Robo-Advising

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Individual investors are known to make significant mistakes relative to the optimal behavior of a standard economic agent. Mistakes range from saving too little to maintain one's living standards after retirement to incorrect exposure to debt and equity instruments throughout one's life cycle. Even though financial advisers have traditionally been considered the main solution to limit the impact of such mistakes on financial decisions, a set of limitations of human advisers have also been documented, ranging from the transmission of their own personal biases into investors' portfolio choices to the high costs of financial advice, which make this form of advice not accessible to large fractions of consumers/investors. Over the last decade, robo-advising—automated algorithmic financial advice—has emerged as a potential solution to these limitations.

In this chapter, we first discuss the limitations of traditional financial advice, which led to the emergence of robo-advising. We then describe the main features of robo-advising and propose a taxonomy of robo-advisors

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based on four defining dimensions—personalization, discretion, involvement, and human interaction (Sect. 1). Building on these premises, we delve into the theoretical and empirical evidence on the design and effects of robo-advisors on two major sets of financial decisions, that is, investment choices (for both short- or long-term horizons) and the allocation of financial resources between spending and saving (Sects. 2 and 3). We conclude by elaborating on five broadly open issues in robo-advising, which beget theoretical and empirical research by scholars in economics, finance, psychology, law, philosophy, as well as regulators and industry practitioners (Sect. 4).

1 From Traditional Financial Advisers to Robo-Advisors

1.1 Limitations of Traditional Financial Advisers

In principle, financial advisers could help investors make better investment choices. Delegating individual portfolio allocations to an adviser who manages multiple portfolios allows for economies of scale, whereby the costs of information acquisition advisers incur are shared across all clients. Also, advisers' financial literacy and skills might be higher than those of most individual investors.

In practice, though, a variety of conflicts of interest plague the client–adviser relation. For instance, Hackethal et al. (2012) show advised accounts perform worse than unadvised accounts largely because advised accounts trade more often, producing commissions for advisers at the expense of investors. Moreover, Linnainmaa et al. (2021) show that advisers make the same mistakes in their own investment accounts as they do in their clients' accounts, and hence transmit their own biases to clients. These results cast doubts on whether traditional financial advisers can create value for the investors whose accounts they manage.

At the same time, traditional financial advisers might be beneficial to individual investors in ways that differ from the implementation of more profitable investment strategies. For instance, Gennaioli et al. (2015) propose a model whereby investing through financial advisers may be rational because it increases risk-taking by generating "peace of mind" in investors. Reducing risk-aversion in financial choices might increase investors' returns enough to compensate for the fees advisers charge. Foerster et al. (2017) confirm empirically that higher trust in advisers results in higher risk-taking by investors. Higher experienced returns, though, are not enough to compensate for the higher fees. Either investors do not know how much they pay for advice or they value aspects other than portfolio-return maximization when interacting with financial advisers. Consistent with the second possibility, after conducting a comprehensive survey to elicit clients' needs in financial advice, Rossi and Utkus (2019b) find that individual investors hire financial advisers largely to satisfy needs other than portfolio-return maximization. Such needs include acquiring "peace of mind," having access to the opinions of an expert, and delegating financial decisions. Also, most investors do not know how much they pay for financial advice.

1.2 The Emergence of Robo-Advising

Robo-advising has been emerging over the last two decades as an alternative to traditional financial advisers and as a way to address their limitations. Robo-advisors are digital platforms that provide financial advice to investors in an automated fashion. Depending on their degree of sophistication, robo-advisers collect and use individual-specific information to construct tailored financial plans and advice for investors, as we discuss in detail below.

Robo-advisors have the potential to benefit end-consumers for a number of reasons. First, they can offer financial advice against low fees, because investors' portfolio allocations are fully automated. Second, robo-advisors can serve individuals with any level of wealth, whereas human financial advisers are time-constrained and hence typically cater to wealthier households. Third, robo-advisors are based on automated algorithms that can be monitored and improved over time. Fourth, unlike the decisions of human advisers, the decisions of robo-advisors are hardwired and can be reviewed and explained to investors as well as to regulators consistently. In Sects. 2 and 3, we discuss the extent to which existing empirical evidence supports these potential benefits of robo-advising.

1.3 A Taxonomy of Robo-Advisors: Four Defining Features

The blanket term "robo-advising" hides a variety of different models and methods that differ among several dimensions, four of which are defining features:

1. **Personalization** of the advice;
2. **Involvement** of the investor in financial plans and choices;

3. Investors' **discretion** to deviate from the automated advice;
4. The presence of any form of **human interaction.**

We delve into each one of these aspects below.

1.3.1 Personalization of Advice

Human advisers claim they can tailor investment strategies to the individual needs of each investor, although mounting evidence casts doubt on this claim (Linnainmaa et al. 2021). Robo-advisors, instead, vary dramatically on the extent to which they can create individually designed investment portfolios and financial plans. Target Date Funds (TDFs) are one end of the spectrum. TDFs can be considered the first and most primitive form of robo-advising, in that the investment strategy they implement abstracts from all investor characteristics, except for investors' age. Depending on the year when investors plan to retire, investors purchase a cohort-specific TDF that is rebalanced automatically over time. The main strategic asset allocation TDFs perform is to reduce the wealth invested in equities and increase the wealth invested in fixed-income securities over one's life cycle.

More recent robo-advisors elicit qualitatively (or quantitatively) a set of demographic characteristics such as investors' income bracket, investment horizon, willingness to take financial risk, and job security. Robo-advisors then propose investment plans and strategies that are the same for each individual investor who falls in the same categorization based on these demographics. This level of personalization is common in US commercial robo-advisors such as Wealthfront, Betterment, and Vanguard's Personal Advisor Services (PAS). Whereas the multi-dimensional characterization of investors allows for more tailored strategies than TDFs, several important aspects that should determine an investors' strategy, such as non-financial investments or upcoming expenses such as children's college education are typically disregarded. Moreover, as we discuss in more detail in Sect. 4, the extent to which information can be elicited directly from investors, who tend to lack financial literacy, without a qualitative human assessment and only based on pre-designed bucketing is an open question in robo-advising. On top of demographic characteristics and risk preferences, robo-advisors designed for investors' trading in individual stocks and short-term investing generally add individuals' existing portfolio allocations to the inputs used to generate optimal weights for portfolio allocations.

In the context of personalization, the trade-off of robo-advising rests between providing tailor-made solutions that are specific to each investor, but could potentially result in poor ex-post performance for some investors, and providing less extreme positions and thus more robust portfolio allocations, which though might fail to consider important unique investors' features at sign up and over time.

1.3.2 Investor Involvement

A second aspect that distinguishes different types of robo-advisors is investor involvement. Robo-advisors for trading usually ask investors to approve every single trading decision before it is executed. In this way, investors can modify the course of action the algorithm suggests and require a re-optimization of their financial plan and strategy at any point in time. D'Acunto et al. (2019c) analyze one such robo-advisor. This form of advice, in which investors are directly involved in approving or denying investment choices, should be labeled "robo-advising" in the strict sense. Indeed, these robo-advisors provide algorithmic advice to the investor and make the implementation of advice extremely simple, for instance by producing automatically all the trades needed to implement a portfolio rebalancing strategy and allowing investors to implement the advice by simply clicking on a button (D'Acunto et al. 2019c). Ultimately, though, any decision-making authority rests with the investor.

At the other end of the spectrum are robo-advisors for long-term investing, who not only provide automatically generated financial plans and strategies, but also place trades automatically on behalf of investors. These robo-advisors request the approval of an initial plan, but once the investment plan has been approved, they manage investors' wealth and trade without any input from investors. A more correct taxonomy would define such form of automated advice "robo-managers" rather than robo-advisors, because robo-managers manage investors' wealth directly rather than providing advice about each step in the implementation of the strategy.

In terms of investor involvement, the main trade-off in robo-advising consists in either allowing investors to retain full control of their portfolio at the expense of paying attention to the management of their wealth, or replacing fully the individual as a decision-maker with an algorithm.

1.3.3 Investor Discretion

Discretion is investors' ability to override robo-advisors' recommendation. Robo-advisors that allow for more discretion let investors modify the portfolio weights the algorithm proposes. In other cases, investors can also choose whether the trades proposed by the algorithm should be implemented. Finally, investors might include stocks and other assets in the financial plan not recommended by the robo-advisor, in which case the robo-advisor would optimize the portfolio formed of the mix of recommended assets and investor-proposed assets (D'Acunto et al. 2019c).

Other robo-advisors allow portfolio weights personalization only within certain pre-set guardrails (see Rossi and Utkus 2019a). They allow investors to take more or less risk, relative to what the algorithm suggests, but are inflexible in terms of picking what parts of the plan to accept and what part of the plan to reject. For instance, fully automated robo-advisors such as Wealthfront and Betterment allow little discretion.[1] Hybrid cases include Vanguard PAS allow investors to voice their preferences with a human financial adviser who, in turn, has the power to override some of the allocations suggested by the algorithm manually.

Client discretion constitutes an important trade-off for robo-advising design. Robo-advising is a paradigm that lies in between pure *libertarianism*, in which individuals are left on their own to make investment decisions, and *libertarian paternalism*, in which individuals are defaulted into what economists believe is the best decisions for them based on standard economic theory, and individuals can only choose to opt out of the assigned defaults. The more discretion is programmed into the robo-advisor, the more libertarian the robo-advisor is. At the extreme where the individual is not granted any discretion, robo-advising can be thought as a form of libertarian paternalism, where investors give up the possibility to make their own individual decisions in managing their wealth and comply to an optimized option chosen based on the prescriptions of standard economic theory.

1.3.4 Human Interaction

The last differentiating feature among robo-advisors is the degree of interaction investors have with human advisers, if any. Many robo-advisors, such as Wealthfront and Betterment, are purely automated and investors cannot

[1] In fact, Betterment recently launched a new product named Flexible Portfolios to cater to the investor that wanted additional discretion in the management of their wealth.

access any human advisers. Not employing human advisers allows these robo-advisors to maintain their operating costs low. Fully automated robo-advisors cater to younger cohorts such as millennials, who are generally comfortable with having their wealth managed by algorithms, without the presence of a human who explains the intricacies of how their wealth is managed.

Other robo-advisors that cater to a wealthier and older clientele are hybrid in nature. The majority of the heavy-lifting in terms of designing the portfolio allocation is performed by the algorithm, but human advisers interact with the investor at key moments, such as at sign-up as well as when investors have important questions about their portfolios. Human advisers' presence is crucial to ensure customers' needs are being satisfied as well as to handle all financial planning tasks—such as opening college funds or IRA accounts, for example—that are not easily automated. Human advisers are also crucial to keep investors participating in equities in periods of bear markets, when investors may become more fearful and may be trying to reduce their exposure to risk.

1.4 What Financial Decisions Do Robo-Advisors Aim to Improve?

1.4.1 Investment Decisions

The first issue robo-advisors aim to target is limited exposure to risky assets. Using the 2001 Survey of Consumer Finances, Campbell (2006) shows a low fraction of individuals at the lower end of the wealth distribution invest in public equity, even though finance theory predicts everybody—absent costs of participation—should participate in the stock market. Surprisingly, stock market participation is not widespread at the higher-end of the wealth distribution either. For example, at the 80th percentile, 20% of consumers are not exposed to the stock market.

A second major shortcoming of individuals' investment decisions relates to portfolio allocations and especially the pervasive lack of diversification. A consistent finding in the literature is investors tend to own few risky assets, which are typically individual stocks or specialized mutual funds. Barber and Odean (2001) report the median client in a large US brokerage house held only 3 stocks in the years 1991–1996. Using a US sample between 2013 and 2015, Gargano and Rossi (2018) find similar patterns—the median US investor held only 4 stocks. These findings are also true internationally—D'Acunto et al. (2019c) find the median investor in a large Indian brokerage house holds 5 stocks. Lack of diversification also arises in terms of lack of exposure to varied geographic shocks. Individuals display local bias in their investments (e.g., see French and Poterba 1991). In particular, US investors have very little exposure to international markets and prefer to purchase local companies rather than companies headquartered in other states. US investors also hold a disproportionate amount of their employers' stocks within their 401(k) plans (Mitchell and Utkus 2004).

Active individual investors are also known to be subject to a variety of behavioral biases when they trade stocks. For instance, Odean (1999) and Barber and Odean (2001) argue investors trade too much. Odean (1998) shows investors are more likely to realize trading gains as opposed to trading losses (disposition effect). This behavior is sub-optimal, because selling gains are taxable items not netted by trading losses.

In Sect. 2, we discuss the extent to which robo-advising has been able to tackle these issues with individual investment decisions thus far.

1.4.2 Consumption-Saving Decisions

Possibly, the most important financial decision individuals make is how much to save for retirement. This is an extremely complicated choice that depends on expected future income growth, the probability of incurring unemployment spells, the expected equity premium, the sustainability of social security benefits, projected healthcare costs, and individual risk-aversion, among other characteristics of which consumers might not even be aware. Indeed, Lusardi and Mitchelli (2007) find that consumers who answer basic financial literacy questions incorrectly are less likely to save enough for retirement. A study by Gomes et al. (2020) uses information on contribution rates, salary, investment plan features, and asset allocation for more than 300K individuals. They show three quarters of the workers in their sample are unlikely to be able to maintain their pre-retirement consumption after retirement.

Robo-advisors aim to tackle these issues in individual consumption-saving decisions by reducing consumers' lack of information about their own inflows and outflows as well as by nudging consumers' choices through individualized messages and other vivid nudges to obtain behavioral reactions that would be hard to implement in the absence of an online platform or internet application.

In Sect. 3, we discuss the applications of robo-advising to this realm and the empirical evidence on the effects of such applications.

2 Robo-Advising in Asset Management

The most developed applications of business-to-consumer robo-advising are in the realm of asset management. Robo-advisors have developed to target both short-/medium-term investment ("robo-advisors for trading") as well as long-term investment and especially the phase of accumulation of resources for retirement ("robo-advisors for passive investors").

Building on the characteristics of robo-advisors we described in Sect. 1, the crucial difference between robo-advisors for trading and robo-advisors for passive investors is that the former have higher personalization of investment advice, promote direct involvement of investors in the definition and implementation of strategies, and allow for discretion in terms of deviating from the advice. Active involvement requires robo-advisors for trading to provide vividly the information investors need to understand and process investment strategies, and thus provide also an educational role that is less relevant in robo-advisors for passive investors.

The second main difference between the two forms of robo-advisors is their focus on different asset classes. Robo-advisors for trading focus on individual stocks or highly specialized mutual funds, whereas robo-advisors for passive investors typically target exchange-traded funds (ETFs) and low-fee mutual funds. D'Acunto et al. (2019c), Reher and Sun (2019), and Rossi and Utkus (2019a) are among the first academic studies of the characteristics, mechanics, as well as direct and indirect effects of robo-advising for short-term and long-term investing. In the rest of this section, we discuss the main features of the design of robo-advisors in asset management and their effects on investment performance.

2.1 Robo-Advising for Short- and Medium-Term Investing

Robo-advisors for trading are based on Markowitz mean–variance optimization and aim to maximize portfolios' Sharpe ratios. D'Acunto et al. (2019c) study a *Portfolio Optimizer* targeting Indian equities, which has a similar scope as US robo-advisors for trading such as *M1 Finance.* In terms of design, the optimizer displays three main features: (i) the feeding of information about the expected returns of individual securities developed by the brokerage house's research team; (ii) the estimate of the variance–covariance matrix based on three years of historical daily observations; and, (iii) the use of shrinkage techniques and short-sale constraints to limit estimation-error effects and guarantee well-behaved portfolio weights.

The robo-advisor produces automatically the buy and sell trades the investor would need to perform to implement the advice, and the investor can place the trades automatically in batch mode by simply clicking on a button on the application's screen. The simplicity of execution of the advice is a fundamental feature that distinguishes robo-advising for trading from other forms of electronic investment advice, which require investors to come up with the implementation of the advice in their own portfolio and for this reason are often ineffective (Bhattacharya et al. 2014). This robo-advisor for trading provides substantial personalization of advice, which is partly based on investors' own starting portfolio of assets and allows for discretion in the assets users want to incorporate in their portfolios.

Using viable counterfactuals in a difference-in-differences design, D'Acunto et al. (2019c) find that robo-advice for trading is beneficial to ex-ante undiversified investors, because it increases the diversification of their portfolios hence reducing portfolio volatility. It also produces slightly higher ex-post mean returns. At the same time, the robo-advisor does not improve the performance or volatility of the portfolios of already-diversified investors. If anything, due to the higher amount of trading when rebalancing their portfolios and the frequency with which active investors engage in rebalancing, average after-fee returns are lower for diversified investors after they start to use the portfolio optimizer relative to before.

A crucial dimension under which robo-advisors differ from human financial advisers is the extent to which advisers' biases and misguided beliefs can be transmitted to investors' portfolios. The robo-advisor judges all potential trades based on the underlying algorithm. Behavioral biases common among individual investors should have little scope under robo-advising, as long as the developers of the algorithms did not embed such biases into their codes. And, indeed, D'Acunto et al. (2019c) find that the incidence of well-known biases, such as the disposition effect, the rank effect, and trend chasing, decreases for all investors after accessing robo-advising, irrespective of their characteristics and levels of diversification.

2.2 Robo-Advising for Long-Term Investing and Retirement

Robo-advisors for long-term investing target mostly indexed mutual funds and ETFs. The main objective of these robo-advisors is to set risk-factor exposures that are compatible with investors' preferences and investment horizons. These robo-advisors do not engage in stock picking, but trade to rebalance portfolios at pre-set regular intervals (usually quarterly). These robo-advisors usually move investors in and out of risky assets as a function of one's time to retirement and do not engage in market timing by increasing equity exposures when expected returns are high and reducing equity exposures when expected returns are low.

A defining feature of robo-advisors for long-term asset management is that they not only provide advice on rebalancing strategies, but they directly manage investors' portfolios. They require minimal to no involvement from investors. In fact, these robo-advisors emphasize that investors should only worry about contributing resources to the managed portfolios without even paying attention to their finances (Gargano and Rossi 2018).

2.2.1 Targeting Performance and Sharpe Ratios

Rossi and Utkus (2019a) study the effects of a large U.S. hybrid robo-advisor on the portfolios of previously self-directed investors. They find that, across all investors, robo-advising reduces holdings in money market mutual funds and increases bond holdings. It also reduces idiosyncratic risk by lowering the holdings of individual stocks and US active mutual funds and raising exposure to low-cost indexed mutual funds. It further eliminates home bias by significantly increasing international equity and fixed-income diversification. Finally, over the sample period the authors analyze, robo-advising increases overall risk-adjusted performance, which is largely driven by lower portfolio risk.

Rossi and Utkus (2019a) use a machine-learning algorithm, known as Boosted Regression Trees (BRT), to explain the cross-sectional variation in the effects of robo-advising on portfolio allocations and performance. Investors who benefit from advice are those with little self-directed investment experience at managing their wealth, with large cash holdings, and with high trading volume before adopting robo-advising. Investors with little mutual fund holdings and investors invested in high-fee active mutual funds also display significant performance gains. Moreover, investors who end up benefiting more from robo-advising are more likely to sign-up and less likely to quit the service over time.

Reher and Sun (2019) study a large US-based robo-advisor for long-term investing, which aims to optimize investors' portfolios Sharpe ratios. They find that underdiversification increases the likelihood of uptaking robo-advising as well as the amount of deposit inflows, especially for middle-class investors, thanks to the low minimum account sizes. The typical drop in minimum account size for the robo-advisor relative to the standard investment accounts, which amounts to a 90% drop in minimum account size, leads to a 56% increase in account flows—new accounts opened by less wealthy individuals. In terms of average performance, users' Sharpe ratios increase by about 10% after the uptake of robo-advising, and the bulk of the improvement in performance is driven by a drop in portfolio's exposure to idiosyncratic risk and a sharp reduction of volatility. Overall, the benefits of diversification and the less stringent requirements to access robo-advising relative to traditional financial advice are the crucial drivers of investors' gains from robo-advising. Conversely, these results, similar to D'Acunto et al. (2019c) for the realm of short-term investing, might suggest that the investors who are most likely to gain from adopting robo-advising are the less financially literate investors.

Several robo-advisors propose specialized features that might attract wealthier and more financially sophisticated investors. For instance, they embed functions to optimize tax-loss harvesting—the practice of replacing an asset at loss within the portfolio with similar assets in terms of expected return and volatility so as to offset capital gains and reduce tax debentures. By construction, tax-loss harvesting is only relevant to investors who hold taxable brokerage accounts, and hence such functions do not target retirement accounts that fall under the types that allow for deferred taxation. Moreover, tax-loss harvesting is obviously only relevant to investors who face high marginal tax rates and for whom offsetting capital gains and capital losses might produce nonnegligible benefits in terms of reduced tax debentures. Because tax-loss harvesting requires monitoring one's portfolio and outside opportunities often throughout the fiscal year, this feature is marketed as a benefit of robo-advising for wealthy investors, who might have a higher opportunity cost of time. In the US, both *Betterment* and *Wealthfront* emphasize their tax-loss harvesting focus. For example, Betterment's "Tax Loss Harvesting+" algorithm checks daily for harvesting opportunities and trades stocks. The algorithm also reinvest every harvested dollar in asset classes that bring the client portfolio back into balance rather than defaulting back to the original asset class.

2.2.2 Targeting Risk Levels: Value-at-Risk (VaR) Strategies

The robo-advisors discussed above propose simple techniques based on Markowitz's principles of mean–variance optimization and in which the assessment of expected returns for individual stocks or funds is a crucial input of investment strategies. Recently, robo-advisors with additional features have been developed. For instance, *scalable.CAPITAL*, a robo-advisor founded in Germany and diffused across several European countries, aims to provide active risk management to portfolios that mainly invest in passive asset classes such as ETFs and mutual funds. The robo-advisor uses a VaR approach in their risk-management strategy, and is targeted to investors whose level of financial literacy would not allow understanding and/or designing an active risk-management strategy. VaR strategies consist of fixing a maximum allowed yearly percentage loss of portfolio value with a high confidence level, usually 95% percent. The robo-advisor models dynamically the expected probability of losses and adjusts the portfolio composition automatically to avoid deviations from the pre-set loss thresholds.

The robo-advisor allows discretion by enabling users to choose the VaR thresholds and other features over time, based on changing circumstances in investors' financial conditions. Moreover, human interaction is allowed in two ways—customer service teams who are specialized in answering questions and concerns about investment strategies and execution, as well as a human team who oversees the execution of trades.

Finally, *scalable.CAPITAL* also includes educational components to enhance investors' understanding of the VaR strategy the robo-advisor uses and their understanding of general principles of financial econometrics. This educational function is implemented through simple and vivid descriptions of the concepts of confidence intervals, portfolio loss, and VaR at the time in which users decide the levels of risk they want to face in their portfolio, as well as through the availability of podcasts that explain the basic statistical concepts behind the robo-advisor's strategies, which can be accessed online and from investors' applications.

3 Robo-Advising and the Consumption-Saving Decision

Whereas the most common applications of robo-advising in the recent years aim to help households in the realm of asset management, more recent application have targeted the daily consumption/saving decisions consumers make, which represent the foundation of any life-cycle model of allocation of financial resources over time. Indeed, the problem of allocating resources between alternative forms of investment, whether in the long or short term, only arises after the allocation between spending and saving is set.

The applications of robo-advising to daily spending and saving choices have developed in response to well-known departures from the standard problem of consumption allocation throughout the life cycle. Such departures have been documented in the field and the laboratory by a large literature in behavioral economics and social psychology. After all, solving an optimal allocation problem throughout one's life cycle to determine the share of spending over income at each point in time goes beyond the cognitive abilities and literacy skills of most consumers (D'Acunto et al. 2019b). For this reason, consumers use rules of thumb, which are often polluted by the lack of information and the formation of distorted beliefs about relevant economic variables, the prevalence of non-standard preferences and beliefs such as present bias and self-control, or the persistence of social norms of behavior to which households conform without critical assessment (for instance, see Guiso et al. 2008; D'Acunto et al. 2019d).

3.1 Robo-Advisors Targeting Consumers' Informational Frictions

The first type of demand-side frictions robo-advisers have targeted is informational in nature. Most households do not collect regularly information about the economic variables that should drive their choices, or are unable to understand and elaborate this information even when it is provided to them (D'Acunto et al. 2019a). Robo-advisers have developed strategies to target this issue directly by making it easy and practical for consumers to form beliefs about such important economic dimensions. The most basic informational friction robo-advisors have targeted is the lack of information about one's own balance sheet in terms of inflows and outflows. Similar to corporation, most households face a mismatch in the liquidity of inflows and outflows (e.g., monthly salaries against one-time large expenditures of durable goods) or in the economic horizon of investment decisions (e.g., choice of spending on durable goods at the time of purchase or with delayed installments). These mismatches are exacerbated by the fact that several households have their inflows and outflows split into several separate accounts, such as checking accounts in which their inflows are transferred and one or more credit card accounts that collect the outflows.

To alleviate this complex budgeting problem, robo-advisors have developed in the form of *income aggregators*. Income aggregators are desktop or phone applications, in which users link their financial accounts, including checking, credit card, and investment accounts. The main function of income aggregators is to elaborate all the transaction-level information they obtain from the individual accounts in one single organized balance sheet, which provides households with a clear and immediate overview of their own financial situation at each point in time (Baker 2018).

On top of this aggregation function, which by itself reduces consumers' lack of information about their own finances, several robo-advisors have designed specific information interventions that warn users about abnormal inflow or spending patterns through the use of notifications. Lee (2019) studies one of such interventions—a FinTech application that provides users with notifications every time their spending patterns increase abnormally relative to average spending. In this way, users face an immediate and vivid nudge to adjust their spending to their own average level, and indeed Lee (2019) finds that users respond to such nudges.

Providing information about one's own finances might not be enough to correct potential distortions in consumption and saving choices relative to the choices of neoclassical economic agents. This issue arises because often households use rules of thumb to assess the ratio of spending over saving in their daily life. A common rule of thumb is the conformity to peers' spending and saving. That is, consumers might think that the observed patterns of spending by peers contain information about their own optimal pattern of spending. Distortions in choice might arise especially in times of social media, in which the most conspicuous part of peers' consumption is public thus causing a *visibility bias*, which makes agents believe that their peers spend more, on average, than what they really spend (Han et al. 2019).

Recent applications of robo-advising have tackled this informational friction. For instance, *Status Money* is an application that, on top of the baseline income aggregation features, provides each user with information about the average spending, assets, debts, and net worth of individuals that have similar demographic characteristics, whose information is crowdsourced using transaction-level data from a large, representative US population. D'Acunto et al. (2019f) study the effects of this intervention on spending behavior. They observe the spending of users in the months before and after sign up and find that on average users converge to the spending level of peers disclosed by the app, thus indicating that users find the signal they obtain about peers informative. Interestingly, users that appear to spend more than their peers react systematically more than users that appear to spend less than the peers—in the overspending domain, users on average reduce their spending by 3 percentage points of their monthly income, which amounts to about $247, whereas those in the underspending domain increase their spending by 1 percentage point of income on average. The authors find that the information content of the signal is important to trigger households' reaction, because the most reactive users are those for which the peer group is based on more similar demographic characteristics, relative to those who face peer groups defined on broader demographic characteristics.

3.2 Robo-Advisors Targeting Consumers' Non-standard Preferences and Beliefs

The second type of demand-side friction derives from the cross-sectional diffusion of preferences and beliefs that do not adhere to the standard neoclassical framework. A common example is present bias deriving from hyperbolic discounting: if economic agents discount consumption in the future more than present-day consumption, they will tend to overconsume at each point in time at the expense of saving and hence future spending (Laibson 1997).

Several robo-advising applications have developed to help agents correct present bias across a large set of domains, such as the provision of electronic messages on the balance of Supplemental Nutrition Assistant Programs (SNAP) for low-income households (Hillis 2017), the use of AI algorithms to predict which consumers might incur in future overdraft fees and warning such users with carefully framed messages (Ben-David et al. 2019), or the use of different framings and designs of information provision to nudge households' spending and saving behavior (Levi 2019; D'Acunto et al. 2019e; Gargano and Rossi 2019).

Recent studies have used the laboratory and synthetic markets to test alternative choice architectures and framings for robo-advisors targeting choice inertia in the realm of financial planning. For instance, Jung and Weinhardt (2018) find that defaults and warning messages reduce financial decision inertia, and uncover interesting differences in inertia in financial decision-making across genders.

4 Open Issues in Robo-Advising

So far, we have focused on a positive analysis of the features and characteristics of robo-advising services. The unprecedented and swift evolution of financial advice propelled by algorithmic applications, though, also proposes a set of issues that are still broadly open questions for researchers, practitioners, and regulators alike. These broad and interdisciplinary questions require attention by scholars in finance, economics, law, social psychology, and philosophy. In this section, we give an overview of the open questions and propose directions for future research.

4.1 From Domain-Specific to Holistic Robo-Advising: Across Realms and Over the Life Cycle

Since its origin, theoretical research on optimal consumption, spending, and investment choices has emphasized the holistic nature of the optimal life-cycle allocation of resources (e.g., see Carroll 1997, 2000). This holistic allocation encompasses two dimensions—(i) the optimal allocation of resources across different realms at each point in time, such as the share of wealth allocated to pay mortgage loans, student loans, and invest in retirement savings during one's working life, as well as (ii) the optimal allocation of resources throughout one's life cycle, from the early stages of investing in human capital and education to the decumulation phase after retirement and the allocation of bequests.

Human advisers, despite the limitations we have discussed above, aim to propose such a holistic approach to financial advice. Instead, the majority of existing robo-advisors focus almost exclusively on one or a few limited domains. Robo-advisors targeting retirement investment, for instance, barely ever provide advice on mortgage uptake, student-loan assessments, or the timing and viability of large durable consumption spending. The design of a holistic robo-advising service requires research on both the theoretical and empirical side. On the theoretical side, existing models of optimal life-cycle consumption, saving, and investment decisions do not delve into all the peculiarities of spending opportunities, or the different types of investments (education, large durable goods, housing) and associated forms of financing (Browning and Crossley 2001). More realistic theoretical approaches have incorporated two or three features at once (e.g., see Cocco 2005; Cocco and Gomes 2005), and more progress is needed to guide empirical applications. In particular, the phase of decumulation after retirement has obtained little attention, which translates into robo-advisors that may fail to address the complex choices retirees have to make. Baker and Dellaert (2019) propose a framework to develop this underexplored dimension.

Designing a holistic robo-advisor also faces empirical challenges. Procedures that truly allow individual-specific tailoring of advice are still lacking. Most existing robo-advisors place users in broad categories related to the willingness to take risk, age profile, and a few other demographics. Users that fall into the same buckets obtain the same advice, although obviously each user might differ under important non-elicited dimensions or the buckets might be too broad to capture preferences and beliefs accurately. The first step is to understand whether the dimensionality of this problem can be reduced by determining which characteristics are more important to be targeted and hence elicited by robo-advisors. Traditional empirical methods can barely help, e.g. linear regressions of investment outcomes on a kitchen-sink list of potential characteristics would face the issue of overfitting and ultimately be uninformative. Rossi and Utkus (2019a) make progress by using machine-learning techniques to assess which individual characteristics explain more of the variation in investment performance across investors, as well as what is the actual (non-linear) relationship between each characteristic and investment outcomes. Another approach is to ask consumers directly which features of advice are important to them (Rossi and Utkus 2019b). Future research should provide additional evidence on which characteristics robo-advisors should target, as well as new methods to elicit these characteristics even if many investors are financially illiterate and unable to express their own economic preferences and beliefs consistently (e.g., see D'Acunto et al. 2019a, e). For instance, Alsabah et al. (2019) propose a reinforcement learning framework in which the robo-advisor does not need to be fed rough qualitative risk preferences of clients manually, but learns risk preferences over time by observing portfolio choices under different market conditions.

The second empirical challenge is the design of data-analytic methods to analyze multi-faceted information encompassing several aspects of one's financial profile at once. Recent providers suggest potential solutions. For instance, *Pefin*, a US-based holistic robo-advisor, uses a feed-forward neural network whose input consists of a broad set of aggregate characteristics (e.g., macroeconomic variables, financial regulatory changes) and individual-user characteristics (e.g., changes in spending and saving profiles) that are allowed to change over time. In this way, *Pefin* proposes a continuously changing set of financial projections and updating financial plans, which instead are typically static for most robo-advisors. More research on the design of such applications and the performance of investors that follow such holistic advice relative to viable counterfactuals is imperative to make progress in this area.

4.2 Algorithmic Aversion: Is Hybrid Robo-Advising a Solution?

Do consumers trust advice coming from a machine, with which, contrary to human advisers, no empathic interactions are possible? Two points suggest that the distrust toward machines, a.k.a. algorithmic aversion, is likely an important issue that deserves further study in finance, social psychology, marketing, and related fields. First, research in social psychology on the extent of users' trust in algorithmic vs. human judgment delivers conflicting results

(Logg et al. 2019; Castelo et al. 2019). How robo-advisors could promote algorithmic appreciation instead of aversion is an important open question. Second, the fact that younger users are more likely to access digital advice than older users (e.g., see Sironi 2016; Ben-David and Sade 2018; D'Acunto et al. 2019f) suggests a strong divide between digital native users and others. This age profile might fade as the new generations grow, but a challenge for the next decades is to understand why middle-age and elderly consumers avoid robo-advice and which interventions might increase uptake. After all, older investors currently own the majority of wealth in the economy, whereas digital natives have barely yet started to accumulate any wealth for retirement.

An important role of human advisers that robo-advising can barely fulfill is that of money doctors, i.e. the responsibilization of the human adviser that leads to investors accepting higher risk in individual portfolios (Gennaioli et al. 2015; Rossi and Utkus 2019b). Hybrid robo-advisors—robo-advisors whose strategies and planning are fully automated, but allow users to interface with a human being—have been proposed as a solution. In hybrid robo-advising, the role of humans is only slightly more involved than in a customer desk of a service company. Several questions about hybrid robo-advising are still open. How do the uptake of robo-advising and hybrid robo-advising differ? Do demographics that trust algorithms less really increase uptake when robo-advisors are hybrid? To what extent does the hybrid nature also fulfill an educational role, whereby financially illiterate investors might learn and use such knowledge in other realms of economic decision-making? Can humans reduce the high drop-out rates of robo-advising users, especially in times of bear markets? Research using observational and experimental methods should inform the role of hybrid robo-advisors positively and normatively.

A specific form of hybdrid robo-advising that has obtained interest in the industry is the *super adviser*. Super advisers are human financial advisers who make use of robo-advising to produce financial plans and strategies, but represent the *only* interface between users and their investment strategies and performance. Super advisers resemble traditional human advisers on the client side, but are closer to robo-advisers in charging lower fees—because super advisers do not need to spend time producing financial plans, strategies, and implementing such strategies—and better performance, on average. Super advisers could also represent a solution to the transmission of human advisers' own biases and misguided beliefs to their clients' portfolios (Linnainmaa et al. 2021). Understanding the pros and cons as well as the costs and benefits of super advisers requires research designs that provide viable counterfactuals.

4.3 Will Robots Democratize Access to Financial Advice or Exacerbate Inequalities?

The dominant narrative about the benefits of robo-advising suggests that low fees allow advising many users that would otherwise be unadvised. And, indeed, the fees robo-advisors charge are substantially lower than those human advisors would typically charge. Consistently, Reher and Sokolinski (2019) document that robo-advising increases the share of households exposed to financial advice, especially in the middle-class segment. Because robo-advisors can manage many small accounts at low cost, common limitations to the take up of financial advice, such as minimum account balances and high fees, can be easily overcome. Robo-advising can thus help reduce wealth inequalities by allowing middle-class consumers to enjoy the higher returns and tax advantages that were typically reserved to high-wealth investors through (costly) human financial advice.

At the same time, the incentives to provide robo-advice by FinTech institutions might also contribute to increase inequalities. On the one hand, the quality of robo-advising services varies substantially with the wealth of investors. Wealthier investors, who are willing to pay higher fees and hence from which robo-advising companies can obtain higher margins, often enjoy more precisely tailored and better directed advice (e.g., see D'Acunto et al. 2019). On the other hand, low-income households, who often barely access financial institutions, who finance their spending with high-interest borrowing such as payday loans, and who make financial mistakes due to the lack of financial literacy, are perhaps the category that would need financial advice the most. And, yet, existing robo-advisors do not cater to this segment because of their limited wealth accumulation for retirement and hence the limited scope for fee extraction.

The lack of products catering to low-income households has two important implications. First, if anything, robo-advising might *increase* wealth inequality in the broader population, as middle-income households would increase their wealth and wealthy households would increase it by even more, but low-income households would not improve. Second, the question of who should provide robo-advising services to low-income households becomes prominent: Is there a business model that might allow private providers to target such population? Otherwise, should the public sector provide rob-advising for low-income households? After all, robo-advising for low-income households might replace costly debt-repayment programs. Answering these questions requires observational evidence or well-crafted randomized control trials (RCTs) to evaluate public programs that provide cheap or free financial advice to low-income households.

4.4 Systemic Implications of Homogenizing Investors Through Robo-Advising

Robo-advisors might also have unpalatable systemic implications. For the case of human financial advice, tailoring advice to clients' needs and wants and the different preferences and beliefs of investors guarantee substantial differentiation in the cross section of portfolios. Most existing robo-advisors, instead, make a large number of users invest in the same exact portfolios. The largest portion of such portfolios is based on indexed ETFs. An economy in which a large part of households follows robo-advice could thus be much more exposed to the effects of aggregate negative shocks (e.g., see Bond and Garcia 2019). Whether indexing and robo-advising produce this higher sensitivity of aggregate wealth to business cycles and other shocks is an open question that is waiting for a setting that allows plausible counterfactuals.

4.5 What Ethical and Legal Standards for Robo-Advisors?

The last open question we discuss is the definition of ethical and legal standards for robo-advisors. We focus on three points. First, is the question of whether robo-advisors are fiduciaries. US regulators require that robo-advisors register under the Investment Advisers Act of 1940. Registration implies robo-advisors are fiduciaries. At the same time, though, robo-advisors display design features that cast doubts on whether they can truly act as fiduciaries, especially in terms of satisfying the duty of care (Fein 2017). Most robo-advisors do not provide holistic financial advice on all assets investors hold, but only on their financial portfolios. In fact, most robo-advisors do not even consider investors' asset holdings at other institutions when framing investment strategies. Moreover, robo-advisors use self-assessment questionnaires in terms of preferences for risk and other characteristics, which casts doubt on whether robo-advisors can perform the appropriate personalized due diligence that would fulfill their duty of care (Fein 2017).

On top of further developing the legal theory behind robo-advising, several questions are open for financial economists. For instance, how to detect potential biases and discrimination in robo-advising algorithms? Are new professional types needed, such as regulator/computer scientists, who can bring together a strong legal background with an understanding of the mechanics of complex algorithms? Ultimately, how can regulators implement their assessments of whether fiduciary duties have been breached in a context in which the language in which the advice is delivered—the algorithms—are barely understandable to many legal practitioners?

A second issue is the unprecedented concentration of sensitive personal data that robo-advisers and their developers obtain. Holistic advice requires access to almost any feature of individuals' private sphere. Do robo-advising developers have the right to exploit such unique data commercially, either by selling the data to third parties or by elaborating them to provide consulting services? To what extent are investors aware of the importance of this issue, and can they form a meaningful assessment of the dollar value of these data given the large algorithmic illiteracy in the broader population? Tang (2019) makes progress on this question by exploiting a unique peer-to-peer lending setting to quantify the value users attach to privacy.

Even if robo-advisors excluded the possibility of selling or using data for purposes other than advice, increasingly frequent cyberattacks and data breaches would make the concentration of individual personal data in the hands of a few robo-advisors risky. Akey et al. (2020) estimate the value of unexpected data breaches in terms of corporate reputation and subsequent firm policies. One might also worry that the concentration of so much personal information about the broader population in the hands of a few providers and the vulnerability of such providers to internal and foreign cyberattacks might represent a matter of national security. Could this argument be developed further to support the recent proposals to break up big tech companies? Financial economists need to contribute to this debate by providing data and facts about the relevance of data breaches and the far-reaching consequences of data leakages, if any.

A third issue refers to the institutional contexts in which robo-advisors develop. If private corporations operate in competitive markets, information on the universe of individuals will not be concentrated, which reduces the potential damage of data leakages and the use of data for purposes other than providing robo-advising services. At the same time, private companies might be reluctant to share their data for public security purposes to avoid breaching the confidentiality of the information on their clients. Recent developments in operations research, such as Cai and Kou (2019), propose algorithms that allow statistical inference with encrypted data, thus guaranteeing individuals' anonymity.

Very different issues arise in settings in which governments control at the same time all major sources of information and means of production in the economy. More theoretical and empirical research is needed to understand the political-economy implications of data concentration and lack of anonymity in these contexts.

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