Will robo-advice make wealth management tasteless?

Georges Hübner - Professor of Finance, HEC Liège, Liège University

The fast development of robo-advice has responded to a growing demand for automation and enhanced capabilities to industrialize investment advisory (IA) solutions in the FinTech landscape. Until recently, the first generation of robo-advisors have naturally focused on the low-end segment of the IA market, mostly thanks to a rather low sophistication of the portfolio allocation systems based on simplistic versions of Modern Portfolio Theory, leaving wealth managers with no serious competition from fully digitized solutions. Nowadays, the second generation of robo-advisors is more ambitious, both from a scientific and an ergonomic point of view. Even though we are not yet witnessing the age of industrialized big data or machine learning fully automated investment advisors, the maturity level of today's robo-advisors is sufficient to accommodate behavioral sources of complexity like mental accounting or loss aversion at the investor's level. The pressure on margins induced by regulation and digitalization gradually increases the competitive advantage of robotized IA in the mass affluent and private banking segments, making them a serious threat to those incumbent firms that cannot adapt with proper tooling or niche offering. In the near future, the mature generation of robo-advisors, with full deep learning and data treatment capacities, will presumably coexist with those firms that have been actively preparing today, that will use performant tools besides human expertise, but in a world in which fees will presumably have largely decreased and service quality will have been improved, at the benefit of the customer.

Introduction

The surge of "robo-advisors", i.e. automated personal financial advisors, in the world of FinTech is (or at least should be) by no means a surprise in the current financial landscape. It corresponds to an unprecedented match between the customer demand for independent, highly cost-efficient investment advice in a MiFID II-driven transparent relationship, and the capacity to industrialize the whole individual portfolio management process in a digital environment.

In parallel with the organic development of automated investment advice, the traditional banking industry has expressed its willingness to gradually shift from traditional financial intermediation to activities generating fees and commissions, amongst which wealth management and asset management (preferably both simultaneously) represent some of the most promising directions. This evolution is fuelled by the low-for-long interest rate environment and the strengthening of capital requirements, which lead to the erosion of the net interest margin and the search for alternative, less capital-intensive sources of profits. The activities surrounding investment advice are a natural candidate for this purpose.

One could reasonably wonder whether the intersection between large banks' growing interest in the investment advice (henceforth IA) business, on the one hand, and the surge of automated and easily scalable end-to-end IA systems could rapidly lead to a tendency to standardize, or even commoditize, the currently largely expert-based wealth management landscape.

In this paper, we investigate the current needs for IA in the different segments of the investors' population and the degree to which an adequate response can be brought by the automatization and digitization of the advisory process, whose ultimate stage is represented by robo-advisors. Then, we discuss the maturity level of the current robo-advisory landscape and the directions in which it is currently evolving from a scientific point of view, but also how it is currently threatening or contribution to the traditional wealth management industry.

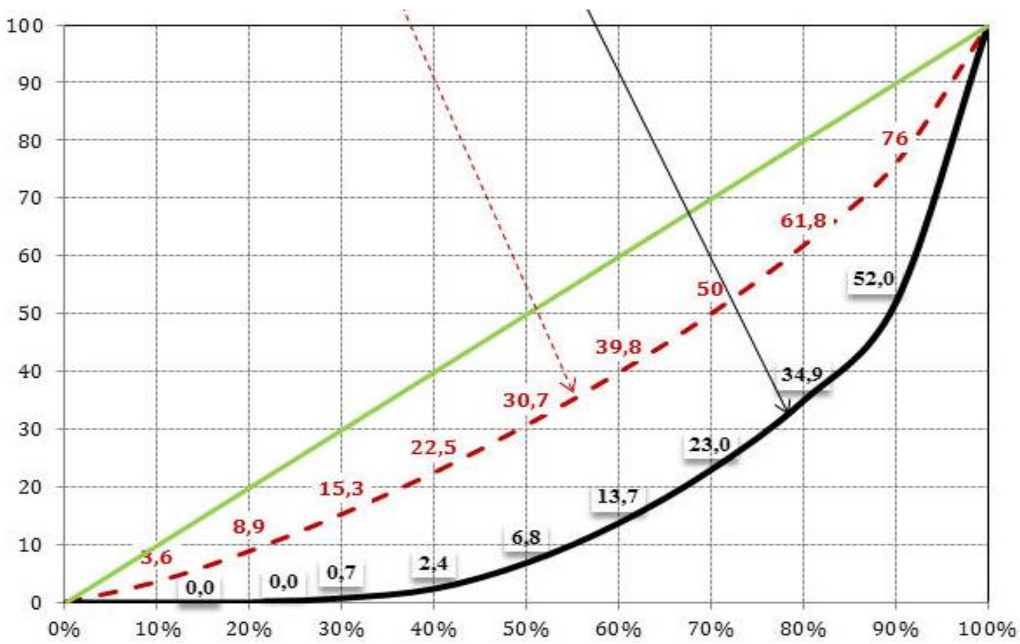
Our thesis is that the tendency to industrial the IA activities in the retail banking industry will inevitably lead to a rather rapid omnipresence of automated systems, be them fully digital or through more traditional channels like the hybrid "phygital" medium. Currently, the real question regarding the coexistence of human-driven and digitally-powered IA approaches mostly affects the intermediate segment between pure retail and high net worth (and higher) sub-populations of individual investors. There is a significant complementarity between man and machine, but this should be well-understood and correctly designed in order to prove to be effective.

In the longer term, a new equilibrium might then prevail, in which the pressure induced by automation on the IA landscape will have led, at the moment the process will have matured, to the coexistence of high-quality human and robot-based offerings to the investor.

People's needs for investment advisory services

The stream of economic research mostly fueled by Thomas Piketty following his investigations of inequalities in France (Piketty, 2003) has led to a debate about the relative dominance of rentiers versus working rich in the developed economies. This debate is underpinned by the robust and repeated finding that capitalist societies generate a significant unequal distribution of income (whatever its source) throughout the population, and that the accumulation of such inequalities naturally lead to a much greater distribution of wealth within the very same population. The following graph represents the Lorenz curves of income and wealth inequality in France.

Figure 1: Illustration of Lorenz curves of income and wealth inequalities



Source: INSEE, Enquête patrimoine 2009-2010

The horizontal axis reflects the percentile of each member the population, from the poorest to the richest, while the vertical axis represents the percentile of income (red line) or wealth (black line) of the same person. The green line represents the full-equality repartition. As the black line is more convex than the red one, this implies a greater inequality of the distribution of wealth than income (as measured by the Gini coefficient).

Our focus is not on the causes of this unbalanced repartition, but rather on the consequences. Inequalities in wealth distribution induce a larger difference between the percentage of population (ranked from poorest to richest) and the percentage of wealth that these people own. This has practical consequences regarding private banking customer segmentation.

More than for many products or services, the vast majority of the investment management clientele owns a relatively small amount of unit wealth. This category of customers does not only encompass the "retail banking" segment, but also the "mass affluent" (aka "personal" or "privileged") customer groups. At the other end of the spectrum, the "ultra-high net worth" (UHNW) customers concentrate a very large fraction of the aggregate wealth within a very small group. In the middle, we find a group of wealthy people, featuring the "private banking" and the lower segment of "wealth management" clients.

The thresholds for these groups of persons and the level of service offered by various banks or wealth managers may considerably differ from one institution to another – this is not the point of this paper – but we focus here on the types of needs of these customers regarding IA services and the ways financial institutions can or do respond to these needs.

The following table reports the dispersion of the "gross patrimony including non-marketable assets"[1] for the three main categories of population according to their potential importance of wealth management.

[1] The inequalities regarding the "gross patrimony excluding non-marketable assets" are even greater (INSEE, enquête Patrimoine 2014-15).

Table 1: Customer segmentation as a function of the challenges of Investment Advisory services

Segment	% pop	% wealth	€ avg.	Challenges	Robo ?
Small to moderate	90%	53%	0.16M	• Not first-order matter (generating income more important) • Limited need for investment management • High relative cost of customized IA • Low propensity to pay for non-subsidized service	**Yes**
High	9%	31%	0.92M	• First-order matter (at least as important as labor income) • High need for specific care for the patrimony • Acceptable cost of customized IA • Average propensity to pay with little bargaining power	**?**
Very high	1%	16%	4.30M	• Quasi-job, with cross-generation responsibility • Need for global care, leading to family office-type of service • High cost and sophistication • High bargaining power, with requirement of value creation	**No or specific**

The third segment of Table 1 is not the easiest one to serve. As wealth management is a primary concern, the dedication of the service provider should be extremely clear. Usually, the services that are requested by the client go way beyond the pure discretionary management of a securities portfolio. Regarding this latter activity, the client's expectations are driven by the quest of excellence in asset management. Investment advice is not only about finding and managing a suitable portfolio, it is about extending asset classes, creating multiple ledgers, and above all creating added-value with respect to peers by yielding positive active return. In asset management terms, this means generating positive and sustained alpha. Such an approach is close to institutional portfolio management and is reasonably not properly met by a robo-advisory service, at least by the ones of the first generation (see below).

On the other hand, the evolution of IA services in the retail and mass affluent segments (small to moderate wealth) is largely inevitable. The combination of the pressure on margins induced by MiFID II, which came into force in 2018, with the increase in competition underlid by the quest for non-interest income channels makes the cost/income ratio of this business less and less compatible with (costly) individualization of advice.

Each customer has little to invest and, as fees are largely proportional to assets under management, the resources (and thus time) that can be devoted by the bank to each customer are too limited to make this worthwhile for each party. To remain profitable, many institutions have no other choice than to industrialize this activity. Robo-advisors represent an element of the multiple solutions that are investigated in order to address this challenge.

In the middle of Table 1, mid-to-high net worth individuals (those that mostly belong to the upper range of private banking and to the lower range of wealth management services) represent at the same time a relatively demanding population and a potentially profitable clientele. The problem for finance professionals is the diversity and complexity of their expectations. A priori, there is no definite case for either purely human or purely automated provision of services. Nevertheless, a deeper investigation into what the machine can bring to the human expert could provide us with a number of valuable insights about this matter.

Robo-advice 1.0 and wealth management market segmentation

A robo-advisor is at the intersection of finance and technology (which explains why robo-advisors are called with the generic name of "FinTech"). On the one hand, it mimics the process that a personal advisor would follow when providing investment advice. If done properly, this process applies a series of rules that combine elements of psycho-sociology, economics and statistics. Even though some of these rules are highly judgmental and qualitative, it is perfectly possible to rest on a series of algorithms in order to reach the desired level of service. This is where the technological aspects, on the other hand, can help: not only the digital environment can simulate the ergonomics of a convenient onboarding and monitoring process, but it can also apply or enrich a number of these algorithms that let the customer progress from the first contact to the portfolio allocation and follow-up processed in a fully disintermediated environment.

The major steps of the fully automated discretionary process are (at least) fivefold (not necessarily in a sequential order):

1. Gather customer data in order to (i) comply with the regulation (MiFID, AML…) and (ii) feed the system with individual-specific inputs that can be used to parametrize the allocation and planning processes;
2. Gather financial data in order to understand the risk, return and diversification properties of assets and portfolios with the aim to feed the system with market-specific inputs that can be used to parametrize the allocation and planning processes;

3. Merge the inputs of steps 1 and 2 into an integrated asset allocation process, leading to the selection of the most suitable portfolio in terms of risk exposures and strategic asset allocation (SAA), as well as the tolerance to diverge from the SAA weights in order to apply tactical bets or to allow temporary allocation drifts;
4. Choose the securities that will fill in the portfolio, both in term of nature (index funds, ETFs, mutual funds, alternative funds, or direct lines) and concentrations, and trade these securities;
5. Ensure the follow-up: inform the investor about the composition and expected properties of the chosen allocation, monitor the portfolio and rebalance it according to a set of rules, and report ex post on the realizations.

From the most basic to the most sophisticated system, one must recognize these five steps in a way or another. What can be "algorithmic" in this setup? The answer is: every single step, and the whole process as well. Step 1 induces the mapping of the investor's information into a set of rules (be it parameters, ranges, ranks, clusters…) through a scoring system or a more sophisticated data gathering process. Step 2 involves the estimation of parameters that faithfully reflect the expected behavior of financial markets during the investment horizon. Step 3 performs, rigorously or not, quantitatively or not, an optimization process with the outputs of steps 1 and 2. Step 4 involves a screening of eligible instruments and weights from a universe of securities. Finally, step 5 involves simulations, risk management tools, and the calibration of a set of reporting guidelines.

Essentially, the engine of a first generation robo-advisor (call it *Robo-Advisor 1.0*) can be implemented with an excel sheet within a short time frame. Why such a strong statement? Because many of these algorithms build on the takeaways of Markowitz's (1952) Modern Portfolio Theory (MPT) and Sharpe's (1964) Capital Asset Pricing Model, which altogether provide convenient shortcuts into the IA process. Specifically, considering the enumeration above, a fairly standard set of principles emerge from the plain application of the more than one-half-century-old theory. In practice, however, the basic robo-advisor will usually apply a series of shortcut rules in order to industrialize the process, as shown in Table 2.

Table 2: Adaptation of MPT and CAPM to the *Robo-Advisor 1.0* algorithmic process

Stage	Principles	Shortcut rules
1. Individual analysis	• Assess the investor's investable wealth • Get the investor's investment horizon • Estimate the investor's risk aversion coefficient	• Get a lump sum amount to invest • Map horizon to a volatility budget • Map risk aversion to a volatility budget
2. Market analysis	• Estimate the risky assets' expected returns • Estimate the risky assets' volatilities • Estimate the risky assets' correlations • Get the risk-free rate for the investment horizon	• Avoid expected returns through constant reward-to-volatility ratio • No shortcut • No shortcut • No shortcut
3. Integrated allocation	• Optimize the risk-return tradeoff of risky assets (mean-variance frontier) • Maximize expected utility through the allocation in the market portfolio and the risk-free asset	No shortcut • Obtain the desired volatility budget through the allocation in the market portfolio and the risk-free asset
4. Securities selection	• Select index funds or equivalent to proxy for the components of the market portfolio • Use derivatives (futures, swaps) to short desired positions	• Select index funds or equivalent (ETFs) to proxy for the components of the market portfolio • Constrain the optimization to be long-only
5. Monitoring	• Run steps 1 to 4 regularly to update optimal portfolio weights • Report on expected and realized risk and return	• Run steps 1 to 4 rarely enough to limit the transaction costs and tax frictions • Report of realized return only

The price to pay for the implementation of a *Robo-Advisor 1.0* is to accept a sort of "financial schizophrenia". The use of the CAPM entails the necessity to adopt its assumptions, but the way it is implemented operationally denies some of its important properties, like the existence of a market portfolio, the objective to maximize the Sharpe ratio, and the linear relation between risk and expected portfolio return at equilibrium, among others.

Such a first generation robo-advisor can easily be rolled-out on a large scale with an industrial approach. To some extent, this generation of mechanized investment advisory service corresponds to a quite straightforward and natural segmentation: it is suited for low sophistication / low financial surface (retail) / low fee investors, i.e. mass market, while the upper segments of investors seeking real individual care will be adequately served with well-equipped advisors whose added value over simple machines can be directly identifiable. Since nothing prevents a financial institution to put in place an automated system without the "FinTech" label, this also explains why a disintermediated investment advisory offering is often proposed to retail and mass-affluent banking clients besides or together with the expert-based service that primarily targets private banking and asset management – which currently is the model adopted by those institutions that implement an omnichannel approach.

Perhaps paradoxically, because of their limited scientific ambitions, these early robo-advisors have protected, at least until recently, the incumbent wealth management industry. Thanks to their ability to easily escape the theoretical framework of Modern Portfolio Theory and their capacity to complete investment advice with a set of ancillary services, experienced investment advisors have durably managed to keep robots out of the reach of their wealthy clients. At best, if some of these clients are attracted by the innovative image of robo-advisor, the opening of an account is usually perceived as a side, pocket money-like component of the global portfolio solution and at best as a marginal complement of "serious" portfolio management carried out by professionals.

Robo-advice 2.0: A Strong Competitor in Wealth Management

The second generation of robo-advisors is nowadays already well-developed. Without being genuinely revolutionary from a scientific point of view, it contributes to making the market segmentation induced by the first generation of robots much less natural. The customer targets of automated investment advice gradually leave the lower end of the wealth management spectrum and these systems start to invade the hunting territories of traditional private banks. The disruptive character of today's robo-advisors is less technical than business-model related.

Unlike what is commonly believed, the main reason for the threat of *Robo-advice 2.0* towards the wealth management industry does not lie *yet* in the advent of Machine Learning or Big Data capabilities. Rather, it is the combination of innovative ergonomic approaches (a new 'customer journey'), efficient industrialization of the personal portfolio management process, and the ability to convincingly integrate the sources of investor complexities regarding their behavioral characteristics into a rigorous, verifiable onboarding process that makes the machine much more anthropomorphic than before.

The implementation of a rigorous mean-variance portfolio construction process involves closely following the principles set forth in Table 2. Nevertheless, constructing a second generation fully mean-variance-compliant robo-advisor is potentially useless for two reasons. First, mean-variance optimization, even when all inputs (investor-specific parameters and market-related variables) are carefully calibrated, results in portfolios that are just leveraged versions of the so-called market portfolio. This is not a very exciting solution and would probably not lead the client to accept a high payment for such a simplistic service.

Second, and most importantly, mean-variance optimization is useless because the MPT simply does not hold. There are many reasons why this would not be the case, but they can be summarized by two (not mutually exclusive) dimensions: portfolio risk is not properly characterized by the variance (or, equivalently, volatility) or returns, and investors' attitudes towards risk are not only depicted by their aversion to volatility risk. The designer of a modern robo-advisor must acknowledge this second dimension and must include the first one into its risk assessment.

There are many ways to account for departures from the MPT. A common and very popular approach is the reliance upon behavioral finance, developed and theorized by Nobel Prize winners Kahneman and Tversky and, more recently, Richard Thaler.[2] Amongst the many ramifications of this approach, we focus here on two of them that appear to be particularly important for our understanding of the evolution of robo-advice: the coexistence of the notion of loss aversion besides the one of risk aversion, and the prevalence of mental accounting in investment decisions.

Loss aversion is a direct consequence of the asymmetry between people's attitudes towards gains or losses. Because many people experience a much larger dissatisfaction by losing something they own rather than not gaining something that they do not own, this translates into a (somewhat) irrational attitude towards financial investments. For instance, the feeling of a loss-averse investor when he/she successively experiences a financial gain and a subsequent equivalent loss (like gaining 100€ and losing it immediately afterwards) will presumably be very negative and associated to a sentiment of regret. One may associate the tendency to observe this behavior with some lack of experience in financial markets: investors who are relatively newcomers (like successful entrepreneurs who have realized a substantial capital gain) might be prone to feeling regrets during adverse financial market conditions. These people are sometimes called 'new money investors'. How does this behavioral trait potentially translate into preferences over risk?

[2] See the seminal papers by Kahneman and Tversky (1979) and Kahneman, Knetsch, and Thaler (1990).

Well, in order to mitigate this feeling, such investors would appreciate their portfolio to feature a certain level of protection (insurance) which, in spite of its upfront cost, might insulate them from severe market crashes. In a sense, highly loss-averse investors are particularly sensitive to the left (negative) tail of the distribution of returns and appreciate investments in securities with a convex payoff – like long positions in options – that reduce the negative skewness and large kurtosis of their portfolio. By contrast, the 'old money investors', who have been acquainted with individual portfolio management sometimes for several generations, are not likely to experience the same epidermal feelings towards large losses, and might even be induced to be net sellers of convexity (issuers of options) in order to capture the loss aversion premium.[3] It is worth noticing that the notions of loss aversion and risk aversion (this latter one being related to the attitudes towards risky prospects), even though they are potentially connected, are distinct and thus complements of each other. Someone can be highly risk averse (sometimes called conservative) but not particularly prone to feeling regrets. On the other hand, some investors can have a high tolerance for risk, leading them to invest in very risky portfolios, but are nonetheless willing to insure their portfolio in order to avoid large losses at the cost of a significant insurance premium. The key to reconciling risk aversion and loss aversion, as shown by Plunus et al. (2015), is to allow the very notion of risk to be defined in a different way by people displaying different levels of loss aversion.

Another strange tendency of individuals to depart from a pure rational, cold-blooded behavior is the largely documented 'mental accounting', as termed by Thaler (1985) and studied by Shefrin and Thaler (1988). This is a simple psychological process whereby individuals tend to categorize economic outcomes in different ledgers being more or less isolated from each other. This has direct implications for portfolio management decisions. For instance, the same person can decide to keep 10.000€ on a savings account that yields 0.01% and *at the same time* to borrow the same amount at the same bank with a rate of 2% to buy a car. For portfolio allocation decisions, that – widespread and well-understood – phenomenon translates into the notion of goal-based investing, in which the global financial portfolio is partitioned into sub-portfolios whose purpose, horizon, risk budget etc. are distinct from one another.

In an IA problem, the goal-based investing approach typically commands a two-step process in customer servicing: firstly, the set of specific goals is identified and parameterized, each of them resulting in a potential investment proposal. Secondly, the residual (when positive, otherwise the advisory process has to go backwards) is analyzed with a generic objective of wealth accrual.

[3] This explains, for instance, why structured products with concave payoffs like covered calls are quite popular amongst investors who have a desire for stable income over long periods of time.

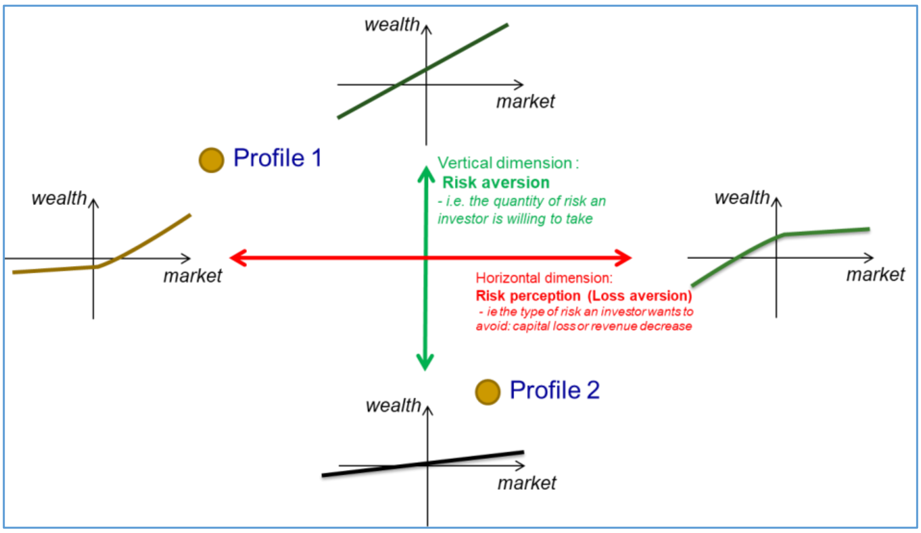
Expectedly, this bottom-up process can become very complex as optimizing the portfolio globally is not similar to summing up the optimized parts, and thus the potential issue of the generic objective portfolio optimization may result in a relatively complex technical issue.

As shown in Figure 2, a profile map that addresses these two behavioral dimensions can actually be designed and can serve as the basis for an automated portfolio optimization process:

- Risk aversion and loss aversion are represented along two axes: one for risk aversion (from the most aggressive to the most defensive profile), and one for loss aversion – also termed risk perception (from the investor most sensitive to extreme losses to the investor most sensitive to volatility), and the archetype of the optimal portfolio composition features more of less quantity of risk (risk aversion) and more or less convexity (loss aversion) depending on the diagnosed investor profile;
- Goal-based investing can adequately result in a set of mapped profiles along with the two relevant dimensions of the investor's aversion intensities.

Once these dimensions have been adequately parameterized in the system, the portfolio choice results from a reverse-profiling process, in which any proposed allocation is confronted to each possible profile and is associated with the one that provides the best match.

Figure 2: Illustration of mental accounts and risk/loss aversion in the profile map



For both goal-based investment and the joint account of a client's loss and risk-aversions, the computational capabilities of robo-advisors, which can deliver real-time portfolio solutions, provide them with a mighty advantage over traditional portfolio allocation systems. For instance, one may choose a compatible structure of investor's preferences over risk and losses, such as Kahneman and Tversky's (1992) Cumulative Prospect Theory (CPT) or Bell's 'linear-exponential' utility function (see Bell, 1988; Bell, 1995), assess (with an ad-hoc questionnaires or through an expert system) the investor-specific parameters, and construct *rigorously optimized* portfolios based on market inputs for each specific goal.

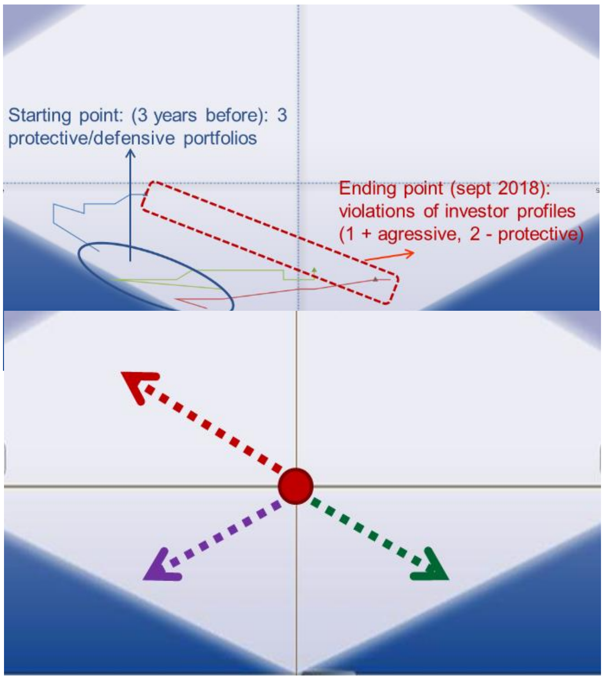
The consolidation of the various goal-based investments is a child's play for the tool, and it can even find an optimal allocation for the part of the patrimony that does not correspond to a specific goal – a remainder of wealth that is often associated to the 'increase in general welfare' objective. The non-normality of returns is not an issue anymore, because the distributional properties of returns (for instance, left-asymmetry (skewness) and fat-tailedness (leptokurtosis)) can be adequately captured by these methods. Including convex or concave securities like options or some simple structured products is technically possible, without losing traction on the analytical portfolio optimization problem.

Furthermore, MiFID II helps automated IA systems in their quest for increasing market shares. Naturally, the ban of kickbacks (commissions paid by fund managers directly to the advisor) and transparency of fees directly influences the investors' perception of the cost/level of service ratio, which has already led to a sharp decrease in the level of fees and commissions in the whole IA industry. But the reinforcement of the monitoring of portfolio adequacy that is imposed by the regulation has also fueled the competitive advantage of second generation robotized portfolio management processes.

Consider a portfolio that has been built at time t according to a profile λ. Because the profile is so complex, the dynamic evolution of the portfolio characteristics may get out of control if the risk type (horizontal axis) and level (vertical axis) are not jointly monitored. This is illustrated in the left part of Figure 3, with three portfolios that had been created three years ago with the same profile (defensive & protective) but which have experienced totally different behaviors over time. But irrespective of the portfolio itself, the investor's characteristics evolve over time. Starting from a given profile, for instance a very neutral one both from the risk aversion and the loss aversion perspectives, many elements can plead for a significant profile drift (see Figure 3, right part). For instance, *ceteris paribus*, a portfolio that has experienced a large capital gain for an investor with decreasing relative risk aversion will automatically induce a higher tolerance for risk, but also an additional need for the protection of past gains: the risk profile drifts to the North-West quadrant (red arrow).

When the portfolio objective involves a specific horizon (like retirement, for instance), as the deadline approaches, one may want to reduce the risk level and simultaneously protect past capital gains, leading the profile to move towards the South-West quadrant (purple arrow). Another phenomenon is the impact of experience gathering: as one becomes older, the desire to accept risk may vanish, but at the same time the learning effect on financial markets, with the experience of several financial cycles, makes the feeling of regret less painful and leads to a lower propensity to loss aversion: the profile moves then South-East (green arrow).

Figure 3: Illustration of reverse-profile portfolio drift (left) and investor profile drift (right)



Source: Gambit Financial Solutions

All these are non-exhaustive examples of two-dimensional portfolio or profile drifts that a well-thought system can anticipate and that a right information gathering process may lead to a semi- or fully-automatic profile revision. The point we wish to make here is not about the modelling choice underlying the process, but well the rather obvious attainability of an IA process that would be able to capture, to a satisfactory extent, the interaction of the rational and behavioral aspects of the investor's complexity into a convincing automated solution.

Today, the real challenge lies in the ability of purely human (physical) or mixed human/machine (phygital) IA systems to catch up with the state-of-the art of *Robo-advice 2.0*. Even though there will still be a long way before robo-advisors get a very significant, if not dominant, market share in the wealth management industry, the seeds are being sowed right now, and the awareness of the current robo-advisors' capabilities should at least ring a bell in a number of institutions. After decades of relative comfort, immobilism is not an option anymore.

What's next? Robo-advice 3.0 or a quasi-revolution… at the benefit of the customer

It is obviously too early to provide a firm forecast of the evolution of the industry. Let us nevertheless try to imagine what could be a virtuous possible future.

Eventually, the maturity of machine learning and ability to treat big (qualitative and quantitative) data in the investment advisory business might not represent such a disruption, at least not as big as the one that the current evolution of robo-advice. Our rationale is Darwinian: the survivors of the (soft) war between humans and robo-advisors 2.0 will simply have adapted, and successful (i.e. remaining) human-driven investment advisory systems will surely be endowed with the same quality of tooling as the one developed in the robo-advisory landscape. So what is the difference then? We are back to square one: confronted with presumably the same quality of basic service, the client will ultimately look for the non-replicable, fully individualized wrapping-up. The evolution of robotization could, if this scenario prevails, have resulted in two major changes: increase in the overall – but generalized – quality of tools, and sharp reduction of invoiced costs to the client. In fine, the customer will be the gainer, and will hopefully still have the choice between very cheap, high quality robotized investment advice, or slightly more expensive, also high quality but more holistic service with a warmer contact with a human being. Instead of a dramatic evolution or a disruption, we might indeed witness a revolution – in the etymologic sense of a 360° rotation.

Bibliography

Bell, D.E. (1988). One-Switch Utility Functions and a Measure of Risk. *Management Science*, **34**, 1416–1424.

Bell, D.E. (1995). Risk, Return, and Utility. *Management Science*, **41**, 23–30.

Kahneman, D. and Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. *Econometrica*, **47**, 263–291.

Kahneman, D. and Tversky, A. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty*, **5**, 297–323.

Kahneman, D., Knetsch, J. and Thaler, R. (1990). Experimental Test of the endowment effect and the Coase Theorem". *Journal of Political Economy*, **98**, 1325–1348.

Markowitz, H.M. (1952). Portfolio Selection. *Journal of Finance*, **7**, 77–91.

Piketty, T. (2003). Income Inequality in France, 1901–1998. *Journal of Political Economy*, **111**, 1004–1042.

Plunus, S., Gillet, R. and Hübner, G. (2015). Equivalent Risky Allocation: The New ERA of Risk Measurement for Heterogeneous Investors. *American Journal of Industrial and Business Management*, **5**, 351–365.

Sharpe, W.F. (1964). Capital asset prices: a theory of market equilibrium under conditions of risk. *Journal of Finance*, **19**, 425–442.

Shefrin, H. M. and Thaler, R. H. (1988). The behavioral life-cycle hypothesis. *Economic Inquiry*, **26**, 609–643.

Thaler, R. H. (1985). Mental Accounting and Consumer Choice. *Marketing Science*, **4**, 199–214.