1 **TITLE PAGE**

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3 Neural precursors of deliberate and arbitrary decisions in the study of voluntary action

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5 **Authors**

6 U. Maoz[1,2,3]*, G. Yaffe[4], C. Koch[5], L. Mudrik[6]

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8 **Affiliations**

9 [1] Department of Psychology and Brain Institute, Chapman University, Orange, CA, USA.

10 [2] Department of Psychology, University of California, Los Angeles, CA, USA.

11 [3] Division of Humanities and Social Sciences, California Institute of Technology, Pasadena, CA, USA.

12 [4] Yale Law School, Yale University, New Haven, CT, USA.

13 [5] Allen Institute for Brain Science, Seattle, WA, USA.

14 [6] School of Psychological Science and Sagol School of Neuroscience, Tel Aviv University, Tel Aviv, Israel.

15 * maoz@chapman.edu

16

17 **Abstract**

18 The readiness potential (RP)—a key ERP correlate of upcoming action—is known to precede
19 subjects' reports of their decision to move. Some view this as evidence against a causal role for
20 consciousness in human decision-making and thus against free-will. Yet those studies focused
21 on arbitrary decisions—purposeless, unreasoned, and without consequences. It remains
22 unknown to what degree the RP generalizes to deliberate, more ecological decisions. We
23 directly compared deliberate and arbitrary decision-making during a $1000-donation task to
24 non-profit organizations. While we found the expected RPs for arbitrary decisions, they were
25 strikingly absent for deliberate ones. Our results and drift-diffusion model are congruent with
26 the RP representing accumulation of noisy, random fluctuations that drive arbitrary—but not
27 deliberate—decisions. They further point to different neural mechanisms underlying deliberate
28 and arbitrary decisions, challenging the generalizability of studies that argue for no causal role
29 for consciousness in decision-making to real-life decisions.

30

31

32   **Significance Statement**

33   The extent of human free will has been debated for millennia. Previous studies demonstrated
34   that neural precursors of action—especially the readiness potential—precede subjects' reports
35   of deciding to move. Some viewed this as evidence against free-will. However, these
36   experiments focused on arbitrary decisions—e.g., randomly raising the left or right hand. We
37   directly compared deliberate (actual $1000 donations to NPOs) and arbitrary decisions, and
38   found readiness potentials before arbitrary decisions, but—critically—not before deliberate
39   decisions. This supports the interpretation of readiness potentials as byproducts of
40   accumulation of random fluctuations in arbitrary but not deliberate decisions and points to
41   different neural mechanisms underlying deliberate and arbitrary choice. Hence, it challenges
42   the generalizability of previous results from arbitrary to deliberate decisions.

43

44   **MAIN TEXT**

45   **Introduction**

46   Humans typically experience freely selecting between alternative courses of action, say, when
47   ordering a particular item off a restaurant menu. Yet a series of human studies using
48   electroencephalography (EEG) (Haggard & Eimer, 1999; Libet, Gleason, Wright, & Pearl,
49   1983; Salvaris & Haggard, 2014), fMRI (Bode & Haynes, 2009; Bode et al., 2011; Soon,
50   Brass, Heinze, & Haynes, 2008; Soon, He, Bode, & Haynes, 2013), intracranial (Perez et al.,
51   2015), and single-cell recordings (Fried, Mukamel, & Kreiman, 2011) challenged the validity
52   of this common experience. These studies found neural correlates of decision processes
53   hundreds of milliseconds and even seconds prior to the moment that subjects reported having
54   consciously decided. The seminal research that launched this series of studies was conducted
55   by Benjamin Libet and colleagues (Libet, Gleason, Wright, & Pearl, 1983). There, the authors
56   showed that the readiness potential (RP)—a ramp-up in EEG negativity before movement
57   onset, thought to originate from the presupplementary motor area (pre-SMA)—begins before
58   subjects report a conscious decision to act. Some have claimed, following these and other
59   findings, that the subjective human experience of freely deciding is but an illusion, because
60   human actions are unconsciously initiated before the conscious decision to act (Harris, 2012;
61   Libet et al., 1983; Wegner, 2002). This debate has been captivating scholars from many
62   disciplines in and outside of academia (C. Frith, Blakemore, & Wolpert, 2000; C. D. Frith &
63   Haggard, 2018; Haggard, 2008; Jeannerod, 2006; Lau, Rogers, Haggard, & Passingham, 2004;
64   Mele, 2006; Wegner, 2002).

65   Critically, in the above studies, subjects were told to arbitrarily move their right hand or flex
66   their right wrist; or they were instructed to arbitrarily move either the right or left hand
67   (Haggard, 2008; Hallett, 2016; Roskies, 2010). Thus, their decisions were always unreasoned,
68   purposeless, and bereft of any real consequence. This stands in sharp contrast to many real-life
69   decisions that are deliberate—i.e., reasoned, purposeful, and bearing consequences (Ullmann-
70   Margalit & Morgenbesser, 1977): which clothes to wear, what route to take to work, as well as
71   more formative decisions about life partners, career choices, and so on.

72   Deliberate decisions have been widely studied in the field of neuroeconomics (Kable &
73   Glimcher, 2009; Sanfey, Loewenstein, McClure, & Cohen, 2006) and in perceptual tasks (Gold
74   & Shadlen, 2007). Yet, interestingly, little has been done in that field to assess the relation
75   between decision-related activity, subjects' conscious experience of deciding, and the neural
76   activity instantaneously contributing to this experience. Though some studies compared, for
77   example, internally driven and externally cued decisions (Thut et al., 2000; Wisniewski,
78   Goschke, & Haynes, 2016), or stimulus-based and intention-based actions (Waszak et al.,
79   2005), these were typically arbitrary decisions and actions with no real implications. Therefore,
80   the results of these studies provide no direct evidence about potential differences between
81   arbitrary and deliberate decisions.

82   Such direct comparisons are critical for the free will debate, because it is deliberate, rather than
83   arbitrary, decisions that are at the center of philosophical arguments about free will and moral
84   responsibility (Breitmeyer, 1985; Roskies, 2010). Deliberate decisions typically involve more
85   conscious and lengthy deliberation and might thus be more tightly bound to conscious
86   processes than arbitrary ones. Thus, one could speculate that different findings might be
87   obtained when inspecting the RP in arbitrary compared to deliberate decisions.

88   A further reason to expect such differences stems from a recent computational model, which
89   challenged the claim that the RP represents a genuine marker of unconscious decisions. Rather,

90 the model suggested that the RP might reflect the artificial accumulation, up to a threshold, of
91 stochastic fluctuations in neural activity. In the model, crossing the threshold directly leads to
92 action (Schurger, Sitt, & Dehaene, 2012). Such stochastic fluctuations are expected to be the
93 sole driver of arbitrary decisions; while it is the values of the decision alternatives that drive
94 deliberate decisions. Therefore, the model appears to predict no RP for deliberate decisions.

95 Demonstrating no, or considerably diminished, RP in deliberate decisions would challenge the
96 interpretation of the RP as a general index of internal decision-making. More critically, it
97 would question the generalizability of studies focused on arbitrary decisions to everyday,
98 ecological, deliberate decisions.

99 Here, we tested this prediction and directly compared the neural precursors of deliberate and
100 arbitrary decisions—and in particular the RP—on the same subjects, in an EEG experiment.
101 Our experiment utilized a donation-preference paradigm, in which a pair of non-profit
102 organizations (NPOs) were presented in each trial. In deliberate-decision trials, subjects chose
103 to which NPO they would like to donate $1000. In arbitrary-decision trials, both NPOs
104 received an equal donation of $500, irrespective of subjects' key presses (Fig. 1). In both
105 conditions, subjects were instructed to report their decisions as soon as they made them, and
106 their hands were placed on the response keys, to make sure they could do so as quickly as
107 possible. Notably, while the visual inputs and motor outputs were identical between deliberate
108 and arbitrary decisions, the decisions' meaning for the subjects was radically different: in
109 deliberate blocks, the decisions were meaningful and consequential—reminiscent of important,
110 real-life decisions—while in arbitrary blocks, the decisions were meaningless and bereft of
111 consequences—mimicking previous studies of volition.

112

113 **Results**

114 *Behavioral Results*

115 Subjects' reaction times (RTs) were analyzed using a 2-way ANOVA along decision
116 type (arbitrary/deliberate) and difficulty (easy/hard). This was carried out on log-
117 transformed data (raw RTs violated the normality assumption; W=0.94, p=0.001).
118 As expected, subjects were substantially slower for deliberate (M=2.33, SD=0.51)
119 than for arbitrary (M=0.99, SD=0.32) decisions (Fig. 2, left; F(1,17)=126.11,
120 p<0.0001 for the main effect of decision type). A main effect of decision difficulty
121 was also found F(1,17)=18.76, p=0.0004), with difficult decisions (M=1.77,
122 SD=0.40) being slower than easy ones (M=1.56, SD=0.28). Importantly, subjects
123 were slower for hard (M=2.52, SD=0.62) vs. easy (M=2.13, SD=0.44) decisions in
124 the deliberate case (hard vs. easy deliberate decisions: t(17)=4.78, p=0.0002), yet
125 not for the arbitrary case (M=1.00, SD=0.34; M=0.98, SD=0.32, for hard and easy
126 arbitrary decisions, respectively; t(17)=1.01, p=0.33; F(1,17)=20.12, p=0.0003 for
127 the interaction between decision type and decision difficulty). This validates our
128 experimental manipulation and further demonstrates that, in deliberate decisions,
129 subjects were making meaningful decisions, affected by the difference in the values
130 of the two NPOs, while for arbitrary decisions they were not. What is more, the
131 roughly equal RTs between easy and hard arbitrary decisions provide evidence
132 inconsistent with concerns that subjects were deliberating during arbitrary decisions.
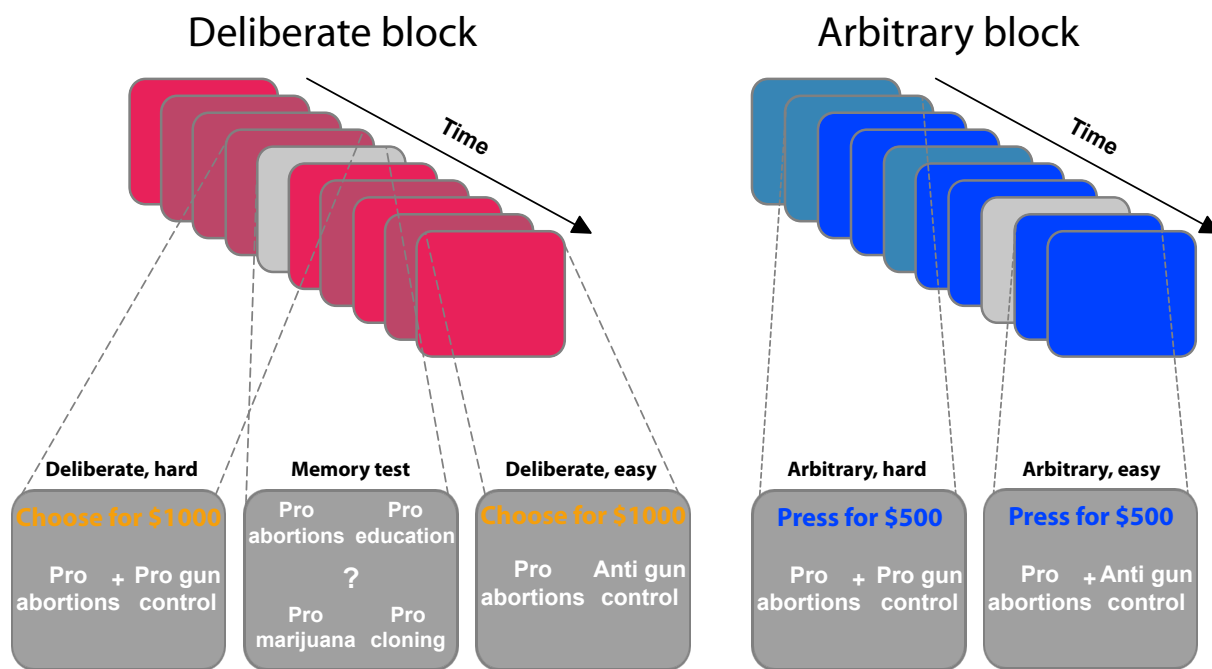
Figure 1: Experimental paradigm. The experiment included deliberate (red, left panel) and arbitrary (blue, right panel) blocks, each containing nine trials. In each trial, two causes—reflecting NPO names—were presented, and subjects were asked to either choose to which NPO they would like to donate (deliberate), or to simply press either right or left, as both NPOs would receive an equal donation (arbitrary). They were specifically instructed to respond as soon as they reached a decision, in both conditions. Within each block, some of the trials were easy (lighter colors) decisions, where the subject's preferences for the two NPOs substantially differed (based on a previous rating session), and some were hard decisions (darker colors), where the preferences were more similar; easy and hard trials were randomly intermixed within each block. To make sure subjects were paying attention to the NPO names, even in arbitrary trials, and to better equate the cognitive load between deliberate and arbitrary trials, memory tests (in light grey) were randomly introduced. There, subjects were asked to determine which of four NPO names appeared in the immediately previous trial. For a full list of NPOs and causes see Supplementary Table 1.

The consistency between subjects' choices throughout the main experiment and the NPO ratings they gave prior to the main experimental session was also analyzed using a 2-way ANOVA (see Methods). As expected, subjects were highly consistent with their own, previous ratings when making deliberate decisions (M=0.91, SD=0.04), but not when making arbitrary (M=0.52, SD=0.04) ones (Fig. 2, right; F(1,17)=946.55, p<0.0001) for the main effect of decision type. A main effect of decision difficulty was also found (F(1,17)=57.39, p<0.0001), with hard decisions evoking less consistent scores (M=0.66, SD=0.05) than easy ones (M=0.76, SD=0.03). Again, decision type and decision difficulty interacted (F(1,17)=25.96, p<0.0001): subjects were much more consistent with their choices in easy (M=0.99, SD=0.02) vs. hard (M=0.83, SD=0,64) deliberate decisions (t(17)=11.15, p<0.0001), than they were in easy (M=0.54, SD=0.07) vs. hard (M=0.49, SD=0.05) arbitrary decisions (t(17)=2.50, p=0.028). Nevertheless, though subjects were around chance (i.e., 0.5) in their consistency in arbitrary decisions (ranging between 0.39 and 0.64), it seems that some subjects were slightly influenced by their preferences in easy-arbitrary decisions trials, resulting in the significant difference between hard-arbitrary and easy-arbitrary decisions above. Finally, no differences were found between subjects' tendency to press the right vs. left key in the different conditions (both main effects and interaction: F<1).

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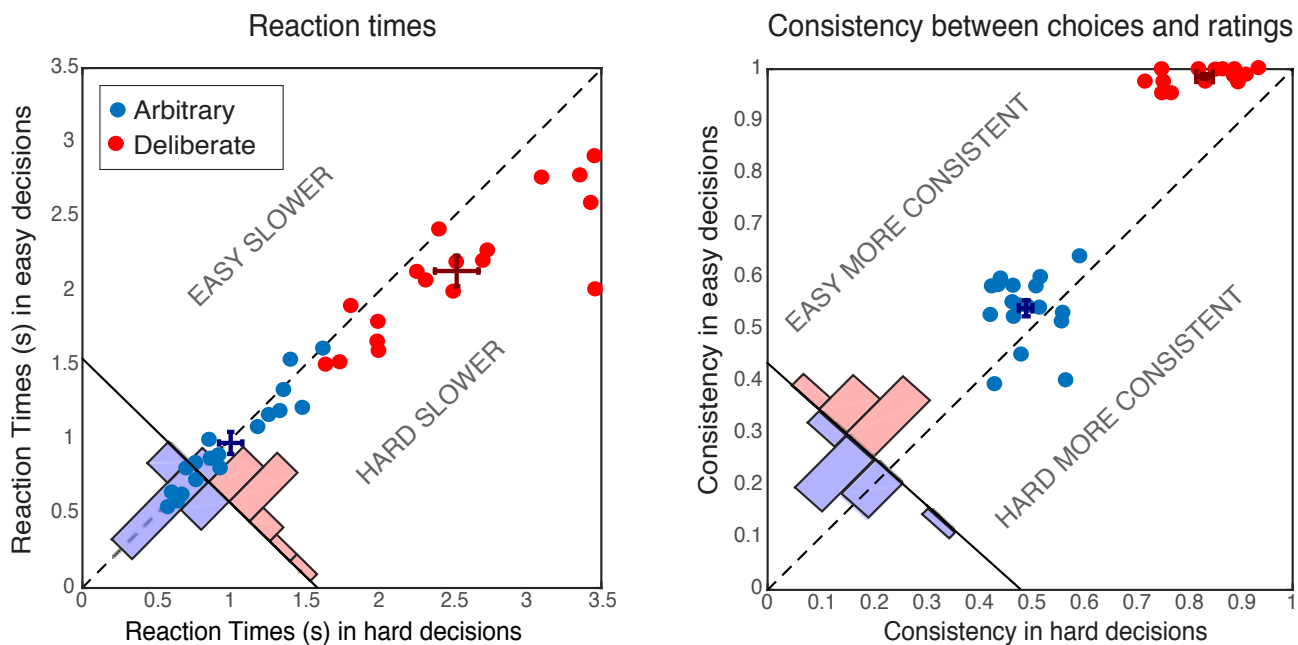
Figure 2: Behavioral results. Reaction Times (RTs; left) and Consistency Grades (CG; right) in arbitrary (blue) and deliberate (red) decisions. Each dot represents the average RT/CG for easy and hard decisions for an individual subject (hard decisions: x-coordinate; easy decisions: y-coordinate). Group means and SEs are represented by dark red and dark blue crosses. The red and blue histograms at the bottom-left corner of each plot sum the number of red and blue dots with respect to the solid diagonal line. The dashed diagonal line represents equal RT/CG for easy and hard decisions; data points below that diagonal indicate longer RTs or higher CGs for hard decisions. In both measures, arbitrary decisions are more centered around the diagonal than deliberate decisions, showing no or substantially reduced differences between easy and hard decisions.

EEG Results: Readiness Potential (RP)

The RP is generally held to index unconscious readiness for upcoming movement (Haggard, 2008; Kornhuber & Deecke, 1990; Libet et al., 1983; Shibasaki & Hallett, 2006); although more recently, alternative interpretations of the RP have been suggested (Miller, Shepherdson, & Trevena, 2011; Schmidt, Jo, Wittmann, & Hinterberger, 2016; Schurger et al., 2012; Trevena & Miller, 2010; Verleger, Haake, Baur, & Śmigasiewicz, 2016). It has nevertheless been the standard component studied in EEG versions of the Libet paradigm (Haggard, 2008; Haggard & Eimer, 1999; Hallett, 2007; Libet, 1985; Libet et al., 1983; Libet, Wright, & Gleason, 1982; Miller et al., 2011; Schurger et al., 2012; Shibasaki & Hallett, 2006; Trevena & Miller, 2010). As is common, we measured the RP over electrode C_z in the different conditions by averaging the activity across trials in the 2 s prior to subjects' movement.

Focusing on the last 500 ms before movement onset for our statistical tests, we found a clear RP in arbitrary decisions, yet RP amplitude was not significantly different from 0 in deliberate decisions (Fig. 3A; $F(1,17)=11.86$, $p=0.003$, BF=309.21 for the main effect of decision type; in t-tests against 0, corrected for multiple comparisons, an effect was only found for arbitrary decisions (hard: $t(17)=5.09$, $p=0.0001$, BF=307.38; easy: $t(17)=5.75$, $p<0.0001$, BF=1015.84) and not for deliberate ones; the Bayes factor—while trending in the right direction—indicated inconclusive evidence (hard: $t(17)=1.24$, $p>0.5$, BF=0.47; easy: $t(17)=1.84$, $p=0.34$, BF=0.97). Our original baseline was stimulus locked (see Methods). And we hypothesized that the inconclusive Bayes factor for deliberate trials had to do with a constant, slow, negative drift

197   that our model predicted for deliberate trials (see below) rather than reflecting a typical RP. As
198   the RTs for deliberate trials were longer than for arbitrary ones, this trend might have become
199   more pronounced for those trials. To test this, we switched the baseline period to -1000 ms
200   to -500 ms relative to *movement* onset (i.e., a baseline that immediately preceded our time of
201   interest window). Under this analysis, we found evidence that deliberate decisions (pooled
202   across decision difficulty) are not different from 0 (BF=0.332), supporting the claim that the
203   RP during the last 500 ms before response onset was completely absent (BF for similarly
204   pooled arbitrary decisions was $5.07 \cdot 10^4$).

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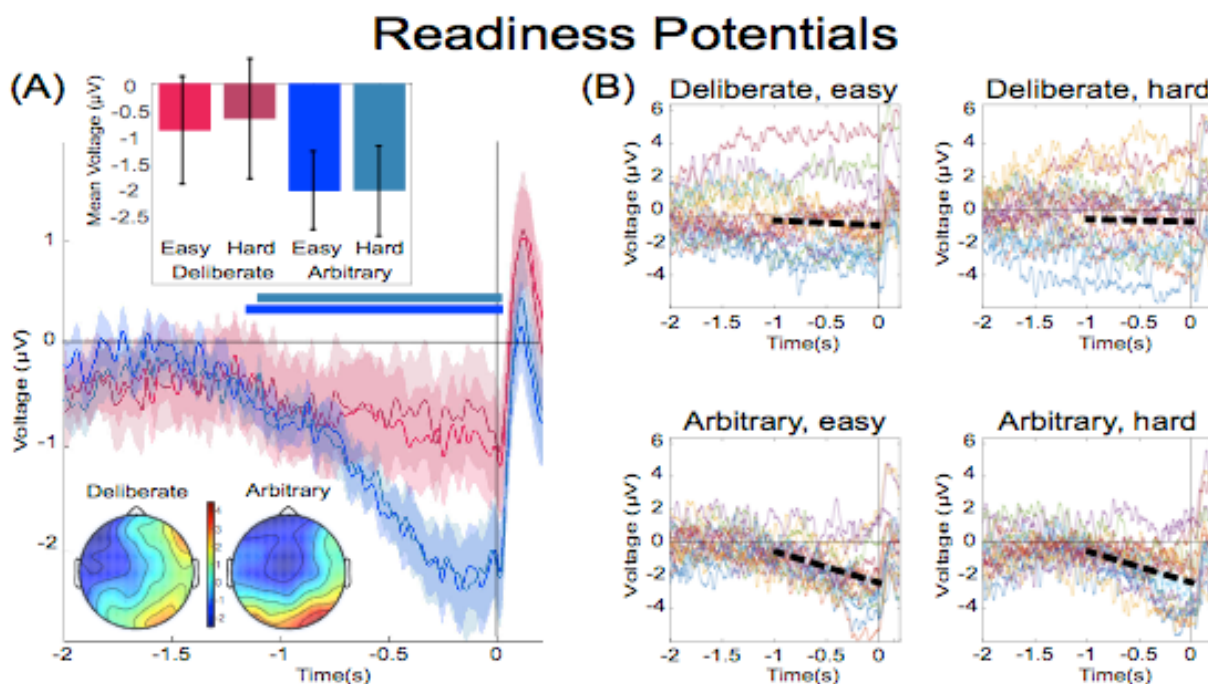
Figure 3: The readiness potentials for deliberate and arbitrary decisions. (A) Mean and SE
of the readiness potential (RP) in deliberate (red shades) and arbitrary (blue shades) easy and
hard decisions in electrode C_z, as well as scalp distributions. Zero refers to time of right/left
movement, or response, made by the subject. Notably, the RP significantly differs from zero
and displays a typical scalp distribution for arbitrary decisions only. Similarly, temporal
clusters where activity was significantly different from 0 were found for arbitrary decisions
only (horizontal blue lines above the x axis). Bar plot insets and scalp distributions depict the
average activity between -0.5 and 0 s, across subjects. The inset shows the mean amplitude of
the RP, with 95% confidence intervals, over the same time window. Response-locked potentials
with an expanded timecourse, and stimulus-locked potentials are given in Fig. 6B and 6A,
respectively. The same (response-locked) potentials as here, but with a *movement-locked
baseline* of -1 to -0.5 s (same as in our Bayesian analysis), are given in Fig. 6C. **(B)** Individual
subjects' C_z activity in the four conditions (n=18). The linear-regression line for voltage against
time over the last 1000 ms before response onset is designated by a dashed, black line. The
lines have slopes significantly different from 0 for arbitrary decisions only. Note that the
waveforms converge to an RP only in arbitrary decisions.

222   In an effort to further test for continuous time regions where the RP is different from 0 for
223   deliberate and arbitrary trials, we ran a cluster-based nonparametric permutation analysis
224   (Maris & Oostenveld, 2007) for all four conditions against 0. Using the default parameters (see
225   Methods), we found a prolonged cluster (~1.2s) of activation that reliably differed from 0 in
226   both arbitrary conditions (designated by horizontal blue-shaded lines above the x axis in Fig.
227   3A). The same analysis revealed no clusters of activity differing from zero in either of the
228   deliberate conditions.

229   In a similar manner, regressing voltage against time for the last 1000 ms before response onset,
230   the downward trend was significant for arbitrary decisions (Fig. 3B; $p<0.0001$, $BF>10^{25}$ for
231   both easy and hard conditions) but not for deliberate decisions, with the Bayes factor indicating
232   conclusive evidence for no effect (hard: $p>0.5$, $BF=0.09$; easy: $p=0.35$, $BF=0.31$; all
233   Bonferroni corrected for multiple comparisons). Notably, this pattern of results was also
234   manifested for single-subject analysis (Fig. 4; 14 of the 18 subjects had significant downward
235   slopes for arbitrary decisions—i.e., $p<0.05$, Bonferroni corrected for multiple comparisons—
236   when regressing voltage against time for every trial over the last 1000 ms before response
237   onset; but only 5 of the 18 subjects had significant downward slopes for the same regression
238   analysis for deliberate decisions; see Methods. In addition, the average slopes for deliberate
239   and arbitrary decisions were -0.28±0.25 and -1.9±0.32 (mean±SE), respectively, a significant
240   difference: $t(17)=4.55$, $p<0.001$, $BF=380.02$).

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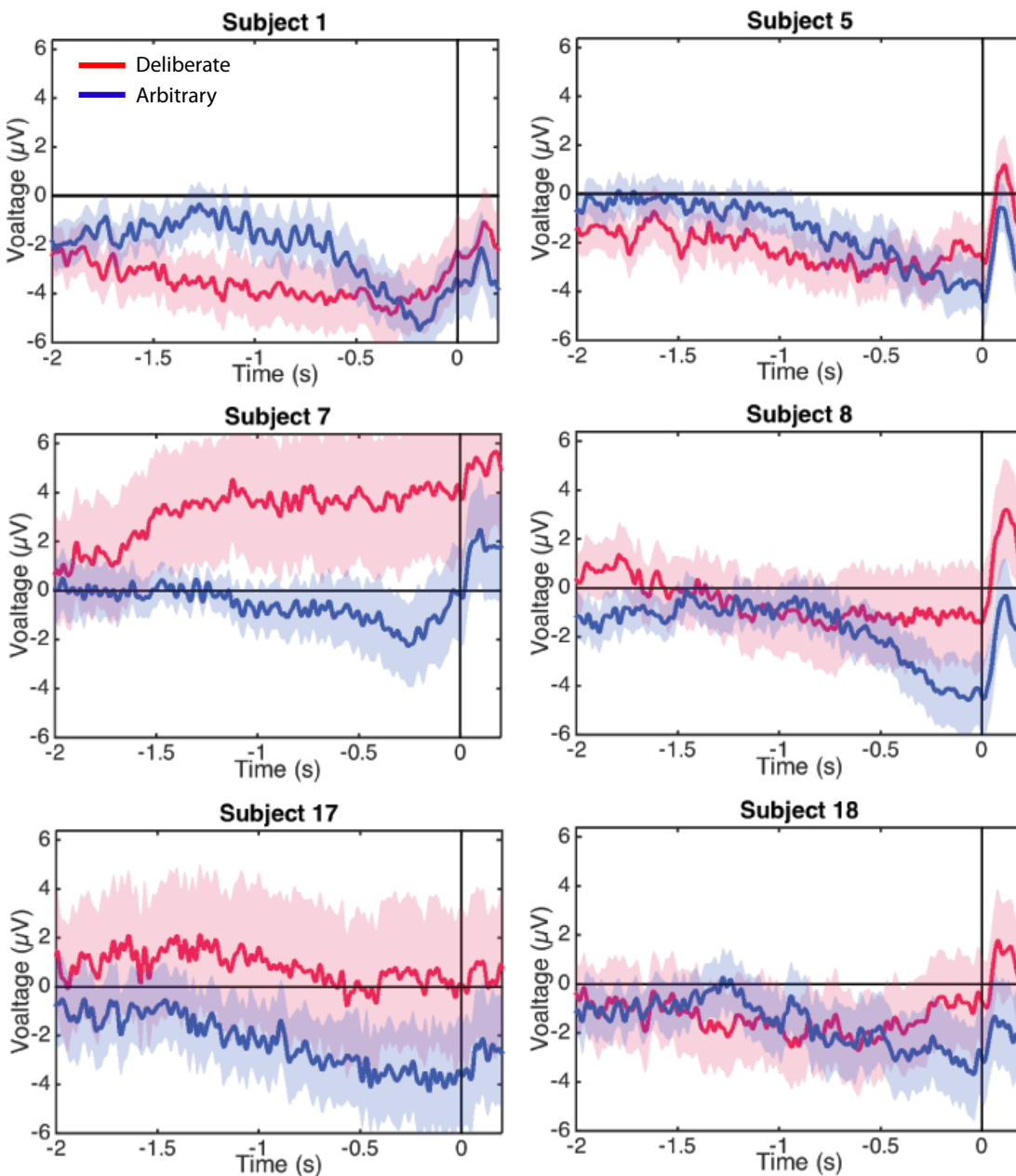
Figure 4: Individual-subjects RPs. Six examples of for individual subjects' RPs for deliberate
decisions (in red) and arbitrary ones (in blue) pooled across decision difficulty.

244 Control analyses

245 We further tested whether differences in reaction time between the conditions, eye movements,
246 filtering, and subjects' consistency scores might explain our effect. We also tested whether the
247 RPs might reflect some stimulus-locked potentials or be due to baseline considerations.

248 *Differences in reaction times (RT) between conditions, including stimulus-locked potentials*
249 *and baselines, do not drive the effect*

250 RTs in deliberate decisions were typically more than twice as long as RTs in arbitrary
251 decisions. We therefore wanted to rule out the possibility that the absence of RP in deliberate
252 decisions stemmed from the difference in RTs between the conditions. We carried out six
253 analyses for this purpose. First, we ran a median split analysis—dividing the subjects into two
254 groups based on their RTs: lower (faster) and higher (slower) than the median, for deliberate
255 and arbitrary trials, respectively. We then ran the same analysis using only the faster subjects
256 in the deliberate condition (M=1.91 s, SD=0.25) and the slower subjects in the arbitrary
257 condition (M=1.25 s, SD=0.23). If RT length affects RP amplitudes, we would expect the RP
258 amplitudes to be more similar between these two groups. However, though there were only
259 half the data points, a similar pattern of results to those over the whole dataset was observed
260 (Fig. 5A; compare to Fig. 3A). Deliberate and arbitrary decisions were still reliably different
261 ($F(1,17)=5.22$, $p=0.03$), with significant RPs found in arbitrary (easy: $t(8)=4.57$, $p=0.0018$;
262 hard: $t(8)=4.09$, $p=0.0035$), but not deliberate (easy: $t(8)=1.92$, $p=0.09$; hard: $t(8)=0.63$,
263 $p=0.54$) decisions. In addition, the RPs for arbitrary decisions were not significantly different
264 between the subjects with above-median RTs and the entire population for the easy or hard
265 conditions (easy: $t(25)=0.14$, $p>0.5$; hard: $t(25)=0.56$, $p>0.5$). Similarly, the RPs for deliberate
266 decisions were not significantly different between the subjects with below-median RTs and the
267 entire population for the easy or hard conditions (easy: $t(25)=-0.34$, $p>0.5$; hard: $t(25)=0.17$,
268 $p>0.5$). This suggest that RTs do not reliably affect C_z activation for deliberate or arbitrary
269 decisions in our results.

270 Second, we regressed the difference between RPs in deliberate and arbitrary decisions
271 (averaged over the last 500 ms before response onset) against the difference between the RTs
272 in these two conditions for each subject (Fig. 5B). Again, if RT length affects RP amplitudes,
273 we would expect differences between RTs in deliberate and arbitrary conditions to correlate
274 with differences between RPs in the two conditions. But no correlation was found between the
275 two measures ($r=0.22$, $t(16)=0.86$, $p=0.4$). We further tried regressing the RP differences on
276 RT differences. The regression did not produce any reliable relation between RT and RP
277 differences (regression line: $y = 0.54$ [CI -0.8, 1.89] x - 0.95 [CI -2.75, 0.85]; the R^2 was very
278 low, at 0.05 (as expected from the r value above), and, as the confidence intervals suggest, the
279 slope was not significantly different from 0, $F(1,16)=0.74$, $p=0.4$).

280 While the results of the above analyses suggested that our effects do not stem from differences
281 between the RTs in deliberate and arbitrary decisions, the average RTs for fast deliberate
282 subjects were still 660 ms slower than for slow arbitrary subjects. In addition, we had only half
283 of the subjects in each condition due to the median split, raising the concern that some of our
284 null results might have been underpowered. We also wanted to look at the effect of cross-trial
285 variations within subjects and not just cross-subjects ones. We therefore ran a third, within-
286 subjects analysis. We combined the two decision difficulties (easy and hard) for each decision
287 type (arbitrary and deliberate) for greater statistical power. And then we took the faster (below-
288 median RT) deliberate trials and slower (above-median RT) arbitrary trials for each subject
289 separately. So, this time we had 17 subjects (again, one was removed) and better powered
290 results. Here, fast deliberate arbitrary trials (M=1.63 s, SD=0.25) were just 230 ms slower than

291 slow arbitrary decisions (M=1.40 s, SD=0.45), on average. This cut the difference between fast
292 deliberate and slow arbitrary by about 2/3 from the between-subjects analysis. We then
293 computed the RPs for just these fast deliberate and slow arbitrary trials within each subject
294 (Fig. 5C). Visually, the pattern there is the same as the main analysis (Fig. 3A). What is more,
295 deliberate and arbitrary decisions remained reliably different (t(16)=3.36, p=0.004). Arbitrary
296 trials were again different from 0 (t(16)=-4.40, p=0.0005), while deliberate trials were not
297 (t(16)=-1.54, p=0.14).
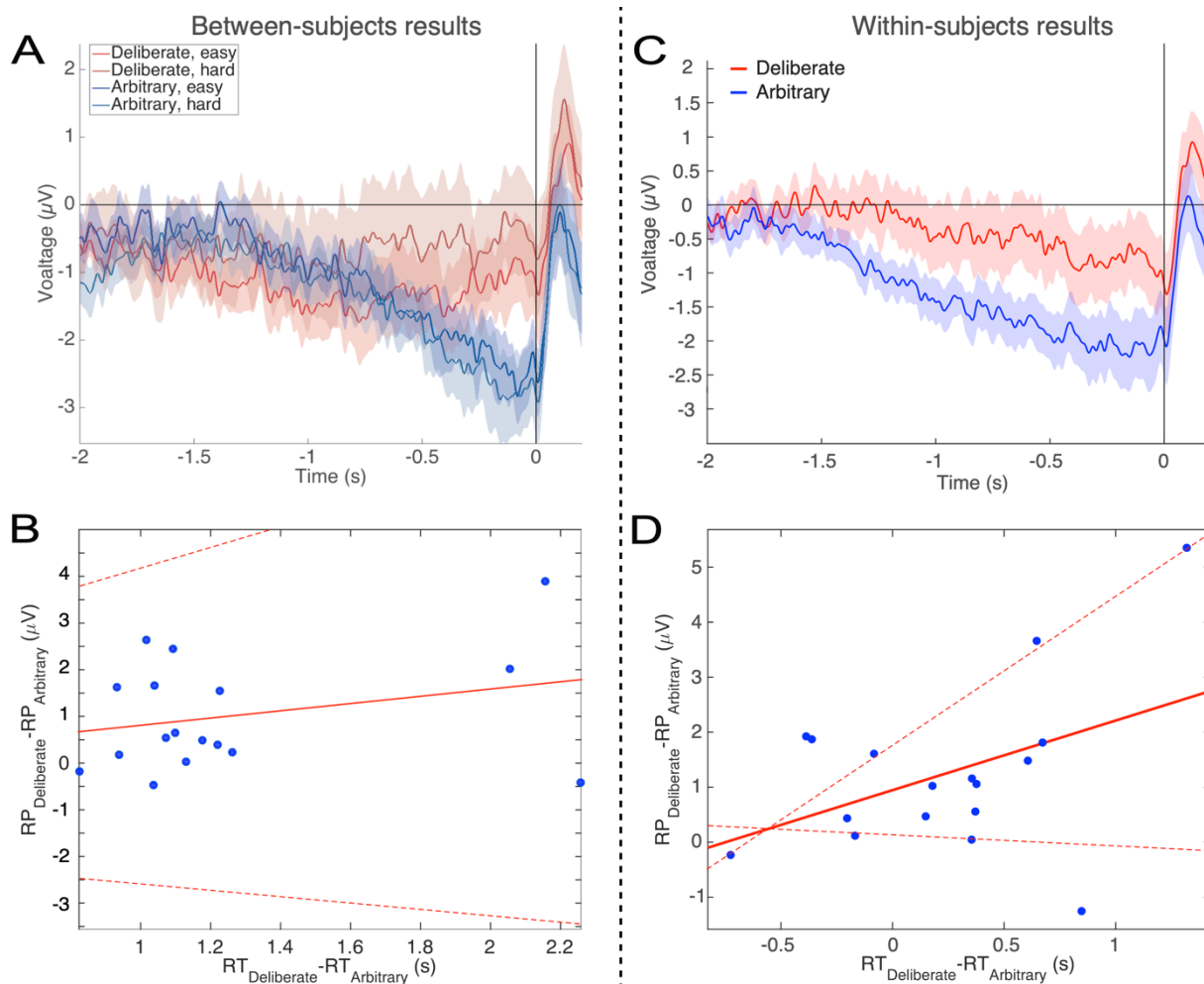
**Figure 5: Relations between RTs and RPs between subjects (A&B) and within subjects
(C&D). (A)** The subjects with above-median RTs for arbitrary decisions (in blue) and below-
median RTs for deliberate decisions (in red), show the same activity pattern that was found in
the main analysis (compare Fig. 3A). **(B)** A regression of the difference between the RPs versus
the difference between the RTs for deliberate and arbitrary decisions for each subject. The
equation of the regression line (solid red) is y = 0.54 [CI -0.8, 1.89] x - 0.95 [CI -2.75, 0.85]
(confidence intervals: dashed red lines). The R^2 is 0.05. One subject, #7, had an RT difference
between deliberate and arbitrary decisions that was more than 6 interquartile ranges (IQRs)
away from the median difference across all subjects. That same subject's RT difference was
also more than 5 IQRs higher than the 75th percentile across all subjects. That subject was
therefore designated an outlier and removed only from this regression analysis. **(C)** For each
subject separately, we computed the RP using only the faster (below-median RT) deliberate
trials and slower (above-median RT) arbitrary trials. The pattern is again the same as the one
found for the main analysis. **(D)** We computed the same regression between the RP differences
and the RT differences as in B, but this time the median split was within subjects. The equation
of the regression line is y = 1.27 [CI -0.2, 2.73] x - 0.95 [CI 0.14, 1.76]. The R^2 is 0.18.

315   We further regressed the within-subject differences between RPs in fast deliberate and slow
316   arbitrary decisions (defined as above) against the differences between the corresponding RTs
317   for each subject to ascertain that such a correlation would not exist for trials that are closer
318   together. We again found no reliable relation between the two differences (Fig. 5D; regression
319   line: y = 1.27 [CI -0.2, 2.73] x - 0.95 [CI 0.14, 1.76]; R^2=0.18).

320   Yet another concern that could relate to the RT differences among the conditions is that the RP
321   in arbitrary blocks might actually be some potential evoked by the stimuli (i.e., the
322   presentations of the two causes), specifically in arbitrary blocks, where the RTs are shorter
323   (and thus stimuli-evoked effects could still affect the decision). In particular, a stimulus-evoked
324   potential might just happen to bear some similarity to the RP when plotted locked to response
325   onset. To test this explanation, we ran a fifth analysis, plotting the potentials in all conditions,
326   locked to the onset of the stimulus (Fig. 6A). We also plotted the response-locked potentials
327   across an expanded timecourse for comparison (Fig. 6B). If the RP-like shape we see in Figs.
328   3A and 6B is due to a stimulus-locked potential, we would expect to see the following before
329   the 4 mean response onset times (indicated by vertical lines at 0.98 and 1.00, 2.13, and 2.52 s
330   for arbitrary easy, arbitrary hard, deliberate easy, and deliberate hard, respectively) in the
331   stimulus-locked plot (Fig. 6A): Consistent potentials, which precede the mean response times,
332   that would further be of a similar shape and magnitude to the RPs found in the decision-locked
333   analysis in the arbitrary condition (though potentially more smeared for stimulus locking). We
334   thus calculated a stimulus-locked version of our ERPs, using the same baseline (Fig. 6A). As
335   the comparison between Fig. 6A and 6B clearly shows, no such consistent potentials were
336   found before the 4 response times, nor were these potentials similar to the RP in either shape or
337   magnitude (their magnitudes are at the most around 1μV, while the RP magnitudes we found
338   are around 2.5 μV; Figs. 3A, 6B). This analysis thus suggests that it is unlikely that a stimulus-
339   locked potential drives the RP we found.

340   Notably, the stimulus-locked alignment did imply that the arbitrary easy condition evoked a
341   stronger activity in roughly the last 0.5 s before stimulus onset. However, this prestimulus
342   activity cannot explain the response-locked RP, as it was found *only in arbitrary easy trials*
343   and not in arbitrary hard trials. At the same time, the response-locked RP did not differ
344   between these conditions. What is more, easy and hard trials were randomly interspersed
345   within deliberate and arbitrary blocks, and the subject discovered the trial difficulty only at
346   stimulus onset. Thus, there could not have been differential preparatory activity that varies
347   with decision difficulty. This divergence in one condition only is accordingly not likely to
348   reflect any preparatory RP activity.

349   One more concern is that the differences in RTs may affect the results in the following manner:
350   Because the main baseline period we used thus far was 1 to 0.5 s before stimulus onset, the
351   duration from the baseline to the decision varied widely between the conditions. To make sure
352   this difference in temporal distance between the baseline period and the response to which the
353   ERPs were locked did not drive our results, we recalculated the potentials for all conditions
354   with a *response-locked* baseline of -1 to -0.5 s (Fig. 6C; the same baseline we used for the
355   Bayesian analysis above). The rationale behind this choice of baseline was to have the time
356   that elapsed from baseline to response onset be the same across all conditions. As is evident in
357   Fig. 6C, the results for this new baseline were very similar to those for the stimulus-locked
358   baseline we used before. Focusing again on the -0.5 to 0 s range before response onset for our
359   statistical tests, we found a clear RP in arbitrary decisions, yet RP amplitude was not
360   significantly different from 0 in deliberate decisions (Fig. 6C; ANOVA $F_{(1,17)}$=12.09,
361   p=0.003 for the main effect of decision type; in t-tests against 0, corrected for multiple
362   comparisons, an effect was only found for arbitrary decisions (hard: t(17)=4.13, p=0.0007;
363   easy: t(17)=4.72, p=0.0002) and not for deliberate ones (hard: t(17)=0.38, p>0.5; easy:

364 t(17)=1.13, p=0.27). This supports the notion that the choice of baseline does not strongly
365 affect our main results. Taken together, the results of the six analyses above provide strong
366 evidence against the claim that the differences in RPs stem from or are affected by the
367 differences in RTs between the conditions.
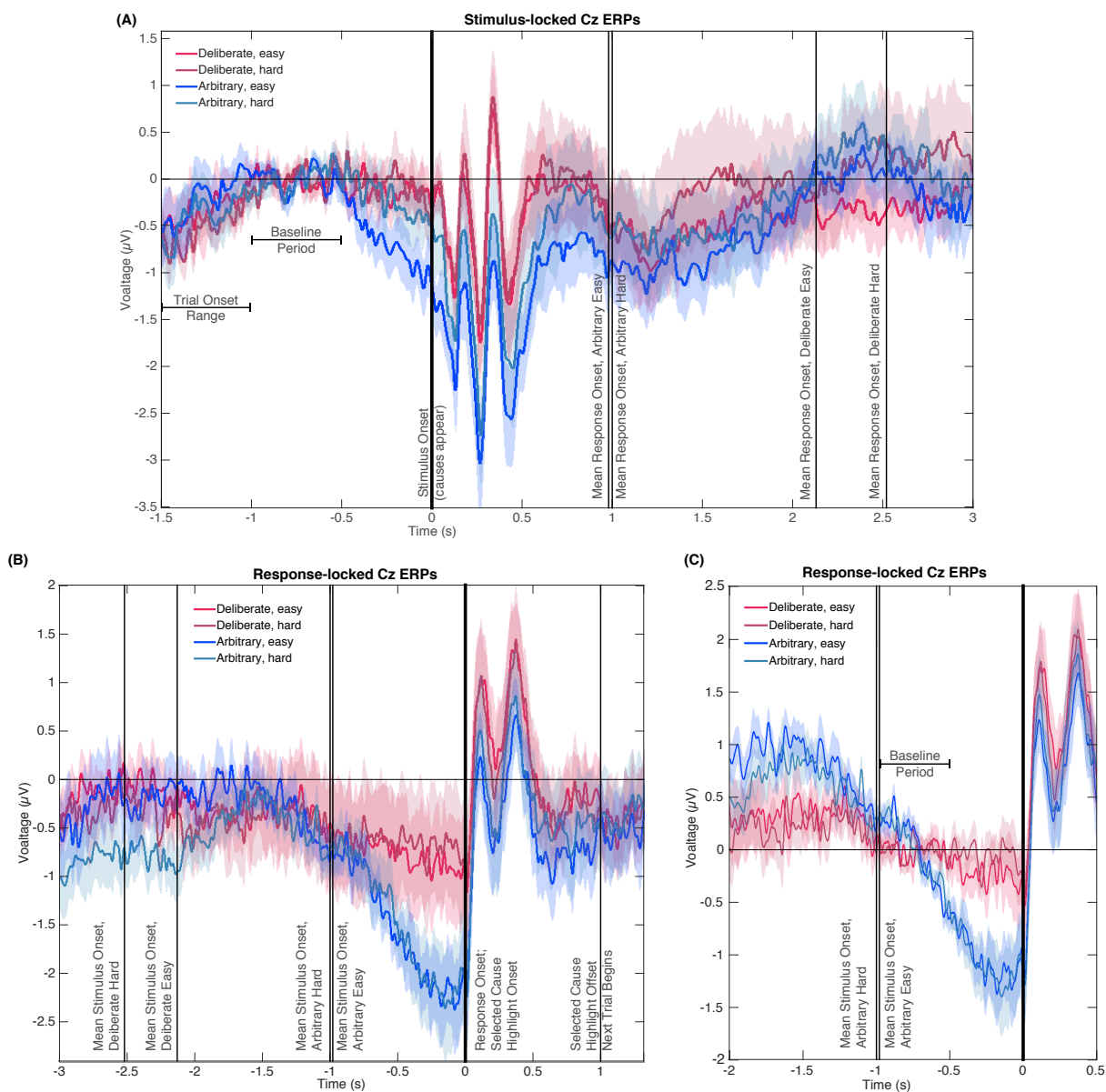
Figure 6: Stimulus- and response-locked Cz-electrode ERPs with different baselines and overlaid events. (A) Stimulus-locked waveforms including the trial onset range, baseline period, and mean reaction times for all four experimental conditions. **(B)** Response-locked waveforms with mean stimulus onsets for all four conditions as well as the offset of the highlighting of the selected cause and the start of the next trial. **(C)** Same potentials and timeline as Fig. 3A, but with a *response-locked* baseline of -1 to -0.5 s—the same baseline used for our Bayesian analysis.

Eye movements do not affect the results

377 Though ICA was used to remove blink artifacts and saccades (see Methods), we wanted to
378 make sure our results do not stem from differential eye movement patterns between the
379 conditions. We therefore computed a saccade-count metric (SC; see Methods) for each trial for
380 all subjects. Focusing again on the last 500 ms before response onset, we computed mean

381 (±s.e.m.) SC values of 1.65±0.07 and 1.67±0.06 saccades for easy and hard deliberate
382 decisions, respectively, and 1.69±0.07 and 1.73±0.07 saccades for easy and hard arbitrary
383 decisions, respectively. We found no reliable differences between the number of saccades
384 during deliberate and arbitrary trials (F(1,17)=2.56, p=0.13 for main effect of decision type).

385 We further investigated potential effects of saccades by running a median-split analysis—
386 dividing the trials for each subject into two groups based on their SC score: lower and higher
387 than the median, for deliberate and arbitrary trials, respectively. We then ran the same analysis
388 using only the trials with more saccades in the deliberate condition (SC was 2.02±0.07 and
389 2.04±0.07 for easy and hard, respectively) and those with less saccades for the arbitrary
390 condition (SC was 1.33±0.07 and 1.31±0.08 for easy and hard, respectively). If the number of
391 saccades affects RP amplitudes, we would expect that the differences in RPs between arbitrary
392 and deliberate trials will diminish, or even reverse (as now we had more saccades in the
393 deliberate condition). However, though there were only half the data points for each subject in
394 each condition, a similar pattern of results to those over the whole dataset was observed:
395 Deliberate and arbitrary decisions were still reliably different within the median-split RPs
396 (F(1,17)=16.70, p<0.001), with significant RPs found in arbitrary (easy: t(17)=4.79, p=0.002;
397 hard: t(17)=5.77, p<0.001), but not deliberate (easy: t(17)=0.90, p=0.38; hard: t(17)=0.30,
398 p>0.5) decisions. In addition, we compared the RP data across all the trials with the median-
399 split RP data above. No significant differences were found for arbitrary decisions (easy:
400 t(17)=1.02, p=0.32; hard: t(17)=0.75, p=0.46) or for deliberate decisions (easy: t(17)=1.63,
401 p=0.12; hard: t(17)=1.47, p=0.16). Taken together, the analyses above provide strong evidence
402 against the involvement of eye movements in our results.

403 *Testing alternative explanations*

404 We took a closer look at subjects' behavior in the easy arbitrary condition, where some
405 subjects had a consistency score that was further above 0.5 (chance) than others. It seems like
406 those subjects had a greater difficulty ignoring their preferences, despite the instructions to do
407 so. We therefore wanted to test to what extent the RP of those subjects was similar to the RPs
408 of the other subjects. Focusing on the 8 subjects that had a consistency score above 0.55
409 (M=0.59, SD=0.03) and comparing their RPs to those of the 10 other subjects (consistency
410 M=0.50, SD=0.06) in easy arbitrary trials, we found no reliable differences (t(16)=0.94,
411 p=0.36). This is not surprising, as the mean consistency score of these subjects—though higher
412 than chance—was still far below their consistency score for easy deliberate decisions (M=0.99,
413 SD=0.02).

414 *High-pass filter cutoff frequency does not affect the results*

415 Finally, another alternative explanation might rely on our selection of high-pass filter cutoff
416 frequency, which was 0.1 Hz. Though this frequency was used in some studies of the RP (e.g.,
417 Lew, Chavarriaga, Silvoni, & Millán, 2012; MacKinnon, Allen, Shiratori, & Rogers, 2013),
418 others opted for lower cutoff frequencies (e.g., Haggard & Eimer, 1999). Arguably, a higher
419 cutoff frequency for the high-pass filter might reduce the chances to find the RP, which is a
420 low-frequency component. And this might have affected the deliberate decision more than the
421 arbitrary one, given the slower RTs there. To examine this possible confound, we reanalyzed
422 the data using a 0.01 high-pass filter. This reduced the number of usable trials for each subject,
423 as it allowed lower-frequency trends to remain in the data. Given that our focus was on
424 arbitrary vs. deliberate decisions (with decision difficulty serving mostly to validate the
425 manipulation), we collapsed the trials across decision difficulty, and only tested RP amplitudes
426 in arbitrary vs. deliberate decisions against each other and against zero. In line with our
427 original results, a difference was found between RP amplitude in the two conditions

428 (t(13)=2.29, p=0.0394), with RP in the arbitrary condition differing from zero (t(13)=-5.71,
429 p<0.0001), as opposed to the deliberate condition, where it did not (t(13)=-0.76, p=0.462). This
430 provides evidence against the claim that our results are due to our choice of high-pass filter.

431 EEG Results: Lateralized Readiness Potential (LRP)

432 The LRP, which reflects activation processes within the motor cortex for action preparation
433 after action selection (Eimer, 1998; Masaki, Wild-wall, Sangals, & Sommer, 2004), was
434 measured by subtracting the difference potentials (C3-C4) in right-hand response trials from
435 this difference in left-hand responses trials and averaging the activity over the same time
436 window (Eimer, 1998; Haggard & Eimer, 1999). In this purely motor component, no
437 difference was found between the two decision types and conclusive evidence against an effect
438 of decision type was further found (Fig. 7; all Fs<0.35; BF=0.299). Our analysis of EOG
439 channels suggests that some of that LRP might be driven by eye movements (we repeated the
440 LRP computation on the EOG channels instead of C3 and C4). However, the shape of the eye-
441 movement-induced LRP is very different from the LRP we calculated from C3 and C4. Also,
442 the differences that we found between conditions in the EOG LRP are not reflected in the
443 C3/C4 LRP. So, while our LRP might be boosted by eye movements, it is not strictly driven by
444 these eye movements.
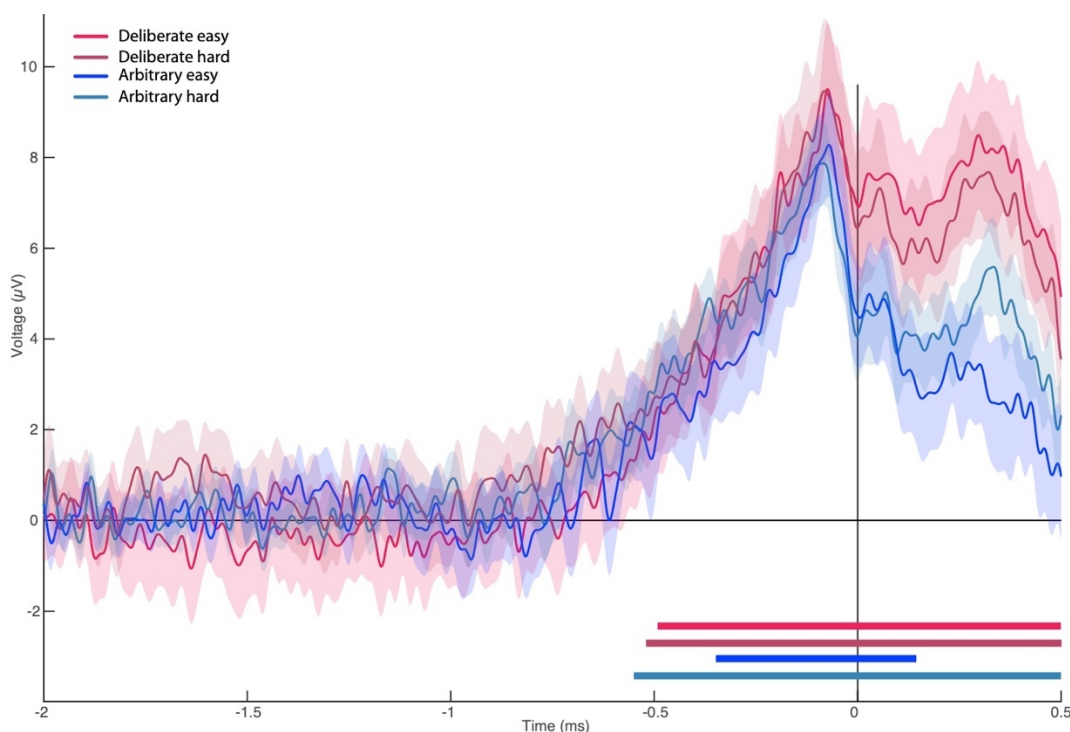
445
446 **Figure 7: Lateralized readiness potential.** The lateralized readiness potential (LRP) for
447 deliberate and arbitrary, easy and hard decisions. No difference was found between the
448 conditions (ANOVA all Fs<1). Temporal clusters where the activity for each condition was
449 independently found to be significantly different from 0 are designated by horizontal thick lines
450 at the bottom of the figure (with their colors matching the legend).
451
452 Modeling

453 The main finding of this study—the absent (or at least strongly diminished) RP in deliberate
454 decisions, suggesting different neural underpinnings of arbitrary and deliberate decisions—is
455 in line with a recent study using a drift-diffusion model (DDM) to investigate the RP (Schurger
456 et al., 2012). There, the RP was modeled as an accumulation of white noise up to a hard
457 threshold. When activity crosses that threshold, it designates decision-onset leading to

458   movement. The model focuses on the activity leading up to the threshold crossing, when that
459   activity is time-locked to the onset of the threshold crossing (corresponding to movement-
460   locked epochs in EEG). Averaging across many threshold crossings, this white-noise activity
461   accumulates, and it resembles an RP (Schurger et al., 2012). Hence, according to this model,
462   the threshold crossing leading to response onset is largely determined by spontaneous,
463   subthreshold, white-noise fluctuations of the neural activity. This interpretation of the RP
464   challenges its traditional understanding as stemming from specific, unconscious preparation
465   for, or ballistic-like initiation of, movement (Shibasaki & Hallett, 2006). Instead, Schurger and
466   colleagues claimed, time-locking to response onset ensures that these spontaneous fluctuations
467   appear, when averaged over many trials, as a ramp-up in neural activity resembling an RP.

468   We wanted to investigate whether our results could be accommodated within the general
469   framework of the Schurger model. We wanted to test the possibility that deliberate and
470   arbitrary decisions are mediated by two different mechanisms. The first mechanism is involved
471   in value assessment and drives deliberate decisions. It may be subserved by brain regions like
472   the Ventromedial Prefrontal Cortex; VMPFC, (Ramnani & Owen, 2004; Wallis, 2007). But,
473   for the sake of the model, we will remain agnostic about the exact location associated with
474   deliberate decisions and refer to this region as Region X. A second mechanism, possibly at the
475   (pre-)SMA, was held to generate arbitrary decisions driven by random, noise fluctuations.

476   Accordingly, we expanded the model developed by Schurger et al. (2012) in two manners.
477   First, we defined two DDM processes—one devoted to value-assessment (in Region X) and the
478   other to noise-generation (in SMA; see Fig. 8A and Methods). Both of them were run during
479   both decision types, yet the former determined the result of deliberate trials, and the latter
480   determined the results of arbitrary trials. Second, Schurger and colleagues modeled only *when*
481   subjects would move and not *what* (which hand) subjects would move. We wanted to account
482   for the fact that, in our experiment, subjects not only decided when to move, but also what to
483   move (either to indicate which NPO they prefer in the deliberate condition, or to generate a
484   meaningless right/left movement in the arbitrary condition). We modeled this by defining two
485   types of movement. One was moving the hand corresponding to the location of the NPO that
486   was rated higher in the first, rating part of the experiment (the *congruent* option; see Methods).
487   The other was moving the hand corresponding to the location of the lower-rated NPO (the
488   *incongruent* option). We used the race-to-threshold framework to model the decision processed
489   between a pair of leaky, stochastic accumulators, or DDMs (see again Fig. 8A). One DDM
490   simulated the process that leads to selecting the congruent option, and the other simulated the
491   process that leads to selecting the incongruent option. Hence, in each model run, the two
492   DDMs ran in parallel; the first one to cross the threshold determined the decision outcome.
493   And so, if the DDM corresponding to the congruent (incongruent) option reached the threshold
494   first, the trial ended with selecting the congruent (incongruent) option. Thus, for deliberate
495   decisions, the congruent cause had a higher value than the incongruent cause; the DDM
496   associated with the congruent option accordingly had a higher drift rate than that of the DDM
497   associated with the incongruent option. For arbitrary decisions, the values of the decision
498   alternatives mattered very little and this was reflected in the small differences, if at all, among
499   the drift rates (Table 1).

500   Therefore, taken together, these two changes to the original model by Schurger and colleagues
501   resulted in a model that included four DDMs, divided into two pairs, each pair racing to a
502   threshold (Fig. 8A); the first pair reflected the value assessment process (taking place in
503   Region X, and determining the result of deliberate decisions). The second reflected a
504   mechanism of threshold crossing by random fluctuations (taking place in the SMA and
505   determining the results of arbitrary decisions). Each such pair included one DDM for the
506   congruent option and one DDM for the incongruent option. And so, in each trial, the four

507 DDMs were run, and the decision outcome was determined by the first DDM to reach the
508 threshold in the noise component for arbitrary decisions and in the value component for
509 deliberate decisions.
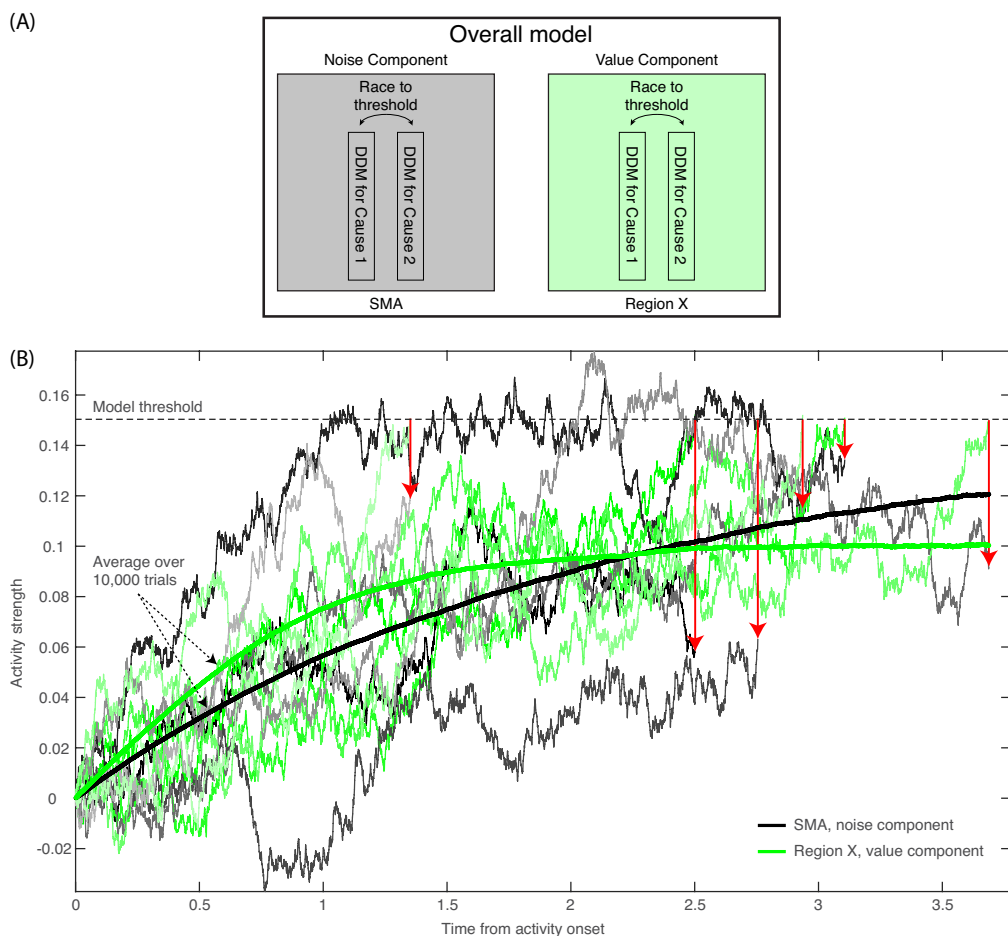
511 **Figure 8: Model description and model runs in the SMA and in Region X. (A)** A block
512 diagram of the model, with its noise (SMA) and value (Region X) components, each
513 instantiated as a race to threshold between a pair of DDMs (or causes—one congruent with the
514 ratings in the first part of the experiment, the other incongruent). **(B)** A few runs of the model
515 in the deliberate condition, in Region X (green colors), depicting the DDM for the congruent
516 option. As is apparent, the DDM stops when the value-based component reaches threshold. Red
517 arrows point from the Region X DDM trace at threshold to the corresponding time in the trace
518 in the SMA (black and gray colors). The SMA traces integrate without a threshold (as the
519 decision outcome is solely determined by the value component in Region X). The thick green
520 and black lines depict average Region X and SMA activity over 10,000 model runs, locked to
521 *stimulus onset*, respectively. (Note that this panel depicts stimulus-locked activity and not
522 response-locked activity. So, we do not expect to find an RP in either brain region.

523 Therefore, within this framework, C_z-electrode activity (above SMA) should mainly reflect the
524 noise-generation component—as was proposed by Schurger et al. (2012). (Note that we
525 suggest that noise generation might be a key function of the SMA and other brain regions
526 underneath the C_z electrode, *at least during this specific task*. When subjects make arbitrary
527 decisions, these might be based on some symmetry-breaking mechanism, which is driven by
528 random fluctuations that are here simulated as noise. Thus, we neither claim nor think that
529 noise generation is the main purpose or function of these brain regions in general.)

530 The critical prediction of our model for our purposes relates to what happens during deliberate
531 decisions in the SMA (C_z electrode). For ease of explanation, and because decision difficulty

532   had no consistent effect on the EEG data, we focus the discussion below on easy decisions
533   (though the same holds for hard decisions). According to our model, the race-to-threshold pair
534   of DDMs that would determine deliberate decisions and trigger the ensuing action is the value-
535   assessment one in Region X. Hence, when the first DDM of the Region X pair would reach the
536   threshold, the decision would be made and movement would ensue. The SMA pair, in contrast,
537   would not integrate toward a decision (Fig. 8B). We modeled this by not including any
538   decision threshold in the SMA in deliberate decisions (i.e., the threshold was set to infinity,
539   letting the DDM accumulate forever). (The corresponding magnitudes of the drift-rate are
540   detailed in the Methods.) So, what happens in the SMA (and supposedly recorded using
541   electrode C_z) when Region X activity reaches the threshold? SMA activity will have
542   accumulated to some random level (Fig. 8B). This entails that, when we align such SMA
543   activity to movement onset, we will find just a simple, weak linear trend in the SMA. This
544   trend is the one depicted in red in Fig. 9C (in red) for the deliberate easy and hard conditions
545   (here model activity was flipped vertically—from increasing above the *x* axis to decreasing
546   below it—as in Schurger et al., 2012). In arbitrary decisions, on the other hand, the SMA pair
547   determines the outcome, and motion ensues whenever one of the DDMs crosses the threshold.
548   Thus, when its activity is inspected with respect to movement onset, it forms the RP-like shape
549   of Fig. 9C (in blue), in line with the model by Schurger and colleagues (2012).

550   Akin to the Schurger model, we fit our DDMs to our average empirical reaction-times, which
551   were 2.13, 2.52, 0.98 and 1.00 s for the different conditions (henceforth, magnitudes are given
552   for deliberate easy, deliberate hard, arbitrary easy, and arbitrary hard, respectively, in this
553   order), and predicted the resulting ERP patterns. The model's corresponding mean RTs were
554   2.04, 2.46, 0.94, and 0.96 s for these conditions (Fig. 9A, B). The model was simultaneously fit
555   to the empirical consistency ratios (the proportions of congruent decisions), which were 0.99,
556   0.83, 0.54 and 0.49. The model's corresponding consistency ratios were 1.00, 0.84, 0.53 and
557   0.53. The model then predicted the shape of the ERP in its noise component, over the SMA
558   (assumed to be reflected by Cz-electrode activity) for each decision type: a continuing, RP-like
559   increase in activity (with a negative sign) for arbitrary decisions, but only a very slight increase
560   in activity for deliberate decisions (Fig. 9C, here a decrease due to the negative sign). This was
561   in line with our empirical results (compare Fig. 3A). Note that that the Schurger model aims to
562   account for neural activity leading up to the decision to move, but no further (Schurger et al.,
563   2012). Similarly, we expect our DDM to fit Cz neural data only up to around -0.1 s (100 ms
564   before response onset). We also make no claims that ours is the only, or even optimal, model
565   that explains our results. Rather, by extending the Schurger model, our goal was to show how
566   that interpretation of the RP could also be applied to our more-complex paradigm. (We refer
567   the reader to work by Schurger and colleagues (Schurger, 2018; Schurger et al., 2012) for
568   further discussions about the model, its comparison to other models, and the relation to
569   conscious-decision onset).

570

Discussion

572   Since the publication of Libet's seminal work claiming that neural precursors of action, in the
573   form of the RP, precede subjects' reports of having consciously decided to act (Libet et al.,
574   1983), a vigorous discussion has been raging among neuroscientists, philosophers, and other
575   scholars about the meaning of these findings for the debate on free will (recent collections
576   include (Mele, 2015; Pockett, Banks, & Gallagher, 2009; Sinnott-Armstrong & Nadel, 2011)).
577   Some claim that these results have removed conscious will from the causal chain leading to
578   action (Haggard, 2005, 2008; Libet, 1985; Wegner, 2002). Others are unconvinced that these
579   results are decisive for, or even applicable to, the free-will debate (Breitmeyer, 1985; Mele,

580 2009; Nahmias, Shepard, & Reuter, 2014; Roskies, 2010). At the heart of much of this debate
581 lies the RP, thought to represent unconscious decision/planning mechanisms that initiate
582 subjects' decisions prior to their conscious experience of deciding (Kornhuber & Deecke,
583 1990; Libet et al., 1983).

584
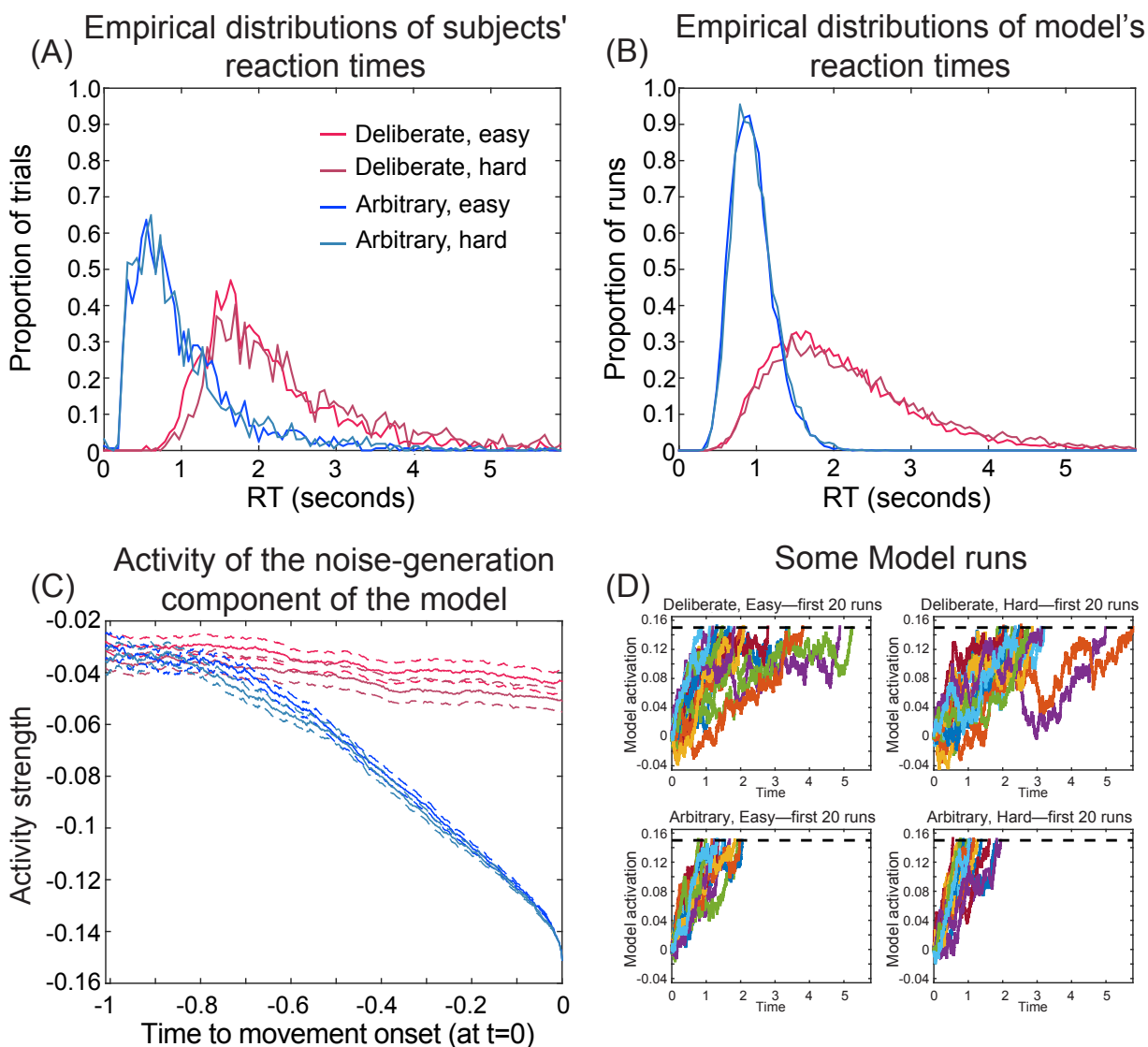
586 **Figure 9: Empirical and model RTs and model prediction for Cz activity. (A)** The
587 empirical distributions of subjects' RTs across the four decision types. **(B)** The equivalent
588 distributions of RTs for the model. **(C)** The model's prediction for the ERP activity in its noise
589 component (Fig. 8A) in the SMA (electrode Cz) across all four decision types. **(D)** The first 20
590 model runs for the value component (Region X) in deliberate decisions (top) and for the noise-
591 generation component (SMA) in arbitrary decisions (bottom). The integration threshold, at
592 0.15, is designated by a dashed line in all decision conditions. Here t = 0 s designates the
593 beginning of the model's run.

594 Notably, the RP and similar findings showing neural activations preceding the conscious
595 decision to act have typically been based on arbitrary decisions (Haggard & Eimer, 1999; Lau
596 et al., 2004; Libet, 1985; Libet et al., 1983; Sirigu et al., 2004; Soon et al., 2008; Soon et al.,
597 2013). This, among other reasons, rested on the notion that for an action to be completely free,
598 it should not be determined in any way by external factors (Libet, 1985)—which is the case for

599   arbitrary, but not deliberate, decisions (where each decision alternative is associated with a
600   value, and the values of alternatives typically guide one's decision). But this notion of freedom
601   faces several obstacles. First, most discussions of free will focus on deliberate decisions,
602   asking when and whether these are free (Frankfurt, 1971; Hobbes, 1994; Wolf, 1990). This
603   might be because everyday decisions to which we associate freedom of will—like choosing a
604   more expensive but more environmentally friendly car, helping a friend instead of studying
605   more for a test, donating to charity, and so on—are generally deliberate, in the sense of being
606   reasoned, purposeful, and bearing consequences (although see Deutschländer, Pauen, and
607   Haynes (2017)). In particular, the free will debate is often considered in the context of moral
608   responsibility (e.g., was the decision to harm another person free or not) (Fischer, 1999;
609   Haggard, 2008; Maoz & Yaffe, 2015; Roskies, 2012; Sinnott-Armstrong, 2014; Strawson,
610   1994), and free will is even sometimes defined as the capacity that allows one to be morally
611   responsible (Mele, 2006, 2009). In contrast, it seems meaningless to assign blame or praise to
612   arbitrary decisions. Thus, though the scientific operationalization of free will has typically
613   focused on arbitrary decisions, the common interpretations of these studies—in neuroscience
614   and across the free will debate—have often alluded to deliberate ones.

615   Here, we show that inference from arbitrary to deliberate decisions may not be justified, as the
616   neural precursors of arbitrary decisions, and in particular the RP, do not generalize to
617   meaningful ones (Breitmeyer, 1985; Roskies, 2010). For *arbitrary decisions*, we replicated
618   earlier results, with an RP recorded in the C_z electrode, having typical scalp topography and the
619   expected waveform shape over time. However, the RP was substantially diminished—if not
620   altogether absent—for *deliberate decisions*; it showed neither the expected slope nor the
621   expected scalp topography. Null-hypothesis significance testing (NHST) suggested that the
622   null hypothesis—i.e., that there is no RP—can be rejected for arbitrary decisions but cannot be
623   rejected for deliberate ones. A cluster-based nonparametric permutation analysis—to locate
624   temporal windows where EEG activity is reliably different from 0—found prolonged activity
625   of this type about 1.2 s before movement onset for both types of arbitrary decisions, but no
626   such activity for either type of deliberate decisions. A Bayesian analysis found clear evidence
627   for an RP in arbitrary decisions and an inconclusive trend toward no RP in deliberate decisions.
628   Changing the baseline to make it equally distant from arbitrary and deliberate decisions did
629   suggest conclusive evidence for no RP in deliberate decisions (while still finding clear
630   evidence for an RP in arbitrary decisions). Further, trend analysis showed that there is no trend
631   during the RP time window for deliberate decisions (here Bayesian analysis suggested
632   moderate to strong evidence against a trend) while there exists a reliable trend for arbitrary
633   decisions (extremely strong evidence for an effect). Thus, taken together, there is
634   overwhelming evidence for an RP in arbitrary decisions (in all six different analyses that we
635   conducted—NHST and Bayesian). But, in contrast, we found no evidence for the existence of
636   an RP in deliberate decisions (in all six analyses) and, at the same time, there was evidence
637   against RP existence in such decisions (in five of the six analyses, with the single, remaining
638   analysis providing only inconclusive evidence for an absence of an RP). Therefore, at the very
639   least, our results support the claim that the previous findings regarding the RP might be
640   confined to arbitrary decisions and do not generalize to deliberate ones. The results further
641   suggest that different neural mechanisms might drive deliberate and arbitrary decisions. This
642   clearly challenges the generalizability of previous studies relying on arbitrary decisions,
643   regardless of whether they were based on the RP or not.

644   Interestingly, while the RP was present in arbitrary decisions but absent in deliberate ones, the
645   LRP—a long-standing, more-motor ERP component, which began much later than the RP——
646   was indistinguishable between the different decision types. This provides evidence that, at the
647   motor level, the neural representation of the deliberate and arbitrary decisions that our subjects
648   made may have been indistinguishable, as was our intention when designing the task.

649 Our finding and the model thus suggest that two different mechanisms may be involved in
650 arbitrary and deliberate decisions. Earlier literature demonstrated that deliberate, reasoned
651 decision-making—which was mostly studied in the field of neuroeconomics (Kable &
652 Glimcher, 2009) or using perceptual decisions (Gold & Shadlen, 2007)—elicited activity in the
653 prefrontal cortex (PFC; mainly the dorsolateral (DLPFC) part (Sanfey, Rilling, Aronson,
654 Nystrom, & Cohen, 2003; Wallis & Miller, 2003) and ventromedial (VMPFC)
655 part/orbitofrontal cortex (OFC) (Ramnani & Owen, 2004; Wallis, 2007) and the anterior
656 cingulate cortex (ACC) (Bush, Luu, & Posner, 2000; Carter et al., 1998). Arbitrary,
657 meaningless decisions, in contrast, were mainly probed using variants of the Libet paradigm,
658 showing activations in the Supplementary Motor Area (SMA), alongside other frontal areas
659 like the medial frontal cortex (Brass & Haggard, 2008; Krieghoff, Waszak, Prinz, & Brass,
660 2011) or the frontopolar cortex, as well as the posterior cingulate cortex (Fried et al., 2011;
661 Soon et al., 2008) (though see Hughes, Schütz-Bosbach, and Waszak (2011), which suggests
662 that a common mechanism may underlie both decision types). Possibly then, arbitrary and
663 deliberate decisions may differ not only with respect to the RP, but be subserved by different
664 underlying neural circuits, which makes generalization from one class of decisions to the other
665 more difficult. Deliberate decisions are associated with more lateralized and central neural
666 activity while arbitrary ones are associated with more medial and frontal ones. This appears to
667 align with the different brain regions associated with the two decision types above, as also
668 evidenced by the differences we found between the scalp distributions of arbitrary and
669 deliberate decisions (Fig. 3A). Further studies are needed to explore this potential divergence
670 in the neural regions between the two decision types.

671 To be clear, and following the above, we do not claim that the RP captures all unconscious
672 processes that precede conscious awareness. However, some have suggested that the RP
673 represents unconscious motor-preparatory activity before any kind of decision (e.g., Libet,
674 1985). But our results provide evidence against that claim, as we do not find an RP before
675 deliberate decisions, which also entail motor preparation. What is more, in deliberate decisions
676 in particular, it is likely that there are neural precursors of upcoming actions—possibly
677 involving the above neural circuits as well as circuits that represents values—which are
678 unrelated to the RP. Note also that we did not attempt to separately measure the timing of
679 subjects' conscious decision to move. Rather, we instructed them to hold their hands above the
680 relevant keyboard keys and press their selected key as soon as they made up their mind. This
681 was both to keep the decisions in this task more ecological and because we think that the key
682 method of measuring decision onset (using some type of clock to measure Libet's W-time) is
683 highly problematic (see Methods). Some might also claim that unconscious decision-making
684 could explain our results, suggesting that in arbitrary decisions subjects engage in unconscious
685 deliberation or in actively inhibiting their urge to follow their preference as well as in free
686 choice, while in deliberate decisions only deliberation is required. But this interpretation is
687 unlikely because the longer RTs in deliberate decisions suggest, if anything, that more complex
688 mental processes (conscious or unconscious) took place before deliberate and not arbitrary
689 decisions. What is more, these interpretations should impede our chances of finding the RP in
690 arbitrary trials (as the design diverges from the original Libet task), yet the RP was present,
691 rendering them less plausible.

692 Aside from highlighting the neural differences between arbitrary and deliberate decisions, this
693 study also challenges a common interpretation of the function of the RP. If the RP is not
694 present before deliberate action, it does not seem to be a necessary link in the general causal
695 chain leading to action. Schurger et al. (2012) suggested that the RP reflects the accumulation
696 of stochastic fluctuations in neural activity that lead to action, following a threshold crossing,
697 when humans arbitrarily decide to move. According to that model, the shape of the RP results
698 from the manner in which it is computed: averaged over trials that are locked to response onset

699 (that directly follows the threshold crossing). Our results and our model are in line with that
700 interpretation and expand upon it, suggesting that the RP represents the accumulation of noisy,
701 random fluctuations that drive arbitrary decisions, while deliberate decisions are mainly driven
702 by the values associated with the decision alternatives (Maoz et al., 2013).

703 Our drift-diffusion model was based on the assumption that every decision can be driven by a
704 component based on the values of the decision alternatives (i.e., subjects' support for the two
705 NPOs we presented) or by another component representing noise—random fluctuations in
706 neural activity. The value component plays little to no role in arbitrary decisions, so action
707 selection and timing depend on when the accumulation of noise crosses the decision threshold
708 for the congruent and incongruent decision alternatives. In deliberate decisions, in contrast, the
709 value component drives the decisions, while the noise component plays little to no role. Thus,
710 in arbitrary decisions, action onset closely tracks threshold crossings of the noise component.
711 But, in deliberate decisions, the noise component reaches a random level and is then stopped;
712 so, the value component drives the decision. Hence, locking the ERP to response onset and
713 averaging over trials to obtain the RP leads to slight slope for deliberate decisions but to the
714 expected RP shape in arbitrary decisions. This provides strong evidence that the RP does not
715 reflect subconscious movement preparation. Rather, it is induced by threshold crossing of
716 random fluctuations in arbitrary decisions, which do not drive deliberate decisions;
717 accordingly, the RP is not found there. Further studies of the causal role of consciousness in
718 deliberate versus arbitrary decisions are required to test this claim.

719 Nevertheless, two possible, alternative explanations of our results can be raised. First, one
720 could claim that—in the deliberate condition only—the NPO names act as a cue, thereby
721 turning what we term internal, deliberate decisions into no more than simple responses to
722 external stimuli. Under this account, if the preferred NPO is on the right, it is immediately
723 interpreted as "press right". It would therefore follow that subjects are actually not making
724 decisions in deliberate trials, which in turn is reflected by the absence of the RP in those trials.
725 However, the reaction time and consistency results that we obtained provide evidence against
726 this interpretation. We found longer reaction times for hard-deliberate decisions than for easy-
727 deliberate ones (2.52 versus 2.13 s, on average, respectively; Fig. 2 left) and higher
728 consistencies with the initial ratings for easy-deliberate decisions than for hard-deliberate
729 decisions (0.99 versus 0.83, on average, respectively; Fig. 2 right). If the NPO names acted as
730 mere cues, we would have expected no differences between reaction times or consistencies for
731 easy- and hard-deliberate decisions. In addition, there were 50 different causes in the first part
732 of the experiment. So, it is highly unlikely that subjects could memorize all 1225 pairwise
733 preferences among these causes and simply transform any decision between a pair of causes
734 into a stimulus instructing to press left or right.

735 Another alternative interpretation of our results is that subjects engage in (unconscious)
736 deliberation also during arbitrary decisions (Tusche, Bode, & Haynes, 2010), as they are trying
737 to find a way to break the symmetry between the two possible actions. If so, the RP in the
738 arbitrary decisions might actually reflect the extra effort in those types of decisions, which is
739 not found in deliberate decisions. However, this interpretation entails a longer reaction time for
740 arbitrary than for deliberate decisions, because of the heavier cognitive load, which is the
741 opposite of what we found (Fig. 2A). Under this interpretation, we would also expect the
742 simpler deliberation in arbitrary-easy trials to result in a shorter reaction-time than that of
743 arbitrary-hard. But this is not what we find (Fig. 2A).

744 In conclusion, our study suggests that RPs do not precede deliberate decisions or is at least
745 strongly diminished before such decisions. In addition, it suggests that RPs represent an
746 artificial accumulation of random fluctuations rather than serving a genuine marker of an

747 unconscious decision to initiate voluntary movement. This further motivates future
748 investigations into other precursors of action besides the RP using EEG, fMRI, or other
749 techniques. It also highlights that it would be of particular interest to find the neural activity
750 that precedes deliberate decisions. And it would also be of interest to find neural activity,
751 which is not motor activity, that is common to both deliberate and arbitrary decisions.

752 **Materials and Methods**

753 *Subjects*

754 Twenty healthy subjects participated in the study. They were California Institute of
755 Technology (Caltech) students as well as members of the Pasadena community. All subjects
756 had reported normal or corrected-to-normal sight and no psychiatric or neurological history.
757 They volunteered to participate in the study for payment ($20 per hour). Subjects were
758 prescreened to include only participants who were socially involved and active in the
759 community (based on the strength of their support of social causes, past volunteer work, past
760 donations to social causes, and tendency to vote). The data from 18 subjects was analyzed; two
761 subjects were excluded from our analysis (see *Sample size and exclusion criteria* below). The
762 experiment was approved by Caltech's Institutional Review Board (14-0432; Neural markers
763 of deliberate and random decisions), and informed consent was obtained from all participants
764 after the experimental procedures were explained to them.

765 *Sample size and exclusion criteria*

766 We ran a power analysis based on the findings of Haggard and Eimer (1999). Their RP in a
767 free left/right-choice task had a mean of 5.293 µV and standard deviation of 2.267 µV. Data
768 from a pilot study we ran before this experiment suggested that we might obtain smaller RP
769 values in our task (they referenced to the tip of the nose and we to the average of all channels,
770 which typically results in a smaller RP). Therefore, we conservatively estimated the magnitude
771 of our RP as half of that of Haggard & Eimer, 2.647 µV, while keeping the standard deviation
772 the same at 2.267 µV. Our power analysis therefore suggested that we would need at least 16
773 subjects to reliably find a difference between an RP and a null RP (0 µV) at a p-value of 0.05
774 and power of 0.99. This number agreed with our pilot study, where we found that a sample size
775 of at least 16 subjects resulted in a clear, averaged RP. Following the above reasoning, we
776 decided beforehand to collect 20 subjects for this study, taking into account that some could be
777 excluded as they would not meet the following predefined inclusion criteria: at least 30 trials
778 per experimental condition remaining after artifact rejection; and averaged RTs (across
779 conditions) that deviated by less than 3 standard deviations from the group mean.

780 Subjects were informed about the overall number of subjects that would participate in the
781 experiment when the NPO lottery was explained to them (see below). So, we had to finalize
782 the overall number of subjects who would participate in the study—but not necessarily the
783 overall number of subjects whose data would be part of the analysis—before the experiment
784 began. After completing data collection, we ran only the EEG preprocessing and behavioral-
785 data analysis to test each subject against the exclusion criteria. This was done before we looked
786 at the data with respect to our hypothesis or research question. Two subjects did not meet the
787 inclusion criteria: the data of one subject (#18) suffered from poor signal quality, resulting in
788 less than 30 trials remaining after artifact rejection; another subject (#12) had RTs longer than
789 3 standard deviations from the mean. All analyses were thus run on the 18 remaining subjects.

790 *Stimuli and apparatus*

791 Subjects sat in a dimly lit room. The stimuli were presented on a 21" Viewsonic G225f (20"
792 viewable) CRT monitor with a 60-Hz refresh rate and a 1024×768 resolution using
793 Psychtoolbox version 3 and Mathworks Matlab 2014b (Brainard, 1997; Pelli, 1997). They
794 appeared with a gray background (RGB values: [128, 128,128]). The screen was located 60 cm
795 away from subjects' eyes. Stimuli included names of 50 real, non-profit organizations (NPOs).
796 Twenty organizations were consensual (e.g., the Cancer Research Institute, or the Hunger
797 project), and thirty were more controversial: we chose 15 causes that were widely debated
798 (e.g., pro/anti guns, pro/anti abortions), and selected one NPO that supported each of the two
799 sides of the debate. This was done to achieve variability in subjects' willingness to donate to
800 the different NPOs. In the main part of the experiment, succinct descriptions of the causes
801 (e.g., pro-marijuana legalization, pro-child protection; for a full list of NPOs and causes see
802 Supplementary Table 1) were presented in black Comic Sans MS.

803 *Study Design*

804 The objective of this study was to compare ERPs elicited by arbitrary and deliberate decision-
805 making, and in particular the RP. We further manipulated decision difficulty to validate our
806 manipulation of decisions type: we introduced hard and easy decisions which corresponded to
807 small and large differences between subjects' preferences for the pairs of presented NPOs,
808 respectively. We reasoned that if the manipulation of decision type (arbitrary vs. deliberate)
809 was effective, there would be behavioral differences between easy and hard decisions for
810 deliberate choices but not for arbitrary choices (because differences in preferences should not
811 influence subjects' arbitrary decisions). Our 2 x 2 design was therefore decision type (arbitrary
812 vs. deliberate) by decision difficulty (easy vs. hard). Each condition included 90 trials,
813 separated into 10 blocks of 9 trials each, resulting in a total of 360 trials and 40 blocks. Blocks
814 of different decision types were randomly intermixed. Decision difficulty was randomly
815 counterbalanced across trials within each block.

816 *Experimental Procedure*

817 In the first part of the experiment, subjects were presented with each of the 50 NPOs and the
818 causes with which the NPOs were associated separately (see Supplementary Table 1). They
819 were instructed to rate how much they would like to support that NPO with a $1000 donation
820 on a scale of 1 ("I would not like to support this NPO at all) to 7 ("I would very much like to
821 support this NPO"). No time pressure was put on the subjects, and they were given access to
822 the website of each NPO to give them the opportunity to learn more about the NPO and the
823 cause it supports.

824 After the subjects finished rating all NPOs, the main experiment began. In each block of the
825 experiment, subjects made either deliberate or arbitrary decisions. Two succinct cause
826 descriptions, representing two actual NPOs, were presented in each trial (Fig. 1). In deliberate
827 blocks, subjects were instructed to choose the NPO to which they would like to donate $1000
828 by pressing the <Q> or <P> key on the keyboard, using their left and right index finger, for the
829 NPO on the left or right, respectively, as soon as they decided. Subjects were informed that at
830 the end of each block one of the NPOs they chose would be randomly selected to advance to a
831 lottery. Then, at the end of the experiment, the lottery will take place and the winning NPO
832 will receive a $20 donation. In addition, that NPO will advance to the final, inter-subject
833 lottery, where one subject's NPO will be picked randomly for a $1000 donation. It was
834 stressed that the donations were real and that no deception was used in the experiment. To
835 persuade the subjects that the donations were real, we presented a signed commitment to
836 donate the money, and promised to send them the donation receipts after the experiment. Thus,

837 subjects knew that in deliberate trials, every choice they made was not hypothetical, and could
838 potentially lead to an actual $1020 donation to their chosen NPO.

839 Arbitrary trials were identical to deliberate trials except for the following crucial differences.
840 Subjects were told that, at the end of each block, the pair of NPOs in one randomly selected
841 trial would advance to the lottery together. And, if that pair wins the lottery, both NPOs would
842 receive $10 (each). Further, the NPO pair that would win the inter-subject lottery would
843 receive a $500 donation each. Hence it was stressed to the subjects that there was no reason for
844 them to prefer one NPO over the other in arbitrary blocks, as both NPOs would receive the
845 same donation regardless of their button press. Subjects were told to therefore simply press
846 either <Q> or <P> as soon as they decided to do so.

847 Thus, while subjects' decisions in the deliberate blocks were meaningful and consequential,
848 their decisions in the arbitrary blocks had no impact on the final donations that were made. In
849 these trials, subjects were further urged not to let their preferred NPO dictate their response.
850 Importantly, despite the difference in decision type between deliberate and arbitrary blocks, the
851 instructions for carrying out the decisions were identical: Subjects were instructed to report
852 their decisions as soon as they made them in both conditions. They were further asked to place
853 their right and left index fingers on the response keys, so they could respond as quickly as
854 possible. Note that we did not ask subjects to report their "W-time" (time of consciously
855 reaching a decision), because this measure was shown to rely on neural processes occurring
856 after response onset (Lau, Rogers, & Passingham, 2007) and to potentially be backward
857 inferred from movement time (Banks & Isham, 2009). Even more importantly, clock
858 monitoring was demonstrated to have an effect on RP size (Miller et al., 2011), so it could
859 potentially confound our results (Maoz et al., 2015).

860 Decision difficulty (Easy/Hard) was manipulated throughout the experiment, randomly
861 intermixed within each block. Decision difficulty was determined based on the rating
862 difference between the two presented NPOs. NPO pairs with 1 or at least 4 rating-point
863 difference were designated hard or easy, respectively. Based on each subject's ratings, we
864 created a list of NPO pairs, half of each were easy choices and the other half hard choices.

865 Each block started with an instruction written either in dark orange (Deliberate: "In this block
866 choose the cause to which you want to donate $1000") or in blue (Arbitrary: "In this block
867 both causes may each get a $500 donation regardless of the choice") on a gray background that
868 was used throughout the experiment. Short-hand instructions appeared at the top of the screen
869 throughout the block in the same colors as that block's initial instructions; Deliberate: "Choose
870 for $1000" or Arbitrary: "Press for $500 each" (Fig. 1).

871 Each trial started with the gray screen that was blank except for a centered, black fixation
872 cross. The fixation screen was on for a duration drawn from a uniform distribution between 1
873 and 1.5 s. Then, the two cause-descriptions appeared on the left and right side of the fixation
874 cross (left/right assignments were randomly counterbalanced) and remained on the screen until
875 the subjects reported their decisions with a key press—<Q> or <P> on the keyboard for the
876 cause on the left or right, respectively. The cause corresponding to the pressed button then
877 turned white for 1 s, and a new trial started immediately. If subjects did not respond within 20
878 s, they received an error message and were informed that, if this trial would be selected for the
879 lottery, no NPO would receive a donation. However, this did not happen for any subject on any
880 trial.

881 To assess the consistency of subjects' decisions during the main experiment with their ratings
882 in the first part of the experiment, subjects' choices were coded in the following way: each

883 binary choice in the main experiment was given a consistency grade of 1, if subjects chose the
884 NPO that was rated higher in the rating session, and 0 if not. Then an averaged consistency
885 grade for each subject was calculated as the mean consistency grade over all the choices. Thus,
886 a consistency grade of 1 indicates perfect consistency with one's ratings across all trials, 0 is
887 perfect inconsistency, and 0.5 is chance performance.

888 We wanted to make sure subjects were carefully reading and remembering the causes also
889 during the arbitrary trials to better equate memory load, attention, and other cognitive aspects
890 between deliberate and arbitrary decisions—except those aspects directly associated with the
891 decision type, which was the focus of our investigation. We therefore randomly interspersed 36
892 memory catch-trials throughout the experiment (thus more than one catch trial could occur per
893 block). On such trials, four succinct descriptions of causes were presented, and subjects had to
894 select the one that appeared in the previous trial. A correct or incorrect response added or
895 subtracted 50 cents from their total, respectively. (Subjects were informed that if they reached
896 a negative balance, no money will be deducted off their payment for participation in the
897 experiment.) Thus, subjects could earn $18 more for the experiment, if they answered all
898 memory test questions correctly. Subjects typically did well on these memory questions, on
899 average erring in 2.5 out of 36 memory catch trials (7% error) and gaining additional $16.75
900 (SD=3.19). Subjects' error rates in the memory task did not differ significantly between the
901 experimental conditions (2-way ANOVA; decision type: $F(1,17)=2.51$, $p=0.13$; decision
902 difficulty: $F(1,17)=2.62$, $p=0.12$; interaction: $F(1,17)=0.84$, $p=0.37$).

903 *ERP recording methods*

904 The EEG was recorded using an Active 2 system (BioSemi, the Netherlands) from 64
905 electrodes distributed based on the extended 10–20 system and connected to a cap, and seven
906 external electrodes. Four of the external electrodes recorded the EOG: two located at the outer
907 canthi of the right and left eyes and two above and below the center of the right eye. Two
908 external electrodes were located on the mastoids, and one electrode was placed on the tip of the
909 nose. All electrodes were referenced during recording to a common-mode signal (CMS)
910 electrode between POz and PO3. The EEG was continuously sampled at 512 Hz and stored for
911 offline analysis.

912 *ERP analysis*

913 ERP analysis was conducted using the "Brain Vision Analyzer" software (Brain Products,
914 Germany) and in-house Mathworks Matlab scripts. Data from all channels were referenced
915 offline to the average of all channels, which is known to result in a reduced-amplitude RP
916 (because the RP is such a spatially diffuse signal). The data were then digitally high-pass
917 filtered at 0.1 Hz using a Finite Impulse Response (FIR) filter to remove slow drifts. A notch
918 filter at 59-61 Hz was applied to the data to remove 60-Hz electrical noise. The signal was then
919 cleaned of blink and saccade artifacts using Independent Component Analysis (ICA)
920 (Junghofer, Elbert, Tucker, & Rockstroh, 2000). Signal artifacts were detected as amplitudes
921 exceeding ±100 µV, differences beyond 100 µV within a 200 ms interval, or activity below
922 0.5 µV for over 100 ms (the last condition was never found). Sections of EEG data that
923 included such artifacts in any channel were removed (150 ms before and after the artifact). We
924 further excluded single trials in which subjects pressed the wrong button as well as trials where
925 subjects' RTs were less than 200 ms, more than 10s, or more than 3 standard deviations away
926 from that subject's mean in that condition (mean number of excluded trials =7.17, SD=2.46,
927 which are 1.99% of the trials). Overall, the average number of included trials in each
928 experimental cell was 70.38 trials with a range of 36-86 out of 90 trials per condition. Channels
929 that consistently had artifacts were replaced using interpolation (4.2 channels per subject, on

930   average). No significant differences were found in the number of excluded trials across
931   conditions (2-way ANOVA; decision type: $F(1,17)=3.31$, $p=0.09$; decision difficulty:
932    $F(1,17)=1.83$, $p=0.19$; interaction: $F(1,17)=0.42$, $p=0.53$).

933   The EEG was segmented by locking the waveforms to subjects' movement onset, starting 2s
934   prior to the movement and ending 0.2s afterwards, with the segments averaged separately for
935   each decision type (Deliberate/Arbitrary x Easy/Hard) and decision content (right/left). The
936   baseline period was defined as the time window between -1000 ms and -500 ms prior to
937   *stimulus* onset, that is, the onset of the causes screen, rather than prior to movement onset. In
938   addition to the main baseline, we tested another baseline—from -1000 ms to -500 ms relative
939   to *movement* onset—to investigate whether the baseline period influenced our main results (see
940   Results). Furthermore, we segmented the EEG based on *stimulus* onset, using the same
941   baseline, for stimulus-locked analysis (again, see Results).

942   To assess potential effects of eye movements during the experiment, we defined the radial eye
943   signal as the average over all 4 EOG channels, when band-pass filtered to between 30 and 100
944   Hz. We then defined a saccade as any signal that was more than 2.5 standardized IQRs away
945   from the median of the radial signal for more than 2 ms. Two consecutive saccades had to be at
946   least 50 ms apart. The saccade count (SC) was the number of saccades during the last 500 ms
947   before response onset (Keren, Yuval-Greenberg, & Deouell, 2010) (see also (Croft & Barry,
948   2000; Elbert, Lutzenberger, Rockstroh, & Birbaumer, 1985; Shan, Moster, & Roemer, 1995)).

949   *Statistical Analysis*

950   EEG differences greater than expected by chance were assessed using two-way ANOVAs with
951   decision type (deliberate, arbitrary) and decision difficulty (easy, hard), using IBM SPSS
952   statistics, version 24. For both RP and LRP signals, the mean amplitude from 500 ms before to
953   button-press onset were used for the ANOVAs. Greenhouse–Geisser correction was never
954   required as sphericity was never violated (Picton et al., 2000).

955   Trend analysis on all subjects' data was carried out by regressing the voltage for every subject
956   against time for the last 1000 ms before response onset using first-order polynomial linear
957   regression (see Results). We used every 10th time sample for the regression (i.e., the 1st, 11th,
958   21st, 31st samples, and so on) to conform with the individual-subject analysis (see below). For
959   the individual-subject analysis, the voltage on all trials was regressed against time in the same
960   manner (i.e., for the last 1000 ms before response onset and using first-order polynomial linear
961   regression). As individual-trial data is much noisier than the mean over all trials in each
962   subject, we opted for standard robust-regression using iteratively reweighted least squares
963   (implemented using the *robustfit()* function in Mathworks Matlab). The iterative robust-
964   regression procedure is time consuming. So, we used every 10th time sample instead of every
965   sample to make the procedure's run time manageable. Also, as EEG signals have a 1/f power
966   spectrum, taking every 10th sample further better conforms with the assumption of i.i.d. noise
967   in linear regression.

968   We further conducted Bayesian analyses of our main results. This allowed us to assess the
969   strength of the evidence for or against the existence of an effect, and specifically test whether
970   null results stem from genuine absence of an effect or from insufficient or underpowered data.
971   Specifically, the Bayes factor allowed us to compare the probability of observing the data
972   given H_0 (i.e., no RP in deliberate decisions) against the probability of observing the data given
973   H_1 (i.e., RP exists in deliberate decisions). We followed the convention that a BF < 0.33
974   implies substantial evidence for lack of an effect (that is, the data is at least three times more
975   likely to be observed given H_0 than given H_1), 0.33 < BF < 3 suggests insensitivity of the data,

976   and BF > 3 denotes substantial evidence for the presence of an effect (H_1) (Jeffreys, 1998).
977   Bayesian analysis was carried out using JASP (ver. 0.8; default settings).

978   In addition to the above, we used the cluster-based nonparametric method developed by Maris
979   and Oostenveld to find continuous temporal windows where EEG activity was reliably
980   different from 0 (Maris & Oostenveld, 2007). We used an in-house implementation of the
981   method in Mathworks Matlab with a threshold of 2 on the t statistic and with a significance
982   level of $p = 0.05$.

Model and Simulations

984   All simulations were performed using Mathworks Matlab 2018b. The model was devised off
985   the one proposed by Schurger et al. (2012). Like them, we built a drift-diffusion model
986   (Ratcliff, 1978; Usher & McClelland, 2001), which included a leaky stochastic accumulator
987   (with a threshold on its output) and a time-locking/epoching procedure. The original model
988   amounted to iterative numerical integration of the differential equation

$$\delta x_i = (I - kx_i)\Delta t + c\xi_i \sqrt{\Delta t} \tag{1}$$

989   where I is the drift rate, k is the leak (exponential decay in x), ξ is Gaussian noise, and c is a
990   noise-scaling factor (we used $c = 0.05$). Δt is the discrete time step used in the simulation (we
991   used $\Delta t = 0.001$, similar to our EEG sampling rate). The model integrates x_i until it crosses a
992   threshold, which represents a decision having been made.

993   In such drift-diffusion models, for a given k and c, the values of I and the threshold together
994   determine how quickly a decision will be reached, on average. If we further fix the threshold, a
995   higher drift rate, I, represents a faster decision, on average. The drift rate alone can thus be
996   viewed as a constant "urgency to respond" (using the original Schurger term) that is inherent in
997   the demand characteristics of the task, evidenced by the fact that no subject took more than 20
998   s to make a decision on any trial. The leak term, k, ensures that the model would not be too
999   linear; i.e., it prevented the drift rate from setting up a linear trajectory for the accumulator
1000   toward the threshold. Also, k has a negative sign and is multiplied by x_i. So, kx_i acts against the
1001   drift induced by I and gets stronger as x_i grows. Hence, due to the leak term, doubling the
1002   height of the threshold could make the accumulator rarely reach the threshold instead of
1003   reaching it in roughly twice the amount of time (up to the noise term).

1004   When comparing the model's activity on the SMA and on Region X, we needed to know how
1005   to set the drift rate for the DDM in the Region X for deliberate decisions. We made the
1006   assumption that the ratio between the drift rate in Region X and in the SMA during deliberate
1007   decisions would be the same as the ratio between the average actual activity in the SMA and in
1008   the rest of the brain during arbitrary decisions. Our EEG data suggested that this ratio
1009   (calculated as activity in C_z divided by the mean activity in the rest of the electrodes is 1.45.
1010   Hence, we set the drift rate in Region X to be 1.45 times smaller than that of the SMA (see
1011   Table 1 for the drift values in the SMA).

1012   Our model differed from Schurger's in two main ways. First, it accounted for both arbitrary
1013   and deliberate decisions and was thus built to fit our empirical results. We devised a model that
1014   was composed of two distinct components (Fig. 8A), each described by a race to threshold
1015   between 2 DDMs based on Eq. (1) (see below), but with different parameter values for each
1016   DDM (Table 1). The first component accumulated activity that drove arbitrary decisions (i.e.,

017   random fluctuations (Schurger et al., 2012)). Such model activation reflects the neural activity
018   that might be recorded over the C_z electrode. We term this component of the model the *Noise*
019   component. The second component of the model reflects brain activity that drives deliberate
020   decisions, based on the values that subjects associated with the decision alternatives. We term
021   this second component the *Value* component. Our model relied on its noise component to
022   reflect arbitrary decisions and on its value component to reflect deliberate decisions.

023   **Table 1: Values of the model's drift-rate parameter across decision types in the**
024   **SMA.** Values of the drift-rate parameter, *I*, in our model across (deliberate, arbitrary) x
025   (easy, hard) decisions x (congruent, incongruent) decision alternatives. Values in
026   Region X are 1.45 times smaller than in this table for each entry.

Drift rate (*I*) values	Congruent		Incongruent	
	Easy	Hard	Easy	Hard
Deliberate	0.0400	0.0396	0.0000	0.0228
Arbitrary	0.1648	0.1650	0.1566	0.1650

027   A second difference between our model and Schurger and colleagues' is that theirs modeled
028   only the decision *when* to move (during arbitrary decisions). As those were the only decisions
029   that their subjects faced. But our subjects decided both *when* and *which hand* to move. So, we
030   had to extend the Schurger model in that respect as well. We did this using a race-to-threshold
031   mechanism between the two decision alternatives. In our empirical paradigm, the difference in
032   rating of the two causes was either 1 (for hard decisions) or 4-6 (for easy decisions; see
033   "Experimental Procedure" in Methods), so there was always an alternative that was ranked
034   higher than the other. Choosing the higher- or lower-ranked alternative was termed a congruent
035   or incongruent choice with respect to the initial ratings, respectively. Hence, we modeled each
036   decision the subjects made as a race to threshold between the congruent and incongruent
037   alternatives in the noise component (for arbitrary decisions) or value component (for deliberate
038   ones).

039   Using a parameter sweep, we found the values of the thresholds, drift rate, and leak that best fit
040   our average empirical reaction times for (easy, hard) x (deliberate, arbitrary) decisions as well
041   as our empirical consistency ratios for those 4 decision types. The model's reaction time was
042   defined as the overall time that it took until the first threshold crossing in the race-to-threshold
043   pair (again, each step took $\Delta t = 0.001$ s). We used the same threshold value of 0.15 and leak
044   value of $k=0.5$ for all model types. The only parameter that was modulated across (deliberate,
045   arbitrary) x (easy, hard) decisions x (congruent, incongruent) decision alternatives was the drift
046   rate, *I* (Table 1). All of these parameters were then fixed when we used the model to derive the
047   simulated C_z activity across all conditions.

048   Each simulation consisted of either 120 runs of the model, equal to the number of empirical
049   trials per condition, or 10000 runs of the model for a smoother reaction-time distribution for
050   the model (see Results). For each run of the model, we identified the first threshold crossing
051   point and extracted the last second (1000 steps) before the crossing in each run. If the first
052   crossing was earlier than sample no. 1,000 by $n > 0$ samples, we padded the beginning of the
053   epoch with *n* null values (NaN or "not-a-number" in Matlab). These values did not contribute
054   to the average across simulated trials, so the simulated average RP became noisier at earlier
055   time points in the epoch. Hence, our model was similarly limited to the Schurger model in its
056   inability to account for activity earlier than the beginning of the trial (see Results).

References

Banks, W. P., & Isham, E. A. (2009). We infer rather than perceive the moment we decided to act. *Psychological Science, 20*(1), 17.

Bode, S., & Haynes, J. (2009). Decoding sequential stages of task preparation in the human brain. *Neuroimage, 45*(2), 606-613.

Bode, S., He, A., Soon, C., Trampel, R., Turner, R., & Haynes, J. (2011). Tracking the unconscious generation of free decisions using uitra-high field fMRI. *PLoS One, 6*(6), e21612.

Brainard, D. H. (1997). The psychophysics toolbox. *Spatial vision, 10*, 433-436.

Brass, M., & Haggard, P. (2008). The what, when, whether model of intentional action. *The Neuroscientist, 14*(4), 319.

Breitmeyer, B. G. (1985). Problems with the psychophysics of intention. *Behavioral and brain sciences, 8*(04), 539-540.

Bush, G., Luu, P., & Posner, M. I. (2000). Cognitive and emotional influences in anterior cingulate cortex. *Trends in Cognitive Sciences, 4*(6), 215-222.

Carter, C. S., Braver, T. S., Barch, D. M., Botvinick, M. M., Noll, D., & Cohen, J. D. (1998). Anterior cingulate cortex, error detection, and the online monitoring of performance. *Science, 280*(5364), 747-749.

Croft, R. J., & Barry, R. J. (2000). Removal of ocular artifact from the EEG: a review. *Neurophysiologie Clinique/Clinical Neurophysiology, 30*(1), 5-19.

Deutschländer, R., Pauen, M., & Haynes, J.-D. (2017). Probing folk-psychology: Do Libet-style experiments reflect folk intuitions about free action? *Consciousness and cognition, 48*, 232-245.

Eimer, M. (1998). The lateralized readiness potential as an on-line measure of central response activation processes. *Behavior Research Methods, Instruments, & Computers, 30*(1), 146-156.

Elbert, T., Lutzenberger, W., Rockstroh, B., & Birbaumer, N. (1985). Removal of ocular artifacts from the EEG—a biophysical approach to the EOG. *Electroencephalography and Clinical Neurophysiology, 60*(5), 455-463.

Fischer, J. M. (1999). Recent work on moral responsibility. *Ethics, 110*(1), 93-139.

Frankfurt, H. G. (1971). Freedom of the Will and the Concept of a Person. *The Journal of Philosophy, 68*(1), 5-20.

Fried, I., Mukamel, R., & Kreiman, G. (2011). Internally generated preactivation of single neurons in human medial frontal cortex predicts volition. *Neuron, 69*, 548-562.

Frith, C., Blakemore, S., & Wolpert, D. (2000). Abnormalities in the awareness and control of action. *Philosophical Transactions of the Royal Society B: Biological Sciences, 355*(1404), 1771.

Frith, C. D., & Haggard, P. (2018). Volition and the Brain–Revisiting a Classic Experimental Study. *TRENDS in Neurosciences, 41*(7), 405-407.

Gold, J., & Shadlen, M. (2007). The neural basis of decision making.

Haggard, P. (2005). Conscious intention and motor cognition. *Trends in Cognitive Sciences, 9*(6), 290-295.

Haggard, P. (2008). Human volition: towards a neuroscience of will. *Nature Reviews Neuroscience, 9*(12), 934-946.

Haggard, P., & Eimer, M. (1999). On the relation between brain potentials and the awareness of voluntary movements. *Experimental Brain Research, 126*(1), 128-133.

Hallett, M. (2007). Volitional control of movement: The physiology of free will. *Clinical Neurophysiology, 118*(6), 1179-1192.

Hallett, M. (2016). Physiology of free will. *Annals of neurology, 80*(1), 5-12.

Harris, S. (2012). *Free will*. New York, NY: Simon & Schuster, Inc.

107   Hobbes, T. (1994). *Leviathan: with selected variants from the Latin edition of 1668*: Hackett
108   Publishing Company.
109   Hughes, G., Schütz-Bosbach, S., & Waszak, F. (2011). One action system or two? Evidence
110   for common central preparatory mechanisms in voluntary and stimulus-driven actions.
111   *Journal of Neuroscience, 31*(46), 16692-16699.
112   Jeannerod, M. (2006). *Motor cognition: What actions tell the self*: Oxford University Press.
113   Jeffreys, H. (1998). *The theory of probability*: OUP Oxford.
114   Junghofer, M., Elbert, T., Tucker, D., & Rockstroh, B. (2000). Statistical control of artifacts in
115   dense array EEG/MEG studies. *Psychophysiology, 37*(04), 523-532.
116   Kable, J. W., & Glimcher, P. W. (2009). The neurobiology of decision: consensus and
117   controversy. *Neuron, 63*(6), 733-745.
118   Keren, A. S., Yuval-Greenberg, S., & Deouell, L. Y. (2010). Saccadic spike potentials in
119   gamma-band EEG: characterization, detection and suppression. *Neuroimage, 49*(3),
120   2248-2263.
121   Kornhuber, H., & Deecke, L. (1990). Readiness for movement—the Bereitschafts potential-
122   story. *Current Contents Life Sciences, 33*(4), 14.
123   Krieghoff, V., Waszak, F., Prinz, W., & Brass, M. (2011). Neural and behavioral correlates of
124   intentional actions. *Neuropsychologia, 49*(5), 767-776.
125   Lau, H., Rogers, R., Haggard, P., & Passingham, R. (2004). Attention to intention. *Science,*
126   *303*(5661), 1208.
127   Lau, H., Rogers, R., & Passingham, R. (2007). Manipulating the experienced onset of intention
128   after action execution. *Journal of cognitive neuroscience, 19*(1), 81-90.
129   Lew, E., Chavarriaga, R., Silvoni, S., & Millán, J. d. R. (2012). Detection of self-paced
130   reaching movement intention from EEG signals. *Frontiers in Neuroengineering, 5*, 13.
131   Libet, B. (1985). Unconscious cerebral initiative and the role of conscious will in voluntary
132   action. *Behavioral and brain sciences, 8*, 529-539.
133   Libet, B., Gleason, C., Wright, E., & Pearl, D. (1983). Time of conscious intention to act in
134   relation to onset of cerebral activity (readiness-potential): The unconscious initiation of
135   a freely voluntary act. *Brain, 106*(3), 623.
136   Libet, B., Wright, E., & Gleason, C. (1982). Readiness-potentials preceding unrestricted
137   'spontaneous' vs. pre-planned voluntary acts. *Electroencephalography and Clinical*
138   *Neurophysiology, 54*(3), 322-335.
139   MacKinnon, C. D., Allen, D. P., Shiratori, T., & Rogers, M. W. (2013). Early and
140   unintentional release of planned motor actions during motor cortical preparation. *PLoS*
141   *One, 8*(5), e63417.
142   Maoz, U., Mudrik, L., Rivlin, R., Ross, I., Mamelak, A., & Yaffe, G. (2015). On reporting the
143   onset of the intention to move. In A. R. Mele (Ed.), *Surrounding Free Will:*
144   *Philosophy: Psychology, Neuroscience*: Oxford University Press.
145   Maoz, U., Rutishauser, U., Kim, S., Cai, X., Lee, D., & Koch, C. (2013). Predeliberation
146   activity in prefrontal cortex and striatum and the prediction of subsequent value
147   judgment. *Frontiers in neuroscience, 7*, 225.
148   Maoz, U., & Yaffe, G. (2015). What does recent neuroscience tell us about criminal
149   responsibility? *Journal of Law and the Biosciences, 3*(1), 120-139.
150   Maris, E., & Oostenveld, R. (2007). Nonparametric statistical testing of EEG-and MEG-data.
151   *Journal of neuroscience methods, 164*(1), 177-190.
152   Masaki, H., Wild-wall, N., Sangals, J., & Sommer, W. (2004). The functional locus of the
153   lateralized readiness potential. *Psychophysiology, 41*(2), 220-230.
154   Mele, A. (2006). *Free will and luck*: Oxford University Press.
155   Mele, A. (2009). *Effective intentions: the power of conscious will*: Oxford University Press,
156   USA.
157   Mele, A. (2015). *Surrounding free will: philosophy, psychology, neuroscience*: Oxford
158   University Press.

159 Miller, J., Shepherdson, P., & Trevena, J. (2011). Effects of Clock Monitoring on
160   Electroencephalographic Activity. *Psychological Science, 22*(1), 103-109.
161 Nahmias, E., Shepard, J., & Reuter, S. (2014). It's OK if 'my brain made me do it': People's
162   intuitions about free will and neuroscientific prediction. *Cognition, 133*(2), 502-516.
163 Pelli, D. G. (1997). The VideoToolbox software for visual psychophysics: Transforming
164   numbers into movies. *Spatial vision, 10*(4), 437-442.
165 Perez, O., Mukamel, R., Tankus, A., Rosenblatt, J. D., Yeshurun, Y., & Fried, I. (2015).
166   Preconscious prediction of a driver's decision using intracranial recordings. *Journal of*
167   *cognitive neuroscience*.
168 Picton, T., Bentin, S., Berg, P., Donchin, E., Hillyard, S., Johnson, R., . . . Rugg, M. (2000).
169   Guidelines for using human event-related potentials to study cognition: recording
170   standards and publication criteria. *Psychophysiology, 37*(02), 127-152.
171 Pockett, S., Banks, W. P., & Gallagher, S. (2009). *Does consciousness cause behavior?* : Mit
172   Press.
173 Ramnani, N., & Owen, A. M. (2004). Anterior prefrontal cortex: insights into function from
174   anatomy and neuroimaging. *Nature Reviews Neuroscience, 5*(3), 184-194.
175 Ratcliff, R. (1978). A theory of memory retrieval. *Psychological Review, 85*(2), 59-108.
176 Roskies, A. (2010). How Does Neuroscience Affect Our Conception of Volition? *Annual*
177   *Review of Neuroscience, 33*, 109-130.
178 Roskies, A. (2012). How does the neuroscience of decision making bear on our understanding
179   of moral responsibility and free will? *Current Opinion in Neurobiology, 22*(6), 1022-
180   1026.
181 Salvaris, M., & Haggard, P. (2014). Decoding Intention at Sensorimotor Timescales. *PLoS*
182   *One, 9*(2), e85100.
183 Sanfey, A., Loewenstein, G., McClure, S., & Cohen, J. (2006). Neuroeconomics: cross-
184   currents in research on decision-making. *Trends in Cognitive Sciences, 10*(3), 108-116.
185 Sanfey, A., Rilling, J., Aronson, J., Nystrom, L., & Cohen, J. (2003). The neural basis of
186   economic decision-making in the ultimatum game. *Science, 300*(5626), 1755-1758.
187 Schmidt, S., Jo, H.-G., Wittmann, M., & Hinterberger, T. (2016). 'Catching the waves'–slow
188   cortical potentials as moderator of voluntary action. *Neuroscience & Biobehavioral*
189   *Reviews, 68*, 639-650.
190 Schurger, A. (2018). Specific Relationship between the Shape of the Readiness Potential,
191   Subjective Decision Time, and Waiting Time Predicted by an Accumulator Model with
192   Temporally Autocorrelated Input Noise. *eNeuro, 5*(1), ENEURO. 0302-0317.2018.
193 Schurger, A., Sitt, J. D., & Dehaene, S. (2012). An accumulator model for spontaneous neural
194   activity prior to self-initiated movement. *Proceedings of the National Academy of*
195   *Sciences, 109*(42), E2904-E2913.
196 Shan, Y., Moster, M. L., & Roemer, R. A. (1995). The effects of time point alignment on the
197   amplitude of averaged orbital presaccadic spike potential (SP).
198   *Electroencephalography and Clinical Neurophysiology, 95*(6), 475-477.
199 Shibasaki, H., & Hallett, M. (2006). What is the Bereitschaftspotential? *Clinical*
200   *Neurophysiology, 117*(11), 2341-2356.
201 Sinnott-Armstrong, W. (2014). *Moral Psychology: Free Will and Moral Responsibility* (Vol.
202   4): Mit Press.
203 Sinnott-Armstrong, W., & Nadel, L. (Eds.). (2011). *Conscious will and responsibility: A*
204   *tribute to Benjamin Libet*: Oxford University Press.
205 Sirigu, A., Daprati, E., Ciancia, S., Giraux, P., Nighoghossian, N., Posada, A., & Haggard, P.
206   (2004). Altered awareness of voluntary action after damage to the parietal cortex.
207   *Nature Neuroscience, 7*(1), 80-84.
208 Soon, C., Brass, M., Heinze, H., & Haynes, J. (2008). Unconscious determinants of free
209   decisions in the human brain. *Nature Neuroscience, 11*(5), 543-545.

210 Soon, C., He, A., Bode, S., & Haynes, J. (2013). Predicting free choices for abstract intentions.
211   *Proceedings of the National Academy of Sciences, 110*(15), 6217-6222.
212 Strawson, G. (1994). The impossibility of moral responsibility. *Philosophical Studies, 75*(1), 5-
213   24.
214 Thut, G., Hauert, C.-A., Viviani, P., Morand, S., Spinelli, L., Blanke, O., . . . Michel, C.
215   (2000). Internally driven vs. externally cued movement selection: a study on the timing
216   of brain activity. *Cognitive Brain Research, 9*(3), 261-269.
217 Trevena, J., & Miller, J. (2010). Brain preparation before a voluntary action: Evidence against
218   unconscious movement initiation. *Consciousness and cognition, 19*(1), 447-456.
219 Tusche, A., Bode, S., & Haynes, J. (2010). Neural responses to unattended products predict
220   later consumer choices. *Journal of Neuroscience, 30*(23), 8024-8031.
221 Ullmann-Margalit, E., & Morgenbesser, S. (1977). Picking and choosing. *Social Research,*
222   *44*(4), 757-783.
223 Usher, M., & McClelland, J. L. (2001). The time course of perceptual choice: the leaky,
224   competing accumulator model. *Psychological Review, 108*(3), 550.
225 Verleger, R., Haake, M., Baur, A., & Śmigasiewicz, K. (2016). Time to Move Again: Does the
226   Bereitschaftspotential Covary with Demands on Internal Timing? *Frontiers in human*
227   *neuroscience, 10*.
228 Wallis, J. (2007). Orbitofrontal cortex and its contribution to decision-making. *Annu. Rev.*
229   *Neurosci., 30*, 31-56.
230 Wallis, J., & Miller, E. (2003). Neuronal activity in primate dorsolateral and orbital prefrontal
231   cortex during performance of a reward preference task. *Eur J Neurosci, 18*(7), 2069-
232   2081. doi:2922 [pii]
233 Waszak, F., Wascher, E., Keller, P., Koch, I., Aschersleben, G., Rosenbaum, D. A., & Prinz,
234   W. (2005). Intention-based and stimulus-based mechanisms in action selection.
235   *Experimental Brain Research, 162*(3), 346-356.
236 Wegner, D. (2002). *The illusion of conscious will*: MIT Press.
237 Wisniewski, D., Goschke, T., & Haynes, J.-D. (2016). Similar coding of freely chosen and
238   externally cued intentions in a fronto-parietal network. *Neuroimage, 134*, 450-458.
239 Wolf, S. (1990). *Freedom within reason*: Oxford University Press.

260   **Data and materials availability:** All data needed to evaluate the conclusions in the paper are
261   present in the paper. Additional data related to this paper may be requested from the authors.

262

263   Neural precursors of decisions that matter—an ERP study of deliberate and arbitrary choice

264   Maoz U, Yaffe G, Koch C, and Mudrik L

265   Supplementary Data

266   **Supplementary Table 1: NPO names and causes acronyms**

NPO	Cause	NPO website
Consensual NPOs		
American Society on Aging	Pro Quality of Life for the Elderly	http://asaging.org/
Conservation Fund	Pro Environment protection	http://www.conservationfund.org/
Bill & Melinda Gates Foundation	Pro Education	http://www.gatesfoundation.org/
Global Fund for Women	Pro Women's Rights	https://www.globalfundforwomen.org/
The Hunger Project	Pro Hunger Relief	https://www.thp.org/
Oxfam International	Pro Poverty & Disaster Relief	http://www.oxfam.org/
World Wild Life Fund (WWF)	Pro Species Conservation	http://worldwildlife.org/
Cancer Research Institute	Pro Cancer Research	http://www.cancerresearch.org/
Habitat for Humanity	Pro Housing for All	http://www.habitat.org/
Reading is Fundamental	Pro Advancement of Literacy	http://www.rif.org/
International Institute for Conservation of Historic and Artistic Works	Pro Culture & Arts Preservation	https://www.iiconservation.org/
Big Brothers and Big Sisters of America	Pro Youth Development	http://www.bbbs.org/site/c.9iILI3NGKhK6F/b.5962335/k.BE16/Home.htm
United Nations Children's Fund (UNICEF)	Pro Child Protection	http://www.unicef.org/
Doctors without Borders (Medecins sans frontieres)	Pro Disaster Medical Care	http://www.msf.org/
Soldiers' Angels	Pro Veterans & Military	http://www.soldiersangels.org/heroes/index.php
Disability Rights International	Pro Disabilities Rights	http://www.disabilityrightsintl.org/

National Crime Prevention Council (NCPC)	Pro Crime Prevention	http://www.ncpc.org/
Amnesty International	Pro Human Rights	https://www.amnesty.org/
Peace Corps	Pro Peace & Development	http://www.peacecorps.gov/
World Health Organization	Pro World Health	http://www.who.int/en/
Controversial NPOs		
Planned Parenthood	Pro Abortion & Family Planning	http://www.plannedparenthood.org/
Pro-Life Alliance	Anti Abortion & Family Planning	http://www.prolifealliance.com/
Human Rights Campaign	Pro LBGTQ Rights	http://www.hrc.org/
National Organization for Marriage	Anti LBGTQ Rights	https://www.nationformarriage.org/
Stem for Life Foundation	Pro Stem Cell Research	http://www.stemforlife.org/
Christian Dental & Medical Association	Anti Stem Cell Research	http://www.cmda.org/
Greenpeace	Pro Action Against Climate Change	http://www.greenpeace.org/international/en/
Global Climate Scam	Anti Action Against Climate Change	http://www.globalclimatescam.com/
National Association for Gun Rights	Pro Gun Rights	http://www.nationalgunrights.org/
Coalition to Stop Gun Violence	Pro Gun Control	http://csgv.org/
American Gas Association	Pro Fracking for Natural Gas	http://www.aga.org/Pages/default.aspx
Americans Against Fracking	Anti Fracking for Natural Gas	http://www.americansagainstfracking.org/
StandWithUs (Israel)	Pro Israel	http://www.standwithus.com/
Palestinian Centre for Human Rights	Pro Palestine	http://www.pchrgaza.org/portal/en/
National Organization for the Reform of Marijuana Laws	Pro Marijuana Legalization	http://norml.org/
Citizens Against Legalizing Marijuana	Anti Marijuana Legalization	http://www.calmca.org/
Understanding Animal Research	Pro Scientific Experiments on Animals	http://www.understandinganimalresearch.org.uk/

International Association Against Painful Experiments on Animals	Anti Scientific Experiments on Animals	http://www.iaapea.com/
Federation for American Immigration Reform	Pro Immigration Reform	http://www.fairus.org/
American Immigration Control	Anti Immigration Reform	http://www.immigrationcontrol.com/
Human Cloning Foundation	Pro Human Cloning	http://www.humancloning.org/
Americans to Ban Cloning	Anti Human Cloning	http://www.cloninginformation.org/
Americans United for Separation of Church and State	Pro Separation of Church & State	https://www.au.org/
Christian Coalition of America	Anti Separation of Church & State	http://www.cc.org/
Death with Dignity National Center	Pro Euthanasia (Assisted Suicide)	http://www.deathwithdignity.org/
Euthanasia Prevention Coalition	Anti Euthanasia (Assisted Suicide)	http://www.epcc.ca/
The Alliance for Better Foods	Pro Genetically Modified Foods	http://www.betterfoods.org/
Non-GMO Project	Anti Genetically Modified Foods	http://www.nongmoproject.org/
Answers in Genesis	Pro Creationism Teaching	https://answersingenesis.org
National Center for Science Education	Pro Evolution Teaching	http://ncse.com/

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