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S.I.: DISAGREEMENT IN SCIENCE

Disagreement in discipline-building processes

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Abstract
Successful instances of interdisciplinary collaboration can eventually enter a process of disciplinarisation. This article analyses one of those instances: agent-based computational social science, an emerging disciplinary field articulated around the use of computational models to study social phenomena. The discussion centres on how, in knowledge transfer dynamics from traditional disciplinary areas, practitioners parsed several epistemic resources to produce new foundational disciplinary shared commitments, and how disagreements operated as a mechanism of differentiation in their production. Two parsing processes are examined to illustrate this claim. The first one is the parsing of the qualitative–quantitative dualism, arguably the most important methodological disagreement in social science. The second one is the parsing of prediction, a key value in contemporary science. The analysis evidences that disagreements have fostered both external and internal dynamics of differentiation in agent-based computational social science. The former have permitted a more efficient use of epistemic resources, whereas the latter have forced practitioners to modify the foundational narrative and the agenda of the field.

Keywords Disagreements · Shared commitments · Discipline-building · Agent-based modelling · Disciplinary identity · Interdisciplinarity

1 Introduction

Agent-based social simulation is a type of computer simulation in which artificial agents, modelled as self-contained portions of code with built-in decision heuristics, are set to interact with each other and with the artificial environment in order to reproduce different social dynamics. Paradigmatic examples include Schelling's (1971) model of segregation and Axelrod's (1984) model of cooperation. In the first model, spatial segregation at the population level occurs as a result of individuals

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autonomously deciding to relocate, depending on a desired level of similarity with their neighbours (measured as a single binary trait). In the second model, cooperation at the population level is the result of individuals adapting their decision-making strategies to maximise their reward in iterated games.

In recent years, the practice of agent-based simulation in social science has experienced a cumulative process of disciplinarisation that has fostered a sense of community in researchers and has led them to think of their work in disciplinary terms. This article analyses the effect of disagreements in this process of discipline-building. The discussion advanced suggests that, at the disciplinary level, disagreements operate as a mechanism of differentiation. They have the potential to reinforce or fragment disciplinary identities, depending on whether differentiation is produced between or within scientific communities. Processes of parsing shared commitments around the qualitative–quantitative divide, arguably, the most important methodological disagreement in social science, and prediction, a key value in contemporary science, are used to illustrate this dual effect of disagreements in disciplinarisation processes. The analysis evidences that disagreements have fostered both external and internal dynamics of differentiation in agent-based computational social science. The former have permitted a more efficient use of epistemic resources, whereas the latter have forced practitioners to modify the foundational narrative and the agenda of the field.

The discussion is divided into four parts: the next section briefly discusses the connection between discipline-building and disagreements. It shows how the latter become a mechanism of differentiation in the formation of a new disciplinary identity. The third section describes the current process of disciplinarisation in agent-based computational social science. The institutional and intellectual features upon which the notion of novel disciplinary work is grounded are presented. The fourth and fifth sections centre on the parsing of shared commitments around the qualitative–quantitative dualism and prediction, respectively. Some general conclusions are presented last.

2 Discipline-building and the empirical understanding of disagreement

A disagreement occurs when individuals or groups realise that they do not share the same beliefs on a given topic. Disagreements are philosophically interesting, for rational agents would be expected to engage in different epistemic processes to achieve partial or total agreement. Yet, these processes are far from trivial (Christensen 2007). The literature on disagreements has focused on characterising the different intervening elements: the individuals or groups that disagree (e.g., whether they have the same competence or expertise), the reasons for disagreement (e.g., whether there is an asymmetric access to relevant evidence), the depth of the disagreement (whether it is actual or merely possible), the procedures to tackle the disagreement (e.g., whether both positions in the disagreement are given equal weight) and the final outcome of the resolution process (e.g., conciliation). The next step is to employ this conceptual apparatus in the analysis of real instances of disagreement.

Discipline-building is a type of disagreement that displays high levels of complexity. Rather than a couple of individuals disagreeing on a single belief, discipline-building involves several individuals (interacting through intricate social groups and structures) and complex networks of beliefs (referring to data, theories, methods, interests, goals, values, among others). In turn, there are multiple mechanisms to deal with disagreement. Disagreements about data, for example, are addressed differently than those about values. Finally, disagreements might persist over time (e.g., the micro–macro tension in social science (Alexander and Giesen 1987)) or be given a non-optimal solution that is only satisfactory within a limited social, cognitive, geographic or historical context (e.g., many disagreements about a paradigm lose their relevance once the paradigm is replaced).

Approaching processes of discipline-building through the lenses of disagreements might provide important insights about the articulation of scientific communities and disciplinary identities. Historically, the study of disciplinary genesis has paid more attention to the institutional setting in which a discipline is formed. Contemporary understanding of disciplinary work, for example, derives from the cognitive division of labour put forward by modern universities and specialised academies/societies (e.g., Royal Society of London or *Académie Française*) (Turner 2017; Weingart 2010). It is also strongly permeated by the notion of professional identity, since current disciplinary boundaries were mainly put forward within the formal education system (Stichweh 1992; Abbott 1988).

To emerge, however, a discipline requires not only the institutional setting, but also the consolidation of a disciplinary scientific community, which is, ultimately, responsible for carrying out the disciplinary work (D'Agostino 2012; Geertz 1982; Kitcher 1993; Kuhn 1970). Like any other self-identified social group, scientific communities build an identity based on shared commitments i.e., normative consensuses that operate as criteria for inclusion and exclusion, and cover the different aspects involved in the practice of science. In a scientific community, these commitments are the result of parsing processes in which members of the community achieve coordination and consensus through the explicitation, standardisation and normalisation of the epistemic resources that underlie the social and cognitive organisation of the community. Every scientific community develops its own identity based on a distinctive approach to aspects such as the identification of principles to judge disciplinary work (Bourdieu 1975), the definition of a foundational narrative (Baehr 2002), the adoption of a common language (Becher and Trowler 2001) and the formulation of an agenda (Krishnan 2009).

The discussion advanced in this text suggests that, at the disciplinary level, disagreements might operate as a mechanism of differentiation. They have the potential to reinforce or fragment disciplinary identities, depending on whether this differentiation is produced between or within scientific communities. Ideally, a scientific community should strive towards increasing differentiation with other communities, while reducing its own internal differentiation. Yet, given the scope and the emergent and self-organising nature of discipline-building processes, it is possible that both types of differentiations coexist and that the proportion between internal and external differentiation changes continuously over time.

In what follows, the ongoing process of disciplinarisation in agent-based computational social science is used to illustrate the differentiating power of disagreements. The discussion centres on the methodological discourse that practitioners of agent-based social simulation have developed to support their novel disciplinary identity. As such, the analysis focuses on the narrative rather than the practical component of shared commitments. As with any other disciplinary area, the normative consensuses do not entirely conform to everyday practices. This gap, as it will be shown later, can potentially become a source of disagreement.

3 The disciplinarisation process in agent-based computational social science

Agent-based computational social science, as an emergent disciplinary field,[1] is the result of interdisciplinary collaboration that brings together major insights from complexity science, computer science and social science (Anzola 2018). Social science delimits the object of study, computer science provides the method and complexity science contributes most of the philosophical underpinnings. While the phenomena studied are in the social domain, the field originated and evolved beyond the frontiers of mainstream social science (Squazzoni and Casnici 2013), in part, because practices are articulated within the complexity framework, which is often both critical and incompatible with much of traditional social research.

The field is distinctive because it has been articulated around a method, agent-based modelling, instead of a set of theories or problems. This feature, initially, makes the field *technology-dependent*, for research practices revolve exclusively around the use of computer simulation. The scope and dimension of its research agenda are significantly influenced by technical features, such as the power of computation. Likewise, researchers converging in the practice of agent-based social simulation have diverse background and expertise in social, biological, physical and artificial sciences, and engineering. Epistemic dependence in the field is high and research activities regularly involve *interdisciplinary* collaboration. Finally, the model-centred nature of computer simulation brings to the forefront empirical concerns during everyday research practices. As a result, the field has been articulated with a characteristic *practical orientation*.

While some foundational models can be traced back decades, the amount of practitioners and research output needed for the emergence of a disciplinary identity was achieved only after a significant increase in the number of personal computers during

[1] Disciplinarisation requires the fulfilment of some institutional (e.g., programmes and procedures of certification, events, academic positions) and intellectual (e.g., foundational narratives, a defined domain and agenda, a set of exemplars) conditions (Becher and Trowler 2001; D'Agostino 2012). While there are a few terms that explicitly denote disciplinary areas (e.g., complexity *theory*, cultural *studies* or decision *sciences*) or are used interchangeably with 'discipline' (e.g., 'field' or 'specialty'), it could be argued that the term 'discipline', as such, is still mostly reserved for traditional disciplinary areas, for they have a wider scope and are more deeply institutionalised, especially in terms of their pedagogical (e.g., undergraduate and postgraduate programmes) and professional (e.g., well-defined labour market) components. The terms 'field' and 'specialty', however, are relatively flexible. They are not only used to refer to disciplines, but also to subdisciplines, relatively novel disciplinary areas or institutionalised scientific collaboration beyond disciplinary borders. This article refers to agent-based computational social science as a field, first, because it captures both the perceived sense of novelty and the interdisciplinary nature of everyday practices of social simulation and, second, because it is the term practitioners seems to favour when referring to agent-based computational social science as a disciplinary area.

the nineties. When practitioners refer to agent-based computational social science as a field, they usually acknowledge three main tenets of disciplinarisation: self-recognition among practitioners, the belief that practices are novel or distinct, and an ongoing institutionalisation process.

The institutionalisation process in agent-based computational social science has been driven by the development of professional associations (e.g., ESSA, CSSSA, PAAA), an exclusive open access disciplinary journal (*Journal of Artificial Societies and Social Simulation*), well-known specialised software (e.g., Netlogo, Repast, Mason) and common resources (e.g., repositories, forums, job and mailing lists, pedagogical materials), exclusive institutional spaces (e.g., laboratories, research centres and faculty positions) and discipline-specific postgraduate programmes.[2] Even though the field lacks common institutional traits of traditional disciplines (e.g., a code of ethics or exclusive labels in disciplinary classificatory systems), the institutionalisation achieved so far has evidently helped to foster in practitioners a new disciplinary identity.

The intellectual elements of the disciplinarisation process in agent-based computational social science are often framed within the context of novelty, for practitioners have usually approached the discipline-building process from a Kuhnian perspective. This ‘novelty’ discourse is constitutive of the foundational literature in the field (e.g., Epstein and Axtell 1996; Gilbert and Doran 1993; Gilbert and Conte 1995; Gilbert and Troitzsch 2005; Troitzsch et al. 1996), and has remained relatively unmodified. The perceived differences in the field’s disciplinary practices are characteristically linked to the methodological features of agent-based modelling and its application to the study of social phenomena. This perceived novelty required, initially, a change in the methodological status of computer simulation in contemporary science and, later, a methodological differentiation of agent-based modelling from other types of computer simulation.

For decades, computer simulation was considered just a tool, a mere technical aid for computation that allowed processing large amounts of data or solving problems with no analytical solution by ‘brute force’. As such, any relevant methodological problem was thought to be derived from, and be solved by, the disciplinary conceptualisation of the phenomenon, instead of its computational implementation. Yet, cumulative technical and philosophical progress have slowly fostered a view of computer simulation as a fully-fledged method. The method is considered distinctive for two reasons: first, because its information processing and production capabilities can be used to inquire about problems that were previously not amenable for research (Keller 2003; Humphreys 2004); second, because it provides an approach to modelling and experimentation that does not entirely depend on formal theoretical formulations or empirical data (Winsberg 2010), and is, at the same time, constrained by particular aspects, such as the materiality of physical computers (Parker 2009).

Regarding the specificity of agent-based social simulation, practitioners emphasise that, unlike equation-based simulation, agent-based modelling, as the name suggests, provides means to explicitly model objects that can be in one-to-one correspondence

[2] Being centred on a method is an obstacle for the articulation of a full structure of certification, since undergraduate programmes are, in general, still organised under traditional disciplinary lines.

with entities in the real world. Agents (e.g., individuals, organisations, countries), artefacts (e.g., tools, buildings, vehicles) and objects in the environment (e.g., trees, mountains, rivers) can be separately modelled with independent features and rules of behaviour. In addition, computer languages are more expressive than mathematical languages i.e., can succinctly and concisely represent a larger set of ideas. Thus, a more diverse set of alternatives for representation can be used in agent-based models. In social science, these methodological features have translated into an inquiry about the structural and functional properties of agency and interaction (Macy and Willer 2002; Anzola 2015). Agent-based models are used by researchers as a tool for the exploration of the micro–macro link through a focus on stable macropatterns that emerge from the interaction of autonomous, heterogeneous and adaptive agents.

Overall, the new disciplinary identity of the field strongly relies on a view of agent-based modelling as an alternative approach to modelling and formalisation in social science. The method is considered distinctive, first, because programming languages offer an interesting trade-off between flexibility and formality, setting the method apart from equation-based simulation and traditional qualitative and quantitative methods. Second, agent-based modelling is believed to bypass traditional problems in social research, such as technical limitations for longitudinal research or ethical obstacles, thanks to its distinctive information processing and production capabilities. Third, and more important, the focus on process and interaction is thought to provide an alternative for the exploration of the micro–macro link, through the reconceptualisation of social phenomena as complex adaptive dynamics. This reconceptualisation heavily relies on a disciplinary narrative that is theoretically (e.g., relying on concepts such as emergence and self-organisation (Anzola et al. 2017)) and methodologically (e.g., framed within the computational paradigm (Cioffi-Revilla 2014)) uncommon in traditional social science.

Achieving this characteristic approach to social phenomena required practitioners to articulate novel shared commitments that, on one hand, provided external differentiation with mainstream social disciplines and, on the other hand, facilitated interdisciplinary collaboration. The next two sections discuss the role of disagreements in parsing processes that permitted the articulation of a new disciplinary identity in agent-based computational social science, and how this role is moderated by the interdisciplinary, technology-dependent and practice-oriented nature of the field.

4 The qualitative–quantitative divide

The qualitative–quantitative divide is, perhaps, the most important methodological disagreement in social science. In its most basic formulation, it is a disagreement about whether social phenomena should be approached from a constructivist or a positivist perspective, associated to qualitative and quantitative methods, respectively. The disagreement is believed by some practitioners to be so profound that it is often formulated in terms of competing explanatory ‘paradigms’.

Agent-based computational social science’s approach to the qualitative–quantitative divide is the result of parsing processes that have impacted both types of differentiation. External differentiation is initially increased because of a reinterpretation of both traditions, and their longstanding tension in social science, to accommodate the technical features of computer simulation, as well as scientific values from other areas, such as complexity theory. The field's idiosyncratic approach to the dualism is grounded on shared commitments that address questions, on the practical domain, about issues such as the type of data the method could handle and, on the theoretical domain, about issues such as whether the field should conform to the traditional conceptualisation of the divide, starting by the very question of whether qualitative and quantitative analysis are incompatible.

At the same time, internal differentiation is reduced by putting forward a view of agent-based modelling as a middle ground between the qualitative and the quantitative. This middle ground view of the method has been both explicitly articulated (e.g., Chattoe-Brown 2013; Gilbert 2004) and addressed in less depth when discussing, from a mainstream disciplinary perspective, how agent-based modelling becomes an interesting methodological alternative because it complements or overcomes the difficulties faced by traditional methods (e.g., Macy and Willer 2002; Smith and Conrey 2007; Tesfatsion 2006). Since, in general science, computer simulation has traditionally relied on quantitative data, it is common to find literature that pays more attention to the method's ability to incorporate elements of the qualitative tradition, for example: how qualitative data can be used for implementation, calibration and validation (e.g., Agar 2003; Barreteau et al. 2013; Yang and Gilbert 2008), how the simulation (re)produces qualitative macropatterns e.g., stylised facts (e.g., Epstein 2006), and how the comparison between the simulation and the phenomenon of interest could be carried out using qualitative criteria (e.g., Railsback and Grimm 2012).

As discussed below, the middle ground view of agent-based modelling has been instrumental in the articulation of the field's disciplinary identity, for it has led to an approach to the qualitative–quantitative divide that, first, strips the disagreement of some of its most conflicting disciplinary elements and, second, incorporates values and shared commitments from other domains beyond social science. It also has the potential to foster future disagreements and fragment the disciplinary identity, depending on how practice-oriented and technology-dependent future parsing processes associated to the dualism are carried out.

4.1 Converging disciplinary traditions

It could be argued that, in addressing the disagreement that separates the qualitative and quantitative traditions, the literature in agent-based computational social science has overblown or misrepresented the methodological implications of agent-based modelling, while taking advantage of the popularity of the disagreement in mainstream social science. The qualitative–quantitative divide became a major theoretical–methodological concern in social science after the popularisation of constructivist and critical accounts of scientific inquiry during the early eighties. These accounts were meant to challenge the assumptions of traditional quantitative research, leading, as it is often suggested, to a 'paradigm war' (Denzin 2010).

Given the popularity of the topic, much of the literature on social research methods since the eighties has aimed at synthesising the qualitative–quantitative divide. A well-known outcome is the mixed methods research movement, advanced as a 'third methodological movement' (Teddlie and Tashakkori 2011, p. 285) between the qualitative and the quantitative. While the movement was meant to thoroughly tackle the sources of conflict between both traditions, philosophical issues were usually downplayed in empirical research. An integrated account was never developed. 'Mixed methods research' often implies using different methods for different parts or stages of the research. The philosophical differences underpinning the disagreement were just left unsolved (Bergman 2008).

Something similar happens to agent-based modelling. The assumption of 'middle ground' does not have a univocal widespread interpretation, for, as mentioned above, the compatibility with the qualitative tradition has been discussed in several different contexts. Usually, however, the synthesising features of the method have been linked to the fact that programming languages feature significant semantic and syntactic flexibility in comparison to other formal languages, yet still operate following formal rules of algorithmic inference.[3] The latter would account for the quantitative; the former, for the qualitative.

While the method is indeed distinctive because of its linguistic expressiveness, matching increased semantic and syntactic flexibility with algorithmic procedures does not necessarily lead to the articulation of a mixed account of research. It would be expected of a disciplinary area that involves 'social science' to explicitly address in its shared commitments the disagreement surrounding the qualitative–quantitative divide, given its methodological significance. At first sight, it might seem that the field is incorporating into its disciplinary identity an oversimplified version of the divide, linking the qualitative with natural language and the quantitative with numbers. This would be, after all, an easy way to reduce internal differentiation.

Yet, something else might be at play with this approach to the dualism. Agent-based computational social science conflates the traditional approach to the qualitative–quantitative divide in social science, depicted as one of opposing philosophical foundations, with an approach to computational modelling as a middle ground between natural and highly formalised languages, a dichotomy that has a longstanding history in computer science (Colburn 2000). More than cashing in on the popularity of the qualitative–quantitative divide in social science, the conflation seems to provide common grounds for practitioners in the field through the normalisation of radically different methodological traditions.

Although the conflation facilitates interdisciplinary work, it also leads to the articulation of shared commitments that are built upon a incomplete parsing of the epistemic resources of the converging traditions. The conflation neglects the role played by each dualism in its respective area. In mainstream social science, for example, the quantitative–qualitative divide is grounded on key philosophical disagreements, such as scientific realism. In computer science and software engineering, conversely, the issue about language flexibility does not lead to questioning scientific realism in any way. Agent-based computational social science seems to follow the latter tradition

[3] Programming languages not only permit to more easily incorporate nominal and ordinal data in the design, operation and validation of the model, but also provide some advantages for the model's implementation. In practice, a production system allows to more easily incorporate complex decision making than typical probability-based heuristics.

on this issue. Radical constructivism and relativism are extremely uncommon. Scientific realism is still a key philosophical principle guiding strongly qualitative-oriented approaches to data collection, calibration and validation in agent-based computational social science (Barreteau et al. 2013).

In the same way, subjectivism, a typical feature of qualitative research, does not really impact the practice of social simulation. While researchers in the field need not directly account for the subjectivity of participants, for computational agents do not have subjective construction of meaning (rendering some traditional qualitative approaches, such as the interpretive, less relevant), they could explore subjectivity, for example, when addressing the external data with which computational models are contrasted or during the process of design, implementation, operation and communication of a computational model. In both instances, however, the link has been poorly explicitated. Practitioners usually account for these issues by relying on a general approach to contextualism in modelling and representation, rather than qualitative approaches. The incorporation of insights from the qualitative tradition are precluded by the relatively widespread consensus, put together during the emergence of the field, around the belief that agent-based models, first, are not accurate representations, second, imply some sort of simplification and, third, are to be validated against external theory or data (Axelrod 1997; Epstein and Axtell 1996; Gilbert and Troitzsch 2005). The question about the role of the observer as a source of error is usually subordinate to a question about correspondence, since modelling is an indirect approach to knowledge (Anzola 2018).

The way in which the field accounts for the qualitative–quantitative divide is grounded on the need to facilitate interdisciplinary communication and collaboration. Conflating shared commitments from different disciplinary traditions during parsing processes helps the field save epistemic resources in everyday practices, considering that practitioners are not formally trained as agent-based computational social scientists (so they might have completely different cognitive and institutional backgrounds), and that there is opaque epistemic dependence among them i.e., there are large asymmetries in their epistemic resources (Wagenknecht 2014). The notion of 'middle ground' through which the qualitative–quantitative disagreement is resolved in the field is sufficiently general to accommodate many other independent shared commitments that revolve around issues such as scientific languages, reasoning and formalisation.[4] It prevents disruption of everyday practices and, at the same time, promotes disciplinary self-recognition among practitioners through the reduction of internal differentiation.

4.2 Direct transfer or neglect in parsing processes

Emergent disciplinary communities tend to promote cohesion and self-recognition by overemphasising what is novel about their practices. Yet, there is often significant

[4] The view of agent-based modelling as a middle ground is also used to conflate additional dichotomies e.g., deductive–inductive, empirical research-formal theory, theory-data (Axelrod 1997; Conte et al. 2001; Epstein 2006; Squazzoni 2012). It is likely these other conflations also save resources by reducing the risk of epistemic tension and disagreement.

continuity, or lack of real rupture, with traditional disciplines, especially in terms of methods and scientific data. The current format of the qualitative–quantitative divide in agent-based computational social science has created points of convergence for practitioners with different backgrounds, but it has also transferred some traditional disciplinary tensions and divisions to agent-based computational social science. There is, for example, a noticeable topic-based separation in the field, which can be traced back to mainstream social disciplines. Currently, qualitative approaches to data collection, calibration and validation of agent-based models are more common in peripheral or relatively new areas of study, such as environmental and land research, but are significantly less popular in traditional topics in social research, especially those closely linked to economics.

It is not clear to what extent this thematic division is due to the relative novelty of the field. As a new disciplinary area, agent-based computational social science faces some contextual and structural obstacles for its methodological unification. Quantitative methods dominate in mainstream economics, so it is expected to find more quantitative data in those topics in agent-based computational social science that are closely connected to this disciplinary tradition. Likewise, people working on subjects closely linked to economics might have a preference for quantitative methods because these are the methods in which they were trained. It is possible that traditional disciplinary differences will be less pronounced as the field matures and new shared methodological commitments are generated, for example, by training new entrants as computational social scientists.

Simplifying the disagreement about the qualitative–quantitative dualism was instrumental in achieving an early consensus. As mentioned, it facilitated interdisciplinary communication through a conflation of shared commitments from different disciplinary areas. Yet, the level of unification the field can eventually achieve partially depends on incorporating into its shared commitments those elements of the disagreements that were directly transferred or neglected in early parsing processes. Some of these elements might prove difficult to parse, for they do not necessarily have a methodological correlate in agent-based modelling. For instance, one aspect in which the qualitative and the quantitative traditions clearly differ is sample size. Since agent-based models use an artificial population, the question about sample size might, at first, seem irrelevant.

There are circumstances, however, where the number of agents in a model affects warrants for belief in the adequacy of the simulation. Hence, concerns about sample size or, in the case of computational models, population size, should not be deemed completely irrelevant. Initially, making sense of these concerns might be challenging because, given the methodological features of agent-based modelling, they could be addressed in more than one way. They could, for example, be linked to the size of the artificial population in the model, but also to the empirical data used for the processes of calibration, verification and validation. In the latter case, the link between sample size and warrants for belief in the adequacy of the simulation is indirect and mediated by the nature of the empirical data used during these processes; in the former, the link is direct and associated with technical aspects e.g., how long would it take for the simulation to run, and conceptual questions or assumptions e.g., whether modelling intricate socio-technical or -ecological systems requires larger numbers of agents, in comparison to simple 'local' phenomena.

When concerns refer exclusively to implementation, additional practical obstacles are found. In several models, for example, researchers reproduce ecological conditions, such as death and reproduction. In those cases, the number of agents in the model could greatly differ through the execution of a simulation. In addition, population size is often a parameter of the model, so conclusions are drawn by, among other things, modifying the value of this parameter. Sometimes decisions about population size are based on practical considerations, for example, to facilitate comparison with external data (Rouchier 2003) or to conform to precepts from other research areas or methods (Epstein 2006). While issues about population size are not addressed in typical methodological literature used to train new entrants (e.g., Gilbert 2008; Railsback and Grimm 2012; Wilensky and Rand 2015), in empirical research, practitioners acknowledge the relevance of parametrising the population size, and operate and report on the models accordingly. The criteria used on every instance, however, depend on tacit knowledge that has yet to be explored or is not adequately conveyed in academic publications.

Most of those potentially problematic resources that are neglected or directly transferred from already established disciplinary areas are probably not parsed within agent-based computational social science because they are not considered to heavily influence everyday practices. Given that abstract models dominated during the emergence of the field, decidedly empirical questions, such as sample size, were left unaddressed. It seems that the field progressively parses resources as they become an issue for everyday practices and a potential cause of fragmentation of the disciplinary identity. This parsing affects diverse scientific activities beyond modelling practices as such (e.g., the logics of reporting (Angus and Hassani-Mahmooei 2015)), and is also affected by variations in the field's epistemic goals and interest (e.g., to accommodate the desire to influence policy-making (Gilbert et al. 2018)). Even though the literature in the field evidences a renewed interest in methodology, after a progressive stage of decline (Meyer et al. 2009; Hauke et al. 2017), it is not clear whether practitioners would address an issue such as sample size, unless it starts creating tensions or disagreements in everyday practices.

While this pragmatic approach to the dualism, again, guarantees the efficient use of epistemic resources, it also has undesired consequences. For example, one clear advantage of using agent-based models pertains precisely to sample size. Given that these models use (virtual) agents, they could, in fact, provide a middle ground between the qualitative and quantitative traditions, since they can be easily scalable (approaching 'sample size' as the relative size of a simulated population). This pragmatic resource parsing during the discipline-building process is consistent with the distinctive practice-orientation of agent-based computational social science. Yet, to a certain extent, it hampers the field's chances to gain external recognition from traditional disciplines, for it hinders practitioners from explicitly addressing aspects of the disagreement that are relevant to researchers in the mainstream disciplines.

4.3 Grounding the parsing process on methodological concerns

The alleged synthesising nature of agent-based simulation rests on a particular interpretation of the key features of the qualitative and quantitative traditions. In the field, as mentioned, shared commitments articulated around the qualitative–quantitative divide are mostly linked to matters of formalisation. In practice, however, it is clear there is an uneven influence of the two traditions, with quantitative assumptions being more often incorporated into the field. There is no inherent incompatibility between agent-based modelling and the methodological assumptions of the qualitative tradition (Yang and Gilbert 2008). Nonetheless, practitioners of agent-based social simulation have only recently started to robustly discuss the way to better incorporate these assumptions into the methodological framework of agent-based social simulation (e.g., Edmonds 2015).

It is likely the technical and methodological features of agent-based models are responsible for the uneven contribution of the two research traditions. The use of quantitative data in agent-based models is relatively straightforward. Computational models can easily deal with the basic character of quantitative methods due to the shared formal underpinnings of both mathematical and programming languages. The use of qualitative data, on the contrary, first requires a discussion about the theories of measurement and properties in agent-based modelling (Agar 2003; Yang and Gilbert 2008). Qualitative approaches to the cognitive foundations of action, for example, have traditionally been relatively intricate. Their intricateness does not derive from the complexity of natural language used to describe them, but from the theoretical–methodological construct developed around the concept of human action. The fact that computer languages are syntactically and semantically flexible does not guarantee that the complexity of qualitative approaches can be captured. The issues at stake are not just a matter of linguistics, but of representation.

Representation becomes a major issue when trying to incorporate insights from the qualitative tradition. Most practitioners in agent-based computational social science approach simulation from a methodological individualist perspective, either through their modelling choices or the narrative built around the model's output (Anzola 2015). Interestingly, most narratives about decision-making in these models lack typical features of qualitative accounts of human action. For instance, in qualitative research, the body has often been conceptualised as a resource for action (Turner 2008). In agent-based models, however, only a relatively small set of bodily features such as memory, reproduction and locomotion are used. When included, bodily functions are mostly used to replicate basic ecological conditions, but rarely account for more intricate issues, such as the body's role in the definition of personal identity, a topic that is common in qualitative accounts of human action.

While there is, in principle, no reason preventing the incorporation of complex bodily features and other aspects that are typical of qualitative research, in practice, there are negative incentives for it. Initially, there is an obstacle derived from the current agenda and the state of knowledge in the field. There are several phenomena for which the effects of the most basic aspects of representation in agent-based models e.g., heterogeneity, are not fully understood. Because of the dynamic and entity-centred character of agent-based social simulation, practitioners might have problems to find commensurable data produced by other methods or might realise that the data and the simulation results are contradictory or incompatible. Researchers could feel deterred from implementing more complex models that capture intricate insights from the qualitative tradition, if there is not consensus about the impact of basic representational choices. In addition, theory-building in the field, given the contextual nature of modelling and the expressiveness of agent-based models, is relatively localised (Anzola 2018; Anzola and Rodríguez-Cárdenas 2018). There are not many instances of models that are progressively made more robust so to account for more intricate theoretical or methodological insights.

At the same time, practitioners might want to avoid intricate approaches to representation due to the potential undesired technical effects. More complex cognitive architectures, environments or interaction dynamics could make the simulation slower or demand extended power of computation. In turn, striving for more intricate models might conflict with what some practitioners believe to be the core explanatory principle in the field: keeping the model's behaviour as simple as possible, so as to unveil the underlying mechanisms (Axelrod 1997; Macy and Willer 2002).

The close link between representation and the methodological/technical features of agent-based modelling has significantly affected the process of discipline-building. It has fostered the incorporation of decidedly methodological concerns into the disciplinary identity of the field, making it difficult to accommodate all the relevant features of the qualitative–quantitative disagreement into the alleged synthesising agenda of agent-based computational social science. The uneven contribution from both traditions has saved epistemic resources, facilitated interdisciplinary communication and, also, prevented conflict, since the qualitative agenda challenges some widespread shared scientific values and principles (e.g., regarding the role of the observer) to which some practitioners, because of their disciplinary background, might be committed. The recent push for a more thorough articulation of qualitative insights, however, is the result of a maturation process that has led the field, first, to produce/demand more data and, second, to recognise the potential benefits of using qualitative research to take advantage of the higher expressiveness of computer languages and agent-based models.

5 Prediction

Agent-based computational social science has parsed several resources linked to prediction. Given the ubiquity of this value in contemporary science and the multiplicity of shared commitments that diverse disciplinary areas have developed around it, transfer and parsing processes are more diffuse and harder to pin down. These commitments are not necessarily equivalent or compatible and there is a significant amount of tacit knowledge involved. This section addresses how disagreements have, implicitly and explicitly, affected shared commitments articulated in agent-based computational social science around prediction. Two key components of the disciplinary identity of the field are analysed. The first one, the KISS–KIDS dualism, is a theoretical disagreement in which prediction is explicitly incorporated into shared commitments through the methodological question of whether agent-based models are able to predict. The second one, the verification–validation evaluation scheme, is a methodological cornerstone of the field that has articulated a disagreement about novelty and prediction in a rather implicit way.

The parsing of epistemic resources associated with prediction were initially oriented towards the production of external differentiation through the methodological characterisation of how this value is instantiated by the method i.e., what epistemic goals it is able to achieve, how, and to what extent, it achieves them, and the way this characterisation conforms to core scientific standards and practices (for there was a need to justify the status of agent-based modelling as a proper scientific method).

Unlike the qualitative–quantitative dualism, shared commitments about prediction developed early during parsing processes have, over time, fostered an increase in internal differentiation, leading to the most well-known theoretical disagreement in the field: the KISS–KIDS disagreement, which emerged because initial shared commitments did not entirely conform to everyday practices. As discussed below, the presence of internal differentiation has not heavily disrupted practices or affected disciplinary self-recognition, for the practice-oriented, interdisciplinary and technology-dependent character of the field has allowed practitioners to articulate these disagreements within the field's agenda, without severely compromising their disciplinary identity.

5.1 Prediction in abstract and empirically calibrated models

Claims about prediction are often framed within the more general KISS–KIDS debate. The labels 'KISS' (Keep it Simple, Stupid) and 'KIDS' (Keep it Descriptive, Stupid) are used in social simulation to refer to alternative modelling approaches: abstract and empirically calibrated modes, respectively. Both approaches differ in the amount of empirical data used for verification, calibration and validation processes. They also tend to promote different sets of scientific goals. Control and optimisation, for example, are goals more often associated with the KIDS approach.

In the domain of abstract models, shared commitments about prediction have remained relatively stable over time. In general, the KISS literature suggests that agent-based modelling is primarily a tool for understanding and that this understanding comes at the expense of prediction (Axelrod 1997; Epstein 2008; Gilbert and Troitzsch 2005; Macy and Willer 2002). Abstract agent-based models are said to focus on unveiling mechanisms and micro–macro processes of emergence. Given the temporal character of the simulation, the features of social phenomena are not merely described in terms of associations between variables, as in some popular social research methods (e.g., correlation or regression), but accounted for mechanistically, that is, through the counterfactual exploration of spatiotemporal patterns and trajectories. This approach to mechanisms and temporal relationships is sometimes described as prediction, but there is usually a qualifier e.g., 'qualitative' prediction (Troitzsch 2004), probably in an effort to avoid dismissing the notion of prediction entirely.

The partial renouncing of prediction in the KISS account has two main reasons, one theoretical and the other methodological. The latter has to do with the fact that abstract models need not rely on data for their design, implementation, operation and communication. Hence, they are not able to provide point-prediction or forecast, a feature that is often considered to be at the core of this scientific value. The theoretical reason is inherited from the general framework of complexity science. Complex phenomena are believed to display features such as non-linearity, path dependence and sensitivity to initial conditions that pose some obstacles for forecasting.

The literature on KISS precedes the literature on KIDS. It is, in fact, the foundational methodological narrative in agent-based computational social science. When the field emerged, there was a relatively widespread consensus about the role of prediction in the field's explanatory narrative. Agent-based modelling was presented as a method focused on explanation, rather than prediction. As the field matured, however, internal differentiation started to grow, for practitioners realised that early shared commitments were too narrow. Eventually, a disagreement about the predictive capabilities of empirically calibrated agent-based models became evident. This disagreement challenged the methodological reason behind the preference for abstract models, although, in general, it conformed to the theoretical.

The foundational narrative i.e., the KISS account, was challenged, not because of major advances in methodology, but because it did not really conform to explanatory practices in the field. From very early on, a core group of practitioners working on empirical issues was constituted (David et al. 2004). The KIDS account is grounded on the acknowledgement that data-heavy approaches to agent-based modelling cannot really be accommodated within the KISS explanatory agenda. Initially, the KIDS account took issue with the principle of simplicity as a truth indicator (Edmonds and Moss 2005). Over time, the call for empirically-calibrated models brought the issue of prediction to the forefront of the field's methodological discussion.

The disagreement about prediction emerged, not only to recognise the explanatory approach of some practitioners in the field, but also as a way to raise the profile of the agent-based social simulation as a method. The belief about the limited predictive capabilities of agent-based models has, first, negatively affected warrants for belief in the adequacy of agent-based modelling and, second, hindered the use of these models in policy-oriented discussions, an area in which an increasing number of practitioners are getting involved (Gilbert et al. 2018), and where prediction is a sought for quality in scientific models. By modifying shared commitment about prediction, agent-based computational social science is expected to cash in on the increasing dissatisfaction with traditional methods in general science and the policy world, as well as on the popularisation of complexity science and its associated concepts (e.g., emergence, self-organization, non-linearity, adaptability).

The KISS–KIDS debate is, arguably, the most important philosophical disagreement in agent-based computational social science. It is clearly connected to processes of internal differentiation through which the foundational narrative broke down. Yet, unlike traditional disciplinary disagreements, the KISS–KIDS debate informs everyday practices without disrupting them. There is not a pressing need for practitioners to resolve the disagreement, since it responds to diverse research agendas that coexist within the field. Empirically calibrated models, for example, are significantly more common in areas such as operational research, where models are used for real-life problem-solving and decision-making. Agent-based computational social science can accommodate this tension within its shared commitments without significantly affecting disciplinary identity or cohesion because, even though new commitments directly challenged the foundational narrative, practical demands seem to trump the need to normalise philosophical conflicts and disagreements.

5.2 Using old-fashioned resources to ground shared commitments

Early shared commitments in agent-based computational social science, as mentioned, separate prediction and understanding, and, at the same time, usually conflate prediction and forecasting. This might have to do, in part, with the process-oriented nature of the method. Since agent-based models are used to understand the temporal evolution of the phenomena of interest, there is always a temporal asymmetry between the initial and final configurations or states. The conflation of prediction and forecasting, along with the separation between prediction and understanding, helped shielding the method against potential criticism regarding its lack of predictive capabilities (e.g., Lehtinen and Kuorikoski 2007) through a reclassification of its epistemic goals. It also allowed advancing the agenda of agent-based modelling as a method that provides *actual* diachronic explanation, that is, based on the 'generative' interaction of entities, and not just transition probabilities or variable associations.

This emphasis on the explanatory power of agent-based modelling, while relying on the methodological strengths of the method, may have led to unnecessarily downplay its predictive capabilities. Agent-based computational social science's approach to prediction seems to be underlain by relatively old-fashioned or outdated beliefs about prediction that, to a certain extent, are misleading and unnecessary. Shared commitments about explanation in the field, following the positivist approach to explanation in the philosophy of science, have often taken prediction and understanding as separate or incompatible. For positivists, a successful explanation is one in which the *explanans* makes the *explanandum* expected. The difference between explanation and prediction is considered to be a pragmatic matter: it is given by the occurrence of the *explanans* (Hempel 1965). Positivists did not try to articulate understanding into their theory of explanation, for it was believed to have only psychological significance. Understanding, however, became a key aspect of post-positivist approaches to explanation. In the case of agent-based computational social science, understanding was brought to the forefront and considered constitutive to explanation. The alleged epistemic difference between prediction and understanding, was kept, though. It was, in fact, further reinforced by the popularisation of theories of explanation such as social mechanisms, where there is a separation between explanation based on the association of variables, aiming mostly at prediction, and explanation based on spatiotemporal variations, seeking to identify causal mechanisms (Hedström and Swedberg 1998). Both dualisms about explanation, while not addressing the same issues, can be easily overlapped.

In part, the KIDS–KISS tension emerged because, early in the disciplinarisation process, practitioners parsed into their shared commitments an old disagreement about the role of prediction and understanding in explanation, which the post-positivist philosophy of science has shown to be founded on a false dichotomy. Keeping the separation between prediction and understanding has ultimately led to a conceptual neglect of prediction in agent-based computational social science. In the field, prediction is naturally not conceptualised in terms of expectability, as in traditional positivism, but a consensual definition has not been articulated. While the value has sparked some debates in the field (e.g., Epstein 2008; Thompson and Derr 2009; Troitzsch 2009), the discussion has not provided an updated and contextually adequate notion of prediction. Hence, the concept remains to be mostly a matter of temporal asymmetry between available and new data. This conceptualisation, however, is at odds with more recent philosophical accounts of prediction. In contemporary philosophy of science, prediction is often understood "not in the temporal sense but in the sense of 'falling out' of the theory without having had to be worked into that theory 'by hand"' (Worrall 2010, p. 129).

By focusing on temporal asymmetry as the main feature of prediction, agent-based computational social science ended up incorporating into its shared commitments a disagreement about the role of prediction in explanation that unnecessarily misrepresents the predictive capabilities of the method.[5] Agent-based models are used to explore phenomena in which there is not enough information available. In turn, researchers often do not know with certainty the connection between the initial and final states of the simulation. In agent-based modelling, as suggested above, the simulation represents processes of emergence. The resulting macropatterns, given the programmed microfoundations, are not really known beforehand, and, occasionally, turn out to be unexpected or counterintuitive. Accounting for the 'mystery gap' between the micro and the macro arguably constitutes prediction in this more refined sense, especially if novelty in prediction is to be determined contextually, according to some hierarchised epistemic goals that need not be universal (Hudson 2007).

It is likely that the interdisciplinary character of agent-based computational social science is partially responsible for the generation of inadequate commitments about prediction. Although the positivist account of prediction has never been common in social science, it has been very influential in many other areas of knowledge. When the agenda for complexity science was articulated, scientific positivism was the main target of criticism (Miller and Page 2007; Mitchell 2009). The account was challenged for, among others, its approach to inference, causation, theory-building and testing. During the disciplinarisation of agent-based computational social science, parsing processes led to explicitly articulate this criticism into the field's shared commitments about prediction.

The resulting shared commitments, thus, responded to the needs of complexity science as a whole (and maybe some practitioners within the field), but do not entirely conform to the practice of agent-based social simulation. These commitments reduced the internal differentiation with the larger area of complexity science, both a precursor and an umbrella disciplinary area for agent-based computational social science, at the

[5] The method could still be criticised for its ability to forecast, particularly in the form of point-prediction. However, given that, up to this point, empirically-calibrated agent-based modelling is not a fully-fledged area of research (mainly because of the lack of suitable data), it is not clear whether this truly is an inherent limitation of the method. While there will be always some challenges posed by elements such the stochastic nature of a computer simulation, there is still much to discuss about how the method instantiates prediction. Practitioners, for example, have yet to inquire about how the indirect nature of the knowledge produced by computational modelling affects prediction, especially given the increasing popularity of fictionalist theories of modelling and representation.

expense of creating a theory-practice gap that fostered the emergence of the KISS–KIDS disagreement.

5.3 Implicit effects on parsing processes and shared commitments

As mentioned, shared commitments about prediction in general science are quite diverse, so they intervene in several instances of knowledge transfer during discipline-building processes. The data asymmetry that practitioners of agent-based social simulation have associated with prediction has implicitly influenced additional shared commitments that involve the notion of novelty. The process of evaluation in the field, particularly, incorporates an approach to novelty that resembles the prediction–accommodation dichotomy in the philosophy of science. Scientific models and theories are commonly judged on their capacity to accommodate existing data and predict new data. Prediction often receives more attention, for it is claimed to have an advantage, either epistemological or pragmatic, over accommodation (Hitchcock and Sober 2004; Worrall 2014).

Unlike prediction, the term accommodation is not really used in the field, even though it is a common procedure in agent-based modelling. In the everyday practice of social simulation, previous data is used at different stages of the design, implementation, execution and validation of the model. It is, perhaps, during the process of verification where the clearest analogue for accommodation could be found. Verification is usually understood as the process of checking whether the computational model is correctly implemented. To do this, the model is sometimes run with known parameter values, to check whether it is able to reproduce an already known output (Gilbert 2008). Interestingly, verification has lower epistemological status than validation (the process of contrasting the computational model's output with the target phenomenon), for it does not yield new knowledge about the phenomenon of interest. A similar approach to novelty in data seems to underlie both dichotomies: verification–validation and prediction–accommodation.

It could be argued that, given the uncertain nature of the macropattern generated by the execution of a simulation, the difference between prediction and accommodation is accounted for in agent-based social simulation by the verification–validation distinction. That view, however, neglects the fact that the distinction between verification and validation is not so clear-cut in everyday practices (David 2013; Winsberg 2010). Formal and representational aspects of the evaluation process are not so easily separable. Given the contextual and subjective features of the practice of modelling, it is difficult for a researcher to separate between those aspects of the model yielding new data and those that are merely accommodating already existing data. This is especially true when the novelty of the data is not defined by temporal asymmetry. In practice, the adequacy of a simulation is corroborated by the reiterative application of several evaluation techniques at different stages of the simulation life cycle. These techniques test technical and representational aspects in a multiplicity of ways that cannot be translated into the traditional prediction–accommodation distinction.

Accommodation is difficult to conceptualise in everyday practices, for the separation between prediction and accommodation is only tenable when a distinction between the contexts of discovery and justification is made. It is in the latter where the two notions can be clearly separated. In philosophy of science, accommodation is often given a lower epistemological status, among other things, because it bears a higher risk of overfitting. This is a genuine concern, but it is hard to pin down in agent-based social simulation. In the wider domain of computer simulation, it has been suggested, for example, that the modeller should only perform ex-ante (Randall and Wielicki 1997) or parametric (Müller and von Storch 2004) modifications of the model or that the data for calibration and validation should be different (Batty and Torrens 2005). While these suggestions could help to prevent overfitting the model, they are not generally applied in agent-based computational social science. As mentioned, agent-based models are mostly used in areas where there is not enough information about the target phenomenon or where mechanisms linking microfoundations with macropatterns are not fully known. Additionally, the semantic and syntactic flexibility of these models increase their structural and parametric plasticity, making these restrictions hard to implement in most cases.

In everyday practices, modifications of parametric and structural properties of the model occupy a large portion of the simulation life cycle. The use of data in agent-based computational social science is linked to guaranteeing the adequacy of the model, more than synthesising or generalising prior findings. Prediction and accommodation, then, cannot be so easily separated because key assumptions underlying this distinction are subordinate to the representational and experimental use of the computational models. By adopting an epistemological account that relies on an asymmetry in data novelty, the field has articulated shared commitments that are not entirely developed after the technical features of agent-based modelling, but adapted from some already existing commitments in general science, scientific modelling and computer simulation.

This situation evidences that, in discipline-building processes, a disagreement might not materialise, even in the presence of conflicting beliefs and evident differentiation, due to the social and cognitive organisation underpinning everyday practices. The lack of specificity and potentially conflicting character of these commitments do not lead to the formation of disagreements or interfere with everyday practices because a disciplinary identity needs not be entirely supported by what practitioners actually do. Verification and validation were inherited in agent-based computational social science from computer science and software engineering (Anzola 2018), but practitioners have always acknowledged the methodological distinctiveness of the method. Potential conflicts and disagreements are avoided simply by acknowledging, among other things, that, in agent-based social simulation, verification and validation can easily overlap (e.g., David 2013; Gilbert and Troitzsch 2005).

Instead of devoting time and resources to close the theory-practice gap in evaluation practices, researchers have focused on the practical issues of evaluation (e.g., how to use replication for evaluation, how to adopt good coding practices, how to evaluate increasingly complex models). This decision does not lead to the reduction of internal differentiation, but certainly helps optimising the use of epistemic resources, first, because, given the practical orientation of the field, theory has a smaller effect on the articulation of disciplinary identity and is not a source of disciplinary tension with the potential to thwart everyday practices; second, because a stronger focus on the technical features on the method allows the field to quickly respond and adapt to technological developments that directly or indirectly affect the practice of agent-based social simulation, such as the popularisation of geographical information systems or big data.

6 Conclusions

This article analysed the effect of disagreements on the articulation of shared commitments in agent-based computational social science. It showed that the parsing of the qualitative–quantitative dualism has resulted in shared commitments that, overall, reduce internal differentiation through the facilitation of interdisciplinary communication and collaboration, yet, at the same time, neglect and oversimplify some crucial aspects of the original disagreement in mainstream social science. Similarly, prediction, a scientific value that has been parsed more diffusely, was argued to influence shared commitments defining the field's explanatory goals and the processes to evaluate a simulation's adequacy. The novelty in data with which prediction has been often associated was incorporated into shared commitments that increased the field's internal differentiation and, therefore, the chances of disciplinary tension, but have not negatively affected everyday practices, given the theory-practice gap on which doxastic attitudes about prediction are grounded.

Discipline-building dynamics present interesting challenges for the analysis of scientific disagreement because they are large-scale long-term processes of negotiation. It is clear, for example, that practitioners perceive the qualitative–quantitative divide as a disagreement. It is less clear, however, if the stripped-down version of the dualism that agent-based computational social science eventually adopted responds to practitioners deliberately seeking to minimise disciplinary conflict. The comparison of the two parsing processes also evidences the need to understand how practitioners, in the everyday practice of science, prospectively and retrospectively, identify and distinguish between actual and merely possible disagreements and ponder their (potential) impact. Resource parsing processes have tended to minimise the effects of the qualitative–quantitative dualism, but have done the opposite for the KISS–KIDS debate. The disagreement about the predictive capabilities of agent-based modelling has produced changes in the field's shared commitments and disciplinary identity because several practitioners have consciously advanced the debate's agenda over the years.

The article centred on actual rather than possible effects of disagreements. Questions about the latter are, nonetheless, fundamental to understand processes of disciplinarisation, and might need the turn to the empirical in the analysis of disagreements to be fully conceptualised. The discussion evidenced that a disciplinary identity can accommodate disagreement without fragmenting. In agent-based computational social science, the theory-practice gap fostered by early shared commitments allowed to keep the disciplinary identity together. There are other instances, however, where disagreements have led to disciplinary fragmentation. Given the dimension and scope of a disciplinary identity, it is necessary to identify how other mechanisms have the power to amplify or minimise the effect of internal and external differentiation and, eventually, promote or hinder disciplinary fragmentation. These mechanisms, contrary to what is expected in the theoretical analysis of disagreements, might not necessarily be grounded or follow rational principles and procedures, for, in the everyday practice of science, disagreements are not simply a matter doxastic states or attitudes, but have the power to become and be used as a resource for action. Ben-David and Collins (1966), for example, discuss a case where disciplinary fragmentation occurs because a group of scientists consciously tries to produce internal differentiation in order to find a new professional role.

The temporal extension of discipline-building processes also set some challenges for the conceptual apparatus developed to analyse scientific disagreements. The field did not come up with the qualitative–quantitative dualism but transferred it from social science. The evidence produced so far is vast and continues to grow, given the continuous improvements in research methods and their application. While insightful, this evidence is impossible to handle in its entirety by any epistemic agent. Reasoning about concepts such as full disclosure of evidence, faultlessness or conciliationism might be affected by the volume and open-ended nature of the evidence in these disagreement dynamics. The rationality and reasonability of the justification in the two instances analysed is also difficult to evaluate. Disagreements associated with the qualitative–quantitative divide and prediction deal with complex belief constructs that have developed over long periods of time. Their conceptualisation involves different epistemic systems, more than one order of justification, and intricate group dynamics effects. As a result, there might be several aspects of the disagreements on which individuals or groups can defer judgement, or even change their beliefs, without solving the overall disagreement.

It is natural to see the turn to the empirical as a test of how the theoretical approach to scientific disagreement conforms to everyday scientific practice. The case discussed in this text, for example, raises some questions pertaining, on one hand, to the participants' behaviour and reasoning in situations of scientific disagreement and, on the other hand, to the way in which crucial theoretical concepts such as evidence should be made sense of. This turn is also useful in providing a roadmap for future research. As suggested by the KISS–KIDS debate, scientists might not necessarily use rational decision-making heuristics when engaging in disagreements (this disagreement arises, in part, from the pragmatic need to impact policy- and decision-making). It is not possible to know the degree to which scientists resort to these non-rational heuristics, unless the study of disagreement is articulated with other areas and methods, such as behavioural sciences or laboratory experiments. Additional case studies are also needed to identify those contextual factors affecting disagreement dynamics that cannot be easily anticipated or accounted for by the theoretical analysis. In the case of agent-based computational social science, it was shown, the nature and extent of the disagreements are closely connected to the interdisciplinary, practice oriented and technology-dependent nature of the field.

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