

# Asymmetric Switch Costs as a Function of Task Strength

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## Abstract

Several studies reported that it is harder to switch from a difficult task to an easy task than vice versa. Previous studies explain this paradoxical effect in terms of differences in task strength, by letting participants switch between different types of tasks. However, these studies failed to isolate the effects of task strength from task identity. Here, we present a series of experiments in which we systematically varied the strength of two tasks independent of their identity. We adapted a computational model of task switching by Yeung and Monsell (2003) to derive predictions about the magnitude of asymmetric switch costs (ASC) as a function of task strength, and compared predictions from the model to behavioral data. Our results reveal that ASC depend on the overall and relative task strength across the two tasks. ASC can therefore flip directions if the strength of two tasks is reversed, irrespective of their identities.

**Keywords:** task switching; paradoxical switch cost; task-set inertia

## Introduction

Humans are remarkably flexible in their ability to switch between different tasks. However, a paradoxical finding in task switching experiments is that participants require more time and exhibit more errors when they switch from a harder task to an easier task than vice versa (Monsell, Yeung, & Azuma, 2000; Yeung & Monsell, 2003). For instance, bilinguals take more time to switch from their first language to their second language compared to switching from their second language to their first language (Meuter & Allport, 1999).

Allport, Styles, and Hsieh (1994) explained such asymmetric switch costs (ASC) in terms of the task-set inertia hypothesis. This postulates that the processes needed to execute a task (the task-set) persist in time, causing interference with the next task, and that switch costs reflect the time needed to resolve this interference. Executing a weak<sup>1</sup> task is assumed to require inhibition of automatic processes from a competing dominant task that would otherwise interfere (e.g. speaking a second language would require inhibition of the first language). According to the task-set inertia hypothesis, this inhibition persists when switching back to a dominant task, yielding high switch costs (Allport & Wylie, 2000). In contrast, switching to a weaker task should result in lower switch

costs since the weak task would not require to be inhibited when performing the dominant task.

Building on the task-set inertia hypothesis, Yeung and Monsell (2003) devised a formal model that explains ASC as an interaction between task priming and top-down control. In their model, task priming corresponds to a carry over of the previous task-set, resulting in a facilitation of task repetitions (positive priming) but a delay for task switches (negative priming). Top-down control is assumed to vary as a function of task strength, with the weaker task requiring and receiving more control than the more dominant task. Without top-down control, both tasks would be subject to the same switch cost as they would be governed by the same amount of negative task priming. However, higher amounts of top-down control for the weaker task can compensate the effects of negative task priming, yielding lower switch costs for the weaker task relative to the more dominant task.

These and other accounts identify differences in task strength as a necessary condition for ASC (Allport et al., 1994; Allport & Wylie, 2000; Yeung & Monsell, 2003; Gilbert & Shallice, 2002). These accounts predict that the asymmetry in switch costs between two tasks should reverse if their task strengths reverse. In the example above, switching from a second language to a first language should be easier if the task strength of the first language was decreased relative to the second language. However, to date, there is no empirical support for this prediction as previous studies confounded task strength with task identity (e.g. the first language is always easier than the second language, at least for the duration of the experiment). The inability to manipulate task strength independent of task identity has also prevented researchers from testing the precise constellations of task strength under which ASC arise. One may ask if ASC would arise as soon as two tasks differ significantly in task strength, even if both are considered weak, or dominant? Finally, several studies have failed to observe ASC in error rates (ERs) (Meuter & Allport, 1999; Costa & Santesteban, 2004), or reported effects for reaction times (RTs) only (Mayr & Keele, 2000; Philipp, Gade, & Koch, 2007), failing to address whether participants traded off speed against accuracy.

So far, it is unclear (a) whether an asymmetry in switch costs between two tasks reverses if the task strength of the two tasks is reversed, and (b) whether the magnitude of ASC depends on the strength of the dominant task, in addition to

<sup>1</sup>Here, we refer to a task as weak if it requires higher amounts of cognitive control in order to overcome processing interference from more automatic (dominant) tasks.

the difference in strength between the dominant and the weak task. Here, we examine these questions across five experiments in which we manipulate the strength of two tasks independent of their identity. To account for tradeoffs in speed versus accuracy, we fit a hierarchical drift diffusion model (DDM, Ratcliff, 1978; Wiecki, Sofer, & Frank, 2013) to RTs and error rates. Finally, we compare experiment results to predictions derived from the task switching model by Yeung and Monsell (2003)

## Experiments

We examined ASC across five experiments in which participants switched between categorizing the motion and categorizing the color of random-dot kinematograms (RDKs) (Kayser, Erickson, Buchsbaum, & D’Esposito, 2010). We manipulated the strength of each task across experiments by varying the signal to noise ratio of the task-relevant stimulus dimension. For each experiment, we then determined the strength of each task, as well as ASC in the drift rate of the fitted DDM.

### Participants

All participants were students from Princeton University and received one hour of course credit. The study was approved by the Institutional Review Board of Princeton University. Participants signed a consent form prior to participation and were debriefed about the purpose of the study at the end of testing. We excluded participants whose performance was below 60% accuracy. Table 1 lists participant information for each experiment.

Table 1: Participants across all experiments.

Exp.	Participants	Age	Excluded
1	76 (37 female)	M = 19.5, SD = 0.56	6
2	25 (13 female)	M = 20.5, SD = 0.96	4
3	76 (42 female)	M = 20.4, SD = 0.54	6
4	33 (18 female)	M = 19.8, SD = 0.71	3
5	33 (17 female)	M = 20.1, SD = 0.63	4

### Method

Each stimulus was an RDK that consisted of blue and red moving dots. Some of the dots consistently moved in either an upward or downward direction (independent of their color) while the remaining dots moved in a random direction. Participants switched between a color task, in which they had to indicate the color of the majority of the dots (red or blue), using the response buttons ‘K’ and ‘L’ respectively, and a motion task in which they had to indicate the direction of coherent motion (up or down), also using the response buttons ‘K’ and ‘L’, respectively. Participants performed each task over a mini-block of four to six trials.

Only the first trial of a mini-block was of interest to our analysis. Thus, in each sequence, we counterbalanced seven factors with respect to the first trial of each mini-block: task (color or motion task), task transition (task switch or task repetition), dot motion (upward or downward), dot color (mostly

blue or red) and correct response (‘K’ or ‘L’ key). Participants were exposed to a total of 256 mini-blocks, divided into four larger experiment blocks.

Each mini-block was preceded by a task cue that instructed participants which task to perform. In some mini-blocks, participants had to repeat the task that they performed in the previous mini-block (task repetition), whereas in other mini-blocks they had to switch to the other task (task switch). The cue was displayed for 700ms before it disappeared for another 500ms. On each trial of a mini-block, the RDK stimulus was shown for 2000ms, followed by an inter-trial interval of 700ms. Participants were asked to respond while the stimulus was on the screen.

Critically, we varied the difficulty for both tasks across experiments, by changing the signal to noise ratio (coherence) for each task (see Tables 2 & 3). Note that variations in the signal to noise ratio of task-relevant stimulus dimensions can mimic the effect of traditional notions of task strength, such as stimulus-response associations in models of cognitive control (Cohen, Dunbar, & McClelland, 1990; Botvinick, Braver, Barch, Carter, & Cohen, 2001) and task switching (Gilbert & Shallice, 2002; Yeung, Nystrom, Aronson, & Cohen, 2006). Thus, differences in the signal to noise ratio between tasks resemble differences in task strength. We defined the color coherence as the percentage of dots that were displayed in the dominant color. For instance, a color coherence of 60% indicated that 60% percent of the dots were colored in blue while the rest of the dots were colored in red. Similarly, we defined motion coherence as the percentage of dots that moved consistently in one direction as opposed to moving in a random direction. In both tasks, coherence was used as a proxy for task difficulty: the higher the coherence, the easier it was to perform the task (Kayser, Buchsbaum, Erickson, & D’Esposito, 2009). It is important to note that equal values for color coherence and motion coherence do not necessarily yield the same level of performance for both tasks.

We adjusted the coherences of both tasks based on results from prior experiments (Tables 2 & 3). The coherence setting for Experiment 1 was determined based on prior pilot studies, with the intention to make the motion task easier than the color task. As expected, we observed that it was easier for participants to perform the motion task relative to the color task in Experiment 1. To test whether this relationship can be inverted, we lowered the coherence of the motion task and increased the coherence of the color task in Experiment 2. In Experiment 3, we tested whether we can invert the relationship observed in Experiment 1 by just lowering the coherence of the motion task while keeping the coherence of the color task the same as in Experiment 1. This manipulation did not yield ASC in terms of RTs, possibly due to a small difference in task strength. We therefore conducted a fourth Experiment in which we decreased the coherence of the motion task even further (relative to Experiment 3) while keeping the coherence of the color task the same as in Experiment 1. Despite significant differences in task strength in terms of both RTs

and error rates, we still failed to observe ASC in Experiment 4, suggesting that ASC may also depend on the strength of the dominant task (in this case, the color task). We therefore decided to increase the coherence of the color task in Experiment 5 while setting the coherence of the motion task to the same value as in Experiment 1.

## Data Analysis

We were specifically interested in the performance costs associated with task switches and therefore focused our analyses on the RTs and error rates associated with the first trial of a miniblock (Rogers & Monsell, 1995). We assessed the effects of task (indexing relative task strength), as well as the interactive effect of task and task transition (indexing ASC) on RTs and error rates using a linear mixed model and logistic mixed model, respectively. We then fit a DDM to RTs and error rates, using the HDDM package (Wiecki et al., 2013). The DDM simulates performance on a task as an accumulation process that integrates information about the stimulus until one of two response thresholds is reached. The rate of evidence accumulation, henceforth referred to as drift rate, can be taken as a proxy for task strength, whereas the threshold indicates the degree to which speed is traded against accuracy (Ratcliff, 1978; Bogacz, Brown, Moehlis, Holmes, & Cohen, 2006; Simen et al., 2009).

Fitting performance with the DDM serves two purposes. First, we quantify behavioral differences in task strength, as well as the asymmetry in switch costs in terms of drift rate, thereby isolating tradeoffs in speed versus accuracy. Second, we can compare performance of human participants to performance of the model. In the behavioral experiment, we manipulated the strength of each task in terms of the signal to noise ratio of the stimulus whereas in the computational model described below, we manipulate the strength of a task in terms of how much a corresponding task processing unit is driven by the stimulus. The DDM parameters collapse across RTs and error rates. Thus, quantifying task performance in terms of drift rate allows us to compare the strength of two tasks in comparable terms, and ASC in terms of the interactive effect between task and task transition on drift.

$$Drift \sim TaskTransition * Task + (1|Subj_i). \quad (1)$$

We fit the DDM using a Monte Carlo Markov Chain of 1000 samples of which the first 300 samples were not considered (burned). Other parameters of the DDM (response threshold, starting point, non-decision time and noise) were fit independent of condition.

## Results

Table 2 and Table 3 show effects for RTs and error rates, respectively. In Experiment 1, participants were faster and made fewer errors during the motion task. The interaction between task and task transition was significant, with the dominant motion task yielding higher switch costs in RTs and error rates. The results from Experiment 1 were reversed in Experiment 2, with the motion task exhibiting higher RTs and higher

error rates, and a significant interaction between task and task transition for error rates, but not RTs. In Experiment 3, participants responded slower to the motion task, but there was no significant difference in error rates between tasks. Moreover, the interaction between task and task transition was only significant for RTs, but not error rates. RTs and error rates were higher in the motion task in Experiment 4, however, we did not observe a significant interaction between task and task transition for RTs and error rates. Finally, in Experiment 5, we observed a speed accuracy tradeoff for the main effect of task, with the motion task showing higher RTs but lower error rates. A significant interaction between task and task transition suggests that participants exhibited higher switch costs in terms of both RTs and error rates for the motion task relative to the color task.

Table 2: RT results for main effects of task and ASC.

Exp.	Color Coh.	Motion Coh.	Fixed Effects	$\beta$	SD	p
1	65%	60%	task***	-51ms	4ms	<0.001
2	80%	30%	task***	132ms	7ms	<0.001
3	65%	30%	task***	37ms	5ms	<0.001
4	65%	24%	task***	57ms	9ms	<0.001
5	80%	60%	task*	16ms	7ms	0.0321
1	65%	60%	ASC***	42ms	9ms	<0.001
2	80%	30%	ASC	21ms	14ms	0.12
3	65%	30%	ASC***	35ms	10ms	<0.001
4	65%	24%	ASC	32ms	18ms	0.0758
5	80%	60%	ASC***	48ms	15ms	0.001

Table 3: Error rate results for main effects of task and ASC.

Exp.	Color Coh.	Motion Coh.	Fixed Effects	$\beta$	SD	p
1	65%	60%	task***	-0.37	0.06	<0.001
2	80%	30%	task***	0.41	0.10	<0.001
3	65%	30%	task	0.02	0.05	0.704
4	65%	24%	task***	0.34	0.09	<0.001
5	80%	60%	task***	-0.36	0.11	<0.001
1	65%	60%	ASC***	0.41	0.12	<0.001
2	80%	30%	ASC*	-0.39	0.19	0.045
3	65%	30%	ASC	-0.082	0.11	0.473
4	65%	24%	ASC	0.10	0.19	0.591
5	80%	60%	ASC*	0.52	0.22	0.018

In addition to the RT and error rate analysis, we fitted the data with a hierarchical drift diffusion model (HDDM), to investigate the effects of task strength and ASC in terms of drift rate. In Experiment 1, the drift rate fitted to the motion task was significantly larger than the drift rate for the color task, ( $M = 0.34$ , 95%  $CI = [0.30, 0.40]$ ), suggesting that the motion task was easier than the color task. Furthermore, the drift rate cost of switching to the easier motion task was higher than the drift rate cost of switching to the color task ( $M = -0.33$ , 95%  $CI = [-0.42, -0.24]$ ). We examined the hypothesis that ASC reverse with the relative strength of two tasks, by comparing ASC of Experiment 1 against ASC in Experiment 2 (with lower coherence of the motion task and higher coherence of the color task). Results indicate that the task effect on drift rate reversed in Experiment 2 ( $M = -0.53$ , 95%

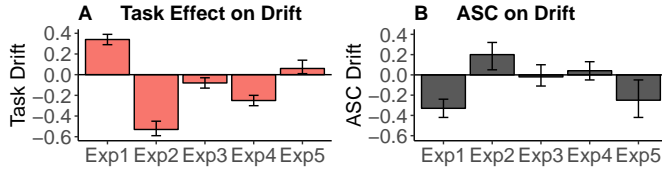


Figure 1: Main effects of task and ASC in terms of drift rate. (A) The main effect of task on drift rate is plotted for each experiment. Positive values indicate that participants accumulated evidence at a higher rate for the motion task relative to the color task (i.e. the strength of the motion task was higher). (B) The ASC effect in terms of drift rates is plotted for each experiment. Positive ASC drift rates indicate that switch costs for the color task were lower than the motion task. Vertical bars indicate 95% confidence intervals.

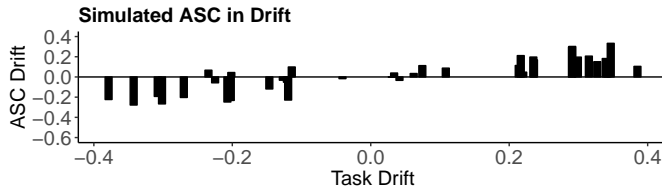


Figure 2: ASC as a function of task effect in drift rate simulated by the model.

$CI = [-0.60, -0.46]$ ), suggesting that the color task was easier than the motion task. Moreover, the cost of switching to the motion task was now lower than the cost of switching to the color task, as indicated by a positive interactive effect of task and task transition on drift rate ( $M = 0.20$ , 95%  $CI = [0.10, 0.36]$ ). We also compared ASC across Experiments 3-5 to examine whether the magnitude of this effect depends on the task strength of the dominant task. In Experiment 3, we observed no effect of ASC in terms of drift rate ( $M = -0.02$ , 95%  $CI = [-0.11, 0.10]$ ), despite significant differences in the task strength of each task ( $M = -0.08$ , 95%  $CI = [-0.13, -0.13]$ ). Similarly, in Experiment 4, we observed no drift rate effect of ASC ( $M = -0.041$ , 95%  $CI = [-0.05, 0.13]$ ), despite high differences in drift rate between tasks ( $M = -0.25$ , 95%  $CI = [-0.30, -0.20]$ ). However, in Experiment 5 where the coherence of both tasks was high, we observed observed ASC ( $M = -0.25$ , 95%  $CI = [-0.42, -0.05]$ ) while the difference in drift rate between tasks was relatively small ( $M = 0.06$ , 95%  $CI = [0.01, 0.14]$ ).

One concern is that observed differences in drift rates between experiments may arise due to differences in sample size. We therefore performed the same analysis for each experiment on a random sample of 25 participants. Results of this analysis yield the same qualitative effects in drift rates.

## Task Switching Model

To test whether our experimental results would be predicted by the model of Yeung and Monsell (2003), we simulated

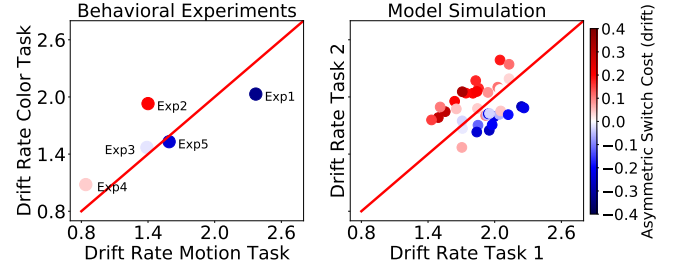


Figure 3: ASC as a function of task drift in the simulated model (left) and 5 behavioral experiments (right). Each colored dot represents a behavioral experiment (left) or a simulation (right) with a different configuration of input strength. Here, we quantified the strength of a task in terms of the drift rate fitted to RTs and error rates for that task. Positive ASC values (red) indicate that switch costs were higher for task 1 relative to task 2, whereas negative values (blue) indicate the opposite. The red line indicates equal strength for both tasks.

ASC as a function of task strength. The model explains the costs of switching between two tasks as a function of their activation. The activation of a task is determined by its strength, the amount of control allocated to a task, as well as task priming. RTs and error rates are generated by two separate equations for response generation and response resolution.

## Model Mechanisms

Here, we outline the mechanisms of the model using the notation of Yeung and Monsell (2003). On each trial, the net input for a given task  $i$  is determined by a linear combination of four sources of input

$$input_i = strength_i + priming_i + control_i + noise \quad (2)$$

Where  $strength_i$  corresponds to the strength of the task<sup>2</sup>,  $priming_i$  corresponds to inertia from the previously executed task and is set to a constant,  $control_i$  is the amount of cognitive control allocated to the task, and  $noise$  is sampled from a Gaussian distribution with zero mean. The activation of each task is a negatively accelerated function of its net input

$$activation_i = 1 - e^{(-c*input[i])} \quad (3)$$

where  $c$  is a scalar that regulates the strength of the net input. Response generation time is computed by first normalizing activation of the two tasks

$$generationrate_i = activation_i / \sum activation \quad (4)$$

and then dividing a threshold by the normalized activation

$$generationtime_i = THRESHOLD / generationrate_i \quad (5)$$

where THRESHOLD is set to 100 in the model. The difference between the generation times for each task determine

<sup>2</sup>Here, the strength of a task is equivalent to the strength of processing weight in a neural network model multiplied by the input signal provided by the stimulus (Cohen et al., 1990; Gilbert & Shallice, 2002)

the time it takes to resolve which task to perform (resolution time). The resolution time depends on the relative time at which response codes for competing tasks are generated, and was computed as follows:

$$resolutiontime = r + f[r - generationtime_j - generationtime_i] \quad (6)$$

where  $r$  corresponds to a sample from an ex-Gaussian distribution. Finally, the RT for each task is computed as the sum of generation time, resolution time, and the two constants  $P$  and  $R$  representing the time taken for perceptual and response-production processes, respectively.

$$ReactionTime_i = P + generationtime_i + resolutiontime_i + R \quad (7)$$

Here, we counted a response as correct if the RT for the currently relevant task was lower than the RT for the currently irrelevant task, and incorrect otherwise<sup>3</sup>.

### Parameterization

The model parameters were adjusted to yield RT and error rate distributions that matched the behavioral data. The priming factor was set to 0.2 for the current task and set to 0 for the irrelevant task. Noise for the net input was sampled from a Gaussian distribution ( $\mu=0$ ,  $\sigma=0.1$ ) and  $r$  was sampled from an ex-Gaussian distribution ( $\mu=200$ ,  $\sigma=240$ ,  $\lambda=150$ ). We fixed  $c$  to 0.5 and set perceptual and response-production parameters,  $P$  and  $R$ , both to 200. In this study, we analyzed switch costs irrespective of stimulus congruency and therefore set  $f$  to 0. The priming factor and  $c$  were adjusted to receive best ASC fits to the data.

Control for both tasks was first initialized to 0.15, and then adjusted using the stair-casing procedure for each task described by Yeung and Monsell (2003). Each time the model made a correct response the control parameter was decremented by 0.01, and each time the model made an error, the control parameter was incremented by 0.1. The task strength parameter was varied across simulations (see below).

### Task Environment

We assessed performance while the model was switching between 64 mini-blocks of two tasks. Each mini-block consisted of four to six trials of the same task. Trial sequences were generated akin to the sequences of the behavioral experiment. We generated the sequence of mini-blocks by counterbalancing which of the two tasks the model is asked to perform, as well as the task transition with respect to the previous mini-block (repetition or switch). Following the analysis procedure of the behavioral experiment, we focused our analyses on RTs and error rates of the first trial of a mini-block (Rogers & Monsell, 1995).

### Simulation Procedure

We used the model to generate predictions about ASC as a function of task strength. To do this, we varied the task strength parameters  $strength_i$  for both tasks from 0.2 to 0.7 in

0.2 steps across simulations, resulting in 36 parameter configurations. For each parameter configuration, we simulated behavior of the model across 30 task switching sequences. In each trial of a sequence, we set  $control_i$  of the relevant task  $i$  to the value determined by the adaptation procedure described above while  $control_j$  of the irrelevant task  $j \neq i$  was set to 0, and fixed all other parameters to their default values. We recorded RTs and error rates for the first trial of each mini-block. We then fitted the drift rate parameter of the DDM separately for each task, as well as for the interaction between task and task transition using the same fitting procedure as described in the Experiment section.

### Results

Our simulation results indicate that ASC increase with the magnitude of the difference between the strengths of tasks (Fig. 2, 3 & 4). Interestingly, the ASC effect was independent of the absolute magnitude of the task strengths, i.e. the magnitude of the ASC effect remained the same with extremely high or low task strength values measured in terms of main effects on drift rates. However, the range of task drift rates produced by the model did not cover the drift rates obtained from Experiments 1, 3 and 4, preventing a direct comparison. We could only obtain lower task drift rates if the model committed a high amount of errors that did not match human behavior. However, our simulation results suggest that, at least for the range of simulated task strengths, ASC are predicted to depend only on the relative but not the absolute strengths of the two tasks.

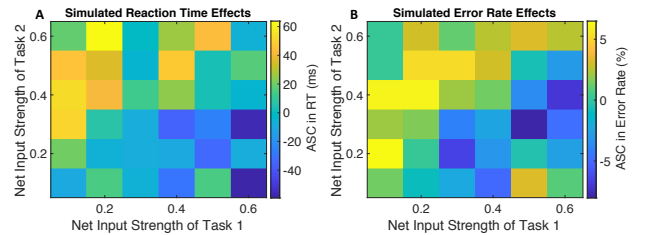


Figure 4: Simulated ASC in RTs and error rates as a function of the input strength for both tasks.

### General Discussion and Conclusion

The seemingly paradoxical finding that switching to an easier task is more difficult has been under investigation for the last two decades. Here, we conducted five task switching experiments to systematically investigate ASC as a function of task strength. We manipulated the strength of two tasks, by varying the signal to noise ratio of the corresponding stimulus dimension, and fitted the behavior of human participants with a DDM to quantify (a) the strength of each task and (b) the ASC in terms of changes in the rate of evidence accumulation (drift rate). Our behavioral results indicate that the asymmetry in switch costs between two tasks can indeed reverse if the more dominant task is weakened and the weaker task is strengthened (Experiment 1 and 2). While previous studies

<sup>3</sup>Note, that Yeung and Monsell only analyzed RTs.

have shown ASC for different tasks, they have typically confounded the difficulty of a task with its identity (Alport et al., 1994; Costa & Santesteban, 2004; Mayr & Keele, 2000; Philipp et al., 2007). Here, we provide empirical support for the hypothesis that ASC can flip if the relative strengths of the two tasks are reversed, even if their identities stay the same. However, our behavioral results suggest that a difference in task strength is not sufficient to yield ASC (Experiment 3-5). That is, we only observed ASC if (a) tasks differed in terms of their strength and (b) the dominant task was relatively easy.

We contrasted human behavior against predictions of a task switching model by Yeung and Monsell (2003) which provides a mechanistic account of this effect in terms of the dynamics of task set priming and top-down control. As in the behavioral experiments, we quantified the strength of each task, as well as the signed magnitude of ASC in terms of drift rate, by fitting the DDM to simulated performance. Our simulation results match the observation that the asymmetry in switch costs should reverse if the strength of two tasks inverts. However, in contrast to participants, the model does not seem to be sensitive to the overall strength of both tasks.

An exhaustive analysis of ASC as a function of task strength can help to inform future models of task switching. While most task switching models do not address ASC (Meiran, 1996; Logan & Bundesen, 2003; Brown, Reynolds, & Braver, 2007; Altmann & Gray, 2008), the connectionist model by Gilbert and Shallice (2002) explains ASC, similar to Yeung and Monsell (2003), in terms of differences in top-down input for both tasks: The easier task yields higher switch costs because a stronger top-down input needed to perform a difficult task persists when switching to the easier task. It is worth noting that both models provide a different explanation than Alport et al. (1994). Allport and colleagues suggest that the easier task is associated with higher switch costs because it needed to be suppressed in order to perform the difficult task. In any case, the dependence of ASC on the absolute strength for both tasks presents an interesting challenge for existing and future models of task switching.

Our study provides an important step towards understanding ASC in that it highlights the importance of absolute task strength. However, it does not explain ASC in terms of the factors that contribute to the strength of a task. Here, we operationalized task strength in terms of drift rate that we fitted from RTs and error rates for each task. While this metric allowed us to compare predictions of the model (with respect to task strength) with behavioral performance, it confounds the effects of task automaticity and top-down control on performance. That is, the measured strength of a task may be high, either because it has a high automaticity or because the task receives a high amount of cognitive control. Recent theories of control allocation suggest that the latter can be manipulated by incentivizing accuracy on task (Shenhav, Botvinick, & Cohen, 2013; Musslick, Shenhav, Botvinick, & Cohen, 2015; Botvinick & Braver, 2015). For instance, Umemoto and Holroyd (2015) associated one of two tasks with a higher

reward, and observed that participants exhibited lower switch costs when switching to the more rewarded task. Prior modeling work suggests that such incentive-driven differences in switch costs can be attributed differences in allocation of top-down control as opposed to differences in task automaticity (Musslick et al., 2015). Future empirical studies may be able to disentangle the contribution of controlled and automatic processing to ASC, e.g. by manipulating the amount of reward participants receive for a given task.

While task strength appears to play an important role in the explanation of ASC, there are other factors to consider. Yeung and Monsell (2003) found that a delayed onset of the task-irrelevant stimulus (high stimulus onset asynchrony, SOA) could either reduce or reverse the effect of ASC. Moreover, the authors observed no ASC if participants responded with different key presses to each task. These findings identify interference between tasks as a necessary condition for ASC. The results presented here indicate that such interference may not occur when both of the tasks are difficult to perform, even if one of the tasks is much easier than the other.

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