Object Salience in the Division of Labor: Experimental Evidence

Article *in* Management Science · March 2015

DOI: 10.1287/mnsc.2015.2216

3 authors:

Marlo Raveendran
University of California, Riverside

Phanish Puranam
INSEAD

Massimo Warglien
Università Ca' Foscari Venezia

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EXPERIMENTAL EVIDENCE

Marlo Raveendran[1]
University of California, Riverside
marlo.raveendran@ucr.edu

Phanish Puranam
INSEAD

Massimo Warglien
Università Ca'Foscari di Venezia

Forthcoming in Management Science

ABSTRACT

When we engage in the process of division of labor, there are typically multiple alternatives, but insufficient knowledge to choose among them. Under such conditions, we propose that not all alternatives are equally likely to be pursued. In particular, when we engage in the process of division of labor for novel and non-repetitive production, we argue that we display a tendency to perceive and select object-based task partitions over activity-based partitions. We experimentally investigate how the salience of objects over activities manifests itself in individuals and groups engaged in division of labor for the assembly of strongly or weaklydecomposable products. We draw implications for organization design as well as the impact of technological change on organizations.

Keywords: organization design, division of labor, decomposability, experiments

[1] The authors would like to thank participants of the workshop on Experimental Organization Science at the Frankfurt School of Finance & Management, three anonymous reviewers for valuable feedback, and Daniel Mack for replicating our analyses. Puranam acknowledges funding from the European Research Council under grant #241132 for the "The Foundations of Organization design" project. Warglien acknowledges funding from the European Union's Seventh Framework Program (FP7/2007-2013) under grant agreement no. 318723 (MATHEMACS) and further support from Swiss & Global to the Ca Foscari Experimental Economics Lab.

Since Adam Smith (1776), it is generally accepted that the division of labor is a fundamental phenomenon underlying economic life. However, it is such an omnipresent feature in our societies that we have developed some blind spots in understanding it. To be sure, the *consequences* of the particular form of division of labor associated with industrial production in market-based economies - such as gains from specialization (e.g. Smith 1776), the impact on social solidarity and individual motivation (e.g. Durkheim 1893), the bargaining power of workers vis-à-vis the providers of capital (e.g. Marx 1906), of hierarchical superiors vis-a vis subordinates (e.g. Bendix 1956), or of suppliers relative to buyers (e.g. Williamson 1975) - have each been extensively addressed in significant literatures. In addition, current research on modularity in organizations (e.g. Baldwin and Clark 2000; Sanchez and Mahoney 1996) examines the reciprocal relationships between technology and organization created by the division of technological labor. However, surprisingly little attention has been devoted to the basic *process* of the division of labor - a process whereby objectives are divided into contributory tasks (task division) which are allocated across individuals (task allocation). A version of this process must necessarily be a part of all organizations whether pre- or post-industrial, whether connected or not to a market, or engaging in any exchange at all, as an organization by definition must aggregate individual efforts into organizational objectives (Babbage 1833; March and Simon 1958: 2).[2]

The limited prior attention to the process by which a division of labor emerges may simply have been the consequence of pervasive functionalist assumptions. For instance, the influential position of Ludwig von Mises was that if a particular division of labor has efficiency advantages (such as gains from trade), its emergence could be taken for granted (von Mises 1949). This may even have been justified in an industrial context dominated by highly repetitive activity on a shop floor, such as that celebrated in Smith (1776), where opportunities for learning through repetition could have helped uncover the efficient division of labor, and opportunities for amortizing that learning through repeated production may have led

[2] In particular, the process of achieving task division may be uniquely important in human organizations. Division of labor also occurs in biological systems, but the key questions there pertain to why some systems evolve towards differentiated allocation of tasks *given* a task division and an initial undifferentiated allocation of tasks (Rueffler Hermisson and Wagner 2012).

to a strong emphasis on particular kinds of division of labor (e.g. Taylor 1911; Wren 1979). However, the degree of repeatability of production that organizations confront today varies significantly (e.g. it is relatively lower in project-based work than on the shop floor). Further, for every existing pattern of division of labor, there must have been a point in time at which the process by which it first emerged unfolded. Put simply, organizations often confront novel goals, and when they do, a process of division of labor must necessarily arise. If so, it is valuable to understand what social and psychological factors beyond the technological properties of the task influence the process through which an equilibrium - *a* division of labor – emerges (Schelling 1960; Skyrms 2004).

In this study, we investigate this process of division of labor under conditions of ***novelty*** and ***non-repetitiveness*** with a focus on its social and psychological micro-foundations. It has been noted that we tend to focus more on 'objects' than 'activities' when making sense of and categorizing our environment (e.g. Gentner 1982; Rosch et al. 1976). We propose that this property should also affect the decisions we make about the division of labor. Our central proposition is that we should see a general tendency in the process of the division of labor to cluster and allocate tasks by the intermediate objects they result in (an ***object-based*** partitioning), rather than by the similarity of activities across different objects (an ***activity-based*** partitioning). We argue that this is because distinct intermediate objects should be easier to visualize and communicate about than the activities that underlie their production in the minds of those undertaking the process of division of labor; we term this the consequence of *'object salience'* in the division of labor. This perceptual feature of division of labor should give rise to measurable objective differences in the nature of division of labor selected.

Our proposition has important implications for the process of division of labor in organizations, and the organization designs that result from them. If decision makers are indeed influenced by object salience, it should lead to predictable patterns in the kinds of division of labor we observe in organizations, and could conceivably lead to predictable departures from the most efficient division of labor. This study therefore not only highlights the psychological and social influences on the process of division of labor itself, but points to areas and ways in which that process could be usefully influenced or adjusted.

Studying the process of division of labor in the field is challenging because it is difficult to observe longitudinally and draw causal statistical inferences. To overcome this challenge, we conduct experiments, in the tradition of prior work that has sought to examine important organizational issues through controlled experiments in the behavioral laboratory (e.g. Burton and Obel 1984a; Cyert and March 1963; Guetzkow and Simon 1955; Malhotra and Murnighan 2002). We develop an experimental protocol in which individuals and groups must decide on a division of labor for assembling mechanical toy models. These production tasks are novel and non-repetitive. We study how object salience in the division of labor manifests itself (i) across the assembly of products with varying degrees of *product decomposability* (the extent to which the final product can be easily broken down into sub-assemblies that have strong interactions within but weak interactions across them (Simon 1962)); and (ii) when the division of labor is conducted by self-organizing groups versus through centralized decision-making.

Our data are unusually rich, in that in addition to observing the division of labor that emerges, we also develop detailed longitudinal data (coded from video recordings) both on how participants decide on a division of labor as well as execute within it; in addition, we also record what aspects of the problem capture the attention of participants as they engage in choosing the division of labor (by tracking their eye movement while they study the instructions).

THEORY

A Vocabulary for Describing Division of Labor

To aid analysis, we conceptualize the process of dividing labor as involving the search for solutions to two related but distinct sub-problems, namely task division and task allocation. *Task division* involves the decomposition of an overall goal into contributory tasks, and their subsequent clustering (also see von Hippel 1990). A task may be thought of as a production technology - it is a transformation of inputs into outputs in a finite (non-zero) time period. *Task allocation* refers to the assignment of (the clusters of) tasks to individuals. It may occur either simultaneously or after task division, or may indeed influence task division.

Some notation may be useful to fix ideas. Define T^R as the task structure - the most fine-grained means-end decomposition of a goal into its constituent tasks and the dependency relationships between these. A task is the fundamental, indivisible unit of a task structure. Lacking omniscience, boundedly rational agents must invariably work with imperfect representations of the true underlying and possibly unknowable task structure. There are multiple ways to represent T^R - Workflow diagrams, Task Structure Matrices, and Linear Programming models being some of them (Baldwin and Clark 2000; Burton and Obel 1984b; Eppinger 1991; Steward 1981; Thompson 1967). These representations capture the possible interdependence relationships between tasks - whether one produces an input to another, whether their joint outputs are complements or substitutes (Milgrom and Roberts 1990; Thompson 1967), or whether they draw on the same (possibly limited) inputs (Burton and Obel 1984b). For the general case of n tasks, we can rely on Task Structure Matrices to represent the pattern of interdependence between tasks in T^R. In this matrix, let a 1 denote that column-task is dependent on row-task (as shown in Figure 1). This abstracts from variations in the magnitude of interdependence, which can be incorporated if known.

INSERT FIGURE 1 ABOUT HERE

There will typically be many different ways to cluster the tasks in T^R. In addition, these clusters of tasks may be allocated in different ways among the agents in the organization. Let the matrix T^A represent the allocation of tasks to agents. Whereas T^R is an n X n matrix where n is the number of tasks, T^A is an m X n matrix, where m is the number of individuals in the organization. Since T^A embodies both a decomposition of the overall goal into clusters of tasks as well as an allocation of these task clusters among the agents, it is a concise abstract representation of *a* division of labor. Thus to consider the original example provided by Adam Smith, pin making could be divided into *"eighteen distinct operations, which, in some manufactories are all performed by distinct hands, though in others, the same man will sometimes perform two or three of them"* (1776 [1999]: 5). These would correspond to two different T^A of dimensions n=m=18 vs. n=18 and m<18 respectively, for the same underlying T^R, in which the tasks corresponded to the operations involved in pin making.

In this paper, our focus is on the process that generates a T^A given a T^R. Given m individuals, there are many ways in which n tasks can be clustered and allocated across m individuals. At a very basic level, some clustering would appear unavoidable to the extent that there are limits on the tasks in T^R an individual can carry out, and m<n. Given bounded rationality and limits on cognitive processing (Simon 1945), clustering tasks and assigning them to different agents is also a means of rationing attention; an agent can focus on managing the interdependencies between the tasks within the cluster assigned to her, possibly at the expense of interdependencies with tasks in other clusters.

As an illustration consider the idea of modularity, which is a strategy for managing complexity in systems with many interdependencies (Baldwin and Clark 2000; Ethiraj and Levinthal 2004; Sanchez and Mahoney 1996). By clustering elements into discrete clusters that effectively ignore interdependencies with other clusters, local improvements within clusters may be obtained, but possibly at the expense of overall system performance. A good modularization is one that ignores interdependencies across clusters in a manner that least impedes system performance, while grouping together elements the attention to which yields the highest returns.

Detecting clusters of tasks that are strongly interdependent with each other, but independent of tasks in other clusters is a cognitively challenging task for even relatively small task structures. For m individuals and n tasks, there are m^n different possible divisions of labor. Since clustering is not an exogenous property of the system but is determined endogenously by the individuals engaged in the division of labor, searching through these options for the best clustering requires significant information processing resources, beyond the ability of most individuals.[3] Further, an ideal clustering would require not only knowledge about the task structure matrix in its entirety, but also the differing weights of interdependence between different tasks. It is extremely unlikely that human beings have the information

[3] To overcome these limitations of the human mind, computer scientists have created several algorithms that can help us permute the rows and columns of a task structure matrix in order to detect clusters. Social network theorists refer to these as "community detection algorithms" (see Clauset, Newman and Moore 2004; Newman 2006).

or the cognitive resources to engage in such cluster detection exercises in their mind. Instead, heuristic bases for clustering tasks are routinely relied upon. Two particular archetypes of clusters are noteworthy.

First, tasks can be clustered in terms of distinctive intermediate objects they generate, leading to an *'object'*-based task division. Intermediate objects exist and have some value independent of each other. The value need not be restricted to the price in a market; it could reflect the ease with which a system can be completed, rebuilt, or reconfigured given the existence of intermediate objects (Simon 1962). Second, tasks can also be clustered on the basis of how similar they are in how they transform inputs into outputs, leading to an *'activity'*-based task division. While both object- and activity-based task clusters comprise the same underlying set of tasks, the principle of clustering is different.

Some examples may clarify this distinction between activity-based and object-based task division: say a group of people is given the raw materials and goal of building a chair. They can either choose to let one person prepare the legs, another to work on the backrest, a third to work on the seat, and a fourth to assemble the pieces (a predominantly object-based task division); or they can let one person cut the wood, another sand it, a third apply the varnish, and yet another to assemble it (a predominantly activity-based task division). We may also think of a firm that is organized by functions (e.g. units organized around R&D, manufacturing, sales) as an organization with a predominantly activity-based task division, and a divisional structure (e.g. units organized around white goods, TVs, and audio equipment) as an organization with predominantly object-based task division (Chandler 1962; Gulick, 1937). Note that the same basic tasks, with the same underlying pattern of interdependencies (i.e. task structure), are being performed in both scenarios – however, the logic of *task division*, how tasks are clustered - is distinct. Differences in perceptions about the underlying task structure and the value of different ways of clustering tasks can thus result in objectively different clustering of tasks.

Task Division by Object vs. Activity

When does a choice exist? While an activity-based task division is always possible (because in the limit each separate task can be treated as a 'cluster'), the choice between object- and activity-based task division does not always exist. It only arises, we argue, under a particular combination of decomposability of the final product, and non-decomposability of the underlying task structure – our arguments are summarized in Figure 2.

INSERT FIGURE 2 ABOUT HERE

Simon's pioneering work on hierarchical systems (1962 [1996]: 189) introduced the notion of decomposability as a key property of a complex system - the extent to which a system can be divided into sub-systems that feature strong interactions within them, but weak interactions between them. Applying Simon's fairly general ideas about decomposability (defined on systems) to the task structure T^R that produces a product, a decomposable task structure matrix is one in which we can permute the rows and columns such that clusters of tasks smaller than T^R can be created with interdependencies within the clusters but not across (Baldwin and Clark 2000). A strongly decomposable task structure is one where there are very few interdependencies between the clusters, but many within the clusters (Simon 1962). Its opposite is a weakly decomposable task structure.

If a task structure is strongly decomposable, the distinct clusters of similar tasks will necessarily also be object clusters. This is because all tasks produce outputs, and a cluster of related tasks *that do not relate to any other tasks* must produce an output that is an intermediate object. Therefore the task clusters in a decomposable task structure can be treated either as object- or activity-based clusters; there is no choice required between the two. To illustrate this case, consider the production of a collected volume of research papers by different scholars, such that the tasks required to produce each paper are independent of the tasks required to produce other papers, though the tasks involved in producing each paper may be interdependent among themselves (assume no final assembly activities, such as an editorial summary, are necessary and none of the researchers collaborates across papers). Thus, in this case there is no distinction between object- and activity-based task division - each paper can represent either an intermediate object or a cluster of activities that are similar within paper but independent across papers. *For a choice to genuinely arise between object- and activity-based task division, it is therefore necessary that the task structure not be strongly decomposable.*

We can conceive of the decomposability of a product as distinct from the decomposability of the underlying task structure that produces it. A product is near decomposable when it has components that have relatively few connections with each other, so that parts within a component can be changed without affecting the functioning of other components (Henderson and Clark 1990; Langlois 2002; Sanchez and Mahoney 1996).[4] Thus, a product that is strongly decomposable is one in which the final assembled product can be broken up into two or more freestanding sub-assemblies that have only few connection points to each other (often only at the final stages of assembly). We can expect that the production of a strongly decomposable product is likely to involve the simultaneous existence of multiple intermediate objects. Conversely, a non-decomposable or weakly decomposable product may feature just one intermediate product at any point in the production process that develops through stages.

Strong product decomposability is a necessary condition for object-based task division to be an option. For instance a chair is decomposable, but soup is not. In the production of a chair, there can simultaneously exist many intermediate objects (e.g. legs, armrests, back). However, from the moment of putting the ingredients onto the fire, the production of soup becomes non-decomposable: at any given point in time only a single intermediate object exists, which is the proto-soup at that particular stage of production (e.g. hot water with carrots, hot water with carrots and coriander etc.). Object-based task division is therefore possible for producing a chair, but not for producing soup.

Thus, *the choice between activity- and object-based task division as two distinct alternatives only emerges when the task structure is non-decomposable, but the product is decomposable.* If the product is not decomposable, no object-based task division is possible. If the task structure is decomposable, then object- and activity-based task divisions are identical and no choice exists.

Determinants of the choice between activity and object based division of labor. Given that the choice exists, how should one choose between task division by object or activity? An extensive body of

[4] While task structure decomposability is sufficient to produce product decomposability, based on everyday examples, it appears that it is not necessary. For instance, as diverse a list of artifacts as common furniture, many garments, automobiles, watches and computers may contain objects that are decomposable, even though the task structures that produce them are not.

work on job design (Hackman and Oldham 1976; Herzberg 1966; Oldham and Hackman 2010) has pointed to the fact that the agents in an organization may not be agnostic to the type of division of labor. For instance, the desire among workers for skill variety (the range of different skills required for carrying out an agent's cluster of tasks) and task identity (the extent to which the tasks performed produce a distinctly identifiable piece of work) seem to tip the balance towards object-based task division, particularly if each object-based cluster is assigned to one individual. However, the desirability of opportunities for interaction (Oldham and Hackman 2010; Turner and Lawrence 1965) may tip the scale back towards activity-based task division. This is because even in an activity-based task division, intermediate objects are produced; given non-decomposability of the task structure, the production of each of these intermediate objects will require the involvement of those performing very different tasks. In an object-based task division this is not the case, as the different kinds of tasks are all performed by the same individual. Thus, the specific choice of object- or activity-based task division in a situation must balance many of these factors and individual preferences.

Abstracting from the question of individual variation, the relative technical advantages of either kind of task division – by activity or by object - are well known. In particular, activity-based task division is associated with specialization: increased repetition and the associated gains from skill building (Mintzberg 1979; Simon 1962: 102; Smith 1776; Stigler 1951) as well as skill to task matching as explored by Argote, Moreland and colleagues (Liang, Moreland, and Argote 1995; Moreland 1999; Moreland, Argote, and Krishnan 1996; Moreland and Myaskovsky 2000). On the other hand, object-based task division creates advantages through allowing more attention on the dependencies between the distinct tasks needed to produce an object by allocating all such activities to one agent. To distinguish this sharply from the gains from specialization, we will refer to this as the gains from customization (of different tasks to each other).[5] Object-based clusters thus allow for local adaptation – in particular for exploitation of gains from customizing different tasks needed to produce an intermediate object, but at the

[5] We could also call this coordination (which is not precise enough as coordination is also involved in an activity-based task cluster) or co-specialization (but that could lead to confusion with specialization).

expense of ignoring the interdependencies that exist between the tasks that are common to different intermediate objects (Leijonhufvud, 1986; Simon 1962; Weick 1976).

Thus, a technically efficient choice between activity- and object-based task division should ideally turn on a comparison of the gains from specialization (i.e. coordination among the similar tasks that make up an activity) vs. customization (i.e. coordination among different tasks needed to assemble an intermediate object). However, for novel and non-repetitive problems of division of labor, boundedly rational agents may seldom if ever find it ex ante obvious whether the gains from specialization outweigh the gains from customization. Indeed the true extent of decomposability of the underlying task structure or the final product may be unknown (Eppinger 2001; Ethiraj and Levinthal 2004; Sosa, Eppinger and Rowles 2004). Therefore, we argue, basic tendencies in how human minds collectively and individually represent and partition their world may be relevant in understanding how a basis for clustering tasks is arrived at.

Object Salience in Task Division for Novel, Non-Repetitive Production

It is well known that the psychology of how individual minds partition the world stresses two fundamental categories - namely, (1) objects and (2) events based on relations between objects (e.g. Gentner 1982; Rosch et al. 1976). Objects refer to those categories that are characterized by a given set of intrinsic features; on the other hand, events are characterized by satisfying a specified relational structure, such as an activity relating one object category to another. While it is generally accepted that we categorize not only things (inanimate or animate) but also actions and events, the study of categories from classical philosophy to contemporary experimental studies has focused predominantly on objects (e.g., Ackrill, 1963; Majid et al., 2004; Mervis and Rosch 1981; Rosch 1999; Rosch et al. 1976).

A possible reason for this relative emphasis on object over event categories lies in the relative stability of these different sets of categories. It is generally recognized that event categories (of which action categories are a part) rely on less stable criteria of definition. The perceptual attributes of objects are more constrained than those of events; for example, a telephone or chair are more constrained in their attributes than the event of making a phone call (Hanson and Hanson 2005: 130). Part of this lower stability is due to the inherently temporal nature of events: *"Whereas objects occupy space, events occupy time. Recognition of objects is immediate under most circumstances, but recognition of events must evolve in time. Perhaps most tellingly, temporal order can change the meaning of events, whereas spatial order rarely affects the meaning of objects."* (Hanson and Hanson 2005: 131).

The relative cognitive difficulty for categories of events as compared to categories of objects has been highlighted by Genter and Kurtz (2005) who show that categories of events rely on sparse rather than dense representations: entity categories, such as object categories, *"are characterized by richly interconnected feature structure. The high intrinsic similarity among members is a natural consequence of the fact that they share many features and feature correlations. In contrast, because the members of a given relational category share only a sparse relational structure, there may be no obvious intrinsic similarities among members."* (Gentner and Kurtz 2005: 153). Furthermore Barsalou's work on 'goal-derived' categories (those relational categories based on the desired goal) highlights that goal-driven categories are less well established in memory and harder to retrieve (Barsalou 1983).

This contrast between object and event categories has been carried over into research on language acquisition. The analogy between objects and nouns on the one hand, and events and verbs on the other, has been used to explore the cognitive differences between them: *"Verbs are slower to be acquired than nouns (Caselli et al. 1995; Gentner 1982; Gentner and Boroditsky 2001); poorer in memory than nouns, both in recognition and in recall (e.g. Kersten and Earles 2004); more mutable in meaning under semantic strain (Gentner and France 1988); less prone to be borrowed in language contact (e.g. Sobin 1982); and less stable in translation between languages than nouns (Gentner 1981). Verbs are also more polysemous than nouns at a given word frequency."* (Gentner and Kurtz 2005: 154). An important caveat to mention here is that while this is a stable observation in 'Western' cultures, more recent work related to language acquisitions in Asian cultures shows that these results may not be universally true (Nisbett 2005).

In sum, objects appear to enjoy relative prominence making them stand out as cognitively more salient than activities. We label the relative facility in singling out and focusing on objects versus activities as *'object salience'*. We do not suggest that the propensity to categorize the world based on objects is a universally efficiency-enhancing heuristic; it is a heuristic that can misfire.[6] As a consequence of object salience, we would expect a strong tendency towards object-based task divisions rather than activity-based task divisions in the division of labor. In the example of the group building the chair, we would expect that the group will be more likely to opt for a task division into the legs, the seat, and the backrest, rather than the wood cutting, sanding, and varnishing, absent information on the relative gains from specialization and customization when this is a one-shot (i.e. non-repetitive), novel activity.

We therefore propose as a baseline that object salience should shape the emergence of a division of labor as follows:

Hypothesis 1: Object-based task divisions should be more likely to emerge than activity-based task division, for both strongly and weakly decomposable products.

Hypothesis 1 does not distinguish between decisions made about the division of labor by an individual versus a group. However, in organizations the extent to which decisions about the division of labor are centralized can vary. It may be conducted in a fairly centralized manner with a single individual making the decisions, subsequently implemented by others, or in a more decentralized and democratic manner by groups which also implement these decisions (e.g. in project teams).

We conjecture that object salience may be amplified whenever individuals are involved in interactions with others requiring some amount of coordination. In these cases, objects may enjoy a further relative advantage due to their secondary salience (*"I expect that most others think of objects, so I focus on objects in order to coordinate with them") and Schelling salience ("it would be easier to communicate if we all spoke of objects")*, in addition to primary salience ("*objects just stand out in my perspective"* Schelling 1960; also see Mehta, Starmer and Sudgen 1994). Recent experimental evidence shows that individuals that have to label a visual scene (e.g. a picture) tend to shift from event- or

[6] It may become a bias in some cases, particularly when product decomposability is low.

activity-related words to object-related ones when labeling has to be coordinated with others (as for instance we expect will occur when division of labor is conducted by a group) instead of being a purely individual activity (Paolacci, Legrenzi and Warglien 2013). Thus, if objects are just easier to articulate and coordinate on as a basis for task division because of higher 'image-ability' (McDonough et al. 2011), then we would expect object salience to influence division of labor by groups more strongly than by individuals:

Hypothesis 2: Object-based task divisions should emerge more often when groups conduct division of labor than when individuals do so.

So far, we have focused on the process of task division alone without saying much about task allocation - the other part of the division of labor. While task division necessarily temporally precedes task allocation decisions, the shadow of the latter may have an important influence on the former. Groups once formed constitute a pattern of social interaction and we argue that for this reason, the influence of object salience on the division of labor will be even stronger in pre-existing than in de-novo groups. There are two parts to the argument: First, there is a general tendency highlighted by different streams of research for groups to maintain their patterns of social interaction once established. Investigating the formation of routines in a laboratory experiment, Cohen and Bacdayan (1994) highlight how dyads of participants tend to maintain their routinized responses once established; Egidi and Narduzzo (1997) show that this may even lead to inefficient path-dependency. Feldman and Pentland (2003, 2005) distinguish between different components of routines, some of which maintain stability while others instill flexibility, and they argue that the stability of routinized processes rests at the group level (rather than the individual level). At the organizational level, Henderson and Clark (1990) note that attempts to maintain a firm's strong-hold in a particular market leads to strong inertial forces, preventing necessary organizational changes and therefore preventing architectural innovation; while Hannan and Freeman (1977) point to the pressures toward reliability and accountability to explain organizational inertia. If a preference exists to maintain interaction patterns once formed, this may have direct implications for task allocation when conducted in a group (e.g. ensuring all group members are involved, and continue to work with whom they were working with before), and may indirectly affect task division as well (e.g. partitioning and clustering tasks so as to allow task allocation as above).

Second, given such a 'stability preference', the group's established interaction patterns are more easily maintained if an object-based task division is applied to the task. This is because freestanding objects can be worked on independently (to exploit the benefits of customization) - or not, as a matter of choice - which offers a better chance of replicating established task allocation structures, i.e. maintaining existing patterns of interaction. In contrast, a task division based on activities places more constraints on the group's interaction structure because it forces acknowledgement of interdependencies between tasks underlying different objects, which may dictate a change in their established interaction patterns. Therefore, we expect that not only should the influence of object salience on the division of labor manifest more strongly in groups than in individuals, but also more strongly in groups with a shared history than in de novo established groups:

Hypothesis 3: Object-based task divisions should emerge more often when pre-existing groups conduct division of labor than when de novo constituted groups do so.

Hypotheses 2 and 3 imply that in the example of building the chair, we would expect that an established group is more likely than an individual (and more likely than a de novo formed group) to choose task clusters relating to the legs, the seat, and the backrest, rather than wood cutting, sanding, and varnishing.

EXPERIMENTAL DESIGN

Our experiments were conducted at a globally reputed science and technology university in a Western country.[7] The 80 participants were recruited from undergraduate classes and were randomly assigned to the different conditions. Each subject either participated in one 'group condition' (16 group

[7] The demographics of the participants reflect the international nature of their institution – 46% of the group participants and 75% of the individual condition participants were broadly defined as Asian. With regard to gender distribution, 56% of the groups had at least one female participant: 25% were composed of two male and two female students, while 31% contained one female student. Among the individual sessions, 25% were conducted with female participants.

sessions) or in one 'individual condition' (16 individual sessions); a summary of the experimental design is shown in Table 2.[8]

INSERT TABLE 2 ABOUT HERE

Group condition

Table 3 provides an overview of the group condition. For each of the sixteen group sessions, participants were randomly distributed into groups of four subjects (there was no contact across groups).[9] Each session lasted about two hours, and was video recorded with the participants' consent. Subjects received a participation fee of twenty currency units each; in addition, subjects earned an average of five currency units during the session. At the beginning of each group session, the four subjects were randomly assigned to seats around a round table. The study instructions were provided in writing and were also read out aloud by the instructor. The task in each session consisted of the planning and assembly of one toy model. Each participant was provided with the assembly instructions of the model and the group was given five minutes to discuss and plan the assembly. They were then provided with the parts and tools to assemble the model in 45 minutes, with monetary incentives for the correct and complete assembly (see Appendix for details). After a performance evaluation, the same group received the instructions for a second model, with five minutes for planning and 45 minutes for assembly, followed by the performance evaluation and debriefing.

INSERT TABLE 3 ABOUT HERE

Individual Condition

Each of the sixteen individual sessions closely followed the planning phase outlined in the group condition (with the marked difference that the subjects in the individual condition did not do any assembly). These sessions lasted about 30 minutes, and were audio recorded with the subjects' consent.

[8] The purpose of this experimental design is to contrast the relative difference between treatments. Given the exploratory nature of the research question, it was not possible to include a traditional control condition (as it is not clear what the baseline should be).

[9] We chose four participants based on two considerations: task difficulty and task structure elements There is a maximum number of four object-based task clusters in the SD task and the pilot studies across varying numbers of subjects revealed four activity-based task clusters. Further, the task was feasible but difficult to accomplish in 45 minutes with four participants.

The task for these subjects consisted in deciding how many group members to recruit for the assembly of the same two Meccano models we showed to the groups, and choosing a task division and allocation for those recruits. The participants were asked to verbalize their choices. While the individual participants were paid a fixed fee of ten currency units independent of their choices, the reward structure for their (fictitious) recruits was identical to that in the group condition. While the group condition captures division of labor by an egalitarian self-organizing team that also executes on those decisions (e.g. in project teams, in volunteer or community organizations), the individual condition approximates a situation where an authoritative individual decides on a division of labor that others must then execute (e.g. in a traditional hierarchical bureaucracy).

In addition to their verbalized choices of task division and task allocation, we observed the non-verbalized behavior of the participants in the individual condition by tracking their eye movements while they studied the instructions. The use of eye tracking to study attention patterns in individuals is well established in a variety of fields (see Duchowski (2002) for an overview; see Rayner 1978, 1998 for decision-making specific usage). This approach allowed us to capture which aspects of the model instructions the individuals focused on more or less closely. Thus, we can draw inferences about the relative attention allocation by the individuals (e.g. Rayner et al. 2001; Wedel and Pieters 2000), and hence measure object salience more directly.

Strong and Weak Product Decomposability

The individuals and groups in our experiment discussed (and assembled) two Meccano models. Meccano is a toy that consists of differently shaped metal parts (such as bars and plates), which can be fitted together with screws and nuts to build helicopters, cranes, cars etc. Each Meccano box comes with an instruction booklet for how to assemble the same pieces into very different models. Please refer to the Meccano website for instruction examples: www.meccano.com.[10]

[10] This toy comes in various levels of difficulty; we chose the Meccano 20 box, which contains a small battery-powered motor, and the models in the instruction booklet are about 20 steps in length.

We manipulated the decomposability of the product by choosing two different Meccano models for assembly: a strongly and a weakly decomposable model. The strongly decomposable (SD) model can be readily decomposed into a number of significant, freestanding sub-assemblies that have only few connection points to each other; the elements within a sub-assembly are tightly connected, but have only weak connections to elements in other sub-assemblies. In contrast, the weakly decomposable model (WD) has few and very short sub-assemblies in addition to one large sub-object. Overall, sub-assemblies are easier to identify, more numerous, and involve more steps in the SD model than in the WD model.

The intuition behind the relative decomposability of the models is highlighted in Figure 3; the numbers in this figure refer to the different steps in the Meccano instructions, lines represent the dependence of a given step on the completion of prior steps. In order to choose the WD and SD models for the experiment we created workflow diagrams like the ones shown in Figure 3 for each of the 13 models provided in the instruction booklet and selected the most and least decomposable ones. Both models have near identical numbers of total steps in the assembly instructions (20 vs. 21). In addition, they have near identical numbers of total parts needed for final assembly (SD model: 60 screws + 78 components vs. WD model: 58 screws + 77 components). However, working backwards from the bottom of the tree, it is easy to see that the SD model can be more easily broken up (beginning with step 21 itself) into more and longer sub-assemblies which themselves can be broken into sub-sub-assemblies (1-4, 5-8, battery, 14-20). In the WD case, we would have to undo up to step 10 before the first sub-assembly could be detached (9) and the sub-assemblies themselves are smaller (have fewer steps). Hence, the difference between the SD and WD task lies in the relative difficulty of dividing it among a group of people, rather than in the tasks themselves. Both, the SD and WD tasks require the same set of activities to be assembled, as well as a very similar number of steps and parts. However, while the WD model can only be divided into activities and sequential sub-objects, the SD model can be divided into activities as well as a number of independent sub-objects that only need to be combined in the final step.[11]

[11] To further highlight this important distinction, we can apply Scott Page's 'two measures of difficulty' to these tasks (1996): the SD task structure has a higher cover size (of 3) than the WD task structure (of 1). On the other

INSERT FIGURE 3 ABOUT HERE

Half the groups and individuals were given the SD model followed by the WD model, while the other groups and individuals received the models in the reverse order. All participants were in effect provided with the same true underlying task structure T^R for each model as they received the same instructions, which show a fine-grained decomposition into tasks and their necessary sequence to build the model. However, there is no prescription for the clusters of tasks they divide the task into, and how they distribute these task clusters (i.e. the division of labor, captured by T^A).

Task Division in Groups

For each model, the groups went through two phases: the planning phase – a five-minute period to plan the assembly in which each participant had an identical copy of the instructions – and the assembly phase – a 45 minute period in which the complete Meccano set and two sets of tools were used to build the model as a group. For each group, we coded detailed task division and task allocation data for the planning phase. Everything was coded independently by at least two of the authors, with discrepancies settled through discussion among all the authors.

We captured the object- and activity-based task clusters identified by the groups by carefully coding the different task divisions suggested by the participants throughout the five-minute planning phase of each session. An *object-based task cluster* refers to sequences of steps that produce an intermediate object. Such objects represent tangible intermediate outputs, which are eventually assembled into the model. For instance, in the SD model in Figure 3, the five sub-assemblies are intermediate objects - the sequence of steps ending in numbers 4, 8, 13, 20, and the battery.

The set of *activity-based task clusters* needed for assembly is identical across models. Based on pilot studies, we observed that the clusters of tasks that consistently occurred in the assembly of both

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hand, Page's second measure, the ascent size is almost identical across the two models (21 and 20, respectively). Alternatively, Van Zandt & Radner's measure (Radner and van Zandt 1992; van Zandt 1999; van Zandt and Radner 2001) captures the relative computability of the two models: If we think of each instruction step as a computation with as many parallel elements as possible, we find that the SD model can be completed in 11 time intervals, while the WD model requires 18 intervals – the difference lies in the number of steps that can be completed in parallel.

models, and indeed within each sub-assembly in each model constituted: (1) reading and understanding the instructions, (2) picking the right pieces from the box, (3) holding the new piece against the existing assembly in the right way, and (4) fixing the new piece onto the assembled pieces with the correct screw. Both Fixing and Picking are explicitly represented in the instruction booklet: for each step there is a small box which lists the type and number of different pieces necessary for that step (the picking activity); and a diagram illustrates how those pieces are fitted together or fitted onto already existing parts of the model (the fixing activity). Participants seemed to display significant variation in skill at these activities, because of differences in manual dexterity and ease at reading technical specifications; these activities were apparently difficult enough to enable potential improvement through practice during the course of our sessions (i.e. gains from specialization).

We captured the participants' task division choices as outlined in Table 1; for example, if one of the participants highlighted that the battery could be assembled separately, we counted that as one object-based task cluster *("battery"* vs. *"rest of the model"*); statements such as *"finding the pieces for each step"* by a participant were coded as an activity-based task cluster, Picking. We coded the entire conversation across the five minutes and recorded each addition (or alternative) task division suggested by the different participants, and to what extent those entailed object-based or activity-based task clusters, or both (and how many). The coding process is highlighted in two actual planning discussions in Table 1. At the end of the planning phase, every group had decided on a task division.[12]

INSERT TABLE 1 ABOUT HERE

Task Allocation in Groups

Task clusters identified during the planning phase were chosen or allocated to 'sub-groups' of different sizes. We labelled any configuration of participants that was allocated to work together as a sub-group; thus the size of a sub-group could range from one (an individual) to four (all four participants working closely together). Task allocation occurred either through self-selection or assignment through

[12] Note that none of the groups seemed to feel that the time allotted for the initial discussion (five minutes) was insufficient: indeed 32% of the groups finished their discussions up to two minutes early and 25% asked to receive the pieces ahead of time to start assembly.

others. In the coding process, the task allocations were captured by the participants' numbers (1-4), and were added and updated throughout the planning phase.

For the assembly phase (45 minutes) we coded who worked with whom on what step, and which participant performed which activity on the different steps for how long (in seconds). We updated the interaction structure when we observed changes in collocation and consistent joint handling of parts, and coordination of activities on objects. We had access not only to video but also the audio of the participants' discussions. We therefore have very detailed data on the social patterns of interaction, as well as each individual's activities and productivity.

Task Division & Allocation by Individuals

For the individual condition we coded the choices regarding the object- and activity-based task clusters in the same way as for the group condition; in addition, we captured the number of recruits the subjects decided on for each of the models. We supplemented the verbalized choices with the use of eye tracking data, using a Tobii T60 built-in desktop eye tracker. The eye tracking data allowed us to observe a non-verbalized aspect of the participants' process of the division of labor, moving a step closer to the direct observation of object salience. The eye tracker accurately records which part of the screen the participant focuses on (based on pixels) and for how long (recorded in milliseconds).

RESULTS

Tables 4 and 5 summarize the results for the group and individual conditions, respectively. We report the session- and model-specific mean values across the sixteen groups and sixteen individuals for each of the treatments (standard errors are reported in parentheses). All differences are tested for statistical significance using the Wilcoxon rank-sum test (also known as the Mann-Whitney two-sample statistic), unless stated otherwise. The Wilcoxon rank-sum test tests the hypothesis that two independent samples are from populations with the same distribution, and is appropriate for small samples. All results are equally robust when the Fisher exact test, or a non-parametric k-sample test on the equality of medians is used.

INSERT TABLE 4 ABOUT HERE

Evidence for object salience. For the group condition, we test Hypothesis 1 at the aggregate level across groups and models, as well as across groups within session 1 (controlling for any experience effects), and within groups across sessions (controlling for any group-specific idiosyncrasies).

In the planning phase, the groups systematically identified a greater number of object-based than activity-based task clusters (this holds throughout the planning phase as well as for the final, agreed-upon task division for the groups, reported here): Aggregating across session and models, groups identified an average of 3.81 object-based and 0.56 activity-based clusters (paired ttest $p<0.001$), a result that holds equally strongly when comparing the type of task clusters identified by model (SD: object-based = 4.31, activity-based = 0.13, paired ttest $p<0.001$; WD: object-based = 3.31, activity-based = 1.00, paired ttest $p<0.001$). This result also holds when comparing the type of task clusters identified by session (Session 1: object-based = 3.25, activity-based = 0.56, paired ttest $p<0.001$; Session 2 object-based = 4.38, activity-based = 0.56, paired ttest $p<0.001$). Hypothesis 1 thus receives strong support with groups.

Similarly, in the individual condition, the subjects identified more object- (2.91) than activity-based (0.78) task clusters (paired ttest $p<0.001$), although this tendency was somewhat weaker for session 2 than session 1 (Session 1: object-based = 3.00, activity-based = 0.63, paired ttest $p<0.001$; Session 2 object-based = 2.81, activity-based = 0.94, paired ttest $p=0.0197$). In the individual condition, we supplemented the verbalized choices with the use of eye tracking data. The eye tracking data allowed us to observe a non-verbalized aspect of the participants' process of the division of labor. We aggregated these data to measure the fixation time (milliseconds spent) on object-based versus activity-based visual information. These data revealed that, in general, individuals displayed greater fixation time on the pictorial representations of the object-based than on the activity-based instructions, regardless of the model (object=125.96; activity=48.78, Wilcoxon p<0.001).[13] This is despite the fact that the activity-based instructions are represented saliently in a separate box for each step of assembly in both models. Thus, Hypothesis 1 is supported with individuals as well.

INSERT TABLE 5 ABOUT HERE

While there is a clear pattern of object salience in the data, an alternative explanation is that an object-based task division is merely more efficient for both, the SD and the WD model. However, given the low product decomposability of the WD model, this is not plausible; we tested whether those groups that did not use the hypothesized heuristic (object salience) in the WD model fared better than those that did. Out of the 16 groups that completed the weakly decomposable model, 12 decided to start the assembly of the WD model with at least some activity-based task clusters, while four groups decided on a purely object-based task division.[14] We can look at two outcome variables to compare their performance, (1) the number of steps that were left incomplete at the end of the 45 minute assembly phase, and (2) the speed at which the group progressed, captured by the number of steps fully assembled at the half point of the allotted time. The results are displayed in Table 6.

INSERT TABLE 6 ABOUT HERE

Note that those groups that had decided to include some activity-based task division from the start fared better on both accounts: at the end of the 45 minute assembly phase, those groups that started assembly with some activity-based task division had on average 4.67 steps left before completion, while those groups who started with a purely object-based task division had an average of 8 steps remaining (Wilcoxon, p=0.0494). Further, the activity-based focused groups had put together an average of 6.75

[13] The manner in which decision makers cognitively process the division of labor, we believe, has both top-down and bottom up components (for a review see Gloeckner and Herbold 2011: 79). Individuals confronted with a division of labor problem will react to the stimuli offered by the visual representation of the final product and assembly process, and our theory suggests that their attention may tend to focus more on objects than activities in a non-conscious bottom-up manner, but may also involve top-down processing in group contexts through consideration of secondary salience. More detailed analyses can be found in the online supplement.

[14] We can also show that the initial decision to include some activity-based task division translated directly into the teams' actions: comparing the total number of seconds spent by the individuals in a group on activities, we find that those groups who decided to include some activities from the start spent an average of 575.4 seconds on activities, compared to 85.9 seconds by those groups that decided to focus solely on objects during the discussion phase.

steps at the half point of the allotted time, slightly more than the average of 5.5 steps for those groups that started with a purely object-based task division (Wilcoxon test, $p=0.2676$, Fisher Exact test, $p=0.083$).

In a separate study (results available in the online supplement), we further tested whether the strong focus on objects itself would disappear if we made activities salient in the instructions. We replicated the individual conditions and primed the focus on activities by including a one-line description of each of the four activities before showing the models to the subjects. If optimality rather than object salience drives the original result of generating object-based task divisions in both weak and strongly decomposable models, then this treatment condition should have no effect. We found that this manipulation was indeed sufficient for the subjects to focus their task division choices on activities in both models. This finding lends further support to the proposed mechanism of object salience as a heuristic in the process of the division of labor for novel and non-repetitive production.

A corollary to Hypothesis 1 is that the discovery of *activity-based* task clusters should be relatively easier in WD than SD models, because object salience would cause individuals to prioritize objects, turning to activities only when running out of objects. We find that in the planning phase, the groups indeed identified a greater number of activity-based task clusters in the WD model than in the SD model, regardless of session (SD=0.13, WD=1.00, Wilcoxon $p<0.001$), even though in principle the same number of activity-based task clusters is feasible in both models (namely four - Explaining, Picking, Holding, and Fixing). The results also hold when comparing the number of activity-based task clusters identified in the WD and SD models by session (see Table 4, session 1 Wilcoxon $p=0.0986$; session 2 Wilcoxon $p=0.001$).

Similarly, in the individual condition, the number of activity-based task clusters identified by the subjects was higher in the WD model than in the SD model (SD=0.38, WD=1.19; Wilcoxon $p=0.0073$; see Table 5, WD vs. SD in session 1 Wilcoxon $p=0.0372$; WD vs. SD in session 2 Wilcoxon $p=0.0751$). From the eye tracking data, we computed the ratio of time spent looking at activity- to object-based task clusters to capture the relative difference across the SD and WD models. We found that the ratio of fixation time on activity-based to object-based instructions was greater for the WD model than for the SD model in session 1 (SD1=0.32, WD1=0.49; Wilcoxon p=0.0357); however this difference disappeared for the second session (SD2=0.39; WD2=0.39).[15]

Evidence for stronger object salience in groups than individuals. Hypothesis 2 predicted that groups should show a greater tendency for object-based task divisions than individuals in the process of division of labor. At the aggregate level, we found that all groups agreed to divide the assembly task predominantly by object, regardless of its degree of decomposability (SD object=4.31, activity=0.13, paired ttest p=0.000; WD object=3.31, activity=1.0, p=0.0003, across sessions). In contrast, the individual decision-makers showed strong object salience in the SD model (object=4.13, activity=0.38, paired ttest p<0.001), while choosing on average about equal number of activity-based and object-based task clusters for the WD model (object=1.69, activity=1.19, paired ttest p=0.3821). Comparing the number of object-based task clusters identified across the group and individual conditions directly, we find that the groups chose a significantly greater number of object-based task clusters compared to the individuals (group objects=3.81; individual objects=2.91, Wilcoxon p=0.051). Thus, hypothesis 2 is supported. Note that this difference across groups and individuals is driven by the groups' greater object salience *in the WD model*: while groups and individuals chose an equal number of objects in the SD model (group objects=4.31, individual objects=4.13, Wilcoxon p=0.669), groups chose a significantly greater number of objects in the WD model (group objects=3.31, individual objects=1.69, Wilcoxon p=0.006), exactly as our theoretical reasoning would suggest.

Evidence for stronger object salience in pre-existing groups than de novo ones. Hypothesis 3 predicted that groups with established interaction patterns should show a greater tendency for object-based task divisions than de novo constituted groups in the process of division of labor. At the aggregate level, we found that groups with established interaction patterns (groups in session 2) chose significantly more object-based task clusters than de novo constituted groups (groups in session 1) (objects in established groups=4.38, objects in de novo groups=3.25, Wilcoxon p=0.021). Comparing the object

[15] Note that those individuals who see the WD task in session 2 have previously studied the SD instructions. We speculate that this has primed them to search for objects in the WD task in session 2, which might be why the difference disappeared for the second session.

salience across de novo and established groups by model, we find that established groups chose significantly more object-based task clusters than de novo constituted groups in the WD model (objects in established groups=4.25, objects in de novo groups =2.38, Wilcoxon p=0.067) while there was no statistically significant difference for the SD model (objects in established groups=4.50, objects in de novo groups=4.13, Wilcoxon p=0.608). Thus, while we find that groups with an established interaction pattern show greater object salience in general, this effect is stronger when the product is only weakly decomposable.

To show that the stability preference is the driving force behind this difference in the strength of the influence of object salience, a closer examination of the mechanism is required. In particular, our prediction was that the object salience is stronger in groups with established interaction patterns, given that such a task division allows them to satisfy their stability preference. The necessary condition for this mechanism to underlie our results is the occurrence of the stability preference in our experiment, and for it to be easier to meet with SD than WD models. In order to capture the established interaction patterns of the groups, we coded who worked with whom for how long on which steps during the 45 minute long assembly phase of session 1. From those data we could identify the dominant social structure for each group and compare that to the task allocation suggestions at the beginning (t=0) and the end (t=5) of the planning phase from session 2. Remarkably, we found that the discussions in *every single group* (regardless of the model encountered in session 2) initially focused on maintaining the existing sub-group structure, i.e. the initial attempts of task division and task allocation were done taking the existing social structure as fixed; these results are reported in Table 7. Thus, stability preference does seem to underlie our results for Hypothesis 3.

INSERT TABLE 7 ABOUT HERE

Further, we examined the effect of product decomposability on this stability preference. Given the constraints imposed by the WD model on the number of available, free-standing objects that can be allocated to different participants (and worked on in parallel), we should expect that the social structure successfully survives to the end of the planning phase to a greater extent in groups assembling the models in the order 1WD-2SD, but to a lesser extent in those groups assembling the models in the reverse order (1SD-2WD). The data support this asymmetry in the preservation of the social interaction patterns: in the groups that worked on the two models in the sequence of WD1-SD2, dominant sub-groups were replicated and maintained into the assembly phase 100% of the time, while in the reverse sequence (SD1-WD2), only 12.5% of groups retained those dominant sub-groups into session 2 (Table 7, WD-SD=1, SD-WD=0.125, Wilcoxon p=0.0006).

Interestingly, the stability of sub-group structures across sessions in the WD1 led to a different task allocation for the SD model – while four object-based task clusters were identified by the groups (average of 4.5 object-based clusters in SD2), the average number of sub-groups used for SD2 was 2.75 (significantly different from 4, paired t-test t=0.0053). Thus, groups *identified* four separable object-based task clusters for the SD model, and noticed that those could be worked on in parallel, but then proceeded to allocate those to the e*xisting sub-groups* rather than the four individuals.

DISCUSSION & CONCLUSIONS

While the division of labor is widely present in Nature (e.g. see Rueffler et al. 2012), this study explores -in the lab- aspects of the division of labor that exist uniquely in human organizations – the process by which tasks are divided, clustered, and allocated with a goal in mind. In this study, we investigated this process with a focus on its behavioral micro-foundations – in particular we tested our key argument for the presence of object salience when individuals (and groups) engage in the process of division of labor for novel, non-repetitive production. We studied how object salience manifests itself in the process of division of labor involving more and less decomposable products, as well as when conducted by self-organizing groups or individuals charged with making this decision for a group.

Our results support our central claim that both individuals and groups show a greater propensity to perceive and select object-based task clusters rather than activity-based task clusters when engaging in the division of labor for novel, non-repetitive production. The propensity is strongest in pre-existing groups and weakest in individuals, with newly formed groups lying in between. This propensity is present for the production of both strongly and weakly decomposable products, and can lead to objectively inefficient choices for the latter, leading possibly to lower performance.

In contrast to the findings for the groups, familiarity with the tasks appears to weaken the individual designers' tendency to choose object-based task clusters, as well as their tendency to focus more on activity-based task clusters in the WD model. It appears that this 'experience' effect is suppressed in groups; we speculate that object salience may weaken with experience of and familiarity with the underlying task structure (in groups and individuals, with or without hands-on experience). However, it may be that the greater ease of naming and describing objects (rather than activities) counteracts the experience effect to a greater extent in groups (Paolacci, Legrenzi and Warglien 2013; Reagans, Miron-Spektor and Argote 2012).

Our analysis also shows that the tendency towards object-based task division seems to be reflected in the subjects' non-verbal behavior (what they pay attention to) as much as in their verbalized choices. Thus, even though object-based task division may be preferred by individuals based on motivational reasons (Hackman and Oldham 1976) or because it enhances the ease of monitoring effort (Zenger and Hesterly 1997), our data on attention allocation based on eye-tracking (as well as additional experiments in which we weaken object salience by raising the salience of activities across models) indicate strongly that these factors alone cannot explain our results.

Implications for Research and Practice

Historically, the decisions regarding the division of labor have been assumed to be driven predominantly by characteristics of the production process (Smith 1776; von Mises 1949). As a result, the notion of a correspondence between technology and organization has been an influential one in organization science (e.g. Baldwin and Clark 2000; Galbraith 1973; Henderson and Clark 1990; Sanchez and Mahoney 1996; Thompson 1967; Tushman and Nadler 1978; von Hippel 1990; Woodward 1958). In this view, the output to be produced determines the choices about optimal task division and task allocation. In contrast, a number of field studies indicate that the process by which individuals in an organization adopt (e.g. Fulk 1993), interpret (e.g. Barley 1988), and use (e.g. Orlikowski and Yates 1994; Poole and DeSanctis 1990) new technologies cannot be explained purely with reference to the properties of the technology itself. Pre-existing social structures (e.g. Barley 1986) as well as individual ways of thinking (Barley 1988) can play significant roles.

This interplay between the technological properties of production and social dynamics have been examined in the modularity literature as the 'mirroring hypothesis'[16] (Colfer and Baldwin 2010): If organizations are structured to enhance coordination between individuals working on tasks with high interdependencies between them, then it seems intuitive that the intended structure of interactions between people should mirror the structure of interdependence between tasks assigned to people; the converse is also possible, with interaction patterns leading to a focus on certain interdependencies (Henderson and Clark 1990). Hence, the mirroring hypothesis suggests correspondence between the structure of tasks (i.e. the pattern of interdependencies within and between task clusters) and the structure of organization (i.e. in the pattern of interactions between individuals working on tasks). Tests of the mirroring hypothesis have been conducted both in the intra-firm (e.g. Sosa 2004) and inter-firm context. For instance, Hoetker (2006) found that modular design of products promote reconfiguration faster than they promote outsourcing. Cabigiosu and Camuffo (2012) found that modular designs reduced information exchange between firms and their vendors, but that thick information exchange could enable modular designs to emerge. Colfer and Baldwin (2010) reviewed 102 studies from both within and between form contexts; two thirds of the studies they analyzed found some support for the mirroring hypothesis. Colfer and Baldwin highlighted that the remaining studies could be categorized into two classes of exceptions: situations in which integrated organizations produced modular technologies, and in which distributed non-integrated organizations worked on highly integrated products. These empirical results show that the relationship between technology and organizational structure is not deterministic, though technological structure shapes what is feasible.

[16] Also referred to as "Conway's Law" in Computer Science.

Our results on object salience in division of labor deepen our understanding of these linkages between the technological properties of the task and behavioral aspects, in three ways. First, we note that the individual tendency to identify object-based task clusters that we document in our studies suggests that the emergence of specialization by activity (which requires the identification of activity-based task clusters) is not spontaneous. That it is observed often in repetitive tasks may have as much to do with the greater ease with which activity-based clusters are identified through repetition, as with the fact that the gains from specialization increase with repetition. Thus in 'one-shot' organizations such as project-, disaster relief-, research- or combat teams, the gains from specialization may remain invisible unless a general template for organizing exists in that domain (e.g. Baron, Hannan and Burton, 2001; Bechky 2006) and is drawn upon, which explicitly identifies activity-based task divisions. Perhaps activity mapping and the construction of process flow diagrams may stimulate the recognition of potential activity-based task divisions in these contexts.

Second, our results also suggest that the process of division of labor when a pre-existing group takes on a production goal is not the same as that when a new group is formed around a goal. In the former case, the tendency to preserve the existing group structure - its boundaries and internal interaction patterns - may preclude certain divisions of labor and make others more likely. This tendency may confront and succumb to objective technological constraints when producing weakly decomposable outputs, but if the technological properties offer many degrees of freedom in organizing the work, then the preservation tendency may prevail. Specifically, the more decomposable model in our study allowed the existing interaction structure to prevail, but the less decomposable model did not. An organization designer who is blind to the existing social structure (as in our study with individual designers) may offer a means by which groups can avoid their past exercising undue influence on their division of labor.

Third, we believe that technological changes that confront an existing organization may have very different impacts depending on whether the change results in a more or less decomposable product. A change to a less decomposable new product may create significant disruption to an organization. A new, more decomposable product may be less disruptive to the organization, but may result in un-exploited gains from customization which de-novo organizations, like start-ups, may perhaps find easier to exploit. These results add texture to the well-known insight that architectural innovations pose particular challenges for organizational adaptation (Henderson and Clark 1990), by highlighting that the degree of decomposability of the new output may critically shape the nature of outcomes.

Limitations and Opportunities for Future Research

In this study, we have examined the process of division of labor, specifically in situations of novel, non-repetitive production. It is important to reiterate this boundary condition and its implications for our theory and evidence: Low repetition implies that gains from specialization are not automatically privileged over gains from customization, and high novelty implies that the decomposability of the task structure is hard to determine ex ante (as are the magnitude of the relative gains from specialization and customization). Project-based organizations with an imperfect understanding of the task structure underlying their goals are a canonical instance of the phenomenon to which our arguments apply. In contrast, our arguments would not be relevant for large-scale production using a well-understood technological process with which an organization has significant experience. Our claims for relevance thus rest on the increase in the relative if not absolute importance of the former vs. the latter kind of production in a knowledge based economy.

Second, our results are very likely culturally bounded. On the face of it, the demographics of our participants reflects the international nature of their institution – 46% of the group participants and 75% of the individual condition participants were broadly defined as Asian (Chinese, Korean, Japanese). While there is evidence of cultural differences between the way 'Easterners' and 'Westerners' make sense of the world (e.g. Nisbett 2005), our results do not show this difference by cultural background. We believe that this may be partly due to a strong selection effect Western universities (like the one from which our subject pool is drawn) impose on their student body, based on language-proficiency. This certainly restricts the cross-cultural generalizability of this study. An interesting opportunity for future research is to obtain culturally representative samples (which our studies had not been set up to do) to compare if there are reliable differences in the division of labor selected for the same production goal across cultures - and if there is a cultural basis for understanding why process oriented management practices like JIT and TQM (which emphasize activity-based task division) took off first in Eastern cultures.

Finally, while we have explored only a specific set of hypotheses in this study that pertain to object salience in the division of labor, we believe the experimental paradigm we have developed may be useful in exploring others, and more generally for studying division of labor and organization design in the lab. This novel experimental paradigm allows for rigorous rank ordering of the experimental tasks in terms of their product decomposability, significant expertise development, and straightforward coding of task division, task allocation, performance, and various related metrics. This study thus embodies useful methodologies that may enable further progress in our understanding of the micro-foundations of organization design.

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FIGURE 1 – Example of T^R and T^A

$$
\begin{bmatrix}
1 & 1 & 0 & . & . & . & 0 \\
1 & 1 & 1 & & & & \\
0 & 0 & 1 & & & & \\
. & & & & & & \\
. & & & & & & \\
. & & & & & & \\
1 & & & & & & 1
\end{bmatrix}
\longrightarrow
\begin{bmatrix}
1 & 1 & 0 & . & . & . & 0 \\
1 & 1 & 1 & & & & \\
0 & 0 & 1 & & & & \\
. & & & & & & \\
1 & & & & & & 1
\end{bmatrix}
$$

T^R nXn $\qquad$ T^A mXn

Figure 2 – Decomposability and the Division of Labor

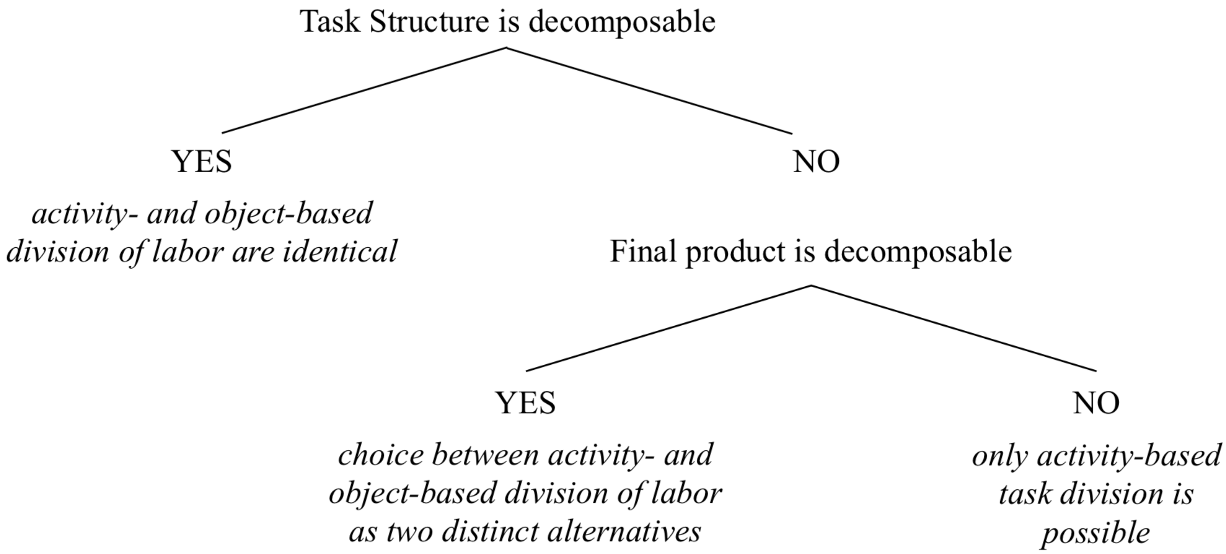

FIGURE 3 - Workflow Diagrams to Highlight Model Decomposability

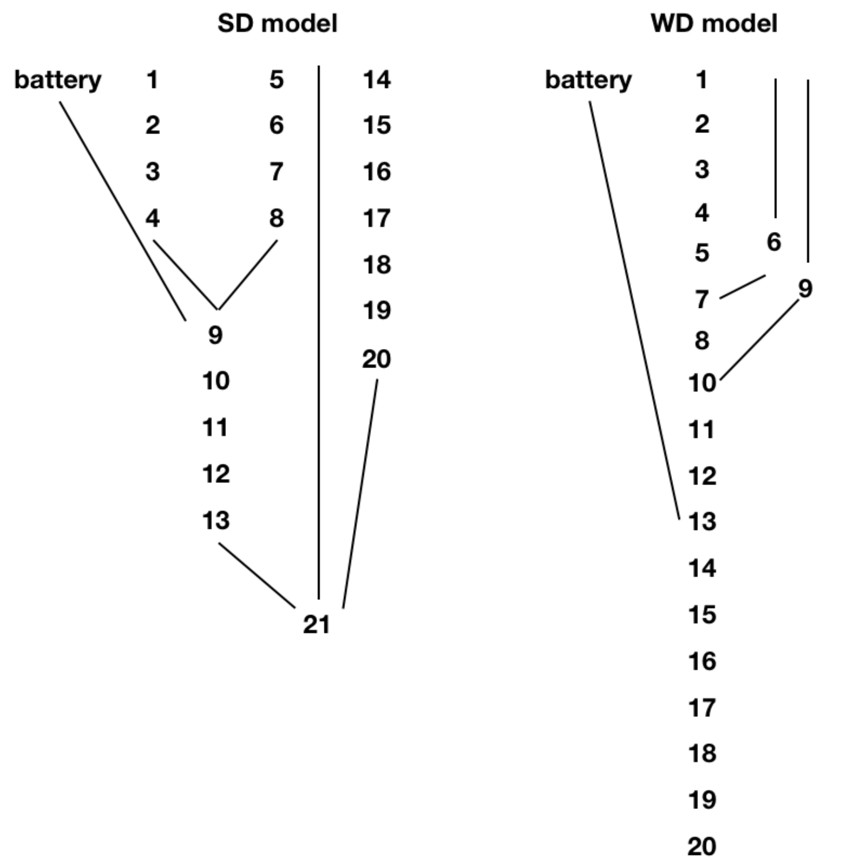

TABLE 1 – Two Coding Examples: Initial Task Division and Allocation during the 5 minute planning Phase of two groups

TABLE 1, panel (a)

Group 4 - First session: Cable Car (SD model) - 5 min discussion - example of a group focusing purely on object-based task division -						
Minute	**Second**	**Subject 1**	**Subject 2**	**Subject 3**	**Subject 4**	**CODING**
SD	**Cable Car**	**5 minutes to discuss**				
0	**0**	R	R	R	R	
1	**50**	“this is the battery, I think?	R	“so I guess we need to make this as quickly as possible”	R	1 sub-object identified (battery)
2	**0**	R	“yea, and there are like separate bits”	“yes, so one person can make this at first - then I can see that like 15 and 14 are like separate, can be made from the very beginning - so one person can start with that, and another can start with 1,2,3,4 and then -”	R	2 additional sub-objects (1-4), (14,15)
	30	R	“so then someone can start from 5, 5-8, and someone can do 1-4 which is the motor" [pointing on his sheet to 3]		R	1 additional sub-object (5-8)
	45	“so 1-4, 5-8,...”	“so there is the battery, the motor, the structure - that’s 3 - and then 14..."	... “then 14,15... until 20 and then all together”	R	summarizing: 4 sub-objects identified
3	**0**	R	R	R	R	
	30	“5-7? ok, I start with 1-4 then”	R	“ok, I can start with these, from 5-7...”	R	task allocation by 2 players
	45	R	“I don’t mind doing 14 to 20 - [to 4] so you can do the battery?”	R	“then I will do the battery”	task allocation by 2 players

Table 1 provides two coding examples. The first table shows the first 4 minutes of the planning phase for group 4, discussing how to assemble the strongly decomposable model. The letter “R” captures participants reading the instructions; “P” refers to the activity of picking the right pieces for each step. The ‘Subject’ columns contain the subjects’ actual conversation (reacting to each other). In those cells, numbers in square brackets describe which other subject they are addressing, e.g. Subject 2 at 2min 30 sec said, *“So then someone can start from 5, 5-8, and someone can do 1-4, which is the motor”* and he was explaining this to subject 3, while pointing at steps 5-8 and 1-4. The last column indicates how we coded this conversation. Every time a new or competing sub-object or activity is identified, discussed or allocated, we code this as an update in the task division and allocation by the group. The second table shows the same planning phase for group 5, discussing the assembly of the weakly decomposable model.

TABLE 1, panel (b)

Group 5 - Second session: Jeep (WD model) - 5 min discussion - example of a group trying to find sub-objects in a weakly decomposable task -						
Minute	**Second**	**Subject 1**	**Subject 2**	**Subject 3**	**Subject 4**	**CODING**
WD	**Jeep**	**5 minutes to discuss**				
0	**0**	R	R	R	R	
	35	“so, let’s split in parts” [1-12]	R	R	R	1 object identified (1-12)
	55	“yea, it can’t be split in parts”	R	R	R	
1	**0**	R	R	“I’ll do the battery again”	R	1 additional sub-object (battery); task allocation by one player
	10	“and then we [points to 2] can do this one” [points to the start of the instructions]	R	“I’ll work on the wheels as well”	R	same as above (1 onwards); 1 additional sub-object (wheels); task allocation by 3 players
	15	“let’s find small parts that need to be done… 6,9”	R	R	R	2 additional sub-objects (6, 9)
2	**25**	“ok, I’ll do 1-5; [to 2] you do 6 and then we’ll put them together”	R	R	R	task allocation by 2 players
	35	“can someone do P [to 3,4]; and whenever we do it, let’s have all the material we need on the side and then check…"	R	R	R	1 activity identified (P)
3	**10**	“this time we’ll be quick!”	R	[to instructor] “if we start now, will we get extra time to complete it?” no - “ok, then let’s keep looking at it”	R	
	45	“9, who will take 9?”	R	R	“I will do 9”	task allocation to 1 player
4	**15**	“oh, do you need to do the battery first”	R	“yes. we’ll be working on the battery and motor part together” [pointing at 4]	R	discussion about task allocation
	45	“no, no, you do the battery, and then I start this, and you do the separate parts”	R	“yes, so we’ll do the motor, you do something else”	R	discussion about task allocation

TABLE 2 – Summary of the Experimental Design

Group condition				Individual condition			
#	Session 1	Session 2	# subjects	#	Session 1	Session 2	# subjects
1	SD	WD	4	1	SD	WD	1
2	SD	WD	4	2	SD	WD	1
3	SD	WD	4	3	SD	WD	1
4	SD	WD	4	4	SD	WD	1
5	SD	WD	4	5	SD	WD	1
6	SD	WD	4	6	SD	WD	1
7	SD	WD	4	7	SD	WD	1
8	SD	WD	4	8	SD	WD	1
9	WD	SD	4	9	WD	SD	1
10	WD	SD	4	10	WD	SD	1
11	WD	SD	4	11	WD	SD	1
12	WD	SD	4	12	WD	SD	1
13	WD	SD	4	13	WD	SD	1
14	WD	SD	4	14	WD	SD	1
15	WD	SD	4	15	WD	SD	1
16	WD	SD	4	16	WD	SD	1

Table 2 provides an overview of the experimental design: Group condition – groups of four members discussed task division and allocation (5 min) and assembled (45 min) two Meccano models; Individual condition – individuals described task division and allocation for two Meccano models; SD – strongly decomposable model; WD – weakly decomposable model.[17]

[17] As mentioned above, it was not possible to include a traditional control condition, as it is not clear what the baseline should be.

TABLE 3 – Overview of the Experimental Design, Group Condition

Group Condition		
Duration	**Task**	**Data coded**
5 minutes	introduction and explanation of the task	
	distribution of first assembly instructions to all participants	
5 minutes	group discussion with toy model instructions	task division and allocation decisions
	distribution of toy parts	
45 minutes	assembly of the first toy model	sub-group stability, size
10 minutes	assessment, splitting of monetary award, questionnaire	performance
	distribution of second assembly instructions to all participants	
5 minutes	group discussion with toy model instructions	task division and allocation decisions
	distribution of toy parts	
45 minutes	assembly of the second toy model	sub-group stability, size
10 minutes	assessment, splitting of monetary award, questionnaire, debrief	performance

TABLE 4 – Summary of Results of the Group Condition

		SD	WD
Session 1 - Planning Phase	**number of object-based task clusters**	4.125 (0.227)	2.375 (0.263)
	number of activity-based task clusters	0.25 (0.164)	0.875 (0.295)
Session 2 - Planning Phase	**number of object-based task clusters**	4.5 (0.378)	4.25 (0.701)
	number of activity-based task clusters	0 (0.0)	1.125 (0.227)

Table 4 shows the detailed results from the planning phase in the group condition, split by type of model and session. Aggregate results and Wilcoxon tests are reported in the text. Standard errors are shown in parentheses.

TABLE 5 – Summary of Results of the Individual Condition

		SD	WD
Session 1 - Verbalized Choices	**number of object-based task clusters**	3.875 (0.295)	2.125 (0.441)
	number of activity-based task clusters	0.25 (0.164)	1.00 (0.267)
	number of group members	3.00 (0.327)	2.875 (0.227)
Session 1 – Eye tracking Data	**ratio of fixation on activity/object**	0.315 (0.052)	0.491 (0.054)

		SD	WD
Session 2 - Verbalized Choices	**number of object-based task clusters**	4.375 (0.532)	1.25 (0.590)
	number of activity-based task clusters	0.5 (0.189)	1.375 (0.375)
	number of group members	3.625 (0.183)	2.00 (0.189)
Session 2 – Eye tracking Data	**ratio of fixation on activity/object**	0.394 (0.031)	0.390 (0.096)

Table 5 shows the detailed results from the individual condition, split by type of model and session. Aggregate results and Wilcoxon tests are reported in the text. Standard errors are shown in parentheses.

TABLE 6 - Effects of Object-Salience in the WD Model on Performance

	Groups with activities	Groups with objects only	Wilcoxon test, p-value
Steps remaining at t=45	4.67 (0.907)	8.00 (1.155)	0.0494
Steps assembled at half point	6.75 (0.566)	5.50 (0.289)	0.2676
Seconds spent on activities	575.42 (90.789)	85.94 (84.692)	0.0152
n	**12**	**4**	

Table 6 shows performance results for two sets of groups: four groups that started the assembly phase of the WD task with object-based task clusters only; and 12 groups that started the assembly with at least some activity-based task clusters. Standard errors are shown in parentheses.

TABLE 7 – Group Condition – Stability Preference

		SD1-WD2	WD1-SD2
		SD1	**WD1**
Session 1 - Assembly Phase	**average time spent in dominant social structure**	1696.5 (237.713)	1899.375 (230.898)
		WD2	**SD2**
Session 2 - Planning Phase	**attempt to maintain dominant social structure at t=0**	100%	100%
	success at maintaining dominant social structure by t=5	12.50%	100%

Table 7 shows summary results for the group condition from the assembly phase of session 1 and the planning phase of session 2. Aggregate results and Wilcoxon tests are reported in the text. Standard errors are shown in parentheses.

APPENDIX

Instructions to Participants:

You will work in a group of four to assemble a Meccano model. We will provide you with the instructions, the tools, and all necessary parts to put the model together correctly. Your group will be evaluated on the basis of (1) the time needed to complete the model, and (2) accuracy of your model. You will have **5 minutes to plan** the assembly of the model, followed by up to **45 minutes** to **plan and execute** the assembly of the model.

- Your group will receive [currency units] 40 if you finish building the model within the time limit. We will evaluate your model in terms of accuracy and functionality and deduct [currency units] 2 for every inaccuracy.
- If you do not finish the model within the time limit, you will receive [currency units] 20 and we will deduct a further [currency units] 2 for every step in the instructions you have not completed and for every inaccuracy.

At the end of the session you will receive the final reward. Your group is then free to decide how to split the money between the four of you.

ONLINE SUPPLEMENT

Additional insights from the eye-tracking data

We find some evidence that bottom-up processing appears to be involved in both, the activity-related parts of the instructions and the object-related parts. Gloeckner & Herbold outline that *"eye-tracking technology allows one to investigate whether individuals mainly scan information (and rely on automatic, intuitive processes of information integration), or whether they compute information on a higher level of attention (and use more thorough deliberate comparison of information)."* (2011: 79); this can be achieved by examining the relative fixation length. Based on a careful review of many prior studies they conclude that fixations longer than 500 milliseconds appear to indicate top-down processing, while fixations shorter than 250 milliseconds appear to indicate bottom-up processing (e.g. Velichkovsky, Challis, and Pomplun, 1995; Rayner, 1998; Horstmann, Ahlgrimm, & Gloeckner, 2009).

Based on these observations, we examined the eye tracking patterns of the individuals across the different instruction parts (reported below). We find that the average fixation duration on object- and activity-related parts of the instructions fall way below the 250 millisecond threshold (125.958 and 48.775, respectively); both numbers are statistically significantly different from the threshold of 250 milliseconds. Hence, individuals appear to engage in bottom-up processing for both, activity- and object-related parts of the instructions (the difference between the average fixation duration between the SD and WD models is not statistically significant).

Within this distinction, object-related instruction parts appear to draw relatively more attention: This is apparent by looking at the difference in average fixation duration, as well as at the difference in the number of fixations: individuals show an average fixation duration on object-related parts of 125.958 milliseconds (compared to 48.775 milliseconds for activity-related instruction parts); and the number of fixations is greater for object-related parts (403.56) than activity-related parts (171.13), indicating a relatively stronger overall focus on objects over activities.

	Object-related instruction parts	**Activity-related instruction parts**	**Wilcoxon, p-value**
Average fixation duration - overall	125.958 (10.780)	48.775 (5.964)	0.000
Average fixation duration – SD model	141.333 (16.704)	49.602 (7.829)	0.000
Average fixation duration – WD model	110.584 (13.031)	47.948 (9.254)	0.001
Total number of fixations - overall	403.563 (33.735)	171.125 (18.507)	0.000
Total number of fixations – SD model	461.625 (51.269)	179.813 (25.857)	0.000
Total number of fixations – WD model	345.500 (40.324)	162.438 (27.150)	0.001

Manipulating activity salience

In a follow up study we test whether the difference in object-salience between the SD and WD models can be 'switched off' by making the activities more salient. In order to maintain comparability, we replicated the individual designer study and included an additional paragraph in the instructions. That paragraph listed the four activities that would go into the assembly of Meccano sets. If optimality rather than object salience drives the original result of generating object-based task divisions in both weak and strongly decomposable models, then this treatment condition should have no effect.

We found that this manipulation was indeed sufficient for the subjects to focus their task division choices on activities in both models. Detailed results by session and model are reported in the table below, both for the original study ("original results" columns, as reported in the paper), as well as for the new study that makes activities salient ("activity salience" columns). Recall that the original individual study showed that subjects chose more object-based than activity-based task clusters for both models (WD and SD). In contrast, in this follow up study, the subjects focused their task division choices on activities for both models: In the SD model, subjects chose – on average – 0.81 object-based and 2.50 activity-based task clusters (paired ttest, p<0.0074), while they chose 0.25 object-based and 3.00 activity-based task clusters for the WD model (paired ttest, p<0.0001). Clearly, the manipulation of spelling out the four different activities that go into the assembly of Meccano models had a strong effect on the individuals' choices and 'switched off' the object salience. This finding lends further support to the proposed mechanism of object-salience as a heuristic in the process of the division of labor for novel and non-repetitive production.

Experiment 2 - Individual Designer		**original results**		**activity salience**	
		SD	**WD**	**SD**	**WD**
Session 1	**number of object-based task clusters**	3.875 (0.295)	2.125 (0.441)	0.625 (0.498)	0.375 (0.183)
	number of activity-based task clusters	0.25 (0.164)	1.00 (0.267)	2.5 (0.378)	3.125 (0.295)
		SD	**WD**	**SD**	**WD**
Session 2	**number of object-based task clusters**	4.375 (0.532)	1.25 (0.590)	1.000 (0.500)	0.125 (0.125)
	number of activity-based task clusters	0.5 (0.189)	1.375 (0.375)	2.5 (0.327)	2.875 (0.295)