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A.V. Pastushkov
International Laboratory for Experimental and Behavioural Economics, HSE University, Moscow, Russia

Evolutionary and agent-based computational finance: The new paradigms for asset pricing[1]

Abstract. Since the 1980s asset pricing in the traditional neoclassical paradigm has been confronting empirical evidence contradicting both the predictions of the models as well as their microfoundations. Simultaneously, the market microstructure literature started probing the details of the trading process, turning the spotlight onto the effects of asymmetric information, clearing mechanisms and agents' learning and belief formation. These details, which were "abstracted away" in the earlier models, are becoming ever more important as the complexity of markets grows due to proliferation of algorithmic and high frequency trading and markets turn into ecologies of strategic, but not necessarily perfectly rational, co-evolving agents. In this review article I argue that the paradigms of agent-based and evolutionary finance are ideally suited to handle the modelling of markets as these complex ecologies. I review the most prominent contributions of evolutionary and agent-based modelling to asset pricing, specifically, categorizing them into three main streams: the research on the effects of institutional details of the markets, the research on the effects of agent heterogeneity, and the research of market selection. Furthermore, I argue that further progress can be made by combining the evolutionary and agent-based paradigms and highlight research questions for which such a mixed-method approach is likely to be the most fruitful.

Keywords: *evolutionary finance; agent-based computational finance; asset pricing; simulations; market selection.*

JEL Classification: B52, C63, C73, G10.

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1. Introduction

The neoclassical paradigm in finance, based on perfectly optimizing representative agents, frictionless markets, and symmetric and instantly available information has been facing challenges posed by contradictory empirical evidence since at least the 1980s. Shiller pointed out that most of the observed volatility of stock prices could not be explained by fundamental value indicators used in theoretical models, such as changes in dividends, real interest rates, or a direct measure of intertemporal marginal rates of substitution (Shiller, 1987). M. Reinganum and R. Thaler reported the small-firm effect[2] and the January effect[3], respectively (Reinganum, 1980, 1981; Thaler, 1987), challenging Eugene Fama's efficient market hypothesis (Fama, 1965). The US stock market crash of October 1987 sparked a number of studies examining the role of factors other than the fundamental value on the behavior of asset prices (see, among

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[2] The small firm effect refers to the observation that small listed firms (by market capitalization) tend to provide higher average returns than large firms.

[3] The tendency to observe abnormally high returns in January.

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others (Amihud, Mendelson, Wood, 1990; Blume, MacKinlay, Terker 1989; Roll, 1988)). More recently, there appeared the evidence that some market anomalies, such as the January effect and the accruals effect, despite being extensively documented in the literature, still persist (Haug, Hirschey, 2006; Haugen, Jorion, 1996; Hirshleifer, Teoh, Yu, 2011; Hirshleifer, Hou, Teoh, 2012), casting doubt on the ability of investors to incorporate all available information into security prices.

The global financial crisis of 2008 gave rise to dissatisfaction among regulators with the mainstream financial models that were unable to predict major market dislocations (Trichet, 2010). The proliferation of high-frequency trading and the related questions of market quality provided motivation for the development of alternative methods, among which is agent-based financial modelling, or ABM (see e.g. (Bookstaber, 2012; Bookstaber, Paddrik, Tivnan 2018; Haldane, Turrell, 2018; Tesfatsion, 2006)). Apart from the capacity to model a desired level of heterogeneity and dynamics, ABMs due to their structure are exceptionally well suited to testing regulatory interventions, as J. Farmer and D. Foley noted (Farmer, Foley, 2009).

Practically simultaneously with the development of agent-based modeling a new approach to the study of financial markets appeared under the names "evolutionary economics" and "evolutionary finance". The main idea behind the evolutionary approach to financial markets is to reject Milton Friedman's axiomatic claim that markets select one particular type of agent (Friedman, 1953) and actually investigate this claim with the help of appropriately specified models. An evolutionary view of economics and finance implies the processes of variation, retention and selection (Hodgson, 2019; Winter, 2014), as well as the notion that it is not the absolute level of rationality that determines an agent's or strategy's success in the market, but rather its relative performance in comparison with other agents and strategies, or in other words, its *relative fitness*.

Despite having some commonalities, such as a focus on dynamics and heterogeneity, agent-based and evolutionary modelling are not completely synonymous. Agent-based models do not necessarily incorporate a selection mechanism (see e.g. (Bak, Paczuski, Shubik, 1997; Challet, Stinchcombe, 2001; Maslov, 2000)), while evolutionary models need not be computational (Levin, Lo, 2021). In this review, however, we argue that both evolutionary and agent-based modeling offer a viable alternative way to explore questions in asset pricing that have not been adequately resolved in the neoclassical paradigm. To demonstrate this, we review the most prominent contributions to asset pricing made in the evolutionary and agent-based paradigms. Furthermore, we argue that a combination of the evolutionary and agent-based approach is the most promising avenue to resolve some of the remaining relevant asset pricing problems.

There exist a number of literature reviews that deal with either agent-based, or evolutionary modelling separately. B. LeBaron summarizes some of the early research in the field of agent-based computational finance, discussing both the issues addressed and the modelling techniques employed (LeBaron, 2000, 2006). T. Hens and K. Schenk-Hoppé present the evolutionary paradigm as applied to asset markets (Hens, Schenk-Hoppé, 2005). S. Chen et al. focus on how ABMs can provide a testbed for econometric techniques (Chen, Chang, Du, 2012). A. Chakraborti et al. discuss, among others, progress in modelling order-driven agent-based financial markets; however, the scope of their review is broader, touching upon the application of ABMs in va-

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rious areas of economics (Chakraborti et al., 2011). More recently, T. Holtfort provides a systematic review of evolutionary finance and identifies which traits differentiate it from the earlier paradigms of neoclassical and behavioral finance (Holtfort, 2019), while J. Segovia et al. carry out a bibliometric analysis of agent-based finance literature, quantitatively identifying emerging and declining themes (Segovia et al., 2022).

However, there is still no review of evolutionary and agent-based finance literature that focuses specifically on how the two paradigms contributed to the resolution of asset pricing problems that had not been adequately addressed by the neoclassical paradigm, such as the effect of institutional details (e.g. market mechanisms, information dissemination channels), agent heterogeneity and market selection. The aim of this paper is to provide such a review and, based on the features of agent-based and evolutionary modeling, identify which unresolved issues in asset pricing are likely to be amenable to analysis within these frameworks.

The remainder of the paper is structured as follows. Section 2 briefly recapitulates the research in asset pricing in the 20th century and highlights the problems that the neoclassical paradigm has faced before. Section 3 describes the salient features of the alternative paradigms of evolutionary and agent-based computational finance in more detail and categorizes the asset pricing problems highlighted in Section 2 into ones that are amenable to analysis within one or the other framework. Section 4 provides a summary of the most prominent results in the agent-based and evolutionary asset pricing literature in each category. Section 5 identifies further research directions and concludes.

2. Neoclassical paradigm in asset pricing and its challenges

The origins of asset pricing as it developed in the 20th century can be traced back to Louis Bachelier's doctoral thesis '*Théorie de la Spéculation*' (1900), in which he described the stochastic process of stock price changes based on the assumption that current prices were an unbiased expectation of future prices. The work of L. Bachelier had, however, relatively little influence in economics up until the development of risk-neutral option pricing models in the 1970s (Davis, 2008). This was largely due to the fact that Bachelier's model was not based on any explicit model of an investor's choice problem. The first such model for financial markets appeared in 1952, when Harry Markowitz published his paper on portfolio selection theory (Markowitz, 1952). Assuming risk-aversion, as implied by expected utility theory, H. Markowitz formulated the mean-variance principle, which represented both a normative and a positive facet of portfolio theory for an individual investor, but stopped short of formulating a model of equilibrium in a market populated by such investors.

This disconnect between Markowitz's portfolio theory and any theory of asset pricing persisted for more than a decade. Indeed, William Sharpe noted in 1964 that "at present there is no theory describing the manner in which the price of risk results from the basic influences of investor preferences…" (Sharpe, 1964, p. 426). The Capital asset pricing model (CAPM) developed by W. Sharpe, as well as its later extensions, such as ICAPM (Merton, 1973a), attempted to bridge this gap.

In parallel to these developments, Eugene Fama (Fama, 1965) formulated the necessary conditions for prices of assets to efficiently reflect all available information, so that riskless profits above the risk-free rate would be impossible. The efficient incor-

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poration of all relevant information into prices would result from the actions of rational arbitrageurs standing ready to trade against any possible mispricing. The efficient market hypothesis, and in particular, the no-arbitrage condition subsequently became the standard assumptions in the derivatives pricing literature (see (Black, Scholes, 1973; Cox, Ross, Rubinstein, 1979; Merton, 1973b)) as well as in more general standard texts on asset pricing (see e.g. (Cochrane, 2009; Duffie, 2010)).

Starting from the mid-1970s, however, both the efficient market hypothesis and the CAPM began facing numerous empirical challenges. On the one hand, empirical studies of asset markets found evidence that asset price fluctuations were unlikely to be driven by reasonable measures of fundamental asset values (Shiller, 1987; Shleifer, Vishny, 1997). On the other hand, CAPM was unable to explain certain cross-sectional patterns in security returns (Bernard, Thomas, 1989; Cont, 2001; Kato, Schallheim, 1985; Reinganum, 1981). Moreover, statistical studies of asset returns revealed a number of stylized facts, "common across a wide range of instruments, markets and time periods" (Cont, 2001, p. 224), which contradicted a reasonable assumption that different markets should be driven by different economic factors.

Simultaneously, it was recognized that arbitrage activities to bring market prices in line with the fundamentals were both costly and risky (Maslov, 2000; Mendenhall, 2004; Shleifer, Vishny, 1997), and therefore "irrational" behaviour driving asset mispricing may not be easily eliminated from the market, leading to market inefficiencies.

As F. Shostak (Shostak, 1997) noted, neoclassical finance focused too much on the long-run equilibrium outcomes, while more or less neglecting the study of processes that lead to these outcomes. Although this could be justified historically[4], further development of economic thought was creating the need for explicit modelling of the trading and price discovery processes. This development gave rise to market microstructure literature. Many details of the trading process that had been previously abstracted away became the primary focus of this literature, prompting the studies of the effects of market mechanisms, information asymmetries and learning on asset prices. Most notable early contributions to the studies on market microstructure include (Grossman, Stiglitz, 1980; Milgrom, Stokey, 1982; Glosten, Milgrom, 1985; Kyle, 1985). S. Grossman and J. Stiglitz (Grossman, Stiglitz, 1980) examined the implications of costly information for market efficiency, arguing that the more informative asset prices are, the fewer incentives traders have to pay the price of becoming informed, and therefore asset prices can never fully reflect costly information. In this model and others inspired by it, asset mispricing results from individual traders attempting to "free-ride" on the costly information acquisition performed by others.

Some authors (Milgrom, Stokey, 1982; Glosten, Milgrom, 1985) also rejected the possibility of full assimilation of costly private information into asset prices, although on different grounds. In their models, traders are assumed to be at a Pareto optimum prior to the receipt of private information and, additionally, it is assumed to be common knowledge[5] among traders that all of them are rational, trade for informational reasons and are seeking to profit from their private information. Under these assumptions, according to (Milgrom, Stokey, 1982; Glosten, Milgrom, 1985), no trade should take place, as each trader would realize that he is trading against an informed counterparty. As trading actually does take place in financial markets, the assumption

[4] For example, (Neumann, Morgenstern, Rubinstein, 1944) argued that it was premature to address questions of economic dynamics before all questions pertaining to static equilibrium were properly understood.

[5] For a formal definition of common knowledge (see (Aumann, 1976)).

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of rational expectations and common knowledge is not supported empirically, and the questions regarding how traders' beliefs are formed and what role the market mechanism plays in their interactions gain importance. The investigation of the role of the clearing mechanisms is pursued by (Kyle, 1985) and papers inspired by him, which constitute another major theme in market microstructure literature. A common theme in the microstructure literature, however, and the one differentiating it from the equilibrium models such as CAPM, is the assumption of strategic behaviour on the part of at least some agents and the explicit modelling of the trading process, allowing to examine how the market actually arrives at an equilibrium.

As the progress of technology made the markets ever more active and liquid (Chordia, Roll, Subrahmanyam, 2001), the interest in the trading dynamics only increased. The arrival of algorithmic and high frequency trading made the markets more complex, with market participants using a variety of strategies and trading on different time scales. As M. O'Hara notes, in the high frequency trading (HFT) world particularly, "trading is strategic because it maximizes against market design, other high frequency traders, and other traders" (O'Hara, 2015, p. 257). Additionally, traders adapt to each other's complex strategies, highlighting "how the learning models used in the past are lacking" (O'Hara, 2015, p. 258), the market ecology affects market performance and the homogeneous risk-neutral preferences assumed in the earlier market microstructure literature become an unrealistic assumption, as liquidity providers' trading behaviour very much depends on pre-defined risk appetites. M. O'Hara further highlights that "the rest of the market does not stand still in the face of change" (O'Hara, 2015, p. 260) brought about by high-frequency trading and therefore the market represents a perpetually evolving system.

Against this background, it becomes apparent that modern models of trading and asset pricing must explicitly account for the role of trading mechanisms, agent heterogeneity in terms of beliefs, learning schemes and preferences, as well as for the evolution of the market ecology. The assumption of the equilibrium models that in the long run markets would select one single type of a representative, perfectly rational agent, and therefore this one agent type is all we need to consider, has been recognized as arbitrary, and therefore it needs to be investigated rather than accepted a priori.

To summarize, therefore, the research in asset pricing performed in the neoclassical paradigm is facing the following main challenges:

1) financial markets appear to be influenced by institutional details (e.g. trading mechanisms, channels of information dissemination, regulatory environment); their impact on asset prices and market efficiency must be studied;

2) a priori, there is no reason to assume that financial markets are populated by representative agents, identical in terms of their preferences, beliefs and learning schemes. Indeed, such homogeneity would contradict the mass of experimental literature documenting various aspects of heterogeneity among economic agents. How interactions between various types of heterogeneous agents affect asset prices and market efficiency is therefore a pertinent question;

3) there exists a feedback loop between the buying and selling actions of market participants, the asset prices, and the traders' wealth. If traders are heterogeneous, it is reasonable to assume that some of them fare better in the market than others. In the limit, the worst performing traders must lose all their wealth and be driven out

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of the market. How and on what timescales this selection proceeds, and what are its results for the market quality is of major interest as well.

These three serious challenges were recently taken up by the paradigms of evolutionary and agent-based computational finance. The next section discusses the nature and salient features of these alternative paradigms and orders the three challenges highlighted above into their respective domains.

3. Agent-based and evolutionary finance

3.1. Agent-based computational finance

The emergence of the agent-based computational approach in asset pricing was initially motivated on the one hand by observations of empirical regularities in asset returns that were hard to reconcile with the distributional properties of fundamental values, and on the other hand by the developments in the so-called noise trader literature (Long et al., 1990). As the idea of non-linear chaotic systems was explored in natural sciences, some researchers in economics and finance began to wonder whether macroeconomic and financial time series were also characterized by the presence of chaos (Brock, 1993), loosely defined as a dynamic system the behaviour of which is highly sensitive to initial conditions. A question arose whether the presence of noise traders in the market, who were assumed to trade randomly, warranted an attempt to model the stock market as a system of a multitude of interacting parts leading to emergent properties, akin to how certain phenomena were modelled in statistical physics (Hsieh, 1991). Additionally, some researchers argued that the traditional modelling approach in economics that involved modelling a collective of individuals by one representative agent was fundamentally flawed (Kirman, 1992), and economics therefore needed to move on to modelling heterogeneous agents. These ideas together with computational power becoming less expensive led to the emergence of agent-based computational finance. Representative examples of some early work done on ABMs include the papers by (Palmer et al., 1994, 1999; LeBaron, Arthur, Palmer, 1999; Chan et al., 1998).

In these models, agents are represented by computer programs, and a stochastic simulation is then run to determine the aggregate dynamics that emerge from the agents' interactions. Some attempts were made to capture the essential characteristics of simple ABMs by analytical models (see e.g. (Alfarano, Lux, Wagner, 2008)); however, the complexity of most ABMs prevents such analysis. For illustrative purposes, below we present one of the early ABMs introduced by (Palmer et al., 1994).

There are n heterogeneous agents, each of which is initialized with a randomly chosen level of cash holdings M and stock holdings h, such that the wealth of each agent at the start of the simulation is given by

$$w(t)=M(t)+\Sigma\big(h(t)\,p(t)\big), \tag{1}$$

where $p(t)$ is the price of the stock at time t. Each stock pays a stochastic dividend, represented by an AR(1) process independent of the agents' actions. The cash holdings pay a constant interest rate of r, such that at period t the wealth of an agent becomes

$$w(t+1)=M(t)(1+r)+\Sigma\Big(h(t)\big(p(t+1)+d(t+1)\big)\Big). \tag{2}$$

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At period t an agent makes a prediction of the price and dividend for the period $(t+1)$ by using an econometric model the inputs of which are past realizations of the price and dividend processes. Given his predictions and some optimization criterion, e.g. myopically maximizing the expected value of his wealth at $(t+1)$, the agent determines his individual demand for the stock and cash holdings.

The individual demands of agents are then aggregated according to

$$B(t)=\Sigma b(t),\ O(t)=\Sigma o(t), \tag{3}$$

where b and o are individual bids and offers, and the price is determined by a clearing mechanism

$$p(t+1)=p(t)\left(1+\eta\left(B(t)-O(t)\right)\right), \tag{4}$$

where η is a constant liquidity parameter.

The simulation is then run for T time steps and k runs, and the endogenously generated price distributions are then compared to the empirically observed ones to examine to what extent the model replicates the observed empirical stylized facts, such as fat-tailed distributions of returns or volatility clustering.

Essentially, the effort to build early agent-based computational models can be seen as an attempt to examine whether the macro-scale behaviour of financial markets can be explained by the interaction of simple behavioural rules at the micro scale. As the early simple ABMs faced the criticism of the lack of empirical foundations for the behaviour of the simulated agents, newer models incorporated progressively more details into the micro-level behaviour, recognizing that ABMs were flexible tools to study implications of agent heterogeneity for asset prices. The modelled heterogeneity could thereby range from the fundamentalist vs. chartist dichotomy of the early ABMs to the cases where each computational agent could be endowed with characteristics differentiating it from all others. Additionally, the recognition of the importance of social learning and networks (see e.g. (Banerjee, 1992; LeBaron, 2011)) led to ABMs incorporating heterogeneity not only among agents themselves but also in their interactions.

It is worth noting that, being a relatively novel approach, ABMs are often faced with critical comments arguing that there is not much new to learn from ABMs that could not be learned from either econometric models or neoclassical equilibrium models of financial markets. However, ABMs are markedly different from both these approaches. On the one hand, ABMs are different from econometric models in that econometric models of financial markets relate aggregate quantities observed in the market to other aggregate quantities of interest, for example, with the help of a time series model one might examine how earlier returns of an asset cause subsequent returns or how trading volume is related to volatility. These models by construction do not model the decision-making of economic agents comprising the market explicitly, and therefore do not take into account a recursive loop that exists between aggregate market quantities, such as prices, and the reasoning and actions of economic agents that in turn shape the price process. Attempts to evaluate regulatory interventions by means of these models are therefore subject to Lucas critique (Lucas, 1976).

On the other hand, ABMs are also radically different from the models of financial markets built in the neoclassical paradigm, as ABMs do not make arguably unrealistic assumptions of agent homogeneity, perfect rationality and equilibrium, assumed in

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Table 1.

Comparison of econometric, neoclassical equilibrium and agent-based models of financial markets

Modelling approach	Strengths	Weaknesses	Applications
Econometric models	Based on empirically observed data. Do not require assumptions on the characteristics of economic agents. Established and well understood procedures for estimation and testing	Lack of microfoundations and hence subject to Lucas critique	Forecasting of financial time series
Neoclassical equilibrium models of financial markets	Based on clearly stated assumptions about the behaviour of economic agents. Analytically tractable	Assumptions can be unrealistic to facilitate the analysis of the model. Equilibrium models, dynamics of how the model settles into an equilibrium are mostly disregarded	Can be used for forecasting and policy evaluation over very long time horizons, at which the model can be reasonably assumed to have reached an equilibrium
Agent-based models	Based on clearly stated assumptions about the behaviour of economic agents. Models of agent behaviour can be made arbitrarily realistic, as the analytical tractability is not a concern. Can incorporate various degrees of agent heterogeneity	May require significant computational resources. Estimation and validation techniques are an active research area. Can be criticized for making ad hoc assumptions	Generating return distributions, e.g. for risk management purposes. Policy evaluation which takes into account both the agents' response to policy changes as well as the path of the model towards an equilibrium following a policy change

standard asset pricing models for the sake of analytical convenience (Cochrane, 2009; Duffie, 2010). They therefore avoid both the pitfall of the lack of any microfoundations, as well as the pitfall of assuming microfoundations that can be seen as highly simplified and unrealistic. Table 1 above provides a summary of strengths, weaknesses and suitable applications of the three modelling approaches in financial markets.

To summarize, agent-based computational finance emerged as an attempt to apply computational methods employed in natural sciences to modelling of financial markets and was later recognized as a flexible tool to model various types of heterogeneity among agents as well as realistic institutional details of the market.

3.2. Evolutionary finance

The evolutionary ideas in finance, in turn, are based on the observation of heterogeneity of agents and, additionally, — on a feedback loop between agents' actions and their "survival" in the market (Fig. 1). The agents' collective trading actions shape the market prices of assets but the market prices of assets, in turn, change the agents' wealth, making some of them richer, while others become poorer and, in the limit, go bankrupt and leave the market. Asset prices may affect the fitness of a particular type of agent in two ways: on the one hand, changing prices of assets change the value of the agent's portfolio, while on the other the agent himself may modify his strategy based on how well it has performed in the past. B. LeBaron terms these two types of feedback mechanisms "passive learning" and "active learning", respectively (LeBaron, 2011). When agents are heterogeneous either in terms of their beliefs or preferences,

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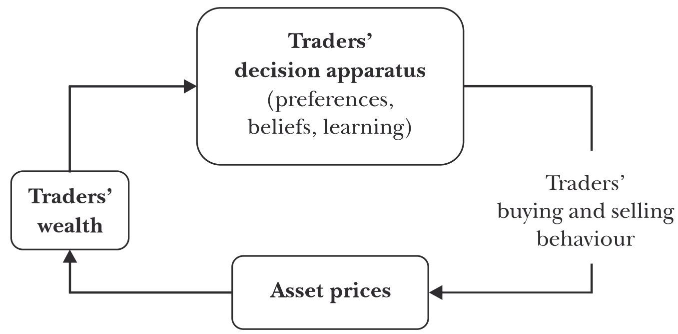

Fig. 1.
The evolutionary feedback loop in financial markets

a natural question is whether the market selects for any particular type of preference and belief.

There are three prominent streams of research within evolutionary finance. The first one studies the dynamics of selection in the context of financial markets, whereby different researchers focus on different objects of selection, i.e. investment strategies, economic agents and financial theories and models. The second one uses evolutionary arguments (in a biological sense) to justify a particular kind of preferences that agents in a financial market should be endowed with. Finally, the third one attempts to define general rules of evolutionary dynamics and examine what implications they have for financial markets. Each of the three research streams is discussed in turn below.

The literature on the evolutionary selection of investment strategies is best exemplified by the research performed by Thorsten Hens and his co-authors (see e.g. (Hens, Schenk-Hoppé, 2005, 2020; Schnetzer, Hens, 2022)). The work done in this domain mainly focuses on mathematical, game-theoretic modelling of interaction of strategies (or portfolio rules) in asset markets, whereby a strategy may be specified, for example, as follows: "allocate your portfolio in proportion to relative dividends paid by assets". The results obtained from this type of models may allow concluding, for example, that a certain portfolio rule is an "evolutionarily stable strategy"[6], i.e. it asymptotically drives out any other competing strategy from the market. Often, no statement is made with regard to how long different strategies can coexist in a market or the dynamics of asset prices *before* all evolutionarily unstable strategies are driven out of the market. In other words, this line of research is mainly concerned with the existence of an evolutionarily stable equilibrium, not with the dynamics by which this equilibrium is reached. Additionally, to be analytically tractable these models often have to rely on a number of strong assumptions with regard to how information is distributed among agents following a particular strategy (obviously, to be able to invest in proportion to relative dividends, agents must be able to correctly predict the dividends in advance), and the preferences of agents (the fact that an agent would prefer an *asymptotically* stable strategy implies certain time and risk preferences on his part).

In contrast, the researchers that focus on individual traders as the primary unit of selection make no a priori assumptions regarding the preference homogeneity

[6] The concept of an evolutionarily stable strategy (ESS) was initially defined by (Smith, Price, 1973). It denotes such a strategy, that in the case where it is adopted by a majority of a population, no other strategy gives its adopters a higher relative fitness, and therefore an ESS cannot be driven out of the market by any other strategy.

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among agents or their ability to accurately predict the distribution of asset prices or dividends. In fact, the survival of traders endowed with particular market forecasting rules and preferences is the main focus of this literature. Methodologically, the researchers working in this domain usually rely on computational methods, as the need to model vast heterogeneity among agents makes these models intractable for analytical approaches. A recent example of this type of models is found in the paper by (Scholl, Calinescu, Farmer, 2021), in which the authors analyze what type of relationship (symbiotic, competitive, or predator-prey) exists among some common types of traders in the market.

Finally, some researchers focus on various financial theories and models as the primary unit of selection in financial markets. Hereby it is often assumed that the survival of a particular investment approach (for example, value investing or passive investing) depends not only on the relative monetary benefits it gives to those who follow it, but also on how easily it spreads among market participants via channels other than direct market interactions (e.g. financial news, commentary of experts, exchange of ideas between traders etc.). This very new domain of research, often also termed "social finance", is exemplified by a recent paper by (Akçay, Hirshleifer, 2021).

The second branch of evolutionary finance attempts to explain why certain idiosyncrasies of investor behavior which were observed in experimental settings by behavioral and experimental economists (see e.g. (Barberis, Thaler, 2003; Holt, 1986; Kahneman, Tversky, 2013; Thaler, 1980)) may represent not departures from substantive rationality[7], but rather a different form of rationality, the so-called bounded rationality (Sargent, 1993), which, although constrained, may still be evolutionarily advantageous. This research can thus be seen as an attempt to find a unifying principle that may explain disparate empirically observed features of investors' behaviour that may be at odds with expected utility maximization. For example, research performed by (Brennan, Lo, 2011; Zhang, Brennan, Lo, 2014a) is representative of this effort. In a recent study published in the special issue of Proceedings of the National Academy of Sciences (PNAS) on evolutionary finance (Koduri, Lo, 2021) explain how evolutionary forces drive agents towards negatively correlated choices in the presence of systematic risk. This finding has implications for financial markets insofar as it implies that a population of agents with differing portfolios is, as a whole, more evolutionarily robust than a population in which investors' portfolios are perfectly correlated as a result of all of them following an optimally diversified strategy. A. Robson and H. Orr show how evolutionary arguments of this kind may explain the long-standing equity premium puzzle (Robson, Orr, 2021). Overall, this research aims to provide a more solid foundation for alternative modelling of investor preferences and thus argues against the critique that experimentally observed departures from the expected utility theory are ad hoc and contradictory and may represent artefacts of particular experimental setups.

Finally, some researchers attempt to formulate general rules of evolution and then see what implications can be drawn from them for financial markets. A representative of this approach is a recent paper by (Burnham, Travisano, 2021). The authors introduce the notion of a fitness landscape and argue that environments where fitness has high peaks and deep troughs are adverse to exploration as represented by horizontal movements on a plane, because any big horizontal move is likely to result in an agent being significantly disadvantaged in terms of relative fitness vis-à-vis other agents

[7] On the distinction between substantive and procedural rationality (see e.g. (Simon, 1976, 1992)).

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and therefore is more likely to go extinct before it manages to find a point giving it greater relative fitness. On the contrary, environments with smooth evolutionary landscape are likely to foster exploration, where agents may make big horizontal leaps and still remain not far from other agents in terms of relative fitness. The authors suggest applying this insight to financial markets to see whether the nature of competition there fosters innovation in investment strategies, or, on the contrary, forces investors to herd into well-explored ones.

3.3. Ordering of asset pricing issues into the purviews of evolutionary and agent-based modelling

Having examined the development and characteristic features of agent-based and evolutionary finance, we now attempt to categorize the asset pricing issues summarized in Section 2 into the particular domains of evolutionary and agent-based finance. Table 2 presents such a categorization. The three asset pricing issues are allocated to the paradigms via the black filled circles in the respective boxes.

First of all, it is apparent that the roles of market institutions, such as trading mechanisms or information dissemination channels are best addressed in the agent-based framework. Dealing with this asset pricing issue, we are not generally concerned with the evolution of the market ecology, only with effects that particular market setups have on trading for a given population of traders or strategies. The same is true for the research on the effects of agent heterogeneity, in which one is interested in the effects of interactions of heterogeneous agents on the properties of the market without considering the feedback loop by which the fitness of agents and strategies depends on the aggregate market properties.

On the contrary, selection in financial markets naturally falls into the domain of evolutionary finance, and specifically into its subdomain dealing with the market selection hypothesis. In situations where selection among a large and very diverse pop-

Table 2.

Asset pricing challenges in the paradigms of agent-based and evolutionary finance

Paradigms. Asset pricing challenges	Agent-based computational finance	Evolutionary finance		
		Market selection hypothesis	Biological basis of investor behavior	General rules of evolution applied to financial markets
The role of market mechanisms and institutions	●			○
The role of agent heterogeneity	●		○	
Selection in financial markets	●	●		

Note. Black filled circles (●) mean that the respective asset pricing challenges are within the paradigms. Empty circles (○) mean that while the respective paradigms are not directly focused on resolving the marked issues, they may provide useful supplementary insights. Empty boxes mean that pricing challenges are out of the particular trends.

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ulation of agents or strategies needs to be modelled, research is also likely to benefit from the agent-based modelling, as analytical evolutionary models quickly become intractable when the degree of heterogeneity grows. Additionally, computational models of selection are needed when the researcher is interested not only in the final outcome of the selection process (that is, in the evolutionary equilibrium), but also in the dynamics by which the market reaches this outcome.

The empty circles mark the subdomains of evolutionary finance that are not directly focused on resolving any of the three identified asset pricing issues, but may provide useful supplementary insights. For instance, studying the biological basis of investor behavior can provide researchers working on the role of agent heterogeneity with some justification as to what types of agent heterogeneity are worth including into the models. The literature on the general rules of evolution applied to financial markets can help, for example, to shed light on why certain market mechanisms and regulatory arrangements either foster or hinder the pace of financial innovation. As will become apparent in Section 4, these two subdomains of evolutionary finance have so far provided much fewer contributions than the market selection literature. As these two subdomains are not *directly* applied to the three asset pricing challenges, the contributions to them are reviewed briefly, for the sake of completeness.

4. Progress of evolutionary and agent-based asset pricing

4.1. Effects of market institutions on asset prices

One of the earliest contributions to the study of influence of market institutions on the behaviour of asset prices is the paper by (Gode, Sunder, 1993), in which the authors compare the price time series generated in an experimental setting with human participants to those generated by the so-called zero-intelligence (ZI) traders with and without a budget constraint. The authors find that whereas the volatility and efficiency of the market (as measured by the distance of the actual transaction price from the equilibrium price) are markedly different in the case of human traders and *unconstrained* ZI traders, with the latter being significantly more volatile and inefficient, the difference is much less pronounced when the human-generated time series is compared to that generated by the *constrained* ZI traders. The authors conclude that the discipline imposed by the double auction mechanism explains the greater part of the market's tendency towards efficiency, whereas learning, rationality and profit maximization are of secondary importance.

As the above example makes apparent, the paradigm of agent-based computational finance very well suits studying the impact of a particular institutional arrangement (in this case, a double auction market) on the behavior of asset prices and other relevant market characteristics. By making few assumptions on the behavior of traders, and in fact, by randomizing it, computational experiments allow to draw conclusions on the effect of various institutions and policy changes on market outcomes. Subsequently, agent-based computational modelling was used by regulators to examine the effects of the so-called decimalization on the NASDAQ market (Darley et al., 2000), examining how the proposed regulation change would affect market volatility and volumes.

More recently, ABMs started examining the effects of other institutional details, apart from trading mechanisms, on the behavior of asset prices. Most prominently, the

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effects of social interactions and interaction networks are increasingly becoming an object of study (see e.g. (Alfarano, Milaković, 2009; Chang, 2007; Huang, Zhang, Wang, 2023)). So far, this line of research did not produce many general results, although much was said about the effects of particular types of networks, which were assumed in a more or less ad hoc way. Despite this, R. Axtell and J. Farmer noted the potential that the study of network interactions had for asset pricing if the structure of networks assumed in the models was grounded in the abundantly available social network data (Axtell, Farmer, 2022).

4.2. Effects of agent heterogeneity

While ABMs helped to probe the effects of market institutions on the formation of asset prices, it was recognized that trading mechanisms, information dissemination channels and social interactions were insufficient to explain *all variations* of market prices of assets. A second line of research in agent-based modelling therefore was focused on the role of behaviors and properties of economic agents themselves in explaining asset prices.

A point of departure for this line of research was the paper by (Brock, Hommes, 1998) in which the authors discussed the implications of interactions of several agent types (the so-called, fundamentalists, trend-followers and contrarians) on the behavior of stock prices, particularly focusing on identifying the bifurcation points at which the price behavior became chaotic. A major result of the paper was discovering the influence of the propensity to switch between various prediction strategies on the behavior of asset prices.

Following W. Brock and C. Hommes, a large number of subsequent papers adopted a similar approach to modelling whereby a particular empirical feature or a number of features of asset markets was identified and subsequently replicated in computational models using agents with various features and various degrees of heterogeneity. The progress in this line of research was generally from replicating the features, or stylized facts, only qualitatively (such as e.g. generating price series with fat tails and clustered volatility) (see e.g. (Chiarella, Iori, 2002; LeBaron, Arthur, Palmer, 1999)) towards replicating them also quantitatively (Lux, Schornstein, 2005; Lussange et al., 2021). Additionally, whereas earlier papers were focusing on matching the empirical statistics concerning the magnitude of leptokurtosis, volatility and autocorrelation, more recently researchers have expanded the number of replicated features to other market characteristics and multiple time frequencies (see e.g. (Staccioli, Napoletano, 2021)). In parallel, extensive literature developed around calibration and estimation of these models (see (Franke, 2009; Franke, Westerhoff, 2012; Ghonghadze, Lux, 2016; Grazzini, Richiardi, 2015; Li, Donkers, Melenberg, 2010; Platt, 2022)), representing one of the most cited subfields within the ABM literature.

Whereas earlier models focusing on the effects of agent heterogeneity followed the paradigm of having only a few distinct types of agents (most commonly, the so-called fundamentalists, chartists and noise traders), more recent works incorporated progressively more features into agent design, including also the behavioral characteristics identified in economic experiments, such as optimism, pessimism, loss aversion and confirmation bias, among others (Cafferata, Tramontana, 2019; Pruna, Polukarov, Jennings, 2018, 2020).

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Despite differences in model complexity and the design of simulated agents, a common approach of the ABMs focusing on modelling the effects of agent heterogeneity consists in assuming a priori the existence of some particular agent characteristic in the market and examining how it affects the price process. These models were therefore often criticized for the lack of empiricism in their assumptions (Lussange et al., 2018). The need for parsimony, however, and the emerging ways to quantify model complexity (Mandes, Winker, 2017) made explicit the need to also model how different types of agents emerge and survive in the market. The effect of agent characteristics on their relative fitness and, consequently, the population dynamics of groups of agents, or strategies, in the market assume the central role in the market selection literature.

4.3. Market selection

As L. Blume and D. Easley pointed out, although it was tempting to carry over the evolutionary framework from biology to economics, one had to deal with the question of what were the economic analogues of "species, genes, and other objects of the evolutionary model landscape" (Blume, Easley, 2009, p. 406). Indeed, excessive optimism on the part of some evolutionary economists with regard to the transferability of evolutionary ideas directly from biology to economics was questioned, among others, by D.P. Frolov (Frolov, 2013) and T.L. Tambovtsev (Tambovtsev, 2024). D.P. Frolov (Frolov, 2013) noted that although evolutionary metaphors borrowed from biology may serve as a powerful tool to explain certain economic phenomena, an overreliance on these metaphors may obscure scientific discussions. For example, as shown in the present review, even the meaning of the term "evolutionary" in the context of economics often requires further clarification whether one is discussing the implications of *biological* evolution for *economic phenomena* or the evolutionary processes (e.g. variation and selection) that take place at the level of markets. T.L. Tambovtsev (Tambovtsev, 2024) highlights the difficulty of finding selection units in economics the characteristics of which match those in biology. However, without such one-to-one correspondence the model of evolution borrowed directly from biology may not apply. Since there is no consensus on what constitutes appropriate selection units in the context of financial markets, various researchers adopted different perspectives, with some modelling market selection of investment strategies, others — of economic agents and yet others — of market theories and models.

The first stream of the evolutionary finance literature is best represented by the works of Thorsten Hens, Igor Evstigneev, Klaus Rainer Schenk-Hoppé and co-authors, in which an investment strategy represents the unit of selection and its relative fitness is represented by the amount of capital invested in it. In (Evstigneev, Hens, Schenk-Hoppé, 2002) the authors found a unique evolutionary stable strategy for a market with endogenous asset prices, in which however the asset returns exhibited ergodicity, i.e. future relative returns could be well estimated by the observation of past returns. In such a market, the strategy that eventually accumulates total market wealth is the one that invests according to the relative returns. In (Amir et al., 2005) the authors extend the results of the previous paper by abandoning the assumption of independent and identically-distributed (i.i.d.) states of the world, and show that in such a market the unique survival strategy is the one that invests in accordance with conditional expected relative payoffs. In (Evstigneev, Hens, Schenk-Hoppé, 2006) the authors show

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that the only market that is evolutionarily stable is one in which assets are evaluated by their expected relative dividends, while all other portfolio selection rules do not exhibit evolutionary stability. In (Hens et al., 2011) the authors use the framework of evolutionary selection over strategies to explain the well-known value premium puzzle. More recently, (Evstigneev et al., 2020) prove the existence of an asymptotically unique evolutionary stable strategy under a very general set of assumptions, including various ways in which traders may evaluate evolutionary fitness, while in (Amir et al., 2021) the authors extend their prior results on the existence of evolutionary stable strategies by considering an economy in which the dividends are not exogenous and increase with the wealth invested in an asset. M. Schnetzer and T. Hens apply the framework of evolutionary selection over strategies to a multi-asset world and show which among a group of well-known investment strategies exhibit the property of evolutionary stability (Schnetzer, Hens, 2022).

Despite the variety of obtained results, the literature on the market selection of investment strategies is, however, characterized by the common assumption that there exist at least some market participants who evaluate investment strategies according to the survival criterion, i.e. whether or not a given investment strategy promises with probability 1 a strictly positive wealth share. Such investors, by definition, do not take into account the risk-return characteristics of a strategy, all that matters is the survival in the long run, no matter how bad the chosen strategy may perform in the meantime. Although this assumption allows disregarding the questions about risk and time preferences as well as investors' beliefs and learning schemes, this assumption is strong in the sense that it requires the existence of investors for whom the only objective is the long-term, i.e. asymptotic survival in the market. Additionally, since the models presented in this stream of literature are typically solved analytically for the long-run evolutionary equilibrium, they leave open the question of how exactly an ecology of interacting strategies or investors settles into such an equilibrium.

These challenges are taken up by the stream of evolutionary finance research that considers investors, and not strategies, to be the object of evolutionary selection. These models consider economic agents endowed with well-defined risk and time preferences as well as belief formation rules and study the survival dynamics of these agents in a financial market setting. Since the modelled agent features can be numerous, including not only preferences and learning schemes, but also behavioral and cognitive biases identified in the behavioral finance literature these models are typically too complex to be solved analytically and therefore are most often computational, which unites this stream of research with the more general field of agent-based computational finance described above.

L. Blume and D. Easley (Blume, Easley, 2006) show that in incomplete markets payoff functions of investors, in addition to their forecasting accuracy, may matter for their survival, thus casting doubt on the hypothesis that only traders with most accurate beliefs survive. S. Chen and Y. Huang (Chen, Huang, 2008) further investigate this claim by constructing an ABM of a financial market and conducting two experiments, in the first of which agents differ only by the form of their utility function and in the second the learning rules are allowed to change as well. The authors find that when traders only differ by their risk preference, the log-utility agents are able to outperform all other groups in terms of accumulated wealth. Additionally, when agents use differ-

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ent learning and forecasting rules, those with more accurate forecasts have a higher probability of survival, however, the effect of forecasting accuracy is only secondary to the effect of having a log-utility function. Interestingly, the log utility function stands out by providing the agents endowed with it a markedly higher probability of survival, whereas there is much less disparity in the performance of traders with all the other utility functions. The paper thus delivers a counterargument to the claim of the irrelevance of risk preference for market performance. Unfortunately, Chen, Huang only present the microscopic results of their simulations, focusing on the agents' wealth shares and risk-return characteristics of their portfolios, whereas aggregate market statistics, such as price history and trade volumes are not presented.

O. Brandouy, P. Mathieu and I. Veryzhenko (Brandouy, Mathieu, Veryzhenko, 2012) considered a large ABM of a financial market populated by 1000 traders, each endowed with a quadratic utility function with various risk-aversion coefficients and having full information on the next-period's asset returns, and showed that in this setup agents with particularly high and particularly low risk-aversion coefficients tended to lose their wealth share, whereas the agents with moderate risk aversion survived. This result provides further support to the claim that risk preferences matter for survival, even when agents are endowed with the same form of utility function and only differ by the risk aversion coefficient. Additionally, (Brandouy, Mathieu, Veryzhenko, 2012) obtain their results in 1000 computational experiments, a marked increase from 100 experiments conducted by (Chen, Huang, 2008), as well as using a much larger number of computational agents (1000 vs. 40 agents used in (Chen, Huang, 2008)), thus providing a more robust evidence for the relevance of risk preferences in market selection, in line with Judd's argument (Judd, 2006).

Y. Huang further investigated the relevance of risk preference, while also focusing on the efficiency of price time series (Huang, 2017). In Huang's artificial agent-based market agents are endowed with risk preferences that allow them to have different constant discount rates. Thus, the relevance of risk preferences is studied in a setup where saving rates (determined by the risk preference) are not critically low (which was found to be the most negative factor influencing survivability in (Chen, Huang, 2008)), but nevertheless different across agent types. Y. Huang found that even in this setup risk preference had a major effect on the survival rates, although it was lower than in the setup considered in (Chen, Huang, 2008), and the forecasting accuracy remained of secondary importance. At the same time, the role of forecasting accuracy is greater than in the setup of (Chen, Huang, 2008), where agents were allowed to have critically low saving rates and that was the primary factor driving them out of the market. Examining the endogenously generated price time series, Y. Huang (Huang, 2017) found that the hypothesis of i.i.d. returns, which in this setup would indicate market efficiency, was rejected in a majority of cases, providing support to an intuitive notion that in a market where not necessarily the best forecasters' survived prices were unlikely to be efficient.

C. Tsao and Y. Huang note, however, that if one would like "to relate the research on survivability to issues with respect to the efficient markets hypothesis, it is better to endow agents with the ability to forecast market prices and dividends" (Tsao, Huang, 2018, p. 537), which was not done in the earlier papers. The authors therefore construct an artificial agent-based market according to the setup described in (Arthur

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et al., 2018), where agents learn to forecast both dividends and prices. Another feature, differentiating this model from the earlier ones is the idea that agents only decide on their portfolio compositions, disregarding the saving rate, unlike in (Chen, Huang, 2008). Thus, the authors argue, that the model represents a market composed of institutional investors who do not make choices between saving and consumption as part of their investment strategy. The authors find that, even when saving rates are uniform across agents, their risk preferences still play a major role in determining agent survivability, with less risk-averse agents tending to accumulate more relative wealth. Forecasting accuracy is found to influence survivability as well; however, the magnitude of this effect is much lower than that of risk preferences.

Y. Huang and C. Tsao (Huang, Tsao, 2018) raise an important question of the effect of agent heterogeneity in terms of their forecast updating frequencies on relative fitness. The authors construct an agent-based artificial market based on (Arthur et al., 2018) and conduct several computational experiments in which agents learn to forecast a dividend and a price process, whereby the dividend process is exogenous and the price is endogenous. The agents are split in several groups, updating their forecasting rules with different frequencies. The authors find that when the market ecology consists of only fast learning traders, the traders who evolve their forecasting rules more frequently tend to make better forecasts. On the contrary, when the market consists of either only slow learning traders or of a mixed ecology of fast and slow learning traders, the traders who evolve their forecasting rules less frequently tend to have better forecasts. The authors therefore conclude that there is no general rule favoring a particular forecast updating frequency, as the performance appears to be dependent on the full ecology of traders interacting in the market. The price time series generated in the computational experiments with a fast-evolving and mixed ecology of traders are not i.i.d. and therefore the authors reject the efficient markets hypothesis (EMH) for the constructed artificial market. Only in an ecology of slow evolving traders the prices tend to be an i.i.d. process and therefore the market tends to the rational expectations equilibrium. Since in real markets, however, agents are likely to have heterogeneous forecast updating frequencies, the authors take the obtained results as supporting the claim that real markets are unlikely to evolve towards efficiency. In an additional experiment, the authors endow the agents using low forecast updating frequencies with heterogeneous risk preferences and observe that in this setup the market evolves toward efficiency less frequently than in the case with slow-evolving agents with homogeneous risk preferences, thus delivering additional support to a hypothesis that in a highly heterogeneous market in terms of both forecasting rules and preferences, prices are unlikely to evolve towards efficiency.

Most recently, some studies appeared that examined not only the survival rates of investors endowed with different preferences or forecasting rules, but also with different behavioral biases. For example, in (Tang et al., 2022) the authors construct an artificial financial market where some of the agents use forecasting rules affected by "anxiety", modelled as a tendency not to revise an erroneous forecasting rule for a long time in light of negative performance. The authors study a market populated by both anxious and rational fundamentalist traders and find that the presence of the anxious traders imparts momentum towards the price process and drives the price away from fundamentals. At the same time, the authors do not find that anxious traders are driven

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out of the market, thus providing additional support to the hypothesis that financial markets do not necessarily select for the most accurate forecasters. Since in (Tang et al., 2022) some computational experiments also allow agents to observe the performance of other types of traders in the market and imitate them, this paper finds itself at the intersection of the market selection literature and the newly emerging field of "social finance" (Akçay, Hirshleifer, 2021), where non-market interactions between traders are allowed. Notably the results obtained by (Tang et al., 2022) agree with some experimental literature the authors of which found that the presence of behaviorally biased traders, such as overconfident traders, was associated with prices deviating from fundamental values (Michailova, Schmidt, 2016) and that the performance of traders was influenced by their behavioral characteristics, such as the tendency to self-monitoring[8].

4.4. Evolutionary basis for economic agents' characteristics and general rules of evolution in financial markets

For the sake of completeness, we also review the two streams of research in evolutionary finance, which have to date provided much fewer contributions to the identified asset pricing questions, but are nevertheless relevant.

Firstly, the research on the biological basis of economic agent characteristics, whereby the agents are considered in a broad sense, not only pertaining to the financial markets, is a relatively new development, dating back to (Robson, 2001; Samuelson, 2001), who highlighted how in a setting where an economic game was played repeatedly, selection may favor agents whose preferences deviated from the dominant strategies. These ideas were further developed by A. Lo and coauthors, who demonstrated how various characteristics of economic agents, such as cooperation or risk aversion, may have developed as a result of natural selection (see e.g. (Brennan, Lo, 2011; Koduri, Lo, 2021; Zhang, Brennan, Lo, 2014a, 2014b). More recently, (Robson, Samuelson, 2022; Heller, Nehama, 2023) discussed the evolutionary origins of aggregate risk aversion as well as of risk preference heterogeneity. Although not directly addressing any

Table 3.

Contributions of agents-based and evolutionary finance to asset pricing

Asset pricing challenges	Results
The role of market mechanisms and institutions	A budget constraint and a double auction mechanism explain a large portion of asset price behavior, even in the absence of individual rationality of agents (Gode, Sunder, 1993). When social interactions among investors are assumed, they may give rise to non-normal asset returns as a result of arising correlations in traders' activity (Alfarano, Milaković, 2009). When traders socially influence each other, a greater degree of influence can lead to the emergence of chaotic time series of asset prices (Huang, Zhang, Wang, 2023). Microstructural properties of trading, such as the smallest allowed price increment, affect macro-scale properties, such as price volatility and volume (Darley et al., 2000)
The role of agent heterogeneity	In a market with interacting chartist and fundamentalist traders, there are bifurcation points in the switching probability between types that lead to the emergence of chaotic behavior in asset prices (Brock, Hommes, 1998). In markets populated by heterogeneous agents, rational expectations *do not necessarily* arise, but they do arise for some values of agent micro-parameters. (LeBaron, Arthur, Palmer, 1999). Various micro-level models of agents can lead to *qualitatively* similar behavior of asset markets at the macro-scale (i.e. volatility, autocorrelations, volumes etc.) (Cafferata, Tramontana, 2019; Pruna, Polukarov, Jennings, 2018; 2020)

[8] Self-monitoring is defined as a tendency to modify one's behavior in response to the social environment.

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Table 3. End

Asset pricing challenges	Results
Selection in financial markets	There exists a unique evolutionarily stable investment strategy for a complete financial market (Amir et al., 2005; Evstigneev, Hens, Schenk-Hoppé, 2002). An evolutionarily stable strategy also exists for a market where dividends are endogenous and increase with the invested wealth (Amir et al., 2021). When saving rates are determined by agents endogenously, log-utility agents outperform all other types of agents in a market due to stable and sufficient saving rates (Chen, Huang, 2008), whereby the effect of the saving rates on agents' survivability is primary, whereas the effect of their forecasting ability is secondary. Risk preferences matter for agents' survivability in financial markets (Brandouy, Mathieu, Veryzhenko, 2012; Huang, 2017; Tsao, Huang, 2018). As markets do not necessarily favor better forecasting agents, prices are driven away from fundamentals (Huang, 2017; Tsao, Huang, 2018; Huang, Tsao, 2018)
Biological basis of investor behavior and general evolutionary concepts applied to financial markets	Various attitudes toward risk, such as aversion to aggregate risk and risk preference heterogeneity may have developed as a result of evolutionary pressures (Brennan, Lo, 2011; Heller, Nehama, 2023; Koduri, Lo, 2021; Robson, Samuelson, 2022; Zhang, Brennan, Lo, 2014a, 2014b). Some financial market anomalies, such as the equity premium puzzle, can be explained by the evolutionarily advantageous aversion to aggregate risk (Robson, Orr, 2021). A smooth evolutionary landscape fosters innovation in financial markets, whereas extremely harsh competition may lead to the crowding of well-explored strategies (Burnham, Travisano, 2021)

questions pertaining to asset pricing specifically, this literature gave guidance on the type of preferences that economic agents could be endowed with for the sake of modelling various economic problems, including those pertaining to trading of financial assets. An example of a somewhat rare case of applying these insights to asset pricing directly is the recent paper by (Robson, Orr, 2021), in which the authors show how the long-standing equity premium puzzle can be explained by the aversion to taking aggregate risk.

Even rarer are financial market applications of the literature that attempt to apply concepts from evolutionary biology, such as e.g. fitness landscape, to study innovation and evolution in financial markets. A recent contribution is the paper by (Burnham, Travisano, 2021), in which the authors examine how the evolutionary landscape of financial markets could have led to the development of index investing.

Overall, however, research of this type is still in its infancy. Table 3 presents a summary of the relevant contributions discussed in Section 4.

5. Conclusion and further research directions

From the examination of Table 3 several conclusions become apparent.

Firstly, neither fundamental values alone, nor the institutional arrangements of financial markets (such as trading mechanisms, information dissemination channels or price increments) are sufficient to fully explain the behavior of financial assets, even though each of these factors does explain them partially. Agent heterogeneity in a broad sense is therefore a factor that influences asset prices as well.

Secondly, agent heterogeneity can explain a wide range of empirically observed stylized facts of asset markets, such as non-normal returns, deviations of prices from the fundamental values, the behavior of bid-ask spreads and clustered volatility. ABMs with heterogeneous agents were more recently able to reproduce the empirically observed

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stylized facts also quantitatively and at different time scales. However, there is a large number of design choices that must be made when constructing micro-level models of economic agents, including the modelling of preferences, forecasting techniques and learning schemes. One way to discipline this search for the appropriate micro-models is to ground the agent parameters in empirical evidence, whereby experimental and behavioral finance literature can play the key role. Another way is to consider whether or not a market ecology tends towards a specific agent type via market selection.

Thirdly, the extensive literature on market selection was split into several streams, one of which considered market strategies as the primary unit of selection, regardless of the characteristics of agents who followed these strategies, and another making the agents the primary unit of selection and modelling them explicitly, by endowing them with risk and time preferences and varying forecasting techniques and learning rules. The first stream documented the evolutionary stable strategies for a range of idealized circumstances. The second found that risk preferences, saving rates and learning rules matter at least as much, or even more than forecasting accuracy for the agents' survival, and therefore markets are not necessarily populated by agents having rational expectations, nor could they be assumed to asymptotically move towards an equilibrium where all agents were rational expectation agents. At the macro-scale, this leads to the well-documented stylized facts and deviations of asset prices from fundamental values.

As it was found that a wide range of micro-level agent heterogeneities led to qualitatively similar behavior at the macro-scale, it appeared that further progress could be achieved by disciplining modelling choices. This progress can proceed along several paths. Firstly, models of agents can be grounded in arguments derived from biological evolution of certain investor qualities as well as experimental evidence provided by literature in psychology and experimental economics. Secondly, parameter calibration of agent-based models could progressively include a wide number of stylized facts pertaining to various time frequencies as well as quantitative replication of these facts.

At the same time, models should remain parsimonious and sufficiently general to represent a wide range of possible agent parameters for the cases where experimental evidence is not available. Research in this direction should provide further insights into what type of empirically founded agents survive in the market and what macro-scale dynamics emerge from their interactions, building upon earlier research in which models of agents have for the most part been founded on ad hoc assumptions.

Additionally, our review has identified a gap in the agent-based and evolutionary finance literature dealing specifically with the issue of asymmetric information in financial markets. These questions, inspired by the seminal paper by (Grossman, Stiglitz, 1980), appear to be prime candidates for the exploration in agent-based and evolutionary frameworks. This is due to the fact, that so far, the analytical results obtained, indicate that due to information asymmetries there either has to be deviations from asset markets from fundamentals or the absence of trading due to adverse selection.

Empirically, however, active trading is observed in financial markets. Furthermore, even though the static result on the mispricing of financial assets is very important, it is interesting to know what the dynamics of price deviations from fundamentals are. Since the above two results were obtained under the assumption of perfect rationality and risk neutrality, it appears a promising direction to consider how infor-

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mation asymmetry would influence asset prices in a market where agents are bounded rational and have specific risk or time preferences. These questions are perfectly suited for studying in the combined framework of agent-based and evolutionary finance.

We thus hope that further research in agent-based and evolutionary asset pricing will proceed along the paths outlined above.

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А.В. Пастушков
Международная лаборатория экспериментальной и поведенческой экономики, НИУ «Высшая школа экономики», Москва

Эволюционная теория финансов и агент-ориентированное моделирование: новые парадигмы для теории оценки активов[9]

Аннотация. С 1980-х годов традиционная неоклассическая парадигма оценки активов сталкивалась с эмпирическими данными, ставящими под сомнение как предсказания моделей, так и их микроэкономические основания. В то же время исследователи микроструктуры финансовых рынков начали изучать детали транзакционного процесса, обращая внимание на эффекты асимметричной информации, рыночных механизмов, а также на обучение и формирование убеждений агентов. Эти детали, которым не уделялось должного внимания в традиционных моделях, становятся все более важными в изучении современных финансовых рынков, превратившихся в сложные экосистемы, в которых взаимодействуют стратегические, но необязательно идеально рациональные, коэволюционирующие агенты. В этом обзоре литературы, посвященном эволюционному и агент-ориентированному моделированию финансовых рынков, рассматриваются наиболее значимые результаты исследований в данном направлении. Предложена классификация исследований, подразделяющая их на три направления: исследования влияния институциональной составляющей финансовых рынков на оценку активов, исследования влияния гетерогенности агентов и исследования, связанные с теорией рыночного отбора. Также в работе приводятся аргументы в пользу сочетания эволюционного и агент-ориентированного моделирования в изучении финансовых рынков и выявляются открытые вопросы в теории оценки активов, изучение которых в эволюционной и агент-ориентированной парадигме было бы, по мнению автора, наиболее продуктивным.

Ключевые слова: *эволюционная теория финансов; агент-ориентированное моделирование; теория оценки активов; имитационное моделирование; рыночный отбор.*

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