

Robo-Advice: Transforming Households into Rational Economic Agents

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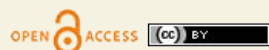
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Abstract

Robo-advice uses big and open data to provide consumers with fully informed and rational-expectation benchmarks in all realms of household finance, including consumption, saving, investment, and debt management choices. It also minimizes the monetary, cognitive, and psychological costs that households face in economic transactions. We review recent research on the features and effects of robo-advice on individual and aggregate economic outcomes through the lens of its differences from traditional human advice. We discuss the distributional implications of robo-advice, its potential role in increasing the effectiveness of economic policies, the role of providers' incentives, and several questions that are still wide open for researchers in finance, economics, social psychology, and related fields.

1. HOUSEHOLD FINANCE PUZZLES AND ISSUES WITH TRADITIONAL SOLUTIONS

Every household around the world, irrespective of its level of income, wealth, or sophistication, needs to make complex financial decisions on a daily basis. First and foremost, households need to decide how much they want to spend for consumption or save to increase future consumption—they need to solve an intertemporal consumption problem. Once the consumption–saving choice is made, they need to allocate resources to durable and nondurable goods and choose how to finance their durable consumption (e.g., income flows, credit card debt, mortgages, personal loans, student loans). Financing options differ based on multiple dimensions that need to be compared—horizons, maturities, interest rates, and amortization plans. Households also need to manage their assets by deciding how to invest savings to accumulate wealth and maximize future consumption and/or bequests. On top of allocating resources across investment assets in their financial portfolios, for instance, they must choose whether and how much to contribute to retirement saving plans—a decision that has become prominent around the world given the global move away from defined benefit pension systems and toward defined contribution individual plans. And, once they reach retirement age, they need to make decisions about the decumulation phase of their accumulated retirement savings, which is a complex problem that is still barely understood by researchers and policymakers.

Ultimately, households, like corporate managers, need to make multiple financial decisions at high frequency and cannot avoid choosing, in the sense that avoiding to decide is a choice in itself that has relevant financial implications for the household (Madrian & Shea 2001). Contrary to corporate managers, though, households cannot specialize in only one type of the multitude of financial choices they need to make. Moreover, households need to make all these choices, even though the vast majority have never been exposed to the most basic principles of finance, such as diversification and compounding of interest rates, or obtained any financial education (Lusardi & Mitchell 2014), because finance is absent from standard primary and secondary school curricula in virtually every country around the world.

Given these premises, the fact that most households make decisions that depart from those predicted by standard economic models should not be surprising. Standard models assume the existence of utility-maximizing agents who have access to all the information needed to make financial decisions, use it to form rational expectations, and have standard economic preferences. A large and growing literature in finance and economics labels departures from standard models in households' financial choices as household finance puzzles (Zinman 2015).

Why do we care to understand and solve household finance puzzles? On top of negatively affecting households' utility, these puzzles have four important and undesirable aggregate effects. First, they tend to produce and widen wealth inequalities because the poorer and most vulnerable households tend to be less sophisticated in terms of economic and financial literacy and hence make choices that depart most from optimality (Calvet, Campbell & Sodini 2007, 2009). Second, they dampen the effects of economic policies that central banks and governments implement, assuming that households understand and react to them in line with the predictions of standard economic models (D'Acunto et al. 2021a). Third, household finance puzzles are likely to have become even more severe over time due to the swift diffusion of FinTech applications that have eased ordinary consumers' access to high-risk financial choices, such as the trading of complex financial products like derivatives and cryptocurrencies using apps on their personal devices or the accumulation of high-interest debt through unsecured financing of consumption expenses and buy now, pay later spending opportunities. Fourth, a detailed understanding of the nature and consequences of the biases households face when making financial choices is crucial to inform

regulators' attempts to design effective policies that can protect households from being exploited by better-informed financial institutions and other counterparts in financial contracts.

Two traditional solutions have been proposed for household finance puzzles. The first solution is the provision of financial advice. Financial advisors are agents who suggest how households should make their multiple financial choices by interpreting their preferences and beliefs and evaluating options. Unfortunately, though, financial advisors have limitations. Their services are too expensive for many households and cannot be scaled at a low cost, which reduces their viability, especially for middle- and low-income households. If anything, the availability of financial advisors might increase rather than reduce wealth inequalities, given that more affluent households can access them but poorer households cannot. Moreover, financial advisors, similar to other experts such as CEOs and institutional investors, often engage in the same departures from rational decision-making that households display and end up providing unsound suggestions (Mullainathan, Noeth & Schoar 2012; Linnainmaa, Melzer & Previtero 2021). At the same time, the literature has documented the unintended consequences of limiting the presence of financial advisors on access to financial investments by unsophisticated households. For instance, Linnainmaa et al. (2022) find that once financial advisors' regulatory oversight was introduced in Canada, the number of financial advisors reduced drastically and so did households' stock market participation, especially by middle-class households. The second solution is the design of nudges—default choices for program participation or design mechanisms that lure households into making choices consistent with those that a representative economic agent would make under the same conditions (Thaler & Sunstein 2009). Although helpful, by construction, nudges can barely be tailored to the individual characteristics of each household, and their effectiveness often depends on the details of their design (Sunstein 2017).

Next to human financial advice and nudges, robo-advice represents a third and more recent solution to household finance puzzles (D'Acunto & Rossi 2021). At first, robo-advice might appear as nothing more than traditional human financial advice produced and delivered automatically to decision-makers with FinTech applications through personal devices. Even if this were the only relevant feature of robo-advice, it would make it more scalable than human advice by reducing its cost and allowing access to advice to a substantially higher share of households. This property would thus improve the distributional consequences of advice by aligning the choices of vulnerable households with those of sophisticated households (Philippon 2019).

Robo-advice, though, is not just traditional advice produced and delivered automatically through personal devices. The crucial feature of robo-advice is that it reduces households' differences from the characteristics of standard neoclassical rational decision-makers and hence allows households, including the least sophisticated, to make choices closer to those a standard utility-maximizing agent would make.

Robo-advising transforms biased decision-makers into standard neoclassical decision-makers through three unique features that differentiate it from traditional forms of advice. First, robo-advising uses big and open data to make households fully informed about their own characteristics and past behavior as well as the characteristics and past behavior of other agents, to which households (and often their human advisors) would otherwise have no access due to their limited ability to recall past actions and collect and elaborate big datasets (D'Acunto & Rossi 2022a). The big data that robo-advisors access are the universe of transactions households produce when making economic decisions, such as purchases of durable and nondurable goods, investment choices, and financing choices. Robo-advisors can access this wealth of information because, since the Digital Revolution, electronic transactions can be stored, and these data are open; that is, households can share them by linking transaction accounts to robo-advising applications.

Second, robo-advising manages households' beliefs and pushes them closer to the rational expectations assumed in standard models. The economic literature has documented several systematic departures of households' beliefs from those of a standard economic agent. The size of these departures is correlated with demographic characteristics and varies over the business cycle. As we discuss in Section 3.1, robo-advisors provide households with beliefs about both their own future financial conditions and aggregate macroeconomic conditions that are closer to those of a standard agent.

Third, robo-advising reduces the transaction costs of executing economic choices, which include not only monetary costs but also the cognitive and psychological costs that households face when trying to make economic decisions.

In the rest of this review, we describe the findings of existing academic research on these three defining features of robo-advice. We also emphasize the large set of open questions and areas of investigation for future research.

2. REDUCING INFORMATION FRICTIONS

Standard neoclassical economic agents are assumed to be fully informed about their characteristics, the characteristics of other agents, and macroeconomic conditions. This assumption of standard models of intertemporal consumption optimization is heavily violated in the data, except for a few special cases, such as highly sophisticated institutional investors in financial markets who actively engage in costly information acquisition (Gargano, Rossi & Wermers 2017).

Most households are barely informed about macroeconomic conditions and often even ignore the definition of basic economic aggregates, such as inflation rates or interest rates (Binder 2017). Households have also been shown, on average, to have a wrong assessment of the economic conditions of other economic agents, which is due mainly to a lack of full information about other people's income flows, spending, and debt positions and the observation of conspicuous and salient transactions that households interpret as representative of the average transactions others execute (Charles, Hurst & Roussanov 2009). Ultimately, and perhaps most surprisingly, households often cannot recall or process information about their own income flows, consumption, and debt transactions, even though all this information is produced by them and hence available to them without the need to collect public or private signals from other sources. For example, households do not keep information about all their transactions but often pay attention to them only temporarily and for short periods (D'Acunto, Rossi & Weber 2019). Households also tend to have a biased recall of their consumption over time, which is driven by their tendency to recall having paid lower prices than the actual prices they faced (D'Acunto & Weber 2022).

The first unique feature of robo-advice is pushing households closer to being fully informed about their own, others', and aggregate economic outcomes. Robo-advice can achieve this goal by collecting and elaborating big and open transaction-level data at various levels of observation: households' own characteristics and past choices, the characteristics and past choices of other decision-makers in the economy, and information about macroeconomic conditions and other aggregate variables that might be relevant to economic decision-making. In the rest of this section, we discuss recent research that has studied the mechanics and effects of this function of robo-advising.

2.1. Information About One's Own Characteristics: Income Aggregators

The fact that providing information about one's own characteristics and past choices influences decision-making might appear surprising at first. After all, this information is produced by households and should therefore be readily available to them at any time. And yet research finds

that households largely neglect essential information about their own behavior due to cognitive constraints in the ability to collect and process information (D'Acunto, Ghosh & Rossi 2022).

Robo-advice allows households to overcome these constraints and obtain full information about their past transactions and finances through income aggregators. Income aggregators are robo-advisors that collect and elaborate households' transaction-level data. These data are open in that households can share them by linking their spending and other financial accounts to the aggregator (Gelman et al. 2014).

Upon obtaining household-level transactions, income aggregators construct household-level balance sheets similar to those that corporations use for financial reporting (D'Acunto & Rossi 2022b). Aggregators elaborate both static balance sheets, which include the current overall value of households' assets and liabilities at each point in time, and dynamic assessments of the past evolution, liquidity, and horizons of households' debts, spending, and investment decisions for each entry of the balance sheet (Baker 2018).

Because not linking all financial accounts would render the aggregator's information elaboration incomplete, households that want to access this feature of robo-advising have an incentive to link all their financial accounts to the aggregator. Consistently, Baker (2018) shows that 95% of the users of a large US income aggregator linked all their checking accounts, over 93% linked all their savings accounts, and 91% linked all their credit card accounts. At the same time, households might be wary of providing so much detailed information to an income aggregator. Income aggregators have a short history of operations and hence lack reputation in terms of data protection and management, which might increase households' expected probability that the data might be appropriated by third parties and be subject to cybersecurity concerns. Consistent with these potential concerns, Rossi & Utkus (2020a) find that a robo-advisor's reputation is one of the main drivers of robo-advice adoption, partly because of users' data privacy concerns (Tang 2019).

Income aggregation can be a form of robo-advice if providing households with information about their own characteristics and past choices influences their decision-making. Consistent with this possibility, Olafsson & Pagel (2018) show that displaying aggregate information about one's own balance sheets to Icelandic households leads to financial choices that are closer to those of a standard economic agent. For instance, households reduce their debt balances to avoid overdraft fees, which is direct evidence that, before the information was provided to them, households were unaware of the existence or size of overdraft fees. Information from income aggregators also makes households realize that the benefits of running higher-than-limit debt balances are lower than the monetary costs of the overdraft fees they are charged. Carlin, Olafsson & Pagel (2023) further document that, after observing their own aggregate balance sheets, households reduce their non-durable spending, especially in frivolous categories such as eating outside the home and traveling. This reaction suggests that, absent the information income aggregators provide, households might underestimate the share of total spending and income flows they allocate across consumption categories. Further evidence of the effects of giving consumers aggregated information about their own finances through income aggregating robo-advisors is provided by Levi & Benartzi (2020) and Olafsson & Pagel (2022). The latter paper also provides a direct empirical test of the ostrich effect, whereby decision-makers select the information to which they want to attend in their daily lives based on their beliefs about the positivity or negativity of such information (Karlsson, Loewenstein & Seppi 2009).

In addition to the mere informational value of income aggregation, robo-advisors use the elaborated information to focus households' attention on specific features of their balance sheets, especially when such features indicate red flags, such as significant increases in spending patterns over time despite constant or declining income flows. Lee (2019) studies a Canadian robo-advisor that, on top of income aggregation features, sends users overspending messages when

their spending in one category is substantially higher than the user's recent spending within the same category. Note that increasing spending in times of constant or declining income flows is not necessarily inconsistent with intertemporal consumption optimization if, for example, households correctly expect higher income growth—a feature that existing robo-advisors cannot observe or include in their assessment of red flags in households' balance sheets. Recent research, though, documents substantial extrapolation in households' expectations of future income after small income increases, which leads to a systematic overestimation of future income levels and growth relative to ex post realized levels and growth (D'Acunto, Weber & Yin 2022).

Lee (2019) compares users who are just above the robo-advisor's threshold to send overspending messages with users who are just below and hence spend similarly more than in their recent past but receive no messages. He finds that message receivers cut their daily spending by approximately 5% more, and this effect, despite reverting in terms of spending flows, is permanent in terms of cumulative spending over time; that is, the temporary shock does not fully revert over time. Lee (2019) also finds that older, wealthier, and more financially savvy households react more to obtaining information about their own transactions. Although this heterogeneity might at least in part capture higher income growth expected by younger households going forward, it also opens the possibility that this form of robo-advising might increase wealth inequalities over time.

Finally, Lee (2019) finds that, despite reacting to overspending messages by reducing spending, several households also reduce the frequency with which they log in and check information about their finances on the income aggregator. This form of the ostrich effect, whereby households tend to avoid facing negative news about their finances, is a feature of robo-advising income aggregators documented first by Olafsson & Pagel (2022).

The detection of an ostrich effect associated with using informative robo-advisors opens a set of research questions. First, we do not know whether providing households with complete and aggregated information about their finances has effects in the long term or whether the ostrich effect (or fatigue from using an application regularly and for long periods) makes the effects only temporary. By construction, because income aggregators have been implemented and commercialized over only the last few years, researchers lack data for repeated interventions over prolonged periods, which would be crucial to answering this question. We also need to understand whether the emergence of an ostrich effect makes robo-advisors that provide information such as income aggregators increase inequalities. This unintended and undesirable consequence could be plausible if detachment from robo-advisors were more common among vulnerable households. Extensive literature in behavioral economics has also documented the prevalence of present bias in choices and new toy effects, which are more substantial for demographic groups who tend to understand their own finances less and make suboptimal consumption and saving choices intertemporally (see, for example, Gargano & Rossi 2020). Understanding whether these common behavioral features reduce the reliance on income aggregators over time for households that would need them most and increase rather than reduce wealth inequalities is an open area for future research.

2.2. Information About Other Economic Agents

Even if households were fully informed about their balance sheets, solving their intertemporal consumption problem and hence determining their optimal consumption and saving rates would be a daunting task for most households and depend largely on their preferences and subjective beliefs, which can hardly even be expressed fully and entirely to a financial advisor by nonexpert economic agents (Bruine de Bruin et al. 2012). To facilitate this task, a strand of research in economics, social psychology, and social finance shows that households make inferences about

their own optimal consumption and saving rates based on the consumption and saving rates of their peers, that is, individuals who have similar demographic characteristics and hence presumably similar preferences, income flows, and expected income growth (for recent reviews of this area of research, see Hirshleifer 2020 and Kuchler & Stroebel 2021).

Intuitively, making inferences based on signals about the behavior of a large mass of peers could be meaningful based on the wisdom of the crowds, whereby a large number of independent forecasts made by different individuals can provide an accurate consensus forecast, with which the household can align their behavior (Da & Huang 2020). At the same time, households cannot access the full set of transactions and full information about the choices their peers make in terms of consumption, saving, investment, and financing: They cannot access or observe transaction-level data about peers in the same way they access their own data. Instead, households are limited to observing the information their peers disclose, and this information tends to not be representative of peers' finances, especially in times of pervasive use of social media (Han, Hirshleifer & Walden 2019). Peers tend to disclose their most conspicuous consumption instances in which they engage (Charles, Hurst & Roussanov 2009) while not disclosing information about parsimonious consumption choices, their income flows, or access to debt financing. In this way, the signals about peers' consumption that households observe lead them to overestimate the overall consumption rates of peers unless households are sophisticated enough to account for peers' partial disclosure (Han, Hirshleifer & Walden 2019).

Contrary to households or human advisors, robo-advisors can access and elaborate information about peers' consumption and saving rates. If households misestimate these variables systematically, they should change their consumption choices when robo-advisors provide them with full information about peers' finances. D'Acunto, Rossi & Weber (2019) study a US robo-advisor that, on top of the standard income aggregation features discussed in Section 2.1, provides users with elaborated information about peers' consumption, saving, and investment transactions. In this context, peers are not users' social acquaintances: The information is based on transaction accounts of households that have similar demographics as users, including income levels, age, residence types, and locations. D'Acunto, Rossi & Weber (2019) find that users' spending levels converge with those of peers for both users who spent more than and those who spent less than their peers. The effects are asymmetric: Overspenders cut their spending substantially more than underspenders over the following 12 months. This observational evidence raises the concern that only the users who are especially interested in information about peers might select into adopting robo-advice. To tackle this concern, D'Acunto, Rossi & Weber (2019) run a randomized control trial with a representative US population that did not select into any robo-advice applications and find the same reactions to the provision of information about peers.

Understanding the channels through which providing detailed information about others with robo-advising changes households' preferences, beliefs, and choices is an open research area. Research has shown that information about debt financing options and investment decisions does transmit across peers (Maturana & Nickerson 2019, Kalda 2020, Ouimet & Tate 2020), but whether such information affects behavior because of its content or due to social pressure or social conditioning (Burszty, Ederer & Yuchtman 2014; Bailey et al. 2019)—and hence has the same effects when delivered through robo-advising after being gathered from the crowds rather than one's personal acquaintances—is an open question.

Moreover, we have no conclusive evidence about whether adapting one's behavior to the average behavior of those with similar demographic characteristics is optimal. The principle of the wisdom of the crowd requires that the assessments and hence choices of a large group of agents are independent from each other to provide accurate average assessments. Still, in times of social media where households observe the same signals from focal network members or influencers and

might read the same comments and interpretations about business cycle shocks circulating in their social network, average signals might not be unbiased.

To the extent that a social planner would care more about avoiding overconsumption by some households (and the potential excessive use of debt financing) than about underconsumption by other households, the asymmetric effects documented by D'Acunto, Rossi & Weber (2021) suggest that robo-advising for spending using information about others could align with the aims of policymakers. However, the distributional consequences of this form of robo-advising are still unknown and should be investigated further.

2.3. Information About Macroeconomic Variables

In standard intertemporal consumption optimization models, beliefs about future macroeconomic conditions, especially inflation, drive perceptions of real interest rates and hence the decision about how much to consume versus save for the scope of future consumption (Bernanke 2009). Research in macroeconomics, applied microeconomics, and social psychology has shown that many households are uninformed about the most basic macroeconomic aggregates (Coibion et al. 2020) and form biased beliefs about them (Armantier et al. 2015; D'Acunto, Malmendier & Weber 2021; Weber et al. 2022). Furthermore, households' beliefs are not based on representative information but rather on the few signals about prices and wages households observe in their daily lives (D'Acunto, Ghosh & Rossi 2022). Cognitive abilities also determine households' understanding of the relationships across economic variables and their ability to elaborate macroeconomic information (D'Acunto et al. 2021a, Andre et al. 2022).

Robo-advice to provide households with unbiased processed information should thus naturally extend to macroeconomic variables, especially inflation and unemployment, whose expected values determine households' perceived real rates and expected income flows in standard models. Because systematic biases and mistakes in economic expectations are more frequent among the most vulnerable households, they can contribute to the widening of inequalities (D'Acunto et al. 2020). And yet research on the provision and effects of macroeconomic information through robo-advisors is extremely scarce (D'Acunto & Rossi 2022b).

Robo-advice that provides unbiased macroeconomic information could also help solve the recent debate on the effectiveness of policies that aim to manage households' expectations through communication (Coibion, Gorodnichenko & Kamdar 2018). Communication as an expectations-management tool is more effective when households trust the policymaking body (D'Acunto, Fuster & Weber 2021) and policies are simple and intuitive (D'Acunto et al. 2021b), but it is less effective when delivered through traditional media such as newspapers, which households barely trust (Coibion, Gorodnichenko & Weber 2022). Robo-advising to deliver unbiased information about current macroeconomic variables and consensus forecasts about future realizations of the same variables could be an effective way to increase policymakers' success in managing expectations and choices. This is not only a widely open area of inquiry but also one that could deliver important practical suggestions that can be implemented for policy design.

3. REDUCING DISTORTED BELIEFS

Standard neoclassical decision-makers are also assumed to form expectations rationally; their beliefs about future own and aggregate outcomes are, on average, consistent with ex post realizations. Contrary to this benchmark, households tend to display multiple biases regarding beliefs about their own, others', and macroeconomic outcomes.

In terms of their own outcomes, for instance, households tend to misestimate their survival probabilities, which leads them to make suboptimal choices about retirement savings and insurance policies (Heimer, Myrseth & Schoenle 2019). Moreover, many households have systematically distorted beliefs about their future income flows and income growth: They extrapolate from recent income increases but not decreases and overestimate future income systematically (see, e.g., Cutler, Poterba & Summers 1990; De Long et al. 1990; Greenwood & Shleifer 2014; Barberis et al. 2015; Gennaioli, Ma & Shleifer 2016; Barberis et al. 2018; Carroll et al. 2020; D'Acunto, Weber & Yin 2022). At the same time, more than one-third of a representative population overestimates the likelihood of negative shocks and the need for precautionary savings and underspending relative to their capacity—a perceived precautionary savings motive that drops when households receive insurance in the form of a credit line (D'Acunto et al. 2020).

Households display biased beliefs also when forming expectations about others—they tend to overestimate others' consumption and underestimate their saving rates, as discussed above (D'Acunto, Rossi & Weber 2019)—and future macroeconomic variables. These systematic distortions are correlated with demographic characteristics such as socioeconomic status (Das, Kuhnen & Nagel 2020), cognitive abilities (D'Acunto et al. 2019), age, and cohorts (Malmendier & Nagel 2016). Stango & Zinman (2023) provide a taxonomy of multiple biases in households' expectations and beliefs and document commonalities and correlation patterns across them, which suggests that many biases in beliefs might have common sources. Ultimately, beliefs appear to be more biased for vulnerable households, which might help perpetuate economic inequalities.

3.1. Beliefs About One's Own Characteristics

Research in economics and social psychology, based primarily on laboratory experiments, has tackled the issue of reducing distortions in households' beliefs about their own future characteristics by using goal setting—the process of letting households think about future potential states of the world, the likelihood of such states absent any interventions, and the commitment to increase the likelihood of the desired state of the world by establishing it as a goal. In the field, Ashraf, Karlan & Yin (2006) show that individuals with preferences that display a higher degree of hyperbolic discounting have a higher probability of opening savings accounts that restrict access to saving goals until the amount saved achieves a certain threshold. The authors show that adopting hard goals of this type increases the households' saving rate.

Goal setting is a primary tool robo-advisors use to reduce the impact of households' biased beliefs about their future income flows and debt repayment ability. Gargano & Rossi (2020) study an Italian robo-advisor and find that the practice of goal setting to manage spending and saving is adopted widely when offered: Forty-one percent of the users who have access to goal setting use it on a continuous basis. In a difference-in-differences analysis based on a natural experiment, Gargano & Rossi (2020) estimate an intention-to-treat effect of goal setting on savings of €20 per month and a local average treatment effect of €60 per month, for an average income of the robo-advisor's users of €1,200 per month. The authors also show that goal setting is particularly effective for individuals who the literature has identified to be at risk of not saving enough for retirement, who display high impatience (Laibson 1997), low levels of education (Cole, Paulson & Shastri 2014), low income and socioeconomic status (Banerjee & Duflo 2011, Kuhnen & Miu 2017), and inattention (Karlan et al. 2016).

Gargano & Rossi (2020) also show that goal setting through robo-advising tools motivates users to save more because once users set a certain state of the world as the one they want to reach (goal), they monitor the robo-advisor often to increase the probability that the state is reached. Goal setting thus increases the likelihood of reaching a valuable future state of the

world by reminding users of their stated beliefs regularly while they make consumption and saving choices.

Whether households are aware or naive about their biases is central to assessing the effectiveness of a solution like robo-advising, which requires active adoption by users, relative to a nudge or default option, which exploits households' inattention and/or inertia in economic decision-making. Researchers have used robo-advising to assess bias awareness and, consequently, households' assessment of the value of robo-advisors. To this aim, Chak et al. (2022) implement a randomized control trial in the realm of robo-advice for household debt management. Households are first left to their own means to solve three debt management problem scenarios whereby they allocate a given disposable income to the repayment of several debt accounts whose features (e.g., interest rates, minimum fees, late-fee payments) vary. Some users are then randomly offered the help of a robo-advisor for allocation suggestions, and, within this group, some are provided robo-advice for free, and others have to indicate their willingness to pay (WTP) for the tool. Note that robo-advice for debt management is a primary application of automated advice because, contrary to choices under risk and uncertainty such as investment decisions, debt repayment choices have a unique optimal solution that does not depend on households' preferences, beliefs, or other characteristics.

Chak et al. (2022) find that the average subject who is offered the robo-advising tool for a cost expresses a WTP above and beyond the actual monetary benefits the subject obtains.¹ The average WTP is higher than the average amount subjects left on the table when making choices unassisted relative to the optimal solutions. This result suggests that households are likely sophisticated about their inability to assess optimal debt repayment strategies.

3.2. Beliefs About Others and the Macroeconomy

As discussed in the previous section, providing households with unbiased and representative information about others' spending affects choices. This effect acts through a beliefs channel: Households must have misestimated the spending of others if observing unbiased information changes their behavior in the direction of their peers' choices (D'Acunto, Rossi & Weber 2019).

Robo-advisors reduce biased beliefs about others' outcomes not only in the realm of consumption–saving choices but also in investment. D'Acunto, Ghosh & Rossi (2022) study a robo-advisor for debt investment by households in the form of providing loans to borrowers on a peer-to-peer platform. This form of investment requires that lenders form beliefs about potential borrowers' probability of default and expected cash flows to assess the expected returns from alternative loan requests. D'Acunto, Ghosh & Rossi (2022) first document that investors use rules of thumb based on cultural norms when assessing the viability of borrowers that belong to alternative social groups but are otherwise observationally similar. They find evidence for an in-group versus out-group bias, whereby lenders who belong to a social group underestimate the probability of default by borrowers from the same social group, and an implicit bias, whereby all lenders overestimate the probability of default by borrowers from a heavily discriminated social group, including the members of such group.

If these distorted beliefs were driven by lenders' conscious willingness to discriminate against the social groups they disliked, even if at a cost, lenders would not choose the borrowers suggested by a robo-advising tool that did not engage in discrimination. By contrast, if lenders used stereotypical rules of thumb to form beliefs but were aware that their beliefs might be inaccurate (inaccurate statistical discrimination), they would follow the suggestions of an unbiased

¹The authors implement a Becker–DeGroot–Marschak mechanism to elicit truthful WTP by agents.

robo-advisor. D'Acunto, Ghosh & Rossi (2022) find that the same investors/lenders start providing funding to borrowers from groups they were less likely to choose before adopting robo-advice and stop providing lending to borrowers belonging to their own social group, whose probability of default they underestimated before adopting robo-advice.

As far as beliefs about aggregate outcomes are concerned, Capponi, Olafsson & Zariphopoulou (2022) study the effects of a robo-advisor that provides unbiased expectations to users with respect to stock market return and the risk–return trade-off of equity investments. The authors find that robo-advising improves the Sharpe ratio and return of households' risky portfolios, especially in times of economic downturns, when households have excessively negative expectations about future market returns and tend to reduce market exposure, whereas maintaining market exposure would be especially profitable given the more favorable risk–return trade-off. D'Acunto, Prabhala & Rossi (2019) further document that robo-advice virtually eliminates a set of biases in individual investors' decision-making that have been attributed to nonstandard beliefs about aggregate and individual stock returns, such as trend chasing, the disposition effect, and the rank effect in trading.

4. REDUCING TRANSACTION COSTS

To optimize future consumption through wealth accumulation, standard portfolio optimization models predict that virtually every household should participate in equity markets by investing a fraction of their savings as long as participation costs are minimal. Conversely, an extensive literature in economics and finance has proposed participation costs as a potential explanation for one of the most common findings in household finance around the world—the stock market participation puzzle, whereby a significant fraction of households do not participate in the stock market and many invest smaller fractions of their wealth than predicted by standard models (Moskowitz & Vissing-Jørgensen 2002).² Costs can also be relevant for consumption/saving transactions (Abel, Eberly & Panageas 2007) and, importantly, do not only take the form of monetary costs. Indeed, the cognitive and psychological costs households face to conceptualize the household finance puzzles they face, to determine the potential choices they can make, to assess their expected value, and to take the responsibility to act are substantial and completely dismissed in settings that assume standard economic decision-makers (Sweet et al. 2013, Chak et al. 2022).

4.1. Monetary Costs

Monetary transaction costs, such as the price of a spending transaction or stock trade, have been declining over the last few decades but might still represent a barrier to participation, especially for the most vulnerable households (Reher & Sokolinski 2021). In line with this argument, Philippon (2019) proposes a model in which a crucial feature of robo-advising and other FinTech platforms is that they cut monetary financial transaction costs. Philippon (2019) argues that FinTech platforms, which include robo-advisors, should increase participation in equity markets and reduce wealth inequalities within and across countries. Reher & Sokolinski (2021) provide empirical evidence supporting this argument. They study a US robo-advisor for financial investments that, during the sample period they observe, cut the minimum amount required for access, which is tantamount to a

²Several other explanations not based on participation costs have also been studied in the literature. For instance, households' lack of financial literacy and understanding of the concept of diversification (Lusardi & Mitchell 2014) and households' lack of trust in the stock market and its participants (Guiso, Sapienza & Zingales 2009; Giannetti & Wang 2016; Gurun, Stoffman & Yonkers 2018; D'Acunto, Prokopcuk & Weber 2019; D'Acunto 2021).

drop in the costs of participation because households are required to maintain the minimum value on their account rather than using such resources otherwise. Reher & Sokolinski (2021) show that the share of households owning equities increases after this intervention and that the performance of their portfolios, which are robo-advised, improves. Because this type of intervention does not affect wealthier households that invested more than the minimum before the change, the benefits are fully concentrated among middle-class and poorer households.

Research shows that whether robo-advisors provide benefits in terms of execution costs depends on their design. US-based robo-advisors for financial investments, which should be more appropriately labeled robo-managers, require an investor to commit cash to an account that is managed automatically, including decisions to trade and rebalance the portfolio, which typically happens at prespecified times (Reher & Sun 2019, Rossi & Utkus 2020b).

Other forms of robo-advice provide suggestions but require households to make active decisions. These robo-advisors are closer to the role of a traditional financial advisor than to that of a robo-manager. D'Acunto, Prabhala & Rossi (2019) study such a robo-advisor in India, which was introduced by a large brokerage house, alongside traditional human advisors. They show that robo-advice, on average, improves the performance of households' portfolios, and the improvement is driven almost entirely by inducing higher portfolio diversification, which reduces portfolio volatility. For this reason, the average performance improvement is entirely captured by households whose portfolios were undiversified before adoption (even though human financial advisors already helped these households). D'Acunto, Prabhala & Rossi (2019) find that diversified households not only face no performance improvement but perform worse after adoption because they use the robo-advisor often, which increases their trading fees relative to before adoption.

Even in the case of robo-managers, the benefits of accessing robo-advice vary across demographics. Rossi & Utkus (2020b) use machine-learning techniques to understand which investors' demographic and portfolio characteristics predict higher performance improvement under robo-advice. The cash share and trading volume at adoption are positively related to the improvement in performance after access to robo-advice, indicating that investors who traded often and/or held a large portion of their wealth in cash benefited most from robo-advice. The authors also find that tenure, the percentage of wealth invested in mutual funds, and the percentage of mutual fund holdings in indexed funds are negatively related to the benefits from robo-advice. Finally, they find a positive monotonic relation between the share of equities held and the benefits of robo-advice, because the portfolio of funds in which a robo-manager invests has higher risk–return trade-offs than does the portfolio managed by the average investor.

Reducing execution costs not only is a feature of robo-advisors for investment but also is common among robo-advisors for consumption. Researchers have studied the effects of mobile wallets—applications that provide households with the ability to engage in low-cost electronic spending transactions, and provide robo-advising features. Agarwal et al. (2020) find that adopting low-cost transaction mobile wallets increases the spending capacity of Indian households by 3% for each 10-percentage-point dependence on cash for transactions before adoption. Agarwal et al. (2020) also detect a potential undesirable feature of robo-advising for consumption: Households' higher spending capacity after adoption is due at least in part to the increased salience and lower search costs for conspicuous purchase opportunities.

Lower transaction costs when using robo-advisors for consumption not only aligns households' behavior with the predictions of standard economic models but also has business cycle effects. Agarwal et al. (2019) and Agarwal et al. (2022) show that the diffusion of a mobile wallet in Singapore, which reduced spending transaction costs substantially, increased sales growth disproportionately for new and small businesses, which are responsible for most employment

growth in the United States and abroad (Haltiwanger, Jarmin & Miranda 2013). These aggregate effects of FinTech and robo-advising adoption are likely to be especially high in emerging countries, as Agarwal et al. (2022) and Crouzet, Gupta & Mezzanotti (2022) document, exploiting the sudden 2016 Indian demonetization event as a shock to technology adoption.

4.2. Cognitive and Psychological Costs

The costs households face to execute economic transactions can also be cognitive and psychological. Even if households fully understood the economic problems they faced and were capable of obtaining close-to-optimal solutions, conceptualizing such problems and determining their solutions require the use of cognitive skills and time, both of which are scarce resources (Abel, Eberly & Panageas 2013). Households often lack the cognitive skills and economic or numerical literacy needed to understand and solve economic problems, which increases the cognitive costs of making decisions (Lusardi & Mitchell 2014). Cognitive abilities also predict the wedge between households' choices and standard neoclassical optimal solutions for forecasting economic variables and making economic decisions (D'Acunto et al. 2022). Moreover, a large line of work in behavioral economics has documented that the complexity of choices whose subtleties consumers cannot fully grasp can lead to choice avoidance (Iyengar & Lepper 2000) and inertia in decision-making (O'Donoghue & Rabin 1999, Madrian & Shea 2001), hence suboptimal choices relative to the ones of a standard neoclassical agent.

By simplifying the decision process and making the future potential benefits of active choices more clear and tangible, robo-advice can reduce cognitive costs, psychological costs, and inertia in decision-making. For instance, Bianchi & Brière (2021) study a French robo-advisor for employees' savings accounts that provides a salient target for portfolio allocations that investors can observe at any time. They find that robo-advice increases attention to one's account. In turn, higher attention leads to higher risk-adjusted returns and lower volatility (Gargano & Rossi 2018). Moreover, the salient graphical target depiction, which the robo-advisor computes automatically, reduces the cognitive costs of assessing whether and to what extent portfolio allocations deviate from an optimal benchmark. This drop in the cognitive costs of elaborating the optimization problem and mapping the solution into an investment action reduces investors' inertia in financial decision-making and leads to more frequent portfolio rebalancing, which induces higher risk-adjusted returns relative to unassisted portfolios. Bianchi & Brière (2021) find that the benefits of robo-advice are higher for investors holding smaller portfolios and displaying lower stock market participation before adoption, which presumably represent less wealthy and lower-income employees. Reducing cognitive costs through robo-advice thus has the same potential distributional consequences as reducing monetary transaction costs—it encourages participation and wealth accumulation by more vulnerable households.

Psychological costs for households facing financial and economic decisions, including anxiety and fear of disappointment in case of bad outcomes, are nonnegligible (Sweet et al. 2013). Gennaioli, Shleifer & Vishny (2015) model the money doctor role of financial advisors, who reduce psychological costs and lead investors to take on more risk, and Linnainmaa et al. (2022) provide empirical evidence in microdata consistent with this model. In Section 4.1, we interpreted the fact that households have a high WTP for robo-advice for debt management relative to the monetary benefits they obtain from switching to robo-advice as evidence of households' awareness of their own biases (Chak et al. 2022). A nonbeliefs-based interpretation is that households might correctly assess their ability to find optimal debt repayment strategies, but the cognitive and psychological costs to do so lead them to be willing to overpay to obtain an automated robo-advisor and avoid facing the problem altogether.

5. OPEN QUESTIONS

5.1. Learning From Robo-Advice

Whether households learn about their biases and how to correct them after being exposed to robo-advice is a wide-open question and one that has important policy implications. With learning, access to robo-advice would not need to be repeated over time, and robo-advisors' role of transforming households into standard economic decision-makers would be quite effective. The effectiveness of robo-advice would be enhanced if it produced spillover effects of learning about biases and how to correct them across areas of economic decision-making. In this sense, robo-advice could be interpreted as a means of delivery of financial literacy, which, contrary to traditional financial literacy programs, is cheap: It does not require recruiting and paying instructors, investing time by users, or facing cognitive costs when trying to apply abstract principles to real-world choices. Instead, users learn by imitation during a time they would have anyway spent making (often flawed) economic choices.

This question is still open because most empirical settings so far include short time series: Robo-advisors, especially in areas different from portfolio management, have only recently started to diffuse. Currently, the evidence for learning is mixed. For instance, Chak et al. (2022) and D'Acunto, Ghosh & Rossi (2022) do not detect any learning from robo-advice by households in either debt management or peer-to-peer lending choices, but Hao et al. (2022) do find evidence of spillover effects of robo-advice-based corrections in investment strategies to nonadvised portfolios by the same households. Bianchi & Brière (2021) find that robo-advice for retirement investments increases households' attention to their own accounts and to trading strategies, which in principle could also improve performance in nonadvised investment accounts, which are unobserved to the econometrician.

More research is warranted to understand whether the conflicting results in the literature arise because of studying different economic problems, some of which might be easier to solve than others in different institutional settings, or because of other reasons. Empirical research needs observational data in which multiple financial accounts of the same household are observed, of which only some are robo-advised, and ideally, the assignment to robo-advice is quasi-random across accounts and within the household. Alternatively, research could use settings in which researchers observe repeated choices by the same user of the same account, for which robo-advice is intermittently available, so that one could assess whether exposure to robo-advice lets users learn about biases and correct them. More experimental research would help isolate the potential mechanisms through which households learn from the transactions from one part of their balance sheet to other parts, if at all.

Economic preferences are another dimension that could be affected by learning from the information gathered through robo-advice but that has been largely neglected by the existing literature. As we discussed in Section 3, most existing work on the information provided to consumers via robo-advice has focused on agents' beliefs. In principle, though, robo-advice could shape users' preferences, too. For instance, learning about the effects of diversification on a portfolio's expected returns and volatility might change users' risk appetite and hence their choices under risk. Research that can disentangle effectively the roles of learning from robo-provided information in consumers' preferences and beliefs would provide a substantial contribution to our understanding of the consequences of the diffusion of robo-advice around the world.

5.2. Algorithmic Aversion Versus Appreciation and Inequalities

The drivers of robo-advice adoption are not yet well understood. Whereas research designs on the effects of robo-advising on choices aim to obtain quasi-exogenous variation in the provision of

robo-advice across observationally similar households, the extensive margin of choosing whether to adopt is important to assess the aggregate effects of robo-advice. Most existing research based on randomized treatment with robo-advice finds that the less sophisticated households benefit most because their unassisted choices typically depart more from standard neoclassical predictions. Less sophisticated households, though, are less likely and slower to adopt new technologies due to a lack of awareness, distrust in unknown applications, and other reasons (Foster & Rosenzweig 2010). If true also for the adoption of robo-advice, the heterogeneous effects on performance conditional on adoption would be counteracted.

Existing research provides mixed evidence for the existence and heterogeneity of distrust toward algorithms (algorithmic aversion) (Dawes 1979). In principle, this form of distrust could have several sources, including the lack of direct access and communication with a human and/or the lack of skills needed to understand robo-advising processes (Rossi & Utkus 2020a). Rossi & Utkus (2020b) survey a large representative sample of traditionally advised, robo-advised, and unadvised households and find that algorithmic aversion is the main predictor of robo-advice adoption. They also show that aversion varies dramatically across age groups and other demographic characteristics. Ramadorai et al. (2022) estimate a structural model that captures interactions between human clients and hybrid robo-advisors that offer different forms of human counseling to complement a robo-manager. The model features three dimensions of algorithmic aversion: a per-period disutility of dealing with the algorithm, pessimism about the algorithm's ability to manage assets, and uncertainty about the algorithm's performance. The authors find evidence that algorithm aversion is driven mainly by ongoing disutility and uncertainty and that human advice is important especially to retain households invested in equities during market downturns.

At the same time, a strand of research in social psychology argues that some households in fact display forms of algorithmic appreciation—they prefer to rely on algorithms more than humans when making decisions. Logg, Minson & Moore (2019) find that decision-makers are more adherent to advice when they know it comes from an algorithm rather than a human, and this is true also for forecasts of choices based on human taste. Algorithmic appreciation is higher for decision-makers who are not used to making forecasts in their daily lives and lower for those whose occupations involve making forecasts.

Understanding the conditions under which algorithmic aversion or appreciation arises allows for assessing whether robo-advice could reduce rather than increase wealth inequalities. Algorithmic aversion reduces the adoption of robo-advice, which could exacerbate differences in outcomes across the wealth and education distributions if more vulnerable households were more algorithmic averse. Algorithmic aversion could produce new types of inequalities, such as across age groups. Understanding the drivers of algorithmic aversion would also help inform the design of next-generation robo-advisors.

5.3. Supply-Side Incentives: Financial Institutions Versus Third Parties

This article has focused on the effects of robo-advice on human decision-making from the users' point of view, but the extent to which the incentives of the suppliers of robo-advice services might affect the characteristics and consequences of robo-advice is also an important open question.

Applications studied in the literature as well as existing commercial applications in the field are provided either by financial institutions, such as banks and credit card companies, or by third parties whose main business aim is the provision of robo-advice. In several applications, financial institutions face a trade-off that third-party providers do not face: On the one hand, catering to users who display behavioral biases in decision-making increases their revenues and profits. For instance, credit card companies benefit from the fact that users do not fully repay their balances at

the end of each cycle and end up paying high interest and potential late fees. Consistently, credit card companies screen for clients' behavioral biases to exploit them (Ru & Schoar 2018) and might design consumer contracts in ways that attract biased clients (DellaVigna & Malmendier 2004). On the other hand, excessive accumulation of credit card debt (and hence of prospective interest and fee payments) could drive households to default, which would be detrimental to providers in terms of missed revenues and regulatory concerns. Contrary to financial institutions, third parties do not face a direct benefit from maintaining households' biases in decision-making, because they do not earn the interest and fees households pay on their accounts. If anything, the business model of third parties often relies on sharing the benefits from robo-advised choices with users based on fees that are directly proportional to users' outcomes, which aligns the incentives of the supply and demand sides.

To date, despite the importance of these differences, research on whether and how the nature and incentives of the providers of robo-advice shape its design and effectiveness is scant. Moreover, the effects of the market for control of FinTech applications on the diffusion and effectiveness of robo-advice, whereby the shareholders of third-party providers might have incentives to exit their equity investment through sale to financial institutions rather than market-based diffused ownership (Wang 2018), are an interesting and open topic for future research.

5.4. Broader Implications for Economics and Society

We conclude this article by discussing a set of broader implications of robo-advice that beget further research in economics, finance, social psychology, sociology, law, and other fields.

In terms of broader implications for economics, this article has advanced the view that robo-advice can be a disruptive feature for decision-making in that it can transform biased and inexperienced households into agents that form beliefs and act in line with standard neoclassical models. This feature could have an important impact on the direction of future research in economics. After developing standard neoclassical models in microeconomics and macroeconomics, the field of behavioral economics has documented many ways in which decision-makers in the field and the laboratory depart from the assumptions of such models. These results have fed back into the original strands of neoclassical economics and have motivated new generations of microeconomic and macroeconomic theories that incorporate features of decision-making documented in the field into representative- and heterogeneous-agent models in order to make the predictions of such models more realistic and to produce further testable implications that would not arise in standard models. As robo-advice diffuses more and more widely, though, traditional standard neoclassical models, based on which robo-advisors are designed, could increase their explanatory power for empirical patterns given that agents behave more in line with standard assumptions. Understanding whether and how endowing households with robo-advice could make standard models more predictive of observed outcomes and hence revive their relevance in an open agenda.

Moreover, robo-advice could be used as a potential solution to the lack of effectiveness of economic policies that require active choices by households to be fully transmitted to the economy. Households' biases often reduce the aggregate effects of policies simply because many households that could act in a way that increases transmission (and would benefit from doing so) are unaware of or do not understand policies—they act as human frictions in the transmission of policy (D'Acunto, Hoang & Weber 2022). Research in macroeconomics and finance has studied a set of potential solutions, such as policy communication (D'Acunto et al. 2020), the design of simple policies (D'Acunto et al. 2022), and an increase in trust and attention to policy institutions (D'Acunto, Fuster & Weber 2021), to limit the effects of human frictions. Robo-advice could be a cheap and effective means of transmission of policy: Most households around the globe can be accessed directly via personal devices.

Finally, an important trade-off that crosses several fields of research and begets further inquiry is the tension between freedom in individual decision-making and designing instruments that allow for socially optimal economic choices. Although existing research is still limited, as we have argued in this article, the evidence so far seems to suggest that robo-advice has the potential to align households' incentives with those of standard decision-makers, which might make policy design and aggregate outcomes more efficient. At the same time, the nature of algorithmic advice, which often does not include explanations to households or provides explanations that many households cannot understand, requires that households follow and accept its suggestions often without a full understanding of them. Over time, robo-advice could create conformity and dependence on algorithmic indications, which, when paired with a lack of understanding of such indications, might reduce critical thinking, induce social conformity, and reduce heterogeneities in preferences and beliefs across individuals, which could have far-reaching implications across many aspects of social life. Understanding this potential trade-off and assessing its prevalence and potential relevance are two of the most important open questions in this area.

6. CONCLUSIONS

Robo-advice has the potential to transform households that display a set of biases and suboptimal decision-making processes across a wide range of economic problems into standard economic agents by providing them with a fully informed and rational-expectation benchmark that can be implemented cheaply and that can barely be provided by human advisors.

In this article, we have emphasized that research on robo-advice is still in its infancy and we have proposed open questions to develop this agenda in the direction of better understanding whether, how, and why robo-advice might achieve the goals indicated above. We have also argued that robo-advice could decrease or widen wealth inequalities across a set of demographic dimensions. Understanding this trade-off is an important area for future inquiry and one that speaks to the policy implications of all the open questions we have indicated in this article.

Making researchers realize that robo-advice is not a mere FinTech application to the allocation of households' investment portfolios, as the media and normal parlance suggest, but rather a potentially transformational force across most dimensions of individual economic decision-making that has consequences for empirical and theoretical research across several fields of economics and finance is the main message coming from this nascent literature.

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