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The Multi-Scale Dynamics of Executive Function

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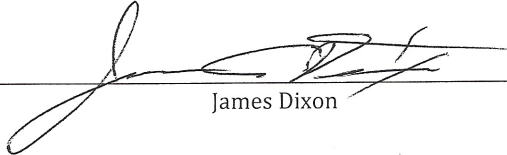
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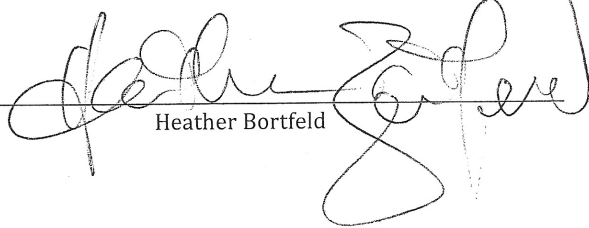
Master of Arts

The Multi-Scale Dynamics of Executive Function

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Abstract

Cognitive control is a central issue in developmental psychology. Traditional theories of psychology solve this problem by positing a top-down central executive, which coordinates cognitive resources in pursuit of goals. We propose an alternative explanation: cognitive control arises from physical interactions across many different timescales within the system. College and preschool aged participants were asked to complete a simple executive function task, card sorting. We found that multi-scale physical interactions differed depending on experimental constraints, and that executive function in these cases was driven primarily by flexibility in multi-scale interactions, rather than the dominance of one scale. This suggests that, rather than being the workings of a higher order central executive, cognitive control may be driven by physical interactions within the system.

The Multi-Scale Dynamics of Executive Function

A central problem in the study of developmental psychology concerns cognitive control. According to standard approaches to cognitive science, the cognitive system is made up of a number of subsystems; somehow, it must control and coordinate these subsystems in order to function. Imagine a task as simple as navigating oneself through the environment. According to the modal view of psychology, navigation requires a number of cognitive capabilities (Wolbers & Hegarty, 2010). Among other things, navigation requires selectively attending to rapidly changing environmental information, storing and retrieving information from memory, and responding to changes in the environment by choosing the correct action from an array of possibilities. Even during something as simple as navigation, a variety of cognitive resources must be utilized and coordinated.

This coordination during complex actions requires explanation. Classical theories of psychology traditionally solve this problem by positing a master subsystem called “executive function.” On this account, executive function has direct control over the rest of the cognitive system. It is responsible for the “monitoring and controlling of thought and action (Carlson, 2005),” deploying cognitive resources in response to the ever-changing circumstances of the cognitive system.

The Development of Executive Function

Executive function goes through a series of developmental steps. Infants have very poorly developed executive function, and show very little ability to plan ahead and make premeditated decisions about things in their environments. For example,

failure on the classic Piagetian A-not-B task has been described as reflecting immature executive function (Diamond, 1998). The reason that the infant is unable to correctly identify the location of the desired object is due to the inability to inhibit a pre-potent response, according to Diamond. The A-not-B task, Diamond (1985) said, "...sets up a competition between the ability to use short-term recall to guide behavior and a conditioned behavioral tendency to repeat a rewarded response" (p. 880). The rewarded response is the behavior that needs to be inhibited. As children grow older, their executive function improves. By 12 months of age children successfully pass the A-not-B task (Smith & Thelen, 2003).

However, more difficult executive function tasks, such as card sorting, still pose a challenge for children during the preschool years. Zelazo and his colleagues (Zelazo et al., 2003; Muller et al., 2008; Zelazo, 2006) have shown that, under many circumstances, children at 3 years of age have trouble switching rules during card sorting, even when the rule is given explicitly. According to the standard account, the successful execution of card sorting requires the use of a variety of subsystems, including storage of feedback and perceptual information in memory, the use of deductive reasoning to determine which of several rules is the correct one, and making and executing a plan of action when a rule is chosen. Because card sorting requires the use and coordination of cognitive subsystems, it provides a sensitive index of executive function (Zelazo et al., 2003).

By 5 years of age, most children smoothly change rules when told to do so (Zelazo, 2006). The development of executive function continues into adulthood (Zelazo, Carlson, & Kesek, 2008; Zelazo, Craik, & Booth, 2004). Other card-sorting

tasks, such as the Wisconsin Card Sort, are designed to evaluate the executive function capabilities of older children and adults (Grant & Berg, 1948). As these examples illustrate, executive function appears to have a protracted developmental course. These developmental changes allow children to perform tasks requiring increasingly complex cognitive coordination.

The Modal Theory of Executive Function

The dominant approach to executive function is to define it as a top down, higher-order process (Carlson, 2003). On this account, executive function exerts direct control over the system. Executive function takes information about the circumstances of the cognitive system, and changes the system in response to those new circumstances.

This explanation and, indeed the term “executive function,” imply that there is a controlling entity in the system, governing its goal-directed behavior. Described this way, executive function is treated implicitly (and sometimes explicitly – see Baddeley, 1996) as a homunculus in the mind. However, endowing the system with a central planner carries some very difficult theoretical problems (Anastas, Stephen & Dixon, 2011). For example, one must explain where the central planner’s ability to plan comes from. The executive must have its own executive to make plans, which in turn must have its own executive, and so on. Obviously, this creates an infinite regress; by invoking an executive as the solution to the problem of cognition, one merely pushes the explanation for control of action back a theoretical level, into a construct that must then have its own workings explained. Much of the work

relating to executive control is an attempt to eliminate the homunculus as an explanation (Yeung, 2010).

A second, less obvious problem is that the executive must have more information about the state of the system and the environment than the system itself does. The gathering and interpretation of information about the environment, the system, and their relationship, is a problem that is being solved by taking explanatory power away from the system itself and assigning it to a central executive. The central executive, therefore, must know more about these things than the system itself does; otherwise, the central executive would not be necessary. Unfortunately, one problem has been exchanged for another. How can the executive possess more information than the system itself?

The Problem of Mind/Body Dualism

More broadly, ascribing executive control to a central executive is a consequence of committing to a physical/mental property dualistic perspective. Under this perspective, the world is divided into those objects that have physical properties, and those that have nonphysical properties. A dualistic approach to cognition would suggest that the brain and mind are separated entities, related but independent. Under this division, the brain is physical, while the mind is nonphysical in nature. Physical information is transformed by some unknown means into nonphysical objects. Cognition is the process by which the mind manipulates these representations in the pursuit of thought and action.

Because the mind is nonphysical, however, physical law cannot explain its workings; the minds' interactions with the world require an alternative explanation.

The mind must take action based on information about the world. The interpretation of that information provides the motivation to change itself, and enact change upon the world. Dualism, therefore, invites an executive entity that is capable of knowing what needs to be done and when. The central executive is a natural consequence of the move to build a theory of cognition around a premise of property dualism. In order to explain cognition independently of a central executive, with all of the logical problems inherent to that approach, we must formulate a new theory of cognition, in which we replace the premise of dualism with one of physicalism.

The mind/body dualism approach to cognition has a long history in psychology. Early theorists in the field, following the example of centuries of philosophy (Descartes, 1901), posited that the mind and the body had to be separate entities (Marvin, 1915). Under this conception, the body is physical and material. The body is inert, and cannot initiate action on its own. It occupies space in the world, interacting with other physical things. Conversely, the mind is nonphysical. It does not occupy physical space, and is active, driving the actions of the physical body. While the body cannot move itself or initiate action, the mind can. The mind and the body interact together to allow the organism to function (Roelofs, 1955).

The problems with this approach are myriad. By adopting this stance, one must explain the process by which physical stimuli are transformed into non-physical representations. Representations are non-physical things; the stimuli one experiences in the world are physical. A dualistic approach must define the way in which the physical become the nonphysical.

Other problems abound. How are representations, which are non-physical objects, manipulated by the mind? How do representations affect and change the physical world? Adopting a dualistic approach necessarily means adopting these philosophical problems along with it.

A Physicalist Theory of Executive Function

One can avoid the problems of dualism by grounding cognition in physical, biological processes; this is the perspective known as physicalism. This alternate theoretical perspective proposes that cognition is the result of multi-scale interactions endogenous to the system. On this account, cognitive structure is derived from the interactions of physical system activity, across many different timescales. Physical activity provides the foundation for cognitive structure.

By grounding cognition in the physical, one avoids the myriad problems with dualism. Cognition no longer requires an explanation for the way that physical information becomes representations. Instead, the biological processes of the living system are what give rise to cognition. Local gradients of energy and matter interact across many different time scales of the physical system. The interactions of these gradients drive the creation of new cognitive structure. We avoid the problems of dualism, then, by grounding the creation of new cognitive structure in physical, biological processes.

Traditionally, psychology holds that the physical and the cognitive are at least partially separated. This dichotomy, however, is illusory, and largely driven by issues of measurement. Because we measure cognitive activity and physical activity in different ways, we have chosen to describe them as two separate things that are

at least semi-independent. We propose that the cognitive and physical are inextricably linked; with the proper tools, it should be possible to use the measurements of one to inform about change in the other.

Figure 1 is an image of the Small Magellanic Cloud, captured by NASA using the Spitzer space telescope. If one were to look for the cloud at night without the aid of a magnification device, one would see something like the leftmost part of the image of a colorful cloud in the night sky. One might falsely conclude that this is the only picture of interest, and that it contains all of the information one might need to make inferences about the nature of the cloud.

This conclusion, however, is driven by the coarse-grained nature of the measurement taken using only the human eye. When magnified, one sees that the cloud is made of many parts, at finer scales of measurement. Magnification allows us to see that the cloud contains planetary nebulae, which can also be magnified, revealing molecules of carbon, represented by the rightmost picture. The nebulae are made up partially of carbon (Kwok, 2005), while the cloud consists partially of planetary nebulae. The smallest scale is nested within the middle scale, which is itself nested within the largest scale; the activity of the smaller scales is an integral part of the structure that we see at the larger one.

Cognition can be thought of in the same way. Behavioral data is a snapshot of the coarsest, longest timescale, the easiest thing for us to observe. An important mistake that much of experimental psychology makes is asserting that this scale of measurement contains most or all of the information one needs to make conclusions about psychology. We propose that, like the Small Magellanic Cloud, the structure

that we observe at the coarse, behavioral scale is driven by activity at finer scales. Coarse, behavioral measurements are only telling part of the story.

This leads to a very important question. We have devised many ways to measure phenomena at the behavioral level. How can we measure activity at finer scales of magnification? Our answer to this question is driven by the underlying assertion that cognition is a physical process. Physical processes require the consumption of energy. As energy consumption increases, local gradients of energy and matter change. Changes in gradients cause changes in the rate of diffusion. Therefore, change in diffusion rates in a physical system should provide an indirect measure of multi-scale activity.

Prior research has shown that changes in the rate of diffusion of physical activity predict success in cognitive tasks. For example, Stephen and Anastas (2011) found that an increase in the rate of diffusion of eye movements were linked with greater levels of success during a visual search task. The rate of diffusion of eye motions has also been found to predict the adoption of new strategies during gear tracing tasks (Stephen et al., 2009). Diffusion patterns have been found in a wide variety of cognitive phenomena, such as word naming (Holden et al., 2009) and lexical decision-making (Gilden, 1997).

Measurements of behavior can be used to obtain information about changes in diffusion rates. Fine-grained body movements (Hand motions, eye movements, and others) contain information about diffusion rates of the system, and can be used to calculate estimates of system activity.

In order to determine how interactions drive the creation of cognitive structure, we motion tracked participants during an executive function task, card sorting, in order to calculate estimates of system activity across multiple time scales. Using analytical techniques adapted from econometrics, we examined the ways in which the multiple scales of the physical system interacted in order to drive the creation of new cognitive structure in response to the task.

In the first experiment, college-aged participants were motion tracked while sorting cards. Participants were either given the rule by which to sort, or were asked to induce the rule based on experimenter feedback. We predict that the multi-scale interactions driving change will be different between the two conditions. Participants who are told which rule to use will exhibit a greater effect of longer, coarser time scales on all other time scales. Those who must induce the rule will exhibit a greater effect of the shorter, finer time scales on all other scales, as evidenced by an increase in system activity across all scales when the shortest time scale is perturbed.

In the second experiment, we asked preschool-aged participants to complete the same type of sorting task. In the middle of the task, the rule by which the cards were sorted was changed without the participants' knowledge. When presented with this kind of task, preschool-aged participants typically fail to switch to the new rule, a phenomenon known as perseveration. We compared motion data gathered both before and after the rule switch, in order to determine whether or not perseveration of the rule had an effect on the multi-scale activity of the system. We

predict that perseveraters will show different multi-scale effects than non-perseveraters.

Experiment 1

Method

Participants

Twenty-six University of Connecticut undergraduate and graduate students participated. All participants gave consent in accordance with University of Connecticut informed consent procedures. Undergraduate participants received credit toward course completion; graduate students were not compensated for participation.

Materials

Participants sorted cards from a specially prepared deck. On each card in the deck was a picture of a brightly colored animal wearing a piece of clothing. These three characteristics (Animal, color, and clothing item) corresponded to the three potential sorting dimensions. Each sorting dimension contained four levels: for color, the four levels were red, green, blue, and yellow. For animal, the four levels were cow, pig, lion, and wolf. Finally, for clothing item, the four levels were glasses, hat, bowtie, and earrings. Each card contained one level from each dimension; for example, one card had a picture of a red wolf wearing a hat, which represents one level from each of the three dimensions. There was one card for each unique combination of the possible levels, making for a deck with 64 cards. Decks were randomly shuffled between runs.

Each participant's sorting hand motions were tracked for each run. Motion tracking data was collected during sorting using a magnetic motion-capture device (Polhemus Fastrak, Polhemus Corporation, Colchester, VT and 6-D Research System software, Skill Technologies, Inc., Phoenix, AZ). The position of the participant's hand was sampled at 60 Hz.

Procedure

Participants were required to take cards from a facedown deck and place them into one of four piles, based on one of the three previously described dimensions. Each pile contained a guide card, with each level of each rule represented once across the four guide cards. For example, one guide card contained a picture of a green lion wearing glasses. This was the only guide card to contain these three characteristics; participants would then place into this pile green cards, glasses cards, or lion cards, depending on which rule was active (See Figure 2). After each card placement, the experimenter told the participant whether or not the card was correctly placed, according to whatever rule was active during that run.

Each run had one unchanging rule. Participants were divided evenly between two conditions. In the explicit condition, participants were told which rule to use in sorting prior to beginning the run. In the induction condition, participants were never informed of the rule; instead, participants were required to induce the correct rule for each run using experimenter feedback. Participants sorted cards into piles until they correctly placed ten cards in succession. Each participant completed five runs.

Analysis

Multifractal Detrended Fluctuation Analysis.

For each run, we created a time series of inter-point distances that was submitted to multifractal detrended fluctuation analysis (Kantelhardt et al., 2002). Multifractal detrended fluctuation analysis is an extension of standard detrended fluctuation analysis (Peng, Havlin & Stanley, 1995), which assesses long-range correlations in non-stationary time series $x(t)$ of length N . First, the time series is integrated to produce a trajectory $y(t)$:

Equation 1
$$y(t) = \sum_{i=1}^N x(i) - \overline{x(t)},$$

where $x(i)$ is the i th interpoint distance and $\overline{x(t)}$ is the average interpoint distance.

Next, the integrated time series is segmented into non-overlapping bins of length n , such that $4 \leq n \leq N/4$. DFA proceeds with a least-squares regression within each bin. The residuals of these regressions provide an estimate of root mean square (RMS) error:

Equation 2

$$F(n) = \sqrt{(1/N) \sum [y(t) - y_n(t)]^2},$$

where $y_n(t)$ is the y coordinate of local trend within each bin.

DFA treats the average RMS error as the fluctuation $F(n)$ for bin size n . The relationship between $F(n)$ and n is the fluctuation function increasing as:

Equation 3

$$F(n) \sim n^H.$$

When the fluctuation function is plotted on double-logarithmic axes, the relationship between $\log F(n)$ and $\log n$ may be linear. The slope of this linear relationship is an estimate of the Hurst exponent.

DFA is occasionally susceptible to sinusoidal trends in time series data. In these cases, the Hurst exponent produced by DFA is affected by low frequency trends, producing an inaccurate estimate of activity (Hu et al., 2001). To protect against this, each time series was filtered prior to analysis. High power, low frequency motions were removed on a run-by-run basis, trimming the adverse effect of outliers in amplitude from the calculation of the Hurst exponent, as described by Chianca et al. (2005).

Standard DFA assumes a certain level of system activity across all scales of interest in a system. Multifractal Detrended fluctuation analysis (MF-DFA) allows for differences in activity at different scales of measurement (Kantelhardt et al., 2002). MF-DFA accomplishes this by nonlinearly transforming the collected residuals in each bin by a factor Q :

Equation 4

$$\int F_Q(s) \equiv \left\{ \frac{1}{2N_s} \sum_{v=1}^{2N_s} [F^2(v,s)]^{Q/2} \right\}^{1/Q}$$

We then proceed through the standard DFA procedure using the new residuals. This transformation allows emphasis of different scales of activity; higher values of Q minimize the effect of smaller scales, and emphasize the effect of larger scales. Lower values of Q achieve the opposite effect. For each gathered time series, we generated a Hurst exponent for Q values ranging from -4 to positive 4 at

intervals of .5. This array of Hurst exponents provides an estimate of system activity at time scales ranging from the very low to the very high.

We used an epoching approach in order to track changes in the Hurst exponent over time (Weber et al, 2005). Epoching is a useful method for examining a non-stationary time series. In the epoch approach a sliding window is moved across the time series; each window is an epoch. MF-DFA is performed for each epoch. Each window was 800 samples wide, and was shifted by 600 cycles for each step, leaving an overlap of 200 samples per step. Approaching the data this way allows us a better understanding of how the Hurst exponent is changing over time.

Estimates of system activity obtained by applying MF-DFA were used in vector autoregression analysis, an analytical technique used to examine the ways in which the components of complex system interact with one another. A more thorough explanation of vector autoregression analysis is presented below, in the results section.

Results

Participants committed few to no sorting errors during each run, regardless of condition. Participants in the explicit condition took less time on average to complete a run ($M = 55.85$ seconds, $SD = 19.5$) than participants in the induction condition ($M = 73.25$, $SD = 27.15$). We used growth curve modeling (GCM) to test whether or not time spent on the task decreased as the participant completed more runs. We found that adding trial as a predictor increased model fit significantly when compared to a model with only a model intercept ($\chi^2(1) = 493.83$, $p < .0001$).

Time taken to finish a run decreased significantly as trial increased; refer to table 1 for model coefficients.

We also used GCM to test whether or not time to completion was the same between the two conditions. We added condition as a predictor to the prior model, which significantly improved model fit ($\chi^2(1) = 10.525$, $p < .01$). Trial was a significant predictor, such that participants in the induction condition took significantly longer than participants in the explicit condition; logically, one would expect that inducing the rule would increase the time necessary for completion. See table 2 for model coefficients.

In addition to testing condition as a time invariant factor in trial length, we tested whether or not condition interacted with trial to change the rate of completion over time. The interaction between trial and condition, however, was non-significant.

The motion tracker measured the 3-D position of the hand 60 times each second. From those 3-D measurements, we created a time series of displacements for each run separately by calculating Euclidean distances between adjacent measurements. Figure 3 shows a sample displacement time series.

We applied MF-DFA to each of the displacement time series. As stated above, MF-DFA non-linearly transforms the binned residuals of each time series in order to emphasize different scales of activity (Kantelhardt et al., 2002). Figure 4 shows the Hurst exponents from one participant for different levels of Q , over the course of one run. Each colored line represents a level of Q .

Figure 5 shows the mean scaling exponents for the explicit and induction conditions. Figure 6 shows the mean R^2 for the fit between RMS error and bin size for each condition; the mean R^2 for both conditions was quite high across time scales, suggesting a strong fit between RMSE and bin size. The factor Q by which each series was transformed ranges from -4 (shortest scale activity) to 4 (longest scale activity).

Vector autoregression (VAR) and vector error correction models are analytical techniques originally developed for use in econometrics. In standard regression techniques, the causal relationship between the independent and dependent variables is unidirectional; the dependent variable is influenced by, but can never change, the predictor variables. In a complex system, individual variables of interest both affect, and are affected by, other variables in the system, rendering standard regression techniques inadequate. Vector autoregression and vector error correction models are designed to more accurately reflect this complex relationship between variables.

In the present case, VAR takes as input estimates of activity across multiple time scales of the system. It produces as outputs coefficients that represent the activity of each scale of the system lagged across time. Equation 5 shows a sample vector error correction equation for a simple three variable system.

Equation 5.

$$\begin{pmatrix} \Delta D_{Q1,t} \\ \Delta D_{Q2,t} \\ \Delta D_{Q3,t} \end{pmatrix} = \begin{pmatrix} \phi_{11} & \phi_{12} & \phi_{13} \\ \phi_{21} & \phi_{22} & \phi_{23} \\ \phi_{31} & \phi_{32} & \phi_{33} \end{pmatrix} \begin{pmatrix} \Delta D_{Q1,t-1} \\ \Delta D_{Q2,t-1} \\ \Delta D_{Q3,t-1} \end{pmatrix} + \begin{pmatrix} \rho_{11} & \rho_{12} & \rho_{13} \\ \rho_{21} & \rho_{22} & \rho_{23} \\ \rho_{31} & \rho_{32} & \rho_{33} \end{pmatrix} \begin{pmatrix} (D_{Q1,t-1} + \beta_{12}D_{Q2,t-1} + \beta_{13}D_{Q3,t-1}) \\ (D_{Q1,t-1} + \beta_{22}D_{Q2,t-1} + \beta_{23}D_{Q3,t-1}) \\ (D_{Q1,t-1} + \beta_{32}D_{Q2,t-1} + \beta_{33}D_{Q3,t-1}) \end{pmatrix}$$

In a standard error correction model, system activity D for a time scale Q at time t is a product of two main predictors. The first, represented in equation 5 by each of the values of ϕ , represents adjustments based on system activity at time $t-1$ for all time scales. System activity at any given time scale is partially the product of system activity at all time scales at the previous time step.

The second, represented in equation 5 by each of the values of ρ , are the cointegration relations between levels of the system. In a complex system, the various components of the system work together to produce equilibrium over time. Cointegration entails that when one of the components of the system is perturbed in such a way as to disturb this equilibrium, the other scales of the system will work to correct it such that equilibrium is restored. When the number of variables in the system, k , is greater than 2, the number of cointegration relations can range from 0 to $k-1$.

Imagine a simple system, where two people work together to carry a box full of weights. Each person must apply force in order to move the box. The movement of the people holding the box should be cointegrated, such that a perturbation to one will require the other to correct for it. If, for example, one of the lifters begins to slacken, the other lifter must increase the amount of force applied in order to keep the box off of the ground. The two holders are endogenous variables in the system; each one affects, and is affected by, the other. The two holders must work together in order to provide a stable equilibrium, where the box is kept off of the ground. Conversely, the weight of the box is an exogenous variable in the system. Regardless

of how much force the two holders applies, the weight of the box will never change. The weight of the box affects the system, but is not affected by it.

The two brackets on the right in equation 5 represent this trend towards equilibrium. The error-correction term, represented as a linear relationship amongst the scales of the system, works to correct system activity at each individual level so as to maintain equilibrium in the system. The cointegration relations, represented by ρ , weight these corrections based on the relationship amongst scales in the system.

Once we have estimated a model that integrates these factors, we can examine how a change in one scale of the system affects both itself and each of the other scales by using an impulse response function (IRF). We first set all of the predictor values and error terms to zero. We then perturb the system by adding one standard deviation to the error value of one, and only one, scale of the system. Finally, we track how this perturbation affects both the perturbed scale and all other scales over later time steps.

Figure 7 shows the effect of perturbation of the longest time scale on itself and all other scales. All of the predictors and error values were set to zero; we then added one standard deviation to the error value of the longest time scale, $Q = 4$. The blue line represents the explicit condition, the magenta line represents the induction condition, and the pink bars are 95% confidence intervals. Significance testing can be found within the plots themselves; if the error bars for a given line do not include zero, then that effect is significantly different from zero at a .05 level. Similarly, when the two lines representing different conditions fall outside of each others

error bars, than changes in activity between the two conditions is significant at the .05 level. For the explicit condition, perturbing the longest time scale ($Q=4$) decreases system activity across itself and all other scales, represented by the significant deviation from baseline; this decrease is most obvious at the lower scales of Q . For the induction condition, perturbing the longest time scale increases system activity at all scales, particularly the shorter scales.

We next looked at the effect of perturbing the shortest time scale. Figure 8 shows this perturbation effect; in both conditions, the effect is similar to the perturbation of the longest scale. System activity decreases over time in all scales for those in the explicit condition, while system activity increases over all scales for the induction condition.

Discussion

As predicted, multi-scale effects between the two conditions differed greatly. In the first condition, participants were told explicitly how they were to sort the cards at the start of each run. In this condition, the perturbation of activity of both the longest and shortest time scales led to a general decrease in system activity across all time scales. In the second condition, participants were required to infer which rule to use in sorting the cards. In this condition, the perturbation of both the longest and shortest time scales led to a general increase in system activity across all other scales. Due to the increased difficulty of the task, a greater degree of interaction amongst levels of the system is required to create the new cognitive structure necessary to complete the task.

In a physical system, gradients of energy of matter interact across multiple timescales; their interactions drive the creation of new structure in response to changes in circumstance. The types of multi-scale interactions will differ depending on the information received. In the explicit condition, being explicitly told the rule led to the fast creation of the cognitive structure necessary to perform the task. Participants in this condition showed a general decrease in activity, evidenced by the significant decrease from baseline at each scale of Q , as the interactions across scales in the system settled around the newly created cognitive structure.

In the induction condition, participants had to acquire the rule during the course of the run. Interestingly, we see that in this condition the unique effects of each scale across all scales of the system were greater than in the explicit condition. This suggests that fluctuations at all scales are involved in organizing to the new rule, as the participant worked to figure out the new rule. The results of the study bear out this prediction; system activity was much greater across all scales, as the amount of activity required to create the necessary structure was greater than in the explicit condition. In the induction condition, activity across all time scales interact to drive the creation of new structure; in the explicit condition, the degree of system activity required to create new structure is much less. In both cases, though, changes in multi-scale activity cause changes in diffusion patterns that can be measured.

It is important to note the contrast between these findings and the findings one would expect from the system under the standard conception of executive function. The mainstream view of executive function holds that it is a higher order, top-down process that imposes order on the system (Carlson, 2003). If this were the

case, one would expect that the longest time scales would be the only ones to have an effect on the cognitive system, regardless of condition. One would predict that perturbing the longest time scale would have an effect on all of the other scales, and that perturbing the shorter time scales would have no effect. This is not the case, however; it would appear that perturbing both the long and short time scales changes the level of activity of the system, suggesting that success on executive function tasks may rely on general cognitive flexibility, instead of the use of a higher-order central planner.

Based on the findings of the first study, we decided to explore multi-scale effects in the card sorting of children. Because preschool-aged children typically have much more difficulty with executive function tasks, preschool data should provide an interesting counterpoint to the data gathered on adult participants, who would normally be expected to easily complete these tasks.

Recall that as children develop, their ability to complete executive function tasks, like card sorting, increases. Preschool-aged children will, when asked to switch from one sorting rule to another, frequently persist in using the already acquired rule; this is typically interpreted as an indicator of poorly developed executive functioning (Zelazo, 2006). Therefore, our main goal was to examine differences in multi-scale interactions between participants who could switch sorting rules mid-run and those who were unable to do so, and continued to sort by the old rule when provided with a new one. In order to do this, the task from study one was modified to include a rule switch halfway through each run. We predict that

participants who are able to switch rules successfully will have different multi-scale effects from those who are unable to switch rules.

Experiment 2

Method

Participants

Seventeen preschoolers between the ages of three and five participated. All participants gave both parental consent and child assent before participating. Participants were recruited from local preschools, along with the University of Connecticut child labs. Participants received no reward for participation.

Materials

Participants sorted cards from the same type of deck as in experiment 1. Also as in experiment 1, each participant's sorting-hand motions were tracked for each run using a magnetic motion-capture device. The position of the participant's hand was sampled at 60 Hz.

Procedure

The experimental field was the same as in experiment 1. Participants were asked to draw cards from a face down deck and place them into piles, as in the first experiment. The same cards were used in the second experiments. As we were working with younger participants, however, only the color and animal dimensions were used as guide rules; the clothing item dimension was never chosen as the sorting rule. Importantly, unlike experiment 1, in the second experiment, participants were never told which rule to use. In the second experiment, each participant was required to induce the rule using experimenter feedback.

Participants were required to sort thirty cards per run, regardless of the level of success he or she had. Participants received experimenter feedback as to whether or not each card was being placed correctly.

The key manipulation in the second experiment is the change in rules during the run. In this experiment, the rule was changed after fifteen cards had been placed, i.e. at the midpoint of the run. As with the initial rule, the participant was not informed that the rule had changed, and was required to induce that a change had occurred through feedback. The rule was switched either from color to animal, or the opposite. This allowed us to examine perseveration, by comparing participants who were able to successfully switch to the new rule with participants who continued to sort by the old rule.

Participants were asked to complete up to five runs during an experimental period. Due to the nature of working with children, many participants chose to opt out of the task after fewer than five runs; as a result, participants completed an average of three runs each. Because we were most interested in studying the effect of perseveration, only complete runs, where a participant was able to place all thirty cards, were submitted for analysis.

Analysis

Participant time series were divided into two parts before analysis, which corresponded to estimates of the point in the run at which the rule was changed. Instead of examining the time series as a whole, analysis was instead done on the two parts. As in the first experiment, the time series of hand motions of each

participant was subjected to Multifractal DFA. MF-DFA estimates were then used in a Vector Autoregression Analysis.

Results

Each participant's runs were divided into two parts, based on when the rule switch occurred. Prior to the switch, participants sorted an average of 12.04 cards correctly out of 15 total placements ($SD = 3.88$). After the switch, participants sorted an average of 8.5 cards correctly out of 15 ($SD = 4.21$). Participants took roughly the same amount of time to place fifteen cards both before ($M = 133.5$ seconds, $SD = 51.85$) and after ($M = 135.2$, $SD = 48.9$) the rule switch.

The comparison of interest is between perseveration and non-perseveration runs. A perseveration run is one in which a child persists in using the initial rule, after a rule switch occurs and feedback from the experimenter indicates that the old rule is no longer correct. A non-perseveration run is one in which the participant is able to successfully switch rules at the midpoint of the trial

For these analyses, we chose to focus on data gathered after the rule switch, as the inability to change rules after the switch is indicative of perseveration. Each post-switch run was placed into one of two groups for analysis, based on whether or not perseveration had occurred. Perseveration was defined as the successful placement of at least 60% of the cards prior to the rule switch, followed by the successful placement of less than 60% of the cards after the switch. Non-perseveration runs were defined as the successful placement of 60% of the cards prior to the rule switch, while successfully sorting 60% or more of the cards after the rule switch. Under these criteria, there were 22 perseveration runs and 16 non-

perseveration runs. Runs in which a participant failed to acquire the initial rule, defined as less than 60% successful placement prior to the rule switch, were not used in these analyses; only two runs excluded under this criteria.

As in the first experiment, we created a time series of displacements for each run by calculating Euclidean distances between each sample in each motion time series. Figure 9 shows a sample time series in the upper panel and its accompanying displacement series in the lower panel.

We applied MF-DFA to each of the pre and post switch time series; because we were interested primarily in perseveration, we focused analyses on post switch data. We have performed preliminary analyses on data collected prior to the rule switch, but more thorough analysis is beyond the scope of this manuscript. As in the first experiment, we transformed each series by a factor Q ranging from -4 to 4 in .5 increments. Figure 10 shows the mean scaling exponent for each time scale, with both pre and post switch means represented. Figure 11 shows the mean R^2 value of the linear fit between RMSE and bin size for each time scale, with both the pre and post switch means represented here as well. As in the first experiment, the fits across each scale of Q were generally strong.

As in the first study, MF-DFA estimates were used in VAR analysis. Runs were divided into two groups based on whether or not the participant perseverated in that run. We looked at system activity effects based on the perseveration/non-perseveration dichotomy.

We first examined the non-perseveration runs – runs where participants sorted the majority of cards correctly both before and after the rule switch. Figure

12 shows the unique effect of perturbation of the longest time scale on both itself and all other time scales. The blue line represents pre-switch runs, while the magenta line represents post-switch runs; the pink lines are 95% confidence intervals. As in the first experiment, differences between lines that exceed the lengths of the error bars are significant at the .05 level. In both the pre and post switch runs, the perturbation of the longest time scale had no effect on itself or on any of the other scales of activity; after the initial perturbation, reflected in the slight bump immediately following the first time step, system activity across all scales soon returned to baseline.

Figure 13 shows the unique effect of perturbation of the shortest time scale on itself and all other scales. The three lines are the same as above. In the pre-switch case, perturbation of the shortest time scale led to small effects across itself and other scales. In the few cases where there was an effect on system activity, that effect was negative. However, in the post-switch runs, the perturbation of the shortest scale has the effect of noticeably increasing system activity at the mid to long scales, while slightly decreasing activity at shorter scales.

Next, we looked at system activity in the perseveration runs. Figure 14 shows the unique effect of the longest time scale on itself and all other scales. In both the pre (blue line) and post (magenta line) switch runs, the longest time scale had little effect on activity at the mid to long scales; however, in both the pre and post switch runs, perturbing the longest time scale had a strong negative effect on activity at the shortest time scales, evidenced by the decrease in system activity for negative values of Q .

Finally, we examined the effect of perturbation of the shortest time scale on all other time scales during perseveration runs. In the pre-switch runs, perturbing the shortest scale had a strong negative effect on system activity on itself and all other time scales. In post-switch runs, perturbation of the shortest scales had a strong positive effect on the shortest scales, and a very small negative effect on the longest time scales. These results are shown in Figure 15.

Discussion

Multi-scale activity of the perseveration and non-perseveration runs differed greatly. Recall that a run is defined by the placement of thirty consecutive cards. In the non-perseveration runs, where participants were able to switch rules successfully, perturbing the longest time scale had no effect during post-rule-switch sorting, while perturbing the shortest time scale had a positive effect on system activity. At the shortest time scales, perseveraters had similar effects – perturbation caused a general increase in activity across all scales. At the longest time scale, however, post-switch perseveration runs had a much different effect, where perturbation led to a decrease in activity, instead of having no effect.

These results suggest that switching rules in the middle of the run creates an effect of the shortest time scales on all other scales in the system. In experiment 1, participants in the induction condition, whose task was similar to the task performed by the preschoolers, showed results similar to those found here. Like the non-perseveraters in experiment 2, perturbing the shortest time scale had the greatest effect on all other time scales. The longest time scale effects are even more interesting, where perseveraters and non-perseveraters differ greatly. For non-

perseveraters, there is no effect of perturbation of the longest time scale; system activity at the other scales quickly returns to baseline. For perseveraters, however, perturbing the longest time scale has a negative effect on system activity. In terms of multi-scale interactions, the prime difference between the two groups is here.

Recall again that the standard method of describing executive function is as a higher order, top down process. As in the first study, if this were the case, one would expect that activity at the longest time scales would have the greatest effect on success in an executive function task. We would expect to see a strong positive effect of perturbing the longest scale in non-perseveraters, and a neutral effect of perturbing the longest time scale in perseveraters, which matches a deficiency in executive function that prevents the perseveraters from changing rules.

The results of the current study contradict these expectations, however. The participants with presumably the most highly developed executive function, who are able to switch rules midway through each run, show no special effect of the longest time scale. The participants with the least developed executive function, those who are unable to switch, have a negative effect of longer time scales. This suggests that higher order capabilities, instead of being the driving force behind executive function, may actively hinder the creation of new cognitive structure.

Central to developmental psychology is the problem of cognitive control. Taken together, the current results suggest that rather than being accomplished through the workings of a central executive, cognitive control is derived from interactions amongst physical gradients of the system. These interactions create new cognitive structure, allowing the system to respond to changes in its

circumstances. Higher order processes, rather than driving change, can actively inhibit the system in the creation of new cognitive structure.

Future Directions

The current studies have established a foundation for future work in this area. This study has shown that cognitive structures may be derived from physical interactions within the system. In order to further investigate this paradigm, there are three primary avenues of research that are worth pursuing.

First, further examination of executive function tasks would help to extend the work presented in this manuscript, particularly in children. Prior research has shown, at least in other domains, that children can be made to succeed at tasks that were previously thought impossible based on their progression through developmental milestones, by manipulating the constraints of the task (Smith et al, 1999). It is possible that manipulating the constraints of card sorting and other executive function tasks could alter the ways in which physical interactions within the system change, allowing the children to succeed at the task.

Because cognitive control is so integral to every day functioning, examining it further is perhaps the most important future direction to explore. It would be wise, however, to extend this research paradigm into other areas of cognitive development. One of the strengths of this approach to cognition is its potential to replace the convoluted picture of cognition that we have now with one unifying method of explanation. Instead of having different theories for the functioning of different cognitive capabilities (executive function, memory, attention, etc.), all of cognition could be explained through the lens of physical interactions. For this

reason, the second avenue of research would be to extend this work into other areas of cognition. The flexible nature of our measurement tools means that we can easily adapt them to a variety of other areas of study within psychology. We would expect that other psychological systems would show the same kinds of patterns as we've seen in executive function, lending strength to the idea that the same physical processes underlie all of cognition.

Finally, it would be wise to explore the measurement of other parts of the body, in order to confirm that the diffusion patterns that we see when measuring hand motions are accurately measuring the underlying processes. We have the tools to examine diffusion patterns of other areas of the body, such as eye movements and postural sway, during a variety of tasks. We would expect that the patterns found in other areas of the body would match those found when tracking the motions of the hand; confirming that multiple areas of the body react in the same way during tasks would strongly suggest that the processes outlined in this manuscript exist, and that they exist independently of any one area of the body.

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Figures

Figure 1: Rendition of the Small Magellanic Cloud at three different levels of magnification, taken using the Spitzer telescope. The leftmost photo is a picture of the cloud itself. The central picture is a magnification of the cloud, showing that it is partially made up of planetary nebulae. The rightmost is a magnification of the nebulae, showing that it is made up of carbon molecules. The smallest scale is nested within the central scale, which is nested within the largest; the structure of the cloud itself is a product of structure at finer scales of measurement.

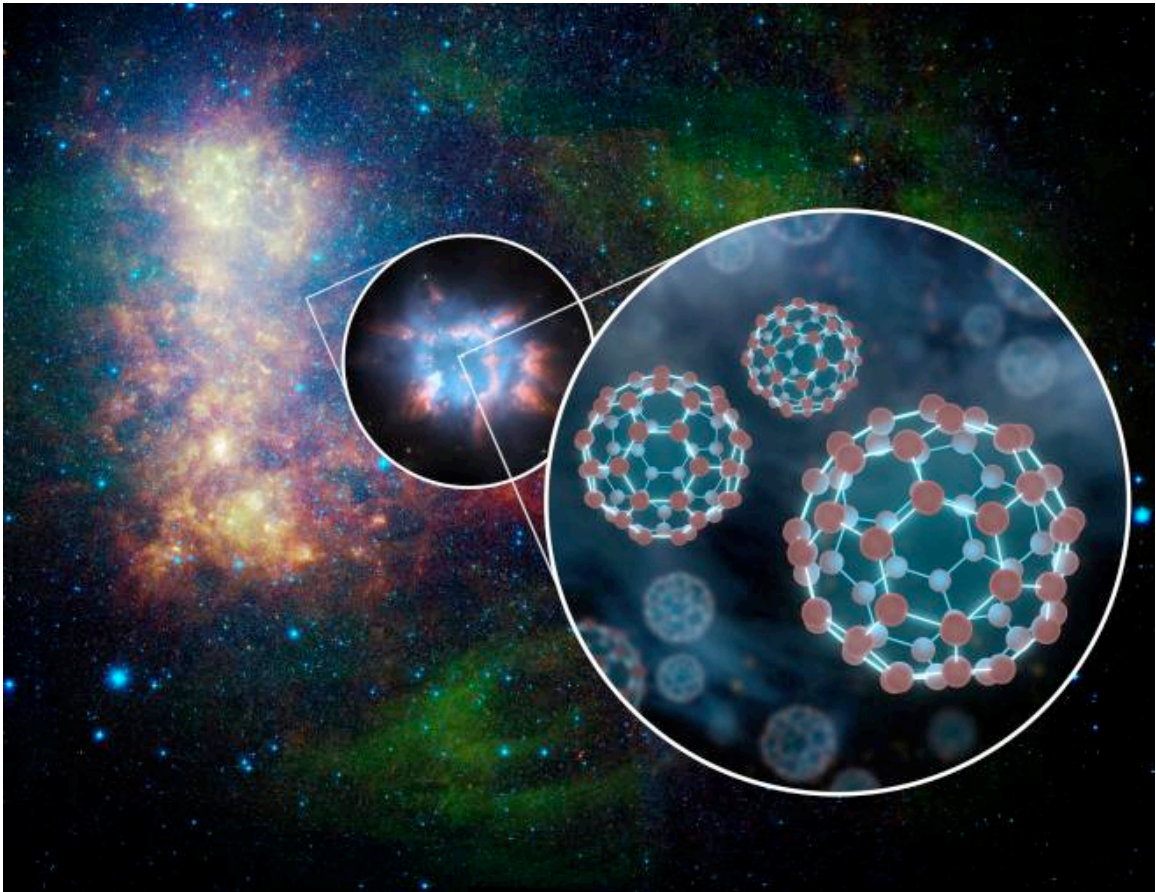


Figure 2: An example of the card-sorting task. Participants were presented with four guide cards. The guide cards each have a unique value of each of the three dimensions (animal, color, and clothing item). Participants were required to draw a card and place it into the correct guide pile, as determined by the rule for that run. In the example below, the blue cow with glasses would be placed into the second pile if the rule was “color”, the third pile if the rule was “clothing item”, or the fourth pile if the rule was “animal”.



Figure 3: Sample interpoint distance time series.

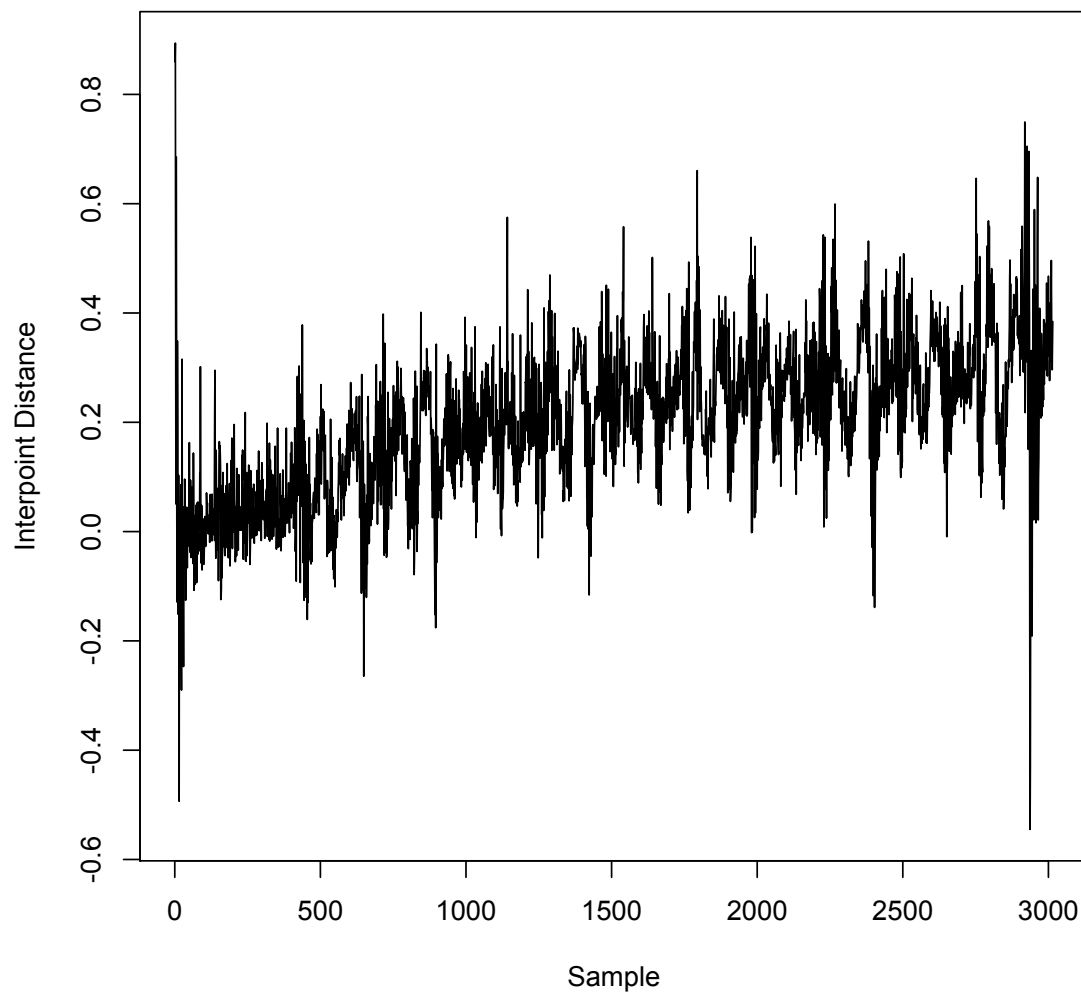


Figure 4. Sample range of scaling exponents over multiple epochs, for one run (22nd participant, first run). Each line represents a series of scaling exponents for a different level of Q .

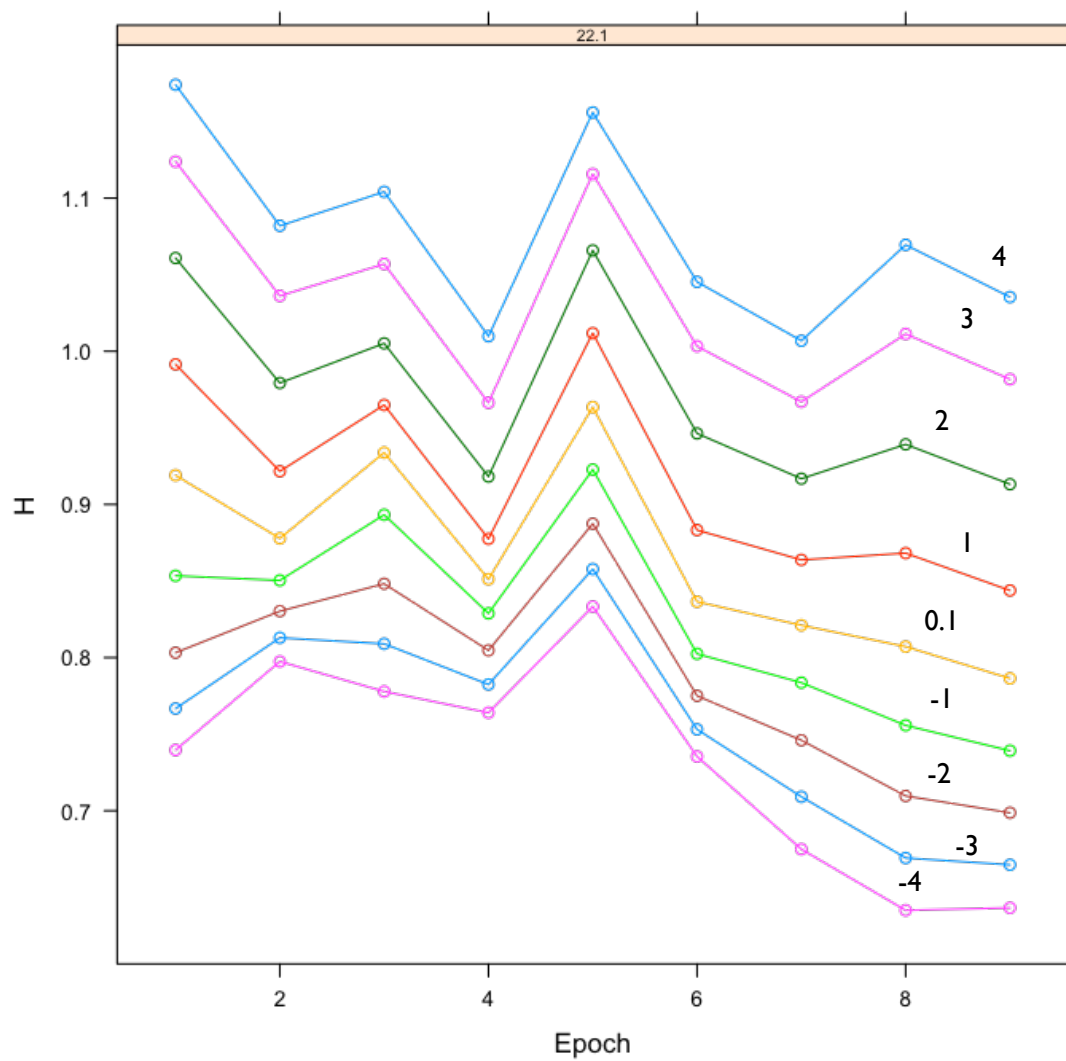


Figure 5. Mean scaling exponent across a range of Q values.

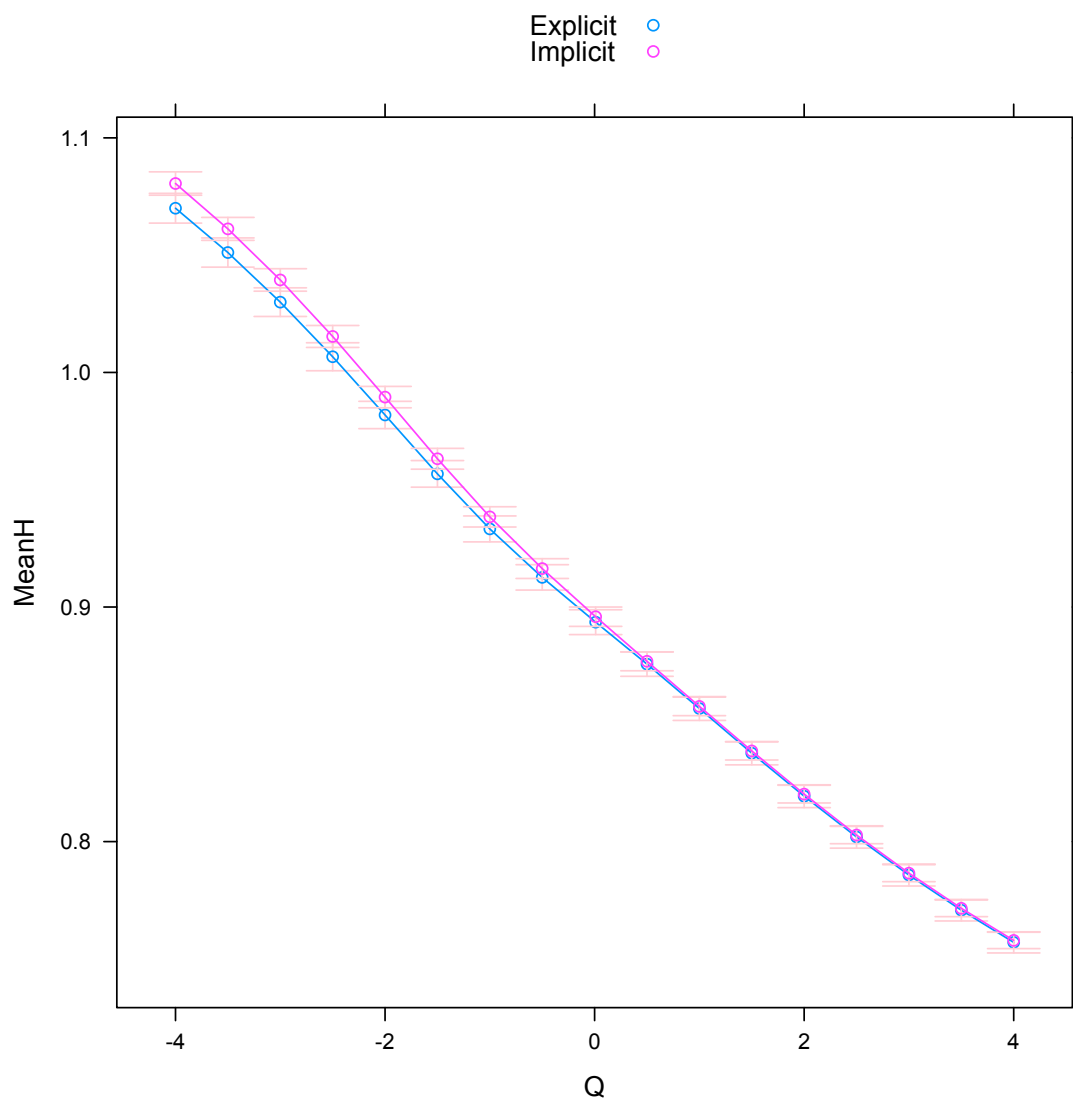


Figure 6. Mean R squared values for the fit between root mean square error and bin size, across a range of Q values.

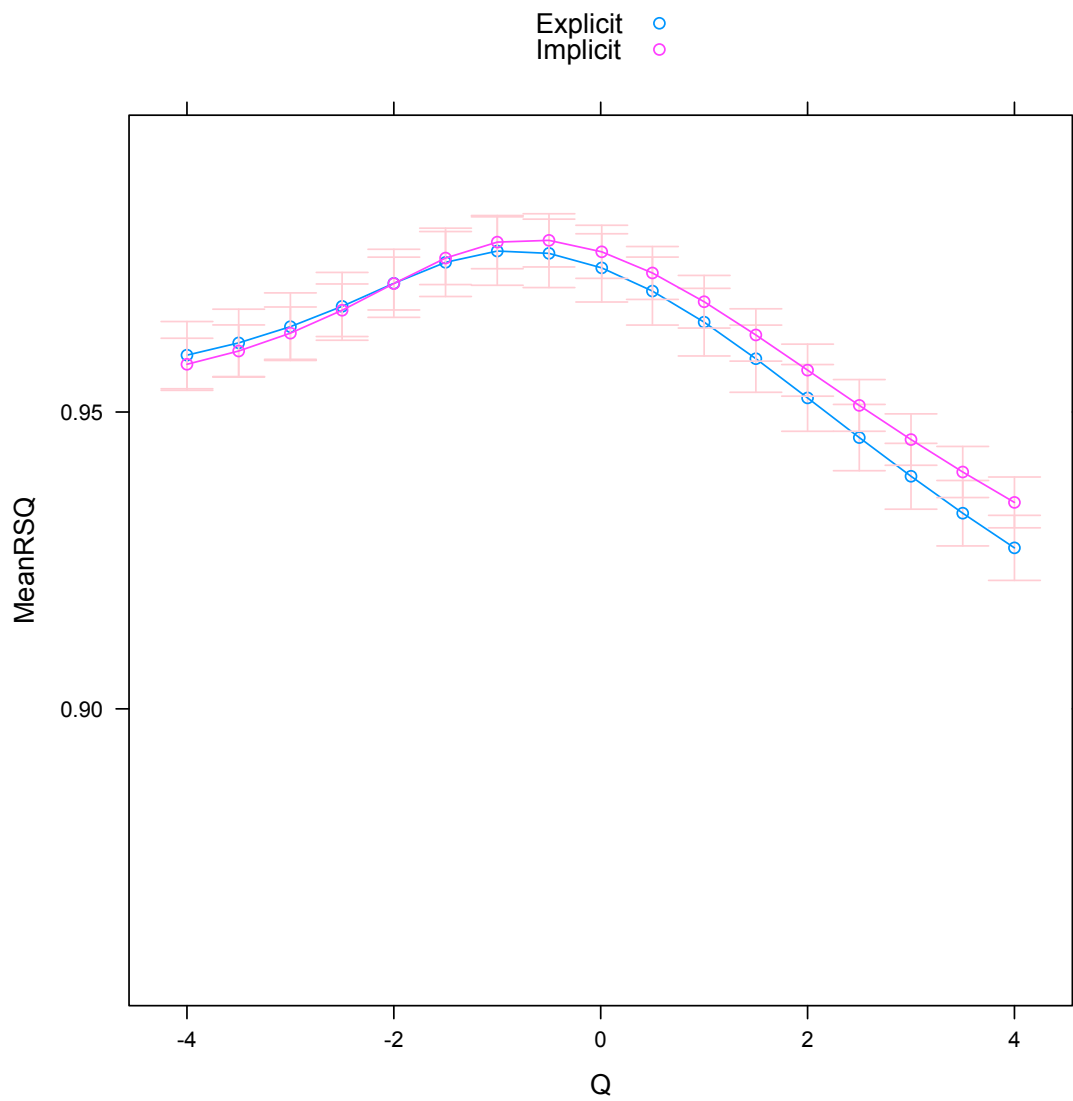


Figure 7: The effect of perturbation of the longest time scale on all other scales. The blue line represents participants in the explicit condition, and the magenta line represents the induction condition. The pink errors bars are 95% confidence intervals. Participants in the explicit condition show a decrease in system activity at all scales; participants in the induction condition show an increase in system activity.

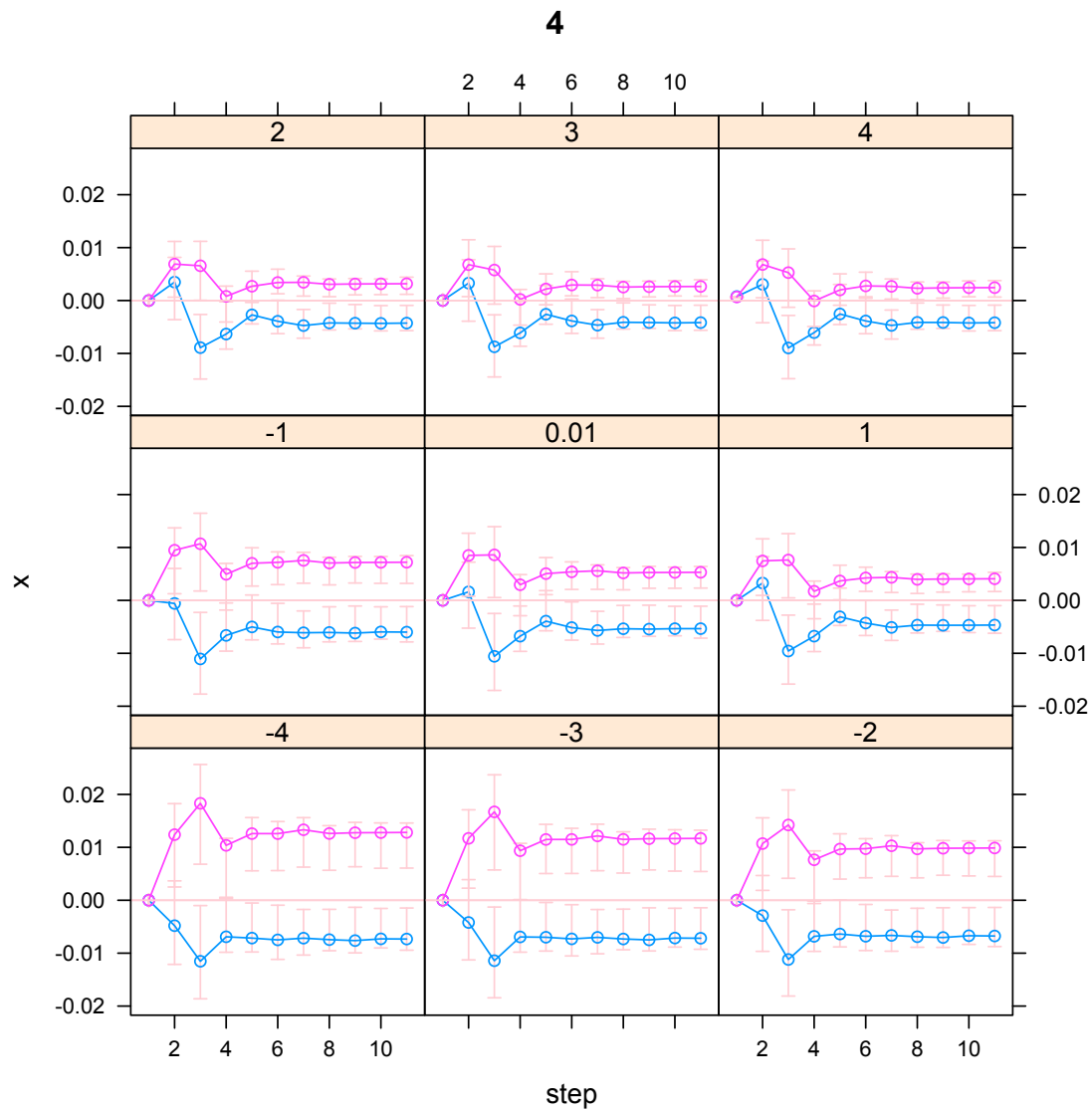


Figure 8: The effect of perturbation of the shortest time scale on all other scales. The blue line represents participants in the explicit condition, and the magenta line represents the induction condition. The pink errors bars are 95% confidence intervals. Participants in the explicit condition show a decrease in system activity at all scales; participants in the induction condition show an increase in system activity.

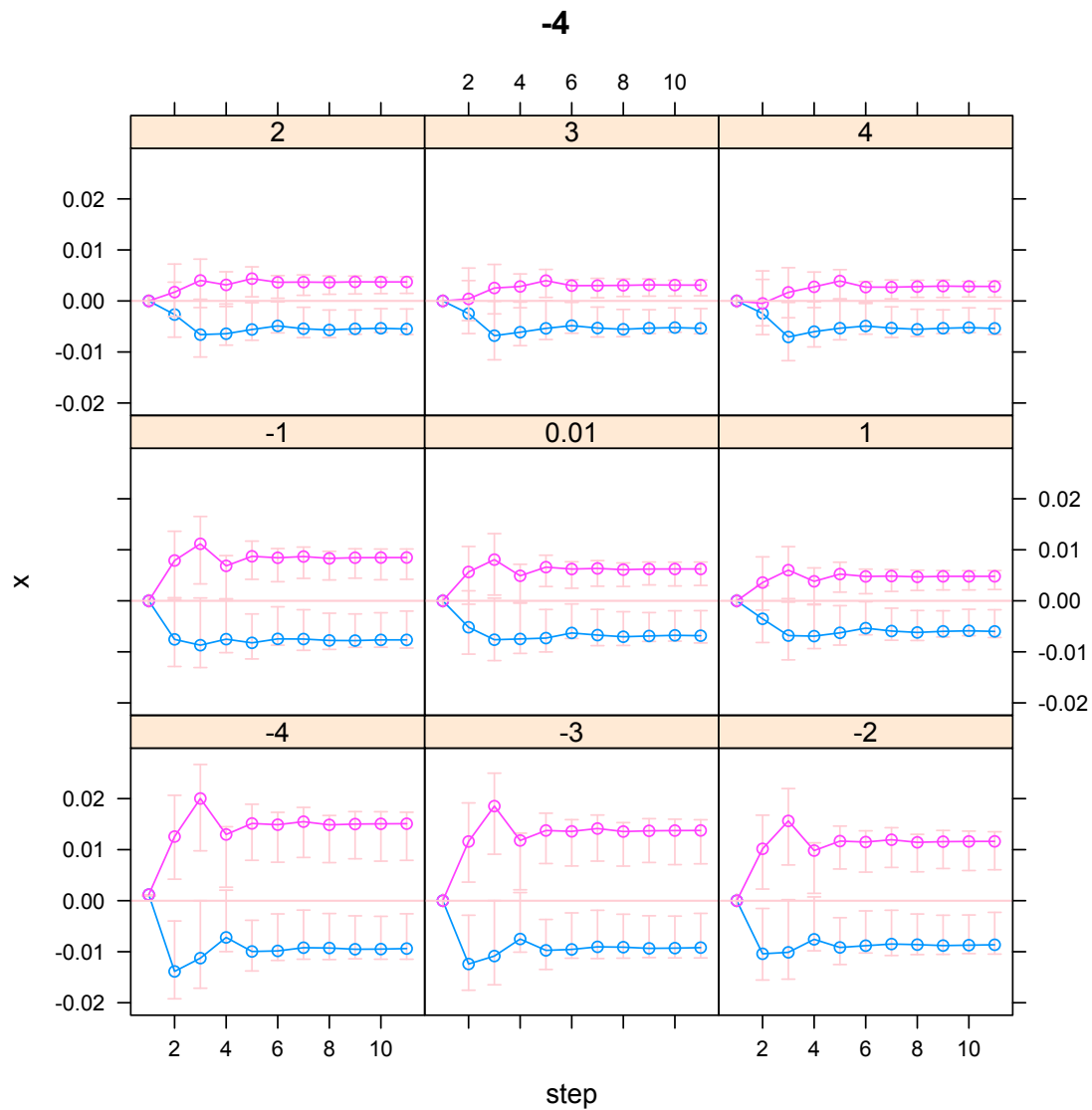


Figure 9: Sample interpoint distance time series, pre-school data.

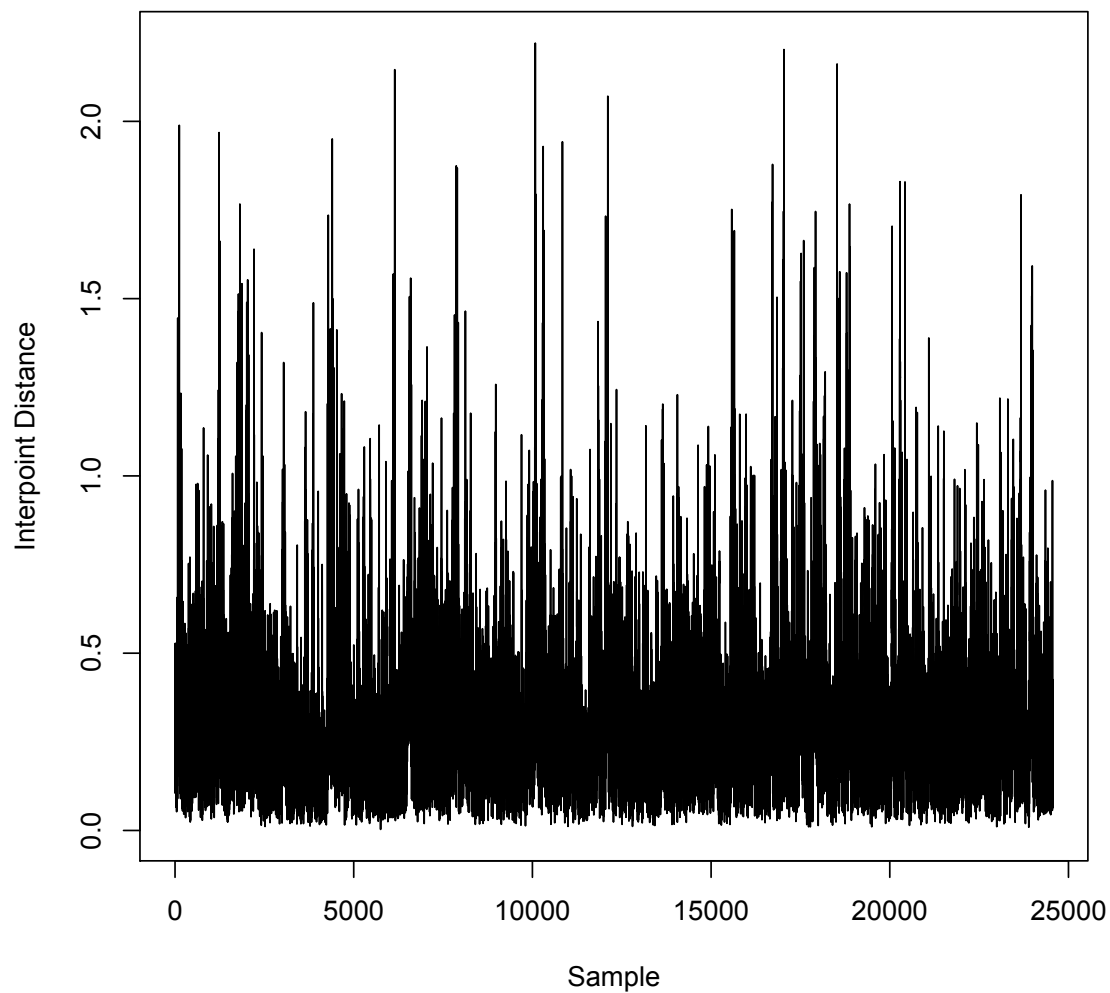


Figure 10. Mean scaling exponent across a range of Q values for the first and second sorts, pre-school data.

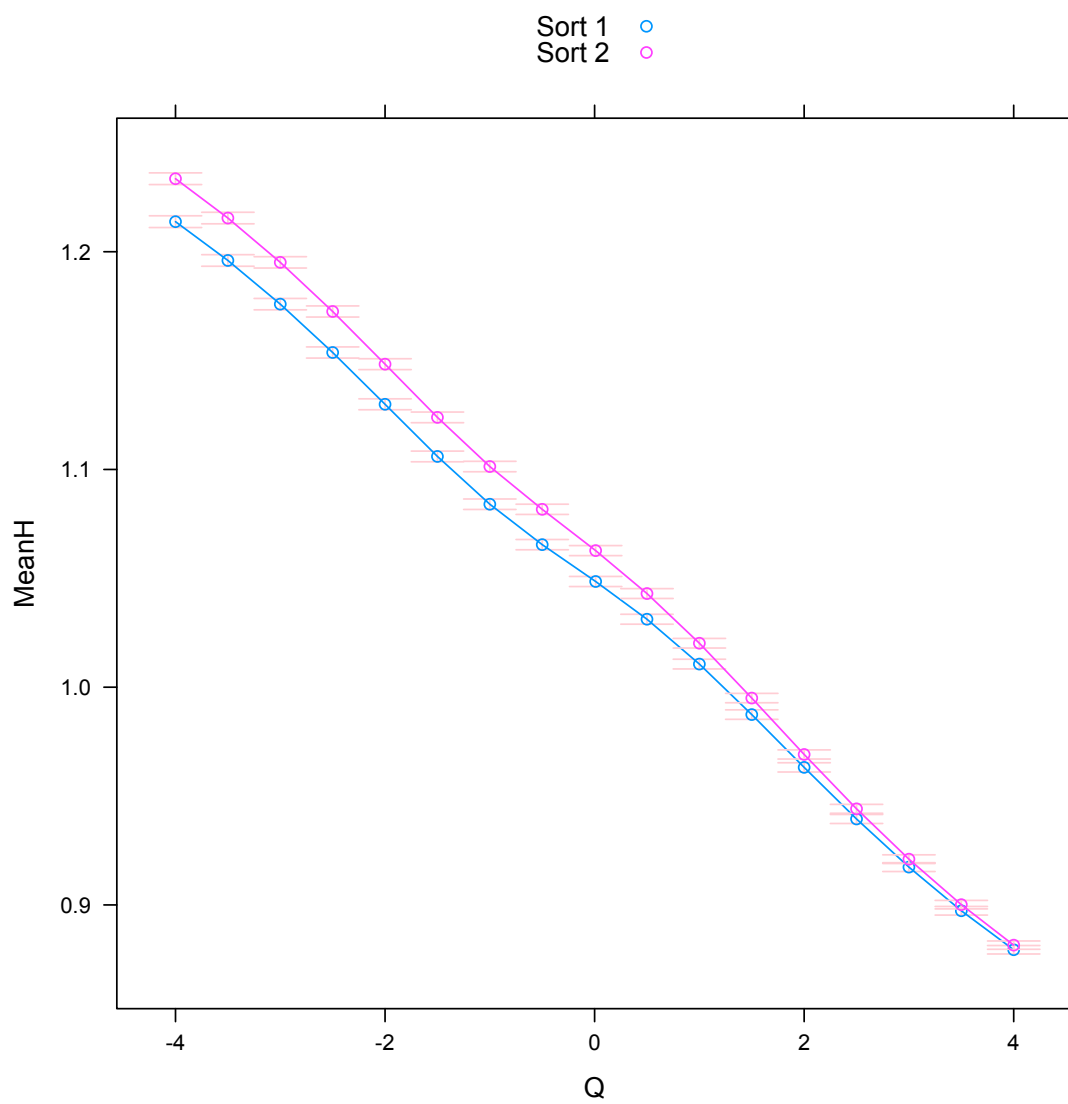


Figure 11. Mean R squared values for the fit between root mean square error and bin size, across a range of Q values, pre-school data.

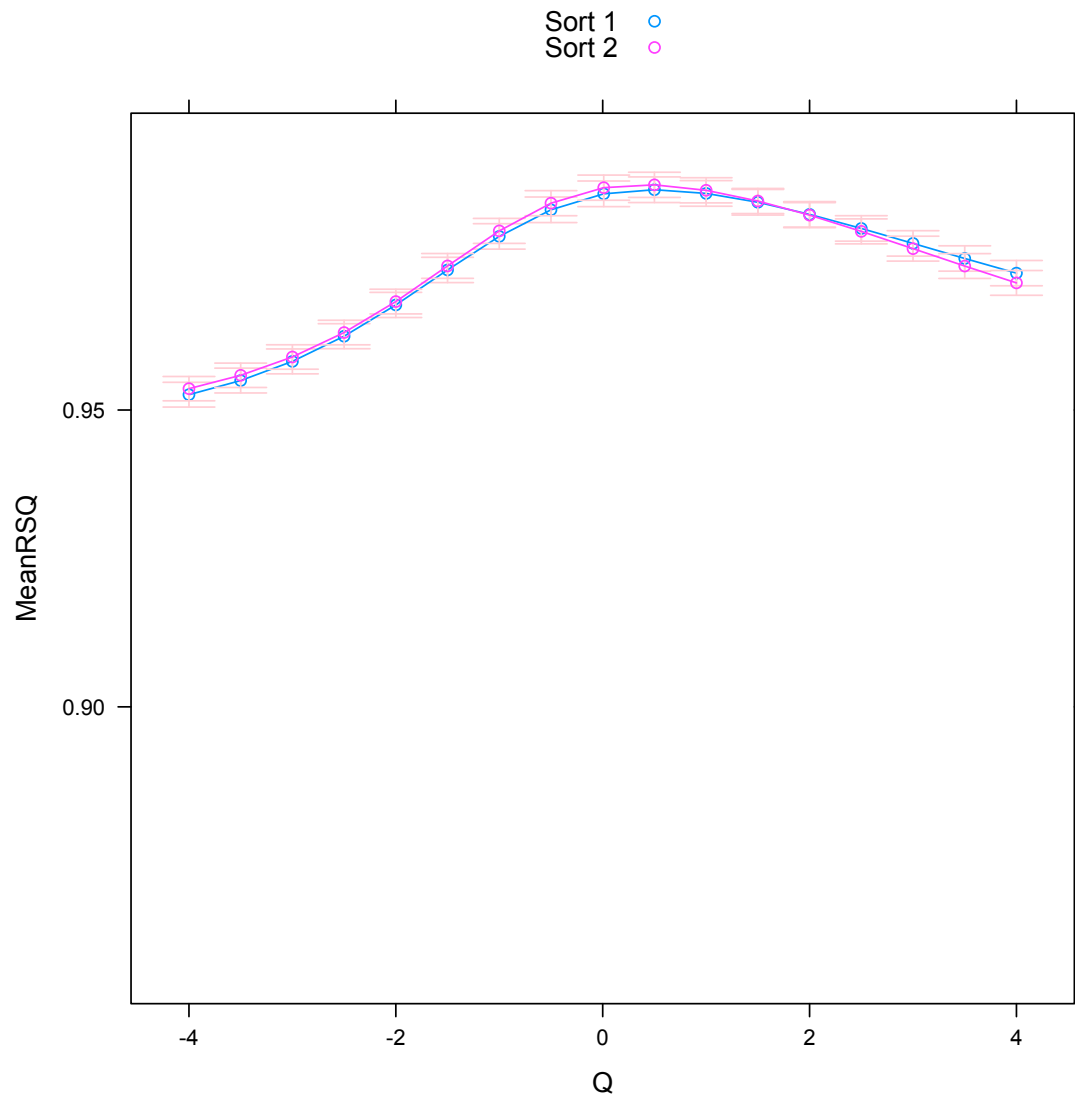


Figure 12: The effect of perturbation of the longest time scale on all other scales, for non-perseveraters. The blue line represents the pre-switch runs, and the magenta line represents post-switch runs. The pink errors bars are 95% confidence intervals. For both pre and post switch, perturbation of this scale leads to a null effect.

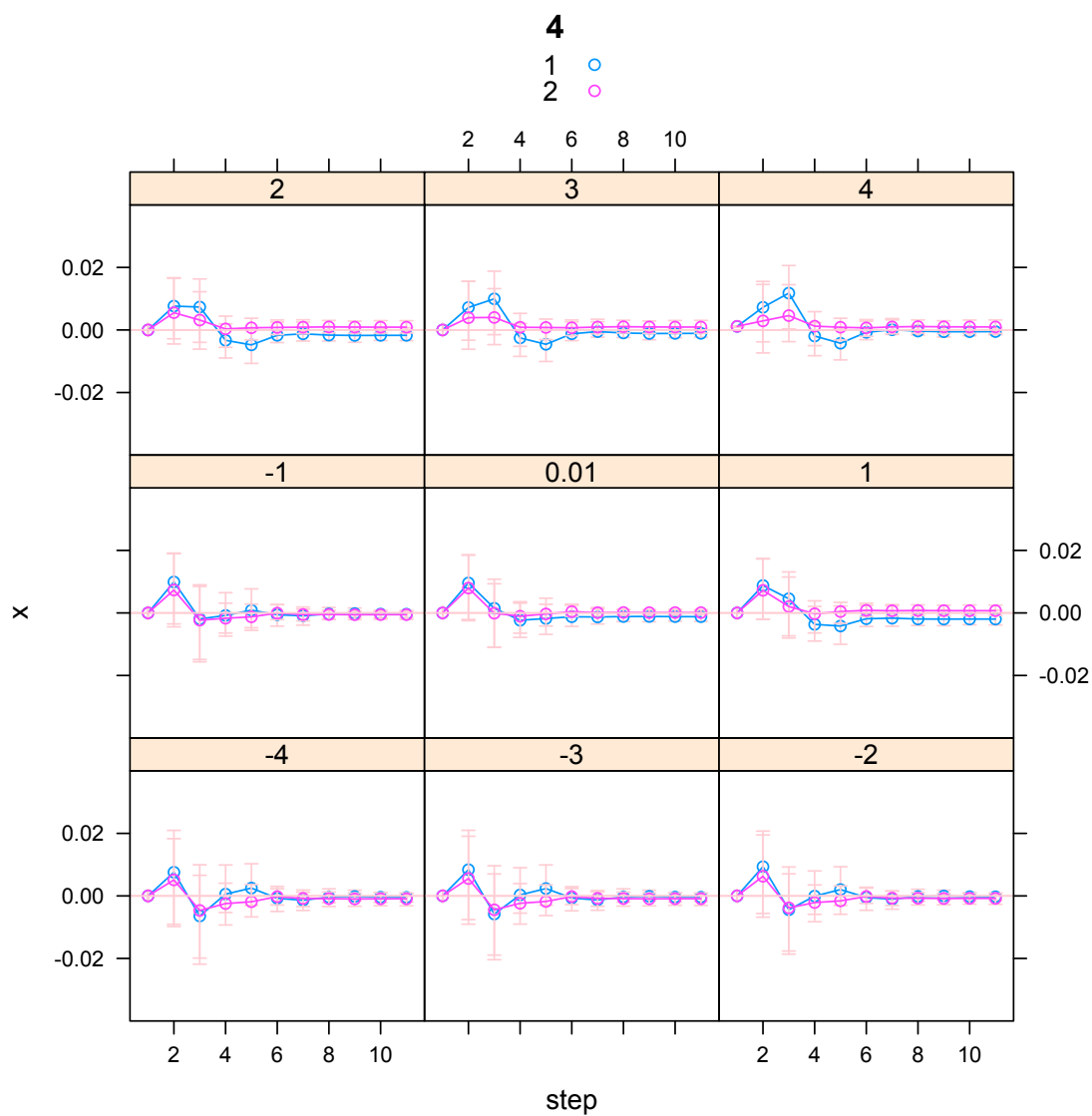


Figure 13: The effect of perturbation of the shortest time scale on all other scales, for non-perseveraters. The blue line represents the pre-switch runs, and the magenta line represents post-switch runs. The pink errors bars are 95% confidence intervals. Pre-switch, perturbation leads to a slight decrease in activity. Post-switch, perturbation leads to a general increase in activity.

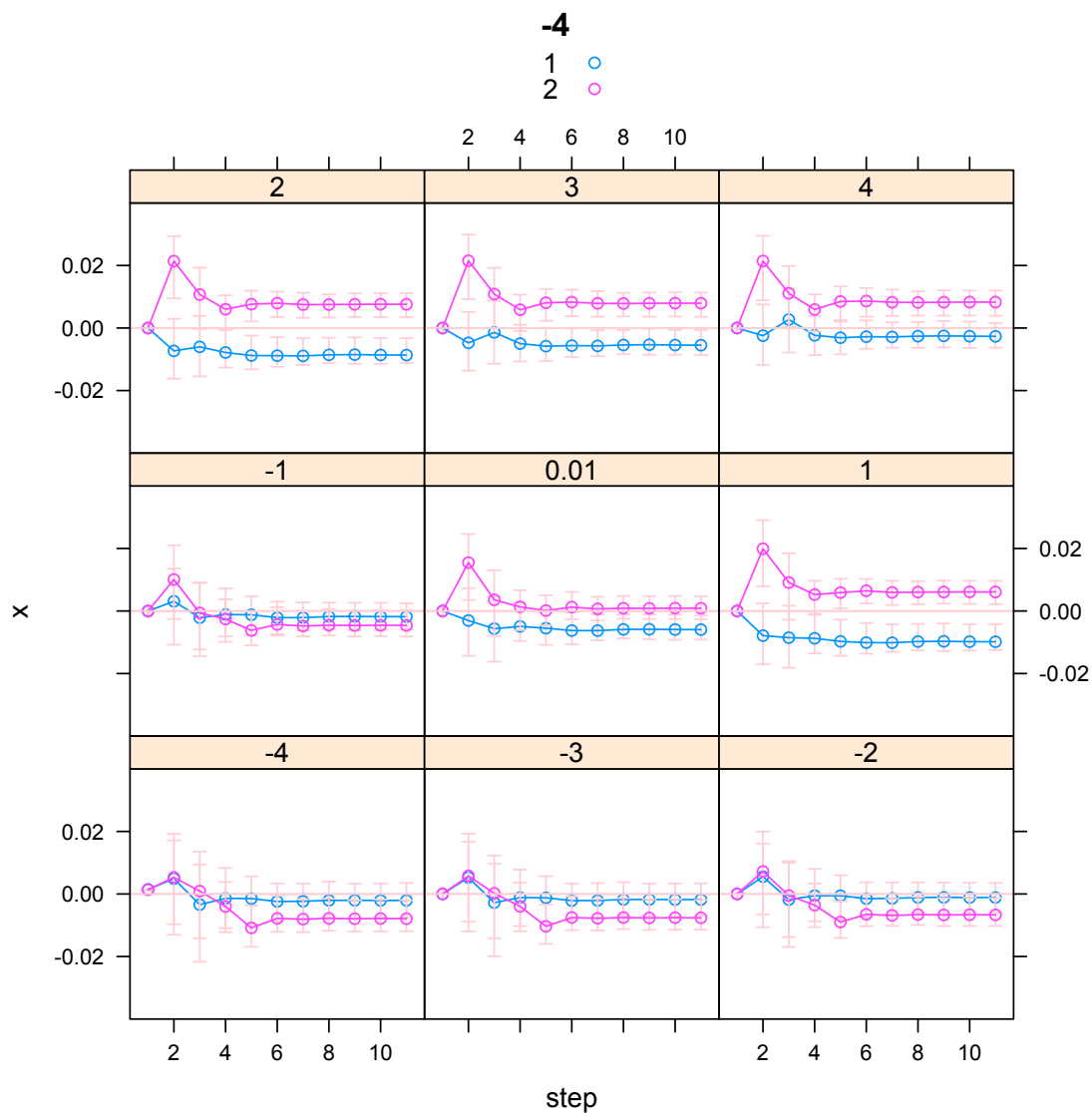


Figure 14: The effect of perturbation of the longest time scale on all other scales, for perseveraters. The blue line represents the pre-switch runs, and the magenta line represents post-switch runs. The pink errors bars are 95% confidence intervals. Perturbation of this scale leads to a decrease in activity pre-switch. Post-switch, perturbation of this scale leads to a decrease in activity at lower scales and a null effect at higher ones.

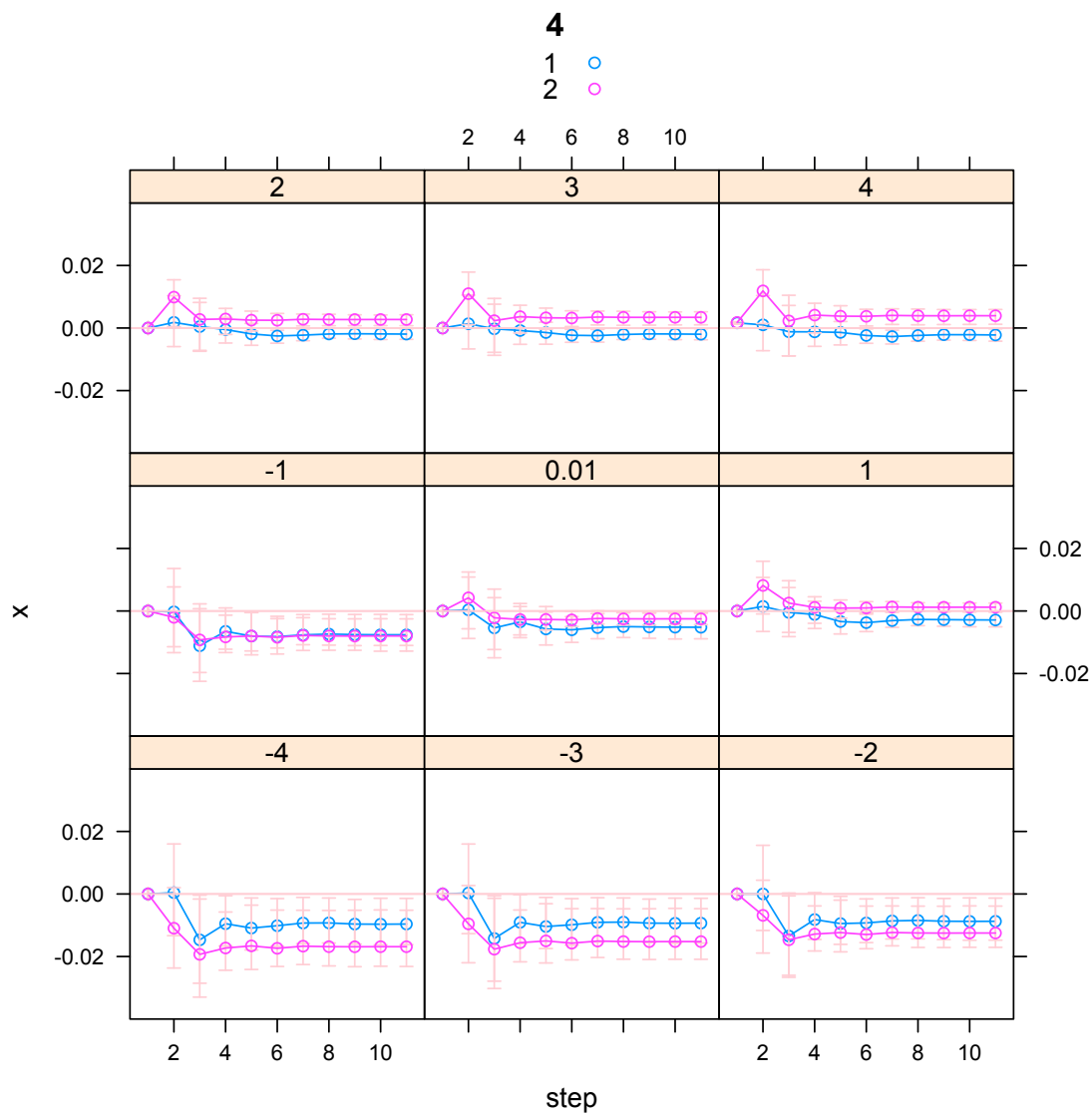
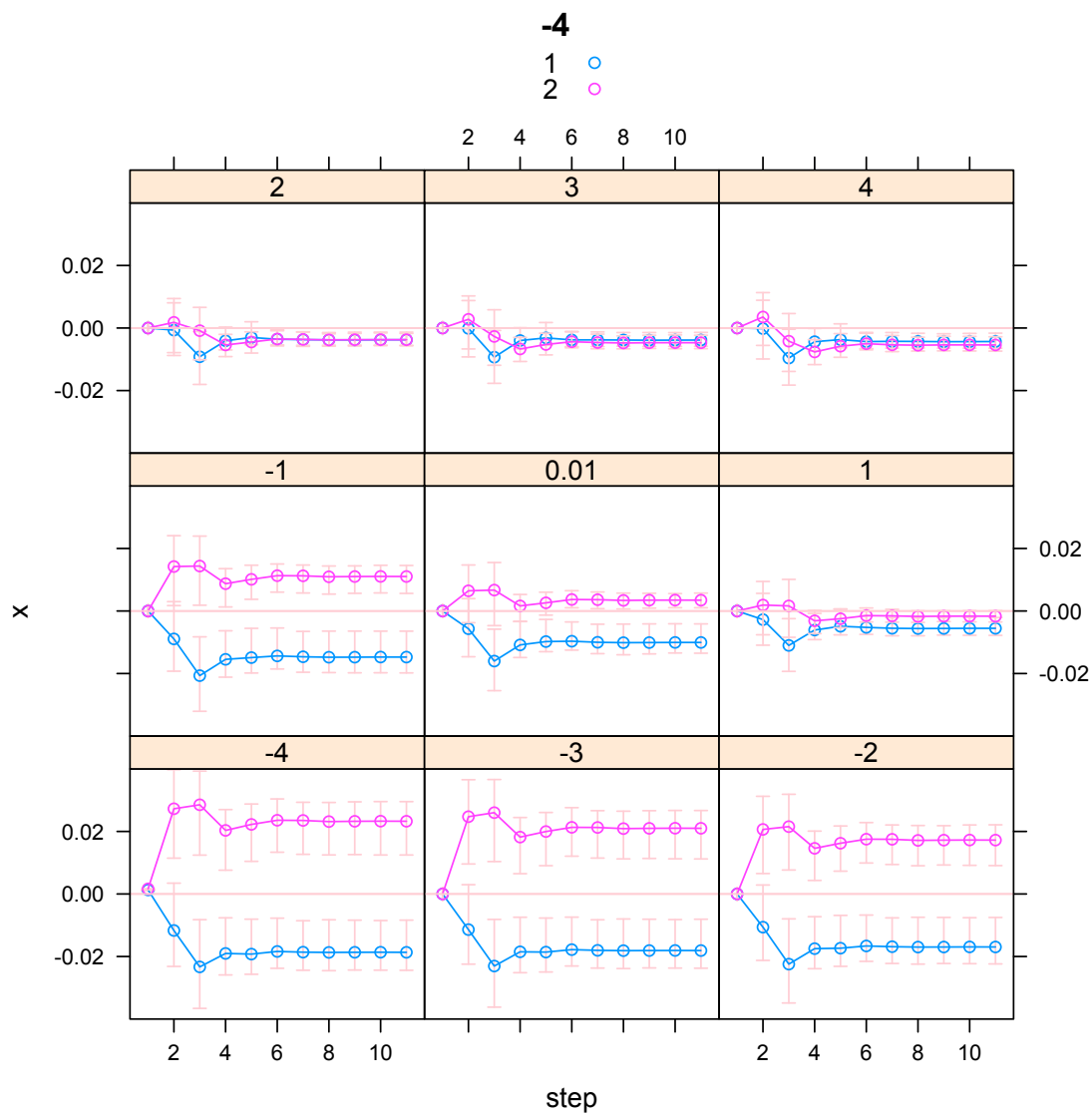


Figure 15: The effect of perturbation of the shortest time scale on all other scales, for perseveraters. The blue line represents the pre-switch runs, and the magenta line represents post-switch runs. The pink errors bars are 95% confidence intervals. Pre-switch, perturbation of this scale leads to a decrease in activity at shorter scales. Post-switch, perturbation of this scale leads to an increase in activity at shorter scales and a slight decrease in activity at longer scales.



Tables

Table 1: Model coefficients for model 1, predicting to length of run. An * indicates that the predictor in question is significant.

Predictor	Estimate	SE	z
Intercept	27.748	.927	29.91*
Run	-1.91	.085	-22.43*

Table 2: Model coefficients for model 1, predicting to length of run. An * indicates that the predictor in question is significant.

Predictor	Estimate	SE	z
Intercept	22.109	1.06	23.557*
Run	-1.911	.085	-22.425*
Group (0 = explicit, 1 = induction)	5.279	1.462	3.604*