Social Macroeconomics

Working Paper Series

An interdisciplinary model for macroeconomics

SM-WP-2019-012

November 2017

Andrew G Haldane, Bank of England

Arthur E Turrell, Bank of England

BANK OF ENGLAND

Staff Working Paper No. 696

An interdisciplinary model for macroeconomics

Andrew G Haldane[(1)] and Arthur E Turrell[(2)]

Abstract

Macroeconomic modelling has been under intense scrutiny since the Great Financial Crisis, when serious shortcomings were exposed in the methodology used to understand the economy as a whole. Criticism has been levelled at the assumptions employed in the dominant models, particularly that economic agents are homogeneous and optimising and that the economy is equilibrating. This paper seeks to explore an interdisciplinary approach to macroeconomic modelling, with techniques drawn from other (natural and social) sciences. Specifically, it discusses agent-based modelling, which is used across a wide range of disciplines, as an example of such a technique. Agent-based models are complementary to existing approaches and are suited to answering macroeconomic questions where complexity, heterogeneity, networks, and heuristics play an important role.

Key words: Macroeconomics, modelling, agent-based model.

JEL classification: E17, E60, C60, A12.

(1) Bank of England. Email: andy.haldane@bankofengland.co.uk
(2) Bank of England. Email: arthur.turrell@bankofengland.co.uk (corresponding author)

The views expressed in this paper are those of the authors, and not necessarily those of the Bank of England or its committees. This paper was prepared for publication in a special issue of *The Oxford Review of Economic Policy* on 'The future of macroeconomic theory'. We are grateful to attendees of a seminar at the University of Oxford, to an anonymous referee, and to James Barker, David Bholat, Shiv Chowla, Giovanni Dosi, Jeremy Franklin, Simon Hayes, Sujit Kapadia, Clare Macallan, Mauro Napoletano, Paul Robinson and Andrea Roventini for their help and comments.

Information on the Bank's working paper series can be found at
www.bankofengland.co.uk/research/Pages/workingpapers/default.aspx

Publications and Design Team, Bank of England, Threadneedle Street, London, EC2R 8AH
Telephone +44 (0)20 7601 4030 email publications@bankofengland.co.uk

ISSN 1749-9135 (on-line)

1 INTRODUCTION

The economic and financial crisis has arguably spawned a crisis in the economics and finance profession. Much the same occurred after the Great Depression of the 1930s when economics was rethought under Keynes' intellectual leadership (Keynes, 1936). The challenge today, to academics and to policymakers, may be every bit as great. A spotlight has been thrown onto the models used prior to the crisis. Critics argue that they were too restrictive and were not supported by empirical evidence. Academic work is beginning to plug these holes and new perspectives are being sought. Rising to the challenge of modelling a broader set of economic circumstances requires macroeconomists to think afresh, perhaps seeking inspiration from other disciplines with different methodological approaches. This paper outlines the difficulties facing macroeconomic modelling, examines how a more pluralistic methodology could be beneficial, and offers one constructive path for rising to these challenges.

The structure of the paper is as follows; §2 presents evidence of insularity in economics and considers why that insularity may not be optimal. §3 discusses this 'macroeconomic mono-culture', perhaps best exemplified by the dominance of the representative economic agent framework operating with rational expectations; it calls for a more diverse set of macroeconomic models, including ones which experiment with different agent behaviours. In §4, the interdisciplinary origins of the agent-based approach are described. §5 contrasts the philosophy of agent-based modelling with other macroeconomic modelling approaches. §6 asks what agent-based models could do for macroeconomics and §7 concludes.

2 AN INSULAR DISCIPLINE?

Economics, particularly macroeconomics, has historically been rather insular as a discipline, at least in comparison with other subjects. This is not a new observation. It has been puzzled over previously (for instance in Hausman (1992)). And, despite progress more recently, there remains evidence to suggest that the Great Financial Crisis has not dispelled entirely this insularity.

Figure 1 shows that over the period 1950–2010 economics papers in academic journals have cited papers in other disciplines less frequently than the average. In turn, those other disciplines have consistently failed to cite economics research. This suggests that new ideas have not flown freely whether into, or out of, economics. Insularity is partly a natural consequence of stratification because academic disciplines exist as partially ring-fenced areas of enquiry where specialists develop and focus their attentions (Jacobs, 2014). But it appears to be peculiarly strong in economics, as reported in Fourcade et al. (2015).

This situation has improved over recent years, as shown in Figure 2. Nonetheless, economics remains more self-referential than many other, arguably, less inter-disciplinary subjects. Even mathematics, considered by many a model of 'purity', sits higher on Figure 2 than does economics. Inter-disciplinary work involves extra costs (Yegros-Yegros et al., 2015), particularly those arising from co-ordination across subject areas, from the most respected journals having a natural bias to that field and from the difficulties of accurate reviewing across subjects. However, there is no reason to assume that these factors are more acute in economics than in other disciplines.

Alongside this evidence of inter-disciplinary insularity in economics, there is evidence of greater intra-disciplinary insularity too. The number of authors per paper in economics is lower than in other major disciplines, as shown in Figure 3. The 'big science' phenomenon has seen increasing returns to scale from academic collaboration over recent years, with scientists clubbing together in ever-larger teams, sometimes collaborating over several generations, in order to deliver the most dramatic breakthroughs (Aad et al., 2012; Abbott et al., 2016). Wuchty et al. (2007) show that research by larger teams is better cited, on average, than research authored by a solo author across all disciplines. Interestingly, this is also true for the top five journals in economics, where a paper with four authors picks up 61% more citations than a paper with one author (Card and DellaVigna, 2013).

Despite these benefits, most natural sciences rank above economics on measures of intra-disciplinary insularity. As the size of the datasets available to macroeconomists grows, working in small teams risks missing out on significant economies of scale in research. And experiments, for some people the gold standard of the scientific method, are associated with an increase in the number of authors per paper (Hamermesh, 2013).

Lack of diversity is another signal of insularity. A recent study found that around 43% of the articles published in the top four economics journals were authored by scholars connected to one of the editors at the time of publication (Colussi, 2017). Female authors accounted for fewer than 15% of papers in three of the top economics journals in 2011. Does this matter for the quality of economic research? Diversity is generally deemed to be good for innovation (Carney, 2017; Page, 2008). And the risks of the opposite, a research mono-culture, are likely to be serious (Bronk, 2011; Bronk and Jacoby, 2016).

The strongest evidence on this comes, interestingly enough, from economists themselves. When asked in 2006 to agree or

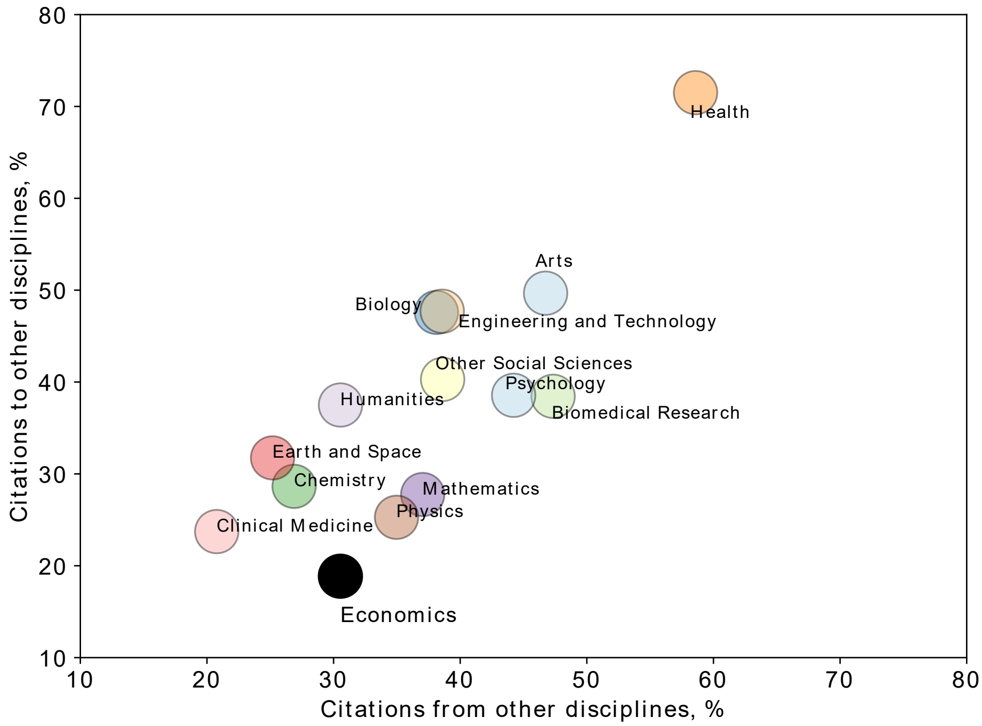


Figure 1. Citations in and out of disciplines by discipline. Source: Van Noorden (2015).

disagree with the statement "In general, interdisciplinary knowledge is better than knowledge obtained by a single discipline", close to 60% of academic economists said that they strongly disagreed versus an average of 21% for practitioners of sociology, political science, psychology, finance, and history (Fourcade et al., 2015).

Macroeconomics is the sub-discipline of economics that is probably most visible to the general public. Yet in the UK, scientists are trusted (see Figure 4a) in a way that economists are not (see Figure 4b) by almost every group in society. This has many likely causes. It cannot be explained by the greater technical content of economics. It might be explained, at least in part, by the way this technical content is conveyed to a lay audience. That, in turn, may generate a lack of trust in economists' models and methods, in a way which does not apply to scientists.

Yet precisely because economics combines elements of both the natural and social sciences, its points of disciplinary tangency are likely to be greater than for many other subject areas. Economics has a long reach. As (Keynes, 1924) said:

> "the master-economist must possess a rare combination of gifts... He must be mathematician, historian, statesman, philosopher – in some degree. He must understand symbols and speak in words. He must contemplate the particular in terms of the general and touch abstract and concrete in the same flight of thought. He must study the present in the light of the past for the purposes of the future. No part of man's nature or his institutions must lie entirely outside his regard."

Keynes' description of the economist is as relevant today as it was in 1924, though these days we could easily add to the list statistician, computer scientist, psychologist, and even evolutionary biologist. Macroeconomics has much to gain from taking inspiration from other disciplines; and other disciplines could in turn benefit from a better understanding of economics (Stern, 2016a), including macroeconomic modelling techniques (Tasoff et al., 2015).

Some specific examples can illustrate some of the potentially fertile areas recently inhabited by cross-disciplinary research in economics. In recent epidemics, the largest economic costs have arisen not from the direct effects of deaths, but from changes in peoples' behaviour in response (Avian Flu Working Group, 2006; Keogh-Brown et al., 2010; Sands et al., 2016). The same is true of the collateral damage to the economy caused by recessions and crises. For example, epidemiological models have shown promise in explaining financial contagion at times of financial crisis (Arinaminpathy et al., 2012; Haldane and May, 2011).

A second example is technology and innovation. There are many examples today of transformative technologies which could

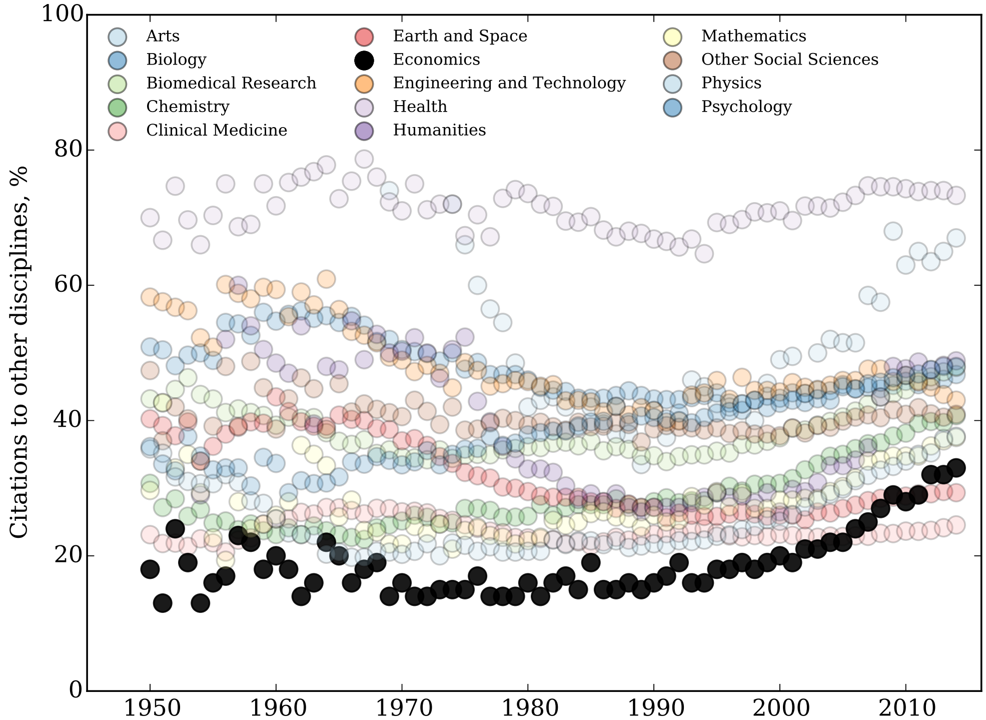


Figure 2. The number of citations from a shown discipline to other disciplines. Source: Van Noorden (2015).

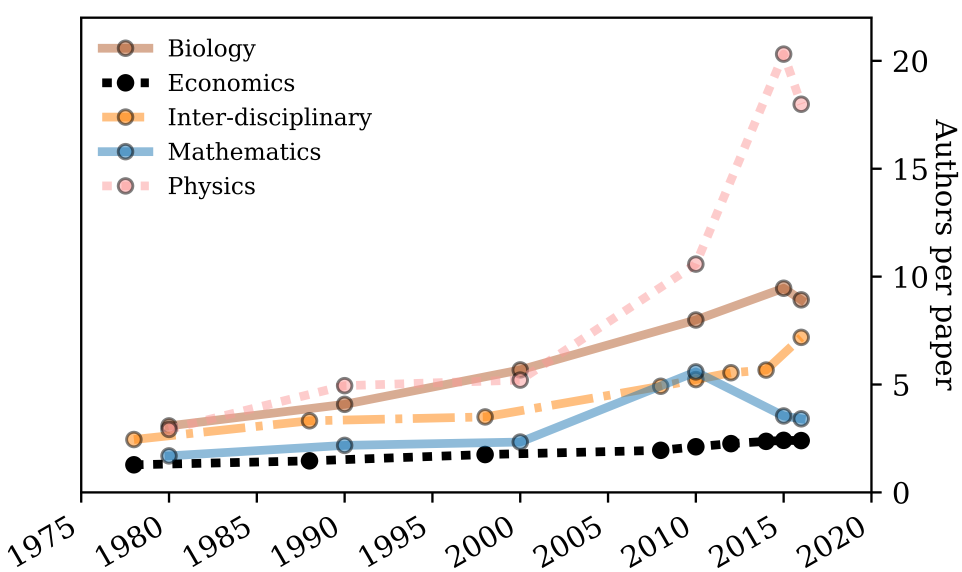
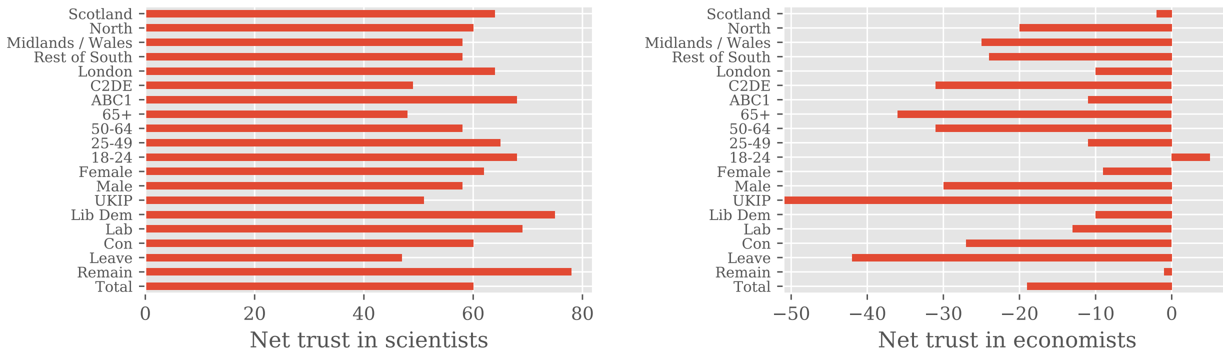


Figure 3. The mean number of authors per paper for the top 20,000 papers by number of citations in each Scopus subject category for each year for selected subjects and years. Source: Scopus.



(a) **(b)**

Figure 4. Net trust by different groupings. Data shown are the results from a poll of 2,040 British adults over 14th–15th February 2017. 'Leave' and 'Remain' refer to respondents voting choice in the UK's referendum of membership of the European Union. Source: YouGov.

have macro effects. Digital markets are improving matching processes and reducing information asymmetry. 'Big data' promises to identify new risk factors, while AI and robotics offer substantial gains in productivity. There are risks too – algorithms could collude on price, or operate in a way that is prejudiced (Ezrachi and Stucke, 2016). Text analysis methods, aided considerably by new algorithms such as Word2Vec (Mikolov et al., 2013), are improving macroeconomic forecasting (Baker et al., 2016; Nyman et al., 2015). An understanding of, and an ability to use, computer and data science techniques is likely to be increasingly useful for economists.

A third example is climate change. The Bank of England has recently published research on some of the implications of climate change (Batten et al., 2016). The effect of global temperatures on productivity, growth and financial stability are highly non-linear and strongly negative beyond a threshold temperature (Burke et al., 2015). Understanding those macroeconomic effects requires a fusion of expertise from the natural and social sciences.

A fourth example, and perhaps the most successful of all, is behavioural economics – the fusion of psychology and the economics of choice (Tversky and Kahneman, 1975). This is reshaping the view of how economic agents make decisions and could in time help to configure models of the macro-economy and macro-economic policy. It is already likely to have helped move economics up the table in Figure 2. Plainly, though, there is a distance left to travel.

3 THE MACROECONOMIC MONO-CULTURE

Why did macroeconomics become insular? The antecedent subject of political economy took a much broader view, as did many of the economists of the 19th and early 20th centuries. The dominance of the field by a single methodology may offer a clue. This had its origins in the 'New Classical Counter Revolution' of the 1970s in which Lucas, Sargent, Kydland and Prescott (Kydland and Prescott, 1982; Lucas and Sargent, 1979) overturned the use of 'structural' or 'policy' modelling of aggregate macroeconomic variables. These structural econometric models, said Lucas and others, had made several mistakes, including saying little about the stagflation of the 1970s and making implausible theoretical assumptions in order to match the data.

Lucas' most famous critique of these models was that they were not robust to changes in policy; that they did not allow for agents' behaviours to change as the incentives of those agents changed (Lucas, 1976). Lucas' critique is reasonable in that robust models should seek to explain how changes in policy might affect aggregate outcomes. In practice, no model is fully Lucas critique-proof; it is a matter of degree.

Lucas and others developed a methodology which they believed would not fall foul of the critique. The paradigm which Lucas believed best achieved this grounded macro-economic fluctuations is so-called 'microfoundations'. Simply put, this said that macro-economic behaviour should be built up from the aggregation of the individual actions of self-interested, typically optimising, agents. Being grounded in optimising behaviour, these self-interested behaviours were less susceptible to change when aggregate macroeconomic relationships changed.

In practice, such microfoundations often became closely associated with a particular type of self-interested behaviour, namely optimisation with rational expectations (Lucas, 1972, 1987; Muth, 1961). The weak form of rational expectations is as follows: let $I_{t-1,i}$ be the information set available to agent i at the beginning of time period t. This agent has an individual expectation $\mathbb{E}_{t-1,i}\{p_{t+s}\}$ for the value of p in period $t+s$ with $s \geq 0$. Define $\mathbb{E}_{t-1,i}\{p_{t+s}|I_{t-1,i}\}$ as the true expectation of p_{t+s} given the available information. The weak form of rational expectations is then defined by

$$\mathbb{E}_{t-1,i}\{p_{t+s}\} = \mathbb{E}_{t-1,i}\{p_{t+s}|I_{t-1,i}\} + \varepsilon_{i,t}, \qquad \mathbb{E}_{t-1,i}\{\varepsilon_{i,t}|I_{t-1,i}\} = 0$$

where $\varepsilon_{i,t}$ is an error term. Note that for this weak form to be true, the objective probability distribution f, where $p \sim f$, must exist. The stronger form of rational expectations as specified in Muth (1961) adds to the weak form the assumptions that each agent knows the behaviours and decisions that all other agents will take, the true values of any deterministic exogenous parameters governing the evolution of the economy, the properties of any probability distributions governing stochastic exogenous variables (such as f), and the realised values of endogenous variables. Coupled with these expectations are assumptions about agent optimality. Typically, this takes the form of an assumption that agents maximise their discounted sum of expected future utilities, subject to a budget constraint.

These microfoundations have a number of desirable properties. They can serve as a useful approximation of real-world behaviour, in at least some situations. They condense the world into a small number of readily-observable factors, which can help in determining what is driving what. And they are sometimes more analytically tractable, and are certainly more analytically elegant, than most of the alternatives.

They do, however, have a number of limitations. For one, they invoke strong assumptions (such as rational expectations and optimisation) which are often not borne out in the data (Estrella and Fuhrer, 2002). One defence of rational expectations is that, even though individuals may not be rational, their irrationalities cancel at the aggregate level. Shaikh (2016) has shown how several different microeconomic behaviours can lead to the same macroeconomic outcomes. But it is well-known from other disciplines that, in general, heterogeneous micro-level behaviour combines to generate complex, non-linear responses and emergent behaviour at the macro-level. There are also simple scenarios where the strong version of rational expectations breaks down, for instance in minority games (Arthur, 2006). In general, there are relatively few cases in which aggregation to the macro-level undertaken in models which use rational expectations are completely sound (Kirman, 1992).

One plausible alternative set of microfoundations would draw instead on empirically observed behaviours among consumers, firms and governments. The observed behaviours are often termed heuristics or "rules of thumb". These often arise from models which draw on insights from psychology to understand human behaviour (Tversky and Kahneman, 1975). What constitutes rationality is itself not clear or well defined (Simon, 1959). Indeed, in a world of Knightian uncertainty (Knight, 2012), imperfect information, altruism, and costly computation, there is an emerging body of evidence suggesting that heuristics are more 'rational', at least as measured by performance, than the narrowly-defined rationality in which agents compute their optimal course of action without any limitations to their information gathering or processing ability (Aikman et al., 2014; Assenza et al., 2017; Gode and Sunder, 1993; Haldane and Madouros, 2012; Hommes, 2006). This is sometimes called the "ecological rationality" of heuristics (Gigerenzer and Brighton, 2009).

The models which arguably dominate the rational-expectations-cum-optimisation methodology in macroeconomics are so-called dynamic stochastic general equilibrium (DSGE) models (Smets and Wouters, 2003). In their most stripped down form, these DSGE models have a unique equilibrium with deviations that are small and smooth, no role for stock variables and micro behaviours of agents which can be simply and linearly aggregated into the behaviour of a representative agent with rational expectations. The majority of central banks take the DSGE framework as their starting point, including the Bank of England (Burgess et al., 2013).

There has been much debate over the pros and cons of DSGE models which we do not seek to repeat here (Colander et al., 2009; Fair, 2012; Smith, 2014). Particularly strong criticism has included that their additions resemble the epicycles of the Ptolemaic system of astronomy (Fagiolo and Roventini, 2012, 2017), their representative agents are "stochastic Robinson Crusoes" (Summers, 2002), and that the models as a whole are "post-real" (Romer, 2016). Post-crisis, researchers are adding heterogeneity in agent types, a role for the financial sector, and bounded rationality for some agents. Some models use exogenous shocks with fat-tailed, rather than Gaussian, distributions (Ascari et al., 2015). These are all useful additions. There are earlier rational expectations models with heterogeneity added via probability mass functions; see, for example, (Heathcote, 2005). The originators of the pre-crisis workhorse DSGE model (Smets and Wouters, 2003) recently published a paper containing many of these modifications, including a zero lower bound, non-Gaussian shocks and a financial accelerator. They find that the extensions go (Lindé et al., 2016)

> "some way in accounting for features of the Great Recession and its aftermath, but they do not suffice to address some of the major policy challenges associated with the use of nonstandard monetary policy and macroprudential

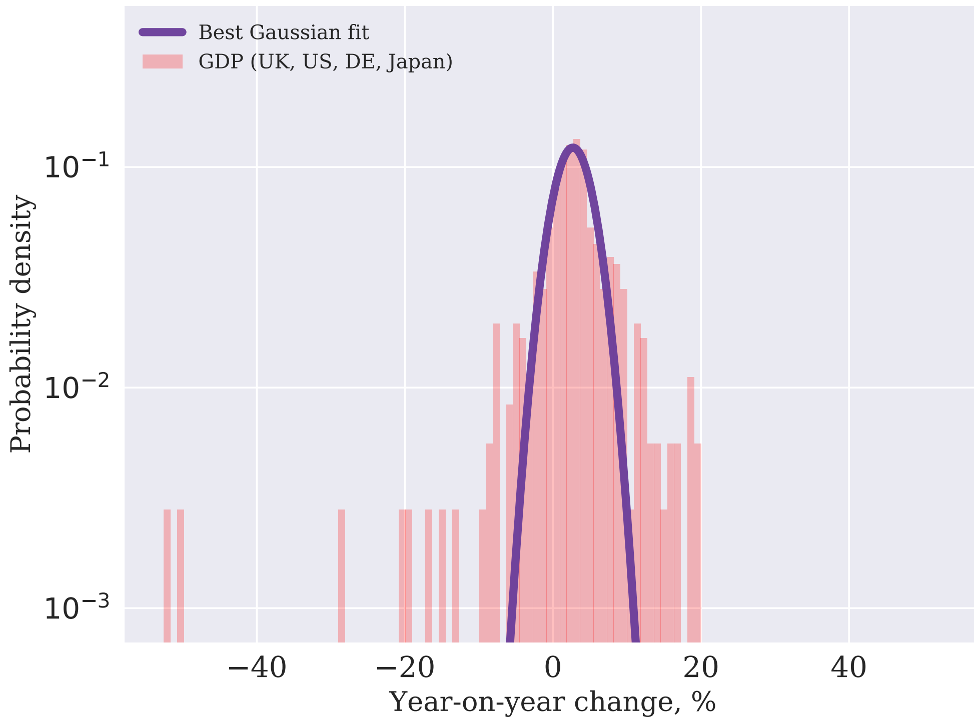


Figure 5. The distribution of year-on-year growth in GDP, 1871–2015. Source: Hills et al. (2016).

policies"

There are also new research directions, such as the heterogeneous agent New Keynesian DSGE models (Kaplan et al., 2016; Ravn and Sterk, 2016), which feature more than one type of equilibrium.

Despite these important modifications, it seems likely some features of economic systems will remain very difficult to reproduce in a DSGE setting – for example, crisis dynamics. DSGE models have struggled to simultaneously explain the stylised facts observed in real economic systems (Fukac and Pagan, 2006). Table 1 shows a selection of these stylised facts. An important example is the distribution of GDP growth seen historically, which is shown in Figure 5. Around 18% of the data across the UK, US, Germany and Japan fall outside the best-fit normal distribution. DSGE models do not tend to reproduce, except by construction, the excessively large variation in GDP growth seen in the historical data (Ascari et al., 2015).

The Global Financial Crisis provides a good example of these limitations. DSGE models struggled to explain either how it started or how it propagated. Figure 6 shows the range of forecasts for UK GDP growth produced by 27 economic forecasters (including the Bank) in 2007. Pre-crisis forecasts were very tightly bunched in a range of one percentage point. The methodological mono-culture produced, unsurprisingly, the same crop. These forecasts foresaw a continuation of the gentle undulations in the economy seen in the decade prior to the crisis – the so-called Great Moderation (Bernanke, 2004). At the time, the damped oscillations of the Great Moderation seemed to match well the smooth motion of DSGE models.

The most important point here is not that this set of models did not forecast the precise timing of the crisis. Almost by definition, costly financial crises cannot be forecast because, if they could, central banks and governments would take actions to prevent them. The real problem was that these models said nothing about the *probability* of a serious crisis arising endogenously at any time, or about the downstream consequences for the economy of a crisis once it had struck. The absence of non-rational expectations, heuristics and non-linear amplification channels was probably key in explaining these problems.

The more general point is that a single model framework is unlikely to best serve the needs of macroeconomists in every state of nature. At its best, the scientific method calls for carefully controlled experiments applied to a rich ecology of models, enabling gradual selection of those models which best fit the known facts. But macroeconomists rarely, if ever, have the luxury of running experiments. And even when they can, experimental model validation is hard because the macroeconomy is a complex system of interacting parts in which cause and effect are difficult to separate.

Facing these constraints, it is likely that a patchwork of models will be more resilient than a single methodology. A group

Table 1. Examples of stylised facts.

Stylised fact	Examples
Endogenous self-sustained growth	Burns and Mitchell (1946); Kuznets and Murphy (1966); Stock and Watson (1999); Zarnowitz (1985)
Fat-tailed GDP growth-rate distribution	Castaldi and Dosi (2009); Fagiolo et al. (2008)
Recession duration exponentially distributed	Ausloos et al. (2004); Wright (2005)
Relative volatility of GDP, consumption and investment	Napoletano et al. (2006); Stock and Watson (1999)
Cross-correlations of macro variables	Napoletano et al. (2006); Stock and Watson (1999)
Pro-cyclical aggregate research and development investment	Wälde and Woitek (2004)
Cross-correlations of credit-related variables	Leary (2009); Lown and Morgan (2006)
Cross-correlation between firm debt and loan losses	Foos et al. (2010); Mendoza and Terrones (2012)
Distribution of duration of banking crises is right skewed	Reinhart and Rogoff (2009)
Distribution of the fiscal costs of banking crises to GDP ratio is fat-tailed	Laeven and Valencia (2013)
Firm (log) size distribution is right-skewed	Dosi et al. (2007)
Fat-tailed firm growth-rate distribution	Bottazzi and Secchi (2003, 2006)
Productivity heterogeneity across firms	Bartelsman and Doms (2000); Dosi et al. (2007)
Persistent productivity differential across firms	Bartelsman and Doms (2000); Dosi et al. (2007)
'Lumpy' investment rates at firm-level	Doms and Dunne (1998)
Counter-cyclicality of firm bankruptcies	Jaimovich and Floetotto (2008)
Firms' bad-debt distribution fits a power law	Di Guilmi et al. (2004)
Firm sizes fit a Taylor power law	Gaffeo et al. (2012)

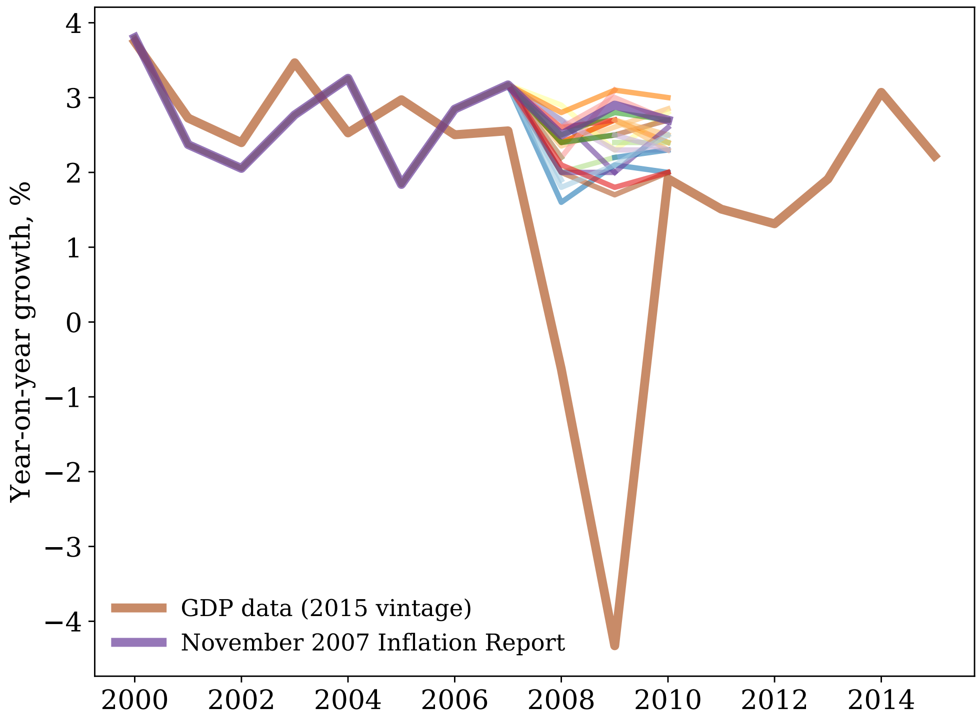


Figure 6. Range of GDP forecasts in 2007Q4. Source: Haldane (2016).

of genuinely distinct models, in competition to match the moments of the real-world, are likely to produce a far richer set of insights than a single class of models, however aesthetically beautiful. In other words, what may be needed is a "Cambrian Explosion" in macro-economic modelling.

From forecasting, there is evidence that combining two or more models leads to greater predictive power than using one model alone (Silver, 2012; Stock and Watson, 2006; Timmermann, 2006). This has been specifically demonstrated for inflation forecasting by Norges Bank in Bjørnland et al. (2012). It is likely to be true qualitatively as well as quantitatively; what one model does not pick up or explain well may be explained by another. A set of models which are distinct, but plausible, will be more informative jointly, perhaps especially so when they disagree. This 'zoo of models' approach has also been adopted at the Bank of England (Burgess et al., 2013).

What types of animal are likely to be most useful in the zoo? At a high level, two types: single equilibrium 'type I' economic models for dealing with close to equilibrium fluctuations; and more complex, multiple equilibrium 'type II' economic models for dealing with far from equilibrium fluctuations. Type I models are stationary and proximately linear. Behaviours are well anchored and close to optimising. Agents' interactions are predictable and aggregate to something close to a single representative agent (Kirman, 1992; Solow, 2008).

Type II models capture behaviours which are 'irrational' or 'heuristically rational' and heterogeneous. Uncertainty, as distinct from risk, is acute. Aggregate behaviour in these models is likely to be fat-tailed and often emergent. Type II models are also likely to help educate us by playing out scenarios we did not expect when constructing the model, combining known micro-level features to produce unexpected aggregate outcomes. This is the "if you didn't grow it, you didn't explain it" philosophy described in Epstein (1999).

Type II macroeconomic models should be able to explain how economic features, including crises, can arise endogenously. To give a concrete example, a type I analysis of the crisis would invoke an exogenous crisis shock – in which a large number of consumers default on a significant fraction of their loans – to understand how the Great Financial Crisis then evolved (Kumhof et al., 2015). A type II model would show how crises unfold not due to any exogenous shock, but as a natural consequence of the rules and behaviours of the agents within the model of the economic system over time. This provides a mechanism for exploring policies which reduce the frequency or severity of crises.

As Krugman and others have pointed out (Colander et al., 2009; Krugman, 2011), some partial (dis-)equilibrium ways of thinking about the economic system could have helped in understanding the crisis before it unfurled, including the ideas of Bagehot (1873), Leijonhufvud (2000), Kindleberger (2001) and Minsky (2008). Before the New Classical Counter Revolution, structural econometric models were also popular (Blanchard, 2017) - the US Federal Reserve's FRB/US macro model fits into this category (Brayton and Tinsley, 1996) (see Welfe (2013) for a review of these types of model). However, all of these models tend to operate at the aggregate level and in general equilibrium, rather than aggregating from the agent-level. Because of that, they are less well-suited to tackling problems with a high degree of agent heterogeneity or with shifting equilibria.

The hegemony of the "representative agent with rational expectations" approach runs deep in macroeconomics. It has similarities to Newtonian physics. But this quasi-mechanistic view, while sometimes a useful approximation, is not a good representation even of modern-day physics. Modern physics research deals with complex systems, emergent behaviours, vast simulations, and outcomes which are probabilistic and stochastic beyond what is implied by the Gaussian distribution. As an example with parallels in economics, aggregate thermodynamic variables like temperature are not sufficient to describe the rich dynamics of systems which are far from equilibrium; granular descriptions of individual particles and their distributions are required (Turrell et al., 2015a). There are well-developed tools for tackling problems that are not analytically tractable, that include complex behaviours and that feature a high degree of heterogeneity. In the next section we describe one of them.

4 THE MODEL FROM MONTE CARLO

In the 1930s, physicist Enrico Fermi was trying to solve a particularly difficult problem: the movement of one of the types of particle which make up the atom, the neutron, through background material. This was a tricky calculation as the neutrons had a distribution over several variables including position $\mathbf{r}$, energy E, and direction $\hat{\Omega}$ according to a distribution $f\left(\mathbf{r}, E, \hat{\Omega}, t\right) dr\, dE\, d\Omega$.

The full equation tracks the position, direction and energy evolution of N particles over time with terms representing numerous discrete, continuous, source, and sink interactions of the neutrons. Initially, Fermi and other scientists tried to solve the entire problem analytically in single equation form but it proved difficult to solve for all but the simplest cases.

Fermi developed a new method to solve these problems in which he treated the neutrons individually, using a mechanical adding machine to perform the computations for each neutron in turn. The technique involved generating random numbers and comparing them to the probabilities derived from theory. If the probability of a neutron colliding were 0.8, and he generated a random number smaller than 0.8, he allowed a 'simulated' neutron to collide. Similar techniques were used to find the outgoing direction of the neutron after the collision. By doing this repeatedly, and for a large number of simulated neutrons, Fermi could build up a picture of the way neutrons would pass through matter. Fermi took great delight in astonishing his colleagues with the accuracy of his predictions without, initially, revealing his trick of treating the neutrons individually (Metroplis, 1987).

The more general method of using random numbers to solve problems soon got a name that reflected its probabilistic nature: Monte Carlo. It was further developed by Fermi, Stanislaw Ulam, John von Neumann and others (Metroplis, 1987; Metropolis et al., 1953; Metropolis and Ulam, 1949). It found wide usage because of the way it naturally weights the scenarios that are explored by the probability of them occurring. It is efficient in problems with a high number of dimensions, and effective in reproducing all of the moments of a distribution function. Monte Carlo is a standard technique in finance, where it is used to calculate the expected value of assets.

Monte Carlo simulation remains widely used in a range of disciplines known under different names, including individual-based models in biology and ecology, agent-based models (ABMs) in economics, and multi-agent systems in computer science and logistics as described in Turrell (2016). Recent applications in physics include calculating how beams of particles could destroy cancerous cells (Arber et al., 2015; Bulanov and Khoroshkov, 2002), and how to produce energy from nuclear fusion reactions (Lindl et al., 2004; Spears et al., 2015). They have made a mark in ecology (Carter et al., 2015), where they have been used to model endangered species; in epidemiology (Degli Atti et al., 2008), where they have been used to make detailed predictions of how influenza could spread given demographics and transport links; and for the decentralised behaviour of autonomous vehicles (Ernest et al., 2016). As in physics, their use in epidemiology sees a set of difficult to solve differential equations being replaced with simulations of individual agents. Monte Carlo simulation passes the market test too. It has been used for project finance modelling under uncertainty, forecasting mortgage repayment rates (Geanakoplos et al., 2012), redesigning the rules of the NASDAQ stock exchange (Bonabeau, 2002), and for simulating the transport of people (Heppenstall et al., 2011). A number of firms, such as Sandtable and Concentric, offer bespoke agent-based models for commercial applications.

Agents in these models might include the consumers in an economy, fish within a shoal, and even galaxies within the Universe as in Davis et al. (1985). As well as interacting directly with each other, agents might also have a connection to their environment – for instance, banks subject to regulation or whales migrating across the ocean. The behaviours or rules that agents follow depend

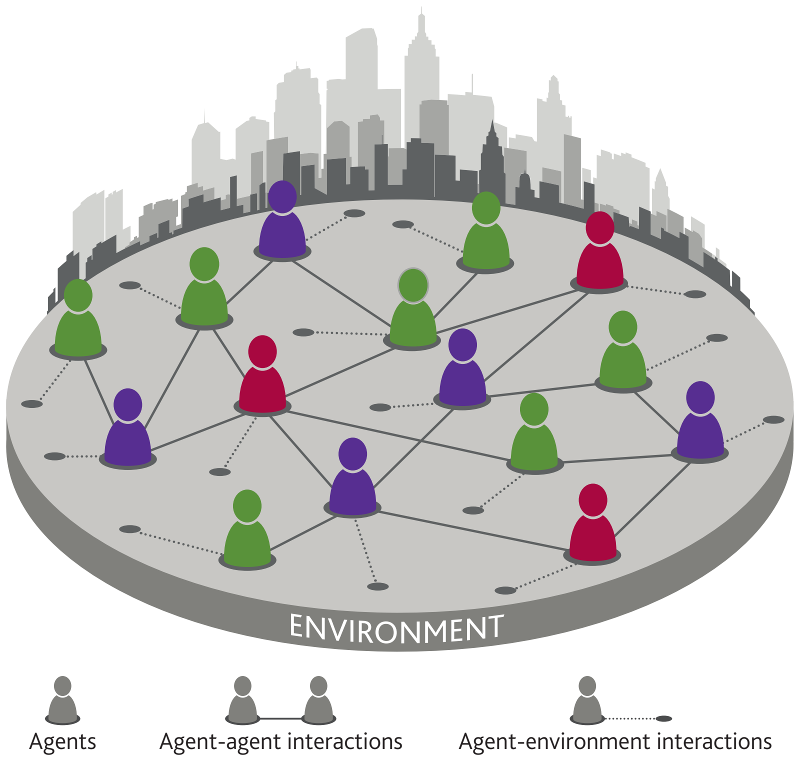


Figure 7. A schematic of the elements of an agent-based model and their interactions. Source: Turrell (2016).

on the question of interest. Some models have many different types of agent, perhaps firms, workers and governments. These may themselves differ, so that while all workers have a chance to be employed by a firm and receive a wage, the human capital and marginal propensity to consume of each worker could be different and determined according to an empirical distribution. A schematic of an agent-based model in economics is shown in Figure 7. Heterogeneous agents interact both with each other within a network structure, and with the wider environment.

The important feature of ABMs is that they explain the overall evolution of a system by simulating the behaviour of each individual agent within it and then explicitly combining their micro-level behaviours to give a macro-level picture. Each agent is a self-contained unit which follows a given set of behavioural rules. This 'bottom-up' approach is very much in the spirit of a "microfoundations" approach, though it differs fundamentally in how it then aggregates to the macro level.

5 HOW ARE AGENT-BASED MODELS IN ECONOMICS DIFFERENT?

There are important differences between ABMs in the sciences and in economics. In economics, agent-level behaviours are not known to the same level of accuracy as the laws of nature which govern the interactions between, for example, particles. In economics, behaviours can change over time in response to the environment. Agent level assumptions in economics thus need to be rigorously tested and varied.

Partly as a consequence of the inherent uncertainty in agent behaviour, ABMs in economics can match the data only probabilistically. They tend to match moments and reproduce stylised facts. Some argue that this is naïve compared to more exactly matching the historical evolution of variables over time. But the latter approach, often using forcing processes, seems to suggest an implausible level of precision. An ABM is a way to generate many possible, plausible realisations of variables in exactly the same manner as different possible price paths are generated in Monte Carlo option pricing. Another way to think of this is in terms of the trade-off between bias and variance. Very broadly, ABMs attain lower bias at the cost of higher variance. Model errors are squared in the bias but only linear in the variance (Friedman et al., 2001). Models with forcing processes aim at low variance at the cost of higher bias.

Where do ABMs fit into the wider modelling landscape? Figure 8 shows this schematically. Models lie on a spectrum. Statistical models rarely say anything about heterogeneous agents. DSGE models say more, and ABMs yet more. But ABMs are not

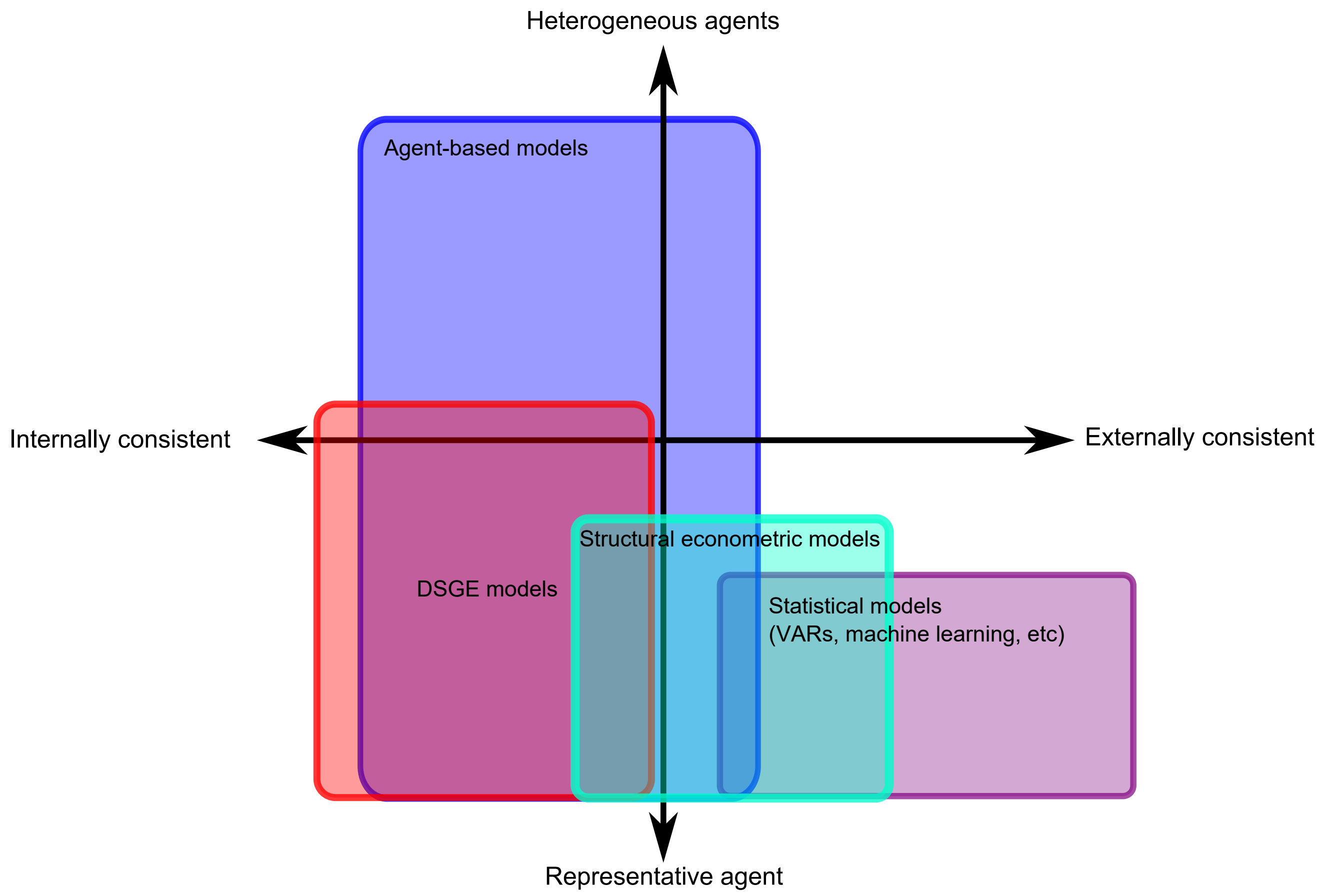


Figure 8. Macroeconomic ABMs may be thought of as lying within a wider modelling space, here shown as having two axes. Internal consistency is best represented by strongly microfounded behaviour, while external consistency is demonstrated by agreement with the data. On the other axis is the degree of agent heterogeneity which the model can include, with representative agents on one end and heterogeneity along many dimensions at the other. The within variation of each model type is likely to be larger than the variation between them, but the figure illustrates their approximate location within the wider modelling space.

useful for every problem. While in principle it would be possible to use them in forecasting, there are already models potentially better equipped for this, such as dynamic factor models (Stock and Watson, 2011) and machine learning (Chakraborty and Joseph, 2017). ABMs are better placed to produce conditional forecasts, where a particular policy is being explored. This is how epidemiologists use agent-based models too (Degli Atti et al., 2008): rather than attempt to forecast the specific time that a virus outbreak will happen, they identify the risk factors for a virus to break out and subsequently spread. In Figure 8, ABMs nest DSGE models as a special case with little heterogeneity, no stock variables and a particular set of assumptions about agent behaviour. Broadly defined, ABMs will add most value when problems revolve around heterogeneity, complexity, non-linearity, emergence, heuristics, and detailed rules.

The models in Figure 8 require quite different approaches and ABMs have a modelling philosophy which is distinct from their closest neighbours. The archetypal DSGE model comes bundled with a number of assumptions, including rational expectations. Rather than offering a 'core' model, ABMs are a flexible toolkit for solving complex problems involving heterogeneous agents. One could use rational expectations, but there is no requirement to do so. This flexibility is one reason why ABMs populate every field from military war games to ecology, and why it is impossible to write down a representative ABM.

As a demonstration of this, Table 2 shows a non-exhaustive list of consumption functions in different macroeconomic ABMs. In DSGE models, a core model has emerged partly because the need for analytical tractability forces the modeller to choose from a restricted set of behaviours. ABMs are a generalisation to more behaviours and more agents. This means ABMs are often bespoke, adapted to the particular question they are answering. For that reason, they have been criticised as 'black box'. Their bespoke nature means that there is also a bigger cost to understanding them.

Yet there is no reason why an ABM could not have what Blanchard (2017) has outlined as being required for a core macroeconomic model: nominal rigidities, bounded rationality and limited horizons, incomplete markets and a role for debt. Indeed, these features are found in many macroeconomic ABMs. One of the major differences is the degree to which these models are solved computationally. The process in a typical DSGE model is to specify agents' behaviours and analytically aggregate them, assuming in the process that markets clear. Usually they would then be linearised and, in the last step, solved numerically. In a typical ABM, the process is quite different. They are solved numerically at the agent level, one behaviour at a time.

This has a number of implications for the strengths and weaknesses of ABMs. Being free of the need to specify equations which can fit together and be solved analytically can be liberating for some problems. This does not mean that ABMs cannot be represented mathematically – there is a theorem which says that all ABMs which can be computed numerically have an explicit mathematical representation[1] (Epstein, 2006; Leombruni and Richiardi, 2005). But usually the direct mathematical translation would be too unwieldy to transcribe and would only be interesting in special cases. ABMs are better thought of as algorithms for aggregating the behaviours of individual actors rather than as systems of equations.

If there is a downside to this flexibility it is that analytical certainty must be replaced with numerical convergence. Sinitskaya and Tesfatsion (2015) highlight this by comparing numerical solutions to a lifecycle optimisation problem within an ABM to a known analytical solution. The numerical solution methods do not reach precisely the same outcome as the analytical solution. But for most problems in macroeconomics, the accuracy in how a problem is posed is likely to be a far larger source of error than the lack of precision in the numerical solution of that problem. Indeed, this is another example of the bias-variance trade-off.

The modelling philosophy also differs with respect to interpretation of results. It is useful to think of ABMs as a machine for generating many alternate realisations of the world. Just as in real experiments, it is useful to make many repeats with both control and treatment groups. If the future distribution of one particular variable were truly uncertain, say income y such that $y \sim f$, an ABM could be run not just with millions of possible draws from the same distribution f but also from an entirely different parametric or empirical distribution g. In an ABM, it is possible to do this by changing a single line of code. In more analytical models, it might not be possible at all to do so. Due to the complexity of the interactions within an ABM, it may also be necessary to treat the outcomes as one would real experimental data, with the machinery of hypothesis testing and confidence intervals.

As with all models, it is nonsensical to have more free parameters than imposed or calibrated parameters. ABMs have been accused of being full of free parameters, but this is bad modelling rather than an intrinsic feature of ABMs. One measure of all models is how parsimoniously they describe the empirical data. Macroeconomic ABMs can match both micro and macro stylised facts for most, if not all, the entries in Table 1. For instance, both Gualdi et al. (2015) and Caiani et al. (2016) match the

[1] Every agent-based model is computable by a Turing machine, and every algorithm computable by a Turing machine may be expressed via sets of partial recursive functions.

Table 2. Examples of consumption used in different macroeconomic agent-based models. For full details see the references.

Consumption model description	Consumption model references	ABM references
Inflation dependent fraction of permanent income; consumption given by $c_t = k_t \hat{y}_t$ where $$k_t = k_{t-1} - f(i_t - \mathbb{E}\pi_{t+1} - r_t)$$	$\hat{y}_t$ is permanent income from Friedman (1957).	Salle et al. (2013)
Aggregate consumption as sum of incomes of all employed and unemployed; $C_t = \sum_{u,e} \sum_i y_{i,t}$	Hand-to-mouth consumers as described in Campbell and Mankiw (1989).	Dosi et al. (2010)
Fixed propensities α_1, α_2 out of expected real disposable income and expected real wealth $$c_t = \frac{1}{\mathbb{E}p_{t+1}} (\alpha_1 y_t + \alpha_2 W_t)$$	Godley and Lavoie (2007)	Caiani et al. (2016)
Adaptive (with memory parameter ξ) expectation of income and fixed fraction of wealth (based on buffer-stock); $$c_t = \xi y_{t-1} + (1-\xi) y_t + 0.05 W_t$$	Carroll (1997, 2009)	Assenza et al. (2015)
Concave, monotonically increasing bounded above fraction of real wealth; $$c_t = \min\left\{ \left(\frac{y_t}{p_t}\right)^{\alpha}, \frac{y_t}{p_t} \right\}$$ with $0 < \alpha < 1$	Carroll and Kimball (1996); Souleles (1999)	Lengnick (2013)
Wealth growth ΔW, average historical consumption of other households $\bar{c}_t$ and a reference consumption level $\tilde{c}_t$; $$c_t = \tilde{c}_t + \alpha \frac{\Delta W_t}{p_{t-1}} + \beta(\bar{c}_{t-1} - c_{t-1})$$ where $\alpha > 0, \quad \beta > 0$	Abel (1990); Jawadi and Sousa (2014)	Guerini et al. (2016)
Numerically solved utility maximisation subject to inter-temporal budget constraint with leisure $(1-l)$ and wealth W; $$\max_{c,l} \mathbb{E}\left\{ \sum_{r=t}^{\infty} \beta^{r-t} u(c_t, 1-l_t) \right\}$$ such that $W_{t-1} - p_t c_t > 0$, $c_t > 0$	Friedman (1957)	Sinitskaya and Tesfatsion (2015)
Consumption as a fixed fraction of wealth and income; $c_t = \alpha(W_t + y_t)$	Godley and Lavoie (2007)	Gatti and Desiderio (2015); Gualdi et al. (2015)
Buffer-stock with mean backward-looking income $\tilde{y}_t$ and target wealth-to-income ratio ϕ; $$c_t = \tilde{y}_t + \alpha(W_t - \phi \tilde{y}_t)$$	Carroll (1997)	Chan and Steiglitz (2008); Cincotti et al. (2010); Dawid et al. (2012, 2014)

frequency and the extent of the cyclicality in productivity, nominal wages, firms' debt, bank profits, inflation, unemployment, prices and loan losses, while Dosi et al. (2015) reproduce, amongst other features, the distributions of output growth and the duration of banking crises. By simulating every individual actor within an economic system, all moments of distribution functions are accessible to ABMs.

If, as described in Wren-Lewis (2016b), DSGE models maintain internal consistency by sacrificing some external consistency, then ABMs are more of a bridge between internal and external consistency: they sacrifice some internal consistency by allowing agents to have behaviours which are not hyper-rational. Nonetheless, the combination of bespoke models, flexibility and a tendency to focus on complex systems can mean that communication is a challenge for agent-based modellers. ABMs are rarely as easy to write down in equation form as, say, the simple three-equation New Keynesian DSGE model. There may not always be an easy fix: complex real systems must sometimes be described with complex simulations, at least initially.

Science has had to deal with the trade-off between bigger, more feature-packed models and more abstract but easier to digest models for a long time. Compromises have emerged. In physics, it is common to use a complex simulation of a system as a way of initially exploring hypotheses or discovering new phenomena. Once a specific effect is identified within the complex simulation, a purely theoretical model (or a much simpler numerical model) is built to explain its salient features. An example is in Turrell et al. (2015b), in which a very fast way for lasers to heat matter was first identified in a model with over 10^7 agents and then explained with a handful of parameters in an analytical model using differential equations. Another example of a theoretical model being overturned by simulation is found in (Sherlock et al., 2014). The poor performance of the original theory, accepted for decades, would have been difficult to understand or describe analytically without the use of an ABM.

Gualdi et al. (2015) are the exemplars of this approach in a macroeconomic ABM. A rich and complex model is boiled down to a much simpler ABM which retains, and explains, the same phenomenon. The difference between this approach and simply beginning with a smaller, perhaps analytical, model is that the bigger and more realistic model genuinely surprises the researcher with a relationship or phenomenon that they did not expect. It is then the researcher's job to unpick this effect and interrogate it further.

The bottom line is that whether an ABM is good or bad will depend on its specific assumptions, how it is used, and how the results are interpreted. The lack of restrictions on modelling assumptions can be a risk. As it is the flexibility of ABMs that gives rise to this risk, the benefits of this flexibility need to be significant to justify this cost. It is argued in the next section that they are.

6 WHAT COULD AGENT-BASED MODELS DO FOR ECONOMICS?

The strength of ABMs for economics lies in their flexibility relative to the other models shown in Figure 8. Fabio Ghironi has identified topics in this special issue which are likely to be important for macroeconomic models in the future. They are topics which can be difficult to capture in established models. But, as shown in Table 3, ABMs are already delivering new perspectives on each of them.

In general, ABMs are well-suited to situations where interactions between agents really matter, where heuristics dominate, where the heterogeneity of agents is important, where policies have agent-level implications, where granular data are plentiful, and where analytical methods fail. Non-Gaussian distributions, non-linear equations, time-inconsistent choices, boundedly rational behaviours – it is possible to solve all of these numerically at the agent-level. Given that many real world problems involve these features, ABMs have many potential uses in economics (Tesfatsion, 2002).

A great deal of research in networks, particularly as applied to financial systems, has shown that there are emergent properties at the system-level which arise out of interactions at the agent-level (Battiston et al., 2007; Gai et al., 2011). As an example, Bardoscia et al. (2017) show that as banks integrate and diversify at the agent-level, they can increase the system-wide risk of instability because they create cyclical dependencies which amplify stress. ABMs can get at this behaviour where agent-level interactions lead to counter-intuitive behaviour at the macro-level. Herding effects (Alfarano et al., 2005) are another example.

One of the most important use cases of ABMs is to explore microfoundations other than rational expectations. Table 2 shows how ABMs run the whole gamut of behavioural assumptions for consumption. There is an emerging body of experimental evidence suggesting that heuristics can outperform 'rational' behaviours (Gigerenzer and Brighton, 2009). To have confidence in the conclusions of ABMs, there is a need for a wider body of work on how best to include realistic agent-level behaviours; see Gabaix (2016) for one example of this. And in understanding agent behaviours, advanced machine-learning techniques are likely to be useful in approximating decisions made by real people. Initial steps down this path have already been taken by DeepMind (Leibo et al., 2017).

Table 3. Topics identified as being important for the future of macroeconomics and the ABMs that study them.

Topic	ABM reference	ABM description
Financial intermediation	Ashraf et al. (2017)	Analysis of the role that banks play in firm entry and exit.
Heterogeneity of firms and households	Assenza et al. (2016)	Exploration of how exporting and domestic firms become heterogeneous in productivity.
Granularity and networks	Bardoscia et al. (2017)	Shows how diversification can lead to increased systemic risk in networks of banks.
Policy interdependence	Popoyan et al. (2016)	A macroeconomic model exploring the interdependence between macroprudential regulation and monetary policy.

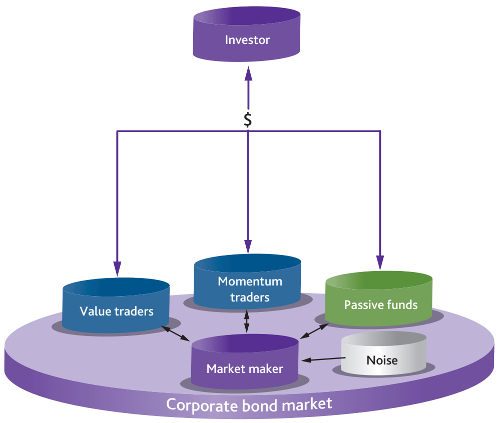
ABMs are perhaps most easily distinguished from other models by their ability to model heterogeneity (Hommes, 2006). There is mounting evidence of the importance of household, firm and consumer heterogeneity in both status (such as wealth) and behaviour (Alfi et al., 2009; Gabaix, 2011; Guvenen, 2011). A special example is when agents' stock variables matter. Under the assumptions of the archetypal DSGE model it does not matter that variables such as wealth or debt are not tracked because flows implicitly describe the information about stocks which are relevant for the model. However, there are situations in which richer information on stocks are relevant, such as when heterogeneous agents target a particular level of wealth or debt (Elmendorf et al., 1996; Muellbauer and Murata, 2009) or when wealth feeds back into behaviour (Cooper and Dynan, 2014).

Models which include accounting identities at the aggregate level have existed for some time (Wren-Lewis, 2016a). But the recent ABM of Caiani et al. (2016) has applied them at the agent level to capture the interaction of agents' decisions through the balance sheet channel. Gatti and Desiderio (2015) show the role of firms' balance sheets in monetary policy. Policies which act heterogeneously also need to be modelled – for instance, the Bank of England Financial Policy Committee's policy in 2015 to ensure "that mortgage lenders do not extend more than 15% of their total number of new residential mortgages at loan to income ratios at or greater than 4.5". For monetary policy, one of the important practical channels for influencing consumption relies for its effectiveness on agent heterogeneity: those who gain from policy easing have higher marginal propensities to consume than those who lose (Auclert, 2015). The chair of the US Federal Reserve, Janet Yellen, has commented (Yellen et al., 2016)

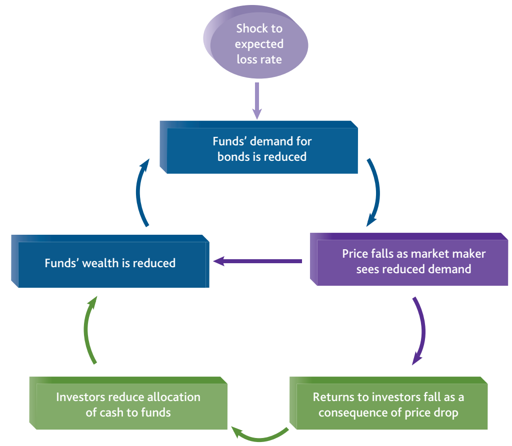
> "Economists' understanding of how changes in fiscal and monetary policy affect the economy might also benefit from the recognition that households and firms are heterogeneous. For example, in simple textbook models of the monetary transmission mechanism, central banks operate largely through the effect of real interest rates on consumption and investment. Once heterogeneity is taken into account, other important channels emerge. For example, spending by many households and firms appears to be quite sensitive to changes in labor income, business sales, or the value of collateral that in turn affects their access to credit–conditions that monetary policy affects only indirectly. Studying monetary models with heterogeneous agents more closely could help us shed new light on these aspects of the monetary transmission mechanism."

An ABM could be used to look at how heterogeneity along several inter-related dimensions affects policy transmission – for instance, marginal propensity to consume as a function of net assets and demographics. Inequality is one type of heterogeneity which is already being explored; see Gibson (2007) and Caiani et al. (2016) for examples where initially egalitarian distributions, such as income, become unequal endogenously. ABMs are not the only way to include heterogeneity, but they do offer an easier route to a higher degree of heterogeneity. Just as Fermi and his colleagues found with neutrons, there is a point where the trade-off between increasingly elaborate mathematical models and numerically solved models favours the latter. New types of DSGE model are closer to that cross-over point, but the other side of the trade-off remains worthy of attention.

The ability to model systems without analytical constraints makes some problems easier to study. Lord Stern, author of a significant review of the economics of climate change (Stern, 2007), has called for agent-based modelling as a way to more realistically incorporate the macroeconomic trade-offs of climate change (Stern, 2016b). See Lamperti et al. (2017a) for an example of a macroeconomic ABM which takes up this challenge. It facilitates the analysis of systems which are out of equilibrium – systems where markets do not necessarily clear, which are in dynamic dis-equilibrium or which transition between different equilibria. One of the unique perspectives from this type of model is showing how a dis-equilibrium can emerge as the result of the self-interested (but not necessarily hyper-rational) choices of individual agents.



(a) A schematic of the ABM of trading in the corporate bond market. Source: Braun-Munzinger et al. (2016).



(b) A schematic of how initial price and yield changes are amplified and propagated in the model. Source: Braun-Munzinger et al. (2016).

Figure 9

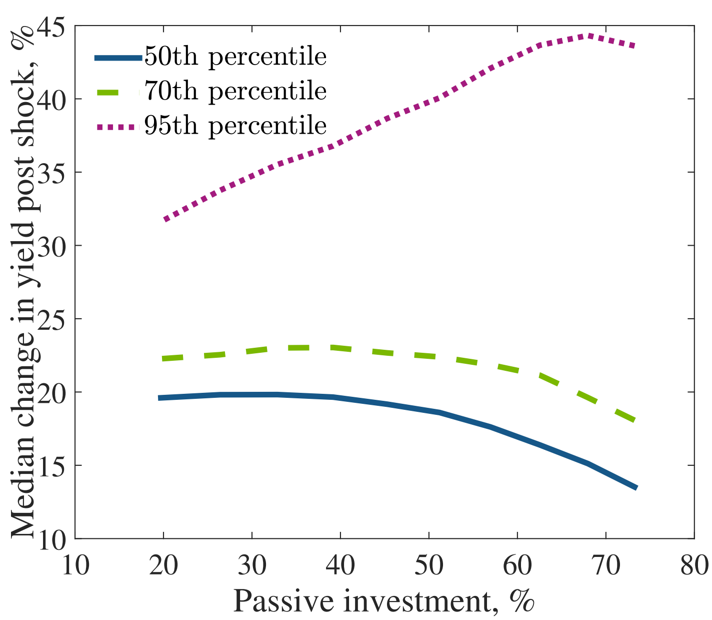
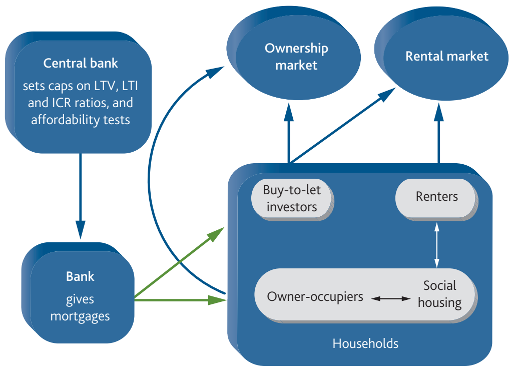
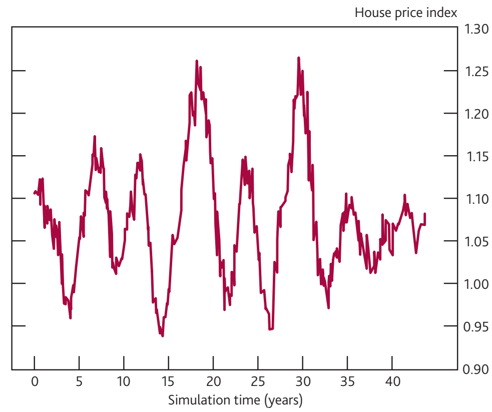


Figure 10. The distribution of outcomes for the median yield of a corporate bond index over the 100 trading days after a sudden increase in the loss rate on the index. Percentiles refer to repeated model runs. Source: Braun-Munzinger et al. (2016).



(a) A schematic of the agents and interactions in the housing market model. Source: Baptista et al. (2016).



(b) A benchmark run of the housing market model showing house price index cycles. Source: Baptista et al. (2016).

Figure 11

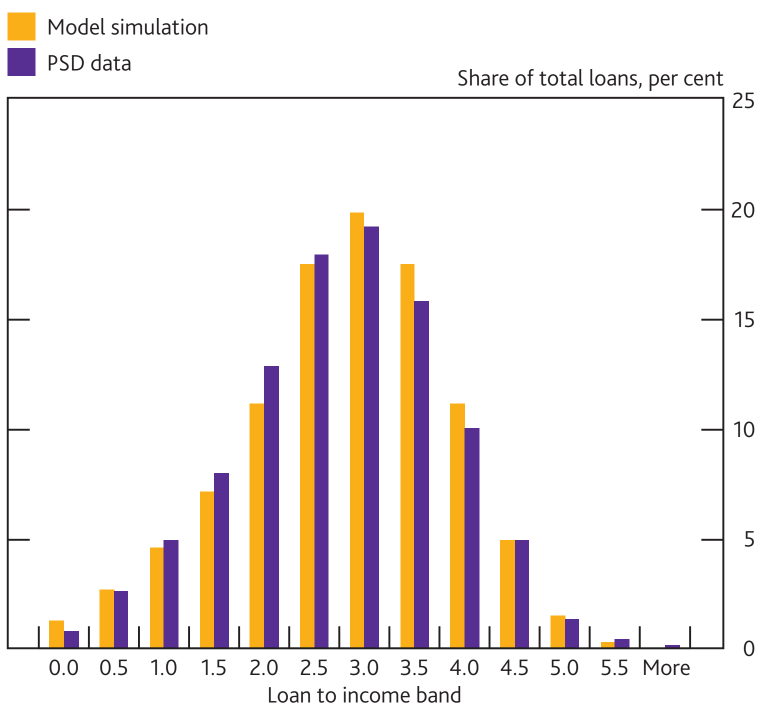


Figure 12. Once calibrated, the housing market ABM reproduces the loan to income probability mass function for the United Kingdom. Source: Baptista et al. (2016).

A dramatic example is the non-linear, dynamic macroeconomic ABM of Gualdi et al. (2015) in which output and employment discontinuously collapse to new values depending on the propensity of firms to hire and fire new staff, in addition to firms' levels of indebtedness. These discontinuous shifts from one equilibrium to another are well known from physics as 'phase transitions'. They have also been identified in contagion in financial networks (Gai and Kapadia, 2010; Watts, 2002) and in the way that opinions and narratives can shift within a population (Shiller, 2017; Sornette, 2014). De Grauwe (2010) develops an ABM that includes this opinion shift effect in an otherwise New Keynesian setup.

There are undoubtedly problems too. Calibration, for instance, is currently a relatively weak area for macroeconomic ABMs. Although the best have been successful in reproducing an impressive range of stylised facts, calibration techniques and standards tend to vary substantially across models. The generalised method of moments is a commonly used approach (Franke and Westerhoff, 2012), but techniques based on vector auto-regressions and machine learning are also being developed (Guerini and Moneta, 2017; Lamperti et al., 2017b).

ABMs have already delivered strong results on some partial (as opposed to general) economic and financial systems. ABMs have provided plausible explanations for phenomena in financial markets including fat tails, clustered volatility and bubbles (Alfi et al., 2009; Cutler et al., 1989; Hong and Stein, 1999; Lux and Marchesi, 1999). Lux and Marchesi (1999) showed that in order to reproduce the fat tails seen in the distribution of absolute returns in markets, a number of market participants who trade based not on fundamentals, but based on optimism and pessimism (known as noise traders) are required. In their model, agents are able to switch groups based on the performance of strategies. The market fundamentals follow a Gaussian distribution so that the fat-tailed distribution of returns is solely due to the interactions between the different types of traders. In the model, if agents see an opportunity to profit by becoming noise traders, they switch strategies. In the short term, they can ride a wave of optimism or pessimism, and so enjoy larger absolute returns than the variation in fundamentals would imply. But the deviation from underlying value has limits because of the remaining fundamentalist agents and, eventually, prices must partially revert. This simple agent-based model provides a compelling explanation for one of the puzzles of financial markets.

At the Bank of England, ABMs have been used to aid understanding of both the corporate bond market (Braun-Munzinger et al., 2016) and the UK housing market (Baptista et al., 2016). The former model, shown schematically in Figure 9a, was used to study how investors redeeming the corporate bonds held for them by open-ended mutual funds can cause feedback loops in which bond prices fall. The non-linear loop induces price overshoots in the bond index (shown schematically in Figure 9b) and the model looks at possible ways to reduce the extent of the overshooting. The model is calibrated to granular empirical data, and produces a reasonable match to the distribution of daily log-price returns. In one scenario, the fraction of funds using passive trading strategies is increased. The increased presence of passive funds is price and yield stabilising in the median case but it introduces a tail-risk of very large price falls (yield rises), as shown in Figure 10. The reason is that when there are few actively trading funds, the market-maker is more likely to observe a sudden glut of positive or negative net demand and so create major price movements in response. This was not a result which was expected *a priori*.

A UK housing market model developed at the Bank of England explores the links between macroeconomic stability and house price cycles (Erlingsson et al., 2014; Geanakoplos et al., 2012). Capturing these cyclical dynamics is not straightforward. One potential reason is that the housing market comprises many types of agent: renters, first-time buyers, owner-occupiers, sellers, and buy-to-let landlords. These agents are all represented in the ABM, and are heterogeneous by age, bank balances, income, gearing and location. Additionally there is a banking sector (a mortgage lender) and a central bank; all are shown schematically in Figure 11a. The combination of the actions of these agents gives rise to the cyclical dynamics seen in Figure 11b. These arise endogenously in the model.

The inclusion of an explicit banking sector is important as banks provide mortgage credit to households and set the terms and conditions available to borrowers. The lending decisions of the banking sector are subject to regulation by the central bank, which sets loan to income, loan to value, and interest cover ratio policies. The model reproduces the probability mass function of the share of loans by loan-to-income band given by the Product Sales Database of UK mortgages, as shown in Figure 12. The model has been used to look at several scenarios, including policy scenarios. For example, a policy which applies at the agent-level – such as no more than 15% of new mortgages being at loan-to-income ratios at or greater than a given multiple – serves to dampen boom and bust cycles in house prices at the aggregate level.

7 CONCLUSION

Economics has been unusually insular and trust in economists is low. At the centre of this insularity has been a particular type of microfounded behaviour. But the type of microfoundation embedded within mainstream macroeconomic models is far from the only, or in some cases the most plausible, choice. And microfounded models are not the only kind of models that are useful for making sense of aggregate economic fluctuations. A more diverse approach to macro-economic modelling may be beneficial when making sense of the economy and when setting policy to shape the economy.

Drawing on the last seven decades of simulation, this paper presents one complementary modelling approach. In agent-based models (ABMs), aggregate behaviour is built around the behaviours of individual agents. In that sense, it is very much in the spirit of the "microfoundations revolution", even if the modelling philosophy is different. These approaches have already proven their worth in partial (dis)-equilibrium settings, both in finance and the natural sciences.

But there is work to be done before ABMs enjoy the same standing in the mainstream economic literature as their cousins. Among the more fundamental issues which need addressing are:

1. what are the most realistic behaviours to incorporate, at the agent-level, once the assumptions of representative agents with rational expectations are relaxed?
2. how should information flow between agents within the macroeconomy best be captured? and;
3. in which situation are ABMs and DSGE models likely to give similar/dissimilar results?

Alongside these technical questions, modellers must also ask themselves how the results of complex simulations of complex systems can best be communicated to researchers and policymakers alike. Challenges aside, ABMs are a promising complement to the current crop of macroeconomic models, especially when making sense of the types of extreme macro-economic movements the world has witnessed for the past decade.

Acknowledgements

We are grateful to attendees of a seminar at the University of Oxford, to an anonymous referee, and to James Barker, David Bholat, Shiv Chowla, Giovanni Dosi, Jeremy Franklin, Simon Hayes, Sujit Kapadia, Clare Macallan, Mauro Napoletano, Paul Robinson and Andrea Roventini for their help and comments.

References

Aad, G., Abajyan, T., Abbott, B., Abdallah, J., Khalek, S. A., Abdelalim, A., Abdinov, O., Aben, R., Abi, B., Abolins, M., et al. (2012). Observation of a new particle in the search for the Standard Model Higgs boson with the ATLAS detector at the LHC. *Physics Letters B*, 716(1):1–29.

Abbott, B. P., Abbott, R., Abbott, T., Abernathy, M., Acernese, F., Ackley, K., Adams, C., Adams, T., Addesso, P., Adhikari, R., et al. (2016). Observation of gravitational waves from a binary black hole merger. *Physical review letters*, 116(6):061102.

Abel, A. B. (1990). Asset prices under habit formation and catching up with the Joneses. Technical report, National Bureau of Economic Research.

Aikman, D., Galesic, M., Gigerenzer, G., Kapadia, S., Katsikopoulos, K. V., Kothiyal, A., Murphy, E., and Neumann, T. (2014). Taking uncertainty seriously: simplicity versus complexity in financial regulation. *Bank of England Financial Stability Paper*, 28.

Alfarano, S., Lux, T., and Wagner, F. (2005). Estimation of agent-based models: the case of an asymmetric herding model. *Computational Economics*, 26(1):19–49.

Alfi, V., Cristelli, M., Pietronero, L., and Zaccaria, A. (2009). Minimal agent based model for financial markets I. *The European Physical Journal B*, 67(3):385–397.

Arber, T., Bennett, K., Brady, C., Lawrence-Douglas, A., Ramsay, M., Sircombe, N., Gillies, P., Evans, R., Schmitz, H., Bell, A., et al. (2015). Contemporary particle-in-cell approach to laser-plasma modelling. *Plasma Physics and Controlled Fusion*, 57(11):113001.

Arinaminpathy, N., Kapadia, S., and May, R. M. (2012). Size and complexity in model financial systems. *Proceedings of the National Academy of Sciences*, 109(45):18338–18343.

Arthur, W. B. (2006). Out-of-equilibrium economics and agent-based modeling. *Handbook of computational economics*, 2:1551–1564.

Ascari, G., Fagiolo, G., and Roventini, A. (2015). Fat-tail distributions and business-cycle models. *Macroeconomic Dynamics*, 19(02):465–476.

Ashraf, Q., Gershman, B., and Howitt, P. (2017). Banks, market organization, and macroeconomic performance: an agent-based computational analysis. *Journal of Economic Behavior & Organization*, 135:143–180.

Assenza, T., Brock, W. A., and Hommes, C. H. (2017). Animal spirits, heterogeneous expectations, and the amplification and duration of crises. *Economic Inquiry*, 55(1):542–564.

Assenza, T., Gatti, D. D., and Grazzini, J. (2015). Emergent dynamics of a macroeconomic agent based model with capital and credit. *Journal of Economic Dynamics and Control*, 50:5–28.

Assenza, T., Gatti, D. D., Grazzini, J., and Ricchiuti, G. (2016). Heterogeneous Firms and International Trade: The Role of Productivity and Financial Fragility. CESifo Working Paper Series 5959, CESifo Group Munich.

Auclert, A. (2015). Monetary policy and the redistribution channel. 2015 Meeting Papers 381, Society for Economic Dynamics.

Ausloos, M., Miśkiewicz, J., and Sanglier, M. (2004). The durations of recession and prosperity: does their distribution follow a power or an exponential law? *Physica A: Statistical Mechanics and its Applications*, 339(3):548–558.

Avian Flu Working Group (2006). The Global Economic and Financial Impact of an Avian Flu Pandemic and the Role of the IMF. Technical report, International Monetary Fund.

Bagehot, W. (1873). *Lombard Street: A Description of the Money Market*. Henry S. King and Co. London.

Baker, S. R., Bloom, N., and Davis, S. J. (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics*, 131(4):1593–1636.

Baptista, R., Farmer, J. D., Hinterschweiger, M., Low, K., Tang, D., and Uluc, A. (2016). Macroprudential policy in an agent-based model of the UK housing market. Staff Working Paper 619, Bank of England.

Bardoscia, M., Battiston, S., Caccioli, F., and Caldarelli, G. (2017). Pathways towards instability in financial networks. *Nature Communications*, 8.

Bartelsman, E. J. and Doms, M. (2000). Understanding productivity: Lessons from longitudinal microdata. *Journal of Economic literature*, 38(3):569–594.

Batten, S., Sowerbutts, R., Tanaka, M., et al. (2016). Let's talk about the weather: the impact of climate change on central banks. Staff Working Paper 603, Bank of England.

Battiston, S., Gatti, D. D., Gallegati, M., Greenwald, B., and Stiglitz, J. E. (2007). Credit chains and bankruptcy propagation in production networks. *Journal of Economic Dynamics and Control*, 31(6):2061–2084.

Bernanke, B. (2004). The Great Moderation. Speech given at the Eastern Economic Association.

Bjørnland, H. C., Gerdrup, K., Jore, A. S., Smith, C., and Thorsrud, L. A. (2012). Does forecast combination improve Norges Bank inflation forecasts? *Oxford Bulletin of Economics and Statistics*, 74(2):163–179.

Blanchard, O. (2017). On the need for (at least) five classes of macro models. `https://piie.com/blogs/realtime-economic-issues-watch/need-least-five-classes-macro-models`.

Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the National Academy of Sciences*, 99(suppl 3):7280–7287.

Bottazzi, G. and Secchi, A. (2003). Common properties and sectoral specificities in the dynamics of US manufacturing companies. *Review of Industrial Organization*, 23(3-4):217–232.

Bottazzi, G. and Secchi, A. (2006). Explaining the distribution of firm growth rates. *The RAND Journal of Economics*, 37(2):235–256.

Braun-Munzinger, K., Liu, Z., and Turrell, A. E. (2016). An agent-based model of dynamics in corporate bond trading. Staff Working Paper 592, Bank of England.

Brayton, F. and Tinsley, P. A. (1996). A guide to FRB/US: a macroeconomic model of the United States. FEDS Paper 96-42, US Federal Reserve.

Bronk, R. (2011). Uncertainty, modelling monocultures and the financial crisis. *The business economist*, 42(2):5–18.

Bronk, R. and Jacoby, W. (2016). Uncertainty and the dangers of monocultures in regulation, analysis, and practice. MPIfG Discussion Paper 16/6, Max Planck Institute for the Study of Societies.

Bulanov, S. and Khoroshkov, V. (2002). Feasibility of using laser ion accelerators in proton therapy. *Plasma Physics Reports*, 28(5):453–456.

Burgess, S., Fernandez-Corugedo, E., Groth, C., Harrison, R., Monti, F., Theodoridis, K., and Waldron, M. (2013). The Bank of England's forecasting platform: COMPASS, MAPS, EASE and the suite of models. Staff Working Paper 471, Bank of England.

Burke, M., Hsiang, S. M., and Miguel, E. (2015). Global non-linear effect of temperature on economic production. *Nature*, 527(7577):235–239.

Burns, A. F. and Mitchell, W. C. (1946). *Measuring Business Cycles*. National Bureau of Economic Research, Inc.

Caiani, A., Godin, A., Caverzasi, E., Gallegati, M., Kinsella, S., and Stiglitz, J. E. (2016). Agent based-stock flow consistent macroeconomics: Towards a benchmark model. *Journal of Economic Dynamics and Control*, 69:375–408.

Campbell, J. Y. and Mankiw, N. G. (1989). Consumption, income, and interest rates: Reinterpreting the time series evidence. *NBER macroeconomics annual*, 4:185–216.

Card, D. and DellaVigna, S. (2013). Nine facts about top journals in economics. *Journal of Economic Literature*, 51(1):144–161.

Carney, M. (2017). Reflecting diversity, choosing inclusion. Bank of England Speech.

Carroll, C. D. (1997). Buffer-stock saving and the life cycle/permanent income hypothesis. *The Quarterly journal of economics*, 112(1):1–55.

Carroll, C. D. (2009). Precautionary saving and the marginal propensity to consume out of permanent income. *Journal of monetary Economics*, 56(6):780–790.

Carroll, C. D. and Kimball, M. S. (1996). On the concavity of the consumption function. *Econometrica*, 64(4):981–992.

Carter, N., Levin, S., Barlow, A., and Grimm, V. (2015). Modeling tiger population and territory dynamics using an agent-based approach. *Ecological Modelling*, 312:347–362.

Castaldi, C. and Dosi, G. (2009). The patterns of output growth of firms and countries: Scale invariances and scale specificities. *Empirical Economics*, 37(3):475–495.

Chakraborty, C. and Joseph, A. (2017). Machine learning at central banks. Staff Working Paper 674, Bank of England.

Chan, C. K. and Steiglitz, K. (2008). An agent-based model of a minimal economy. *Dept. of Computer Science, Princeton University Princeton*.

Cincotti, S., Raberto, M., and Teglio, A. (2010). Credit money and macroeconomic instability in the agent-based model and simulator Eurace. Economics Discussion Papers 2010-4, Kiel Institute for the World Economy (IfW).

Colander, D., Goldberg, M., Haas, A., Juselius, K., Kirman, A., Lux, T., and Sloth, B. (2009). The financial crisis and the systemic failure of the economics profession. *Critical Review*, 21(2-3):249–267.

Colussi, T. (2017). Social ties in academia: A friend is a treasure. *The Review of Economics and Statistics*, (0).

Cooper, D. and Dynan, K. (2014). Wealth effects and macroeconomic dynamics. *Journal of Economic Surveys*.

Cutler, D. M., Poterba, J. M., and Summers, L. H. (1989). What moves stock prices? *The Journal of Portfolio Management*, 15(3):4–12.

Davis, M., Efstathiou, G., Frenk, C. S., and White, S. D. (1985). The evolution of large-scale structure in a universe dominated by cold dark matter. *The Astrophysical Journal*, 292:371–394.

Dawid, H., Gemkow, S., Harting, P., van der Hoog, S., and Neugart, M. (2012). The eurace@ unibi model: An agent-based macroeconomic model for economic policy analysis. *Bielefeld Working Papers in Economics and Management*.

Dawid, H., Harting, P., and Neugart, M. (2014). Economic convergence: Policy implications from a heterogeneous agent model. *Journal of Economic Dynamics and Control*, 44:54–80.

De Grauwe, P. (2010). Top-down versus bottom-up macroeconomics. *CESifo Economic Studies*, 56(4):465–497.

Degli Atti, M. L. C., Merler, S., Rizzo, C., Ajelli, M., Massari, M., Manfredi, P., Furlanello, C., Tomba, G. S., and Iannelli, M. (2008). Mitigation measures for pandemic influenza in italy: an individual based model considering different scenarios. *PloS one*, 3(3):e1790.

Di Guilmi, C., Gallegati, M., and Ormerod, P. (2004). Scaling invariant distributions of firms' exit in OECD countries. *Physica A: Statistical Mechanics and its Applications*, 334(1):267–273.

Doms, M. and Dunne, T. (1998). Capital adjustment patterns in manufacturing plants. *Review of economic dynamics*, 1(2):409–429.

Dosi, G. et al. (2007). Statistical regularities in the evolution of industries. a guide through some evidence and challenges for the theory. *Perspectives on innovation*, pages 1110–1121.

Dosi, G., Fagiolo, G., Napoletano, M., Roventini, A., and Treibich, T. (2015). Fiscal and monetary policies in complex evolving economies. *Journal of Economic Dynamics and Control*, 52:166–189.

Dosi, G., Fagiolo, G., and Roventini, A. (2010). Schumpeter meeting keynes: A policy-friendly model of endogenous growth and business cycles. *Journal of Economic Dynamics and Control*, 34(9):1748–1767.

Elmendorf, D. W. et al. (1996). *The effect of interest-rate changes on household saving and consumption: a survey*. Citeseer.

Epstein, J. M. (1999). Agent-based computational models and generative social science. *Complexity*, 4(5):41–60.

Epstein, J. M. (2006). Remarks on the foundations of agent-based generative social science. *Handbook of computational economics*, 2:1585–1604.

Erlingsson, E. J., Teglio, A., Cincotti, S., Stefansson, H., Sturluson, J. T., and Raberto, M. (2014). Housing market bubbles and business cycles in an agent-based credit economy. *Economics: The Open-Access, Open-Assessment E-Journal*, 8(2014-8).

Ernest, N., Carroll, D., Schumacher, C., Clark, M., Cohen, K., et al. (2016). Genetic fuzzy based artificial intelligence for unmanned combat aerial vehicle control in simulated air combat missions. *J Def Manag*, 6(144):2167–0374.

Estrella, A. and Fuhrer, J. C. (2002). Dynamic inconsistencies: Counterfactual implications of a class of rational-expectations models. *The American Economic Review*, 92(4):1013–1028.

Ezrachi, A. and Stucke, M. (2016). Virtual competition the promise and perils of algorithmic-driven economy.

Fagiolo, G., Napoletano, M., and Roventini, A. (2008). Are output growth-rate distributions fat-tailed? Some evidence from OECD countries. *Journal of Applied Econometrics*, 23(5):639–669.

Fagiolo, G. and Roventini, A. (2012). Macroeconomic Policy in DSGE and Agent-Based Models. *Revue de l'OFCE*, 5(124):67–116.

Fagiolo, G. and Roventini, A. (2017). Macroeconomic Policy in DSGE and Agent-Based Models Redux: New Developments and Challenges Ahead. *Journal of Artificial Societies and Social Simulation*, 20(1):1.

Fair, R. C. (2012). Has macro progressed? *Journal of Macroeconomics*, 34(1):2–10.

Foos, D., Norden, L., and Weber, M. (2010). Loan growth and riskiness of banks. *Journal of Banking & Finance*, 34(12):2929–2940.

Fourcade, M., Ollion, E., and Algan, Y. (2015). The superiority of economists. *Revista de Economía Institucional*, 17(33):13–43.

Franke, R. and Westerhoff, F. (2012). Structural stochastic volatility in asset pricing dynamics: Estimation and model contest. *Journal of Economic Dynamics and Control*, 36(8):1193–1211.

Friedman, J., Hastie, T., and Tibshirani, R. (2001). *The elements of statistical learning*, volume 1. Springer series in statistics New York.

Friedman, M. (1957). *A theory of the consumption function*. Princeton University Press.

Fukac, M. and Pagan, A. (2006). Issues in adopting DSGE models for use in the policy process. *Australian National University, Centre for Applied Macroeconomic Analysis, CAMA Working Paper*, 10:2006.

Gabaix, X. (2011). The granular origins of aggregate fluctuations. *Econometrica*, 79(3):733–772.

Gabaix, X. (2016). Behavioral macroeconomics via sparse dynamic programming. Technical report, National Bureau of Economic Research.

Gaffeo, E., Di Guilmi, C., Gallegati, M., and Russo, A. (2012). On the mean/variance relationship of the firm size distribution: Evidence and some theory. *Ecological Complexity*, 11:109–117.

Gai, P., Haldane, A., and Kapadia, S. (2011). Complexity, concentration and contagion. *Journal of Monetary Economics*, 58(5):453–470.

Gai, P. and Kapadia, S. (2010). Contagion in financial networks. *Proceedings of the Royal Society of London A: Mathematical, Physical and Engineering Sciences*.

Gatti, D. D. and Desiderio, S. (2015). Monetary policy experiments in an agent-based model with financial frictions. *Journal of Economic Interaction and Coordination*, 10(2):265–286.

Geanakoplos, J., Axtell, R., Farmer, D. J., Howitt, P., Conlee, B., Goldstein, J., Hendrey, M., Palmer, N. M., and Yang, C.-Y. (2012). Getting at systemic risk via an agent-based model of the housing market. *The American Economic Review*, 102(3):53–58.

Gibson, B. (2007). A multi-agent systems approach to microeconomic foundations of macro. Technical report, Working Paper, University of Massachusetts, Department of Economics.

Gigerenzer, G. and Brighton, H. (2009). Homo heuristicus: Why biased minds make better inferences. *Topics in cognitive science*, 1(1):107–143.

Gode, D. K. and Sunder, S. (1993). Allocative efficiency of markets with zero-intelligence traders: Market as a partial substitute for individual rationality. *Journal of political economy*, 101(1):119–137.

Godley, W. and Lavoie, M. (2007). Monetary economics. *Hampshire, Palgrave Macmillan*.

Gualdi, S., Tarzia, M., Zamponi, F., and Bouchaud, J.-P. (2015). Tipping points in macroeconomic agent-based models. *Journal of Economic Dynamics and Control*, 50:29–61.

Guerini, M. and Moneta, A. (2017). A method for agent-based models validation. *Journal of Economic Dynamics and Control*.

Guerini, M., Napoletano, M., and Roventini, A. (2016). No man is an island: The impact of heterogeneity and local interactions on macroeconomic dynamics. Sciences Po publications 2016-18, Sciences Po.

Guvenen, F. (2011). Macroeconomics with heterogeneity: A practical guide. Technical report, National Bureau of Economic Research.

Haldane, A. G. (2016). The Dappled World. Bank of England Speech.

Haldane, A. G. and Madouros, V. (2012). The dog and the frisbee. *Revista de Economía Institucional*, 14(27):13–56.

Haldane, A. G. and May, R. M. (2011). Systemic risk in banking ecosystems. *Nature*, 469(7330):351.

Hamermesh, D. S. (2013). Six decades of top economics publishing: Who and how? *Journal of Economic Literature*, 51(1):162–172.

Hausman, D. M. (1992). *The inexact and separate science of economics*. Cambridge University Press.

Heathcote, J. (2005). Fiscal policy with heterogeneous agents and incomplete markets. *The Review of Economic Studies*, 72(1):161–188.

Heppenstall, A. J., Crooks, A. T., See, L. M., and Batty, M. (2011). *Agent-based models of geographical systems*. Springer Science & Business Media.

Hills, S., Thomas, R., and Dimsdale, N. (2016). Three centuries of data version 2.3. http://www.bankofengland.co.uk/research/Pages/onebank/threecenturies.aspx.

Hommes, C. H. (2006). Heterogeneous agent models in economics and finance. *Handbook of computational economics*, 2:1109–1186.

Hong, H. and Stein, J. C. (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *The Journal of finance*, 54(6):2143–2184.

Jacobs, J. A. (2014). *In defense of disciplines: Interdisciplinarity and specialization in the research university*. University of Chicago Press.

Jaimovich, N. and Floetotto, M. (2008). Firm dynamics, markup variations, and the business cycle. *Journal of Monetary Economics*, 55(7):1238–1252.

Jawadi, F. and Sousa, R. M. (2014). The relationship between consumption and wealth: a quantile regression approach. *Revue d'économie politique*, 124(4):639–652.

Kaplan, G., Moll, B., and Violante, G. L. (2016). Monetary policy according to HANK. Technical report, National Bureau of Economic Research.

Keogh-Brown, M. R., Wren-Lewis, S., Edmunds, W. J., Beutels, P., and Smith, R. D. (2010). The possible macroeconomic impact on the UK of an influenza pandemic. *Health economics*, 19(11):1345–1360.

Keynes, J. M. (1924). Alfred marshall, 1842-1924. *The Economic Journal*, 34(135):311–372.

Keynes, J. M. (1936). *General theory of employment, interest and money*. Palgrave Macmillan.

Kindleberger, C. P. (2001). Manias, panics, and crashes: a history of financial crises. *John Wiley & Sons*, 32(2):379.

Kirman, A. P. (1992). Whom or what does the representative individual represent? *Journal of Economic Perspectives*, 6(2):117–136.

Knight, F. H. (2012). *Risk, uncertainty and profit*. Courier Corporation.

Krugman, P. (2011). The profession and the crisis. *Eastern Economic Journal*, 37(3):307–312.

Kumhof, M., Rancière, R., and Winant, P. (2015). Inequality, leverage, and crises. *The American Economic Review*, 105(3):1217–1245.

Kuznets, S. and Murphy, J. T. (1966). *Modern economic growth: Rate, structure, and spread*, volume 2. Yale University Press New Haven.

Kydland, F. E. and Prescott, E. C. (1982). Time to build and aggregate fluctuations. *Econometrica: Journal of the Econometric Society*, pages 1345–1370.

Laeven, L. and Valencia, F. (2013). Systemic banking crises database. *IMF Economic Review*, 61(2):225–270.

Lamperti, F., Dosi, G., Napoletano, M., Roventini, A., and Sapio, A. (2017a). Faraway, so close: coupled climate and economic dynamics in an agent-based integrated assessment model. Sciences Po OFCE Working Paper 10, Sciences Po.

Lamperti, F., Roventini, A., and Sani, A. (2017b). Agent-Based Model Calibration using Machine Learning Surrogates. Papers 1703.10639, arXiv.org.

Leary, M. T. (2009). Bank loan supply, lender choice, and corporate capital structure. *The Journal of Finance*, 64(3):1143–1185.

Leibo, J. Z., Zambaldi, V., Lanctot, M., Marecki, J., and Graepel, T. (2017). Multi-agent reinforcement learning in sequential social dilemmas. Working paper, DeepMind.

Leijonhufvud, A. (2000). *Macroeconomic Instability and Coordination: Selected Essays*. Edward Elgar, Cheltenham.

Lengnick, M. (2013). Agent-based macroeconomics: A baseline model. *Journal of Economic Behavior & Organization*, 86:102–120.

Leombruni, R. and Richiardi, M. (2005). Why are economists sceptical about agent-based simulations? *Physica A: Statistical Mechanics and its Applications*, 355(1):103–109.

Lindé, J., Smets, F., and Wouters, R. (2016). Challenges for central banks' macro models. *Handbook of Macroeconomics*, 2:2185–2262.

Lindl, J. D., Amendt, P., Berger, R. L., Glendinning, S. G., Glenzer, S. H., Haan, S. W., Kauffman, R. L., Landen, O. L., and Suter, L. J. (2004). The physics basis for ignition using indirect-drive targets on the National Ignition Facility. *Physics of Plasmas*, 11(2):339–491.

Lown, C. and Morgan, D. P. (2006). The credit cycle and the business cycle: new findings using the loan officer opinion survey. *Journal of Money, Credit and Banking*, pages 1575–1597.

Lucas, R. E. (1972). Expectations and the neutrality of money. *Journal of economic theory*, 4(2):103–124.

Lucas, R. E. (1976). Econometric policy evaluation: A critique. In *Carnegie-Rochester conference series on public policy*, volume 1, pages 19–46. Elsevier.

Lucas, R. E. (1987). *Models of business cycles*, volume 26. Basil Blackwell Oxford.

Lucas, R. E. and Sargent, T. J. (1979). After Keynesian macroeconomics. *Quarterly Review*, 3(Spr).

Lux, T. and Marchesi, M. (1999). Scaling and criticality in a stochastic multi-agent model of a financial market. *Nature*, 397(6719):498–500.

Mendoza, E. G. and Terrones, M. E. (2012). An anatomy of credit booms and their demise. Technical report, National Bureau of Economic Research.

Metroplis, N. (1987). The beginning of the Monte Carlo method. *Los Alamos Science*, 15(548):125–130.

Metropolis, N., Rosenbluth, A. W., Rosenbluth, M. N., Teller, A. H., and Teller, E. (1953). Equation of state calculations by fast computing machines. *The journal of chemical physics*, 21(6):1087–1092.

Metropolis, N. and Ulam, S. (1949). The Monte Carlo method. *Journal of the American statistical association*, 44(247):335–341.

Mikolov, T., Chen, K., Corrado, G., and Dean, J. (2013). Efficient estimation of word representations in vector space. *arXiv preprint arXiv:1301.3781*.

Minsky, H. P. (2008). *Stabilizing an unstable economy*, volume 1. McGraw Hill New York.

Muellbauer, J. and Murata, K. (2009). Consumption, land prices and the monetary transmission mechanism in japan. *Columbia University Academic Commons*.

Muth, J. F. (1961). Rational expectations and the theory of price movements. *Econometrica: Journal of the Econometric Society*, pages 315–335.

Napoletano, M., Roventini, A., and Sapio, S. (2006). Are business cycles all alike? A bandpass filter analysis of the Italian and US cycles. *Rivista Italiana degli Economisti*, 11(1):87–118.

Nyman, R., Gregory, D., Kapadia, S., Ormerod, P., Tuckett, D., and Smith, R. (2015). News and narratives in financial systems: exploiting big data for systemic risk assessment. Staff Working Paper Mimeo, Bank of England.

Page, S. E. (2008). *The difference: How the power of diversity creates better groups, firms, schools, and societies*. Princeton University Press.

Popoyan, L., Napoletano, M., and Roventini, A. (2016). Taming macroeconomic instability: monetary and macro prudential policy interactions in an agent-based model. *Journal of Economic Behavior & Organization*.

Ravn, M. and Sterk, V. (2016). Macroeconomic Fluctuations with HANK & SAM: An Analytical Approach. Discussion Papers 1633, Centre for Macroeconomics (CFM).

Reinhart, C. M. and Rogoff, K. S. (2009). The aftermath of financial crises. Technical report, National Bureau of Economic Research.

Romer, P. (2016). The trouble with macroeconomics. *September, forthcoming in The American Economist*.

Salle, I., Yıldızoğlu, M., and Sénégas, M.-A. (2013). Inflation targeting in a learning economy: An ABM perspective. *Economic Modelling*, 34:114–128.

Sands, P., Mundaca-Shah, C., and Dzau, V. J. (2016). The neglected dimension of global security – a framework for countering infectious-disease crises. *New England Journal of Medicine*, 374(13):1281–1287.

Shaikh, A. (2016). *Capitalism: Competition, conflict, crises*. Oxford University Press.

Sherlock, M., Hill, E., Evans, R., Rose, S., and Rozmus, W. (2014). In-depth plasma-wave heating of dense plasma irradiated by short laser pulses. *Physical review letters*, 113(25):255001.

Shiller, R. J. (2017). Narrative economics. Working Paper 23075, National Bureau of Economic Research.

Silver, N. (2012). *The signal and the noise: the art and science of prediction*. Penguin UK.

Simon, H. A. (1959). Theories of decision-making in economics and behavioral science. *The American economic review*, 49(3):253–283.

Sinitskaya, E. and Tesfatsion, L. (2015). Macroeconomies as constructively rational games. *Journal of Economic Dynamics and Control*, 61:152–182.

Smets, F. and Wouters, R. (2003). An estimated dynamic stochastic general equilibrium model of the euro area. *Journal of the European economic association*, 1(5):1123–1175.

Smith, N. (2014). Wall street skips economics class. Bloomberg View; https://www.bloomberg.com/view/articles/2014-07-23/wall-street-skips-economics-class.

Solow, R. (2008). The state of macroeconomics. *The Journal of Economic Perspectives*, 22(1):243–246.

Sornette, D. (2014). Physics and financial economics (1776–2014): puzzles, Ising and agent-based models. *Reports on progress in physics*, 77(6):062001.

Souleles, N. S. (1999). The response of household consumption to income tax refunds. *The American Economic Review*, 89(4):947–958.

Spears, B. K., Munro, D. H., Sepke, S., Caggiano, J., Clark, D., Hatarik, R., Kritcher, A., Sayre, D., Yeamans, C., Knauer, J., et al. (2015). Three-dimensional simulations of National Ignition Facility implosions: Insight into experimental observables a). *Physics of Plasmas*, 22(5):056317.

Stern, N. (2016a). Current climate models are grossly misleading: Nicholas stern calls on scientists, engineers and economists to help policymakers by better modelling the immense risks to future generations, and the potential for action. *Nature*, 530(7591):407–410.

Stern, N. (2016b). Economics: Current climate models are grossly misleading. *Nature*, 530(7591):407–409.

Stern, N. H. (2007). *The economics of climate change: the Stern review*. cambridge University press.

Stock, J. and Watson, M. (1999). Business cycle fluctuations in us macroeconomic time series. In Taylor, J. B. and Woodford, M., editors, *Handbook of Macroeconomics*, volume 1, Part A, chapter 01, pages 3–64. Elsevier, 1 edition.

Stock, J. H. and Watson, M. (2011). Dynamic factor models. *Oxford Handbook on Economic Forecasting*.

Stock, J. H. and Watson, M. W. (2006). Forecasting with many predictors. *Handbook of economic forecasting*, 1:515–554.

Summers, L. H. (2002). Some skeptical observations on real business cycle theory. *A Macroeconomics Reader*, page 389.

Tasoff, J., Mee, M. T., and Wang, H. H. (2015). An economic framework of microbial trade. *PloS one*, 10(7):e0132907.

Tesfatsion, L. (2002). Agent-based computational economics: Growing economies from the bottom up. *Artificial life*, 8(1):55–82.

Timmermann, A. (2006). Forecast combinations. *Handbook of economic forecasting*, 1:135–196.

Turrell, A. (2016). Agent-based models: Understanding the economy from the bottom up. *Bank Of England Quarterly Bulletin Series*, 2016Q4.

Turrell, A., Sherlock, M., and Rose, S. (2015a). Self-consistent inclusion of classical large-angle Coulomb collisions in plasma Monte Carlo simulations. *Journal of Computational Physics*.

Turrell, A., Sherlock, M., and Rose, S. (2015b). Ultrafast collisional ion heating by electrostatic shocks. *Nature communications*, 6.

Tversky, A. and Kahneman, D. (1975). Judgment under uncertainty: Heuristics and biases. In *Utility, probability, and human decision making*, pages 141–162. Springer.

Van Noorden, R. (2015). Interdisciplinary research by the numbers: an analysis reveals the extent and impact of research that bridges disciplines. *Nature*, 525(7569):306–308.

Wälde, K. and Woitek, U. (2004). R&D expenditure in G7 countries and the implications for endogenous fluctuations and growth. *Economics Letters*, 82(1):91–97.

Watts, D. J. (2002). A simple model of global cascades on random networks. *Proceedings of the National Academy of Sciences*, 99(9):5766–5771.

Welfe, W. (2013). *Macroeconometric models*, volume 47. Springer Science & Business Media.

Wren-Lewis, S. (2016a). More on stock-flow consistent models. https://mainlymacro.blogspot.co.uk/2016/09/more-on-stock-flow-consistent-models.html.

Wren-Lewis, S. (2016b). Unravelling the new classical counter revolution. *Review of Keynesian Economics*, 4(1):20–35.

Wright, I. (2005). The duration of recessions follows an exponential not a power law. *Physica A: Statistical Mechanics and its Applications*, 345(3):608–610.

Wuchty, S., Jones, B. F., and Uzzi, B. (2007). The increasing dominance of teams in production of knowledge. *Science*, 316(5827):1036–1039.

Yegros-Yegros, A., Rafols, I., and D'Este, P. (2015). Does interdisciplinary research lead to higher citation impact? The different effect of proximal and distal interdisciplinarity. *PloS one*, 10(8):e0135095.

Yellen, J. L. et al. (2016). Macroeconomic Research After the Crisis: a speech at "The Elusive 'Great' Recovery: Causes and Implications for Future Business Cycle Dynamics" 60th annual economic conference sponsored by the Federal Reserve Bank of Boston, Boston, Massachusetts, October 14, 2016. Technical report, United States Federal Reserve.

Zarnowitz, V. (1985). Recent work on business cycles in historical perspective: A review of theories and evidence. *Journal of Economic Literature*, 23(2):523–580.