deposit on a given day make the estimates less extreme than one would logically expect. On any given day, the most common behavior by far is to deposit nothing (zero euros). At the same time, unscheduled deposits tend to be much larger than scheduled deposits. To roughly approximate what the estimates would be if all the zeroes from these non-depositors were removed, one could multiply the estimates provided by one hundred.

Unsurprisingly, income has easily the strongest relationship with the value of unscheduled deposits. Other variables with a meaningfully large positive impact include, from greatest to least, financial literacy, sex (male), age, financial wealth, and property assets. On the other side, home ownership and investment horizon had negative relationships with unscheduled deposit value. Number of children and liquidity needs also had marginal negative relationships. In other words, investors made larger unscheduled deposits if they had higher incomes and higher financial literacy and were men, older, or wealthier. But they made smaller unscheduled deposits if they owned their home or had a longer investment horizon. Variables with inconclusive relationships to unscheduled deposit value in our sample include the stock market level, stock market volatility, and risk preferences.

3.5. STUDY 3: LINEAR AND LOGISTIC REGRESSIONS ON DIFFERENT TRANSACTION TYPES

Table 3.8: **Linear regression - Average trade value of unscheduled deposits, daily**

***, **, * indicate that the coefficient is statistically significant at the 1%, 5% and 10% confidence level, respectively.

	Group 1 (N = 6857)			Group 2 (N = 3043)			Group 3 (N = 5291)		
	Est.	St.Err.	Sig.	Est.	St.Err.	Sig.	Est.	St.Err.	Sig.
Intercept	-5.0880	2.1949	**	-6.4278	4.5252		-12.3830	6.8648	*
GSPC (per 100 points)	0.1367	0.0368	***	-0.0076	0.0772		-0.0089	0.1221	
GSPC volatility	-0.5303	1.5953		-1.9700	3.0837		2.9810	5.0579	
Sex (male)	2.8671	0.4885	***	-0.9908	0.9262		4.1506	1.0807	***
Age	0.0808	0.0152	***	0.2456	0.0289	***	0.4402	0.0343	***
Number of children	-1.7075	0.2144	***	-1.4576	0.4404	***	-0.8758	0.5499	
Annual income 25k to 50k	2.1677	0.8093	***	1.8918	1.4756		5.0678	1.8486	***
Annual income 50k to 100k	4.6741	0.8035	***	4.6645	1.4937	***	7.9170	1.8604	***
Annual income 100k to 150k	8.8517	0.9039	***	7.4427	1.7504	***	18.6720	2.1867	***
Annual income more than 150k	9.4910	1.0633	***	5.5374	2.1291	***	24.4470	2.7192	***
Home owner	-0.7024	0.4645		-3.0105	0.9254	***	-4.1881	1.1458	***
Property assets (per 10,000 EUR)	0.0755	0.0067	***	0.0870	0.0137	***	0.0896	0.0172	***
Financial wealth (per 10,000 EUR)	0.1083	0.0050	***	0.1954	0.0120	***	0.1313	0.0125	***
Horizon	-0.0314	0.0345		-0.2151	0.0637	***	-0.3179	0.0775	***
Liquidity Q1 Two years	-0.8471	0.2402	***	-0.6169	0.4863		-0.5885	0.5980	
Liquidity Q2 Half of deposit	-3.2443	0.5001	***	-1.9545	1.0341	*	1.7974	1.2509	
Risk Q1 Five year gamble	0.3482	0.2706		1.1830	0.6928	*	-0.4899	0.8468	
Risk Q2 Ten year gamble	0.1373	0.2572		0.7964	0.6855		0.4932	0.8338	
Risk Q3 Buy when market dips	0.2558	0.1463	*	0.5664	0.3046	*	-0.4574	0.3731	
Risk Q4 Experienced losses	-0.6971	0.1822	***	0.1165	0.3839		-0.5350	0.4701	
Knowledge Q1 Correct	-0.5943	1.0872		-0.8693	2.2357		0.3436	3.1626	
Knowledge Q2 Correct	1.4459	0.4823	***	4.1981	0.9481	***	1.9985	1.2112	*
Knowledge Q3 Correct	1.4938	0.4347	***	2.4332	0.8778	***	3.9152	1.0982	***
Stock market correction of 2018	-0.4827	0.8516							
Stock market crash of 2020	6.7621	1.5674	***	7.4995	2.7253	***			
Crash of 2020 * First lockdown	-3.0344	2.2912		-6.7085	3.8313	*			
First Covid-19 lockdown	-0.4626	1.2181		0.2826	2.0911				
Second Covid-19 lockdown	-0.6230	1.2446		-1.7449	2.0841		-2.8513	2.0269	
Third Covid-19 lockdown	3.3583	1.3350	**	1.2556	2.2287		3.2755	2.1008	
R-squared	0.0003			0.0005			0.0005		

A brief summary of these results is in order. Evidently, not every variable has the same relationship to each of the four outcome variables. While there is no reason to expect that each demographic, financial, or behavioral variable affects all four investment behaviors identically, there is reason to suspect that they will at least affect all three groups identically. If unobserved heterogeneity renders a variable unstable across these three groups, then it is unlikely to be a good predictor for other samples of investors. Income, property assets, financial wealth, age, and number of children emerged as stable predictors of investment behavior across all three groups and all four investment behaviors. Whether it is the propensity or value or (un)scheduled deposits, these five variables are always important. Meanwhile, the remaining variables are circumstantially useful, capable of predicting some investment behaviors but not others.

3.6 Discussion

Study 1 analyzed the broad trends present in our dataset from an exceptionally distant perspective, as though we were looking upon earth from the moon. The results of this fixed effects study showed that, although the asset manager from which we received our data grew in terms of the total number of clients, the long-horizon retail investors in our sample saved less during the overall pandemic period February 2020 - June 2021 with respect to surrounding months. These results were robust to considering overall stock market trends and several definitions of the "pandemic period." A slightly closer look revealed that investors saved less specifically during the lockdowns and the stock market crashes. However, the overlapping period between the stock market crash of 2020 and the first Covid-19 lockdown had a moderating effect as investors were not doubly panicked, a motif consistent in the subsequent analyses.

Keeping the fixed effects methodology, Study 2 zooms in to observe the different types of transactions that retail investors can perform at this asset manager, including scheduled and unscheduled deposits, and analyzes them in two ways, by value and by propensity. All four dependent variables had a statistically significant relationship with the stock market correction of 2018, the stock market crash of 2020, and the first Covid-19 lockdown, though the directions of the relationships were not always identical. These results show that analyzing different kinds of transactions in different ways is crucial to understanding how investors really reacted to the historical events, since top-level statistics can hide these nuances. Finally, Study 2 indicated that the second and especially the third Covid-19 lockdowns were not exact replications of the first, as investors were to some extent becoming habituated to the good old lockdown.

At the expense of the historical variables which are best studied through a panel regression, Study 3 switched to a logit and linear regression strategy to gain more insight on how demographic, financial, and behavioral variables influenced the investors' decision-making on these four dependent variables over the whole period. In this analysis, we discovered that income is reliably the strongest predictor of all four

investment behaviors and always has a positive relationship. Meanwhile, other variables such as number of children can have a positive relationship with one measure but a negative relationship with another. These results demonstrate the importance of precision when describing the relationship between a given independent variable and its outcome on investment behavior: what exactly is affected – scheduled or unscheduled deposits, value or propensity?

3.7 Conclusion

Within the finance community, there is an ongoing multinational debate about exactly what happened during the Covid-19 pandemic. Like all other financial crises before it, this debate will only continue as more diverse datasets including different types of investors become available. This history is a painting that will take many years and thousands of artists to create. With this study on long-horizon household investors in France, we add our brushstroke.

Chapter 4

How Do Households Invest on Behalf of Their Children?: Evidence from a Robo-advisor

Co-written with Alexis Direr

4.1 Introduction

Governments around the world encourage residents to invest on behalf of their children through awareness campaigns or tax-advantage savings and investment accounts like the 529 Plan in the USA, the Junior SIPP in the UK, and the Livret Jeune in France. In those countries and others, laws distinguish assets owned by parents and assets owned by children and custodied by parents until age of majority. However, despite the practice being commonplace, how parents manage child investment accounts has not received attention in the household finance literature.

This paper studies the way child saving accounts are opened and managed by parents and focuses on age and gender differences. Do fathers or mothers subscribe child accounts? Do they choose riskier investment portfolios for their sons or daughters? To answer those questions, we use extensive data from the leading robo-advisor operating in France over the period 2017-2022. We link 3000 child investment accounts with their parent's own accounts and exploit a rich set of information about parent's income and wealth, risk preferences, liquidity need and financial literacy in addition to sex and age.

We find that fathers are more likely to open investment accounts for their sons than their daughters for teenagers aged 12 and above. As fathers subscribe 4 child contracts out of 5, this son preference

results in a higher number of savings contracts opened for boys. Additionally, although fathers tend to choose riskier investment profiles than mothers for their children, no discernible difference in investment strategy is observed between sons and daughters for either parent.

The questions raised and the results found by the paper are important for several reasons. First, it is of prime importance to assert to what extent the traditional and common practice of gender bias in wealth transmission found in Western societies has regressed, thanks to evolving laws, cultural norms, and societal changes. Most legal systems have evolved to ensure equal treatment of sons and daughters in inheritance matters. In France, the Civil Code stipulates that the hereditary reserve (*réserve héréditaire*) should be split among children, regardless of gender. Cultural norms have also shifted toward more equal treatment for boys and girls on a variety of dimensions including financial capacity. Our results are consistent with the persistence of within-family differential treatment between boys and girls with respect to wealth management and transmission.

Second, the choice by parents of the child account's risk profile is akin to a principal-agent relationships in which the problem of moral hazard and incentives misalignment are presumably minimized thanks to parents' altruism and investment of their own money. However the portfolio delegation problem may still lead parents to choose inadequate risk level for their children. Experimental evidence suggest that people are weakly more risk-averse when dealing with others' money (Eriksen and Kvaløy, 2010; Eriksen et al., 2020). Using a dataset of saving accounts, Direr and Visser (2016) show that male financial advisors lead their customers to invest more in risky assets compared to female advisors. The present study finds a similar result transposed to parental relationship in which fathers choose riskier portfolio for their children than mothers do. A child may therefore obtain different financial risk exposition whether the father or the mother is in charge of the account.

Third, there is evidence that investing on behalf of children aids the intergenerational transmission of financial values and education. A sizeable literature documents a correlation between parents' and children's risk preferences, saving behaviors, and asset ownership (Dohmen et al., 2011; Charles and Hurst, 2003; Kimball et al., 2009; Arrondel, 2013; Fagereng et al., 2021). Opening an investment contract on behalf of one's child may establish lifelong financial habits, strengthen his propensity to save, signals trust in financial markets and provide first-hand financial experience and education. Jorgensen and Savla (2010) show that the financial socialization from parents significantly influence the financial literacy of young adults. Webley and Nyhus (2006) find that parental influences play a significant role in shaping children's attitudes towards saving. Our results indicate that fathers favor their sons in matters of financial transmission and education.

Fourth, a key financial choice for which early gender differences may appear is the risk profile chosen by parents on behalf of their children. Traditional gender norms may influence the way parents treat their children in the context of risk-taking behavior. It's often perceived that boys are encouraged to be more adventurous, while girls are often guided towards being more cautious. Research also suggests that confidence in financial decision-making can be lower among women (Barber and Odean, 2000), which could potentially be linked to childhood experiences and parental influences. In contrast, the present study does not find any differential treatment between boys and girls with regard to portfolio risk.

Fifth, another interesting research question is who within the family is in charge of managing children's saving. Within households, women spend more time in childcare on average whereas men make the majority of the household investment decisions. Because investing on behalf of children is a behavior that is at once both childcare and household investment, it is not immediately clear how this responsibility will be borne by households. Our results show that men are disproportionately in charge of managing child investment accounts.

More generally, a broad literature points to gender differences in financial markets. Significant gender gaps have been observed in the participation to financial markets (Ke, 2018) and financial knowledge (Fonseca et al., 2012). Behavioral differences have also been documented regarding to risk taking (Charness and Gneezy, 2012), portfolio choice (Sunden and Surette, 1998), and trading behavior (Barber and Odean, 2001). Our study contributes to this literature by showing that men are predominantly in charge of the household investments both within the couple and on behalf of children.

The remaining of the article is organized the following way. Section 2 explains the process of opening an account for oneself and one's child. Section 3 presents summary statistics about parental and child accounts and documents gender differences in subscriptions and risk profiles. Section 4 uses econometric models to assert significant gender differences in subscriptions and risk profiles. Section 6 concludes.

4.2 Opening an investment account

To open an account with the robo-advisor, customers have to visit the company's website and fill out a questionnaire. The questionnaire, administered in French, collects a rich information set about customers used by the robot-advisor's in-house algorithm to recommend a risk profile.¹

¹See Boulu-Reshef et al. (2022) for an analysis of the advising algorithm based on the same data source, and the way savers abide to the financial recommendation.

4.2.1 Questionnaire

The questionnaire collects detailed information about the client's financial situation, previous investment experience, attitudes towards risk, demographic status, contact information and investment goals. Possible goals include 'Increase savings', 'Prepare a major purchase', 'Bequeath an inheritance', 'Plan their retirement', 'Save in the event of hard times', 'Prepare a real estate investment', 'Finance their children's studies' or 'Open an account for one's child'. Questions about the client's demographic status include date of birth, number of children, city and country of birth, nationality, legal capacity, gender, employment status, employment sector, and profession.

Questions about the investment include the initial capital invested, the additional capital invested monthly, the investment horizon, the odds of the investment being liquidated in two years, and the odds of the investment being liquidated before the stated investment horizon. Questions about the client's financial status include tax residency status, pre-tax annual income, homeownership, monthly rent or mortgage repayment, total real estate property, total financial property, and monthly savings rate.

Prospective clients begin by defining their investment project. If the option "Open an account for my child" is selected, the following text box appears: "This project allows you to open an account in your child's name. The savings will belong to your child, and they will have full access to the account when they come of age. In the following section, the questions about the savings plan concern your child. The questions concerning knowledge of the financial markets, risk appetite and the need for liquidity concern the legal representatives." The questionnaire also collects the demographic status of the client's child (date of birth, city and country of birth, nationality, legal capacity, and gender) and the contact information of the child's second legal representative, if one is listed.

All of the information in the questionnaire is self-reported, but some fields require proof. Before signing a contract, a client must provide an identity card, a proof of address, a mobile phone bill, and bank account identification details (*relevé d'identité bancaire*). When signing a contract on behalf of a child, in addition to the aforementioned documents, a client must also provide an up-to-date summary of the vital records (*livret de famille*) of their child as well as a proof of identity for their child to establish a relationship as the child's authentic parental authority. Because of fail-safes during the questionnaire and the identity verification process, it is not possible to open a children's account on behalf of an adult or of any child except one's own. Therefore, all of a client's demographic details are accurate and externally verified, and their parental relationship to the child on behalf of which they are opening a contract is certain.

In contrast, no documents are requested to justify a client's financial situation, such as a pay stub or a

tax form. The self-reports on financial details are thus approximate and not externally verified. That said, while proof is not required, prospective clients are nevertheless incentivized to provide correct information about their financial situation in order to receive relevant advice from the robo-advisor. Without providing at least approximate information, the advice received from the robo-advisor is practically useless.

4.2.2 Risk Profiles

A recommendation is calculated based on the responses to the questionnaire. The client must create an account to proceed. After creating an account, the client accepts or modifies the suggestion. Thereafter, additional questions are asked about the demographic characteristics about the child and the legal representative who filled out the questionnaire.

The company offers ten discrete investment portfolios which are arranged from 1 to 10 based on the proportion of the capital invested in various risky assets. The composition of the portfolio advertised as the lowest risk, "Risk Profile 1," is 100% money market assets, 0% bond exchange traded funds (bond ETFs), and 0% stock exchange traded funds (stock ETFs). As the risk profile increases to the middle of the risk spectrum, money market assets are phased out in favor of bond ETFs, then again as the risk profile increases to the riskiest end of the risk spectrum, bond ETFs are phased out in favor of stock ETFs.

Table 4.1 summarizes the composition of the ten risk profiles.²

Table 4.1: Portfolio composition by risk profile, in percentages

Risk Profiles	1	2	3	4	5	6	7	8	9	10
Money Market Assets	100	70	60	40	20	0	0	0	0	0
Bond ETFs	0	15	20	30	40	50	40	30	20	0
Stock ETFs	0	15	20	30	40	50	60	70	80	100

4.3 Summary statistics on child and parental accounts

As the analysis will focus on parental and child accounts, it is worth first assessing to what extent adults opening accounts on behalf of their children are observationally different from other adults, either the ones declaring children but without opening child accounts or the ones declaring no children.

There are reasons to suppose that investment behavior will differ between parents and non-parents. The presence of children may provide higher incentives to set long term goals and invest in risky assets.

²As of September 10th, 2020, it is no longer possible to select risk profile 1. Contracts which selected this risk profile before this date were not changed. As of April 30th, 2021, the composition of Risk Profile 2 was rebalanced from the former 80-10-10 to the current 70-15-15. Contracts which selected this risk profile were updated.

On the other hand, parents may take fewer financial risks when it comes to preserving their offspring's standard of living (Love, 2010). In addition, opening an investment account for one's child may signal confidence and optimism about the long-term prospects of financial markets and propensity to take risks (Hong et al., 2004). This would imply riskier portfolios for parents who invest for their children than those who do not.

Descriptive statistics on the variables of interest and of control are provided in Table 4.2 for five groups: adult non-parent investors, parent-only investors (declaring having children without child accounts), parent-child investors with at least one child account, parent-child investors' children and child-only investors which are child account without linked parents' accounts. The dataset includes all contracts subscribed from August 28th, 2015 to April 11th, 2022.

<Insert Table 4.2>

Some trends are noticeable in the descriptive statistics. We will call attention to a few, starting from the top of the table. Consistent with previous literature, men are more likely to subscribe a contract than women. The proportion is even higher among parent-child investors. Logically, fathers open more frequently than mothers a contract on behalf of their children. Meanwhile, the gender distribution for children (parent-child child and child-only) is much more even, with only a slightly larger number of boys.

Across a set of financial variables such as income, home-ownership, property assets, and financial wealth, parent-only, parent-child parent, and parent-child child are better off than child-only, who are better off than non-parent. However, regardless of whether their parents opened a contract on behalf of themselves, children with contracts share several similarities, such as initial deposits which are much lower than those for adults, horizons which are several years longer, and parents with lower liquidity needs.

Risk profiles chosen by non-parent investors are on average slightly less than risk profiles selected by parent-only investors, which are less than risk profiles chosen by parent-child investors. Risk profiles chosen by parents on behalf of their children is even greater, which could be explained by higher investment horizons. Finally, while differences in risk attitudes seem negligible, clients who open accounts for both themselves and their children demonstrate greater financial literacy.

To summarize, parents opening a contract for their children are different from other adults. They are more likely to be male, more financially wealthy and educated, indicate higher risk preferences and hold riskier portfolios. Those differences should be kept in mind when analyzing the behavior of parents with child accounts.

4.4 Gender differences in subscriptions and risk profiles

While marked gender differences have been documented in the financial literature, little is known about their evolution over the life cycle starting from cradle. As we are interested in within-family preferences, we focus on families with opened accounts both for at least one adult and one child. This corresponds to two groups presented in previous descriptive statistics: parent-child investors with at least one child account (N=2792) and parent-child investors' children (N=3033). Parent-only investors and child accounts without linked parents' accounts are discarded.

4.4.1 Gender differences in subscriptions

In this section, we ask whether fathers or mothers open more child contracts and more contracts are subscribed for their sons or daughters.

<Insert Figure 4.1>

Fig. 4.1 plots the share of contracts opened by parents on behalf of their sons. It also plots as a reference the share of contracts opened by the male head of family for subscribers older than 18. In stark contrast to parents among which the share of male subscribers is at least $2/3$, the share of contracts opened for sons is closed to 50% for ages below 13 (51.7% for 0-5 y.o. and 49.4% for 6-11 y.o.). The gender gap becomes significant for teenagers (55.1% for 12-17 y.o.). The Figure also documents a gender gap which consistently declines with parents' age, from 89.7% for ages between 18-29 down to 66.7% for ages greater than 60.

In other words, parents open as frequently a contract for their young sons and daughters, but express a discernible son preference for teenagers. Gender bias remains smaller to those observed among fathers and mothers.

<Insert Figure 4.2>

Fig. 4.2 shows that the male head of family is predominantly in charge of managing savings both within the couple and on behalf of their children. 87.5% of contracts for their children aged 0-5 are opened by fathers. The share then declines for older children (80.7% for ages 6-11 and 79.6 for ages 12-17). The proportion of fathers who subscribe for their children is in line with the share of men opening an investment contract among adults.

<Insert Figure 4.3>

Since fathers make up the large majority of parents opening a child contract, it is worth investigating a possible preference for sons. Fig. 4.3 shows the share of boys' and girls' accounts opened by their father. While no or limited differences are observed for ages 0-5 (87.1% for sons vs. 87.9% for daughters) and 6-11 (81.9% vs. 79.5%), a clear preference is observed for teenagers (83.0% vs 75.3%). This could be equivalently interpreted as mothers expressing a daughter preference for their teenagers. Yet as fathers subscribe a larger share of child contracts, son preference emerges at the family level.

4.4.2 Gender differences in risk profiles

Another key financial choice for which early gender differences may appear is the risk profile chosen by parents on behalf of their children.

<Insert Figure 4.4>

Figure 4.4 shows no systematic difference in risk profiles between sons and daughters. Mean risk profiles are pretty equal for children aged 0-5 (7.77 for boys vs. 7.81 for girls) and 6-11 (7.95 for boys vs. 7.89 for girls). Boys are given higher risk profiles at age 12-17 (7.63 for boys vs. 7.46 for girls). While the difference is small, it is consistent with the pattern found for parents where men select higher risk profiles for themselves than women. Risk profiles are relatively even across age groups and high compared to what parents choose for themselves.

<Insert Figure 4.5>

Figure 4.5 shows that fathers choose higher risk profiles for their sons than their girls and that the gap between the two sexes broadens with child's age (7.81 vs. 7.63 for ages 0-5, 7.99 vs. 7.62 for ages 6-11 and 7.67 vs. 7.12 for ages 12-17). Differences in risk profiles are in line with differences between fathers and mothers when they decide for their own savings, with a gender gap increasing with age.

<Insert Figure 4.6>

Last, Figure 4.6 shows that although fathers choose higher risk profiles than mothers for their children, they both tend to not differentiate between their sons and daughters. Only marginal differences are observed for father at ages 12-17 (7.75 for boys vs. 7.55 for girls) and mothers at ages 0-5 (7.54 for boys vs. 7.31 for girls), 6-11 (7.72 for boys vs. 7.52 for girls) and 12-17 (7.02 for boys vs. 7.20 for girls)

In summary, parents choose similar risk profiles for their sons and daughters although fathers select higher risk profiles than mothers do. This explains why risk profiles in child accounts are not significantly different across sexes.

4.5 Econometrics

The previous section found some evidence of a son preference for their older children aged 12-17, which is mostly explained by the disproportionate share of child contracts subscribed by fathers. The aim of the econometrics is to test whether previous descriptive results are statistically significant and robust to the addition of other factors. The dataset is restricted to child accounts with at least one linked parent account (N=3033) as key information from parent accounts such as their age and sex are leveraged. This corresponds to the group of parent-child investors' children in Table 4.2.

4.5.1 Gender differences in subscriptions

To study gender differences in subscriptions, we test the logit model:

$$\begin{aligned} \text{SON}_i = f & \left(\alpha + \beta_0 \text{DAD}_i + \beta_1 \text{AGE1}_i + \beta_2 \text{AGE2}_i \right. \\ & \left. + \beta_3 \text{DAD}_i \times \text{AGE1}_i + \beta_4 \text{DAD}_i \times \text{AGE2}_i + \gamma X_i \right) \end{aligned}$$

in which:

- $\text{SON}_i = 1$ if the contract was subscribed on behalf of a boy (0 of a girl)
- $\text{DAD}_i = 1$ if the contract was opened by the father (0 by the mother)
- $\text{AGE1}_i = 1$ if the child was 6 to 11 year old at subscription
- $\text{AGE2}_i = 1$ if the child was 12 to 17 year old at subscription
- X_i is a set of covariates from questionnaire's and contracts' information

With previous descriptive results in mind, the model allows to examine various forms of son preferences, whether associated with parent's sex, specific age group or a combination of the two. Three versions of the model are tested in Table 4.3. Model 1.1 includes information about parent's sex, child's age and interaction terms. Model 1.2 adds demographic variables (family size and parent's age) and subscription years. Model 1.3 includes a full set of covariates including income and wealth indicators obtained from the questionnaire filled by parents at subscription.

<Insert Table 4.3>

In baseline model 1.1, the only variable which significantly affects at 5% level the probability of a contract to be subscribed for a son is the interaction term $\text{DAD}_i \times \text{AGE2}_i$. In accordance with descriptive

statistics, contracts subscribed for teenagers aged 12-17 are more frequent for sons than daughters and the effect is explained by fathers subscribing more contracts for their sons for this specific age group. There are no significant difference between sons and daughters for other age groups and/or whether the contract is subscribed by the father or mother. The result is robust to the inclusion of additional covariates in models 1.2 and 1.3. Family size, parent's age, income and wealth do not affect the probability of opening a contract for one's son.

4.5.2 Gender differences in risk profiles

To examine gender differences in risk profiles, an ordinary least-squares model is used:

$$\begin{aligned} RP_i = & \alpha + \beta_0 SON_i + \beta_1 DAD_i + \beta_2 AGE1_i + \beta_3 AGE2_i \\ & + \beta_4 DAD_i \times AGE1_i + \beta_5 DAD_i \times AGE2_i + \gamma X_i \end{aligned} \quad (4.1)$$

where SON, DAD, AGE1, AGE2 and X have been defined in previous subsection. The dependent variable RP is the risk profile, scaled from 1 to 10, which determines the risk level of the client's portfolio, as explained in Section 4.2. The model allows to investigate whether the risk profile selected by a parent on behalf of his child depends on child's sex or age group, parent's sex or a combination of those characteristics. Four versions of the model are tested in Table 4.4:

- Model 2.1 includes information listed in Eq. (4.1) without any additional variables ($X = 0$).
- Model 2.2 adds demographic variables (family size and parent's age) and subscription years.
- Model 2.3 adds to model 2.2 parent's income and wealth information obtained from the questionnaire filled at subscription.
- Model 2.4 adds to model 2.3 parent's own risk profile and answers about investment horizons (for their child and own accounts), liquidity needs, risk attitude and financial knowledge (see Appendix for a description).

<Insert Table 4.4>

Results show that risk profiles do not vary with child's sex or age. As documented in the descriptive section, fathers choose higher risk profiles than mothers for their children in models 2.1 and 2.2, although the effect disappears once income/wealth indicators are included (model 2.3) and other information used by the algorithm to make a recommendation (model 2.4). The same way, children aged 12 to 17 are

given higher risk profiles at 5% (model 2.1) or 10% level (model 2.2), but the age group is not significant in larger models 2.3 and 2.4 anymore. Overall, demographic effects found in the Section 4.4 tend to disappear once additional non-demographic characteristics are taken into account.

The lack of significance could be explained by two complementary reasons. First, the full model exploits a rich set of control variables which measure a wide range of factors associated with the propensity to take financial risk such as indicators of wealth and income, risk aversion, financial knowledge and experience, liquidity needs, age and investment type and horizon. Those characteristics are possibly correlated with gender and reduce its explanatory power. For instance, a major reason why men invest in riskier portfolio than women is lower risk aversion Charness and Gneezy (2012); Croson and Gneezy (2009), which is controlled for in the econometrics by several preference measures. Second, all this information is used by the robo-advisor to make a recommendation of risk profiles that many clients follow. In the sample, 69.6% of all child accounts abide to the recommendation at subscription. Since the algorithm is gender neutral, most clients' portfolio decisions will be as well. This illustrates a benefit of algorithmic choice in terms of reducing human bias in financial decisions.

In addition, the econometric results indicate higher risk profiles given to children in family with more than one child, by parents with higher incomes, higher property wealth, higher financial wealth to some extent, higher risk profiles for their own saving contracts, less liquidity needs, lower risk aversion, who wait or buy when markets dip and have previously experienced financial losses.

4.6 Conclusion

This article find evidence of a son preference for their older children aged 12-17. For this age group, fathers are more likely to open investment accounts for their sons. As they predominantly manage children's contracts within the family this effectively leads to a higher number of savings contracts opened for boys. Additionally, while fathers tend to choose riskier investment profiles for their children compared to mothers, no discernible difference in investment strategy is observed between sons and daughters for either parent. Father's higher propensity to take financial risk on behalf of their children weakens or disappears altogether when control variables are included. This is mainly explained by the fact that 70% of child contracts follow the gender-neutral algorithmic recommendation.

This study could be extended in several ways. It would be interesting to analyze how children's portfolio change with age in a longitudinal study and not only at subscription. It remains unclear whether contracts subscribed for younger children could also be characterized by a son preference in the form of higher contributions when they age. A son preference could also exist and is still to be investigated

in other parent-child relationship in which money is involved, like pocket money, the opening of a bank and saving accounts, financing higher education and inter-vivo transfers.

Appendix: Description of control variables

Savers's characteristics are obtained from the the questionnaire filled by clients during the subscription process. In case of the opening of a child account, the user interface indicates that the questions and possible answers are for the legal representative.

Investment horizon: "In how much time would you like to benefit from this investment? (Answer entered in years)"

Liquidity needs Q1: "Could you need all the savings held with [Name of the company] within the next two years?"

- ☐ Certainly not [coded 1 in Table 4.2]
- ☐ Likely not [coded 2 in Table 4.2]
- ☐ Likely [coded 3 in Table 4.2]
- ☐ Very likely [coded 4 in Table 4.2]

[Note: Table 4.2 reports a mean score of liquidity based on the numerical coding]

Liquidity needs Q2: "Could you need half of your investment before the end of the selected investment period?"

- ☐ Certainly not [coded 1 in Table 4.2]
- ☐ Likely not [coded 2 in Table 4.2]
- ☐ Likely [coded 3 in Table 4.2]
- ☐ Very likely [coded 4 in Table 4.2]

[Note: Table 4.2 reports a mean score of liquidity based on the numerical coding]

Risk aversion Q1: "What profit/loss ratio are you willing to accept by investing €10,000 over 5 years? There is no right or wrong answer."

- ☐ Potential gain of €5,000 / Potential loss of €2,000 [coded as *very high* in Table 4.4 and 1 in Table 4.2]
- ☐ Potential gain of €2,000 / Potential loss of €1,000 [coded as *high* in Table 4.4 and 2 in Table 4.2]
- ☐ Potential gain of €1,000 / Potential loss of €400 [coded as *medium* in Table 4.4 and 3 in Table 4.2]
- ☐ Potential gain of €500 / Potential loss of €0 [coded as *low* in Table 4.4 and 4 in Table 4.2]

[Note: Table 4.2 reports a mean score of risk aversion based on the numerical coding]

Risk aversion Q2: What profit/loss ratio are you willing to accept by investing over 10 years?

- ☐ With an expected final gain of 20%, but with a risk of loss of 5% [coded as *very high* in Table 4.4 and 4 in Table 4.2]
- ☐ With an expected final gain of 30%, but with a risk of loss of 10% [coded as *high* in Table 4.4 and 3 in Table 4.2]
- ☐ With an expected final gain of 50%, but with a risk of loss of 15% [coded as *medium* in Table 4.4 and 2 in Table 4.2]

- ☐ With an expected final gain of 70%, but with a risk of loss above 15% [coded as *low* in Table 4.4 and 1 in Table 4.2]

[Note: Table 4.2 reports a mean score of risk aversion based on the numerical coding]

When market dips: If your investment loses 10% of its value in 3 months, what do you do?

- ☐ I reinvest to benefit from this opportunity [coded as *Buy* in Table 4.4]
- ☐ I wait without panicking [coded as *Wait* in Table 4.4]
- ☐ I sell a portion to limit my potential losses [coded as *Sell part or all* in Table 4.4]
- ☐ I sell everything [coded as *Sell part or all* in Table 4.4]
- ☐ I do not know [coded as *Doesn't know* in Table 4.4]

Experience loss: "Have you already endured losses on your financial investments?"

- ☐ Non, I have not endured a loss on my financial investments [coded as *Never* in Table 4.4]
- ☐ Yes, of 10% maximum [coded as *Max 10%* in Table 4.4]
- ☐ Yes, of 20% maximum [coded as *Max 20%* in Table 4.4]
- ☐ Yes, of more than 20% [coded as *> 20%* in Table 4.4]

Knowledge Q1: "A high gain prospect implies a high risk of capital loss. Does the statement seem true to you?"

- ☐ True [coded as *Correct* in Tables 4.4 and 4.2]
- ☐ False [coded as *Wrong* in Tables 4.4]
- ☐ I do not know [coded as *Doesn't know* in Tables 4.4]

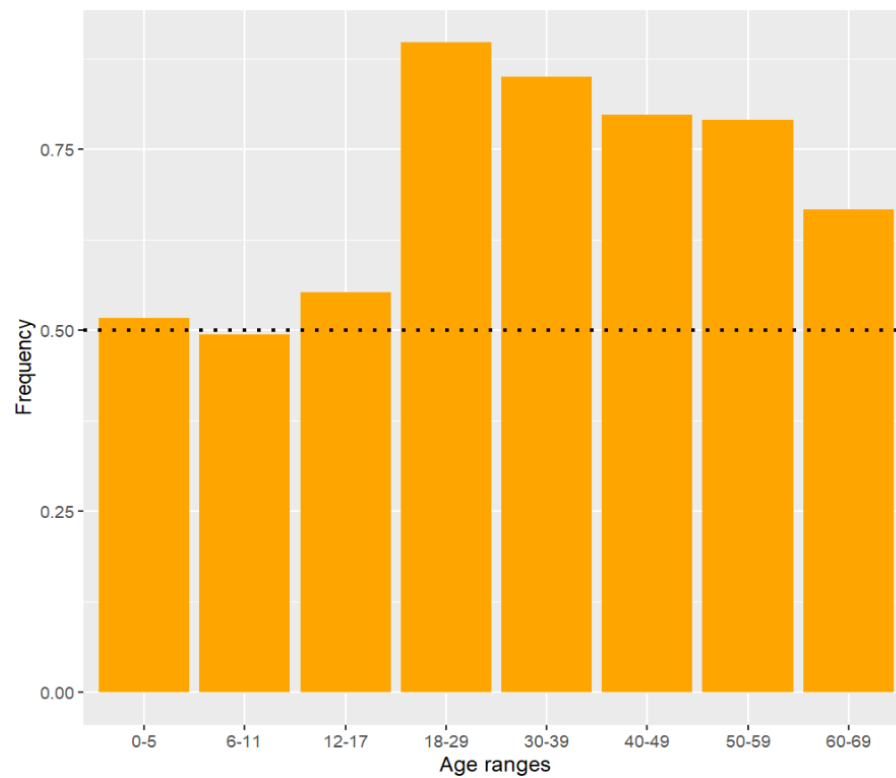
Knowledge Q2: "An ETF is a fund for which the capital is guaranteed. Does the statement seem true to you?"

- ☐ True [coded as *Wrong* in Tables 4.4]
- ☐ False [coded as *Correct* in Tables 4.4 and 4.2]
- ☐ I do not know [coded as *Doesn't know* in Tables 4.4]

Knowledge Q3: "By delegating the management of my portfolio to a management company, I renounce making any investment decisions myself on it. Does the statement seem true to you?"

- ☐ True [coded as *Correct* in Tables 4.4 and 4.2]
- ☐ False [coded as *Wrong* in Tables 4.4]
- ☐ I do not know [coded as *Doesn't know* in Tables 4.4]

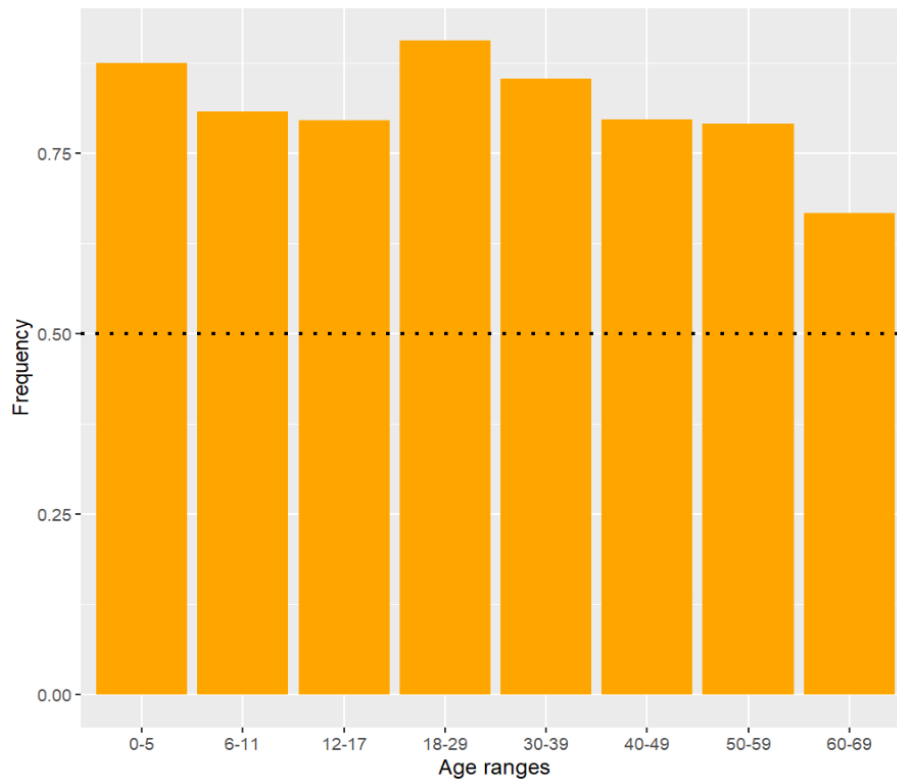
Figure 4.1: Proportion of contracts opened for sons (before 18) or by men (after 18)



Dataset: contracts subscribed by at least one adult and for one child belonging to the same family.

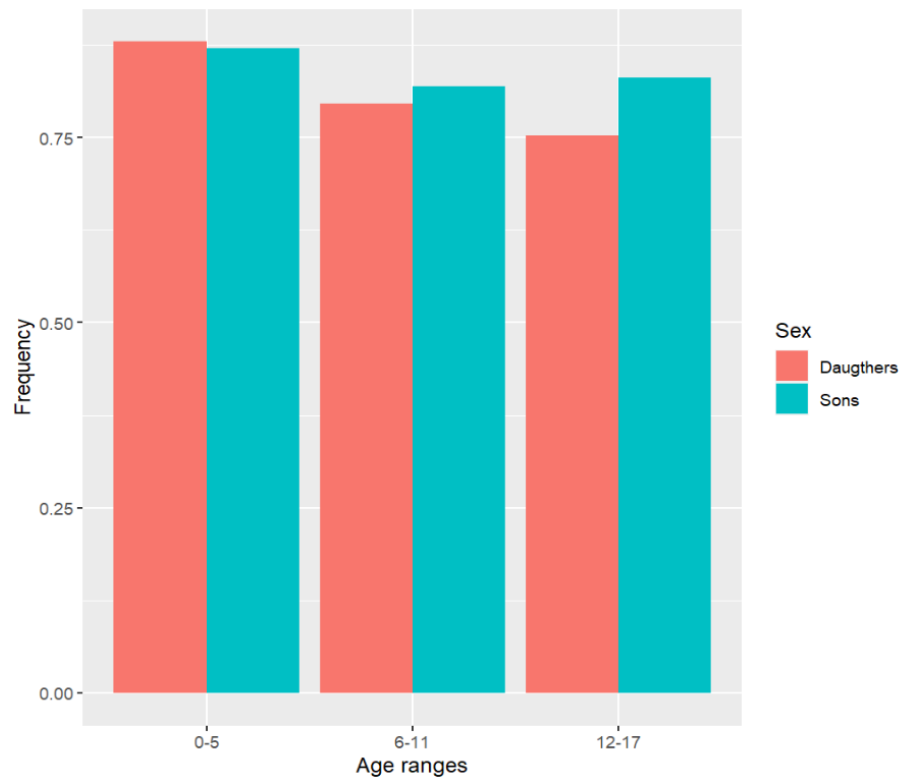
Reading: Among all contracts opened for children aged 0 to 5, 51.7% are subscribed for boys. Among all contracts opened by adults aged 30 to 39, 85.0% are subscribed by men.

Figure 4.2: Proportion of fathers (ages 0-17) or men (ages 18+) opening a contract



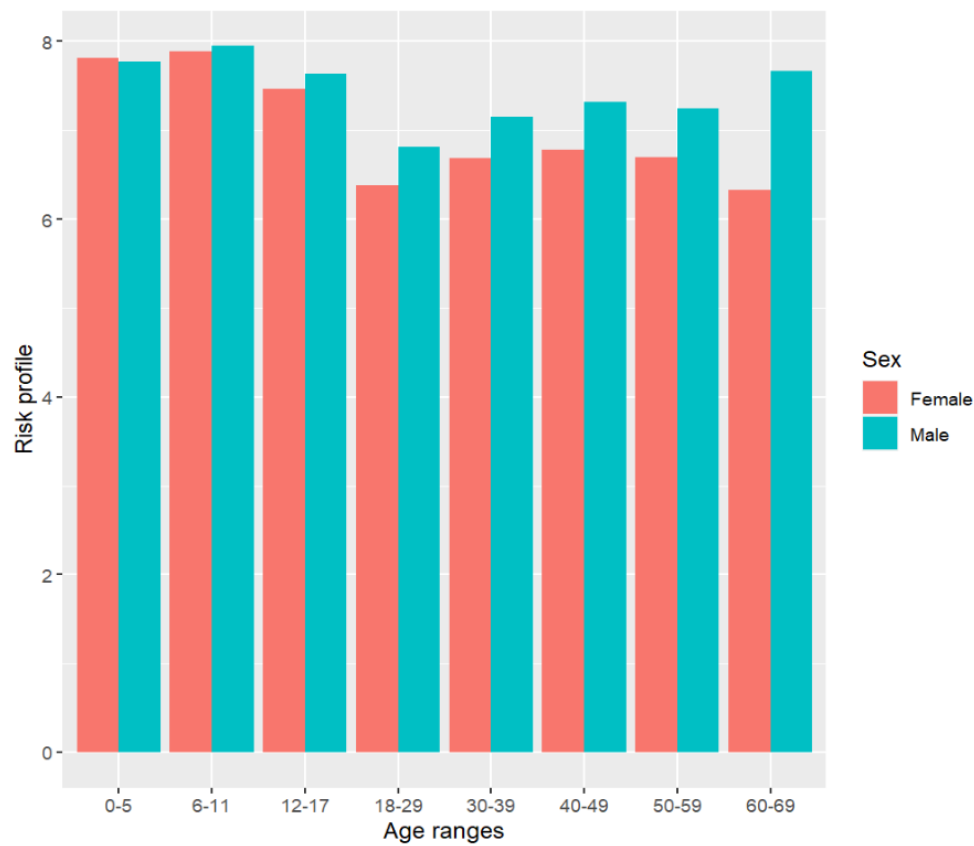
Dataset: contracts subscribed by at least one adult and for one child belonging to the same family.

Reading: Among all contracts opened for children aged 0 to 5, 87.5% are subscribed by fathers. Among all contracts opened by adults aged 30 to 39, 85.0% are subscribed by men.

Figure 4.3: *Share of fathers opening a contract for their sons and daughters*

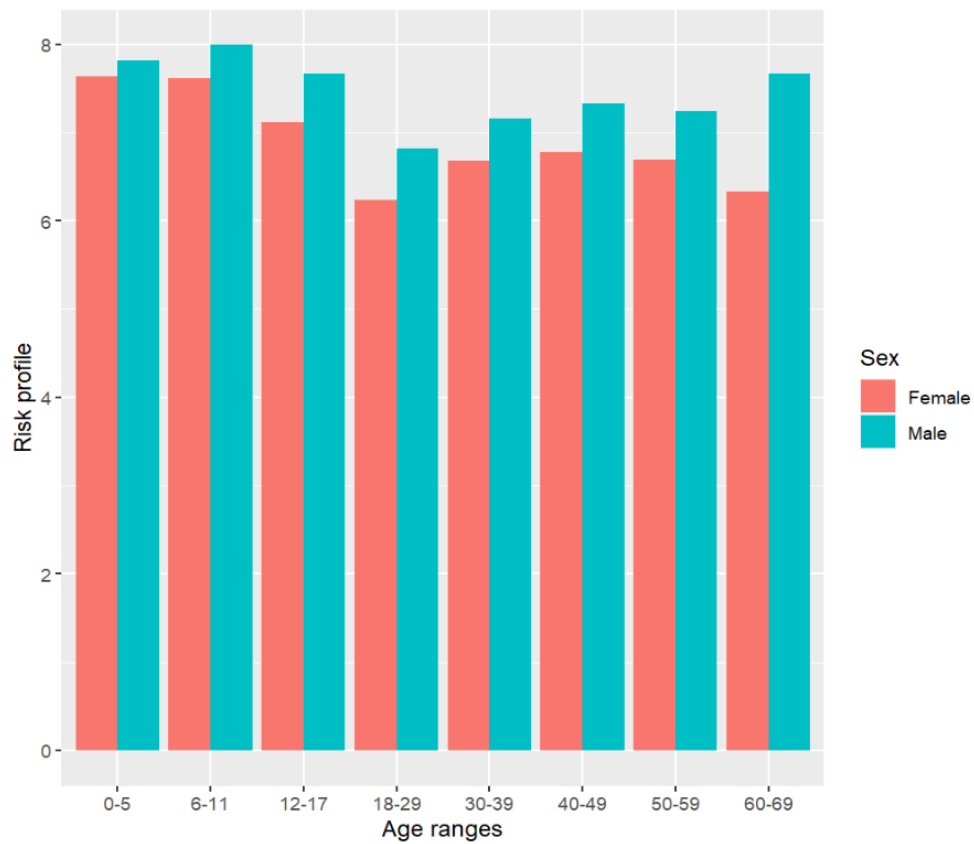
Dataset: contracts subscribed by at least one adult and for one child belonging to the same family.

Reading: Among all contracts opened for sons aged 0 to 5, 87.1% are subscribed by fathers. Among all contracts opened for daughters aged 0 to 5, 87.9% are subscribed by fathers.

Figure 4.4: *Mean risk profiles by sex and age*

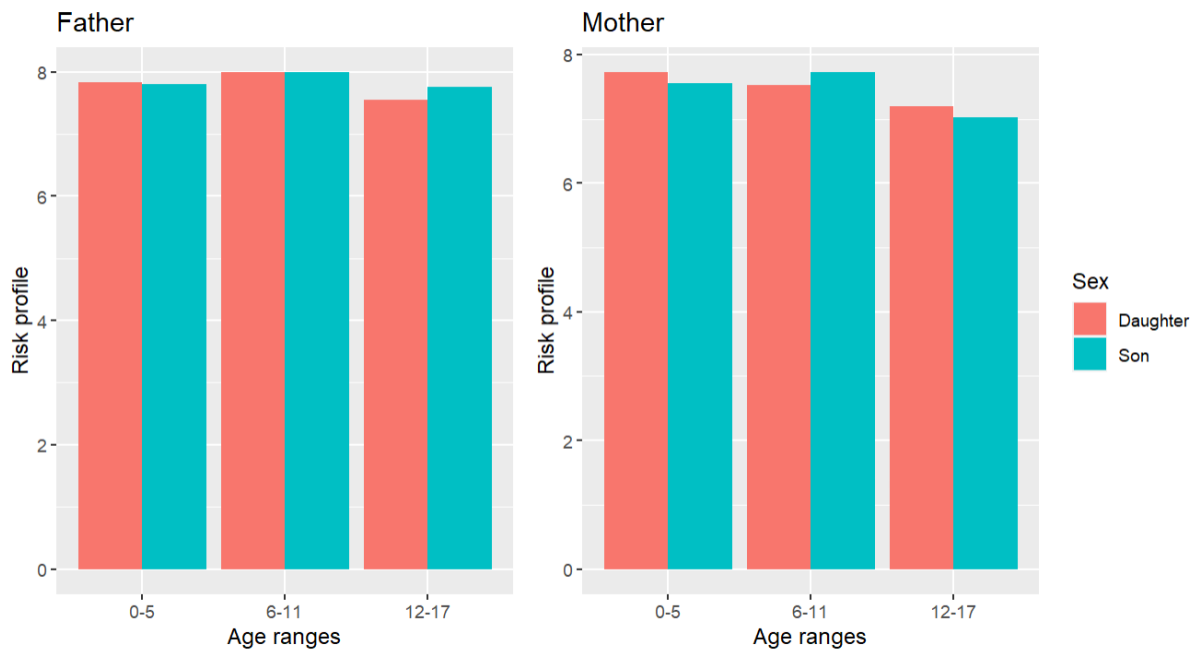
Dataset: contracts subscribed by at least one adult and for one child belonging to the same family.

Reading: Mean risk profile of contracts opened on behalf of children aged 0 to 5 is 7.7 for boys and 7.8 for girls. Mean risk profile for contracts subscribed by adults aged 30 to 39 is 7.1 for men and 6.7 for women.

Figure 4.5: *Mean risk profiles by chooser's sex and age*

Dataset: contracts subscribed by at least one adult and for one child belonging to same family. Reading: Mean risk profiles of contracts opened on behalf of children aged 0 to 7 is 7.8 when subscribed by fathers and 7.6 when subscribed by mothers. Mean risk profiles for contracts subscribed by adults aged 30 to 39 is 7.1 for men and 6.7 for women.

Figure 4.6: Mean risk profiles chosen by fathers and mothers decomposed by child's sex and age



Dataset: contracts subscribed by at least one adult and for one child belonging to the same family.

Reading: Mean risk profiles of contracts opened on behalf of a child aged 0 to 5 subscribed by his fathers is 7.8 for a boy and 7.8 for a girl. Mean risk profiles of contracts opened on behalf of a child aged 0 to 5 subscribed by her mother is 7.5 for a boy and 7.7 for a girl.

Table 4.2: Descriptive statistics for non-parent investors, parent-only investors, parent-child investors, parent-child investors' children and child-only investors.

Means	Non-parent	Parent-only	Parent-child parent	Parent-child child	Child-only
N	20415	9895	2792	3033	1748
Sex	0.72	0.7	0.84	0.52	0.51
Age at subscription	35.53	40.43	36.68	5.07	5.26
Annual income less than 25k	0.15	0.03	0.02	0.01	0.04
Annual income 25k to 50k	0.42	0.21	0.18	0.16	0.2
Annual income 50k to 100k	0.33	0.45	0.47	0.48	0.5
Annual income 100k to 150k	0.08	0.2	0.22	0.22	0.19
Annual income more than 150k	0.02	0.11	0.11	0.12	0.07
Home-owner	0.41	0.78	0.78	0.8	0.78
Property assets	155379	325697	301686	329020	290925
Financial wealth	129907	195890	178759	197882	137498
Initial deposit	8776	11060	8229	2400	2983
Risk profile	6.88	7.07	7.42	7.6	7.34
Horizon	10.75	11.37	12.19	15.05	14.81
Liquidity needs Q1	1.59	1.57	1.55	1.26	1.25
Liquidity needs Q2	0.94	0.88	0.75	0.56	0.57
Risk aversion Q1	0.68	0.66	0.60	0.58	0.63
Risk aversion Q2	1.10	1.07	0.91	0.99	1.08
Knowledge Q1 Correct	0.96	0.97	0.98	0.99	0.97
Knowledge Q2 Correct	0.77	0.78	0.84	0.89	0.79
Knowledge Q3 Correct	0.7	0.71	0.79	0.87	0.72

See Appendix for the description of variables horizon, liquidity needs, risk aversion and knowledge.

Table 4.3: Logit model of gender differences at subscription

	Model 1.1		Model 1.2		Model 1.3	
	Estimate	Pr(> t)	Estimate	Pr(> t)	Estimate	Pr(> t)
Father	-2.03	0.562	-2.93	0.403	-2.54	0.472
Age at subscription 0-5			<i>reference</i>			
Age at subscription 6-11	-7.13	0.137	-6.60	0.219	-5.83	0.279
Age at subscription 12-17	-0.65	0.231	-5.66	0.400	-6.06	0.366
Father × age 0-5			<i>reference</i>			
Father × age 6-11	5.87	0.306	6.11	0.286	4.75	0.409
Father × age 12-17	13.85	0.050 *	14.56	0.040 *	14.40	0.042 *
One child family			<i>reference</i>			
Two child family			0.35	0.871	0.03	0.988
Three + child family			-1.62	0.569	-2.34	0.419
Parent aged 18-29			<i>reference</i>			
Parent aged 30-39			-2.25	0.463	-2.28	0.462
Parent aged 40-49			-3.07	0.401	-3.39	0.364
Parent aged 50-59			-7.17	0.208	-8.06	0.164
Subscribed in 2017			5.51	0.080 .	4.65	0.142
Subscribed in 2018			6.10	0.081 .	6.14	0.078 .
Subscribed in 2019			3.73	0.248	3.29	0.310
Subscribed in 2020			1.53	0.503	1.61	0.509
Subscribed in 2021			<i>reference</i>			
Subscribed in 2022			-6.19	0.040 *	-6.21	0.040 *
Annual income < 25k					-10.30	0.170
Annual income 25k to 50k					2.09	0.434
Annual income 50k to 100k			<i>reference</i>			
Annual income 100k to 150k					-1.20	0.617
Annual income > 150k					0.43	0.893
Financial wealth < 10k			<i>reference</i>			
Financial wealth 10k to 50k					-5.55	0.228
Financial wealth 50k to 100k					-5.76	0.225
Financial wealth 100k to 250k					-3.08	0.528
Financial wealth 250k to 1m					-4.13	0.420
Financial wealth > 1m					-1.39	0.860
Property assets 0			<i>reference</i>			
Property assets 0+ to 10k					-1.45	0.878
Property assets 10k to 50k					-1.07	0.794
Property assets 50k to 100k					5.52	0.166
Property assets 100k to 250k					0.91	0.770
Property assets 250k to 1m					2.73	0.352
Property assets > 1m					7.83	0.213

Dependent variable is 1 if the contract is subscribed on behalf of a boy and 0 of a girl. See Appendix for description of the explanatory variables. Significance codes: ***: 0, **: 0.001, *: 0.01, .: 0.05, .: 0.1.

Table 4.4: OLS model of gender differences in risk profiles

	Model 2.1		Model 2.2		Model 2.3		Model 2.4	
	Estimate	Pr(> t)	Estimate	Pr(> t)	Estimate	Pr(> t)	Estimate	Pr(> t)
(Intercept)	7.33	0.000 ***	7.61	0.000 ***	6.45	0.000 ***	8.08	0.000 ***
Son	-0.01	0.884	0.03	0.077	-0.02	0.818	-0.01	0.912
Father	0.27	0.015 *	0.28	0.019 *	0.19	0.108	-0.01	0.897
Age at subscription 0-5				<i>reference</i>				
Age at subscription 6-11	0.05	0.730	0.05	0.074	0.01	0.920	-0.05	0.522
Age at subscription 12-17	-0.35	0.049 *	-0.50	0.094 .	-0.51	0.081 .	-0.01	0.962
Father × age 0-5				<i>reference</i>				
Father × age 6-11	0.12	0.522	0.10	0.572	0.15	0.398	0.12	0.217
Father × age 12-17	0.09	0.700	0.02	0.907	0.12	0.603	-0.07	0.557
One child family				<i>reference</i>				
Two child family			0.03	0.783	-0.10	0.286	-0.13	0.009 **
Three + child family			0.24	0.056 .	-0.01	0.913	-0.12	0.066 .
Parent aged 18-29				<i>reference</i>				
Parent aged 30-39			-0.16	0.227	-0.24	0.066 .	-0.03	0.685
Parent aged 40-49			0.16	0.314 .	-0.33	0.035 *	-0.08	0.356
Parent aged 50-59			-0.26	0.284	-0.64	0.009 ***	-0.04	0.756
Subscribed in 2017			-0.08	0.521	-0.26	0.049 *	-0.13	0.416
Subscribed in 2018			-0.86	0.000	-0.86	0.000 ***	-0.43	0.000 ***
Subscribed in 2019			-0.69	0.000	-0.77	0.000 ***	-0.30	0.000 ***
Subscribed in 2020			-0.37	0.000	-0.38	0.286	-0.15	0.007 **
Subscribed in 2021				<i>reference</i>				
Subscribed in 2022			0.26	0.045 *	0.27	0.036 *	0.03	0.643
Annual income < 25k					-0.69	0.026 *	-0.40	0.016 *
Annual income 25k to 50k					0.25	0.027 *	-0.05	0.363
Annual income 50k to 100k				<i>reference</i>				
Annual income 100k to 150k					0.44	0.000 ***	0.10	0.059 .
Annual income > 150k					0.59	0.000 ***	0.13	0.081 .
Financial wealth < 10k				<i>reference</i>				
Financial wealth 10k to 50k					0.70	0.000 ***	0.20	0.049 *
Financial wealth 50k to 100k					0.94	0.000 ***	0.21	0.049
Financial wealth 100k to 250k					0.86	0.000 ***	0.18	0.110
Financial wealth 250k to 1m					1.13	0.000 ***	0.25	0.028 *
Financial wealth > 1m					1.41	0.000 ***	0.20	0.260
Property assets 0				<i>reference</i>				
Property assets 0+ to 10k					0.68	0.009 .	0.08	0.708
Property assets 10k to 50k					0.37	0.032 *	0.05	0.603
Property assets 50k to 100k					0.66	0.000 ***	0.22	0.013 *
Property assets 100k to 250k					0.35	0.000 **	0.14	0.039 *
Property assets 250k to 1m					0.12	0.008 ***	0.30	0.000 ***
Property assets > 1m					0.26	0.000 ***	0.74	0.000 ***

Table 4.4: Continued

	Model 2.1		Model 2.2		Model 2.3		Model 2.4	
	Estimate	Pr(> t)	Estimate	Pr(> t)	Estimate	Pr(> t)	Estimate	Pr(> t)
Parent's risk profile							0.08	0.000 ***
Child's investment horizon							0.00	0.430
Parent's investment horizon							-0.00	0.232
Liquidity needs Q1 Certainly not			<i>reference</i>					
Liquidity needs Q1 Likely not							-0.10	0.031 *
Liquidity needs Q1 Likely							-0.49	0.000 ***
Liquidity needs Q1 Very likely							-0.29	0.543
Liquidity needs Q2 Certainly not			<i>reference</i>					
Liquidity needs Q2 Likely not							-0.23	0.000 ***
Liquidity needs Q2 Likely							-0.67	0.110 *
Liquidity needs Q2 Very likely							0.42	0.525
Risk aversion Q1 Low			<i>reference</i>					
Risk aversion Q1 Medium							-0.44	0.000 ***
Risk aversion Q1 High							-0.82	0.000 ***
Risk aversion Q1 Very high							-0.85	0.000 ***
Risk aversion Q2 Low			<i>reference</i>					
Risk aversion Q2 Medium							-0.54	0.000 ***
Risk aversion Q2 High							-2.61	0.000 ***
Risk aversion Q2 Very high							-4.58	0.000 ***
When market dips Wait			<i>reference</i>					
When market dips Buy							0.32	0.000 ***
When market dips Sell part or all							-0.43	0.041 *
When market dips Doesn't know							-0.11	0.417
Experience loss Never			<i>reference</i>					
Experience loss Max 10%							0.05	0.318
Experience loss Max 20%							0.17	0.011 *
Experience loss > 20%							0.16	0.009 **
Knowledge Q1 Correct			<i>reference</i>					
Knowledge Q1 Doesn't know							-0.23	0.345
Knowledge Q1 Wrong							0.02	0.937
Knowledge Q2 Correct			<i>reference</i>					
Knowledge Q2 Doesn't know							-0.01	0.921
Knowledge Q2 Wrong							0.00	0.989
Knowledge Q3 Correct			<i>reference</i>					
Knowledge Q3 Doesn't know							0.14	0.472
Knowledge Q3 Wrong							0.02	0.751

Dependent variable is risk profile 1 to 10 chosen by the parent on behalf of his child. See Appendix for description of the explanatory variables. Significance codes: ***: 0, **: 0.001, *: 0.01, .: 0.1.

Table 4.5: Descriptive statistics for adult non-parent investors (ANP), parent-only investors (P-O), child-only investors (C-O), parent-child investors (PC-P), and parent-child investors' children (PC-C).

	ANP Mean	P-O Mean	PC-P Mean	PC-C Mean	C-O Mean
N	20415	9895	1760	2533	1748
Sex	0.72	0.7	0.84	0.52	0.51
Age	37.2	42.32	39.07	6.36	6.43
Age at subscription	35.53	40.43	36.68	5.07	5.26
Number of children	-	1.73	1.7	1.92	1.82
Opened contract for a son	-	-	0.63	-	-
Opened contract for a daughter	-	-	0.58	-	-
Contract opened by father	-	-	-	0.85	0.75
Contract opened by mother	-	-	-	0.15	0.22
Birth order	-	-	-	1.35	1.28
Annual income less than 25k	0.15	0.03	0.02	0.01	0.04
Annual income 25k to 50k	0.42	0.21	0.18	0.16	0.2
Annual income 50k to 100k	0.33	0.45	0.47	0.48	0.5
Annual income 100k to 150k	0.08	0.2	0.22	0.22	0.19
Annual income more than 150k	0.02	0.11	0.11	0.12	0.07
Home owner	0.41	0.78	0.78	0.8	0.78
Property assets	155379	325697	301686	329020	290925
Financial wealth	129907	195890	178759	197882	137498
Multiple contracts	0.18	0.17	0.3	-	-
Initial deposit	8776	11060	8229	2400	2983
RP Recommended	6.79	7.1	7.41	7.86	7.58
RP Selected	6.88	7.07	7.42	7.6	7.34
RP Selected w. avg.	6.87	7.05	7.35	7.6	7.34
RP Selected w. avg. of parents	-	-	-	7.4	-
Horizon	10.75	11.37	12.19	15.05	14.81
Horizon w. avg.	10.72	11.33	12.14	15.05	14.81
Horizon w. avg. of parents	-	-	-	12.24	-
Liquidity Q1 Two years	3.41	3.43	3.45	3.74	3.75
Liquidity Q2 Half of deposit	3.06	3.12	3.15	3.44	3.43
Knowledge Q1 Correct	0.96	0.97	0.98	0.99	0.97
Knowledge Q2 Correct	0.77	0.78	0.84	0.89	0.79
Knowledge Q3 Correct	0.7	0.71	0.79	0.87	0.72
Risk Q1 Five year gamble	3.32	3.33	3.4	3.42	3.37
Risk Q2 Ten year gamble	2.9	2.93	3.09	3.01	2.91
Risk Q3 Buy when market dips	4.13	4.14	4.22	4.28	4.19
Risk Q4 Experienced losses	1.84	2.09	2.15	2.43	2.18

General Conclusion

General conclusion

During much of the twentieth century, Rational Choice Theory was the uncontested lens through which economists viewed economic decisions and financial markets. Now that micro-level data is widely available, this theory can be tested. And it simply does not hold. This thesis identifies a number of puzzling actions taken by investors in financial markets that are not simple to explain through anything other than a behavioral lens.

In Chapter 1, investors who used the schedule deposits feature included in the robo-advisor's service saved less money in the medium- and long-terms compared to investors who did not use this feature. In Chapter 2, many more investors adjusted their portfolio to be more aggressive than more conservative, but when investors adjusted their portfolio to be more conservative they did so much more extremely. In Chapter 3, a stable group of investors had many different ways depending on the precise measure used of responding to similar crises that would plausibly affect their savings rates. In Chapter 4, investors largely failed to see their child as a distinct economic agent, and so invested for them as they would for themselves, and were also slightly biased in favor of their sons than their daughters. With big data sources such as those available with robo-advisors, documenting behavioral biases among investors has never been easier and defending Rational Choice Theory has never been harder.

Public policy should take note that the younger, middle-class, smallholder investors who traditionally use robo-advisors make these mistakes, because this demographic is already large and will only grow in most countries. If policymakers want their jurisdictions to make decisions which more closely approximate rational profit maximization, then intelligent use of behavioral economics tools such as nudges, defaults, and automation can improve investor outcomes. Simply expanding the choice set will not do much for the average person and may even backfire.

Asset managers can take the lead and get a competitive advantage by designing their services to be more resilient to behavioral biases. Field experiments (A/B tests, pilot studies, and trials) are a promising avenue for future research, particularly for industry-academy collaborations (List, 2024). With a network of customers wanting a change and a little help from a researcher, industry actors are in a unique position to address the behavioral shortcomings identified by the literature at scale for the common good.

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Résumé français

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Dans quatre articles empiriques réalisés au cours de trois années d'étude, mes recherches examinent le comportement des investisseurs qui épargnent chaque mois (Jones, 2024, chapitre 1), qui modifient leurs portefeuilles passifs (Benoit et al., 2024, chapitre 2), qui ont épargné pendant la pandémie de Covid-19 (Boulou-Reshef et Jones, 2024, chapitre 3), et qui épargnent au nom de leurs enfants (Direr et Jones, 2024, chapitre 4). Cette introduction générale comporte trois parties. Tout d'abord, je décrirai brièvement puis techniquement chacune des trois grandes tendances qui façonnent une fraction croissante des actifs mondiaux sous gestion et constituent le contexte intellectuel du présent travail : la finance des ménages, la finance comportementale et l'utilisation des robo-advisors. Ensuite, j'expliquerai en détail la méthodologie empirique générale adoptée et la base de données unique des robo-advisors utilisée dans les quatre articles de ce travail unifié. Enfin, je fournirai des aperçus de chacun de mes articles et relierai les contributions de ce travail au contexte intellectuel général dans lequel il s'inscrit.

L'économiste Harry Markowitz (1952), lauréat du prix Nobel, a souligné qu'un investisseur pouvait construire un portefeuille qui maximise le rendement attendu pour un niveau de risque donné grâce à la diversification d'actifs non parfaitement corrélés, inventant ainsi la théorie moderne du portefeuille (TMP). La TPM a largement remplacé la stratégie de diversification naïve utilisée par les investisseurs avant son invention. Les extensions de la TMP, telles que le modèle d'évaluation des actifs financiers [*Capital Asset Pricing Model*, CAPM] de l'économiste William Sharpe (1964), lauréat du prix Nobel, ou le modèle à trois ou cinq facteurs de l'économiste Eugene Fama et French (1992, 2015), lauréat du prix Nobel, sont des références dans le secteur. Cependant, la TPM présente trois limites importantes. Premièrement, les rendements attendus et la covariance des actifs sont calculés à partir de données historiques qui ne permettent pas nécessairement de prédire l'avenir (Fama, 1965), une limitation qui affecte également les modèles fondés sur la TPM. Deuxièmement, le risque en finance est considéré comme probabiliste plutôt que structurel, ce qui signifie que les risques potentiels avec peu ou pas de données historiques sont régulièrement ignorés (Taleb, 2007). Troisièmement, empiriquement, les investisseurs s'écartent des stratégies de maximisation de l'utilité sous contrainte de nombreuses manières et pour de nombreuses raisons (Barberis et Thaler, 2003; Shiller, 2003). Malgré ces défauts, la TPM et les autres

modèles qui s'en inspirent sont la manière dont les institutions financières contemporaines pratiquent la diversification. Cette recherche contribue au sous-domaine centré sur la troisième limitation citée, un sous-domaine appelé finance comportementale.

Il est courant d'épargner et les avantages de la diversification sont bien connus, mais il est difficile de constituer et surtout de maintenir un portefeuille scientifiquement diversifié qui corresponde à la situation financière unique d'un investisseur. C'est pourquoi des technologies financières ont été inventées pour faciliter la diversification. Depuis au moins 1924, les investisseurs mettent en commun leurs ressources et délèguent la gestion d'un portefeuille d'investissement diversifié, appelé fonds commun de placement (FCP). Toutefois, en raison des frais liés à la rémunération du gestionnaire et au remboursement de ses transactions, la plupart des fonds communs de placement affichaient des rendements inférieurs à la moyenne (Sharpe, 1966). En outre, les fonds communs de placement qui ont surperformé une année ont rarement maintenu cette tendance les années suivantes (Carhart, 1997). Ce phénomène est prévisible. Dans une transaction donnée, le rendement moyen de l'acheteur et du vendeur est légèrement négatif : l'un réalise un bénéfice et l'autre une perte, mais ils paient tous deux des frais de transaction. Si les marchés financiers sont efficients (Fama, 1970), un point de vue imparfait mais plausible et largement répandu, le fait que peu de gestionnaires puissent obtenir de manière fiable des rendements supérieurs à la moyenne après déduction des frais de transaction en découle logiquement. Pour remédier à cette lacune du fonds commun de placement typique, Jack Bogle a lancé Vanguard en 1975 avec un fonds commun de placement appelé « fonds indiciel », qui renonce à la possibilité de surperformer pour garantir des rendements moyens en suivant un large indice boursier tel que le S&P 500 (Bogle, 1999). D'autres technologies financières ont amélioré ce modèle. L'achat et la vente d'actions d'un fonds commun de placement pouvant s'avérer délicats, les fonds négociés en bourse [*Exchange Traded Fund*, ETF] ont été inventés en 1989 pour faciliter la négociation des fonds indiciels. Les robo-advisors (ou robo-conseillers) ont donc été inventés en 2008 pour donner des conseils et gérer des portefeuilles composés uniquement d'ETF (Fisch et al., 2019). Cette recherche se concentre sur les robo-advisors, la dernière technologie financière de cette évolution.

Avec chaque nouvelle technologie simplificatrice, la diversification des portefeuilles devient plus accessible et plus inclusive pour des publics diversifiés (voir Chatterjee, 2020). Alors qu'auparavant seuls les institutions et les individus les plus riches pouvaient accéder à une diversification sophistiquée, avec les ETF et surtout les robo-advisors, les barrières financières et informationnelles à l'entrée ont été considérablement réduites. Tout comme d'autres technologies qui ont réduit les obstacles à la participation au marché boursier ont augmenté les taux de participation (Bogan, 2008), les robo-advisors amènent de nouveaux entrants sur les marchés financiers (Reher et Sokolinski, 2019). Les mesures prises par ces personnes de la classe moyenne sans formation sont d'un grand intérêt pour les gouvernements, les régulateurs, les gestionnaires d'actifs, les marchés financiers et les chercheurs, précisément parce qu'elles sont typiques de

la personne médiane, une personne qui a très peu d'expérience en finance ou qui n'est même pas encore entrée sur les marchés financiers. À mesure que la classe moyenne mondiale s'élargit (Kochhar, 2015), que la participation au marché boursier augmente dans de nombreux pays (Campbell, 2006), et que les retraites d'un plus grand nombre de personnes sont couvertes par des régimes à cotisations déterminées [*defined contribution plans*] plutôt que par des régimes à prestations déterminées [*defined benefit plans*] (Broadbent et al., 2006; Gomes et al., 2021), le nombre de ménages investisseurs participant au marché boursier ne fera qu'augmenter. Cette étude se penche sur l'investisseur ménager, de plus en plus courant.

Combinons maintenant ces trois tendances. Partout dans le monde, les robo-advisors recueillent une quantité sans précédent d'informations sur les caractéristiques démographiques, financières et psychologiques de millions de ménages investisseurs et proposent à ces clients un ensemble d'investissements distincts et simplifiés. Il n'a jamais été aussi facile d'observer, de comparer et d'étudier le comportement des investisseurs individuels. Ces trois tendances – la finance des ménages, la finance comportementale et l'utilisation des robo-advisors – sont essentielles pour comprendre chacun des quatre articles inclus dans cet ouvrage.

Finance des ménages

Finance populaire des ménages

Il existe un fossé important entre les ouvrages de vulgarisation et les ouvrages académiques sur la finance des ménages, tant en termes d'écoles de pensée que de lectorat. Choi (2022) résume les best-sellers de la finance populaire, dont certains livres se vendent à des dizaines de millions d'exemplaires. En revanche, le nombre de citations le plus courant pour un article académique est zéro, et il est extrêmement rare d'obtenir des milliers de citations (Redner, 1998). Il suffit de dire que la portée de la finance populaire est bien plus grande que celle de la finance académique.

Pourtant, les travaux de vulgarisation ignorent souvent les résultats de la recherche ou sont en contradiction directe avec eux. Choi (2022) a résumé que sur huit dimensions, le consensus entre la finance populaire et la finance académique des ménages ne s'accordait que sur une seule. (Par coïncidence, cette seule dimension d'accord est d'investir dans des fonds indiciels passifs, par exemple avec des robo-advisors). Le chapitre 1 de cette thèse aborde de front cette tension entre la finance populaire et la finance académique des ménages en trouvant une dimension sur laquelle les conseils diffèrent – épargner régulièrement – et en observant comment les ménages réels se comportent empiriquement.

Pour mieux comprendre cette tension entre les deux disciplines connexes, prenez l'exemple du budget.

La finance populaire des ménages est obsédée par les budgets. Les budgets sont mentionnés dans tous les livres populaires sur les finances des ménages, y compris les best-sellers comme *The Millionaire Next Door* de Stanley et Danko (1996) et *I Will Teach You to Be Rich* de Sethi (2009). Dans cette littérature, chacun devrait avoir un budget qui devrait suivre certaines règles, comme épargner quinze centimes de chaque dollar ou ne pas dépenser plus d'un tiers de ses revenus pour le logement. D'autre part, la finance académique des ménages n'a pas de théorie acceptée sur la budgétisation. Les agents rationnels dépensent et épargnent simplement de la manière qui maximise leur utilité tout au long de leur vie, automatiquement et sans faute. Dépenser trop ou ne pas épargner assez ne sont pas des problèmes que rencontrent les agents rationnels.

Autre exemple de conseil financier caractéristiquement populaire, Dave Ramsey (2013), auteur du troisième livre le plus vendu de la liste de Choi (2022) *The Total Money Makeover*, conseille à ses lecteurs d'utiliser la technique de la « boule de neige », dans laquelle les débiteurs remboursent leurs créanciers dans l'ordre du plus petit solde au plus grand au lieu de l'ordre plus rationnel du plus grand taux d'intérêt au plus petit. Ramsey justifie la technique de la boule de neige par le fait qu'il est important d'obtenir des « victoires rapides » pour maintenir la motivation de sortir de l'endettement. De leur côté, les chercheurs académiques traditionnels en finance conseilleraient de rembourser les dettes par taux d'intérêt, car ils partent du principe que les émotions n'influencent pas la prise de décision financière et que la motivation n'est pas un problème.

D'où vient ce clivage entre les ouvrages de vulgarisation et les ouvrages académiques sur la finance des ménages ? Plus probablement, le fossé s'explique par une différence de perspective et de culture industrielle entre les auteurs de vulgarisation et les économistes académiques. La plupart des auteurs de vulgarisation financière sont issus du monde de l'entreprise ou de l'industrie, et non du monde universitaire ou scientifique. Ils travaillent avec des clients ordinaires, alors que les économistes académiques travaillent avec d'autres économistes académiques, qui les examinent minutieusement. Les auteurs populaires ne peuvent pas surestimer les capacités réelles de leurs clients, tandis que les économistes académiques ne peuvent pas affirmer sans preuve que les gens normaux ne peuvent pas résoudre les problèmes qu'ils peuvent résoudre.

Où sont donc les preuves ? Pourquoi les économistes académiques défendent-ils des positions non intuitives telles que les individus épargnent autant qu'ils en ont besoin, que leurs émotions n'affectent pas leurs dépenses et que la motivation est infinie ? Tout se résume à ce concept de « rationalité ». La rationalité est un concept théorique, important pour la construction de modèles mathématiques qui font des prédictions sur le comportement global. Contrairement à l'approche empirique adoptée dans les quatre chapitres de cette thèse, la finance académique des ménages adopte une approche théorique et rationnelle.

Finance académique des ménages

Si la finance populaire des ménages est pessimiste quant aux capacités de l'individu ordinaire, la finance académique des ménages est optimiste. Pour éviter de s'endetter, Dave Ramsey (2013) encourage ses lecteurs à louer jusqu'à ce qu'ils aient l'argent nécessaire pour acheter leur résidence principale au comptant, car on ne peut pas leur faire confiance avec des dettes. Parallèlement, Ando et Modigliani (1963) part du principe que les gens peuvent résoudre des problèmes d'optimisation de la consommation tout au long de leur vie ou, du moins, se comporter comme s'ils l'avaient fait. Ces deux perspectives n'ont pas grand-chose en commun.

Alors que les conseillers financiers populaires travaillent avec des êtres humains ordinaires, les économistes académiques étudient *homo economicus*, un optimiseur de l'utilité attendue ajustée au risque et actualisée dans le temps, disposant d'un temps infini, d'une information parfaite, d'une maîtrise totale de soi et n'ayant pas d'autres responsabilités que de résoudre des problèmes de mathématiques de niveau universitaire. Ce sont les agents parfaitement rationnels de la théorie du choix rationnel, la pensée dominante en économie, du moins au cours du vingtième siècle. Notre espèce d'humains ordinaires, *homo sapiens*, n'est pas comme cela (voir Thaler et Sunstein, 2021, pour une discussion détaillée). Et les économistes l'acceptent. Du moins, c'est désormais le cas (voir Thaler, 2015, pour un historique de la façon dont la profession économique en est venue à accepter que la théorie du choix rationnel fonctionne mieux comme un outil prescriptif que comme un outil descriptif). Les économistes définissent le comportement optimal afin de disposer d'une norme à laquelle comparer le comportement observé. Selon Richard Thaler (2015), un économiste lauréat du prix Nobel qui a consacré une grande partie de sa carrière à remettre en question la finance académique des ménages avec des résultats comportementaux empiriques incompatibles avec la théorie, « Sans le cadre rationnel, il n'y a pas d'anomalies à partir desquelles nous pouvons détecter un comportement erroné. » En tant que telles, les principales conclusions de l'étude académique sur la finance des ménages, pertinentes pour ce travail, sont la mesure dans laquelle les gens ordinaires s'écartent des gens rationnels, présentée sous la forme d'« énigmes » [*puzzle*]. Le chapitre 4 de ce travail comprend plusieurs énigmes qui ne peuvent être expliquées dans un cadre rationnel, notamment le fait que les parents investissent pour leurs enfants de manière remarquablement similaire à la façon dont ils investissent pour eux-mêmes, bien que leurs enfants soient dans des situations financières plausiblement différentes.

Mehra et Prescott (1985) ont d'abord défini la prime de risque [*equity premium*] comme une énigme. La prime de risque est le fait que les rendements historiques des fonds propres (actions) ont dépassé les rendements historiques des titres de créance sans défaut (bons du Trésor ou *Treasury bills*). Bien entendu,

les agents rationnels sont quelque peu réticents à l'égard du risque et exigent donc une compensation plus élevée pour un risque plus élevé. Là n'est pas l'énigme ; l'énigme réside dans le fait que les actions sont rémunérées, voire surcompensées. Mehra et Prescott (1985) a constaté que le coefficient d'aversion relative au risque nécessaire pour expliquer l'histoire était absurde : pour que les mathématiques fonctionnent, les gens doivent être prêts à payer 49% de leur richesse pour éviter une chance sur deux de perdre 50% de leur richesse. Bien que de nombreux articles aient été publiés pour tenter de rationaliser ce résultat, Weil (1989) a démontré qu'aucune solution rationnelle plausible ne peut être trouvée à l'énigme de la prime de risque, car toute explication purement rationnelle aboutirait à la contradiction suivante. Une économie composée d'individus rationnels peut présenter des niveaux élevés d'aversion au risque ou un faible taux sans risque, mais pas les deux. Les individus extrêmement averses au risque feront grimper le taux sans risque pour maintenir des niveaux lisses de consommation intertemporelle, tandis que les faibles taux sans risque observés historiquement impliquent que l'économie réelle est peuplée d'individus relativement neutres vis-à-vis du risque. C'est ainsi que Weil (1989) a nommé cette énigme contradictoire : l'énigme du taux sans risque [*the risk-free rate puzzle*].

Si les rendements des actions sont inexplicablement élevés et les rendements des bons du Trésor inexplicablement bas, on pourrait s'attendre à ce que tous les ménages d'une économie composée d'agents rationnels détiennent des actions. Il s'agit en effet d'une implication de la TPM (Markowitz, 1952). Or, c'est loin d'être le cas, et cette incongruité est connue sous le nom d'énigme de la participation au marché boursier [*stock market participation puzzle*] (?). Là encore, il n'existe aucune explication rationnelle plausible à l'énigme de la participation au marché boursier (Haliassos et Bertaut, 1995). Les taux de participation aux marchés boursiers aux États-Unis ont doublé depuis que l'énigme a été identifiée pour la première fois, mais le taux actuel d'environ 50% reste bien inférieur à 100%, et de nombreux autres pays riches ont des taux de participation proches de 0% (Campbell, 2006).

Étant donné que ces trois énigmes – l'énigme de la prime de risque, l'énigme du taux sans risque, et l'énigme de la participation au marché boursier – ne peuvent être résolues dans le cadre rationnel, un autre cadre doit être adopté : un cadre comportemental.

Finance comportementale

L'influence de l'économie comportementale

Si une prémisse ne mène qu'à des conclusions peu plausibles, c'est qu'elle est erronée. Dans une économie d'agents rationnels, pourquoi y a-t-il autant de paradoxes ? La réponse est simple : nous ne sommes

pas dans une économie d'agents rationnels. C'est le principe fondateur de l'économie comportementale. Tout comme la finance n'existe pas sans l'économie, la finance comportementale n'existe pas sans l'économie comportementale. Plusieurs résultats clés de l'économie comportementale démontrent que nous ne sommes pas dans une économie d'agents rationnels.

Adam Smith (1759), souvent cité comme le premier économiste, a reconnu que les êtres humains ne prennent pas leurs décisions économiques uniquement en fonction de l'argent. Mais les préoccupations concernant « Dieu, la famille, et la patrie » sont difficiles à quantifier et ont été progressivement perdues au fur et à mesure que la théorie du choix rationnel s'est développée. À l'ère moderne, l'économiste Herbert Simon (1955), lauréat du prix Nobel, a proposé pour la première fois de limiter l'omniscience de *homo economicus* par ce qu'il a appelé la « rationalité limitée » [*bounded rationality*]. Les agents qui sont rationnels à l'intérieur des limites optimisent toujours, mais ils sont limités par des informations imparfaites, des contraintes de temps, des capacités mathématiques, etc. La rationalité limitée n'était pas une attaque directe contre la théorie du choix rationnel, mais plutôt une modification en douceur des comportements.

Les véritables attaques contre la théorie du choix rationnel ont été lancées par les économistes Daniel Kahneman & Amos Tversky, lauréats du prix Nobel.³, qui sont à l'origine des psychologues. Contrairement aux périodes antérieures de l'histoire où les « philosophes naturels » (scientifiques) étaient censés connaître des domaines aussi variés que l'astronomie, la biologie et la géométrie, au XXe siècle, les académiques étaient cloîtrés dans des facultés qui communiquaient rarement entre elles. C'est ainsi que se sont développées deux perspectives inconciliables du comportement humain : les économistes pensaient que les gens prenaient des décisions économiques parfaitement rationnelles pratiquement tout le temps, tandis que les psychologues ne croyaient pas que les gens pouvaient prendre des décisions rationnelles, même dans les meilleures circonstances.

Avant d'entrer en contact avec la profession économique, Kahneman & Tversky ont fait le travail de routine des psychologues en documentant les biais du jugement humain (Tversky et Kahneman, 1974). Ils ont ensuite proposé une alternative à la théorie du choix rationnel qu'ils ont appelé « théorie des perspectives » [*prospect theory*] (Kahneman et Tversky, 1979). Dans la théorie du choix rationnel, le niveau actuel de richesse d'un individu n'a aucune importance ; les agents traitent les gains et les pertes de manière à peu près égale et ont des préférences stables en matière de risque. Dans la théorie des perspectives, le niveau actuel de richesse d'un individu a une importance considérable ; les agents considèrent les pertes comme plus importantes que les gains et sont peu enclins à prendre des risques pour percevoir des gains, mais recherchent le risque pour éviter les pertes. Contrairement à la rationalité limitée, la théorie des

³Les prix Nobel ne sont pas décernés post-mortem, et Amos Tversky est malheureusement décédé assez tôt dans sa vie. Toutefois, de nombreux spécialistes considèrent que le prix décerné à son coauteur de longue date, Daniel Kahneman, est essentiellement un prix pour eux deux

perspectives est impossible à concilier avec la théorie du choix rationnel. Le contact entre la psychologie et l'économie a été établi ; la révolution de l'économie comportementale a commencé.

Pour les psychologues Kahneman & Tversky, cette vision du monde dans lequel les humains commettent des erreurs prévisibles allait de soi. Au fil du temps, la profession économique s'est orientée dans cette direction, rassemblant une longue liste de preuves empiriques montrant que les êtres humains ne se comportent pas de la manière décrite dans la théorie du choix rationnel. Les quatre chapitres de cet ouvrage contribuent à cette collecte de preuves empiriques dans laquelle les données du monde réel sont les plus importantes. Ces résultats incluent, sans s'y limiter, l'aversion aux pertes, la pondération non linéaire des probabilités, la satisfaction, l'ancrage, la comptabilité mentale, l'heuristique de disponibilité et de représentativité, les effets de dotation et de cadrage, les sophismes du joueur et de la main chaude, ainsi que les biais de récence, de confirmation et de statu quo (voir Angner et Loewenstein, 2007, pour une revue). Le chapitre 3 de cet ouvrage examine comment ce type d'émotions et de préjugés aurait pu entraîner un comportement irrationnel chez les clients de Yomoni pendant la pandémie Covid-19.

Avant que l'économie comportementale ne commence à gagner du terrain, la théorie du choix rationnel influençait fortement les politiques publiques dans de nombreux pays. Le raisonnement était le suivant : l'élargissement de l'éventail des choix augmente l'utilité, et comme les agents rationnels sont pratiquement omniscients, peu importe que ces choix soient enfouis sous des montagnes de tâches administratives ou rédigés en jargon juridique, qu'il faille des centaines d'heures pour les apprendre ou des décennies d'autodiscipline pour les mettre en œuvre. Le passage d'un régime de retraite à prestations déterminées à un régime de retraite à cotisations déterminées illustre bien ce raisonnement. Dans le cadre du régime à prestations déterminées, l'individu moyen n'a rien d'autre à faire que d'occuper un emploi, ce qu'il ferait probablement de toute façon, alors que dans le cadre du régime à cotisations déterminées, l'individu moyen doit prendre des dizaines, voire des centaines de décisions concernant son plan de retraite au cours de sa vie. Et pourtant, le modèle rationnel sur lequel reposaient ces politiques publiques avait été profondément ébranlé par les économistes comportementaux.

C'est là qu'intervient le nudge (un coup de pouce). En 2008, Richard Thaler, lauréat du prix Nobel d'économie, et Cass Sunstein, éminent juriste, ont publié *Nudge : Improving Decisions about Health, Wealth, and Happiness*. Cet ouvrage s'appuie sur des travaux antérieurs (e.g. Thaler et Benartzi, 2004), mais c'est le livre qui a donné son nom au nudge et l'a fait entrer dans le débat public. Le nudge fonctionne de la manière suivante : étant donné que les personnes qui proposent des choix aux autres doivent nécessairement décider de la manière dont ces choix sont présentés, une personne bien intentionnée peut présenter ces choix de manière à ce qu'il soit aussi facile que possible pour l'électeur de choisir ce qui lui convient le mieux en dépit de ses préjugés comportementaux. Pour les lecteurs qui ont appris le langage parlé par Thaler et Sunstein, il s'agit d'un architecte de choix paternaliste libertaire qui donne

des nudges à un être humain (Thaler et Sunstein, 2021). Le nudge a eu une influence considérable, inspirant notamment la Behavioral Insights Team (AKA the « nudge unit ») au sein du gouvernement britannique et des centaines d'organisations imitatrices au sein de gouvernements et d'entreprises dans le monde entier. Yomoni met en œuvre des nudges dans son offre d'investissement de base, et le chapitre 1 de cette thèse suggère que des nudges involontaires peuvent avoir conduit les investisseurs qui épargnent régulièrement à épargner moins, et quels contre-nudges pourraient être mis en œuvre pour résoudre ce problème.

Telles sont les grandes lignes de l'économie comportementale aujourd'hui. Si cette lutte intellectuelle entre les perspectives rationnelles et comportementales s'est étendue à tous les niveaux de la recherche économique, de la théorie aux expériences naturelles et en laboratoire, un champ de bataille clé a été la recherche sur les marchés financiers. L'argument était le suivant : personne ne se préoccupe de savoir si les étudiants se comportent bizarrement lorsque vous leur offrez des tasses à l'effigie de l'université ; un marché de professionnels expérimentés prenant des décisions avec des milliards de dollars en jeu se comportera de manière rationnelle. Ou bien le fera-t-il ?

Finance comportementale au niveau macro

Comme pour l'économie comportementale en général, l'histoire montre des traces de l'idée que les marchés financiers peuvent être affectés par des phénomènes irrationnels tels que les émotions. La première incidence de la finance comportementale au niveau macroéconomique a sans doute été de qualifier les bulles spéculatives de « manies » et les crises financières de « paniques ».

Comme Herbert Simon, précurseur de l'économie comportementale, John Maynard Keynes (1936) a écrit une idée essentielle pour la finance comportementale au niveau macroéconomique avec sa métaphore des « concours de beauté ». Les investisseurs n'essaient pas nécessairement de choisir les actions des entreprises présentant les meilleurs aspects fondamentaux ; si telle est leur stratégie, ils risquent de faire faillite en attendant que le cours de l'action augmente (, ceci est connu sous le nom de « limite à l'arbitrage » [*limit to arbitrage*] voir [barberis2003survey](#)). Les investisseurs essaient de choisir les actions des entreprises que les *autres* investisseurs voudront bientôt tous acheter. Ce n'est pas la compétence du conseil d'administration d'une entreprise ou la constance de ses bénéfices qui fait monter le cours de ses actions, mais uniquement la demande. Si tout le monde joue le jeu de ce concours de beauté, comme il se doit d'ailleurs puisque leurs profits en dépendent, alors les cours des actions ne reflètent rien d'autre que ce que tout le monde pense que tout le monde pense.

L'économiste Robert Shiller, lauréat du prix Nobel, a rédigé les premiers articles modernes sur la finance comportementale au niveau macroéconomique. Shiller et al. (1981) a démontré que les dividendes

moyens sont relativement stables alors que les prix moyens des actions (une revendication formelle de ces dividendes futurs) varient considérablement. C'est ce que l'on a appelé « l'énigme de la volatilité » [*volatility puzzle*]. En outre, Shiller (1984) a (re)popularisé l'idée, parmi les économistes académiques, que les mouvements des marchés boursiers sont au moins en partie explicables simplement par le « sentiment », la « mode » ou l'« humeur » en vogue parmi les investisseurs à un moment donné, une idée qu'il a développée dans le livre *Irrational Exuberance*. (Shiller, 2000). De Bondt et Thaler (1985) a poursuivi les travaux de Shiller en posant une question hérétique : « Le marché boursier réagit-il de manière excessive ? » Ils ont constaté que les prix du marché boursier régressent vers la moyenne – de manière fiable, les anciens gagnants perdent plus tard et les anciens perdants gagnent plus tard – ce qui implique que les actions évaluées aux extrêmes ont été mal évaluées. Cette constatation est surprenante, car des agents rationnels opérant sur un marché efficient où les prix reflètent toutes les informations disponibles ne pourraient jamais se tromper de la sorte dans l'évaluation des actions. Puis Fama et French (1992, 1996, 2015) ont commencé à démontrer que l'inclusion de critères tels que la petite taille de l'entreprise et des ratios book-to-market élevés (plus tard également des bénéfices constants et une stratégie d'investissement conservatrice au niveau de l'entreprise) améliorait le pouvoir prédictif du CAPM. En d'autres termes, les investisseurs prenaient en compte des facteurs supposés non pertinents dans leurs décisions d'investissement, ce qui avait un effet sur l'ensemble du marché. C'est ce que l'on a appelé le « puzzle de la prévisibilité » [*predictability puzzle*]. Il est de plus en plus évident que même s'il existe des agents rationnels intelligents et informés sur les marchés financiers, ils peuvent être surpassés en nombre et en qualité par les « suiveurs » [*noise traders*].

La preuve la plus convaincante de l'existence de la finance comportementale, même au niveau macroéconomique, a été apportée par les anomalies des marchés boursiers. Lamont et Thaler (2002) ont documenté de nombreuses anomalies qui ne pouvaient pas se produire sur un marché financier efficient composé d'agents rationnels, comme le fait que les actions de Shell et de Royal Dutch n'ont pas de prix liés alors qu'il s'agit d'actions jumelées. Un an plus tard, (Lamont et Thaler, 2003) décrivait en détail la scission Palm-3Com. Le marché était prêt à payer beaucoup plus pour les actions de Palm que pour celles de 3Com, bien que 3Com possède Palm et disposant d'un certain nombre d'autres actifs et sources de revenus. Si des agents irrationnels ont des effets aussi pernicioeux sur les prix au niveau macroéconomique, que pensent-ils et que font-ils au niveau microéconomique ?

Finance comportementale au niveau micro

La finance comportementale au niveau microéconomique cherche à documenter, comprendre et expliquer les écarts des investisseurs par rapport à la théorie économique traditionnelle. Elle donne la priorité

aux preuves empiriques plutôt qu'à la théorie, exploite les grandes données relatives aux actions des investisseurs dans le monde réel et ne cherche pas d'excuses pour les comportements bizarres. C'est dans ce sous-domaine que les quatre chapitres de cet ouvrage peuvent être classés.

Les modèles microfondés et les preuves microéconomiques peuvent-ils résoudre les énigmes macroéconomiques de la finance comportementale mentionnées ci-dessus ? Deux explications principales de l'énigme de la prime de risque et du taux sans risque ont été avancées : La théorie des perspectives (Benartzi et Thaler, 1995; Barberis et al., 2001) et l'aversion pour l'incertitude (Maenhout, 2004; Camerer et Weber, 1992). En outre, l'énigme de la participation au marché boursier a plusieurs explications plausibles : cadrage étroit (Barberis et al., 2006), culture financière (Van Rooij et al., 2011), confiance dans le marché boursier, (Guiso et al., 2008), et même QI (Grinblatt et al., 2011). Le « momentum », ou la sous-réaction et la sur-réaction aux nouvelles, pourrait expliquer les énigmes de la volatilité et de la prévisibilité (Chan et al., 1996), bien que cela violerait aussi gravement l'hypothèse du marché efficient. Par coïncidence, le chapitre 2 de cette thèse documente empiriquement une forme de momentum : les clients augmentent lentement et progressivement la part d'actions dans leurs portefeuilles, en particulier lorsque le marché boursier est en hausse, mais effectuent des changements plus radicaux lorsqu'ils décident de réduire leur part d'actions.

Cependant, la finance comportementale au niveau microéconomique a découvert ses propres énigmes. Les énigmes liées au « choix du portefeuille » observent que les individus détiennent des portefeuilles qui ne sont pas conformes à la théorie économique (Dimmock et al., 2016). La théorie du choix rationnel consiste à diversifier les actifs à l'échelle internationale en fonction de leur part de marché (Markowitz, 1952), voire à court-circuiter le marché financier national en raison de la valeur nette de son logement et de son capital humain (Baxter et Jermann, 1995). Mais en réalité, les investisseurs sont sous-diversifiés (Benartzi et Thaler, 2001). Ils détiennent trop d'actions de l'entreprise dans laquelle ils travaillent [*company stock*] (Benartzi, 2001) et d'actions du pays d'origine (French et Poterba, 1991), et effectuent des transactions excessives (Barber et Odean, 2000, 2001). Dans la recherche sur la finance comportementale au niveau microéconomique, on peut entendre des échos de la finance populaire des ménages, avec son insistance sur le fait que les gens ordinaires ont besoin de règles simples à suivre, et que même dans ce cas, ils sont susceptibles de commettre des erreurs.

Tant d'autres explications ont été proposées et tant d'énigmes ont été identifiées, mais nous n'avons pas la place de les aborder ici. Il est remarquable de constater à quel point la finance comportementale a progressé en tant que domaine. Alors que les énigmes étaient censées ne pas exister dans le cadre du modèle classique, la recherche et l'explication des énigmes par le biais de la psychologie sont désormais devenues un travail de routine pour les chercheurs en finance. On pourrait parler d'« impérialisme psychologique ». En effet, les quatre chapitres de cette thèse suivent ce mode de pensée « énigme au niveau micro » [*micro-level*]

puzzle] : les investisseurs qui épargnent chaque mois épargnent globalement moins (Jones, 2024, Chapitre 1), les investisseurs affichent un comportement similaire à celui de la théorie des perspectives lorsqu'ils ajustent la répartition de leur portefeuille (Benoit et al., 2024, Chapitre 2), les investisseurs épargnent moins pendant les crises majeures (Boulou-Reshef et Jones, 2024, Chapitre 3), et les investisseurs épargnent au nom de leurs enfants comme s'ils épargnaient pour eux-mêmes (Direr et Jones, 2024, Chapitre 4).

Ces énigmes microéconomiques ont été découvertes en étudiant les clients d'un robo-advisor. Les robo-advisors sont une nouvelle technologie et donc un environnement atypique pour étudier le comportement des investisseurs. Quelques explications s'imposent.

Robo-advisors

Comment fonctionnent les robo-advisors

Une brève description de la fonction technique des robo-advisors (également connus sous le nom de conseillers financiers automatisés [*automated financial advisors*]) sera utile pour comprendre le reste de ce travail. D'Acuneto et al. (2019) définissent le robo-advisoring comme « la fourniture et l'exécution de conseils financiers au moyen d'algorithmes automatisés sur des plateformes numériques. » Maume (2021) identifie deux fonctions clés des robo-advisors : donner des conseils personnalisés et gérer le portefeuille d'un client. Tous les robo-advisors remplissent la première fonction, mais pas tous la seconde. Je commencerai donc par la première.

Les robo-advisors peuvent être et ont été utilisés pour donner des conseils sur de nombreux sujets. Jusqu'à présent, ils ont été utilisés principalement pour dispenser des conseils en matière d'investissement. En recherchant « robo-advisor » sur l'internet, vous obtiendrez principalement les gestionnaires d'actifs. Cependant, le robo-advisor est une technologie de base. N'importe quel type de conseil pourrait être donné de manière algorithmique. On pourrait imaginer un robo-advisor qui donnerait des conseils sur l'adoption de races de chiens. Mais dans cette série d'études, je me concentre sur les robo-advisors traditionnels, liés à l'investissement.

Tout d'abord, un robo-advisor doit décider quelles informations influenceront les conseils qu'il donnera aux investisseurs. Certaines informations peuvent ne pas être pertinentes, comme la couleur préférée d'un investisseur. En revanche, certaines informations peuvent être essentielles, comme les préférences d'un investisseur en matière de risque. Il peut être illégal de prendre en compte certaines informations, comme le sexe d'un investisseur. Par ailleurs, il peut être illégal de prendre en compte certaines informations, telles que les connaissances financières d'un investisseur. Des questions peuvent être posées sur

l'âge, l'éducation, le statut professionnel, le secteur, le revenu, l'horizon d'investissement, le versement initial, le patrimoine financier, les plans de retraite, les connaissances financières, l'expérience en matière d'investissement, le statut de propriétaire, les membres de la famille proche, l'objectif d'investissement, l'enveloppe fiscale préférée, les dettes en cours, l'épargne actuelle, les événements majeurs de la vie, les contributions mensuelles prévues, et les préférences en matière de risque et d'ESG, d'investissements locaux, immobiliers et alternatifs. Une fois cet ensemble de questions formalisé, généralement entre dix et trente questions, un robo-advisor demande ces informations à ses clients potentiels sous la forme d'un sondage. Bien que rien n'empêche les clients potentiels de mentir, ils doivent répondre sincèrement afin d'obtenir des conseils adaptés à leur situation.

Ensuite, le robo-advisor doit décider *dans quelle mesure* chaque question influencera ses conseils. Les informations les plus importantes peuvent avoir dix, voire cent fois plus de poids que les informations les moins importantes. Prenons par exemple les revenus d'un client potentiel. Dans quelle mesure les revenus d'une personne doivent-ils influencer sur la répartition des actifs de son portefeuille ? Un robo-advisor peut décider que le revenu est le facteur le plus important dans ses conseils, tandis qu'un autre peut penser que cette information n'est presque pas pertinente. Souvent, les pondérations choisies s'appuient sur des recherches académiques, bien que dans certains cas, même les recherches ne soient pas claires quant à l'importance d'un facteur donné.

Les facteurs et leurs pondérations se combinent en une longue équation, l'*algorithme*. L'algorithme d'un robo-advisor est une boîte noire, souvent connue seulement de quelques personnes au sein d'une organisation. Si les facteurs de cet algorithme sont connus du public en raison des questions posées, les pondérations sont des secrets commerciaux. Après avoir répondu à l'enquête, les clients potentiels reçoivent les conseils générés par l'algorithme. Ces conseils prennent normalement la forme d'une répartition des actifs, par exemple 60% d'actions et 40% d'obligations, et peuvent inclure des conseils sur le montant à épargner chaque mois ou sur la date à laquelle le client pourrait raisonnablement prendre sa retraite.

Pour les robo-advisors qui ne donnent que des conseils personnalisés, le processus s'arrête là. Cependant, les robo-advisors qui donnent des conseils personnalisés et gèrent le portefeuille d'un client sont plus courants. Le modèle économique du conseil uniquement est difficile à monétiser. Peu de gens sont prêts à payer pour des conseils avant de les recevoir, car ils ne savent pas s'ils seront bons. Encore moins de personnes sont prêtes à payer pour un conseil *après* qu'elles l'ont reçu, parce qu'elles le connaissent déjà. Pire encore, le modèle d'entreprise fondé uniquement sur le conseil ne répond pas au véritable besoin de nombreux investisseurs particuliers : quelqu'un d'autre pour le faire à leur place.

C'est là qu'intervient le robo-advisor qui gère également les comptes de ses clients, ce qui est le cas de la majorité des robo-advisors. Dans ce cas, le robo-advisor personnalisé fonctionne comme une publicité

ou une rampe d'accès pour la gestion d'actifs. En tant que gestionnaires d'actifs, les robo-advisors peuvent investir dans n'importe quoi et le font. Au moment de la rédaction de ce document, en 2024, la plupart des robo-advisors permettent à leurs clients d'investir dans les FPI [*Real Estate Investment Trust*, REIT], l'or et les crypto-monnaies. Mais la majorité des actifs de tout portefeuille de robo-advisor sont des ETF. Les ETF sont le pain et le beurre des robo-advisors parce qu'ils ont des frais peu élevés, parfois aussi bas que trois points de base (0,03%), et offrent une voie facile vers la diversification, même avec de petits montants de capital. En effet, le chapitre 2 de cet ouvrage se penche sur cet aspect « paresseux » des robo-advisors et se demande pourquoi une personne qui choisit cette forme d'investissement purement passive reviendrait en arrière et modifierait l'allocation de son portefeuille.

Les robo-advisors qui gèrent des comptes gagnent de l'argent grâce aux frais, aux pots-de-vin, aux services premium et aux prêts. La plupart des robo-advisors prélèvent un certain pourcentage des actifs gérés à titre de frais, à l'instar des conseillers financiers humains, mais à une fraction du coût. Cependant, de plus en plus de robo-advisors optent pour un modèle sans frais, en s'appuyant sur des moyens moins évidents de faire des bénéfices. Certains robo-advisors sont rattachés à un gestionnaire d'actifs qui crée ses propres ETF et peut donc recevoir des commissions pour ces frais, comme Fidelity Go qui recommande les ETF de Fidelity. Certains robo-advisors offrent des services premium moyennant un abonnement mensuel ou un pourcentage plus élevé des actifs sous gestion, comme Merrill Guided Investing. Enfin, certains robo-advisors peuvent exiger de leurs clients qu'ils conservent une partie de leur portefeuille sous forme de liquidités que le robo-advisor prête ensuite, comme c'est le cas pour Schwab Intelligent Portfolios.

Bien entendu, les robo-advisors se font concurrence sur la base de la qualité et de la pertinence de leurs conseils. Mais les robo-advisors se font également concurrence sur les frais, les services, l'étendue du choix et l'image de marque. Certains robo-advisors attirent les clients avec le réinvestissement automatique des dividendes, le rééquilibrage automatisé ou la récolte des pertes fiscales, promettant une expérience totalement autonome pour l'investisseur, comme Betterment. D'autres robo-advisors ne proposent volontairement pas ces services pour ne pas submerger leurs clients potentiels, comme le Robo-Advisor d'Amundi. Certains robo-advisors sont également des courtiers et permettent à leurs clients d'accéder à un univers d'investissement plus large, comme Wealthfront, tandis que d'autres robo-advisors limitent intentionnellement leur offre pour la rendre aussi simple que possible, comme SoFi Automated Investing. Enfin, certains robo-advisors tentent de s'adresser à des niches, comme Ellevest pour les femmes investisseuses, Goodvest pour les investisseurs ESG, ou Acorns pour les acheteurs compulsifs. Les robo-advisors ont parcouru un long chemin depuis leur invention en 2008, et il existe aujourd'hui des centaines de robo-advisors qui s'adressent à tous les segments de marché imaginables.

Recherche sur les robo-advisors

Les robo-advisors sont une technologie récente, mais ils ont déjà attiré l'attention des chercheurs académiques (voir Torno et al., 2021, pour une revue systématique de la littérature). D'une manière générale, cette recherche peut être divisée en recherche sur les robo-advisors eux-mêmes, traitée dans cette section, et en recherche utilisant les ensembles de données des robo-advisors pour répondre à d'autres questions, traitée dans la section suivante. Alors que les chapitres 1, 3 et 4 sont principalement des recherches utilisant les données des robo-advisors, le chapitre 2 de ce travail est en fait une recherche *concernant* les robo-advisors, posant la question de savoir pourquoi quelqu'un utiliserait un robo-advisor s'il souhaite gérer activement ses investissements.

Les robo-advisors peuvent donner des conseils financiers à leurs clients et gérer leurs comptes d'investissement. Il s'agit exactement des mêmes services que ceux fournis par les conseillers financiers humains. Les conseillers financiers humains et les robo-advisors sont des substituts. À cet effet, Brenner et Meyll (2020) a constaté que « l'utilisation de robo-advisors est associée à une diminution de 15,8 points de pourcentage de la probabilité que les investisseurs consultent des conseillers financiers humains » après les contrôles. Bien qu'ils ne soient pas en concurrence directe les uns avec les autres, les robo-advisors s'adressent souvent à un segment de marché peu fortuné sur lequel les conseillers financiers humains ne pourraient jamais faire de bénéfices, et la persistance des conseillers financiers humains parmi le segment de marché très fortuné atteste de leur demande continue (Jung et al., 2018). Les personnes dites « allergiques aux algorithmes » [*algorithm averse*] préfèrent tout simplement avoir un humain dans la boucle (Greig et al., 2023). Les robo-advisors peuvent également agir comme un « enseignant IA » infiniement patient, montrant aux investisseurs comment mieux diversifier leur portefeuille sans nécessairement prendre le temps d'un conseiller financier humain ou le remplacer (Loos et al., 2020). En outre, il arrive que des conseillers financiers humains utilisent des robo-advisors pour automatiser des tâches de routine, augmenter leur productivité ou parvenir à une plus grande cohérence. C'est ce qu'on appelle le conseil « hybride » (Merkle, 2020). Le conseil hybride peut être proposé par les gestionnaires d'actifs comme une passerelle entre le robo-advisoring et le conseil financier traditionnel pour les clients du segment de marché de la richesse moyenne – dépassant le solde de compte minimum pour un robo-advisor mais n'ayant pas encore assez d'actifs sous gestion pour justifier une attention sur mesure. Néanmoins, les chercheurs ont comparé les deux.

De nombreux conseillers financiers humains sont diplômés, expérimentés et scientifiques. Mais beaucoup ne le sont pas. Certains défauts des conseillers financiers humains ont été bien documentés. Pour commencer, les conseillers financiers humains peuvent conseiller à leurs clients de détenir des portefeuilles qui reflètent leurs propres portefeuilles (Foerster et al., 2017; Linnainmaa et al., 2021). Ce n'est pas né-

cessairement un bon conseil. Non seulement chaque client a besoin de conseils différents adaptés à sa situation financière unique, mais, selon Linnainmaa et al. (2021), les conseillers humains peuvent « effectuer des transactions fréquentes, courir après les rendements, préférer les fonds onéreux à gestion active et sous-diversifier ». Chalmers et Reuter (2020) a constaté que les portefeuilles des clients qui ont demandé des conseils financiers à des courtiers ont sous-performé les fonds à date cible, en partie parce que les conseillers ont orienté les clients vers des produits à frais plus élevés. Les conseillers humains peuvent orienter leurs clients vers des instruments financiers à frais élevés, souvent intéressés (Mullainathan et al., 2012). Mullainathan et al. (2012) ont également relevés des preuves de discrimination fondée sur l'âge et le sexe à l'égard des clients. Sharpe (1966) a observé que le fonds commun de placement moyen avait des performances inférieures à la moyenne du marché ; un demi-siècle plus tard, il est toujours vrai que le conseiller financier humain moyen a des performances inférieures à celles du marché et parfois même à celles d'investisseurs naïfs sans conseils (Hackethal et al., 2012; Chalmers et Reuter, 2020).

Le fait que les conseillers financiers humains puissent faire preuve de discrimination, répondre à des incitations perverses et être trop confiants ne devrait pas être trop surprenant, car il s'agit là de défauts humains. Les robo-advisors n'ont pas ces problèmes. Bien que de nombreux conseillers financiers humains soient travailleurs et honnêtes, les mauvaises expériences les poussent à chercher d'autres solutions. Même lorsque les investisseurs particuliers apprécient leur conseiller financier et lui font confiance, ils peuvent demander un second avis auprès des robo-advisors (Zhang et al., 2021). Certains utilisateurs préfèrent les robo-advisors parce qu'ils sont plus responsables (Philippon, 2019), objectifs (Jung et al., 2019), précis (Wexler et Oberlander, 2021) ou pratiques (Mesbah et al., 2019) que les conseillers financiers humains.

Recherche utilisant les données des robo-advisors

Naturellement, le robo-advising a fait l'objet de recherches et de comparaisons avec le conseil financier traditionnel, mais les données des robo-advisors peuvent-elles réellement être utilisées pour répondre à des questions dépassant cette spécialité étroite ? En fait, cela a déjà été fait pour découvrir que les courriels de rappel peuvent accroître l'attention des investisseurs (Bianchi et Briere, 2022), que l'attention des investisseurs et la performance des investissements sont positivement corrélées (Gargano et Rossi, 2018), et que la fixation d'objectifs augmente les taux d'épargne (Gargano et Rossi, 2023). Les chapitres 1, 3 et 4 du présent ouvrage cherchent à comprendre le comportement général des investisseurs, même en dehors du contexte des robo-advisors. Mais comme la question de savoir si la recherche peut utiliser les données des robo-advisors concerne chacun des quatre chapitres du présent travail, je l'aborde ici.

Bien sûr, alors que la recherche utilisant les robo-advisors répond aux limites d'autres recherches financières avec des ensembles de données plus importants et de meilleure qualité que ceux accessibles

précédemment, cette recherche n'est pas sans ses propres limites. Il y a au moins quatre angles morts dans la recherche utilisant les robo-advisors : les investisseurs institutionnels qui n'utilisent pas de robo-advisors, les investisseurs particuliers qui n'utilisent pas de robo-advisors, la variabilité entre les différents robo-advisors, et l'ambiguïté entourant les activités des investisseurs en dehors du robo-advisor.

L'une des limites de la recherche sur les robo-advisors est que les investisseurs institutionnels n'utilisent pas de robo-advisors. Pour les titres cotés à la bourse de New York, environ 70% sont détenus par des investisseurs institutionnels, et ces investisseurs institutionnels représentent également 98% du volume des transactions (Griffin et al., 2003; Evans, 2009). Une seule catégorie d'investisseurs institutionnels, les fonds d'investissement, contrôle des actifs financiers supérieurs au PIB de certains pays de l'OCDE, notamment les États-Unis, où ce chiffre était de 125% en 2020 (?). Les investisseurs institutionnels tels que les gouvernements, les banques, les agences d'assurance et les fonds emploient des départements de professionnels de la finance hautement spécialisés. Les investisseurs institutionnels ne font pas appel à des robo-advisors, ils *sont* les conseillers. Toute recherche qui n'étudie pas les investisseurs institutionnels ne peut pas décrire le comportement des marchés financiers en général.

Une deuxième limite est que tous les investisseurs particuliers n'utilisent pas non plus les robo-advisors. En surface, les robo-advisors sont plus susceptibles d'être adoptés par ceux qui n'ont pas de relation préexistante avec un conseiller financier, c'est-à-dire les investisseurs plus jeunes et moins fortunés (Fulk et al., 2018; Todd et Seay, 2020), bien que cela puisse changer à l'avenir à mesure que les clients vieillissent et que les attitudes à l'égard des robo-advisors évoluent (Belanche et al., 2019). Plus profondément, le service offert par les robo-advisors – conseils pour le choix et la gestion de portefeuilles d'ETF prêts à l'emploi – attirera certains investisseurs et en rebutera d'autres. Les investisseurs qui cherchent à faire du day trade, à utiliser des produits dérivés, à construire leur propre portefeuille ou à s'enrichir rapidement n'utiliseront pas les robo-advisors. Toute recherche qui n'étudie pas les traders actifs ne peut décrire le comportement des investisseurs particuliers en général.

Une troisième limite est que chaque robo-advisor est différent. Maume (2021) définit trois types de robo-advisors en fonction du type de services qu'ils offrent : robo-advice générique, robo-advice personnalisé et comptes gérés par des robots ; tandis que D'Acunto et Rossi (2021) décrit quatre dimensions selon lesquelles les robo-advisors diffèrent : la personnalisation, l'implication, la discrétion et l'interaction humaine. C'est sans parler de la structure des frais, des services supplémentaires, de la distribution géographique et de l'image de marque qui peuvent influencer le choix final du robo-advisor par les investisseurs. Toute recherche qui n'étudie qu'un seul robo-advisor ne peut décrire la manière dont les investisseurs utilisent les robo-advisors en général.

Enfin, les robo-advisors sont limités dans la mesure où ils observent l'activité financière de leurs investisseurs au-delà de l'utilisation de leur service. Tous les clients ne délèguent pas l'intégralité de leur

portefeuille d'actifs liquides à un robo-advisor pour le gérer. La plupart des robo-advisors posent des questions sur les revenus et les autres actifs financiers de leurs clients pour générer les conseils, et bien que les clients soient incités à répondre sincèrement à ces questions afin de recevoir des conseils utiles à leur situation, il s'agit néanmoins d'une mesure imprécise. Les robo-advisors gérés par les banques peuvent avoir accès aux données de transaction des comptes courants des clients, mais cela ne révèle pas nécessairement quoi que ce soit sur les autres comptes d'investissement détenus dans d'autres institutions. Les dossiers fiscaux pourraient aider à compléter ces informations, mais ils sont notoirement difficiles d'accès pour les chercheurs (Chetty et al. (2014) a dû se soumettre à un processus de sélection concurrentiel, à une vérification des antécédents et à la prise d'empreintes digitales pour accéder aux dossiers fiscaux de l'IRS). Au-delà des problèmes pratiques, le fait de s'immiscer à ce point dans la vie financière des gens soulève également de sérieuses questions éthiques et de respect de la vie privée.

Saurons-nous jamais vraiment comment fonctionne le marché boursier ? Il est vrai que les robo-advisors ne sont pas la réponse définitive à cette question. Bien sûr, ce serait formidable s'il existait une base de données contenant toutes les transactions de chaque personne depuis sa naissance, qu'elles soient légales ou illégales. Mais ce type de données n'existe pas.

Limites constatées. En utilisant des données plus nombreuses et de meilleure qualité que jamais auparavant, la recherche des robo-advisors permet de répondre à la question de savoir comment les investisseurs passifs de la classe moyenne épargnent. Les investisseurs de la classe moyenne ne contrôlent pas la majeure partie des actifs du marché boursier, mais ils constituent un groupe démographique important et en pleine croissance. Certains investisseurs de la classe moyenne ont le temps et la volonté d'être des traders très actifs, mais il est difficile d'imaginer un avenir dans lequel les day traders constitueront un jour la majorité des investisseurs de la classe moyenne. Tous les robo-advisors ne sont pas identiques, mais la plupart d'entre eux partagent le même modèle d'entreprise, qui consiste à proposer et à gérer un portefeuille d'investissement pour leurs clients. Les ensembles de données des robo-advisors ne sont pas complets, mais la quantité et la qualité de leurs données dépassent de loin les enquêtes d'auto-déclaration limitées ou les données macro agrégées que les chercheurs en finance ont l'habitude d'utiliser. En résumé, la recherche utilisant les données des robo-advisors n'est pas parfaite, mais c'est l'un des outils les plus puissants pour comprendre le groupe de plus en plus important d'investisseurs de la classe moyenne répartis dans le monde entier. Elle est également très efficace pour identifier le type d'énigmes financières comportementales au niveau microéconomique présentées dans les quatre chapitres suivants.

La base de données Yomoni

Comment fonctionne Yomoni et le questionnaire d'introduction

Les données de ce travail unifié proviennent du gestionnaire d'actifs et robo-advisor Yomoni. L'ensemble de données couvre toute l'histoire de l'entreprise, depuis sa première transaction le 25 août 2015 jusqu'à la date à laquelle les données ont été récoltées, le 10 avril 2022. Ce jour-là, la société comptait 36 836 clients et 795,7 millions d'euros d'actifs sous gestion. Les données comprennent de nombreuses informations démographiques et financières sur chaque client, ainsi que l'historique de leurs transactions avec Yomoni.

En tant qu'entreprise en pleine croissance, Yomoni modifie occasionnellement ses offres, mais tout ce qui suit est vrai au moment de la collecte des données. Yomoni n'a pas de magasin physique en contact avec les clients, tous les comptes d'investissement sont donc ouverts en ligne sur leur site web. S'agissant d'une opération entièrement B2C, un investisseur de détail potentiel entend parler de Yomoni par le biais d'une recherche sur Internet, d'une publicité ou du bouche-à-oreille. Une fois sur le site web de Yomoni, le client potentiel remplit un questionnaire pour recevoir des conseils automatiques sur les dix portefeuilles d'investissement de Yomoni qui conviennent le mieux à sa situation financière (ces portefeuilles sont décrits plus en détail dans la section suivante). Ce n'est qu'une fois le questionnaire rempli que le client peut ouvrir un compte d'investissement géré par Yomoni, bien qu'il soit libre d'ignorer les conseils s'il le souhaite.

Le questionnaire d'introduction comprend 45 questions au total, divisées en deux parties : 24 questions utilisées pour calculer le robo-advice, à partir desquelles le client potentiel s'arrête pour lire et considérer ce conseil, et ensuite, si le client souhaite investir dans l'un des dix portefeuilles de Yomoni, 21 autres questions sont posées pour répondre à toutes les exigences réglementaires. Le questionnaire complet est inclus dans l'annexe en ligne. En bref, le questionnaire interroge les clients sur leur âge, leur sexe, leur lieu de résidence, leur famille, leur revenu, leur patrimoine, leur emploi, leurs connaissances financières, leur tolérance au risque, leurs besoins de liquidité, ainsi que sur l'objectif, le montant, l'horizon et la contribution mensuelle de leur investissement. Les informations relatives à l'identité du client sont vérifiées de manière indépendante à l'aide d'une pièce d'identité délivrée par le gouvernement, telle qu'un passeport. Les autres informations sont considérées comme données. Les clients sont incités à fournir sincèrement des informations au moins approximatives afin d'obtenir une recommandation d'investissement pertinente. La réglementation exige également que les clients mettent à jour leurs réponses à ce questionnaire tous les 1 à 2 ans, et Yomoni leur rappelle à intervalles réguliers de le faire.

Pour ouvrir un compte, il faut signer un contrat en ligne, fournir quelques documents supplémentaires tels qu'un justificatif de domicile et, dans de rares cas, appeler un agent du service clientèle pour confirmer tous les détails. Après un délai de quelques jours ouvrables en moyenne, toutes les formalités

sont accomplies et le compte d'investissement est officiellement ouvert. Par la suite, le client type dépose occasionnellement de l'argent sur son compte, mais ne modifie que rarement, voire jamais, la répartition de son portefeuille (voir chapitre 2), ne retire pas d'argent et ne ferme pas son compte (voir chapitre 3). Des opérations plus complexes, telles que la négociation d'options, ne sont pas possibles. La valeur totale moyenne économisée par un investisseur chez Yomoni est de 21.602 € (écart-type = 62.208 €). La valeur totale médiane économisée est de 7.273 €.

Dans la base de données, les données sont organisées de la manière suivante : *familles* sont composées d'un ou plusieurs *individus*, chacun d'entre eux ayant un ou plusieurs *comptes*, dans lesquels il y a *transactions* et *changements sur le compte*, qui ont tous deux lieu au fil du temps. Ces informations sont réparties sur plusieurs ensembles de données, ce qui nécessite un véritable nettoyage des données pour relier les transactions aux comptes, aux individus et aux familles, pour regrouper plusieurs comptes en un seul individu, pour séparer les comptes ouverts des comptes fermés, pour distinguer les clients réels des clients potentiels, pour trier les nombreuses catégories de transactions en catégories claires et pour tenir compte de l'évolution de l'entreprise au fil du temps. En outre, l'accès aux données nécessite une habilitation de sécurité et est entièrement anonymisé par défaut ; toutes les familles, tous les individus et tous les comptes sont désignés exclusivement par une étiquette hexadécimale. La base de données ne contient aucune information sensible sur un investisseur individuel ; par exemple, les adresses n'apparaissent pas dans la base de données, mais seulement les codes postaux. Le niveau d'analyse par défaut utilisé dans ce travail est le niveau individuel, bien que le chapitre 4 s'intéresse à la fois aux individus et aux familles. Les chapitres 1 et 3 analysent les transactions au niveau de l'individu, tandis que le chapitre 2 analyse les modifications apportées au niveau du compte.

Composition des portefeuilles, profils de risque et enveloppes fiscales

Lors de l'ouverture d'un nouveau compte d'investissement auprès de Yomoni, les clients potentiels répondent à un questionnaire d'introduction. Au cours du processus d'ouverture du compte, les données recueillies à partir du questionnaire d'introduction sont introduites dans un algorithme, qui recommande la composition de portefeuille (« profils de risque ») la plus adaptée aux objectifs d'investissement, aux caractéristiques individuelles et à la situation financière du client, parmi les dix compositions de portefeuille disponibles du robo-advisor. La fonction exacte de l'algorithme est une information exclusive, mais les variables qui affectent la recommandation de l'algorithme et dans quelle mesure sont motivées par la recherche académique évaluée par les pairs (Boulou-Reshef et al., 2022). Par exemple, les clients ayant des horizons d'investissement plus courts se voient recommander des portefeuilles contenant plus d'obligations et moins d'actions. Les dix portefeuilles disponibles sont appelés « profils de risque » car leur

composition varie en fonction de l'exposition au risque de marché. Les dix profils de risque sont étiquetés de 1 à 10. Le profil 1 est un portefeuille composé à 100% de fonds en euros (dont le capital est garanti et le rendement connu à l'avance)⁴, tandis que le profil 10 est un portefeuille composé d'ETF 100% actions. Le profil pivot est le profil 6 (le portefeuille stratégique), avec 50% d'actions et 50% d'obligations. Les huit autres profils de risque mélangent trois types d'instruments financiers dans les proportions décrites dans le tableau 4.6.⁵ Les profils avec une exposition croissante au risque de marché sont plus risqués par définition.

TABLE 4.6 : **Composition et répartition du portefeuille.**

Ce tableau présente la composition et l'allocation du portefeuille par classe d'actifs pour chaque profil de risque.

Composition par profil de risque (exprimée en pourcentage)										
Profils de risque	1	2	3	4	5	6	7	8	9	10
Fonds Euro	100	70	60	40	20	0	0	0	0	0
Profil 6	0	30	40	60	80	100	80	60	40	0
Profil 10	0	0	0	0	0	0	20	40	60	100

Composition par classes d'actifs (exprimée en pourcentage)										
Profils de risque	1	2	3	4	5	6	7	8	9	10
Fonds Euro	100	70	60	40	20	0	0	0	0	0
Obligation ETFs	0	15	20	30	40	50	40	30	20	0
Actif ETFs	0	15	20	30	40	50	60	70	80	100

Lorsque les épargnants choisissent Yomoni comme gestionnaire d'actifs, ils font deux choix en ce qui concerne leur investissement : un profil de risque et une enveloppe fiscale. La seule autre interaction financière qu'un client peut avoir avec le robo-advisor, outre les dépôts et les retraits, est la modification de son profil de risque, même si ce dernier n'est pas recommandé par le gestionnaire d'actifs. Le profil de risque ne devrait être modifié qu'en réponse à un changement de style de vie, tel qu'il ressort des réponses au questionnaire de profilage. Les chapitres 2 et 4 analysent en détail le profil de risque.

Une enveloppe fiscale consolide les investissements d'une manière fiscalement avantageuse. Yomoni propose quatre enveloppes fiscales : (i) assurance-vie ; (ii) Plan Epargne Actions (PEA) ; (iii) Plan Epargne Retraite (PER) ; et (iv) compte-titres ordinaire (CTO). Chaque type d'enveloppe fiscale a un impact différent sur l'imposition à la clôture du compte. Cette imposition ne concerne que la plus-value réalisée. Ces quatre enveloppes fiscales s'appuient sur le même indice de référence, également connu sous le nom de portefeuille stratégique, pour répartir l'investissement. Si le profil de risque sélectionné pour un épargnant

⁴Uniquement en France, les « fonds en euros » sont des produits financiers qui versent un rendement garanti sans risque de perte du capital initial. Les rendements corrigés de l'inflation des fonds en euros ont été positifs pendant la majeure partie de la période étudiée dans ce document. Cinq des dix profils de risque proposés aux clients de l'échantillon, ceux qui sont les moins risqués, incluent les fonds en euros à risque zéro dans leurs portefeuilles.

⁵Le profil de risque 1 n'est plus disponible pour les nouveaux contrats à compter du 10 septembre 2020, mais les contrats qui ont sélectionné ce profil de risque avant cette date sont restés inchangés. Le profil de risque 2 a été modifié le 30 avril 2021, lorsque la répartition des instruments financiers est passée de 80-10-10 à 70-15-15. Les contrats qui avaient choisi le profil de risque 2 ont été modifiés en fonction de la nouvelle répartition.

donné reste le même quelle que soit la structure fiscale choisie, l'allocation et la performance peuvent différer de manière significative entre les trois structures fiscales, de la manière suivante :

- Les produits financiers éligibles aux PEA sont limités aux Exchange-Traded Funds (ETF) et aux fonds indiciels. Cet univers d'investissement restreint ne permet pas nécessairement une reproduction parfaite du portefeuille stratégique.
- L'assureur en charge du compte d'investissement à avantage fiscal standard ne dispose pas systématiquement des produits nécessaires (ETF ou fonds indiciels) dans son univers d'investissement.
- Dans les PEA, les épargnants détiennent des parts d'ETF qui, comme les actions, ne peuvent pas être fractionnées. Par conséquent, lorsque le montant investi est faible, certains ETF peuvent être mis de côté car leur valeur est trop élevée. Ce n'est pas le cas des polices d'assurance-vie, où l'assureur détient les actions, alors que le client n'a qu'une part synthétique, et ne possède donc qu'une fraction d'actions appelée unité de compte.

Une fois que le client a choisi son enveloppe fiscale préférée, l'objectif de Yomoni en tant que gestionnaire de patrimoine est de maximiser la performance de ses comptes gérés tout en restant dans les allocations d'actifs définies par le profil de risque choisi par le client. L'objectif de l'équipe de gestion de patrimoine est de ne jamais s'écarter du mandat qui lui a été confié par le client. En d'autres termes, les transactions que l'équipe de gestion de patrimoine peut effectuer ne doivent jamais modifier les portefeuilles d'investissement des clients au point qu'un investisseur ayant choisi le profil de risque 6 se retrouve avec une allocation d'actifs plus proche de celle du profil de risque 7, par exemple. Le chapitre 2 est consacré à ces modifications apportées au profil de risque.

On peut raisonnablement supposer que les informations fournies dans le questionnaire sont à peu près exactes. Toutes les informations contenues dans le questionnaire sont autodéclarées, mais certains champs requièrent une preuve. Avant de signer un contrat, le client doit fournir une pièce d'identité, un justificatif de domicile, une facture de téléphone mobile et le relevé d'identité bancaire (RIB). Des documents supplémentaires doivent être fournis lors de l'ouverture d'un compte au nom d'un enfant. Ces documents sont examinés plus en détail au chapitre 4, consacré à la relation d'investissement parent-enfant. En revanche, aucun document n'est demandé pour justifier la situation financière d'un client, tel qu'un bulletin de salaire ou un avis d'imposition. Les informations financières déclarées par le client sont donc approximatives et ne font pas l'objet d'une vérification externe. Cela dit, si aucune preuve n'est exigée, les clients potentiels sont néanmoins incités à fournir des informations correctes sur leur situation financière afin de recevoir des conseils pertinents de la part du robo-advisor. Sans fournir des informations au moins approximatives, les conseils reçus du robo-advisor sont pratiquement inutiles.

Les organismes de réglementation AMF (Autorité des marchés financiers) et ACPR (Autorité de contrôle prudentiel et de résolution) exigent que l'entreprise mette à jour les informations démographiques de chaque client (KYC ou « Know Your Customer ») tous les 1 à 2 ans. Conformément à cette réglementation, Yomoni demande régulièrement à chaque client de mettre à jour ses informations par le biais d'une fenêtre contextuelle lorsqu'il se connecte à son compte en ligne. La durée moyenne pendant laquelle un client ne met pas à jour ses informations est de 318 jours, soit 0,87 année.

Versements programmés et non programmés

Dans pratiquement toutes les banques et tous les gestionnaires d'actifs, les clients peuvent effectuer deux types de dépôts : les versements non programmés et les versements programmés. Les versements non programmés peuvent être effectués à tout moment et pour n'importe quel montant, tandis que les versements programmés sont assortis d'intervalles fixes et de montants promis à l'avance. Chez Yomoni, ces deux types de dépôts reçoivent différents noms dans les données de transaction, ce qui permet de les étudier indépendamment. Si un investisseur décide de programmer des versements, il peut le faire soit mensuellement, soit trimestriellement, bien que la programmation mensuelle soit beaucoup plus courante. Dans cet ensemble de données, les versements non programmés sont plus importants que les versements programmés en termes de valeur. Le versement non programmé moyen ($M = 3.409 \text{ €}$, $SD = 20.071 \text{ €}$) est quinze fois plus important que le versement programmé moyen ($M = 216 \text{ €}$, $SD = 621 \text{ €}$), $t(94.761) = 48,95$, $p < ,001$. Par ailleurs, le versement non programmé médian (500 €) est cinq fois plus important que le versement programmé médian (100 €). Chez Yomoni, le versement minimum est de 50 €, identique pour les versements programmés et non programmés. Toutefois, les plafonds sont différents : 150.000 euros par mois pour les versements programmés et 10.000 000 euros pour un seul versement non programmé, bien que les clients n'aient déposé plus de 150.000 euros en un mois que 120 fois au total. Au cours de la période de collecte des données, la valeur minimale avec laquelle un investisseur pouvait ouvrir un compte était de 300 €.

Au moment de la collecte des données, la troisième question du questionnaire d'introduction était la suivante : « Combien aimeriez-vous investir chaque mois ? » Cette question pouvait être ignorée et la réponse par défaut était 0 €. De nombreux tests A/B basés sur les nudges ont été menés en interne sur cette question au fil des ans (voir Thaler et Sunstein (2021) pour une explication des nudges). Il est amusant de constater que j'en ai moi-même reçu un au hasard lors de la rédaction du chapitre 1. À partir de janvier 2024, la question officielle est désormais la suivante : « Combien aimeriez-vous investir chaque mois ? Investir de l'argent chaque mois peut faire une grande différence en quelques années. 55% de nos clients ont fait ce choix et investissent en moyenne 200 euros par mois. » Désormais, le client potentiel

ne peut pas ignorer cette question et il n'y a pas de réponse par défaut, bien qu'il soit toujours possible de répondre par 0 € par mois. De manière anecdotique, la mise en œuvre des nudges de preuve sociale, de réponse forcée et d'ancrage a été corrélée à une augmentation progressive du taux de réalisation des versements programmés de quelques points de pourcentage et de la valeur de ces versements de quelques euros en moyenne. Toutefois, les résultats de ces expériences ne sont pas traités dans ce document. Le questionnaire d'introduction prend un certain temps, et l'entreprise s'efforce de le raccourcir autant que possible en posant des questions brèves qui peuvent être ignorées. Si l'entreprise a ajouté plusieurs phrases à la question et a obligé tous les clients à répondre, c'est uniquement parce que les avantages l'emportent sur les inconvénients à ses yeux. En résumé, le montant qu'un investisseur souhaite investir chaque mois est un *entrée* du conseil, et non un *sortie* du conseil. Bien que de nombreuses informations non personnalisées sur les taux d'épargne optimaux soient affichées publiquement sur le site web, les clients potentiels ne reçoivent pas de conseils sur le montant à épargner au cours de la procédure d'inscription.

Si un client ne fixe pas de date de versement lors de l'ouverture du compte, il peut activer l'option plus tard dans l'interface en ligne. L'utilisation de l'interface en ligne est également le seul moyen d'activer l'option de versement programmé trimestriel ou d'annuler ses versements programmés. Le chapitre 1 examine une conséquence inattendue de cette conception, à savoir que les clients qui utilisent cette fonction pour épargner finissent par épargner moins dans l'ensemble, et donc peut-être moins qu'ils ne l'auraient fait sans cette option.

La représentativité de la base de données Yomoni

Comme indiqué précédemment, il n'y a pas deux robo-advisors identiques, et c'est l'une des façons dont ils se font concurrence. En outre, le robo-advisoring est un service financier spécifique et tous les investisseurs n'y ont pas recours. À ce titre, il est raisonnable de se demander dans quelle mesure la base de données de Yomoni est représentative.

Par ordre alphabétique inverse, les robo-advisors français comprennent Yomoni, Ramify, Nalo, Mon Petit Placement, Grisbee, Goodvest, Fundvisory, Fundshop, Birdee, Advize, et Amundi, et cette liste n'est pas exhaustive. Pour une comparaison complète, Rama (2022) a compilé un rapport comparant plusieurs de ces robo-advisors selon des axes spécifiques tels que les classes d'actifs et les enveloppes fiscales disponibles. En 2024, Yomoni est le plus grand robo-advisor français, avec plus de 50.000 utilisateurs et 1 milliard d'euros d'actifs sous gestion.

En ce qui concerne les concurrents internationaux, les barrières réglementaires telles que le Foreign Account Tax Compliance Act (FATCA) empêchent les investisseurs français et même les Américains vivant à l'étranger d'investir en utilisant plusieurs grands robo-advisors américains tels que Betterment,

Fidelity et Wealthfront. Cependant, il existe encore plusieurs robo-advisors américains qui surmontent les barrières réglementaires pour rivaliser en France pour les clients, y compris les géants de l'industrie tels que Vanguard et Charles Schwab. Bien que leur clientèle soit généralement beaucoup plus restreinte, les barrières réglementaires posent moins de problèmes aux robo-advisors ayant leur siège dans l'UE, tels que Curvo (Belgique), inbestMe et Indexa Capital (Espagne), Mintos (Lettonie) et Whitebox (Allemagne), bien qu'il y ait des dizaines de petits robo-advisors et que de nouveaux soient lancés chaque année. Si les quelque 50.000 utilisateurs de Yomoni et le milliard d'euros d'actifs sous gestion sont modestes par rapport aux institutions financières internationales établies, ils sont considérables sur le marché européen, où les taux de participation au marché boursier sont généralement inférieurs à ceux des États-Unis (Campbell, 2006).

Le robo-advisor belge Curvo publie des informations détaillées sur son service et même des données agrégées sur sa clientèle directement sur son site web. Cette disponibilité peu commune des données offre une occasion rare de faire une comparaison directe entre la clientèle de Yomoni et les utilisateurs d'un autre robo-advisor européen. Curvo a été fondé en 2021, tandis que Yomoni a été fondé en 2015. Au moment de la rédaction de ce document, à la mi-2024, Curvo compte environ 1.300 clients et 6.500.000 euros d'actifs sous gestion, ce qui signifie que sa croissance est plus lente que celle de Yomoni, qui comptait environ 7.000 clients trois ans après son lancement et a engrangé près de 6.000.000 euros d'actifs sous gestion au cours du seul mois de janvier 2018 (voir le tableau 3.2 à la page 101). Curvo propose cinq portefeuilles au lieu de dix, mais ils sont également classés par exposition au marché et conseillés en fonction de l'appétit du client pour le risque. Les portefeuilles des deux sociétés sont basés à 100% sur des ETF, diversifiés à l'échelle internationale, rééquilibrés automatiquement et ESG par défaut, et ces portefeuilles n'incluent pas d'investissements dans l'immobilier, la cryptomonnaie ou d'autres classes d'actifs alternatives. Comme pour Yomoni, la majorité des clients de Curvo déclarent que leur motivation pour investir est la vague et générique « tirer le meilleur parti de mon épargne », tandis que des minorités déclarent que leur motivation est de « préparer la retraite », « acheter un bien immobilier » et « épargner pour mon (mes) enfant(s) », toutes choses qui motivent également certains clients de Yomoni. Environ 70% des clients de Curvo effectuent des versements programmés, contre 50% pour Yomoni, mais le montant moyen de ces versements est étonnamment similaire, avec 205 € pour Curvo contre 216 € pour Yomoni. En résumé, certains éléments suggèrent que le modèle commercial de base et la clientèle de Yomoni sont similaires à ceux d'autres robo-advisors.

La question de la représentativité peut être posée autrement : dans quelle mesure les clients de Yomoni reflètent-ils les investisseurs français ? L'OECD (2023) fournit des statistiques qui distinguent les « nouveaux investisseurs » français (qui ont commencé à investir en 2020 ou plus tard) et les « investisseurs traditionnels » (qui ont commencé à investir avant 2020), et ces données peuvent être

comparées aux statistiques descriptives que cette recherche met au jour sur les investisseurs de Yomoni. Le tableau 4.7 résume les similitudes et les différences entre les clients de Yomoni (dont 90% sont français), les nouveaux investisseurs français et les investisseurs traditionnels français. En bref, les investisseurs de Yomoni sont plus proches des nouveaux investisseurs français à certains égards (plus jeunes, plus riches) et plus proches des investisseurs traditionnels français à d'autres égards (plus souvent des hommes, horizons d'investissement plus longs), bien que la stratégie d'investissement passif soit encore relativement peu orthodoxe.

TABLE 4.7 : Comparaison entre les investisseurs Yomoni, les « nouveaux investisseurs français et les » investisseurs traditionnels » français tels que définis par l'OECD (2023).

	Clients	Nouveaux investisseurs FR.	Investisseurs traditionnels FR.
Sexe	79% hommes	64% hommes	68% hommes
Age	33	36	51
Revenu	90% plus de 25k	75% plus de 30k	"plus que la moyenne"
Patrimoine financier	168.462 EUR	97.435 EUR	68.500 EUR
Patrimoine immobilier	211.925 EUR	-	-
Taux de détention des ETF	100%	11%	9%
Horizon, moins de 10 ans	46%	66%	37%
Horizon, plus de 10 ans	54%	13%	29%
Éducation financière*	97.5%	71%	-
Dépôt initial	8.447 EUR	6.743 EUR	-

Pour des statistiques descriptives plus détaillées sur divers groupes d'investisseurs dans la base de données Yomoni, voir le tableau 2.3 sur 76 (Chapitre 2) pour les investisseurs qui modifient leurs profils de risque, le tableau 3.4 à la page 107 (chapitre 3) pour les investisseurs qui se sont inscrits entre différentes dates, et le tableau 4.5 à la page 145 (chapitre 4) pour les investisseurs de différentes situations familiales.

Un ensemble de données idéal – représentatif au niveau national, plusieurs décennies, chaque transaction, des informations démographiques et financières complètes – n'existe pas pour la France. La base de données Yomoni présente des avantages et des inconvénients que le lecteur doit garder à l'esprit. Mais des éléments suggèrent que les investisseurs de Yomoni sont remarquablement similaires aux clients des robo-advisors dans d'autres pays et, au moins, pas radicalement différents des autres investisseurs en France.

Après avoir établi le contexte intellectuel nécessaire, décrit l'approche empirique et détaillé la base de données Yomoni, je vais maintenant donner un bref aperçu de chacun des chapitres inclus dans cet ouvrage et définir comment ces articles contribuent à la recherche sur la finance des ménages, la finance comportementale et l'utilisation des robo-advisors.

Chapitre 1 : Mauvaise planification : Les investisseurs qui épargnent régulièrement épargnent moins dans l'ensemble

La théorie économique standard prévoit que les agents économiques rationnels lisseront leur consommation tout au long de leur vie (Ando et Modigliani, 1963). En bref, le lissage de la consommation au cours de la vie consiste à accumuler des dettes pendant la jeunesse, à rembourser les dettes et à épargner au milieu de la vie, et à dépenser pendant la retraite. Les agents rationnels épargneront le montant dont ils ont besoin chaque fois qu'ils en ont la possibilité. Cependant, Choi (2022) remarque que tous les livres de finances personnelles les plus populaires encouragent leurs lecteurs à épargner chaque mois, quels que soient leur âge et leurs revenus. Ces conseillers financiers donnent ce conseil avec l'intuition que cela augmentera l'épargne de leurs lecteurs. Mais le fait de suivre cette stratégie – épargner régulièrement chaque mois au lieu de le faire sporadiquement (ou naïvement) – permet-il réellement d'accroître l'épargne ? En d'autres termes, le fait d'être un planificateur augmente-t-il l'épargne d'une personne par rapport à une personne qui n'est pas un planificateur ?

Peut-être pas. En utilisant une méthodologie très simple de test *t*, les investisseurs qui ont programmé leurs versements ont épargné 32,6% (8.630 €) de moins que les investisseurs qui n'ont pas programmé leurs versements. La moyenne de ces deux groupes était de 21.602 €. Cependant, un test *t* n'exploite aucune des données supplémentaires relatives aux investisseurs qui sont disponibles dans la base de données Yomoni, de sorte qu'une régression linéaire *ceteris paribus* qui contrôle ces facteurs a le potentiel d'inverser la tendance observée dans ces statistiques de surface. Mais ce n'est pas le cas. Avec cette méthodologie plus sophistiquée, les programmeurs ont encore économisé 16,0% (3.466 €) de moins que les non-planificateurs. Comme la base de données compte beaucoup plus de nouveaux clients qui ont eu moins de temps pour accumuler des économies, peut-être qu'après plusieurs années, les programmeurs ont économisé davantage. Mais ce n'est toujours pas le cas. Aucune cohorte annuelle de planificateurs n'a économisé de manière statistiquement significative plus que les non-planificateurs, et ce depuis la création de Yomoni en 2015. Cependant, ces tests n'exploitent pas la composante temporelle de la base de données Yomoni. Peut-être qu'une régression à effets fixes, une méthodologie beaucoup plus sophistiquée qui permet de contrôler même la variabilité non observée en maintenant constant un individu dans le temps, révélera un effet positif au cours des années où l'individu était un planificateur par rapport à un non-planificateur. En fin de compte, non. Les épargnants programmés n'ont pas épargné significativement plus durant les années où ils ont programmé des versements, tant qu'ils ont continué à épargner de manière sporadique. De multiples tests de robustesse et même la modification de la définition de l'« épargne » pour inclure différents types de versements ont toujours donné le même résultat de base : les planificateurs n'ont pas épargné significativement plus que les non-planificateurs, et ont souvent épargné

significativement moins.

En outre, de nombreux facteurs tels que l'âge, le sexe, le nombre d'enfants, le revenu, le patrimoine, l'horizon d'investissement, le statut ESG, l'objectif d'investissement et les connaissances financières de l'investisseur sont liés de manière significative à la décision de l'investisseur d'effectuer des versements programmés et/ou au montant qu'il a finalement épargné. Alors que les résultats concernant l'épargne totale ont tous été obtenus à l'aide des méthodes de régression décrites ci-dessus, les résultats concernant la probabilité pour un investisseur d'effectuer des versements programmés ou non ont été obtenus à l'aide d'une régression logistique. Une régression logistique permet de prédire le résultat d'une variable catégorielle binaire, telle que le fait d'être ou non un programmeur.

Cette étude ne clôt pas le débat sur la question de savoir si la programmation des versements augmente réellement l'épargne au fil du temps, mais l'ouvre plutôt. Le conseil populaire ne fonctionne pas pour tous les investisseurs. La base de données Yomoni présente suffisamment de limites pour ne pas apporter de réponse définitive. Mais il est clair que la sagesse populaire qui consiste à programmer des versements quels que soient le moment et la personne n'augmente pas réellement l'épargne de tous les investisseurs, du moins à moyen terme. Des recherches supplémentaires doivent être menées pour déterminer qui a besoin ou bénéficie de ce conseil.

Chapitre 2 : Gérer un investissement paresseux : Être activement passif

Les économistes s'intéressent aux facteurs qui déterminent théoriquement et empiriquement les préférences d'un investisseur en matière de risque (ou l'exposition au risque de son portefeuille), mais ces mesures ne sont normalement effectuées qu'au début d'un investissement. Cependant, les investisseurs investissent au fil du temps. Nous pouvons donc nous demander dans quelle mesure les facteurs déterminant les préférences/profils de risque au moment t de la création d'un portefeuille d'investissement reflètent ou contredisent les changements apportés à un portefeuille au moment $t + 1$.

Les robo-advisors sont issus d'une longue lignée d'instruments financiers qui cherchent à simplifier le processus d'investissement et à permettre aux investisseurs de prendre du recul et d'investir de manière passive. Yomoni, en particulier, est un robo-advisor qui propose des portefeuilles d'ETF à 100%, ce qui met plusieurs couches entre l'investisseur et le contrôle direct des actifs de son portefeuille. La technologie intrinsèquement passive des robo-advisors et leur philosophie d'investissement sous-jacente, selon laquelle les changements de portefeuille ne devraient être motivés que par des changements significatifs et inattendus dans les circonstances de la vie, impliquent que les changements de portefeuille devraient être peu fréquents. Pourtant, la base de données de Yomoni enregistre 9.250 changements pour seulement

36.836 clients, et certains clients changent plusieurs fois par an. Ces clients n'utilisent apparemment pas le robot-conseiller comme prévu, ce qui en fait un environnement parfait pour étudier si les facteurs qui influencent les changements de risque du portefeuille à la création ont des relations similaires pour les portefeuilles dynamiques que la littérature a trouvé pour les portefeuilles statiques.

Pour comprendre pourquoi et comment les investisseurs modifient leurs portefeuilles de robo-advisor, mes coauteurs et moi-même avons étudié les 6.247 clients de la base de données Yomoni qui ont apporté ces 9.250 modifications à leurs portefeuilles d'investissement. Les facteurs de la décision de changer de portefeuille comprennent les rendements et la volatilité du marché au niveau macroéconomique, qui suggèrent des tentatives de synchronisation du marché. Mais les facteurs comprennent également des variables financières microéconomiques telles que l'âge du portefeuille, le rendement, la volatilité, la valeur, le statut ESG et l'objectif, ainsi que des variables démographiques telles que l'âge de l'investisseur, le sexe, le nombre d'enfants et les préférences en matière de risque. Ces résultats suggèrent que la décision d'un investisseur de modifier son portefeuille a de nombreux précédents en dehors de ceux que la théorie du choix rationnel pourrait expliquer. Bien que de nombreux investisseurs choisissent de ne pas modifier leur portefeuille sur de longues périodes, l'ensemble de ces résultats peut être interprété comme indiquant que les investisseurs ne suivent pas uniformément le conseil du robo-advisor de modifier l'allocation de leur portefeuille uniquement en raison de changements significatifs et inattendus dans les circonstances de la vie.

Pour répondre à notre question initiale, à savoir dans quelle mesure les relations entre ces variables et les portefeuilles au fil du temps sont soit des prolongements, soit des contradictions, ces relations ont été étudiées de manière différenciée pour les changements vers une exposition plus ou moins importante au marché. Nous avons adopté une méthode de régression logistique multinomiale. Une régression logistique multinomiale permet de prédire le résultat d'une variable catégorielle non binaire, par exemple si un investisseur a modifié son portefeuille pour être plus, moins ou autant exposé au marché. Nous utilisons un algorithme d'appariement K-Nearest Neighbor (KNN), courant dans la science des données, pour trouver des « stayers » démographiquement et financièrement similaires aux « changers » positifs et négatifs, afin de ne pas biaiser ces résultats avec un sous-échantillon qualitativement différent (par exemple, un type de personne qui ne changerait jamais son portefeuille en aucune circonstance). En adoptant cette méthodologie, nous constatons que la littérature sur le risque statique des portefeuilles ne se réplique pas parfaitement aux portefeuilles dynamiques : par exemple, une réplification pour l'âge de l'investisseur mais des contradictions pour l'horizon d'investissement et le revenu de l'investisseur. Ainsi, nous ne pouvons pas simplement supposer que, par exemple, les investisseurs ayant un horizon plus long conserveront toujours le portefeuille risqué avec lequel ils ont commencé.

Étant donné que les investisseurs montrent des signes indiquant qu'ils anticipent le marché, nous

avons étudié l'impact de ces changements sur les rendements des investisseurs. Un test contrefactuel a montré qu'en moyenne, les comptes qui ont ajusté leur allocation de portefeuille ont surperformé des comptes hypothétiques identiques dans lesquels aucun changement n'a été effectué. Cela signifie que les investisseurs ont effectivement pu anticiper le marché, du moins dans une certaine mesure. Toutefois, on pourrait dire que ces gains n'ont pas encore été encaissés et qu'ils ne sont donc que théoriques. Nous avons donc refait l'analyse en utilisant un ensemble de données plus restreint comprenant uniquement les gains réalisés (autrement dit, les comptes fermés). Avec cet ensemble de données plus restrictif, le bon résultat du market timing ne s'est pas reproduit, comme on pouvait s'y attendre, puisque la littérature indique que l'investisseur moyen ne peut pas anticiper le marché et qu'il perd des sommes importantes en essayant de le faire.

Chapitre 3 : Le bon vieux confinement : Le comportement des ménages en matière d'investissement pendant la crise du Covid-19

La pandémie de Covid-19 a constitué un moment historique monumental, les principales conditions macroéconomiques et les attentes concernant l'avenir ayant changé du jour au lendemain en réponse à une variable exogène plausible, la propagation d'une maladie implacable. Les gouvernements du monde entier ont réagi en imposant des fermetures obligatoires. Le marché boursier a également réagi, provoquant le krach boursier de 2020. Pourtant, la littérature financière n'est pas encore parvenue à un consensus sur le comportement des ménages investisseurs. Là encore, il y a une division entre la théorie et l'empirique. À moins de croire que la pandémie se poursuivra pendant une décennie, aucun de ces chocs ne devrait avoir d'importance en théorie pour les investisseurs particuliers ayant des horizons d'investissement très longs, tels que ceux qui constituent la grande majorité de la base de données de Yomoni. Mon coauteur et moi-même cherchons à établir empiriquement comment ces ménages investisseurs en France ont réagi à ces chocs pendant qu'ils se produisaient.

Pour ce faire, nous avons utilisé une régression à effets fixes similaire à celle qui vient d'être décrite pour le chapitre 1. Cependant, étant donné qu'une impulsion annuelle est beaucoup trop lente pour mesurer le comportement pendant les crises aiguës qui ont duré des semaines, voire des mois, nous avons utilisé une impulsion quotidienne pour les versements non programmés, qui peuvent avoir lieu n'importe quel jour, et une impulsion mensuelle pour les versements programmés, qui ne peuvent avoir lieu qu'une fois par mois.

Les investisseurs de cet échantillon ont moins épargné pendant le krach boursier et les périodes de

blocage, et moins pendant la période Covid en général. La coïncidence du krach boursier de 2020 et de la période de blocage Covid-19 a eu un effet modérateur, car les investisseurs n'ont pas été doublement paniqués. Toutefois, les effets des crises sont différents selon qu'il s'agit de versements non programmés, qui reflètent des réactions à court terme à ces événements, ou de versements programmés, qui donnent un aperçu de la manière dont les investisseurs ont ajusté leurs plans pour l'avenir. En résumé, les investisseurs n'ont pas réagi de la même manière à toutes les crises et n'ont pas réagi de la même manière en ce qui concerne les versements programmés et non programmés.

La régression à effets fixes est conçue pour étudier des variables temporelles telles que le fait qu'une crise se produise un jour donné ou non. L'un des inconvénients de la méthode des effets fixes est que les variables invariantes dans le temps (du moins à court terme), telles que le sexe d'une personne ou la structure familiale, ne peuvent pas être étudiées. Par conséquent, nous ne pouvons pas obtenir d'estimations pour les variables du questionnaire, qui sont mesurées lors de la création du contrat, sans adopter également une autre méthodologie pour étudier le riche ensemble de données de variables financières, démographiques et comportementales. C'est pourquoi nous utilisons des régressions logistiques pour étudier la probabilité qu'un investisseur effectue un versement (non) programmé, puis des régressions linéaires pour étudier la valeur de ce versement.

Chapitre 4 : Comment les ménages investissent-ils au nom de leurs enfants ? Les données d'un robo-advisor

Les gouvernements, les gestionnaires d'actifs et les parents souhaitent tous que les enfants disposent d'une épargne. Pour faciliter l'épargne au nom des enfants, les gouvernements parrainent des comptes d'investissement assortis d'incitations fiscales, tels que le compte 529 aux États-Unis ou le Livret Jeune en France, les gestionnaires d'actifs créent des comptes d'investissement pour les enfants et en font la publicité, et les parents ouvrent ces comptes d'investissement pour le compte de leurs enfants. Bien que cette pratique soit courante, on sait peu de choses sur la manière dont les parents investissent au nom de leurs enfants. La théorie du choix rationnel prédit qu'en tant qu'agents du mandant de leurs enfants, les parents investiront parfaitement en tenant compte des nombreuses différences entre la situation financière de l'enfant et la leur. Mais si les données empiriques indiquent que les investisseurs ne se comportent pas selon la théorie du choix rationnel pour eux-mêmes, il est peu probable qu'ils le fassent lorsqu'ils investissent pour le compte de leurs enfants.

La base de données Yomoni permet d'étudier ces paires parent-enfant et, une fois de plus, il apparaît que les investisseurs réels se comportent d'une manière qui ne peut être expliquée par la théorie du choix rationnel. Il n'est pas évident *a priori* de savoir si les pères s'occupent des comptes d'investissement de

leurs enfants, puisque les comptes d'investissement d'un ménage ont tendance à être gérés par l'homme de la famille, ou si cette tâche est confiée aux mères, parce qu'elle pourrait être considérée comme une forme de garde d'enfants. Ces données montrent que ce sont surtout les pères qui gèrent ces comptes.

Mon coauteur et moi-même identifions deux écarts spécifiques par rapport à la rationalité. Premièrement, nous montrons que les pères ont une préférence pour les fils, ce qui signifie qu'ils ouvrent plus fréquemment des contrats d'investissement pour leurs fils que pour leurs filles. Comme les pères représentent la majorité des gestionnaires de comptes, leur préférence pour les fils est suffisante pour apparaître dans les statistiques sommaires globales. Ces résultats sont obtenus à l'aide d'un test du chi-carré de Pearson, un outil standard de la littérature psychologique utilisé pour tester les différences entre des groupes triés par des variables catégorielles telles que le sexe. Deuxièmement, le profil de risque du portefeuille d'investissement des enfants est fortement corrélé au profil de risque de leurs parents, ces derniers s'écartant souvent des conseils du robo-advisor pour avoir le même profil de risque. Dans la théorie du choix rationnel, les profils de risque des enfants sont plausiblement décorrélés de ceux de leurs parents, parce que tout héritage ne viendra probablement que beaucoup plus tard dans la vie et que la situation financière personnelle à long terme des enfants n'a pas grand-chose à voir avec celle de leurs parents. L'un est un adulte qui travaille, qui a terminé ses études et qui doit payer des factures à court terme, tandis que l'autre a jusqu'à dix-huit ans avant de devoir prendre sa première décision financière autre que celle de dépenser son argent de poche.

Contributions de la recherche

En résumé, cette thèse contribue à la littérature sur la finance comportementale, la finance des ménages et l'utilisation des robo-advisors avec quelques résultats surprenants. Dans le chapitre 1, les investisseurs qui suivent le conseil financier populaire d'épargner régulièrement sont considérés comme épargnant moins que les investisseurs qui épargnent sporadiquement, ce qui nous incite à nous demander dans quelle mesure ce conseil devrait être universel. Dans le chapitre 2, les résultats de la littérature sur le risque statique des portefeuilles ne s'étendent pas aux portefeuilles dynamiques dans tous les cas, ce qui soulève des questions sur la manière dont les investisseurs qui commencent avec des préférences risquées ou conservatrices peuvent évoluer au fil du temps. Le chapitre 3 étudie le comportement des investisseurs individuels pendant la pandémie de grippe aviaire de 19 ans en établissant une distinction entre la planification à court et à long terme, qui sont des motivations notoirement difficiles à distinguer dans les ensembles de données standard. Dans le chapitre 4, des informations rares sur les finances d'une famille entière sont exploitées pour comprendre comment le comportement d'investissement peut (ou non) être

transmis d'une génération à l'autre. Ce travail contribue également à l'abandon des articles purement théoriques au profit d'un mélange de théorie et de résultats empiriques dans les domaines de l'économie et de la finance. Les quatre articles suivants remettent en question le paradigme traditionnel, répondent à des questions importantes et ouvrent la voie à des travaux futurs.

J. Indigo JONES

Behavioral household finance and robo-advising

Finance comportementale des ménages et robo-advising

Résumé :

Cette recherche étudie le comportement des ménages investisseurs qui utilisent un robo-advisor français à travers quatre articles empiriques. Dans la première étude, les investisseurs qui épargnent régulièrement épargnent moins à moyen et long terme que ceux qui n'épargnent que sporadiquement, ce qui remet en question l'universalité de ce conseil financier populaire. Dans la deuxième étude, les investisseurs actualisent le risque de leur portefeuille au fil du temps d'une manière qui ne reproduit pas toujours les résultats obtenus avec des portefeuilles statiques, ce qui remet en question la mesure dans laquelle la recherche sur les portefeuilles statiques devrait éclairer les conseils pratiques sur les portefeuilles dynamiques. Dans la troisième étude, les investisseurs ont globalement moins épargné pendant la pandémie de Covid-19 et ont actualisé différemment leurs plans à long et à court terme, comblant ainsi une lacune à laquelle les données au niveau de marché ne peuvent pas répondre et donnant un aperçu de la manière dont les investisseurs pourraient réagir aux crises à venir. Dans la quatrième étude, les parents investissent pour leurs enfants de la même manière que pour eux-mêmes et ouvrent un peu plus de comptes pour leurs fils que pour leurs filles, ce qui met en évidence les domaines dans lesquels les gestionnaires de patrimoine doivent mieux informer les familles sur la manière de planifier les finances de leur ménage. Dans l'ensemble, cette recherche documente de nombreux écarts comportementaux au niveau microéconomique par rapport à la théorie financière traditionnelle et démontre que la recherche scientifique utilisant des données sectorielles peut donner lieu à des découvertes surprenantes.

Mots clés : Finance comportementale, finance des ménages, robo-advising, comportement d'épargne, dépôts programmés, choix de portefeuille, investisseurs individuels, pandémie de Covid-19, krach boursier, choix de portefeuille délégué, préférence pour les fils.

Abstract :

This research studies the behavior of household investors who use a French robo-advisor across four empirical papers. In the first study, investors who save regularly save less in the medium- to long-run than those who only save sporadically, calling into question the universality of this popular financial advice. In the second study, investors update their portfolio risk over time in a way that does not always replicate findings from static portfolios, challenging the extent to which research on static portfolios should inform practical advice about dynamic portfolios. In the third study, investors saved less overall during the Covid-19 pandemic and updated their long- and short-term plans differently, addressing a gap that market-level data cannot answer and providing insights into how investors may react to future crises. In the fourth study, parents invest for their children similar to how they invest for themselves and open slightly more accounts for sons than for daughters, highlighting areas where wealth managers must better inform families about how to plan their household finances. Overall, this research documents many micro-level behavioral departures from traditional finance theory and demonstrates how scientific research using industry data can yield surprising discoveries.

Keywords : Behavioral finance, household finance, robo-advising, saving behavior, scheduled deposits, portfolio choice, individual investors, Covid-19 pandemic, stock market crash, delegated portfolio choice, son preference.

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