AI meets narratives: the state and future of research on expectation formation in economics and sociology

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Abstract
This article presents contemporary concepts of economic beliefs in economics and sociology: (a) behavioural accounts; (b) learning; (c) narrative approaches; and (d) Science and Technology Studies-inflected integrative accounts. The review argues that cutting-edge research on expectations in both disciplines has paid insufficient attention to the fact that human agents are supported and partly substituted by modern technology while forming their beliefs. Thus, this article discusses how models, algorithms and artificial intelligence co-determine and profoundly change the theoretical and empirical understanding of expectation formation, and outlines a joint research agenda for studying economic expectations.

Key words: economic sociology, economic thought, financial markets, rational choice, uncertainty, technology

JEL classification: Z130 economic sociology, economic anthropology, language social and economic stratification, D010 microeconomic behaviour, underlying principles, B21 history of economic thought: microeconomics, B84 expectations, speculations

1. Introduction
Most central decisions in economics, for example, about consumption or investments, are based on expectations. Moreover, expectations and subsequent decisions determine the most important macroeconomic outcomes, such as aggregate supply and demand, the business cycle as well as financial bubbles and crashes. Expectations can stabilize but also destabilize economies and drive big events. The global financial crisis of 2008 demonstrated emphatically that agents’ beliefs matter (Gennaioli and Shleifer, 2018). Various
policymakers recognize that shaping beliefs and intervening in expectational dynamics might be crucial for the successful governance of the economic system and financial markets.

Thus, it is not a big surprise that—in the aftermath of the crisis—there was a spike in interest in the question of how economic expectations are formed and spread. Economists realized that the rational expectations hypothesis (REH), which dominated their field, precluded a serious investigation of how people form beliefs. Within the REH framework, expectation formation was irrelevant because agents supposedly used similar models that were correct on average. Economic sociologists and anthropologists were also not much concerned with the category of ‘expectation’ as they either diluted it within the macro-sociological concepts of institutions and norms or subscribed to ‘an ultimately psychological notion of expectation’ without ‘re-appropriating’ it for sociological analysis (Langenohl, 2010, p. 23).

After the crisis, not only economists and sociologists, but also anthropologists and psychologists, made critique of the REH a point of departure for their interest in economic expectations and came up with numerous alternative concepts. The first aim of this article is to reconstruct the landscape of this current debate. It includes and compares concepts from both economics and sociology on equal terms, and this cross-disciplinary approach constitutes an important research contribution. The goal is to demonstrate that recent economic research on expectations has gone beyond the scope of the REH in a much more nuanced and multi-faceted way than one might suppose. At the same time, there are interesting complementary ideas in sociology and related sciences on how to understand expectation formation.

While analysing cutting-edge research on expectations, this article demonstrates that both economics and sociology have been primarily concerned with how economic agents use their limited cognition to make sense of information they receive. Economists have developed concepts that highlight the types of mistakes individual actors make when they deviate from rational expectations and the biases these actors are exposed to in the process of expectation formation. Sociologists and anthropologists stress the importance of narratives and imaginaries for understanding beliefs; the idea of fictional expectations and imagined futures has become an instrument for ‘re-appropriating’ the category of expectations for sociological analysis.

However, it is striking that leading research on expectations in both disciplines has not paid sufficient attention to the fact that human agents are supported and partly substituted by technology while forming their beliefs. Expectation formation in the modern economy is not purely a matter of human cognition and its limitations. Models, algorithms and various technological devices (ranging from smartphones to big data centres at stock exchanges) aim to compensate for agents’ bounded rationality and, hence, co-determine and profoundly change the information agents search for, how they proceed with the collected data and which futures they imagine.

This applies to an increased number of economic domains. Nowadays, algorithms are used on the labour market for recruitment purposes to predict the performance of prospective workers in companies (Kiviat, 2019) and at on-demand crowdworking platforms (Li and Liu, 2015). Artificial intelligence (AI)-based forecasting is applied by retailers to anticipate sales trends and demand in order to hold the right amount of inventory and minimize waste; manufacturers use AI to automate the supply chain and anticipate spare part requirements (Bughin et al., 2017). Algorithms profile customers to determine their creditworthiness and calculate insurance fees. Central banks use algorithms to evaluate big data sets to forecast macroeconomic variables in the short- (nowcasting) and long term (Wibisono et al.,
In auditing firms, AI is starting to substitute human judgement in risk assessment and fraud detection (Munoko, et al., 2020). In finance, AI algos manage asset portfolios, help financial analysts to trawl social media posts, news trends and macroeconomic data in a variety of forms such as audio, pictures, maps and text, and even compile company reports (robo-writing). Lay investors are increasingly guided by robo-advisors. Importantly, while performing those tasks, machines can learn, adjust their strategies and achieve a degree of autonomy.

All those changes have been addressed in the current literature on expectations only vaguely (Marwala and Hurwitz, 2017). Thus, in addition to mapping out the landscape of expectation formation concepts, the second goal of this article is to introduce the existing attempts reported in the literature to comprehend the role of technological changes in economic agents’ belief formation. Thereby I emphatically do not mean the exogenous technological shocks to which expectations react (as in most economic and some sociological accounts). Rather I refer to technological devices as instruments for forming expectations.

I will show that economists have begun to pay attention to AI methods within learning approaches to expectations, and have tentatively probed the concept of an AI agent. However, they use this concept as a tool for solving a model and not to directly consider the influence of technology on belief formation. Science and Technology Studies (STS)1-inflected sociologists, for their part, have elaborated an integrative approach to economic activities that highlight the importance of cognition, sociality but also of technology and calculative devices (e.g. formal models and algorithms) for economic actions, although without making the issue of expectations their central concern.

I see this review of those theoretical and empirical attempts in both disciplines as an opportunity to highlight a number of important questions that should be addressed by a modern theory of expectations. Will new technologies make the theory of rational expectations more or rather less valid? Will expectations become more rational but in an unknown (black-boxed) way? Whose expectations—those of humans or of machines—matter in the modern technology-driven market ecology? Who or what is an AI agent which might replace the (boundedly) rational agent? This article opens first doorways to those questions and discusses perspectives for a joint research agenda for studying beliefs in economics and sociology.

The remainder of the article proceeds as follows. In Section 2, I will briefly discuss the REH and major points of criticism of it; this discussion is important as the REH is still the ultimate benchmark for expectation concepts. I will proceed with the presentation of alternative approaches in economics (Section 3) and in sociology (Section 4). Section 5 summarizes the findings and suggestions of the article and concludes with a discussion of the joint research agenda for studying economic expectations.

2. Which problem regarding economic expectations does the literature aim to solve?

In this section, I will briefly summarize critique of the most prominent theory applied to expectation formation in economics, the REH, and outline the issues which alternative concepts in economics and sociology have been actively aiming to address in recent years.

1 STS research the mutual feedback loops between society, politics and culture, on the one hand, and scientific knowledge and technological innovations, on the other hand.
Economics generally presupposes that the agents maximize their expected utility based on probabilistic expectations. They observe an information set (e.g. news, central banks’ and companies’ announcements, past and current economic data) and process those signals to arrive at expectations about particular variables, such as inflation, interest rates or stock prices. The beliefs are assumed to take the form of probability distributions of the variables’ future realizations and provide the basis for agents’ utility maximization. The existing expectation formation approaches differ according to how they conceptualize the rules governing the information set and information processing.

The REH emerged out of critique of the so-called ‘mechanical’ concepts of expectations which are based on very simple information processing rules. Static (naïve) expectations (Kaldor, 1934; Ezekiel, 1938) suggest that economic agents expect future realization of an economic variable to be only the current value of this variable. The concept of extrapolative expectations (Hicks, 1939) implies that the value of an economic variable (e.g. inflation) in the next period will be equal to the price level in the previous period adjusted by a factor accounting for the change rate of inflation. The adaptive expectations approach (Fisher, 1930; Cagan, 1956; Nerlove, 1958) is based on the premise that expectations are revised up or down in accordance with the last forecasting error, calculated as the difference between the actual realization of the variable and its expected value.

Those concepts were deemed ‘mechanical’ because they are back-looking, blindly self-feeding and do not incorporate the fact that economic agents have (at least some) understanding of the underlying causal mechanisms of the economy and process the available information. This was the point of departure for the REH, according to which expectations are ‘informed predictions of future events’ (Muth, 1961, p. 316).

Within the REH framework (Muth, 1961; Lucas, 1972), agents are assumed to update their prior beliefs (probabilities) in light of new information in a similar manner. Rationality is an instrument to model consistent expectations that are related to agent’s understanding of how the economy works, that is, to the systematic processes that generate economic variables. The REH agents rely on one fully predetermined model to form their forecasts. Thus, expectations, that is, the probability distribution of future events, are assumed to be common knowledge and correct on average. If the world were stationary, that is, if the same events repeated themselves again and again, rational people would learn the true probability distribution. The ‘communism of models’ (Sargent, 2005, p. 567) and homogeneity of beliefs are the result. The REH is very powerful because it has made the exact understanding of how agents form beliefs obsolete.

The REH concept was questioned in the aftermath of the 2008 crisis by economists and sociologists alike. The major objection—as voiced across disciplines—was that it is considered inappropriate for a situation of radical uncertainty, innovation and surprising change (e.g. Akerlof and Shiller, 2009; Frydman and Goldberg, 2013; Beckert, 2016; King and Kay, 2020). The critics revived the insight already discussed by Lucas (1977) who argued that the REH is most useful in a situation of Knightian risk in which the probabilities of events can be unambiguously and objectively determined as they relate to well-defined, recurrent events. In a situation of Knightian uncertainty, probabilities cannot be accurately measured and, moreover, the list of possible events is never complete. In more general terms, surprises, ‘unknown unknowns’, novelty (Shackle 1972, 1979), non-ergodicity (Davidson, 1991; Peters, 2019) and ‘black swans’ (Taleb, 2007) imply that past data cannot be used to adequately predict the future behaviour of a system; perfect knowledge of the full information
set and processes underlying the economy are unattainable. This non-knowledge might give rise to diverse—and constantly changing—views on what is going on in the economy. Thus, expectation formation, the politics of expectations and heterogeneity of beliefs matter and must be understood in their own right (Hommes, 2013; Beckert and Bronk, 2018).

Economic decision makers are not fully aware of future events, not only because they do not have the ‘right’ model but also because they are part of the system which they are observing and about which they make decisions. In other words, an economic decision-making situation involves many independent heterogeneous actors who interact with one another and orient their expectations and decisions towards the expectations and decisions of others. Thus, the REH critics call for a richer picture of an economic agent who not only observes and processes signals imperfectly but also interacts and communicates with other agents (Colander 2013). As a result of those interactions, some views of the future might become dominant, and some might disappear unnoticed.

Strikingly, although very concerned with heterogeneity and sociality of beliefs, the critics are not worried about the REH’s neglect of the role that technology plays in processes of expectation formation. Clearly, the REH critics have put forward the familiar argument that financial models are abstract and unworldly constructs, which are insufficient under the condition of radical uncertainty and thus misguide their users, who blindly follow them into an abyss (Salmon, 2009; Derman, 2011; Triana, 2011). However, this criticism has not led to an explicit call to think about how various calculative devices facilitate and change belief formation in the economy and how the theory of expectations might be adjusted. As discussed above, the focus has rather been on the imperfection of human knowledge and cognition and heterogeneity and the sociality of expectations. To illustrate this in more detail, let us now discuss the most prominent reactions to the REH critics in economics and sociology. Figure 1 maps the presented concepts and facilitates navigation within the article.

3. Alternatives to the REH in economics

The majority of concepts that challenge the REH within economic science assume various frictions and imperfections related to the agents and move in a psychologically more realistic direction, trying to incorporate and explain the evidence from experimental and survey data. They relax some central assumptions of the REH; for instance, the assumption that economic actors can access the full information set or can perfectly process the observed data. I will briefly review two strands of this literature. One stems from the behaviouristic tradition, and the other focuses on how individuals learn from experience and adapt their expectations in light of incoming news and the behaviour of others.

3.1 Behavioural alternatives to the REH

The idea of these concepts is to show that the REH does not fit the empirical data well because agents form expectations based on less sophisticated schemes and rules than the REH presupposes. As a result, economic actors make predictable forecast errors; beliefs are not perfectly consistent with actual performance. In contrast to the ‘mechanical’ expectation formation concepts, which preceded the REH and similarly resulted in predictable errors, the agents in recent frameworks react to information and news, but not to the right extent: they either overreact or underreact.
Because economic agents face an abundance of information as well as costs related to information gathering (time, money, cognitive efforts, etc.), the assumption that full information exists can be relaxed. Agents have to decide which information to pay attention to and which to disregard—they exhibit rational inattention (Mankiw and Reis, 2002; Sims, 2003; Muth, 1961; Lucas, 1972).

**Figure 1** Overview of expectation formation concepts.

| Static (naive) expectations                  | Extrapolative expectations       | Adaptive expectations             |
|---------------------------------------------|----------------------------------|-----------------------------------|
| *Kaldor, 1934; Ezekiel, 1938*               | *Hicks, 1939*                    | *Fisher, 1930; Cagan, 1956; Nerlove, 1958* |

Rational expectations hypothesis (REH)

*Muth, 1961; Lucas, 1972*

**Behavioural deviations**
- Sticky expectations *(Coibion and Gorodnichenko, 2012, 2015; Bouchaud et al., 2019)*
- Anchored expectations *(Jørgensen and Lansing, 2019, Ball and Mazzumer, 2018)*
- Diagnostic expectations *(Gennaioli and Shleifer, 2018)*

**Learning approaches**
- Bayesian learning *(Veldkamp, 2011)*
- Non-Bayesian (e.g. adaptive least-square learning) *(Evans and Honkapohja, 2001)*
- AI agent *(Hou, 2020; Marwala and Hurwitz, 2017)*

**Narrative accounts of expectations**
- Fictional expectations *(Beckert, 2016)*
- Conviction narrative theory *(Chong and Tuckett, 2015; Tuckett, 2018)*
- Economy of words *(Holmes, 2013; 2018)*

**Integrative approaches (STS/SSF)**
- Cultures of model use *(Beunza and Stark, 2012; Svetlova, 2018; Beunza, 2019)*
- Algorithmic governance *(MacKenzie, 2018, 2019; Pardo-Guerra, 2019; Borch, 2020; Rona-Tas, 2020; Hansen, 2020)*

Narra*ve accountsof* expecta*ve/ions*  
- Fic*onal expecta*ve/ions (Beckert, 2016)  
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- Algorithmic governance (MacKenzie, 2018, 2019; Pardo-Guerra, 2019; Borch, 2020; Rona-Tas, 2020; Hansen, 2020)
Steiner et al., 2017; Ellison and Macaulay, 2019). This avenue of research can help to explain why economic agents update their beliefs infrequently and too slowly, that is, why they underreact to news: the actual performance of variables exceeds the forecast. In other words, agents exhibit sticky expectations (Hong and Stein, 1999; Mankiw and Reis, 2002; Coibion and Gorodnichenko, 2012, 2015; Bouchaud et al., 2019; Carroll et al., 2020; Coibion et al., 2020).

The slow adjustment of expectations can also be explained by the fact that expectations are anchored, for example, by stock fundamentals or macroeconomic numbers, such as the inflation target of a central bank (Ball and Mazumder, 2019; Jørgensen and Lansing, 2019). Anchored expectations—based on anchoring heuristics—can contribute to understanding of why some long-term expectations stay stable despite short-term fluctuations in the economy. At the same time, the most recent research points out that expectations can become de-anchored (Nautz et al., 2017; Gobbi et al., 2019), leading to a situation where short-term price shocks and central bank announcements can change long-term expectations in a surprising way.

The concept of diagnostic expectations (Bordalo et al., 2018; Gennaioli and Shleifer, 2018), on the contrary, suggests that agents depart from the REH in the other direction, rather than underreacting to news, they overreact. The core idea is the judgement error of representativeness, as formulated by Kahneman and Tversky (1979). People tend to give more weight to most recent information and thus focus on future outcomes that are more likely in light of incoming data; as a result, beliefs exaggerate true patterns in the data. If only good macroeconomic or stock news comes in, and good future outcomes become more likely, agents give this news more weight in their judgements about the future state of the world, become overoptimistic and disregard risks. Such forward-looking and extrapolative expectations may explain collective movements of ‘optimism’ and ‘pessimism’ which drive ‘animal spirits’ (Akerlof and Shiller, 2009), behavioural credit cycles (Minsky, 1977), risk neglect and financial instabilities more generally (Hommes, 2013; Assenza et al., 2021).

In all of these concepts, expectations are conceptualized as deviations from the REH that remains a valid sub-case. The deviations are caused by the fact that economic agents—while coping with imperfect knowledge and their inability to perfectly process information—rely on identical simple rules (heuristics) and err in the same direction: they either underreact (sticky expectations) or overreact (diagnostic expectations). Rooted in the behavioural research initiated by Kahneman and Tversky (1979) as well as in the concept of bounded rationality (Simon, 1955; Sargent, 1993), the approaches to expectations presented above focused on limitations to human mental resources and neglect the fact that these limitations might—at least partly—be rectified by means of modern technology. One has reasons to assume, for example, that if economic agents use algorithms, the issue that expectations are revised infrequently or too slowly might become less relevant. Mankiw and Reis (2002, p. 1319) concluded their programmatic paper on sticky expectations with a call to develop a better understanding ‘of how quickly people incorporate information [. . .] into their plans, and why their response is faster at some times than at others.’ The answers to these questions today should take into account the fact that expectation formation is a technologically facilitated activity, with algorithms processing information at an amazing speed and frequency.

Similarly, how strongly particular pieces of news anchor expectations might depend on which models and algs support consumers, firms and investors in their belief formation, as they co-determine which information deserves attention and which weight it is assigned. Thus, the reasons for joint movements in markets (Minsky moments) might lie not only in
human emotions and biases but also in how algos process information and react to each other (as I discuss further below). Although Shiller (2019) pointed out the role of new technologies, such as social media and search engines in the reinforcement and contagion of beliefs, behaviouristic literature has so far neglected to fully consider how new technologies might influence and co-shape expectation formation.

3.2 Advances in the economic literature on learning

The other strand of economic research on expectations assumes that agents adjust their beliefs and behaviour over time as new information becomes available. The literature on learning has a long tradition (Eusepi and Preston, 2018, for a recent review). Some concepts assume that agents rely on the Bayesian rule, according to which they can be passive learners for whom information is an endowment or arrives stochastically, or they can make active decisions about which information to access, as in the models of rational inattention (see Veldkamp, 2011 for an overview). At the same time, some literature on non-Bayesian learning originates in models of bounded rationality (Sargent, 1993), for example, adaptive least-square learning, where agents try to discover the optimal linear forecasting rules and behave as perfect econometricians (Evans and Honkapohja, 2001). Although econometric learning models still operate in the proximity to the REH solution, they deviate from the REH by allowing agents’ predictions not to coincide with the predictions of the theoretical model, at least for a while.

Economists who work on learning have been applying advanced concepts from computational science, such as genetic and evolutionary algorithms, neural networks and others, for quite a while. Now, they are experimenting with replacing (bounded) rationality with AI when modelling agents’ expectations (Marwala and Hurwitz, 2017; Hou, 2020; Charpentier et al., 2020; Chen et al., 2021). New AI approaches aim to enrich the modelling of agents’ forward-looking behaviour by relaxing restrictive assumptions—usually made in both the REH and the traditional learning models—about the relationship between signals agents receive and their expectations. AI agents can be modelled to learn in complex environments in accordance with non-parametric and non-linear machine learning rules, that is, without assuming learning structures in advance. This approach generates a richer set of results while allowing modelling of expectation changes and attention shifts. For example, Hou (2020) applies Recurrent Neural Networks to estimate a generalized model of expectation formation without making any priori parametric assumptions about the relationship between macroeconomic signals and expectational variables. Furthermore, he applies the Double Machine Learning approach (Chernozhukov et al., 2018) to analyse the effects of a rich set of macroeconomic signals on households’ expectations. He shows that agents’ expectations respond to signals in an asymmetrical and non-linear manner and vary depending on the state of the economy. Households behave as ‘adaptive learners’ (pay attention to past signals) when economic conditions are stable, and they become more ‘forward-looking’ when the situation worsens. Furthermore, Hou demonstrates that the content of

2 This research should not be confused with economists’ use of algorithms in agent-based models (ABM) and game theory. Typically, ABMs incorporate simplistic assumptions regarding agent expectations (cf. Hommes 2013). While allowing for heterogeneity of beliefs, they simply divide economic agents into those that are fully rational and those that are ‘less-than-fully rational’ (as described in Section 3.1). The introduction of AI agents into such models could be an enrichment.
signals related to economic conditions, rather than the amount of news coverage, plays a crucial role in triggering the attention shift.

This pioneering research amends the REH, behaviouristic concepts and some simple learning models without rejecting them. An AI agent is represented by decision rules encoded in artificial neural networks; those rules can be rational or accommodate some behaviouristic phenomena, such as rational inattention (as in Hou’s paper) or overconfidence (Camerer, 2019).

Please note, however, that these innovative approaches to learning and expectations apply an AI agent as a modelling approach. It is a tool for solving a model, exactly like the concept of the rational agent that is used as a modelling instrument. At the same time, as we saw in Section 2, the idea of an agent who relies on rational expectations has had wide-ranging consequences for the economic theory. Thus, there is a need to interpret an AI agent and understand the implications of this concept for the theory of expectations (Marwala and Hurwitz, 2017; Camerer, 2019; Wagner, 2020).

The issue is crucial and controversial, though. For example, Marwala and Hurwitz (2017) suggest that—with advances in machines that make independent decisions—the REH will become more valid. AI will give rise to unbiased and cheaper predictions that utilize information from various sources more fully. Hence, the incompleteness of an information set might become less of an issue, as AI can, for example, fill in the information gaps using techniques for estimating missing data. In other words, according to Marwala and Hurwitz (2017), AI extends the limits of bounded rationality and necessitates the concept of flexibly bounded rationality. Technology pushes human cognition beyond its behavioural limits.

Such considerations can be seriously countered, though. The literature has widely discussed biases associated with algorithms (Angwin et al., 2016; Dastin, 2018; Kaplan and Haenlein, 2020; Venkataramakrishnan, 2021); the agent’s perfection in learning often cannot compensate for the initial deficiencies of either data or models on which learning relies. The resulting biases (e.g. the strong preference of male candidates by a recruitment algorithm) might undermine the rationality of algorithmically supported expectations, exactly as human biases jeopardize the rationality of human beliefs.

Also, as Agrawal et al. (2019) argue, AI expectation techniques are not automatically better and cannot simply replace human cognition independently from the context. While AI-based predictions are superior in a world that can be easily described (Knightian risk), human judgement excels under conditions that are indescribable and unfamiliar (Knightian uncertainty). Furthermore, an important aspect of an AI agent is that it might circumvent the issue of expectation formation altogether. Expectations might become a non-linear and non-parametric function which is a black box without any obvious economic interpretation (Joseph, 2019). As Hou’s (2020) paper shows, the deep learning approach produces some interesting, stylized facts without explaining how they come about.

It is, however, difficult to address all of these questions and emerging controversies with economic approaches in which modern technology either does not play a role (as in behaviouristic concepts) or in which technology is a modelling tool that does not require further interpretation (as in learning approaches). One hopes that sociology might open a door to a more holistic perspective.
4. Alternatives to the REH in sociology

Sociologists and anthropologists make fundamental uncertainty the point of departure of their critique on the REH (Chong and Tuckett, 2015; Beckert, 2016; Beckert and Bronk, 2018; Tuckett et al., 2020). Economic decision-makers do not have full access to the information set or the ‘right’ model of the world, not only because their cognition is imperfect but also because economies are non-ergodic and constantly changing as they are driven by non-predetermined creativity, innovations and interdependent actions of other agents. Thus, the central theoretical and empirical task with regard to expectations is not to understand how strongly beliefs deviate from the (unattainable) REH but to work out how economic agents make an uncertain situation manageable and decidable.

The most prominent sociological investigations of expectations currently focus on the actors’ ability to imagine futures, form narratives and, more generally, to make sense of what is going on. I will discuss those approaches first and argue that—similar to behavioural concepts—they do not sufficiently consider the profound role of the technological tools that economic agents use to form expectations. Then, I will outline what I call the integrative approach to economic action which puts material calculative devices at the centre of agents’ dealing with uncertainty.

4.1 Narratives and imaginaries

While providing an alternative to the REH, current sociological approaches consider fictional expectations to be cognitive devices for coping with uncertain futures (Beckert, 2016). Especially the ability to narrate helps economic actors to ‘overlook’ uncertainty and make actions possible. Beckert’s concept depicts expectations as imaginaries of what could happen or of how the future could develop. Economic actors strongly anchor their expectations in narrative fictions: ‘Expectations often adapt a narrative form that sets out credible causal relationships between the known present and imagined futures’ (Beckert and Bronk, 2018, p. 10). Fictional expectations can be compared with literary fictions or stories. The point is that literary narratives are read because they are convincing, not because they are true. They create a plausible world. Note that, in the realm of rational expectations, the expected world coincides with reality whereas, in the case of behavioural expectations, the discrepancy between expectations and reality is an issue related to human error. Now, in the case of fictional expectations, reality is ‘doubled’ in a different sense (Beckert, 2016, p. 64): ‘A world created in the imagination—a ‘doubling reality’, in other words—makes it possible for an actor to experience a reality that only exists in her or his imagination.’ The imagined reality provides the basis for decision making and helps one to overcome uncertainty. We find similar argumentation in the conviction narrative theory (Chong and Tuckett, 2015; Tuckett, 2018) and the economy of words account (Holmes, 2013, 2018).

The narrative accounts distance themselves from the behavioural approaches discussed in the previous section. Beckert and Bronk (2018, p. 9) claim that behavioural economics does not take radical uncertainty seriously enough and considers human information processing to be imperfect but predictable; thus, it merely offers ‘bolt-on amendments to rational expectations models’ and ignores non-ergodicity of the future, that is, the fact that ‘novel products, processes, imaginaries, and policies are disrupting systematic regularities of behaviour’. This is also Tuckett’s reading of Shiller’s behavioural ‘narrative economics’ (2019). For Shiller, narratives often have a negative connotation; they could lead people astray and...
make them deviate from rational behaviour, causing economic instabilities such as stock market booms and busts. However, under condition of radical uncertainty, narratives are rather tools for coping with non-ergodicity. It is only by actively imagining and inventing the future and creating narratives about it that actors arrive at subjective certainty, which allows them to act. In this sense, narratives are a true alternative for rational expectations (Tuckett et al., 2020).

Furthermore, proponents of narrative accounts are at pains to stress that the imaginaries and stories on which expectations are based are not random and individualistic. They are socially embedded in institutional settings (Wansleben, 2018), cultural structures, networks, geographical regions (Pellandini-Simányi and Vargha, 2018), and thus their dispersion is limited.

Importantly, narrative accounts also acknowledge the role of calculative devices as a force that shapes expectations, although this role is presented as rather secondary. As formal tools have notorious difficulties in capturing the causal relationship between past and present in a situation of radical uncertainty, imagination and narratives carry out the job. Thus, models primarily support, coordinate and legitimate storytelling. They are props (Beckert, 2016, p. 68), which fake and stage the reasons where there are no rational reasons for any decision whatsoever; they back up stories that ultimately guide expectations and actions. Furthermore, models might improve ‘the epistemic quality of fictional expectations’ by stress-testing the imaginaries for plausibility (Beckert and Bronk, 2018, p. 16). Nevertheless, in narrative accounts, ‘[t]here is nothing inherently calculative about the way that capitalist actors imagine the future’ (Deringer, 2017, p. 245); indeed, the focus is still on the specific cognitive ability of agents to imagine and narrate the future.

4.2 An integrative approach: two generations of research

The expectation formation concepts presented so far in this article subscribe to either an over- or under-calculative view. Whereas the REH and the emerging AI approach model economic agents’ beliefs as resulting from more or less perfect calculations, behavioural economics and narrative accounts conceptualize expectations as products of unaided human cognition. However, there have been developments towards a third, integrative, view on the formation of economic expectations, presented in sociological and anthropological accounts informed by STS. They pay attention to the psychological, social and material complexity of the formation of economic beliefs while putting technology at the core.

The programmatic sociology of expectations (Brown et al., 2000; Brown and Michael, 2003; Borup et al., 2006; van Lente, 2012) conceptualizes beliefs as looking at the future—a study of ‘how the future is mobilized in real time to marshal resources, coordinate activities and manage uncertainty’ (Brown and Michael, 2003, p. 4). Such accounts highlight the materiality, temporality, spatiality and performativity of expectation formation and accommodate ‘the interdependence between the social and the calculative’ (Beunza and Stark, 2012). Under condition of radical uncertainty, calculations and technologies are combined with judgement, market observations, stories, emotions, rumours and so on in the process of expectation formation. This integrative programme was developed primarily in sociological literature on finance 3 in two waves. The first wave focused on market participants who are

3 Also known as Social Studies of Finance.
equipped and constantly intervene with models and formulae; the second highlighted the rise of automation and independent algorithms and the shifting balance between human agency and technology.

Cultures of model use
The first generation of integrative accounts stressed the constitutive role of formal models (Callon, 1998; MacKenzie and Millo, 2003; MacKenzie, 2006; Svetlova, 2018; Beunza, 2019) and technological devices, such as hardware, software, computer screens (Knorr Cetina and Bruegger, 2002), stock tickers and charts (Preda, 2006) in financial markets. It provided empirical accounts of how calculative tools and technologies are involved in and shape the process of expectation formation without denying the importance of narratives, judgement and sociality. The most prominent examples are calculative frames (Beunza and Garud, 2007), reflexive modelling (Beunza and Stark, 2012), views (Wansleben, 2014), the plausibility check of models and plausibility check of consensus (Svetlova, 2018).

We learn from those accounts that, while forming expectations, professional market participants (e.g. security analysts, merger arbitrageurs and portfolio managers) interact with their models and algorithms. Calculative devices essentially determine which information is collected and taken into account as well as which profit opportunities one could reasonably expect. At the same time, model users are aware of models’ deficiencies under condition of Knightian uncertainty. However, instead of abandoning their models and merely relying on heuristics (e.g. mimesis) or narratives, financial market professionals navigate uncertainty with calculative tools while questioning them by means of narratives, judgements and social cues received from neighbouring trading desks, business contacts, networks or market news. In other words, social cues are used to check models and to form judgements that might override models’ prescriptions.

Within those cultures of model use, models are subject to a plausibility check. Judgement, which might assume the form of commentary or a story, compensates for models’ insufficiency under uncertainty and connects them to the constantly changing world. In this process, models are treated as an additional source of information and help for structuring expectations and serve as anchors for beliefs. Users of financial calculative tools develop a specific kind of mindfulness with models and about models as well as with markets (What do others think? What do they believe?) and about markets (What are my expectations? Where do I disagree with the market?). Importantly, market professionals are aware of their potential mental biases and proneness to emotions and rely on models exactly because they want to avoid them. Thus, integrative approaches amend the behaviouristic accounts by suggesting that—at least in professional finance settings—biases and the related crowding-in of expectations might be less relevant due to the use of models.

For example, in the reflexive modelling approach, the specific calculative device—the spread plot (i.e. the graphical representation of the aggregate opinion of market participants about the likelihood of a merger)—allows a comparison of one’s own views with the views of others. Thus, a position can be taken in market based on this socially informed calculation. This is an important response to the REH critique but also to that of narrative accounts.

Such a reflexivity is not a narrative order and is emphatically not an intellectual exercise of transcending subjective experience. Neither is it ‘objective’, but it is nonetheless objectified
in the instrumentation, market devices, and material practices of merger arbitrage in the era of quantitative finance (Stark, 2011, p. 334, my emphases).

Similarly, the plausibility check of consensus\(^4\) (Svetlova, 2018) demonstrates how financial market participants account for higher-order beliefs by relating their individual judgement to the collective market view. They observe the consensus estimate, not because they intend to follow it but to find out what the consensus implies and where and when revisions in consensus expectations are likely to occur. These considerations enable investors to compare their individual views with the market estimates and mindfully deviate from the consensus.

This peculiar form of calculative mindfulness—as a constant switch between individual and collective expectations, between models and judgement—still puts human sociality and reflexivity at the core of expectation formation. However, the rise of more independent technologies requires updates of this type of integrative accounts.

Algorithmic governance
The concepts of culture of model use described above were further developed and partly challenged by the second, more recent wave of sociological research on finance. This research claims that the increased importance of automation, AI and independent algorithms, for example, in high-frequency trading and at stock exchanges (Lenglet, 2011; Lange et al., 2016; MacKenzie, 2018, 2019; Pardo-Guerra, 2019; Borch, 2020), in quantitative finance (Hansen, 2021), market regulation (Coombs, 2016), consumer credit (Rona-Tas, 2020) and robo-advising (Hayes, 2019; Tan, 2020), further transforms the balance between human cognition, technology and sociality. Although this research is not explicitly concerned with expectations, in this sub-chapter, I will elaborate on its possible implications for our understanding of belief formation.

A central tenet of this literature is that human cognition—with its advantages (e.g. ability to form a judgement, to narrate, to be reflexive) and disadvantages (e.g. proneness to biases and emotions)—is gradually being forced into the background. This shift of human influence transforms our understanding of how expectations are formed, what they are and whether they matter at all.

Whereas the early-day algorithms were quite simple and just performed, or enacted, human expectations (such as mean reversion or momentum) at a high speed, the more advanced contemporary algorithms are discovering their strategies independently and develop ‘views’ on the market based on which they trade.\(^5\) In the latter case, human beings become increasingly detached from markets and might even not need to form expectations to guide their investment activities, as technology increasingly makes decisions. Such distancing might generally relativize the role of human expectations in economics. Relevant expectations take the form of algorithmic predictions. In this respect, Rona-Tas (2020, p. 905) suggests that algorithmic governance is ‘the replacement of social institutions and processes with algorithmic decision making’.

\(^4\) Consensus, or a consensus estimate, is a forecast of a company’s earnings based on the forecasts of financial analysts who follow the stock. Consensus estimates are officially published numbers which are readily available on Bloomberg and on the Internet.

\(^5\) I am grateful to Christian Borch for highlighting this difference to me.
These advances in programming and automation further question the relevance of the behavioural and narrative accounts of expectations but also of the early integrative approaches. As an AI agent takes the front stage, human actors are reduced to observers of decisions, who struggle to understand and control their algos (Lenglet, 2011; Hansen, 2021). The role of technology users is changing; their influence is more evident ‘during the initial phases of problem formulation, model selection, and parameter setting’ but not when an automated algorithm is working in the market (Hansen, 2021, p. 606). Here, the theory of expectations might want to ask whether quants still determine algorithms’ expectations while collecting, cleaning and preparing data, and which form AI-based expectations assume. Rona-Tas (2020) questions whether algorithmic predictions—which are merely pattern recognitions and not predictions of change—can qualify as (rational) expectations at all. Is expectation a valid category in the case of an algorithmic agent? Here, we are taken back to the initial issue of the REH: What are ‘informed predictions’ of the future?

Furthermore, in the automated markets, constant, active intervention in the form of judgement and storytelling might not be possible, for example, because the algos act at a speed beyond human cognition. Also, such interventions are undesirable as reliance on algorithms helps to keep human emotions in check (Borch and Lange, 2017). For example, investors who use robo-advising are purposefully restrained from adjusting algos’ strategies to prevent them from succumbing to loss aversion, overconfidence and other biases; in other words, they are nudged towards objective rationality (Hayes, 2019).

It is important to keep in mind, though, that integrative empirical studies on the use of modern technology in markets support the view that we are far from a situation of ‘financial singularity’ in which powerful computers and sophisticated algorithms have fully replaced human intelligence (Shiller, 2015). We can hardly find a model or an algorithm that is used without a human component at one or the other stage; social cues, narratives and judgement are constantly ‘folded’ into a market in various forms (Muniesa, 2007).

Financial markets today constitute a complex human–machine ecology in which the cultures of combining formal models and algorithms with human judgement and narratives vary between market segments (merger arbitrage, high frequency trading (HFT), portfolio management, quantitative finance, etc.) but also within the segments, that is, among the HFT companies (MacKenzie, 2018). Thus, various cultures available in the markets do not automatically promote a particular style of expectation formation. For example, some of them produce black-box predictions; some are absolutely transparent (Hayes, 2019). Some companies aim to exclude human influence from their processes altogether, whereas others allow it to a greater or lesser extent. Human beliefs co-exist with fully automated predictions. This rather complex market ecology provides a possible explanation for the heterogeneity of expectations, the issue that the REH struggles to account for.

One might assume that the observed diversity of expectations—and actions—might reduce the mimetic tendencies in markets and thus the danger of herding (Wigglesworth, 2017). However, also this is not a firmly established finding as, in light of increasing automation, the sociality of beliefs and the balance between mimetic and anti-mimetic tendencies require reconsidering. Instead of focusing on human agents who observe and guess each other’s beliefs, there might be a necessity to analyse the interaction order of algorithms (MacKenzie, 2019), for example, in automated trading ‘interactions between fully automated algorithms as a form of sociality’ (Borch, 2020, p. 237). ‘Cognitive interdependence’ and mutual observations happen among algorithms that are programmed to guess and
outsmart each other (Arnoldi, 2016) and thus rather prone to lock in their predictions. For example, ‘algorithmic collusion’, the situation in which algos autonomously learn to engage in anti-competitive behaviour, could cause severe market disruptions (WEF, 2019).

As we see, this research brings the contemporary theories of expectation formation into uncharted territory. As of now, there are more questions than unequivocal answers. In the remaining part of this article, I will briefly sketch a research programme on expectations that take into account the central challenges posed by modern technology.

5. Discussion: identifying a research programme

The article has provided an overview of the contemporary concepts of economic expectations and discussed how they address major points of criticism of the REH, namely, its neglect of radical uncertainty, heterogeneity and the sociality of beliefs. Although a lot of progress has been observed in economics and sociology on this front, the central tenet of the review is that none of the presented concepts sufficiently consider the influence of contemporary technology on the process of belief formation. Future research should account for this omission because technologically enhanced beliefs are becoming widespread in various economic fields, such as central and commercial banking, e-commerce, organization of supply chains and labour markets. Diverse forms of expectations in those domains require careful empirical research with respect to which economic agents use which kind of technology and how they do it. This type of analysis could guide joint efforts to understand expectation formation in economics and sociology.

In each field, it is important to understand the degree to which algos are independent. If we discover cases in which algorithms can decide autonomously without human overlay, joint research should be devoted to investigating the questions posed in this article: What is an AI agent? What kind of agency is it? How to integrate it into the economic discussion on expectations?

For example, the economic literature has realized that expectations of professional forecasters (e.g. asset managers) differ from those of households and firms, and that this difference matters for the management of expectations in monetary policy (Coibion et al., 2020). Central banks’ signals do not have equally strong effects among economic agents; thus, a layered communication strategy should be on the agenda. This research omits the fact that nowadays algorithms (e.g. applied by hedge funds) also evaluate and react to central banks’ signals and thus co-determine the effectiveness of monetary policy. Important questions would be whether AI agents overreact or underreact to news and whether they follow mimetic or anti-mimetic tendencies with their behaviour.

At the same time, the discussion in this article suggests that a balanced research strategy is required. While amending contemporary expectation concepts, which too strongly focus on human cognitive abilities and the tendency to succumb to biases and emotions, to imagine and to narrate, researchers should not blindly over-emphasize the importance of technology. As the integrative accounts within the sociology of finance demonstrate, algorithms and AI are gaining importance very fast but they still co-exist with humans, whose areas of control and magnitude of influence are shifting. So, in the case of central banking, it would be interesting to find out how storytelling by the regional agencies and in meetings of the Monetary Policy Committee at the Bank of England observed in Tuckett et al. (2020) is complemented by algorithmic forecasting of economies in the process of expectation
formation. In other words, more detailed research is required on how human and algorithmic biases, (in)attention, data management, stories and so on influence beliefs in markets, in households and firms.

Furthermore, more research is required on the technology-driven interconnectedness of economic expectations. There is a need for a valid account that explains how human and algorithmic agents retain independence and heterogeneity in some contexts and then gravitate in one direction in other contexts, for example, due to ‘locked-in’ patterns in data or influential narratives whose spread is supported by technological artefacts and platforms. It is crucial to find out empirically how digital technologies influence agents’ information sets and co-create and spread narratives (e.g. in automated journalism or robo-writing in financial markets). AI applications might lead to stronger interconnectedness of human and algorithmic beliefs by means of new types of contract and relationship (e.g. algorithmic collusion). In finance, independent or light-touch-controlled AI programmes—while interconnecting and interacting with human market participants and with each other—can cause negative systemic events such as a liquidity crunch, price collapse (e.g. ‘flash crash’) or severe market disruptions. Such research could further advance contemporary debates on economic crises, business cycles and systemic risks.

Finally, to find solid common ground among economists and sociologists, researchers have to move beyond empirical case studies and elaborate on the theoretical consequences of 21st century technology for expectation formation accounts. One issue is the very nature of expectations. Can we still use the term ‘expectation’ in the case of an algorithmic agent? Is temporality (the difference between past and future) still meaningful for algos? The other issue is the rationality of expectations which has been addressed in this article several times. When AI and algorithms increasingly dominate economic life, the REH could become more valid, on the one hand, because advanced technology might move closer to perfect information processing and discover the ‘right’ model of the economy. On the other hand, the neglect of expectation formation within the REH framework might start to make sense due to human distancing from decisions. Then, the AI agent as a modelling instrument which has emerged in economic theory today would be the right choice. At the same time, the growing literature on artificial stupidity (Lo, 2019), algorithmic biases, AI’s inability to recognize causality (Pearl, 2019) and the inferiority of algorithmic decisions compared with human judgement in complex uncertain situations (Rona-Tas, 2020) would challenge the absolute theoretical claim with respect to the rationality of technology-driven expectations. Thus, the theoretical debate about the major flaw of the REH—radical uncertainty—remains as vivid as ever because, as the integrative accounts discussed in the article suggest, the imperfection of formal models and algorithms in complex uncertain situations brings human judgement, stories, communication and cultures of technology use to the theoretical frontstage, rather than excluding them.

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