Economy and Society Volume 49 Number 4 2020: 1–34
https://doi.org/10.1080/03085147.2020.1782054

Enacting a rational actor: Roboadvisors and the algorithmic performance of ideal types

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Abstract

Weber famously invoked 'ideal types' as an analytic device with which to measure empirical reality against some hyper-rational fabrication. Case in point: non-professional (lay) investors appear to be the antithesis of rational economic man. They have been cast as less-informed, less-skilled, and less-knowledgeable than professional market practitioners, and with ample evidence that they tend to lose money in the market as a result. This study builds the case that a new class of algorithmic financial advisor, commonly known as 'roboadvisors', enacts lay investors as rational market actors. This is achieved through algorithmic devotion to modern portfolio theory (MPT), which the roboadvisors embody, automate, and perform, conjuring some version of *Homo economicus* into existence. Through this example, I show how Weberian ideal types and the particular kind of rational action associated with them (e.g. the ideal type investor) become the very empirical reality they were intended to be a foil to – accomplished through the technological articulation of financial models, even in the hands of ordinary individuals.

Keywords: rationality; ideal types; performativity; non-professional investors; financial markets; economic sociology.

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In *Economy and society*, Max Weber (1978 [1922], p. 6) establishes that,

> for the purposes of scientific analysis it is convenient to treat all irrational, affectually determined elements of behavior as factors of deviation from a conceptually pure type of rational action … it is then possible to introduce the irrational components as accounting for the observed deviations from this hypothetical course.

For Weber, and much of the sociological tradition that has followed, the concept of an *ideal type* has been a fictive construction of the analyst, useful for comparative purposes to study (for Weber: *verhesten*) how the social world and the actors within it actually function. Portes (2010, p. 4) describes this as 'rubbing the ideal type against reality' in order to advance social science. Or, as Swedberg (2018, p. 188) endorses, 'you need to confront the ideal type with reality'. Invariably, there is a clear separation between that which is 'ideal' and that which is observed in the world. To be sure, Weber (1978 [1922], p. 7) counsels that ideal types are not meant to define some normative, optimal reality, 'but [used] only as a methodological device'.[1]

Weber (1978 [1922]) particularly singles out the concepts and 'laws' of standard economic theory as the paradigmatic example of an ideal type.[2] These formulations, he states,

> are what course a given type of human action would take if it were strictly rational, unaffected by errors or emotional factors and if, furthermore, it were completely and unequivocally directed to a single end, the maximization of economic advantage. (Weber, 1978 [1922], p. 9)

The ideal type economic actor would have to be instrumental, calculative, and conscious of his actions.[3] Indeed, for Weber the rational economic actor, which he describes not as human but a '*homo oeconomicus*' (Weber, 1978 [1922], p. 599), does not exist as an empirical subject and would only be glimpsed under 'unusual cases, as sometimes on the stock exchange; and even then there is usually only an approximation to the ideal type' (Weber, 1978 [1922], p. 9). Lopreato and Alston (1970, p. 89; emphasis added) similarly reason, 'by virtue of the very meaning of the ideal type, we are left with deliberate distortions of reality. The outstanding feature of ideal types is that *they literally describe nothing beyond mere logical possibilities*'.

With the advent of new algorithmic processes, however, Weberian ideal types may indeed come into being – manifest in cooperation with technology, no longer fashioned for analytical purposes but for practical effect. Even as human beings remain fallible and systematically irrational in the realm of economic action (made plain in the abundant literature in behavioural economics), the notion of an assembled ideal type has cropped up from time to time –

though it has never before been an empirical reality. Marcel Mauss in 1960 commented that:

> *Homo economicus* is not behind us, he is ahead of us: like the moral and dutiful person; like the person of science and of reason. The person has long been something else, and only recently has the person been a machine, complicated by a calculator.

Similarly, Michel Callon (1998, p. 22) made the notable assertion:

> yes, *Homo economicus* does exist, but [he] is not an a-historical reality; he does not describe the hidden nature of the human being. He is the result of a process of configuration … He is formatted, framed and equipped with prostheses which help him in his calculations, and which are, for the most part, produced by economics.

These pronouncements by Mauss and Callon have yet avoided detection. The role of technology in financial markets has certainly garnered a great deal of scholarly attention in recent years, with empirical work on the materiality and technicity of financial markets emerging from the social studies of finance tradition, where it has focused largely on traders located in Wall Street banks, trading rooms, or hedge funds (e.g. Beunza & Stark, 2004; Knorr-Cetina & Bruegger, 2002; MacKenzie, 2018; MacKenzie & Millo, 2003). These studies have highlighted both the influence and equivocality of calculative finance cultures, formal and informal financial models, regulatory regimes, electronic markets, and various trading algorithms (especially those used high-frequency trading [HFT]) in concert with professional market practitioners. A major conclusion in this literature is that the human beings working in finance are decidedly *not Homo economicus* – as MacKenzie and Spears (2014) make clear, traders and 'quants' are not 'model dopes'. Svetlova (2012, 2018, p. 420), too, shows that despite their technological systems, market practitioners significantly undermine the performative power of economic models through tinkering and second-guessing: '[models] are manipulated, regularly overruled by humans and used … simply [as] channels to transmit financial actors' judgements into numbers'. Even in the highly quantitative and arcane world of high-frequency trading, traders become emotionally attached to the algorithms that they design and code (Borch & Lange, 2016).

Homo economicus may still be upon us, emerging not out of Wall Street trading rooms but from the portfolios of ordinary investors. In this paper, I examine a new class of financial technologies known colloquially as the 'roboadvisors', which are already enrolling ordinary individuals as investors. These are a new class of digital financial advisor that provides advice and automated investment management online with minimal human intervention, at little cost. Roboadvisors provide these services via algorithms that automatically allocate, manage, and optimize clients' assets based on personalized information

entered through a website or mobile app, after which time users are obliged to set-it-and-forget-it (Hayes, 2019). Through their efforts, roboadvisors figure outcomes that a rational actor (i.e. the ideal type investor) would achieve.

The type of ideal type that is conjured by the roboadvisors is novel. Like Weber's definition, they constitute a type of meaningful action (i.e. investment choices and trading decisions) where the meaning is explicitly and singularly oriented to maximizing investment returns.[4] But, unlike Weber's understanding of *Homo economicus, this* action is not sentient in the minds of investors – nor is it otherwise governed by impulse, habit, or half-consciousness. It is instead automated at a distance by the roboadvisors' algorithms, which embody and perform a family of economic models under the heading, Modern Portfolio Theory (MPT).

Based on autoethnographic study of actual roboadvised accounts, I analyse the investment decisions made on my behalf to describe how such a Weberian ideal type emerges through the specific articulation of human beings, algorithmic processes, and template models (e.g. MPT*)*. The methodological premise of this paper is therefore to confront the ideal type investor as empirical fact. This is not to imply that I (or any other user of roboadvisors) was personally transformed into a rational actor through my engagement with these platforms. On the contrary, if asked to pick my own investments or run the necessary calculations alone I would surely fail. The ideal type that emerges is *synthetic*. Without the proper model to follow and algorithms to automate and execute those tasks the ideal type cannot be formed. At the same time, I (the user) became a necessary component, providing the inputs required by the model's equations and the money for the algorithms to invest. One way to think about this association is that the user provides the scaffolding upon which the ideal type is assembled, the model contains the blueprints, and the algorithms afford the machinery that carries out the work.

Broadly, the substantive insights from the case of roboadvisors can map on to other instances of algorithmic optimization in modern-day practice; for instance (to name just two): self-driving vehicles that enact ideal type (i.e. shortest time or shortest distance) driver-navigators. Or, in medical settings where physicians and nursing staff are increasingly reliant on precise diagnostic and treatment decisions rendered by algorithmic systems – these invoke ideal type clinicians that rival 'Dr. House'. With an autonomous car, the 'driving' depends on map route optimization models which, in turn, rely on the starting point and destination desired by the specific user of the vehicle. For a physician, the 'diagnosing' falls on machine learning techniques that detect and identify patterns or aberrations, but only based off the medical records and tests of a particular patient. With a roboadvisor, an investor brings his or her particular risk tolerance, financial goals, and time horizon. Thus, there is no *single* ideal type investor, driver, or physician, but a plurality – they are not enacted in a wholly uniform way.

More specific to economic sociology, the ideal type investor brought about through roboadvisors contributes an empirical case of strong, or 'Barnesian'

performativity (MacKenzie, 2006, p. 18), where 'the practical use of an aspect of economics makes economic processes more like their depiction by economics'. Because models of financial economics require the theoretical assumption of rational actors, when such models are embodied and performed by the roboadvisors' algorithms this assumption is fulfilled in practice. This is a particular case where the model performs the actor (or some version thereof), rather than actors performing market prices through the widespread use of a model (cf. MacKenzie & Millo, 2003); that is, the roboadvisors select the investments that theory postulates as optimum.[5] However, the 'actor' in this case is not (just) the human end-user, whose role is simply to set the stage – the model here is performative through the instantiation of the ideal type based on that actor (i.e. it is the *assemblage in toto* that is the rational actor). Everything outside of the raw materials needed for the 'scaffold' (i.e. risk tolerance, time-horizon, money to fund the account), including financial acumen but also emotions, social relations, and personal history is excluded and is indeed irrelevant to investors' outcomes. In fact, ignorance could presumably thrive because one can always rely on their algorithms for optimal results rather than obtaining financial literacy (or e.g. learning how to read a map, or diagnose patients). It describes a logic where individuals appear to be always calculative yet never themselves calculating.

In what follows, I first recover the ideal type investor and establish how that idealization is defined by the specifications of MPT. This ideal type is then confronted with the empirical reality of ordinary investors' behaviour. Next, I introduce the roboadvisors as an empirical object, illustrating how they operate, and importantly that as a group they perform MPT. This is an important descriptive step that reinforces the particular ideal type investor the roboadvisors specify. I then set out my methodological approach used to analyse the portfolio recommendations of 20 North American roboadvisors framed in reference to the optimal choice dictated by MPT. I conclude with a general discussion that explores this type of ideal type performed by algorithmic systems, and allude to some broader implications for the economy and society.

Investors vs. *Homo economicus*: An exercise in comparing with an ideal type

Constructing ideal types

Despite being a foundational concept in classical sociology, Weber's (sociological) ideal type-as-analytic device has been dismissed by some contemporary social scientists (Biernacki, 2012; Hekman, 1983), and as Swedberg (2018, p. 181) reflects, seldom been used in empirical research (but cf. Portes, 2010).[6] In a recent paper, Swedberg (2018) advances a renewed interest in Weberian ideal types as a valuable tool for sociological use, stating: 'It is now more than a century since Weber created the ideal type; and hopefully, the

time has come when we will start using it' (Swedberg, 2018, p. 192). He proceeds to offer a practical guide for how to construct and use an ideal type in contemporary analysis, which is what I undertake at the outset in this section – identifying and contrasting the ideal type investor with real investors.

According to Weber (1978 [1922]), and following Swedberg (2018, pp. 188–189), the first step in constructing an ideal type is to pinpoint the element of social action in the object of study, 'that is, on the behavior as well as the meaning with which this is invested'. For my purposes, such action is oriented to the capital markets, and the invested meaning is indeed with selecting *investments*: acquiring and maintaining an optimal portfolio of securities. The meaning of this action is decidedly *instrumentally rational*.[7] Second, and relatedly, Weber tells us that there needs to be some identifiable course of action that fits, or possesses 'adequacy', with that meaning. For investing, that course of action is defined by a process of 'mean-variance optimization', first formalized through MPT (Markowitz, 1952). This process and theory of investment selection are discussed in the following subsection.

Once we have defined the way of going about the meaningful action, four assumptions must be made about the ideal type actor as he or she engages in that action: (1) they are calculative; (2) they have full information; (3) they are fully aware of what they are doing; and (4) they make no mistakes. Next, 'causal adequacy' should be ensured. That is, following the prescribed course of action 'should lead to the sought effect in a probable and decisive way … The action, in brief, should be of such strength that it leads to the intended result' (Swedberg, 2018, p. 188). For an ideal type investor, following MPT should consequently result in choosing the *one* best portfolio that will optimize risk versus return.

Once the ideal type has been constructed, it is to be compared with the phenomenon of interest. Differences and conflicts between the ideal type and the empirical subject – e.g. between the mean-variance optimizer and the lay investor – are then identified and measured. In what follows, I corroborate the way that MPT provides a normative framework for developing the ideal type investor, and then proceed to set that in contrast with real-world investors. Afterward, I will compare this ideal type with the investments managed by roboadvisors to argue that these do approach rational outcomes.

The ideal type investor: MPT

MPT is a calculative approach to investing first introduced in 1952 by Harry Markowitz in a paper modestly titled, *Portfolio selection,* for which he would later earn the Nobel Prize in economics. His work took the concept that diversification could enhance portfolio return while reducing overall risk (i.e. 'don't put all of your eggs in one basket') and formalized it into a *theory* of investment that 'covered the effects of diversification when risks are correlated; distinguished between efficient and inefficient portfolios; and analysed risk –

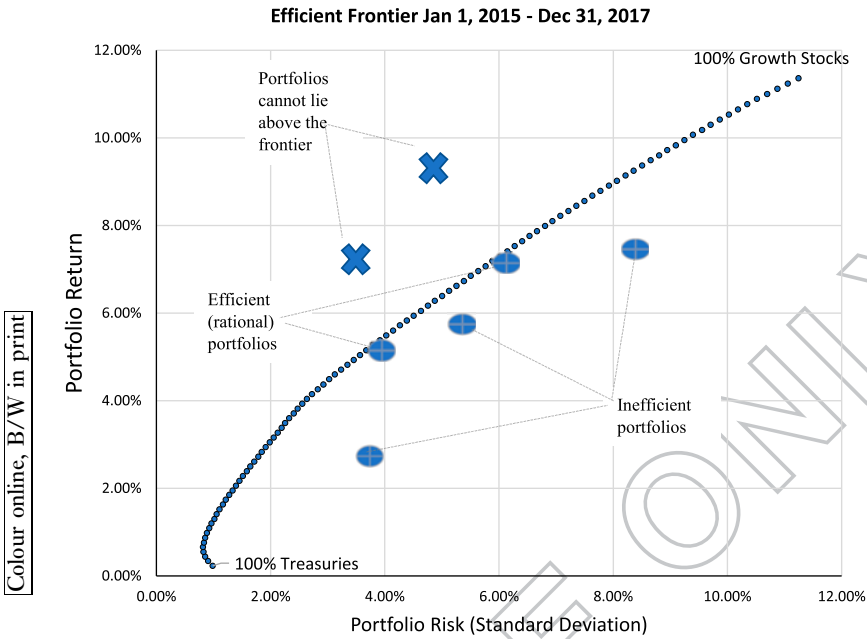
return trade-offs on the portfolio as a whole' (Markowitz, 1999, p. 5). In an overview of the principles of MPT, Kaplan (1998, p. 267) explains that Markowitz, 'identified the trade-off facing the investor: risk versus expected return. The investment decision is not merely *which* securities to own, *but how to divide the investor's wealth amongst securities*' (emphasis added). Simply put, MPT instructs how investment dollars should be allotted to the purchase of various stocks, bonds, and other assets.[8]

Markowitz (1952) discriminated between so-called 'efficient' and 'inefficient' portfolios based on whether or not some alternative asset allocation theoretically exists that would provide a greater expected return (the portfolio's mean) given the same level of risk (the portfolio's variance). An *efficient* portfolio is one that has undergone a process of mean-variance optimization, so that no other such allocation exists. For a particular level of risk (i.e. portfolio variance), MPT provides the solution for the allocation weights that would construct an efficient portfolio – and so an 'efficient frontier' can be designated that classifies the entire 'set of efficient mean–variance combinations' across all risk preferences (Markowitz, 1952).

Figure 1 illustrates the historical efficient frontier from the period 1 January 2015 through 31 December 2017.[9] Note the parabolic shape representing the set of theoretically optimal portfolios that offer the highest expected return for a defined level of risk (or, alternatively the lowest risk for a given level of expected return), as determined by MPT. Portfolios that lie below the efficient frontier are sub-optimal because there exists a different portfolio allocation that will provide more expected return for the same risk. No possible allocation exists that will plot above the frontier.

Thus, an investment strategy that allocates portfolios according to MPT's direction is a maxim for *the choice that a rational actor would employ*. Although he makes no mention of sociological theory, Markowitz had, in fact, specified the Weberian ideal type investor. To be sure, Markowitz (1959, 1999, p. 9, emphasis added) underscored that MPT 'applies to an *idealized rational decision maker* with limited information but unlimited computing powers and is *not necessarily a hypothesis about actual human behavior*'; and moreover that, 'its objective was to provide a theoretical foundation for portfolio analysis as a practical way to approximately maximize the derived utility function of a rational investor'. James Tobin (1958), a contemporary of Markowitz also working on portfolio choice at the time disparaged that MPT's 'main interest is prescription of rules of rational behavior for investors'. Beyhaghi and Hawley (2013, p. 21) in a more recent reflection on Modern Portfolio Theory similarly point out that 'the rational investor assumption ('*homo economicus*' that is utility-maximizing and calculating) is the basis for … MPT'.

Accordingly, MPT is a framework that defines and enumerates a meaningful course of action: how to go about optimizing portfolio choice. It furthermore makes the required assumptions that the MPT investor is rational, informed, and calculating. The MPT investor is fully aware not only of the calculations but of the investable universe of securities from which he can choose, and



Colour online, B/W in print

Figure 1 The efficient frontier and efficient vs. inefficient portfolio allocations.
Note: The curve formed by the solid dots represent the historical efficient frontier over the 3-year period 1 January 2015 through 31 December 2017, which represents the set of optimal portfolio possibilities that offer the greatest expected return for a defined level of risk (or, alternatively the lowest risk for a given expected return), defined by Modern Portfolio Theory (MPT). Portfolios that lie below the efficient frontier are sub-optimal because there exists an alternative portfolio configuration that provides a greater expected return for the same level of risk. No portfolios exist that can fall above the efficient frontier. Efficient frontier data points.
Source: www.portfoliovisualiser.com

following the process of mean-variance optimization arrives at the precise mix of securities to produce an efficient portfolio.

Real-world investors

Before proceeding, it is beneficial to clear up one focal point of terminology: As Preda (2017, p. 57) rightly calls attention to, being an *investor* is not the same as being a *trader*. Indeed, MPT is the axiomatic strategy for a long-term (buy-and-hold) investor and *not* that of an active trader – and so, it would be a false equivalence to construe the likes of Wall Street trading desks, HFT shops, or retail 'noise traders' with investors, lay or otherwise (however, the ideal type trader might indeed be brought about through different financial models and e.g. HFT algorithms). To clarify the syntactic distinction, a trader is one who actively buys and sells securities in order to generate short-term profits, while

an investor intends to hold securities over extended time horizons in order to enjoy long-term capital gains.

As with any ideal type, the MPT investor described by Markowitz and his colleagues was never intended to exist. Undeniably, behavioural economics has revealed time and again that people *do not* maximize, rather they follow a set of heuristics or mental shortcuts in an attempt to satisfice (Simon, 1978). Moreover, people are subject to cognitive errors and the vexing sway of emotions (DellaVigna, 2009), herding behaviour (MacKenzie, 2006), and inconsistent preferences (Kahneman & Tversky, 1979) when it comes to economic decision making.

Even without such limitations, the number of complex calculations required to identify an optimized asset allocation (the complexity of which compounds as more asset classes are considered), pinpoint the ideal securities used to represent each asset class, and assess an individual's true risk tolerance are beyond the ability of most individuals as well as the scope of free, web-based investment tools. The process becomes even more intractable in view of the fact that maintaining an efficient portfolio demands continuous monitoring and periodically rebalancing a portfolio to sustain the optimal allocation as markets move. It is unlikely that *any* investor, no matter how knowledgeable or disciplined, can compute and re-compute such calculations on their own. To be sure, in a detailed evaluation of how investments are selected in real-world retirement plans in the United Kingdom and the United States, Benartzi and Thaler (2007, p. 81) demonstrate that households do not have the cognitive ability to solve the necessary optimization problem; and that even if they did, households lack sufficient willpower to execute an optimal plan.

Preda (2017, p. 241) portrays lay market participants in comparison to experts as 'less-informed, less-skilled, and less-knowledgeable'. Similarly, Chen and Roscoe (2017, p. 577) describe the lay investor as the 'counterfactual to the expert practitioner' (also see Roscoe & Howorth, 2009; Weiss, 2018), casting non-professional market participants as caught in an unfortunate double-bind of 'irrationality'. On the one hand they are at the mercy of detrimental emotional and cognitive errors such as those identified by behavioural economics (e.g. Barber & Odean, 2000; Barberis & Huang, 2001; Benartzi & Thaler, 2007; DellaVigna, 2009), which leads to overconfidence, reluctance to sell losing positions, and an inability to learn from past mistakes. On the other hand, recent work has argued that ordinary individuals are furthermore caught up in a web of institutional relations and cultural expectations that encourage market participation through discursive techniques that promote both self-reliance and success through competition – e.g. marketing campaigns directed at maintaining individual retirement accounts or personal finance 'classes' for lay investors (Weiss, 2018). Roscoe (2015) suggests that lay market participation is produced by investment services firms that construct docile and productive consumers, where 'the investor becomes self-entrepreneur, … manager of his/her own capital, and foundational member of the social contract under neo-liberalism'. Likewise, Preda (2017) argues that the institutional logics of

securities markets *require* the reproduction of uninformed market participants to sustain the system as an ongoing profit-center for professional participants, where the non-professional has little hope of making any money.

It seems that ordinary investors are woefully ill-equipped to enjoy financial success, and yet they are constantly lured to the market. Empirical evidence is abundant for the actual underperformance of lay actors: Several studies in the behavioural economics literature show that ordinary individuals consistently make 'irrational' decisions that lose them money, either in experimental set-ups (e.g. Fehr & Gächter, 2000; Kahneman & Tversky, 1979; Mullainathan & Thaler, 2000) or from observational data obtained from brokerage records (e.g. Benartzi & Thaler, 2007; Grinblatt & Keloharju, 2001; Hoffmann *et al.*, 2013; Odean, 1998). In one study of 70,000 self-directed individual brokerage accounts, the average investor's return for the year 2016 lagged the S&P 500 index by more than seven percentage points.[10] Another, which considered the 20-year period ending 31 December 2015, reported that the average investor earned 4.66 per cent less each year (on an annualized basis) than the market index.[11] The report concludes that, 'behavioral biases that lead to poor investment decision-making are the single largest contributor to underperformance over time'. The lay investor thus appears to be the antithesis of rational economic man.

Yet, professional investors, too, fail to live up to the ideal type. Malkiel (2005, p. 1), for instance, shows that mutual fund managers, both in the United States and abroad, consistently underperform their benchmark index, with Swensen (2005) showing that between 86 and 95 per cent of actively managed mutual funds did not fulfil their goal of beating the market on an after-tax basis throughout the 2000s. More recently, Soe and Poirier (2017) find that over the fifteen-year period ended 2017, only about 8 per cent of professionally managed portfolios were able to outdo their benchmarks. After accounting for taxes and trading costs, the number of successful funds drops to just 2 per cent. Several other analyses report similar findings (e.g. Cremers, *et al.*, 2016; Fama & French, 2010). '[Professionals] in financial markets might seem to fit the economist's ideal type of decision-maker, using an extraordinarily rich flow of information in the unbridled pursuit of gains', writes Abolafia (1998); 'nevertheless they are cognitive and social beings, and as a result, imperfect information processors who are susceptible to habit, custom, and the institutionalized myths of trading' (see also MacKenzie & Spears, 2014; Svetlova, 2012). The evidence is extensive and compelling that ideal type investors do not naturally reside in financial markets.

The roboadvisors

In 2010 a technology start-up called Betterment launched as the world's first roboadvisor, a new class of digital financial advisor that provides advice and automated investment management online with minimal human intervention,

at little to no cost. Roboadvisors provide these services via algorithms to automatically allocate, manage, and optimize clients' assets based on personalized information that each client enters through a website or application (Hayes, 2019). This is achieved through the prolific use of algorithmic processes that serve the end goal of performing MPT, an emblematic model of financial economics that describes how an investment portfolio should be allocated to optimize expected return for a given level of risk. Through automating investment decisions and algorithmic devotion to MPT, roboadvisors remove the cognitive and emotional biases identified by behavioural economics.

Broadly, roboadvisors also represent an improvement in client financial advice over human advisors. Mullainathan *et al.* (2012) find in an audit study that financial advisors fail to de-bias their clients and often reinforce certain biases that serve their own interests. They find that advisors furthermore encourage returns-chasing behaviour and push for actively managed funds that carry higher fees, regardless if a client starts with a well-diversified, low-fee portfolio. Even when unbiased financial advice is made available, lay investors are reluctant to listen. In a field experiment, Bhattacharya *et al.* (2012) show that investors who most need the financial advice are least likely to obtain it; and, among the small number of investors who do obtain the advice (about 5 per cent in their study) hardly any follow it and they do not improve the efficiency of their portfolios. Calcagno and Monticone (2015) add to these findings, showing that more knowledgeable investors are more likely to consult advisors, while less informed ones invest by themselves.

Roboadvisors are particularly attuned to lay investors, explicitly courting 'low-affluence' clientele to acquire an individual's first investible dollar (Hayes, 2019). Indeed, several roboadvisors require as little as $1 to open an account and charge a modal fee of just 0.25 per cent per year of assets under management (AUM). Compare this with the 1 per cent or more of AUM charged by human advisors, who typically require opening account balances of five, six, or even seven figures, effectively excluding large numbers of potential investors in need of advice or professional portfolio management.

Over the past several years the number of roboadvisors has increased to several hundred worldwide (Kocianski, 2016), with startups competing with financial incumbents like Vanguard, Schwab, and TIAA-CREF who are building out their own offerings. At the same time, the amount of assets under 'robo' management constitute a large and fast-growing segment of the market. As of 2018, roboadvisors collectively managed more than half a trillion dollars of client money representative of nearly 26 million accounts.[12] According to industry forecasts, this sum will grow to more than $2 trillion by the year 2020, and by 2025 it is estimated that in excess of $7 trillion globally will be managed by roboadvisors, making up an impressive 15 per cent of all retail investment (Srinivas & Goradia, 2015). Roboadvisors are *already* an important group of financial actors that work on behalf of ordinary investors, whose influence is likely to grow in the coming years – and which remains an under-studied sociological object.

It is important to my argument to show that the portfolios constructed for these tens of millions of roboadvised accounts predominantly follow the principles of MPT (Vukovic & Bjerknes, 2017), which, as shown above, prescribes the formula for producing the ideal type investor. Indeed, as I quote elsewhere (Hayes, 2019), the head of investments and strategy at one prominent roboadvisor emphasized: 'I think you can say robos' use of Modern Portfolio Theory, mean-variance optimization, … that we're making the argument that that's how you should be investing. That that is the model you should be using and it's the rational way to go about it'. Harry Markowitz himself sits on the academic advisory board at another.

Examining the websites and mandatory regulatory filings of 20 North American roboadvisors that represent a popular cross-section of the space, it is clear that MPT plays an important role in how they construct and manage client portfolios, the findings of which are summarized in Table 1.[13] Either MPT is used directly, or it is enhanced with additional optimization layers, or with the Black–Litterman approach that incorporates expert opinions of predicted asset class returns. In the empirical analysis below, I test how well roboadvisors do in performing MPT in practice, that is, how well they enact the ideal type investor.

Data and methodology

In order to determine if and to what extent roboadvisors enact ideal type investors in the framework of MPT, I first obtained the actual portfolio allocations of twenty popular North American roboadvisors by opening and funding accounts (listed in Table 1). The roboadvisors in my sample collectively represent roughly 90 per cent of the American roboadvisor market and represent the offerings of both start-ups and incumbent financial firms. I then use the MPT equations *in reverse* in order to back out each portfolio's objective risk and return, and how that would plot against the efficient frontier. This entailed becoming a participant-user to analyse the roboadvisors' asset allocation, selection, and optimization algorithms (see also: Hayes, 2019; Lange *et al.*, 2018). In addition, I conducted interviews with 28 well-informed roboadvisor executives, employees, or former employees, each lasting approximately one hour. Interviews were open-ended and followed a semi-structured format. Finally, I engaged in an extensive archival review of regulatory documents filed by the roboadvisors in my sample with the Securities and Exchange Commission's investment advisor public disclosure website.[14]

I established accounts at sixteen of the roboadvisors in my sample posing as both a hypothetical 55-year old and 35-year old with moderate risk tolerance (an older investor has a shorter time horizon and thus a lower objective risk tolerance). At four other roboadvisors I was unable to open a live account due to practical issues including larger account minimums than I could muster, but was nonetheless able to begin the account opening process and view what my proposed portfolio would be.[15]

Table 1 Roboadvisors' use of modern portfolio theory (MPT)

Roboadvisor	Uses MPT?	Excerpt
Acorns	Yes	'Acorns manages client portfolios in the Program with strategies based on Modern Portfolio Theory.'[a]
Ally Invest	Yes	'services are based on Modern Portfolio Theory ("MPT")'[b]
Betterment	Yes, w/Black-Litterman	'Betterment's asset allocation is based on a theory by economist Harry Markowitz called Modern Portfolio Theory'[c]
Covestor (Interactive Brokers)	Yes, w/Black-Litterman	'We use an approach that is guided by the Black-Litterman approach to portfolio construction.'[d]
Ellevest	Yes	'The asset allocations are based upon tenets of modern portfolio theory.'[e]
E*TRADE Core Portfolios	Yes	'E*TRADE Capital Management follows a disciplined investment strategy based on principles of modern portfolio theory.'[f]
FidelityGO	Yes	'The model portfolio construction process . . . when viewed as a portfolio, are designed to be similar to those of an appropriate asset allocation strategy for a particular risk profile of an investor.'[g]
Future Advisor (Blackrock)	Yes	'Our asset allocation strategy incorporates Modern Portfolio Theory, which suggests that investors should build portfolios that are as well diversified as possible among assets expected to provide positive long term return.'[h]
Honest Dollar (Goldman Sachs)	Probably	'The investment recommendation relies entirely on the responses you provide regarding your time horizon and risk tolerance.'[i]
Merrill Lynch Guided Investing	Yes, w/Black-Litterman	'We forecast long-term expected return, risk, and correlation assumptions for each asset class.'[j]
Schwab Intelligent Portfolios	Yes, w/Full Scale Opti-mization	'The optimized portfolio is equal to the average weights of the results from the mean variance optimization and full scale optimization.'[k]

(*Continued*)

Table 1 Continued.

Roboadvisor	Uses MPT?	Excerpt
SigFig	Yes	'SigFig creates portfolios matched to a range of risk tolerances through the Modern Portfolio Theory ("MPT") techniques'[l]
SoFi	Yes	'We use mean-variance optimization … rooted in the modern portfolio theory work of Harry Markowitz and others.'[m]
TD Essential Portfolios	Yes	'The asset allocation tactical asset allocation tool based on modern portfolio theory'[n]
TIAA Personal Portfolio	Probably	'the model portfolios are based on the portfolio management team's judgment of how different combinations of Funds can achieve exposure to each asset class targeted for a strategic asset allocation, while also limiting the correlation among the investments.'
Vanguard Personal Advisor	Probably	'methodology uses a strategic approach by first focusing on the mix of asset classes (i.e. stocks, bonds, cash) that align with your willingness and ability to take risk'[p]
Wealthfront	Yes	'Wealthfront Advisers offers an automated investment advisory service based on Modern Portfolio Theory'[q]
WealthSimple	Yes	'Using proprietary models and research based on Modern Portfolio Theory (MPT), Wealthsimple manages individually tailored Client portfolios through primarily a passive investment strategy'[r]
Wisebanyan	Yes	WiseBanyan's focuses on building fully diversified model portfolios while minimizing fees and tax consequences. This strategy is based upon Modern Portfolio Theory'[s]

Zack's Advantage	Yes	'Zacks Investment Management developed our own strategic approach for allocating assets within investment portfolios. The first step in the process is to apply the MVO (Mean Variance Optimization) within a portfolio based upon the Modern Portfolio Theory (MPT) of investing.'[t]

Notes:
a: https://adviserinfo.sec.gov/IAPD/Content/Common/crd_iapd_Brochure.aspx?BRCHR_VRSN_ID=530981
b: https://adviserinfo.sec.gov/IAPD/Content/Common/crd_iapd_Brochure.aspx?BRCHR_VRSN_ID=529386
c: https://www.betterment.com/resources/research/betterment-portfolio-strategy/
d: https://ibkram.com/white-papers/asset-allocation
e: https://adviserinfo.sec.gov/IAPD/Content/Common/crd_iapd_Brochure.aspx?BRCHR_VRSN_ID=531278
f: https://us.etrade.com/frequently-asked-questionstab_1
g: https://adviserinfo.sec.gov/IAPD/Content/Common/crd_iapd_Brochure.aspx?BRCHR_VRSN_ID=521166
h: https://www.futureadvisor.com/content/what-we-do/investment-philosophy/overview
i: https://help.honestdollar.com/hc/en-us/articles/360000091288-How-do-you-recommend-what-portfolio-I-should-invest-in-
j: https://adviserinfo.sec.gov/IAPD/Content/Common/crd_iapd_Brochure.aspx?BRCHR_VRSN_ID=531133
k: https://intelligent.schwab.com/public/intelligent/insights/whitepapers/asset-allocation.html
l: https://adviserinfo.sec.gov/IAPD/Content/Common/crd_iapd_Brochure.aspx?BRCHR_VRSN_ID=495038
m: https://adviserinfo.sec.gov/IAPD/Content/Common/crd_iapd_Brochure.aspx?BRCHR_VRSN_ID=516931
n: https://adviserinfo.sec.gov/IAPD/Content/Common/crd_iapd_Brochure.aspx?BRCHR_VRSN_ID=530900
Q1 *o:* https://www.tiaa.org/public/pdf/TIAA_Personal_Portfolio_Fee_Wrap_Program_Disclosure_Brochure_FormADV.pdf
p: https://personal.vanguard.com/pdf/vpabroc.pdf
q: https://adviserinfo.sec.gov/IAPD/Content/Common/crd_iapd_Brochure.aspx?BRCHR_VRSN_ID=530796
r: https://adviserinfo.sec.gov/IAPD/Content/Common/crd_iapd_Brochure.aspx?BRCHR_VRSN_ID=530234
s: https://adviserinfo.sec.gov/IAPD/Content/Common/crd_iapd_Brochure.aspx?BRCHR_VRSN_ID=493823
t: http://go.pardot.com/l/375142/2017-07-14/575bcj/375142/218333/ZA_white_paper1a.pdf

The first step in the account opening process is to complete a risk-profiling questionnaire to determine the appropriate level of portfolio risk (the x-axis on the efficient frontier). This provides the input that the MPT model requires to operate. Different roboadvisors approached this step in nuanced ways, however, all of them ultimately employ an algorithm to take this client input and quantify it as an objective risk preference (an example of *Wealthfront's* risk-profiling questionnaire appears in the Appendix. I will continue to use *Wealthfront* as an exemplar roboadvisor for the procedure employed at all twenty roboadvisors analysed). Each roboadvisor subsequently assigned a risk score, where I answered the questionnaires in such a way as to produce a 'moderate' level of risk across each roboadvisor in my sample. For instance, my responses to *Wealthfront's* risk assessment produced a score of 5.5 out of 10. Based on these assigned risk scores, the roboadvisors then provided a specific portfolio recommendation consisting almost universally of various ETFs, each representing a particular asset class or industry sector: the portfolio recommended to me for a 55-year old at *Wealthfront* produced the following six asset class weights:

Asset Class	Allocation	ETF Ticker	ETF Provider and representative index
US Stocks	26%	VTI	Vanguard Total Stock Market
Foreign Stocks	16%	VEA	Vanguard FTSE Developed Markets
Emerging Markets Stocks	5%	VWO	Vanguard FTSE Emerging Markets
Real Estate (REITs)	9%	VNQ	Vanguard REIT Index
US Corporate Bonds	31%	LQD	iShares iBoxx Invest Grade Corp Bond
Emerging Markets Bonds	13%	EMB	iShares JPM Emerging Mkts Bond Indx

Following the formulae provided by MPT, these target portfolio weights were then used to back out each portfolio's ex-post annualized return over the study period 1 January 2015 through 31 December 2017, along with each portfolio's corresponding variance of returns (i.e. risk) for the same period.[16] Details of this stepwise procedure appear in the Methodological Appendix to the paper.

Results

Do roboadvisors provide rational outcomes on behalf of investors? Using the above methodology, it is possible to answer this question objectively by comparing the risk-return characteristics of the portfolios constructed by roboadvisors' algorithms in reference to the efficient frontier. To recall, the efficient frontier is the set of optimal portfolios defined by MPT that offers the theoretically highest expected return (the y-axis) for a defined level of risk (the x-axis). Put differently, the portfolio of an instrumentally rational actor would lie as close to the efficient frontier as possible.

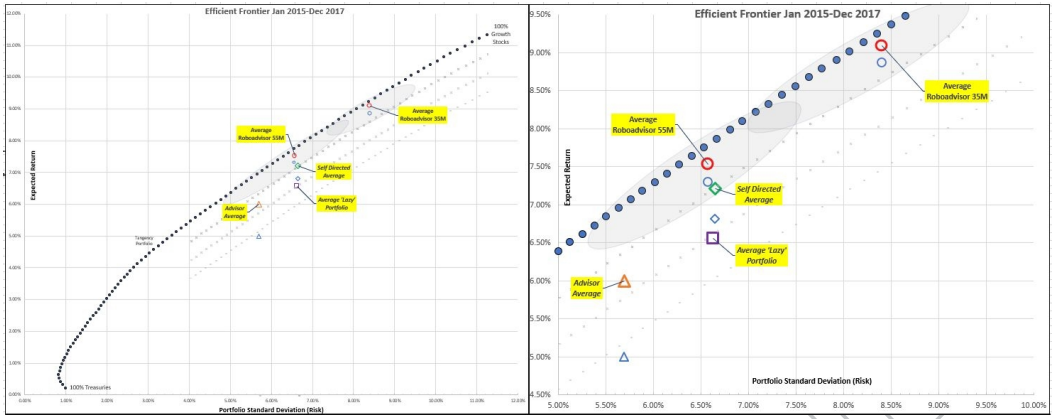


Figure 2 Roboadvisor portfolio allocation risk-return characteristics plotted against the historical efficient frontier (Jan 1, 2015 through Dec 31, 2017).

Q35 *Note*: This figure plots how well investment portfolios maximize expected return (y-axis) for a given level of risk (x-axis). The efficient frontier is denoted by the solid dots. A rational economic actor would allocate to portfolios that lie on or very close to efficient frontier. Portfolios that lie below the efficient frontier are sub-optimal because there exists an alternative portfolio configuration that provides a greater expected return for the same level of risk. No portfolios exist that can fall above the efficient frontier. Grey tick marks that run parallel to the efficient frontier are simply points of reference as to the objective distance to the efficient frontier.

The circles plotted in this risk-return space represent the average roboadvised portfolios constructed for a hypothetical 35- and 55-year-old male. Returns net of fees are indicated by the smaller shape directly below. The grey shaded areas represent the distribution of the twenty individual portfolios in risk-return space for each demographic Triangles represents the average risk-return characteristics of portfolios represented by traditional financial advisors before and net-of-fees. Diamonds represents the average risk-return characteristics of portfolios constructed by self-directed investors, and squares represents the average risk-return characteristics of so-called 'lazy portfolios', off-the-shelf passive indexed strategies found in investment advice books or promulgated by investment 'gurus'

Figure 2 confirms that the average roboadvised portfolio (indicated by open circles) for both the hypothetical 55- and 35-year-old plot remarkably close to the efficient frontier – indicating that they do indeed approximate rational outcomes.[17] While the 35-year old's portfolio plots farther to the right (they are riskier), the distance from the efficient frontier is just as close as the more risk-averse 55-year old, indicating that the two are equivalently efficient portfolios. I also account for the 0.25 per cent modal fee charged by roboadvisors, where the return net-of-fees is plotted beneath, indicated by the smaller circles.

If the allocations that lie on (or very close to) the efficient frontier represent the portfolios of ideal type investors, it is important to also frame the risk-return characteristics of roboadvised portfolios in reference to alternative ways of investing, plotted in the same risk-return space. In this manner, I first compare roboadvised portfolios to the average of sixteen so-called 'lazy portfolios' (indicated on Figure 2 by the open square), which are a class of basic off-

the-self portfolio allocations that support the paradigm of passive index investing, but which lack both formal economic theory and the algorithmic machinery of roboadvisors. These set-it-and-forget-it strategies are often promulgated by financial 'gurus' or are found in self-help investment books like Bill Schultheis (2013) *The Coffeehouse Investor* and David Swensen's (2005) *Unconventional success;* as well as on investor education websites like *Bogelheads*.[18] Most of these portfolios contain a small number of low-cost index funds that make it easy to manually rebalance. They are 'lazy' in that the investor can maintain the same asset allocation for an extended period of time and they generally contain 30–40 per cent bonds, suitable for most pre-retirement investors. As Figure 2 shows, while the average lazy portfolio carries a similar risk exposure as the average 55-year old roboadvised portfolio, they fail to achieve returns approaching the efficient frontier.[19]

Next, I plot the results of the average self-directed (do-it-yourselfer) portfolio over the same timeframe, denoted by the diamond shape in Figure 2. The risk-return characteristics of self-directed portfolios were sourced from the American Association of Individual Investor's (AAII) Asset Allocation Survey using the average of monthly survey results over the study period.[20] Self-directed portfolios, on average, carry approximately the same risk levels as the 55-year old roboadvised portfolio, but experience noticeably lower returns. Net-of fee results are even more indicative of portfolio *in*efficiency. According to Barber and Odean (2000), the average individual investor sees their annual return reduced by five-and-a-half per cent due to transaction costs and trading fees (e.g. a 7.2 per cent gross return would be reduced to 6.8 per cent). After-fee returns are represented by the smaller figure plotted below the larger diamond in Figure 2. On an after-fee basis, roboadvised portfolios have significantly greater returns for a comparable amount of risk than self-directed accounts, and even perform somewhat better than self-directed accounts before fees are taken into account.

Finally, I compare the roboadvisors to investors advised by human financial planners over the study period, marked in Figure 2 by the triangle, which is representative of the asset allocation of the typical financial advisor (Shepherd *et al.*, 2018, pp. 2–10).[21] These portfolios are noticeably more risk-averse *and* farther from the efficient frontier than any other option, especially after taking account of the average 1 per cent fee that advisors charge their clients. The difference between human-advised and roboadvised accounts illustrates a striking dichotomy, especially since human advisors typically grant access to their services only to the more affluent.

Roboadvised portfolios as a whole are the most efficient; they appear to approach rational outcomes for their users that exceed the competency of all other options, providing compelling evidence for their ability to enact lay investors as the ideal type investor.

Discussion and conclusions

The roboadvisors are a phenomenon that implicate a Weberian ideal type turned practical reality. On paper, roboadvisors are transforming (presumably ignorant, unskilled, and irrational) lay investors into hyper-rational market actors. Consequently, an objective of this paper is to show empirically that the portfolio choices made by roboadvisors are what a rational actor would do; and, the data generated from the above analysis supports this claim with objectively verifiable portfolios that, on average, lie close to the efficient frontier. Moreover, roboadvisors as a group construct the *most* efficient portfolios (both before and net of fees) compared to alternative methods of market participation including self-directed investment or through a professional human advisor.[22] In fact, a roboadvised account with just $5.00 invested is far more likely to possess an efficient portfolio than that of a wealthy investor with $5 million and a pricey human advisor, leading to a potential inversion of rationality across the SES distribution as roboadvisors vie for an individual's first investible dollar. But, if we were to look these roboadvised users in the eye, we would not see *Homo economicus* staring back – just ordinary human beings. The ideal type investor is a chimera, an abstraction translated through formal mathematical procedures and enacted by algorithmic systems. Thus, I devote much of the discussion to unpacking the algorithmic performance of ideal types.

MPT along with the algorithms of the roboadvisors and their end-users together form a socio-technological assemblage. In this way, MacKenzie (2009, p. 20) explains, 'an economic actor is not simply an individual human being, nor even a human being 'embedded in institutions, conventions, personal relationships or groups'. Instead, economic action is comprised of humans combined with 'technical elements, incorporated competencies, rules, … sets of theories, models and statements' joined with material devices of calculation (Callon, 1998, p. 20). Several other necessary antecedents must also be enrolled into the roboadvisor assemblage, such as the capacity to place trades electronically and the advent of low-cost ETFs that cover a multitude of asset class indices (see e.g. Braun, 2016). Consequently, it is the 'actor-network' (Callon, 1986; Latour, 1999), i.e. the roboadvisor assemblage in its totality, that constitutes the ideal type investor; and what differentiates a roboadvised user from other investors is that this assemblage is precisely attuned to MPT and executes it flawlessly and tirelessly.

Following Deleuze and Guattari (1998), an ideal type like this is perhaps more accurately an '*agencement*', a word that Callon (2005) identifies as more nuanced and flexible in meaning than the related 'assemblage'. *Agencement* conveys the more acute idea that specific combinations of heterogeneous elements have been carefully adjusted to one another for a specific purpose, 'endowed with the capacity of acting in different ways depending on their configuration' (Callon, 2005). From this perspective, the economic action that is articulated through roboadvisors forms ideal type *agencements* that can serve an array of efficient portfolios, each one suited to a particular individual that

will approach the efficient frontier at various spots along the x-axis.[23] This suggests that there is no one universal ideal type investor – rational action is not necessarily homogenous action. Rather, just as different prescriptions are needed to bring various people up to 20/20 (optimal) vision, meaningful action, too, is often configured in individualized ways. Regardless of one's eyes, the means of enhancing near-sightedness is through the use of corrective lenses. Similarly, given any particular individual's risk profile the remedy is still MPT for an efficient portfolio. Glasses without eyes to see through them are moot. The economic action coordinated through roboadvisors, too, relies crucially on human inputs (objective and subjective information obtained from the risk-profiling questionnaire, the client's money, etc.) just as much as it does on the algorithmic processing and execution based upon those inputs.

This describes a *synthetic* ideal type. Not only because it is fashioned with manmade artifacts, but also because it is synthesized from the very mental constructs (what Weber called *gedankenbild*) that idealize some phenomena: it is not used to confront reality, but to fashion it. This is where an ideal type such as this can be construed as a type of *performativity,* following Callon (1998) and elaborated by MacKenzie (2006). In the performativity thesis (as scholars in economic sociology and the social studies of finance understand it), a theoretical model possesses the force to make aspects of the empirical world in its image (as MacKenzie [2006] explains, a financial model is more like an engine that shapes the economy rather than a camera that objectively and passively captures the economic world [see also: MacKenzie & Millo, 2003]). Studying roboadvisors affords the opportunity to look under the hood at one of these engines. Indeed, Callon (2005, p. 5) affirms, 'the performativity program starts with an ethnography of socio-technical agencements'.

Beneath the surface, performativity research has often provoked Weber's ideal types, though this relationship has only been alluded to – for instance, in the construction of a French strawberry market in the image of a neoclassical ('Walrasian') auction (Garcia-Parpet, 2007), the conformation of law schools to printed rankings (Espeland & Sauder, 2007), or with ideal romantic matches made through online dating sites (Roscoe & Chillas, 2014). Similarly, rare concrete examples of ideal types that have been identified in the past, such as Benthamite panopticon prisons (Foucault, 1977), illustrate how social theory (e.g. disciplinary power through surveillance) performatively shapes certain microcosms of society.

The results presented in Figure 2 could thus be interpreted as a measure of how successfully various socio-technical assemblages succeed in creating an ideal investor. Aside from MacKenzie's descriptive of strong 'Barnesian' cases, here we can see that various configurations of theory and technology produce a spectrum of 'goodness of fit' with MPT's prescription for rational action (i.e. enactments of 'effective performativity'). Certainly, professional financial advisors come equipped with theory and technology, yet they produce only very weak performativity, on average. Likewise, contemporary self-directed investors have several calculative tools and theoretical frameworks

at their disposal from books and newsletters to web-based tools offered through online brokerage platforms. This way, one could think of performativity as that performance measured against the yardstick of the ideal type market actor implied by a dominant model.

What is novel about how MPT is performed through the roboadvisors is that neither the enactment of the model nor the ideal type outcome is directly accomplished from human agency. The agency is instead located within the algorithms and technological systems that carry out the theory, that execute all buy and sell orders directed by that theory, and that continuously monitor and rebalance to ensure portfolios remain efficient even as markets move – on behalf of the user, of course. Indeed, no human being could plausibly do those things unaided. This practical fact is not too different from the ability of HFT algorithms to execute trades on the millisecond-scale on behalf of Wall Street professionals, trades which are not humanly possible for even the most dexterous and skilled trader. However, as work in the social studies of finance reveals, human agency is still privileged in that these algorithms are continuously tinkered with, adjusted, and ultimately carry out strategies proposed by human traders (see e.g. MacKenzie, 2018; Svetlova, 2012). The roboadvisors seem to dislocate human agency more fully by distributing investment strategy and execution wholly to the models and algorithms.

Is this point at odds with Weber's conception of ideal types as portraying *socially meaningful* action? While the locus of agency is transferred to the roboadvisor *agencement*, the investor alone maintains *intent* in desiring the best portfolio returns possible – even if the investor lacks the knowledge or skill to be his or her own agent. While the semantic and theoretical distinctions between 'intent' and 'agency' are beyond the scope of this paper, Weber does provide some clarity as it relates to social action: 'An unintended collision of two cyclists, for example, shall not be called social action', he writes (Weber, 1981 [1913], p. 159), 'But we will define as such their possible prior attempts to dodge one another'. Thus, social action is meaningful insofar as it is oriented to others in *intention*, where investors purposefully confront a sea of anonymous others that constitute the stock market (others who may themselves delegate algorithmic agency). A second, and perhaps more nuanced point made by Weber is that social action can be characterized by

> its meaningful orientation to the *expectations* of certain behaviour on the part of others … In particular, instrumentally rational action, as defined earlier, is oriented toward such expectations. In principle, therefore, it seems initially immaterial whether an action is guided by the expectation that certain *natural* [i.e. non-social] events will occur, with or without the actor's purposive intervention. (Weber, 1981 [1913], p. 159, emphases in original)

If investors reasonably believe that other market actors are also striving to be instrumentally rational, then 'the meaning orientation therefore is, in general, to one's own interests in one's own want satisfaction and also indirectly, to

the perceived individual interests of others in their own want satisfaction' (Weber, 1981 [1913], p. 166). Indeed 'the market' is itself an ideal type that agglomerates rational calculation through a variety of material devices and economic formulae (see: Callon, 1998; Fourcade & Healy, 2017). Therefore, the behaviour of roboadvisors is social action since these assemblages involve meaningful relatedness to the behaviour of others in the market (but cf. Gane, 2012).[24]

This nevertheless leaves the end-user as a sort of residual actor once their information has been taken up and processed: Even as a portfolio is constructed and optimized, rebalanced and monitored, the human user can remain perfectly ignorant to MPT or the basic facets of financial literacy – and still achieve ostensibly rational outcomes. The mathematician and philosopher Alfred North Whitehead (1992 [1911], p. 46) wrote, 'civilization advances by extending the number of important operations which we can perform without thinking about them'. Indeed, granting financial calculation to the masses could be a positive and egalitarian achievement for society, especially since economic outcomes of individuals are increasingly tied to their navigation of securities markets. Identifying this sort of idealized investor, however, is also to recognize a disjuncture between knowledge and agency. Is the fount of rational action in calculating risks and returns when choosing investments, or is it simply with choosing to use a roboadvisor in the first place? If it is indeed the latter, then rational choice need not be essentially tied to one's own competence for calculation. Instead, an altogether different set of skills are favoured that can discriminate between different roboadvisors in order to choose the best possible platform.[25]

Once calculative devices are a given, maintaining individuals as ideal type investors shifts focus from computation to regulating other elements of human behaviour. Hayes (2019) shows that managers and executives at various roboadvisory firms are acutely aware of the self-defeating consequences of emotions and other biases or errors that pervade actual human behaviour. As a result, the roboadvisors have consciously built corrective nudges into design elements of the user experience that draw directly from behavioural economics (e.g. Thaler & Sunstein, 2009). The purpose is to counteract the natural propensity to tinker, second-guess, or otherwise override the algorithms' decisions (cf. Borch & Lange, 2016; Svetlova, 2018). These tendencies arise from biases like overconfidence, myopic loss-aversion, and emotions like fear and greed. Behavioural elements again come in to play when profiling users in order to tailor messaging that also attends to keeping emotions in check (for instance, proactively emailing only those users who log on frequently following a market crash with a message to stay the course, while avoiding those users who did not). The idea is to perform ideal type investors not only on behalf of, but *despite* the end-users. 'It's our job', remarked the head of behavioural finance and investing at a major American roboadvisor, 'to sort of help manage the psychological side of things so that you can do the rational thing' (quoted in Hayes, 2019).

Through combining behavioural economics and MPT, roboadvisors mobilize a conceptual basket in which their joint use, in effect, *functions as a counterperformative invalidation of the former*.[26] The irrational aspects of investment are well-recognized by roboadvisors, but the influence of these is minimized through adherence to MPT while strategically deploying behavioural elements as disciplinary checks. Put differently, the corrective usage of behavioural economics makes roboadvisor users appear *less like* the behavioural model's depiction of investors – leaving users to appear instead as MPT-following ideal types.

This is not the only possibility for counterperformativity that roboadvisors call forth. As MacKenzie (2006, p. 60) cautions, 'economically rational action may not always promote stability'. The rise of the roboadvisors can therefore have important implications on the socio-technological structuration of securities markets and on investor behaviour. As more lay investors come to follow MPT there is less 'noise' in the market (Preda, 2017) for professionals to respond to. Indeed, if we take the limiting case where every single market participant uses a mean-variance model and that's it, then the market *cannot* be efficient and MPT itself falls apart. The fundamental reason here is that MPT is price *in*sensitive – it only prescribes the asset class weights for what indices to own since the model assumes that markets are efficient. If people only own index funds, however, then nobody is left to do the fundamental research necessary to fairly price the components of those indices, and so markets become *inefficient* (for an extended discussion of the counterperformative potential of MPT and roboadvised investments see Hayes, 2019; as well as Fichtner & Heemskerk, 2018, for an explanation of some consequences of widespread passive index investing). Paradoxically, too much 'efficient' investing can itself lead to market failure. In reality, this risk is likely small because any new market inefficiencies created by a slavish devotion to MPT would be quickly exploited by active traders such as arbitrageurs or HFT bots.[27]

But, if Lopreato and Alston (1970) are correct that ideal types are inherently 'deliberate distortions of reality', then the algorithmic performance thereof could still have a distorting effect. Indeed, while it may be individually rational to use a roboadvisor, it is impossible for it to be collectively rational for every investor to use MPT. Similarly, if every driver were enacted as an ideal type route optimizer, traffic jams could actually get worse. Cabannes *et al.* (2017) show how GPS and traffic-beating apps are logical for individuals, but make congestion worse overall, 'and autonomous vehicles, touted as an answer to traffic-y streets, could deepen the problem'. These examples depict a *tragedy of the common 'ideal'*, where the social capacity for rationality is taken as a limited and shared resource – where individual users, acting independently according to their own self-interest, behave contrary to the common good of all users by depleting or spoiling the shared resource through their collective action (Hardin, 1968).[28]

To conclude, I draw attention to Roscoe and Chillas (2014) advice that a performativity analysis must include a critical politics: 'what sort of world would we like to see performed?' (MacKenzie, 2006, p. 275). While Portes (2010, p. 227)

dismisses this point of issue as rhetorical flourish, the question carries new weight in a society where ideal types can be readily assembled and performed. Scholars and practitioners alike should additionally ask: which ideal types do we want to see in the world? While an ideal type investor may be positive for ordinary people, do we also desire technological systems that can put in place ideal type bureaucracies where Weber's 'iron cage' can trap and restrict individual freedom and creativity in the name of rational-legal efficiency?

When an ideal type leaps off the paper or out of the mind of the social analyst and instead becomes the practical tool of businessmen, policymakers, or computer programmers working on a hobby project, we must consider who is the one introducing the ideal type. Who gets to decide what the ideal type specifications are, and at the exclusion of what alternatives? Some roboadvisors are beginning to offer portfolios built around ideologies of social responsibility and ESG investing, but this is still not widespread.[29] Yet, these 'social' portfolios are still optimized around MPT principles that privilege the tradeoff between risk and return rather than any other value dialectic. As another example, GPS routes allow drivers to optimize shortest distance or shortest time but exclude equally 'ideal' options like most emissions-efficient or most scenic route (but see: Zheng *et al.*, 2013).

In addition to the questions posed above, future work should ask which people get access to ideal type-making platforms and who are left out? If cost is no longer a material consideration for enrolment into an ideal type *agencement*, how do competing versions of that enactment (e.g. to choose one roboadvisor over another) attract new users? Once there is a critical mass of enrolees, if there is some threshold level of rationality that a microcosm of society can bear, who is to say to the next person that they should forgo being enacted as an ideal type?

Moreover, what happens to ideal type enactments when technological systems fail? And, what becomes of the residual human beings who outsource more and more modes of action to optimizing systems? As algorithmic systems in finance and elsewhere become ever more commonplace, these and other questions are ripe for sociological inquiry and provide a basis for new and exciting directions for future research.

Disclosure statement

Q2 No potential conflict of interest was reported by the author(s).

Notes

1 Weber initially conceived of 'ideal types' in his 1904 essay on Objectivity which has been identified by scholars to refer specifically to his theory of history (e.g. Kalberg, 1994). The *Economy and Society* version of ideal types, on the other hand, was fashioned

exclusively with sociology in mind (see: Swedberg, 2018, p. 182; Schutz, 1967; Hekman, 1983). In this paper, I consider exclusively the 'sociological' rendition of ideal types.

2 Weber indeed identifies several dozen ideal types in his writings, including the ideal type bureaucracy and ideal type capitalist entrepreneur, but devotes most space to economic action.

3 Weber (1978[1922], p. 26) instructs that, 'action is instrumentally rational (*zweckrational*) when the end, the means, and the secondary results are all rationally taken into account and weighed. This involves rational consideration of alternative means to the end, of the relations of the end to the secondary consequences, and finally of the relative importance of different possible ends'. Swedberg (2018) adds that an ideal type actor has full knowledge of the situation and is fully aware of what he/she is doing.

4 This point is elaborated in greater detail in the discussion that follows the empirical section.

5 In fact, in the case of MPT asset price does not even come into play, only portfolio weights.

6 While this is true of the sociological version of Weber's ideal type, the historical version has been more frequently employed, especially in comparative-historical work (e.g. Kalberg, 1994; Biernacki, 2012; see also endnote 1).

7 Weber acknowledges that ideal types can alternatively be oriented to other modes of action (specifically: value-rational; affectual; and traditional), but that to be an ideal type only one mode of meaningful action is chosen. It is by identifying other modes of meaning in contrast to the ideal type that sociological inquiry can proceed.

8 In practice, MPT would allocate dollars to representative indices (i.e. ETFs or mutual funds) corresponding to a specific asset class, including (e.g.): domestic/foreign/emerging markets large-/mid-/small-/micro-cap stocks; domestic/foreign corporate bonds (of various credit rating); domestic/foreign government debt; commodities (e.g. gold, silver, oil, etc.); domestic/foreign real estate (e.g. REITs); and so on.

For a detailed account of the development of Markowitz's work on MPT, see chapter 2 of Bernstein, 1992.

9 Efficient frontier data points obtained from portfoliovizualiser.com

10 https://www.cnbc.com/2017/01/04/most-investors-didnt-come-close-to-beating-the-sp-500.html

11 https://www.dalbar.com/Portals/dalbar/Cache/News/PressReleases/2017QAIBPressRelease.pdf

12 https://www.statista.com/outlook/337/100/robo-advisors/worldwide

13 Since roboadvisors manage client money for lay investors, they fall under the regulatory scrutiny of the securities and exchange commission (SEC) as registered financial advisors. Because of this they are required to file mandatory disclosures speaking to the investment methodology used and the extent to which algorithms are deployed in their practice, in what is known as the Form ADV Part 2 Brochure.

14 https://www.adviserinfo.sec.gov/IAPD/

15 Personal Capital requires a starting balance of $100,000, Vanguard Personal Advisor $50,000, Zack's Advantage because it uses Schwab's roboadvisor to implement its allocation, where I already had an account established, and Honest Dollar which only offers retirement accounts.

16 Operationalized as annualized standard deviation, or the square root of the variance over the same period.

Roboadvisors are a relatively new phenomenon with the majority of those in my sample launching since the year 2014. Therefore, this study period was used to capture overlapping multi-year data covering my entire sample.

17 Portfolio returns are pre-tax annualized historical returns from 1 January 2015 through 31 December 2017. Portfolio standard deviations of returns are annualized over the same period.

18 https://www.bogleheads.org/wiki/Lazy_portfolios

19 Since lazy portfolios are low-maintenance set-it-and-forget it allocations there is no meaningful annual cost associated with them.

20 https://www.aaii.com/files/surveys/asset.xls

21 These data for the study period were sourced from Research Affiliates, LLC's (RA) Asset Allocation Interactive Tool. RA is an investment manager and financial analytics firm that provides its services mainly to investment companies. See also Shepherd et al. (2018). https://interactive.researchaffiliates.com/asset-allocation#!/?category=Model&currency=USD&model=ER&scale=LINEAR&selected=225&terms=REAL&type=Portfolios

22 It is revealing that having a human advisor produces, on average, the least efficient portfolios, especially on an after-fee basis.

23 This is an important distinction that sets the like of roboadvisors apart from other passive indexed strategies such as target-date funds, which take a one-size-fits-all approach. Thus, while a particular target-date fund that matures in the year 2035 may prove optimal for some small subset of investors, its underlying portfolio will fail to be the rational (efficient) choice for many others – even if they do plan to retire in that year.

24 In the most basic form, a buyer of securities must confront a seller and vice-versa.

25 From my own engagement with these platforms, this choice seems to boil down essentially to cost, since all the roboadvisors are effectively doing the same thing (see Table 1).

26 My gratitude to the anonymous reviewer who pointed out this apparent paradox.

27 It is worth noting that just as too much MPT investing can lead to instability, so too can a large proportion of high-frequency trading – which has been blamed for the occurrence of 'flash-crashes' (Lewis, 2015; Lange et al., 2018), sudden price drops facilitated by negative feedback loops where certain HFT algorithms trigger others in a downward spiral. But, interestingly, it may be the HFT's active orientation that balances the potential dangers of MPT-following algorithms. It is important to note that HFTs already trade against roboadvisor order flow since the former acts as market-maker in many ETFs. Ultimately, a new market logic may establish itself where the more passive algorithms of roboadvisors and the active ones of high-frequency trading end up supporting and sustaining one another, as well as promoting systemic stability as they trade against each other.

28 These examples are similar to 'paradoxes of rationality' invoked in game theory; see e.g. Grüne-Yanoff, 2012.

29 ESG stands for 'environmental', 'social', and 'governance'.

30 https://www.wealthfront.com/questionnaire

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Appendices

Appendix A. Methodological Appendix

MPT starts out with the following proposition: Suppose there are N risky assets (6 in the case of our example case, *Wealthfront*), whose rates of return are given by the random variables $R_1, \ldots, R_N$, where we purchase an asset n for $S(0)$ dollars on one date and then later sell it for $S(1)$ dollars:

$$R_n = \frac{S_n(1) - S_n(0)}{S_n(0)}, \quad n = 1, 2, \ldots, N$$

Next, let $\boldsymbol{\omega} = (\omega_1 \ldots \omega_n)^T$, where ω_n denotes the proportion of funds invested in asset n, with $\sum_{n=1}^{N} \omega_n = 1$. The total rate of return for a diversified portfolio of risky assets is the simple weighted average:

$$R_P = \sum_{n=1}^{N} \omega_n R_n \tag{1}$$

The goal of MPT is then to choose the optimal portfolio weighting factors that maximizes the rate of return, constrained by some minimal level of variance (i.e. risk) (Burke, 2017, *p*. 2; Markowitz, 1952), where the variance of the rate of return of an instrument is taken as its risk. But, since asset returns are not perfectly correlated with one another, the total variance of a portfolio must be

computed while considering a series of pairwise interaction effects:

$$\sigma_P^2 = \mathrm{var}(R_P) = \sum_{i=1}^{N}\sum_{j=1}^{N} \omega_i\omega_j \mathrm{cov}(R_i R_j) = \sum_{i=1}^{N}\sum_{j=1}^{N} \omega_i\omega_j\sigma_{i,j} \tag{2}$$

Let Ω denote the covariance matrix among asset class returns such that: $\sigma_P^2 = \boldsymbol{\omega}^T\Omega\boldsymbol{\omega}$.

For example, when we have just $n = 2$ asset classes:

$$(\omega_1\ \omega_2)\begin{pmatrix}\sigma_{1,1} & \sigma_{1,2}\\ \sigma_{2,1} & \sigma_{2,2}\end{pmatrix}\begin{pmatrix}\omega_1\\ \omega_2\end{pmatrix} = \omega_1^2\sigma_1^2 + \omega_1\omega_2(\sigma_{1,2} + \sigma_{2,1}) + \omega_2^2\sigma_2^2$$

Thus, in order to work MPT in reverse, I needed as inputs the historic annualized return and standard deviation over the study period for each asset assigned to my portfolio, as well as the correlations between asset class returns over the same period, which I computed with Excel. (Historical price data obtained from Morningstar, a publicly available website for obtaining price and performance data on mutual funds and ETFs.) For *Wealthfront*, this amounted to:

Table A1. Roboadvisor Portfolio Allocation and Asset Class Correlations.

Ticker	Return	Standard Deviation
VTI	11.70%	10.28%
VEA	9.60%	11.13%
VWO	8.66%	15.04%
VNQ	6.21%	13.58%
LQD	4.06%	4.96%
EMB	6.93%	5.47%

Ticker	VTI	VEA	VWO	VNQ	LQD	EMB
VTI	1.00					
VEA	0.82	1.00				
VWO	0.61	0.77	1.00			
VNQ	0.43	0.34	0.29	1.00		
LQD	0.09	0.26	0.41	0.71	1.00	
EMB	0.31	0.50	0.67	0.47	0.78	1.00

Portfolio return as defined by Equation 1 above is the simple weighted average of asset class returns and so R_p for *Wealthfront* is

$$\begin{aligned}&0.26(.117) + 0.16(0.096) + 0.05(0.0866) + 0.09(0.0621) + 0.31(0.0406)\\ &\quad + 0.13(0.0693)\\ &\quad = 7.73\%.\end{aligned}$$

Portfolio risk is operationalized as its annualized standard deviation and calculated according to Equation 2 above:

$$\begin{aligned}\sigma_p = [&0.262(.1028)^2 + 0.162(.1113)^2 + 0.052(.1504)^2 + 0.092(.1358)^2 \\ &+ 0.312(.0496)^2 + 0.132(.0547)^2 + 2(.26)(.16)(.1028)(.1113)(.82) \\ &+ 2(.26)(.05)(.1028)(.1504)(.61) + 2(.26)(.09)(.1028)(.1358)(.43) \\ &+ 2(.26)(.31)(.1028)(.0496)(.09) + 2(.26.)(.13)(.1028)(.0547)(.31) \\ &+ 2(.16)(.05)(.1113)(.1504)(.77) + 2(.16)(.09)(.1113)(.1358)(.34) \\ &+ 2(.16)(.31)(.1113)(.0496)(.26) + 2(.16)(.13)(.1113)(.0547)(.5) \\ &+ 2(.05)(.09)(.1504)(.1358)(.29) + 2(.05)(.31)(.1504)(.0496)(.41) \\ &+ 2(.05)(.13)(.1504)(.0547)(.67) + 2(.09)(.31)(.1358)(.0496)(.71) \\ &+ 2(.09)(.13)(.1358)(.0547)(.47) + 2(.31)(.13)(.0496)(.0547)(.78)]^{1/2} = 6.62\%\end{aligned}$$

The *Wealthfront* asset allocation for a 55-year old with moderate risk tolerance thus corresponds to (6.62%, 7.73%) in the risk-return space with which the efficient frontier exists.

This procedure was carried out for all of the roboadvisors in the sample, and then the portfolio risks and returns were averaged. These results are presented in Table A2:

Table A2. Roboadvisor portfolio risk-return characteristics.

Roboadvisor	Std.Dev.	Return
Betterment	8.08%	8.84%
Wealthfront	6.62%	7.73%
Ellevest	7.67%	8.49%
Acorns	6.15%	7.15%
WiseBanyan	7.39%	8.22%
WealthSimple	5.31%	6.85%
Schwab Intelligent Portfolio	7.42%	7.68%
eTrade Adaptive Portfolio	6.07%	7.39%
FutureAdvisor	6.18%	6.63%
TIAA Personal Portfolio	7.64%	7.61%
Fidelity Go	6.90%	8.43%
Honest Dollar (GS)	6.83%	7.67%
Ally/TradeKing	5.80%	7.23%
SigFig	6.83%	7.40%
Hedgeable	7.54%	8.79%
TD Essential Portfolio	4.92%	6.25%
Zack's Advantage	6.28%	7.62%
ML Guided Portfolio	5.72%	7.02%
Vanguard	5.95%	7.36%
SoFi	6.38%	7.35%
Covestor (IB)	5.78%	6.38%

(*Continued*)

Table A2. Continued.

Roboadvisor	Std.Dev.	Return
Average	**6.55%**	**7.53%**
(standard deviation of columns)	*(0.85%)*	*(0.71%)*

Source: Author's calculations

Appendix B. Roboadvisor risk profiling.

Risk Profiling Questionnaire Example using roboadvisor: *Wealthfront*:[30]

1. What is your primary reason for investing?
   a. ○ General savings
   b. ◉ Retirement
   c. ○ College Savings
   d. ○ Other
2. What are you looking for in a financial advisor?
   a. ☑ I'd like to create a diversified investment portfolio
   b. ☑ I'd like to save money on my taxes
   c. ☑ I'd like someone to completely manage my investments, so that I don't have to
   d. ☑ I'd like to match or beat the performance of the markets
3. What is your current age?
   a. 55
4. What is your current pre-tax income?
   a. $75,000
5. Which of the following best describes your household?
   a. ○ Single income, no dependents
   b. ○ Single income, at least one dependent
   c. ◉ Dual income, no dependents
   d. ○ Dual income, at least one dependent
   e. ○ Retired or financially independent
6. What is the total value of your cash and liquid investments? e.g. savings, CDs, mutual funds, IRAs, 401(k)s, public stocks
   a. $150,000
7. When deciding how to invest your money, which do you care about more?
   a. ○ Maximizing gains
   b. ○ Minimizing losses
   c. ◉ Both equally
8. The global stock market is often volatile. If your entire investment portfolio lost 10% of its value in a month during a market decline, what would you do?
   a. ○ Sell all of your investments

b. ○ Sell some
c. ○ Keep all
d. ◉ Buy more

———

'Based on your answers, here's your recommended investment plan that aims to maximize your returns while managing your risk: Risk Score: 5.5'

(from 0.0 to 10.0) [this is a *moderate* risk tolerance]