New Frontiers of Robo-Advising: Consumption, Saving, Debt Management, and Taxes

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Abstract

Traditional forms of robo-advice were targeted to help individuals make portfolio allocation decisions. Based on the balance-sheet view of households, the scope for robo-advising has been expanding to many other personal-finance choices, such as households' saving and consumption decisions, debt management, mortgage uptake, tax management, and lending. This chapter reviews existing research on these new functions of robo-advising with a special emphasis on the questions that are still open for researchers across several disciplines. We also discuss the attempts to optimize jointly all personal-finance decisions, which we label "holistic robo-advisors." We conclude by assessing fruitful avenues for research and practice in finance, computer science, marketing, decision science, information systems, law, and sociology.

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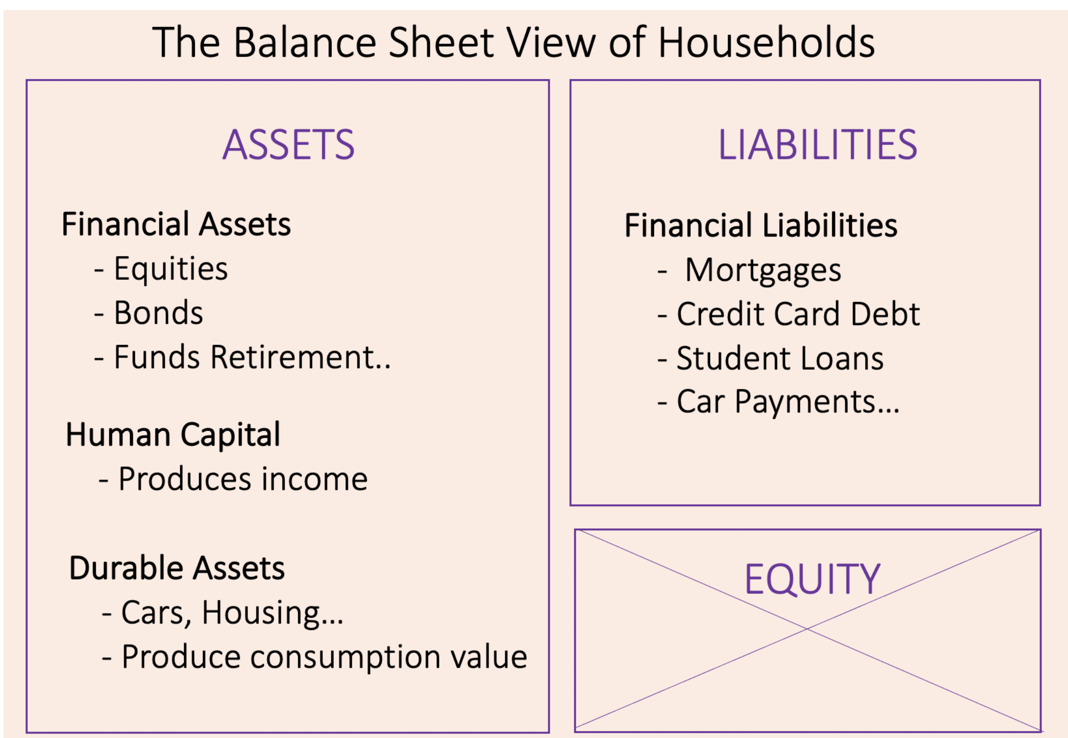
1 Robo-Advice and the Balance-Sheet View of the Household

Robo-advice is any form of financial advice provided to human decision makers by algorithms. Even though many early applications of robo-advice were concentrated in the context of helping individual investors make portfolio allocation decisions, no inherent characteristic of algorithmic advice limits its application to that narrowly-specified context. And, indeed, the scope of robo-advice has broadened dramatically across all the areas of personal finance and more broadly to all contexts in which inexpert and often financially illiterate consumers need to make important choices that will affect their life-time wealth.

The breadth of applications of robo-advising are defined through the lens of the "balance-sheet view" of the household, which we depict schematically in the figure below.



Balance Sheet View of the Household

Under the balance-sheet view, households run dynamic budgets similar to those of firms:

households have assets (left-hand side of the budget), which include, among others, housing, durable goods, human capital, financial investments, and health. Households also have liabilities to finance such assets (right-hand side), which include mortgages, credit-card debt, student loans, taxes, and insurance premia. Households need to make decisions about all these dimensions throughout their lifetime. Many such decisions will have enormous implications for their long-run wealth and financial sustainability.

Contrary to firms, though, the typical household lacks the knowledge and experience needed to make such important choices. For instance, most households only make a decision about purchasing a house and hence borrowing money through mortgages once in a lifetime. Moreover, households only face the problem of which form of education to provide to their offspring and how to finance such education once per child. The disconnect between the importance of all these decisions for households' budgets and the lack of knowledge and experience in making such decisions stresses the need and scope for advice. Indeed, a large literature shows that, when left to their own devices, households make significant and costly mistakes that limit their ability to accumulate wealth over time (see Odean (1999), Agarwal et al. (2017), and Laibson et al. (1998)).

Despite their limitations as economic decision makers, households still need to make decisions that shape their balance sheets both statically and dynamically. For instance, how much and what type of human capital to acquire. Or, what kind of durable goods to purchase—what car to use and what housing condition to live in. All these asset purchases have dramatic implications on the liability side, too. For example, car purchases or leases involve choosing only one out of the very many financing solutions and contracts available. The choice of acquiring human capital—obtaining college and/or graduate education—involves decisions on the ways in which such asset acquisition can be financed, for instance choosing appropriate student loan conditions or even planning on college funds many years before the offspring reaches college age. Also, think about what is possibly the most important choice households make, i.e. the purchase of a house, which requires choosing appropriate mortgage characteristics based on household members income paths and horizons, a decision-making problem under risk and uncertainty that is incredibly hard to solve even for experts.

Historically, whenever choosing how to manage their balance sheets, households had the option of hiring human advisors. This option is less than desirable, however. First, human advisors are relatively costly and have been shown to make suboptimal choices. Suboptimal choices could be due to conflicts of interest in principal-agent relationships with asymmetric information, such as advisors' incentive to propose high-fee financial products to their clients, who are often unaware of the differences across financial products. Behavioral and cognitive biases could drive suboptimal human advisors' decisions as well (Foerster et al. (2017); Linnainmaa et al. (2018)). By relying on human advisors households face at the same time a potentially high cost of advice paired with an often suboptimal quality of advice. Second, supply-side forces might also restrain the availability of human advice to households and especially to lower-income households, who tend to be the most vulnerable when making decisions to manage their balance sheets. Catering to individuals with low net worth might be unpalatable to human advisors due to the low prospective revenues such clients would generate over time (Reher and Sokolinski (2020)).

These severe limitations of human advice in a context in which potential advisees often lack the ability to understand, let alone solve, the decision-making problems they face has represented fertile ground for the swift diffusion of robo-advice, also known as algorithmic advice (see D'Acunto and Rossi (2020b), Rossi and Utkus (2020a)). Robo-advice eliminates the barriers to access advice represented by the cost of human advisers because, contrary to human advisers, it can be scaled up without virtually any constraints. For this reason, providers of robo-advising services can reduce their fees to a fraction of those commanded by human advisers. Moreover, robo-advice has been shown to make better decisions than humans and experts in several contexts on both the assets and liabilities side of the household balance sheet, such as the allocation of financial investments (e.g., see D'Acunto et al. (2019d); Rossi and Utkus (2020b)) or the take-up of peer-to-peer (P2P) loans (e.g., see D'Acunto et al. (2020a)).

In the rest of this chapter, we highlight important recent developments in the evolution of robo-advising services based on the balance-sheet view of the household. We discuss the institutional details of each form of advice as well as the findings of existing research on the characteristics and performance of robo-advice across various domains. In particular, we focus on robo-advice in the domains of households' consumption and savings decisions, borrowing decisions, tax management, and lending choices. Robo-advisors for lending choices are allowing consumers and households who need financing to obtain funds without the need to pay fees to intermediaries. Moreover, they allow households to use their own savings to finance other borrowers and hence reduce the scope for institutional financial intermediaries. For each area, we discuss open questions and opportunities for researchers. We then envision the possibility of forms of robo-advice that optimize jointly households' choices subject to their budget constraint across all the individual parts of households' balance sheets. We label these forms of robo-advice "holistic robo-advisors." Throughout the chapter, we discuss the challenges and opportunities these recent forms of robo-advice imply and how these challenges and opportunities can translate into fruitful avenues of future research for scholars in as disparate fields as finance,computer science, marketing, decision science, information systems, and sociology.

2 Robo-advising for Consumption–Saving Choices

A fundamental factor that determines households' ability to accumulate wealth throughout the life cycle is the choice of how much to consume and save out of households' income in each period in which they earn any income. Computing the optimal saving rate requires solving a complicated optimization problem (D'Acunto et al. (2019a)) that can prove challenging even for experienced economists. Non-economists are at a further disadvantage, because they often lack a clear understanding of the status of their finances, they cannot assess their own budget constraints, and they do not understand the implications of macroeconomic shocks for their individual consumption-saving decisions (see Agarwal et al. (2009); Agarwal and Mazumder (2013); Christelis et al. (2010); D'Acunto et al. (2019b)). Most households may find it hard to merely conceptualize this problem, even intuitively (see D'Acunto et al. (2019c)), let alone to assess the optimal behavior throughout the life-cycle path and subject to budget constraints.

And, indeed, unsurprisingly many households fail to choose a saving rate during their working years that allows them to maintain a lifestyle comparable to the one they enjoyed before retirement (e.g., see Banks et al. (1998); Bernheim et al. (2001); Lusardi and Mitchell (2007), among many others). This phenomenon represents not only a problem for individual households, but also produces negative externalities for society as a whole as the average tax payer needs to contribute higher taxes to maintain minimal living standards for the undersavers.

Even if potentially less problematic under the societal point of view, the opposite mistake in households' consumption–saving choices has also been detected: several US and European households tend to save large amounts based on perceived rather than actual precuationary savings motives (D'Acunto et al. (2020d)). This phenomenon has been detected even during retirement—the phase of their life in which they should be engaging in the process of "decumulation" (See Mitchell and Utkus (2004))—even when bequest motives are absent. Households' use of rules of thumb based on cultural norms, which substitute for their inability to understand and solve the dynamic optimization problem, have been proposed to explain this type of decisions (e.g., see D'Acunto (2015)). Households' consumption–saving choices are also at the heart of the balance-sheet view of the household discussed above, because the allocation of income across these two alternative types of assets has substantial dynamic implications in terms of long-run net worth.

Pairing the importance of the consumption–saving choice for individual households with the widespread inability of households to conceptualize and optimize such choice represents fertile ground for robo-advising applications. In this context, robo-advising applications might solve two different types of needs. First, they should provide households with information about their own balance sheet, size of assets and liabilities, and budget constraints, in a unified and simple format so that households can understand the parameters of the decision-making problem they face. This information role of robo-advising is especially important for households who have irregular income inflows or those who are self-employed and business owners, and hence whose income streams are irregular and not always easy to forecast.

Second, robo-advising applications to consumption–saving decisions should provide suggestions and advice to households on how to improve their choices as well as easy implementation of such advice. Suggestions can cover several aspects of decision-making such as the choice of which credit card(s) to use, which share of income to save each month based on projections of future values of saved amounts, as well as potential nudges to increase households' incentives to save rather than spend, which would be especially helpful for households who tend to spend more than what the permanent-income hypothesis implies at each point in time.

Real-world applications of robo-advising to the consumption–saving choice based on the criteria discussed above abound. In particular, one class or robo-advisors known as "income aggregators" fulfils this role (e.g., see Olafsson and Pagel (2017, 2018)). As the name suggests, income aggregators are a class of robo-advisors that covers the first scope of robo-advsing in the consumption–saving choice, i.e. providing households with clear and easy-to-grasp information about their own balance sheet and constraints.

Income aggregators require users to provide access to their asset and liability accounts. Asset accounts might include checking, saving, and other forms of financial investment accounts, such as brokerage accounts and retirement accounts. Liability accounts include mortgages, student debt, credit cards, and other forms of debt. In this way, robo-advisors collect information from the households' accounts, typically at the level of the individual transaction. By collecting this large amount of big data across accounts that would otherwise be unlinked, income aggregators are able to construct the balance sheet of each household following the balance-sheet view of the household discussed above. The accuracy of the information income aggregators produce depends on whether users link all their accounts to the robo-advising platform. For this reason, users have a strong incentive to link all their accounts.

The information income aggregators produce has a set of unique characteristics. First of all, income aggregators provide a just-in-time holistic representation of an household's balance sheet, which the household can check at any point in time (Amin and Mohamed (2009)). This feature is especially compelling for households who have substantial wealth invested in financial markets, the volatility of whose returns might be high. Moreover, income aggregators display information about households' balance sheet and budget constraints vividly in simple graphical forms that are intuitive for households and allow them to grasp basic concepts of household finance even without being trained, such as the balancing of budgets or the sustainability of assets and liabilities accounts. Having access to such intuitive display of information about one's own finances is crucial to create awareness in investors' mind and was shown to have a major impact in helping individuals make better financial decisions (Olafsson and Pagel (2017, 2018)).

However, advising individuals on how much to consume, what items to purchase, and how to split spending between durable and non-durable consumption is more complicated that helping individuals form well-diversified investment portfolios, because an algorithm would need to input specific information regarding individuals' preferences over all possible consumption bundles as well as their beliefs about a large range of future outcomes.

To overcome these limitations, innovative FinTech Apps have proposed alternative ways to help individuals by providing them with simple rules of thumbs. A recent example is the US application *Status Money.* Status Money is an income aggregator, and hence as discussed above can compute users' net worth and observe all their transactions, including spending transactions. The unique feature of this App, which provides advice in the form of a rule of thumb, is providing users with information about peers' spending, where peers are defined as individuals observed in a US-representative sample outside the App and who are similar to users based on a set of demographic characteristics. Upon subscribing to the App, users fill in a form about demographic characteristics that include their annual income, age, home-ownership status, location of residence, and location type.

Based on this information Status Money assigns a peer group to each users and provides users with information about the average spending, assets, debts, and net worth of such peers. In this way, users can calibrate their spending to the spending of individuals who look similar to them. This rule of thumb is based on the notion of *the wisdom of the crowd*, whereby agents might obtain valuable signals about their (unknown to users and to the robo-advisor) optimal spending and saving rate based on the average values of these ratios in a large population of decision makers that look similar to them (Chen et al. (2014); Da and Huang (2020)).

Delivering information about crowds through media outlets has been shown to be effective in persuading consumers to change their behavior through the management of their subjective beliefs (Barone et al. (2015)). Another channel behind this form of advice is *peer pressure*, whereby it is especially those users who spend substantially more than their peers—and hence are likely to spend more than their own optimal rate—who feel more compelled to react to the peer information and converge to peers' spending than those who spend less than their peers (Rosenberg (2011)). This potential asymmetric reaction to peers' spending information based on users' position relative to their peers would be valuable because overspending, and hence accumulating fewer savings and lower wealth for retirement, is a mistake that creates more issues for individual households and society than underspending.

D'Acunto et al. (2019f) study the effectiveness and the mechanisms behind this form of robo-advice. They find that providing salient peer information through the App has a large effect on users' consumption behavior. Users who were overspending with respect to their peer group at the time of sign-up ended up reducing their spending after signing up for the App. Those individuals who, instead, underspent increased their spending, but the reaction was much less pronounced for underspenders. D'Acunto et al. (2019f) also show that the informativeness of the peer group plays in important role in explaining users' changes in consumption. The authors conclude that FinTech Apps can provide valuable advice to individuals by collecting and summarizing in an unbiased fashion the decisions made by others and exploiting mechanisms such as the *the wisdom of the crowd* and *peer pressure*.

Another form in which income aggregators provide robo-advice for spending and saving decisions is through nudges, which are based on App notifications and reminders (Acquisti et al. (2017)). Notifications and reminders from Apps are becoming ubiquitous and have proven useful in motivating individuals to stay active and eat healthy, among other outcomes. In the context of income aggregators, recent studies have documented the importance and effectiveness of these notifications. For example, Lee (2019) studies individuals' responses to overspending alerts, which are based on the robo-advising algorithm of an income aggregator that compares users' own spending over time and identifies unusual patterns of spending within one's own spending history. Lee (2019) finds that users who receive overspending alerts reduce their spending 5.4% more than users who do not receive overspending alert. These changes in spending affect long-run cumulative spending. Lee (2019) also finds that the effect of nudges vary across the user population, with older, more financially-savvy, and more educated users adjusting their spending more after receiving overspending notifications, which suggests that more sophisticated users rather than the least sophisticated find notifications about their own unusual spending patterns useful. This result begets further research on how robo-advising could be used to reach to the least sophisticated parts of the population, whose consumption, saving, and education choices tend to be stickier over time than those of the highly educated (D'Acunto (2014)).

Whereas the robo-advising income aggregators discussed so far provide advice on users' spending decisions, another class of robo-advisors target users' saving choices. Consumption and saving choices are obviously strongly interlinked, but the principles extant robo-advisors use to provide advice on these two dimensions are quite different. For example, Apps such as Acorn in the US and Gimme5 in Italy provide robo-advice to their users by helping them to set saving goals and reach such goals using nudges (Gargano and Rossi (2020)).

Goal setting exploits a behavioral mechanism that is not contemplated in standard life-cycle consumption-saving models. According to such models, agents should care about their overall savings but not about the specific objectives for which a certain amount is saved. This is because, for the most part, savings are fungible—they can be used for any purpose at any time (Browning and Crossley (2001)). However, setting budgets and goals is a common feature of agents' daily life, because as a large literature in experimental social psychology shows, agents are intrinsically motivated by goals and work hard to achieve them (Locke and Latham (1990, 2002, 2006)).

Using data from the robo-advisor for saving Gimme5, Gargano and Rossi (2020) provide the first field analysis of whether goal-setting for specific savings objectives makes individuals save more. They establish a causal effect of goal setting on saving behavior using a formal identification strategy. Overall, Gargano and Rossi (2020) show that goal-setting leads the average user to increase monthly savings by 90%. They find that any goal, as long as it is stated, increases saving propensities, irrespective of the specific purpose of the goal. For instance, users that save for concrete objectives such as a trip or a car achieve their saving goals as often as those who set a generic saving objective without any concrete aims. Whereas goal concreteness seems irrelevant, the feasibility of the time deadline associated with the goal has an important impact on the effectiveness of goal setting on saving choices: users who set long-term deadlines are less likely to achieve their goals relative to users who set short-term deadlines.

The robo-advisors for spending and saving reported in this section focus on consumers' difficulties in computing the optimal spending and saving rate (D'Acunto et al. (2019f)). Whereas the robo-advisor cannot compute such optimal ratios for the user, it can provide information, rules of thumb, nudges and reminders, as well as benchmarks in the form of aspirational goals to provide consumers with easy-to-grasp information about their optimal spending and saving rate.

2.1. Open Areas of Inquiry in Robo-Advising for Consumption-Saving Choices

The potential applications and research questions in the space of robo-advising for spending and saving are many. The extant research discussed in this chapter has analyzed the effectiveness of robo-advice interventions based on the wisdom of the crowd and a set of psychological mechanisms, but many more forms of robo-advisors and mechanisms await to be studied by researchers in several disciplines.

For instance, scholars in finance, economics, marketing, decision science, and social psychology should study how existing mechanisms such as nudges based on one's own past spending behavior could be applied to the fast-growing area of digital-wallet apps (Agarwal and Qian (2014)). Currently, digital wallets, such as WeChat in China or Paytm in India act as instruments for managing households' liquidity. They are helpful insofar as they give households the possibility to engage in electronic payments without the need to rely on credit cards or other high-fee services provided by traditional financial intermediaries (Crouzet et al. (2019)). Digital wallets, though, could be transformed into robo-advisors for spending and saving. The digital wallet might warn the user whenever he/she is engaging in anomalous spending or is spending on goods whose price is substantially higher than similar goods the user has purchased in the past.

The principle of social pressure and peer information could also be applied to many other designs of robo-advisors for spending and saving. For instance, developers could create a "FitBit for Finance," whereby users are connected to friends and peers they know in their real life and compete with these peers on achieving goals about spending and saving. This type of robo-advice would add a gamification aspect to the delivery of information about peers (Fitz-Walter et al. (2013); Piteira et al. (2018); Sailer et al. (2017)). Gamification might add to peer information and peer pressure in further motivating users to put more effort into maintaining healthy spending and saving rates. This form of robo-advice—which, to the best of our knowledge, has not yet been implemented in the context of consumption and saving decisions—could be studied by scholars in disparate fields in terms of both providing the technical ability to implement such a strategy into apps as well as studying the effects of this form of robo-advice and its mechanisms, both in the laboratory and in the field.

Another direction that begets more research is the deepening of our understanding of the causes of adoption and effects of existing forms of robo-advising for spending and saving. For instance, existing research has not yet been able to assess the extent to which the effects of robo-advising in this context are long-lived. The main limitation to answering this question is that many Apps have only been released in the recent years. Moreover, the structure of Apps often changes over time and hence does not allow researchers to compare the behavior of agents who receive the same exact form of advice repeatedly over time. Also, the churning of users of robo-advising apps is quite high, which implies that within-agent studies of the effects of robo-advising over time are often hard to design with data from Apps in the extant literature. In this vein, further understanding the dimensions that predict adoption is important to ensure that categories that might tend to adopt robo-advising less but for whom the potential benefits from adoption might be high (e.g., see D'Acunto et al. (2020c)), are specifically targeted. Progress along any of these dimensions would be a crucial contribution to deepen our understanding of the effectiveness of robo-advising for saving and spending.

3 Robo-advising and Durable Spending Choices

Whereas income aggregator robo-advisors focus on spending on non-durable goods and services, a substantial portion of households' balance sheet consists of durable goods, such as housing, cars, large furniture and electronic items (D'Acunto et al. (2020b)). Durable spending displays several features that make it different from non-durable spending as far as the scope for robo-advising is concerned. First, because durable goods provide consumption utility over time and often for several years after purchase, they resemble firms' fixed-asset investments and, contrary to non-durable goods, are often financed through consumption loans, credit card debt, or other forms of consumer debt. A robo-advisor that targets durable consumption choices should thus not only advise agents on the types of goods they should purchase but also on the optimal ways to finance such goods.

A second peculiar feature of durable spending that affects the design of robo-advising tools for durables is the fact that the choice of which durable goods to purchase involves more dimensions than the choice of non-durable goods. In the case of non-durable goods, price and quality are the most relevant features consumers consider in their purchase choices. In the case of durable purchases, instead, agents need to consider not only price and quality but also the good's depreciation, the tax implications of usage and depreciation over the years, as well as the costs of maintaining the good over time (Waldman (2003)). A robo-advisor for durable spending thus needs to provide agents with information and/or suggestions about all these aspects that are typically irrelevant for the case of non-durable choices.

In the rest of this subsection, we focus on existing robo-advising tools for two important durable purchases most households make—houses and cars—and we conclude by suggesting how robo-advising should evolve to adapt to other types of durable goods.

3.1. Robo-advising for Housing Choices

In the absence of robo-advising, house purchases entail multiple days spent with a real estate agent touring homes and discussing budgets. Part of the real estate agents' job is to understand the taste and preferences of their clients and help them navigate housing options that include multiple dimensions to be assessed. Real estate agents thus act as human advisors to prospective home owners.

Over the last few years, robo-advising tools for durable spending decisions have also emerged as an alternative to real-estate agents. For instance, Apps such as REDFIN and ZILLOW in the US fulfill the role of robo-advisors for durable spending based on the two directions discussed above: on the one hand, they provide information about a large set of dimensions agents need to consider when making housing decisions, such as the quality of nearby amenities, the quality of nearby public schools, the extent of walkability of neighborhoods, the crime rates and other characteristics of neighborhoods, and the price trends in various areas (Green and Walker (2017), Eraker et al. (2017), Gargano and Giacoletti (2020), Gargano et al. (2020)). By providing information on all these dimensions in a concise and easy-to-grasp format, these robo-advisors for housing choices reduce the complexity of the multi-dimensional problem agents have to solve.

Moreover, housing Apps fulfil the second main feature of robo-advisors for housing decisions—they also provide information about the financing choices available to agents for each potential housing solution they might consider. Advice about financing options focuses on two features: (i) it simplifies agents' assessment and computation of the financial needs they might face for each housing option, and (ii) it helps agents compute the estimated monthly payments of mortgages with different characteristics (fixed rate vs. adjustable rate, different maturity options, conforming vs. non-conforming mortgages) (Karch (2010)). Moreover, some Apps also provide direct suggestions on actual options for mortgages from financial institutions for which they agents can apply online (Fuster et al. (2019)), thus making the house purchase choice and its financing fully automated. The role of robo-advisors for financing housing solutions through mortgage advice is likely especially important for low- and middle-income households, for whom the supply of mortgage credit by traditional financial institutions has been declining consistently since 2010 (see D'Acunto and Rossi (2020a)).

Academic research in the area of robo-advising for housing choices is still in its infancy. More work focusing on the integration of mortgage calculating services with the proposal of actual market offers on mortgages that have the characteristics users require is needed. Moreover, assessing the quality of advice and its effectiveness is crucial to understand the economic and psychological mechanisms behind these forms of robo-advice.

3.2. Robo-advising for the Purchase of Vehicles

The choice of purchasing vehicles and other durable goods, such as big furniture items, can be interpreted as a middle point between non-durable spending choices and durable spending choices as far as the advice to be produced by robo-advising tools is concerned. On the one hand, similar to housing choices, the purchase of vehicles typically needs to be financed. On the other hand, the dimensionality of the sets of characteristics agents have to consider when assessing the purchase of cars or other durables is substantially lower than for the case of housing. Whereas housing requires assessments about amenities, school districts, crime rates, and many other dimensions, cars and other durables are fully movable and hence their quality does not depend on any other dimension.

An example of an extant form of robo-advising for the purchase of vehicles are Apps such as TRUECAR and CARVANA (Garcia III et al. (2018)). Similar to the other robo-advising tools we discussed in different domains, the first feature of these Apps is that they provide agents with easy-to-grasp information about otherwise complicated assessments, such as used car valuations as well as distributions of prices of similar cars that have transacted over time across different suppliers. Providing agents with this information abates their search costs and allows them to make informed decisions based on a large-scale number of transactions for similar goods, which would otherwise be impossible to observe given the high costs of obtaining data on individual car transactions for the average US consumer.

Moreover, even in the case of the purchase of vehicles, robo-advisors provide detailed information about financing options. The typical financing option for cars is a lease (Johnson et al. (2014)). Robo-advisors for the purchase of vehicles provide agents with estimates and computations of monthly installments based on the maturity and size of the lease.

Despite their rising popularity in the US and abroad, robo-advisors for the purchase of vehicles have been barely studied in terms of their effects on consumers' choices.

3.3. Open Areas of Inquiry in Robo-Advising for Durable Spending

The study of the characteristics of robo-advising for durable spending is still in its infancy. A set of features that are unique to durable goods make several open questions in this area worth of inquiry by researchers.

First, the choice of durable good investments requires a multi-dimensional assessment of several characteristics at once, and hence is more complex than the choice of non-durable purchases. For this reason, consumers have traditionally relied on human advisors when assessing durable-good investments. An open area of inquiry is thus understanding to what extent robo-advisors for durable spending are complements or substitutes of traditional human advisers. On the one hand, the simplicity and affordability of robo-advisors could often allow agents to automate their choices fully and not resort to human advisers, such as real estate agent. At the same time, though, because the purchase of durable goods requires a substantial investment on the part of consumers as well as financial commitments that bind the consumer for years, consumers might prefer to still resort to a human adviser to at least check on the suggestions of the robo-advisor and validate its choices. The second option might be especially compelling if consumers displayed forms of distrust towards algorithms and finance (for instance, see D'Acunto (2020); Dietvorst et al. (2015) but also Logg et al. (2019)).

A second broadly open question for economists is the extent to which robo-advisors might modify the structure of market prices in markets where information about transaction prices is suddenly made easy to access and analyze on the part of retail consumers. Whereas the prices of housing transactions as well as those of vehicle transactions are in principle, in many cases, public, access to this information is prohibitively costly for the average US consumer. Sellers could therefore assess transaction prices more easily and meaningfully than buyers prior to the advent of robo-advising tools. This advantage of sellers has virtually disappeared since when any interested buyer, even those who have has never experienced the purchase of a durable good before, can simply and cheaply access a large amount of information about historical transaction prices from their phone.

4 Robo-advising and Consumers' Lending Decisions

One of the most studied innovations associated with FinTech is the potential for banking disintermediation associated with peer-to-peer (P2P) lending. P2P lending fosters disintermediation in that consumers do not borrow from brick-and-mortar banks or online financial institutions, but from one individual or a pool of individuals who participate in a syndicated loan. P2P platforms connect borrowers and lenders directly and, depending on the borrowers' characteristics, set the rates and terms of the loans.

There are a number of P2P lending firms in the US, including Prosper, LendingClub and Peerform among others. These platforms differ somewhat in the terms of the loans, eligibility criteria, but the underlying idea is to connect directly borrowers and lenders without the need of a traditional banking intermediary.

In its base implementation, P2P lending is unlikely to disrupt the banking system for a number of reasons (Balyuk and Davydenko (2019)). First, while the P2P platforms screen borrowers, individual lenders may not know how to construct a well diversified portfolio of loans. Banks are able to diversify away the idiosyncratic risk of individual borrowers by issuing thousand of loans. On the other hand, investors lending a couple of thousand dollars on a lending platform may not realize that it is sub-optimal to lend to just a few borrowers, because of the relatively high probability of losing a large part of the investment. On the other hand, wealthy individuals that are willing to lend hundreds of thousands of dollars may find themselves in the impractical situation of having to manually select hundreds of loans to contribute to. Also, individual lenders may be subject to a number of biases and may therefore lend to individuals rather than others not because of their creditworthiness, but because of dimensions that affect their trust in the borrower (D'Acunto et al. (2020e)), which might also include demographic characteristics such as their gender, race or other observable characteristics on the platform (Duarte et al. (2012)).

Because of these limitations, P2P platforms have started to introduce automated lending portfolios for their investors who do not want to pick their investments manually. An example in the US is Lending Club, where its investors can choose a fully automated investment portfolio and a customized semi-automated investment portfolio rather than picking loans automatically. As the platform advertises, this allows its investors to generate well-diversified lending portfolios with the click of a button.

Another example is Faircent, a leading Indian P2P lending platform, which gives its investors access to a robo-advising tool named "Auto Invest." Lenders can adopt Auto Invest at any time. At the time of adoption, lenders choose how much of their wealth they want to allocate manually and how much they want to invest using Auto Invest. In addition, for the funds allocated to Auto Invest, lenders can allocate their wealth across six risk-based categories of borrowers. The intent of choosing risk-based categories of borrowers is to mimic lenders' manual choices, because the six risk categories among which lenders allocate their funds on Auto Invest are the same risk categories they see as attached to borrowers once they appear in the pool.

D'Acunto et al. (2020a) provide a comprehensive analysis of the difference in performance between investors that lend manually on the platform and those who adopt the robo-advisor. They show that, before using the robo-advisor, investors tend to make rather poor investment decisions. For example, they lend to individuals of their own religion and shy away from lending to borrowers of different religions. They also lend to borrowers of higher social castes, such as the Brahmins, Kshatriyas, and Vaishyas at the expense of members of the Shudra caste, which traditionally were at the bottom of the social pyramid. The adoption of Auto Invest corrects these biases, evidenced by the fact that the proportion of loans issued by robo-advised investors across borrowers of different religions and castes reflect the respective proportions on the platform. Finally, D'Acunto et al. (2020a) show that correcting for these cultural biases improves investors' lending performance: robo-advised investors face 32% lower default rates and 11% higher returns on the loans they issue to borrowers who belong to favored demographic groups relative to available borrowers in discriminated groups.

The results in D'Acunto et al. (2020a) emphasize an important and often neglected role of robo-advising tools: they can eliminate biases in decision-makers' choices even in cases in which such biases are implicit, as is the case with ingrained cultural biases that affect decision-makers' choices under the form of rules of thumb in unfamiliar decision contexts (for instance, see D'Acunto et al. (2019e))

5 Areas of Consumer Finance with a Scarce Presence of Robo-advising

So far, we have discussed several areas of consumer finance in which the use of robo-advising has been diffusing swiftly. Reviewing the peculiar features of each setting, which are often tailored to the characteristics of the decision-making problem agents need to solve, helps to take stock of our existing knowledge as well as to pave the way for future research endeavors in this area.

At the same time, the balance-sheet view of the household also includes several more types of households' assets and liabilities for which, so far, robo-advising applications are quite rare. In this section, we discuss these areas as well as the reasons why the problems households need to solve in these areas might also benefit from robo-advising applications. We hope that this discussion can influence both the development of robo-advising tools in these areas as well as the study of the adoption and effects of such tools on the quality of households' choices and their decision-making mechanisms.

5.1. Robo-advising and Consumer Credit Management

A fundamental portion of households' liabilities, especially in the US, is represented by consumer credit (Agarwal et al. (2007)). Consumer credit is an important source of financing for non-durable and durable consumption for many US households and its take up follows some empirical regularities in observational data. First, typically less sophisticated households and low-income households tend to accumulate consumer credit debt on their balance sheets (Chang (2019); Melzer (2011)). Second, the costs of this form of debt are typically substantial and often not fully transparent to non-expert households, which raises the issue of whether households that rely heavily on this form of debt understand its current and future costs fully (Brown et al. (2010)).

Because of these two peculiar features of consumer credit, this area should represent an obvious arena in which robo-advising tools can be applied: for the first feature—high-cost debt taken up by unsophisticated households—robo-advising tool could provide simple rules of thumb to help households understand the trade offs of higher current consumption and higher future debt. For instance, inspired by the tools of robo-advising for the purchase of durable goods discussed above, robo-advising for consumer credit would provide automated calculators that allow households to assess the present value of their future debt debentures as well as the horizon of repayment based on the features of the consumer's credit card at hand, when considering whether to engage in a certain expense and after providing the maximum monthly payment the consumer is willing to face. Moreover, a robo-advising tool for consumer credit might monitor the credit options available on the market, e.g. credit card characteristics across financial institutions, and suggest that agents switch to alternative cards to reduce their APRs and annual fees. Robo-advising features similar to this last one have started to appear in some income-aggregating robo-advisors for spending, e.g. on Status Money.

The second peculiar feature of consumer credit is the lack of information and understanding about the costs of this form of credit, especially on the part of less sophisticated households. Even in this respect, robo-advising tools could provide more vivid information about, for instance, credit cards' APRs as well as shrouded attributes of credit cards and payday loan contracts. This function is likely to have a relevant impact on households' understanding of the characteristics of consumer credit contracts, because research finds that, despite the mandated disclosure of credit-card characteristics, many consumers do not understand the implications of such features in terms of the cost of debt and the relationship between principal and interest in debt repayment (Salisbury and Zhao (2020)).

Despite representing such an obvious potential application for robo-advising tools, the extent to which such tools have been developed so far is scant. One obvious difference between this potential application of robo-advising and the applications that have obtained more diffusion so far lies in the incentives that supply-side actors have to provide the two forms of robo-advising. When it comes to investment allocation, financial institutions have a clear incentive to enlarge their pool of advisees—who pay fees on such advice, invest money in the institutions' products, and are a target of cross-selling of other products by the institutions—to agents who would otherwise not participate in financial investments. Robo-advising for investment allocation thus provides financial institutions with a means to acquire customers that would have otherwise not been using the institutions' services.

When it comes to consumer credit management, based on the features of this form of debt discussed above, financial institutions lack incentives to provide robo-advising services. Because of the high costs of this form of debt, their opacity, and the fact that it is often low-income and unsophisticated households who take up this type of product, financial institutions would only reduce their margins by providing borrowers with more transparent information on the costs of consumer credit and/or with strategies that would reduce the costs agents pay to access this form of debt (which represent financial institutions' revenues in this case). The lack of strong incentives on the supply side is likely to help explain why this component of households' balance sheets has seen fewer applications of robo-advising to date.

A potential solution to the misalignement of incentives in the introduction of robo-advising tools between consumers and financial institutions is the intervention of regulators. In terms of providing more easily accessible information about the characteristics of consumer credit contracts, regulators are already imposing disclosure requirements to financial institutions.

However, those households who appear to rely substantially on credit card debt also happen to be households that do not understand the information disclosed to them. Because the objective of regulators is that information is understood by households and not just delivered in an incomprehensible format to households, a natural perspective for robo-advising is that regulators mandate financial institutions to provide information in the format of a robo-advising tool. For instance, instead of reporting the structure of interest rates households are required to pay if they accumulate debt (i.e., the typical structure of zero introductory APR and high APRs after a certain period of time) regulators could require institutions to introduce an automatic calculator that allows the household to input the amounts they want to borrow and the maximum monthly payment they are willing/able to make and delivers the present value of the debentures to the institution as well as the timing of full repayment of this debt based on households' inputs.

A second way to enhance consumers' understanding of their debt-management decisions with robo-advising is the introduction of "hints" that act as substitutes for households' (lack of) financial literacy. Indeed, most households lack an understanding of basic financial concepts such as the compounding of interest rates or the optimality of paying down debts subject to higher interest rates before other debt, all else equal. Whereas one solution to this problem would be requiring households to sit in financial literacy classes, this solution is extremely costly on the side of both households (both economically and cognitively) and regulators. Robo-advising would be a natural solution to this problem, because when households face several debts with different characteristics, they could be provided with rules of thumb based on basic financial principles. For instance, households would see a hint suggesting that "debts for which you pay the highest interest rate should always be paid before others."

Studying the design and effects of robo-advising for debt management and comparing the costs and benefits of this form of robo-advising with the costs and benefits of providing financial literacy content to consumers are wide open areas for future research and policy assessment.

5.2. Robo-advising and Human Capital Investments

A second area in which robo-advising applications are surprisingly lacking is the choice of financing human-capital investments. A notable example being the choice of how to finance children's college education.

Decisions about the financing of human capital investments have three peculiar features that make robo-advising applications particularly beneficial to households' decision-making. First, because in countries like the US the cost of higher education (e.g., college, professional schools, and master-level programs) is quite substantial, households who do not belong to the highest portions of the wealth distribution need to plan on financing options many years before the actual expense is incurred. Second, contrary to all other households' investments whose timing is endogenous and can be moved by households over time, the timing of expense of college tuitions and other college costs is pre-specified at the time of birth of the child and corresponds to the age of graduation from high school. A third aspect is that households face very different options to finance this expense. Whenever thinking about consumer credit contracts, agents would typically compare credit card accounts based on details of their characteristics, but the decision is among financial contracts that are similar. Instead, for the case of financing the higher education of their offspring, households need to compare as disparate options as college saving accounts that need to be built up for decades before the child becomes of age for college with, for instance, student loans that would need to be taken up at the time in which households face the actual college expense. And, adding to the complication of this problem, because most governments around the world recognize a positive externality to society from the increase of education levels of their citizens, some of these options are subsidized by governments but others are not.

As of the time of drafting this chapter, we are not aware of robo-advising applications that help households consider the alternative options for the financing of their child's higher education and to simplify the complex dynamic problem they need to solve to choose the best option. One direction robo-advising in this area could experiment is to simplify the comparison of choices across different horizons in terms of vividly representing these choices in terms of present value, so as to make the costs of each option easily comparable even though these costs would be paid by households at very different horizons.

5.3. Robo-advising and Tax Management

The last component of households' balance sheet we discuss explicitly in this section, and which would represent an important potential area of application of robo-advising, is households' tax management. Direct taxes, and especially income, wealth, utility, and estate taxes are an important liability that households face at pre-specified dates.

The peculiar characteristic of tax management that makes it viable for robo-advising applications is that minimizing tax debentures requires substantial and detailed institutional knowledge of the tax code which would be too costly for most households to build, both financially and cognitively. At the same time, because the institutional features of the tax code are pre-specified and do not require judgement based on preferences (they are not risky) or beliefs (they are not uncertain), optimization could be done virtually instantaneously by a well-designed algorithm.

And, indeed, tax-planning robo-advisors such as Turbotax, H&R Block, and TaxAct have quickly gained very large market shares around the world over the past two decades. Goolsbee (2004) provides an early assessment of the Turbotax from 2004, where the firm was not as sophisticated as it is today. Using a sample of 90,000 users Goolsbee (2004) shows that Turbotax users have incomes 40% higher than non-users. They are also much more likely to have a retirement and a brokerage account. Finally, they are more technologically sophisticated than non users.

Because the extent of digital literacy of the broader population has increased dramatically over the last two decades, the characteristics of users and non-users of robo-advisors for tax planning might be completely different at the present day. Updated research on these aspects is thus warranted.

Other open questions about this application of robo-advising relate to the quantification of the monetary and non-monetary benefit of using an robo-advisor like Turbotax, as opposed to having households filing their own taxes or through the more expensive services of a human accountants. Outcome variables that would provide a broad view of these pros and cons include the overall tax amount paid by otherwise similar households who use different types of services, the incidence of mistakes in tax reporting and fines households have to pay conditional on the occurrence of such mistakes, and the overall costs of using these different services, including the labor cost of the time households employ when filing their taxes individually.

Moreover, existing robo-advisors for tax management, especially in the US, are mainly focused on helping households decide whether they should file full requests of various forms of deductions or just pay the alternative minimum tax. At the same time, though, a broader robo-advisor for tax management would not only be used by households at the time of filing. Rather, such robo-advisor could be consulted by households throughout the fiscal year so as to obtain information about how certain expenses, if incurred, might be deducted as well as compare spending and investment options households face in their daily lives based on their tax implications at the end of the fiscal year. Indeed, most consumers tend to focus their attention on tax management only at the time of tax filing and robo-advisors might instead make consumers recognize that all their consumption and investment choices have implications in terms of direct taxation. We are not aware of robo-advisors for tax planning of this type and welcome their design, implementation, and study of their characteristics and effects of households' choices.

6 E pluribus unum: Is the Holistic Robo-Advisor the Future of Robo-Advising?

So far, we have discussed a set of independent applications of robo-advising to various areas of households' balance sheets. Because most robo-advising applications are independently provided by supply-side operators, such as financial institutions and tax-management companies, the fact that different areas of households' balance sheet are the focus of separate and independent robo-advising tools and applications seems natural. Moreover, as we have argued in each of the previous sections, most components of households' balance sheets have peculiarities in terms of type of decision-making problems to be solved. We should thus not be surprised that the first attempts to introduce robo-advising tools would focus on providing tailored information and solutions for each of these problems separately.

And, yet, the balance-sheet view of the household we introduced at the beginning of this survey stresses an obvious route for the future of robo-advising: households do not need dozens of applications and tools to assist with one specific type of choice at once. Rather, the ideal robo-advisor for households, and especially for those with lower levels of sophistication, is a robo-advisor that provides a holistic approach to the dynamic optimization of households' balance sheets. Households need a "Holistic Robo-Advisor" that allows them to jointly optimize all the decision-making problems discussed in this survey.

Obviously, the conceptualization and realization of such a Holistic Robo-Advisor is extremely complicated. Although economic theory proposes rich models of dynamic optimization of households' consumption-saving life cycle choices, a unifying theory of households' balance-sheet management is still missing and perhaps will never exist. Whereas economic theory and psychology might thus inspire the design of robo-advising tools targeted at specific decision-making problems, as we have also emphasized when discussing each individual area of application of robo-advising, the possibility that economic theory or psychology might provide a unifying treatment of all these problems to inspire the design of a Holistic Robo-Advisor seems out of reach.

A direction that instead might be more promising for the realization of a Holistic Robo-Advisor is relying on data-based methods. In particular machine-learning techniques might allow robo-advising researchers and developers to train algorithms based on the observed joint choices of millions of households in the field across different parts of their balance sheets. Researchers and developers would first need to set criteria to assess the quality of joint households' choices; for instance, a bundle of life-time choices might be assessed based on the difference between the wealth accumulated up to retirement with the wealth needed for maintaining a households' standards of living for a certain period of time. Once the criteria are set, the choices of those households who perform better based on such criteria could be analyzed as desirable choices, whereas the choices of those households who perform worse as undesirable choices. Ultimately, this theory-free analysis of the data would thus allow to isolate "optimal" joint choices across various areas of households' balance sheets, which would represent the guiding principles for the design of a Holistic Robo-Advisor to households.

Although some recent commercial applications argue that they are already able to provide such a form of holistic robo-advice—for instance, see PEFIN in the US—the viability and effectiveness of these platforms has not yet been assessed empirically. And, yet, robo-advising will not be able to fully replace more expensive reliance on human advisors unless Holistic Robo-Advisors are produced that can fully replace the global financial-planning services human advisors currently provide.

7 Conclusions

This chapter argues that robo-advising, also knows as algorithmic advice, involves every aspect of the balance sheet of households, including, among others, consumption-saving choices, debt management, tax management and financing of human capital investments.

So far, the term robo-advisor has been mainly used to label the first form of robo-advice that has been developed in personal finance—robo-advisors for the management of households' financial assets. The fact that this specific component of households' balance sheet has been the first target of robo-advising is not surprising, because the returns to providing advice in this realm, which mainly involves wealthy households, are higher than the returns to providing robo-advising for the optimization of other household-finance related choices.[1]

And, yet, all forms of algorithmic advice applied to household finance choices of any type represent robo-advising applications. Because different components of households' balance sheet require households to solve different types of optimization problems, this chapter has re-

[1] Moreover, note that many early applications of robo-advising to households' financial portfolio allocation do not provide households with advice, which households can decide to follow, but manage households' portfolios directly without barely any involvement on the side of households. For this reason, a more appropriate label for what industry participants label robo-advisors would be "robo-managers."

viewed the existing applications of robo-advising to alternative problems as well as the peculiar features of each robo-advising application based on the underlying mechanisms and common mistakes in households' decision making as documented in the field and the laboratory across several areas of research such as economics, finance, marketing, accounting, social psychology, and information systems.

Further research is needed to understand more deeply the mechanisms and effects of each specific forms or robo-advising for specific types of optimization problems. Ultimately, the goal of robo-advising has to be the conceptualization and development of a Holistic Robo-Advisor, which can provide households with advice across, and not just within, each component of their balance sheets.

Moreover, whereas this chapter has focusedon direct algorithmic advice to decision-makers, further research has to be devoted into understanding the optimal design, effects, and regulation around the use of algorithmic advice to improve the decisions of experts, i.e. human financial advisors. Rather than replacing human advice, robo-advising might also have relevant applications in reducing the mistakes, cognitive constraints, and conflicts of interest of human advisors while still maintaining a human connection in the advisor-advisee relationship. Recent work has documented the superiority of algorithmic-based decision-making over human expert decision-making across various settings, ranging from loan underwriting (e.g., see Jansen et al. (2020)) to patent filing and innovation production (e.g., see Zheng (2020)). Future research should focus on providing human advisors with robo-advising tool to improve their advising quality might differ from the attempt of replacing the human advice step altogether.

Overall, our understanding of robo-advising design and effects across all household-finance choices is still in its infancy and the multi-disciplinary research efforts of scholars across several fields will be needed to deepen our still superficial knowledge on robo-advising.

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