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ABSTRACT

Passive Choices and Cognitive Spillovers*

Passive behavior is ubiquitous - even when facing various alternatives to choose from, people commonly fail to take decisions. This paper provides evidence on the cognitive foundations of such "passive choices" and studies implications for policies that encourage active decision-making. In an experiment designed to study passive behavior, we document three main results. First, we demonstrate that scarcity of cognitive resources leads to passive behavior. Second, policies that encourage active choice succeed in reducing passivity and improve decisions in the targeted domain. Third, however, these benefits of choice-promoting policies come at the cost of negative cognitive spillovers to other domains.

JEL Classification: D91, D01, D04, C91

Keywords: passivity, cognitive resources, scarcity, spillover effects, active decision-making, default options

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1 Introduction

Passive behavior is a widespread phenomenon. In many situations, we can choose between various alternatives—yet we remain passive and do not take any decision. As a consequence, we stick to our current health insurance plans (Handel 2013, Heiss et al. 2016), fail to cancel contracts with auto-renewal policies (DellaVigna and Malmendier 2006), buy (partially) pre-configured products (Levav et al. 2010), and do not make use of saving subsidies, tax benefits, or other social support programs (Chetty et al. 2014, Bhargava and Manoli 2015, Finkelstein and Notowidigdo 2018). Often, our passivity is associated with leaving money on the table compared to other available alternatives (see, e.g., Bhargava et al. 2017). In light of such observations, academics and policy makers have proposed a variety of interventions to foster active decision-making. To overcome passivity, we remind people of decisions that are to be taken (Altmann and Traxler 2014, Calzolari and Nardotto 2016, Karlan et al. 2016, Damgaard and Gravert 2018), provide them with information (Kling et al. 2012, Fellner et al. 2013, Kaufmann et al. 2018), impose deadlines (Heffetz et al. 2016, Altmann et al. 2017), or force them to make active decisions (Carroll et al. 2009, Stutzer et al. 2011).

In this paper, we study the role of scarce cognitive resources as a source of passive behavior. Cognitive resources are fundamental for any economic decision. Making choices requires us to pay attention, process information, and evaluate trade-offs between the available alternatives. A growing body of literature documents that our resources for carrying out these tasks are inherently limited (see, e.g., Caplin et al. 2011, Mullainathan and Shafir 2013, and Gabaix 2017 for a comprehensive overview). Moreover, we commonly face multiple tasks or judgments that require our attention simultaneously. This in turn may further curtail the resources available for each of the judgments and, as a result, diminish our propensity to make active decisions. While the link between cognitive resources and passive behavior is intuitively plausible, a number of questions are not well understood. We focus on three of them that appear particularly important. First, does cognitive resource scarcity lead to an increase in passive decision-making? Second, how do interventions that foster active decision-making affect the choices of individuals when cognitive resources are scarce versus abundant? Third, does fostering active choice in one domain reduce the amount of cognitive resources devoted to others, i.e., do choice-promoting policies lead to negative "cognitive spillovers" on other decisions?

We study these questions in a controlled laboratory setting. Three features of our experiment make it ideally suited towards this end. First, to identify the causal impact of cognitive resource scarcity on passive behavior, we can exogenously vary the scarcity of individuals' cognitive resources across different treatments of our experiment. Second, we can gather information on the cognitive resources underlying individuals' decisions, shedding light on the mechanisms through which cognitive resource scarcity affects passivity. Third, we can assess the consequences of fostering active choice in the targeted domain, but also in terms of potential cognitive spillovers in other decision domains.

Participants in our experiment work on two tasks simultaneously—a "background task" and a "decision task". For the background task, subjects memorize and recall numbers, requiring them to bring up cognitive resources. In the first treatment dimension, we manipulate how demanding the background task is. In doing so, we exogenously vary whether subjects' cognitive resources are scarce or ample (denoted as Scarce and Ample condition, respectively). We then examine how the induced difference in cognitive resource scarcity affects participants' inclination to stay passive in the decision task, in which they have to find the correct solution to simple math problems with three possible solutions. If individuals do not actively choose an option in the decision task, a randomly selected default governs their choices. Participants' propensity to stick to the default option gives us a direct measure of passivity. Moreover, the default option provides a natural opportunity for participants in our experiment to abstain from devoting any cognitive resources to the decision task, and rather focus on the background task alone. A key feature of our experiment is that we can readily measure this allocation of cognitive resources. Specifically, in our Baseline environment, participants enter the decision task by pressing a button on the keyboard. If they do not hold the corresponding button, they face a blank screen. This feature allows us to track whether subjects attend to the decision task at all, and how much time they dedicate to the task—the amount of visual attention they allocate to the decision task.

The data from our experiment demonstrate that cognitive resource scarcity causes a strong increase in passive decision-making. Participants in the Baseline-Ample condition predominantly decide actively and stick to the default option only as often as it is expected to be the correct choice (32%). In contrast, subjects in Baseline-Scarce remain passive significantly more often, following the default in 60% of the cases. Hence, scarcity of cognitive resources leads to an increase in passivity. We further show that the strong treatment difference in behavior is attributable to a re-allocation of cognitive resources. In particular, under cognitive resource scarcity, subjects shift their attention away from the decision task. This shift happens both at the extensive and intensive margin. If cognitive resources are scarce, subjects completely disregard the decision task in about 32.0% of cases, while they do so in only 2.5% of cases in Baseline-Ample. In the same spirit, subjects in Baseline-Scarce also devote less cognitive resources to the decision task, conditional on paying any attention to the task.

In the second part of our experiment, we study how choice-promoting interventions—i.e., policies that encourage active decision-making—affect individuals' choices and the allocation of cognitive resources. We study behavior in two additional decision environments. These capture essential features of commonly observed policies to help people overcome passivity, by directing their attention to a particular task or decision (Kling et al. 2012, Calzolari and Nardotto 2016, Karlan et al. 2016), or by asking or effectively forcing them to make an active decision (Carroll et al. 2009, Stutzer et al. 2011). Specifically, in the Directed Attention environment, we steer participants' attention to the decision task by permanently displaying the task on their screen. We do, however, still allow for passive behavior, by leaving one option preselected as the default. In contrast, the decision task in the Active Choice environment features no default option. Subjects in this environment are, thus, required to take an active decision.

The Directed Attention and Active Choice environments, therefore, allow us to examine the behavioral consequences of choice-promoting interventions, and to study how the effects of the policies depend on the relative scarcity of individuals' cognitive resources. In particular, we would expect the influence of the interventions on the allocation of cognitive resources—and, hence, choices—to be particularly pronounced under cognitive resource scarcity. This is indeed what we observe: when cognitive resources are scarce, passive behavior decreases from 60% in Baseline-Scarce to 41% in Directed-Scarce, while the rate of passive choices is almost identical in Baseline-Ample (32%) and Directed-Ample (30%). At the same time, we find that passive behavior under cognitive resource scarcity is not eliminated entirely by the Directed Attention intervention. Relative to the Active Choice environment, a choice alternative that is preselected as default in the Directed Attention environment is about 10 percentage points more likely to be chosen than the identical (non-default) alternative in the Active Choice environment.

Last but not least, our experiment allows us to examine how choice-promoting interventions affect the quality of individuals' decisions. In both the Directed Attention and Active Choice environment, we observe that the higher frequency of active decisions comes along with an improvement in the quality of individuals' choices in the decision task, relative to the Baseline condition. If cognitive resources are scarce, however, inducing active choice in some decision domain might also lead to a reduction in cognitive resources devoted to other domains, with potentially negative consequences for decisions in the latter. Our experiment has the unique feature that we can readily measure whether such cognitive spillovers occur. Our data show that choice-promoting interventions can indeed have detrimental effects on other decisions: relative to the Baseline environment, both the Directed Attention and Active Choice policy impair the quality of individuals' decisions in the background task. Indeed, in our experiment, these negative spillovers on the background task completely offset the observed gains in the decision task. As a result, subjects' overall payoffs do not differ across decision environments.

Our findings contribute to the literature that studies the cognitive and perceptual foundations of passive behavior. By establishing a direct causal link between a person's available cognitive resources and passive behavior, we advance the literature that has studied the relationship between cognitive resources and passivity, using proxies of cognitive capacity such as financial literacy (van Rooij and Teppa 2014, Brown et al. 2011), self-rated knowledge of the decision situation (Levav et al. 2010), or exhaustion of decision makers (Danziger et al. 2011). Our paper also complements findings by Caplin and Martin (2016) and Caplin and Martin (2017), who show that better defaults lead to more passive behavior, indicating that individuals devote fewer cognitive resources to decisions that feature high-quality defaults.

Cognitive resource scarcity as a driver of passive behavior might be aggravated by scarcity of other resources. There is, for instance, an ongoing discussion whether concerns about financial resources, hunger, and other aspects of poverty induce a "tax" on individuals' cognitive resources or bandwidth (Mullainathan and Shafir 2013, Mani et al. 2013, Carvalho et al. 2016, Sharafi 2018, Shah et al. 2018). To the extent that this is the case, our results may also shed further light on the behavioral consequences of poverty. For example, the finding that defaults are more sticky among subjects with scarce cognitive resources suggests that the correlation between household income and default adherence that has been observed in cross-sectional data (Brown et al. 2011, Bhargava et al. 2017) might, at least partially, work through a reduction in bandwidth among subjects with lower financial resources. When seen through this lens, our results also suggest that well-chosen defaults can yield a double dividend for (financially or cognitively) deprived parts of the population. They do not only mechanically improve outcomes for passive individuals, but they may also "free up" cognitive resources that are sorely needed for other tasks. Conversely, however, cognitive resource scarcity is also likely to make individuals more susceptible to being exploited by "bad" defaults imposed by parties with misaligned interests, e.g., firms attempting to sell particular preconfigured products.

On a more general level, our results suggest that choices in decision domains that are typically evaluated in isolation should be considered jointly when they compete for a person's cognitive resources. This is of particular interest for the evaluation of "nudges" and behavioral policy interventions. Many of these policies remind people of upcoming tasks and available choice options (Altmann and Traxler 2014, Calzolari and Nardotto 2016, Karlan et al. 2016) or provide additional information (Kling et al. 2012, Tiefenbeck et al. 2016, Kaufmann et al. 2018), thereby drawing subjects' attention to one particular decision. Our findings inform the design and evaluation of such policies in two ways. First, they help to understand for whom the interventions are likely to have the strongest effects: individuals whose available cognitive resources are limited (e.g., because they have a low stock of cognitive resources or face multiple demanding tasks simultaneously) are more likely to remain blissfully ignorant about some decisions and, hence, they are also more likely to be affected by interventions that redirect their attention. Second, our results indicate that evaluating choice-promoting interventions solely based on individuals' decisions in the targeted choice domain may not suffice to demonstrate the interventions' usefulness: Directing individuals' cognitive resources to one choice domain may come at the cost of negative cognitive spillovers on other domains, which ultimately could lead to worse outcomes overall.

By showing that a "nudge" in one decision domain can affect the quality of choices in other domains, we also add to the literature that warns about possible unintended consequences of behavioral policy interventions. First indications for such unintended consequences have been established by research in psychology showing that directing people's attention to one task may induce them to overlook other, unexpected events (e.g., Simons and Chabris 1999). It has also been documented that libertarian paternalistic interventions can backfire as they may impair individual (Caplin and Martin 2016, de Haan and Linde 2017) or social learning about the decision environment (Carlin et al. 2013), or as firms' strategic responses limit the effectiveness of the intervention (Duarte and Hastings 2012).

To understand whether differences in passivity are driven by differences in the allocation of cognitive resources, we enrich our behavioral data with measures of the attentional processes underlying subjects' choices. From a methodological perspective, our paper thus stands in the tradition of studies that use related process-tracing methods, such as Mouselab (e.g., Johnson et al. 1989, Gabaix et al. 2006), eye-tracking (e.g., Wang et al. 2010), or data on search processes (Caplin et al. 2011). By providing insights on the factors that shape individuals' allocation of attention, our results can also inform a growing literature that theoretically explores the behavioral implications of limited attention and the determinants of attention allocation (Kőszegi and Szeidl 2012, Bordalo et al. 2012, 2013, Gabaix 2014, Mackowiak et al. 2018), and tests the corresponding results in the lab (Caplin and Dean 2013, Dertwinkel-Kalt et al. 2016, Dean and Neligh 2017, Martin 2017, Nielsen et al. 2018) or field (Bartoš et al. 2016).

The remainder of the paper is organized as follows. In the next section, we present the design of our experiment. Section 3 discusses behavioral hypotheses for the different treatments. Section 4 presents our empirical results and Section 5 concludes.

2 Design of the Experiment

The goal of our experiment is to study the impact of cognitive resource scarcity on passive behavior. For this purpose, we set up a stylized decision environment that captures two key features of situations in which people commonly stay passive. First, individuals regularly have to juggle various tasks or decisions simultaneously. For instance, they prepare an important meeting with clients at work, take care of their kids, visit their doctor for a check-up appointment, choose a restaurant for a family dinner, and additionally decide on their next mobile phone contract and health care plan. Each of the tasks requires some cognitive resources. If these are scarce, people might make some decisions based on a cursory first glance, or disregard them entirely and remain passive. Second, in many decision environments it is specified what happens if people stay passive—i.e., there are explicit or implicit defaults that prevail unless a decision maker actively decides otherwise.

To capture these features in a laboratory setting, we implemented a simple decision environment in which participants are simultaneously confronted with two tasks—a "background task" and a "decision task". The background task functions as an abstract representation of the bundle of tasks and choices that a decision maker has to handle, with the exception of the decision task. For the implementation of the background task, we build on a well-established paradigm from cognitive psychology for which it is straightforward to manipulate the level of difficulty and, hence, the amount of cognitive resources required to solve the task correctly (see, e.g., Carpenter et al. 2013, Deck and Jahedi 2015, Huh et al. 2014, Sprenger et al. 2011). Specifically, as *background task*, subjects in the experiment had to memorize and recall numbers. At the beginning of each round of the experiment, a new number was displayed for 10 seconds on subjects' screens. Subsequently, the number disappeared and subjects had to keep it in mind. After another 30 seconds, subjects had to type in the memorized number in a field on their screen, earning €0.40 if their answer was correct and €0 otherwise. We made sure that subjects had no opportunity to write down the numbers of the background task: they had no access to scratch paper and had to hand over their mobile phones for the duration of the experiment.

During the 30 seconds in which they had to keep the number from the background task in mind, subjects additionally faced the *decision task*. Specifically, subjects were presented with three summations, each of which consisted of six addends. Their task was to decide which of the three options yielded the highest sum (see Figure 1 for an example). Subjects earned €0.10 for a correct answer and €0 otherwise. The decision task featured a default option that was implemented if subjects did not make an active decision. In particular, in each round, one randomly selected option of the decision task was displayed as the default choice (cp. the middle option in Figure 1). Subjects were informed about the existence of a default and that it was randomly determined which option was the default in a given round of the experiment.

We designed the decision task to resemble multi-attribute choices that feature a payoff-maximizing option, the identification of which requires cognitive resources (e.g., finding the cheapest health-care plan for a known expected demand profile; cp. Caplin et al. 2011, Kaufmann et al. 2018). More broadly, our task can also be thought of as representing menu choices between products or services with uncertain value. Such uncertainty might arise if individuals need to inquire the different attributes of the product and/or their own preferences for the attributes. A consumer who decides about a retirement savings plan, for example, might need to bring up cognitive resources to learn about the risk/return profiles of the assets included in the plan, and his own valuation of the respective fluctuations in wealth.

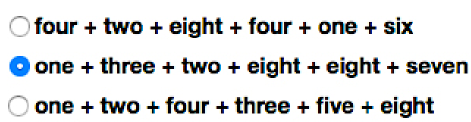


Figure 1: *Example of a decision task.*

Two points are worth noting regarding our choices of parameters in the experiment. First, to hold the difficulty of the decision task roughly constant across different rounds of the experiment, each option resulted in a sum between 20 and 34. Second, the rewards for correctly solving the background task are relatively high compared to the ones for the decision task. We opted for this parameter constellation to ensure "treatment take-up", i.e., to make sure that subjects tried to correctly solve the background task, even if this was demanding.

2.1 Treatments

We implemented a 3x2 between-subjects design. In the first treatment dimension, we exogenously varied the amount of cognitive resources needed to solve the background task. Subjects in treatments

Table 1: Treatment overview

	Baseline	Directed Attention	Active Choice
Ample	Baseline-Ample	Directed-Ample	Active-Ample
Scarce	Baseline-Scarce	Directed-Scarce	Active-Scarce

with Scarce cognitive resources had to memorize seven-digit numbers in the background task. In contrast, the numbers to memorize in treatments with Ample resources had only two digits. Solving the background task in the Ample condition thus essentially requires zero cognitive resources, whereas the more difficult task in the Scarce condition will induce cognitive resource scarcity. Comparing behavior between the two conditions thus allows us to identify the causal impact of cognitive resource scarcity on subjects' propensity to stay passive in the decision task.

In the second treatment dimension, we varied the characteristics of the decision environment faced by participants. In particular, we study three decision environments, denoted as Baseline, Directed Attention, and Active Choice environment (cp. Table 1). These environments differed only in how the decision task was displayed to subjects. In the Baseline environment, subjects faced a blank screen after the number to memorize for the background task had disappeared.[1] To access the decision task, they had to press and hold a key on their keyboard. The blank baseline screen only contained information on which key subjects had to hold in order to see the decision task. If they released the key, the decision task disappeared and subjects returned to the blank screen again. Subjects were informed about this procedure in advance.

This feature of the Baseline environment allows for the possibility that subjects may not devote any cognitive resources to the decision task, in line with the idea that passivity might be triggered by individuals not even entering "decision mode" (see Sunstein 2014, Heiss et al. 2016). Furthermore, we can directly track whether subjects in the Baseline environment entered the decision task in a given round of the experiment, i.e., whether they pressed the key at least once. We can therefore distinguish whether subjects remained passive because they completely ignored the decision task, or whether they followed the default despite paying attention to the task. Moreover, for a subsample of participants in the Baseline environment, we additionally gathered detailed information on the precise length of the time spans in which subjects attended to the decision task.[2] These attention

[1]A translated version of all screens can be found in Figure B.1a–B.1d in Appendix B.

[2]We elicited this enriched attention data in 50% of sessions of the Baseline environment (balanced across the Baseline-Scarce and Baseline-Ample condition). Subjects were not aware that their attention spans were

spans provide us with an intensive-margin measure of the amount of cognitive resources that subjects in Baseline-Scarce and Baseline-Ample allocate to the decision task.[3]

The two remaining decision environments, Directed Attention and Active Choice, were designed to investigate how encouraging active decision-making affects individuals' behavior. These environments mirror some core features of commonly observed policies that aim to reduce passivity by directing people's attention to a particular decision or task (e.g., Altmann and Traxler 2014, Calzolari and Nardotto 2016, Karlan et al. 2016) or forcing them to make an active decision (e.g., Carroll et al. 2009, Stutzer et al. 2011). In the Directed Attention environment, we steered participants' attention to the decision task by permanently displaying the task on their screen. Hence, we impaired subjects' ability to completely disregard the decision task. The Directed Attention environment, however, still allowed for passive behavior—the decision task involved a (randomly) preselected default option. The latter feature was removed in the Active Choice environment, in which the decision task was also displayed permanently, but none of the options was preselected. Hence, subjects had to actively choose one of the options in the decision task.[4] To study how the interplay between the choice environment and cognitive resource scarcity shapes behavior, we implemented treatments with Ample and Scarce cognitive resources for all decision environments. This leaves us with a total of 6 different treatment cells (see Table 1 for an overview).

2.2 Procedures

Each session of the experiment consisted of four parts. In the first and second part, we familiarized subjects with the background task and decision task, respectively. In addition, these parts of the experiment also serve as a validation check to make sure that there are no systematic treatment differences in subjects' ability of solving the tasks. The first part consisted of ten rounds in which subjects had to memorize numbers of varying difficulty (from 5 to 9 digits). As in the main experiment, numbers were displayed for 10 seconds and subjects had to keep them in mind for 30 seconds. Subjects earned €0.40 if they correctly recalled the number and €0 otherwise. In the

recorded.

[3]Dean et al. (2017) define attention as the "ability to focus on particular pieces of information by engaging in a selection process that allows for further processing of incoming stimuli.[..]". Attention is, thus, one part of cognitive functioning. Solving the decision task in our experiment, however, also involves memory and higher-order cognitive functions. Attention spans therefore only provide a proxy of the total amount of resources allocated to the problem. Yet, as attention is a necessary prerequisite to solve the decision task, it moderates other cognitive resources in the decision process. In particular, devoting zero visual attention to the decision task is analogous to not devoting cognitive resources to the task.

[4]In 5.35% of cases, subjects in the Active Choice environment nevertheless remained passive and did not choose any of the three options in the decision task. As they had not picked the correct solution, subjects' earnings for the decision task were €0 in these cases.

second part of the experiment, subjects worked on the decision task (but no background task) for ten rounds. Each round lasted 30 seconds and subjects earned €0.10 per correct answer. The third and main part of the experiment consisted of 20 rounds in which subjects simultaneously faced the background task and decision task, as described above. Only after the end of the third part, subjects received feedback on their performance in the different parts of the experiment. The experiment ended with a short post-experimental questionnaire. Table C.1 in the appendix summarizes descriptive statistics and balancing checks for the baseline ability measures from Phase 1 and 2 and a number of sociodemographic characteristics.

At the beginning of each part of the experiment, subjects received written on-screen instructions explaining the rules and details of the corresponding part.[5] In all rounds of the experiment, subjects could never leave a screen by themselves, but were automatically forwarded to the next screen when the time for a given screen had elapsed. The tasks, numbers, defaults, and their order were identical across all subjects and treatments. Furthermore, to eliminate potential session-level effects in the corresponding treatment comparisons (see Fréchette 2012), we randomized between individuals within a given session whether cognitive resources were Scarce or Ample.

The experiments were conducted in the BonnEconLab at the University of Bonn, implemented with Otree (Chen et al. 2016), and the online recruitment system by Bock et al. (2014). A total of 564 subjects participated in our experiment. We conducted 8 sessions each for the Baseline, Directed Attention, and Active Choice environment, corresponding to approximately 96 subjects in each treatment cell (cp. Table C.1 in the appendix). On average, sessions lasted 75 minutes. Subjects' mean earnings in the experiment were €16.53, including a show-up fee of €4.

3 Behavioral Predictions

In what follows, we discuss how we expect cognitive resource scarcity to influence passive behavior. Our behavioral predictions are informed by an illustrative theoretical framework, which builds on the premise that individuals have a limited stock of cognitive resources and optimally allocate these resources across tasks. While both of these assumptions naturally provide a simplistic perspective on individuals' decision processes in the experiment, they help to structure thoughts about the behavioral consequences of cognitive resource scarcity. We discuss the theoretical framework in more detail in Appendix A, where we also derive a set of conditions under which the following behavioral hypotheses hold. Here, we focus our attention on the intuitions leading to the hypotheses.

[5] A translation of the instructions of the experiment can be found in Appendix B.

A key building block of our experiment is that participants face two tasks, both of which require cognitive resources to be solved. Formally, individual j is endowed with the fixed stock of cognitive resources X^j and solves the following decision problem:

$$\max_{x_B, x_D} u(x_B, x_D) = \pi_B(x_B)u_B + \pi_D(x_D)u_D \tag{1}$$
$$s.t. \;\; x_B + x_D \leq X^j$$

where x_B, x_D are the cognitive resources devoted to the background task (B) and decision task (D), respectively, $\pi_B(\cdot)$ [$\pi_D(\cdot)$] denotes the probability of solving task B [D] correctly, and u_B, u_D denote the individual's payoffs from solving task B and D, respectively.

As discussed in Section 2, our experiment design rests on the idea that memorizing two-digit numbers essentially requires zero cognitive resources. We conceptualize this idea by setting $\pi_B(x_B) = 1$ for all $x_B \geq 0$ in the AMPLE conditions. Individuals in BASELINE-AMPLE can thus solve the background task even with minimal cognitive resources and, consequently, they should dedicate all available resources to the decision task. The data from our experiment allow for a straightforward test of whether subjects indeed to do. Specifically, we can compare the frequency at which subjects in BASELINE-AMPLE correctly solve the decision task in the main part of the experiment (83.6%) to the corresponding number in the second phase of the experiment (86%), in which they work on the decision task, but face no background task. The difference between the two frequencies is small and not statistically significant (Wilcoxon signed-rank test, p=0.308), lending support to the notion that the background task in BASELINE-AMPLE requires no cognitive resources.[6]

In contrast, individuals in BASELINE-SCARCE face a trade-off when allocating cognitive resources between the background and decision task: dedicating more resources to the background task increases the probability of solving this task, but comes at the costs of allocating fewer resources to the decision task, with resulting negative consequences for the probability of solving the latter. The optimal solution to this trade-off will naturally depend on the overall stock of cognitive resources available to an individual. Intuitively, when cognitive resources are scarce, subjects with a relatively small stock of cognitive resources will find it profitable to completely ignore the decision task and instead allocate all their available resources to the (more highly incentivized) background task. As a result, we expect an extensive-margin reduction in cognitive resources devoted to the decision

[6]Furthermore, in roughly 98% of cases, subjects in BASELINE-AMPLE also solve the background task correctly (cp. Table 2 in Section 4).

task, relative to the Baseline-Ample environment: while all subjects devote cognitive resources to solving the decision task in Baseline-Ample, some subjects will find it optimal not to pay any attention to the decision task when cognitive resources are scarce. For subjects with a relatively large stock of cognitive resources, in turn, it will still be optimal to devote some resources to the decision task. These subjects thus divide their resources between both tasks in Baseline-Scarce, whereas they devote all resources to the decision task in Baseline-Ample. For subjects with a relatively large stock of cognitive resources, we therefore expect an intensive-margin reduction in cognitive resources allocated to the decision task, relative to Baseline-Ample. Both effects imply that fewer resources are allocated to the decision task when cognitive resources are scarce. Hence, the cumulative distribution of cognitive resources devoted to the decision task in Baseline-Scarce should first-order stochastically dominate the one in Baseline-Ample.

Hypothesis 1. *The fraction of subjects who devote no cognitive resources to the decision task is larger in* Baseline-Scarce *than in* Baseline-Ample*. The cumulative distribution of cognitive resources that subjects allocate to the decision task in* Baseline-Scarce *first-order stochastically dominates the corresponding distribution in* Baseline-Ample*.*

Next, we consider how these differences in cognitive resource allocation affect the degree of passive behavior across treatments. We expect that both the extensive- and intensive-margin reduction in cognitive resources dedicated to the decision task will result in more passive behavior. It is directly apparent that individuals who decide not to pay any attention to the decision task—i.e., those who show an extensive-margin reaction—will automatically follow the default. Furthermore, individuals who devote positive, but lower amounts of cognitive resources to the decision task will stay passive more often, as long as (i) a reduction in cognitive resources leads to a higher likelihood of making mistakes (a lower $\pi_D(\cdot)$ in our framework) and (ii) individuals who dedicate fewer resources to a task are more likely to follow an ill-specified default than to actively opt for another wrong option (see Appendix A for further details). As a result of both the extensive- and intensive-margin reduction in cognitive resources devoted to the decision task, we thus expect higher rates of passive behavior in Baseline-Scarce as compared to Baseline-Ample.

The above arguments also imply that the difference in passive behavior between Baseline-Scarce and Baseline-Ample should be particularly pronounced in situations in which the default is incorrect. In this case, the reduction in cognitive resources devoted to the decision task increases the rate of passive behavior in Baseline-Scarce for two reasons. First, some individuals completely disregard the decision task and stay passive. Second, individuals who partially reduce the cognitive resources allocated to the decision task are more likely to make a wrong decision and (mistakenly) follow the incorrectly specified default. In contrast, in situations in which the default is correct, individuals who completely disregard the task still stay passive, whereas a partial reduction in cognitive resources might induce people to opt out too frequently of a correctly specified default. Which of the two effects dominates is, ex ante, unclear. Hence, differences in default adherence between Baseline-Scarce and Baseline-Ample should be especially strong for situations involving "bad" defaults.

Hypothesis 2. *Passive decision making is more pronounced in* Baseline-Scarce *than in* Baseline-Ample. *Likewise, passivity rates are higher in* Baseline-Scarce *than in* Baseline-Ample *if the default option is incorrect. If the default option is correct, the treatment comparison is ambiguous.*

Our framework also provides a natural setting to examine how the choice-promoting interventions in the Directed Attention and Active Choice environments affect the allocation of cognitive resources, and the resulting decisions. We assume that, as a result of the interventions, some amount of cognitive resources x_T—which depends on treatment $T \in \{Directed, Active\}$—is exogenously directed towards the decision task.

As subjects in the Ample environment devote all available resources to the decision task anyways, the interventions will not distort their allocation of cognitive resources. We thus predict that there should be no systematic differences between Active-Ample, Directed-Ample, and Baseline-Ample in terms of cognitive resource allocation, subjects' behavior, and the resulting quality of their decisions. In contrast, in Directed-Scarce and Active-Scarce, the additional constraint ($x_D \geq x_T$) will be binding for subjects who would otherwise allocate no or only few cognitive resources to the decision task. Relative to the Baseline-Scarce treatment, these subjects will increase the amount of cognitive resources devoted to the decision task. Following the same arguments as above, we should thus observe lower rates of passivity in Directed-Scarce compared to Baseline-Scarce. Nevertheless, the defaults in Directed-Scarce will attract choices at a higher-than-random frequency (see Appendix A). As a result, we expect subjects in Directed-Scarce to choose the default option more often than they choose the corresponding choice alternative in Active-Scarce.

Hypothesis 3. *There are no differences in behavior between* Baseline-Ample, Directed-Ample, *and* Active-Ample. *Under cognitive resource scarcity, subjects stay passive more often in* Baseline-Scarce *than in* Directed-Scarce. *The options which are displayed as defaults are chosen more frequently in* Directed-Scarce *than in* Active-Scarce.

Last but not least, we can extend our analysis to examine the consequences of our treatment interventions for the quality of subjects' decisions. In line with the arguments above, the Directed Attention and Active Choice interventions should only affect subjects in treatments with Scarce resources. It is also directly apparent that the decision problem of subjects in the Active and Directed environments is a constrained version of the one in Baseline. As a consequence, average payoffs should be weakly higher in Baseline-Scarce compared to Directed-Scarce and Active-Scarce. This overall effect is composed of two countervailing sub-effects. On the one hand, subjects who devote no or only few resources to the decision task in Baseline-Scarce experience an increase in resources allocated to that task. Hence, we expect the quality of choices in the decision task to be higher in Directed-Scarce and Active-Scarce than in Baseline-Scarce. On the other hand, as the cognitive-resource constraint is binding, the exogenous reallocation of resources to the decision task forces subjects to withdraw scarce cognitive resources from the background task. This reallocation should have negative consequences for the quality of subjects' decisions in the background task. As a consequence of this cognitive spillover, we expect decision quality in the background task to be higher in Baseline-Scarce than in Directed-Scarce and Active-Scarce.

Hypothesis 4. *There are no differences in decision quality between* Baseline-Ample*,* Directed-Ample*, and* Active-Ample*. Relative to* Baseline-Scarce*, overall payoffs should be weakly lower in* Directed-Scarce *and* Active-Scarce*. While performances in the decision task are better in* Directed-Scarce *and* Active-Scarce *than in* Baseline-Scarce*, the opposite holds true for performances in the background task.*

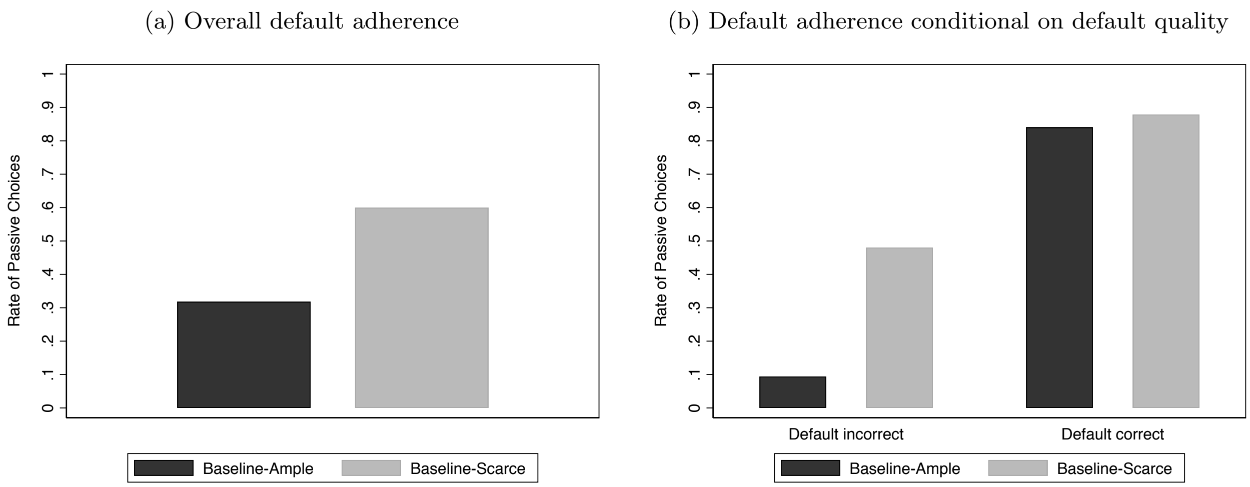
To summarize, our framework provides four main predictions for subjects' behavior in the experiment: (1) A more demanding background task causes subjects to withdraw cognitive resources from the decision task at the extensive and intensive margin; (2) This reduction in cognitive resources leads to a higher rate of passive decision-making when cognitive resources are scarce; (3) Directing subjects' attention to the decision task or implementing an active-choice environment reduces passivity in the decision task; (4) Both interventions improve subjects' performance in the decision task, but they also cause a withdrawal of cognitive resources from the background task, leading to negative cognitive spillovers and worse performance in this domain. The discussion of our empirical results in the following sections will be structured according to these main predictions.

4 Results

4.1 Cognitive resource scarcity and passive choices

To analyze how scarcity of cognitive resources affects passivity, we first examine how frequently subjects stick to the default option in the decision task in the Baseline environment. Panel (a) of Figure 2 compares default adherence rates between the Baseline-Scarce and Baseline-Ample condition. In line with the first part of Hypothesis 2, the figure shows a striking increase in default adherence under cognitive resource scarcity. While subjects stick to the default in only 31.8% of cases in Baseline-Ample, the default adherence rate increases to 60.0% in Baseline-Scarce.[7] The difference in default adherence is highly significant (Mann-Whitney-U test, $p < 0.01$).[8]

Figure 2: Passive Behavior in Baseline



Note: Panel (a) depicts average default adherence rates in Baseline-Ample and Baseline-Scarce. Panel (b) shows default adherence rates in Baseline-Ample and Baseline-Scarce conditional on quality of the default option.

Panel (b) of Figure 2 further shows that the treatment difference between Baseline-Ample and Baseline-Scarce is predominantly driven by an increase in default adherence in situations in which sticking to the default is a "bad" choice. Specifically, the figure depicts default adherence rates separately for situations in which the (randomly determined) default option did versus did not coincide with the correct solution to the decision task. We find only small differences in default

[7]Note that the randomly determined default option ended up being correct in 6 out of 20 rounds, i.e., in 30% of cases.

[8]Unless otherwise noted, all non-parametric tests are based on subject-level averages across the 20 rounds of the experiment. The reported parametric tests, which are based on observations at the individual subject-round level, account for potential clustering at the subject level. Reported p-values are always two-sided.

adherence rates if the default option corresponds to the correct solution; subjects stick to the default in 84.0% (Baseline-Ample) versus 87.9% (Baseline-Scarce) of cases (Mann-Whitney-U test, $p = 0.069$). In contrast, we observe a strong divergence in the rate of passive choices if the stipulated default option is incorrect. In this case, subjects follow the default in 48.1% of cases when cognitive resources are scarce. This compares to only 9.4% of cases in Baseline-Ample. Supporting the second part of Hypothesis 2, the difference across treatments is statistically significant (Mann-Whitney-U test, $p < 0.01$). The finding that subjects are substantially more prone to stick to "bad" defaults in Baseline-Scarce is a first indication that the high rate of passive choices in this treatment is indeed driven by a reduction of cognitive resources devoted to the decision task: when the background task is more demanding, subjects remain passive in situations where an active choice would improve their decisions, but would also require them to spend scarce cognitive resources. We will return to this point in Section 4.2 below.

Result 1. *Scarcity of cognitive resources causes an increase in passive decision-making. Subjects who face a cognitively more demanding background task are significantly less likely to make active choices in the decision task.*

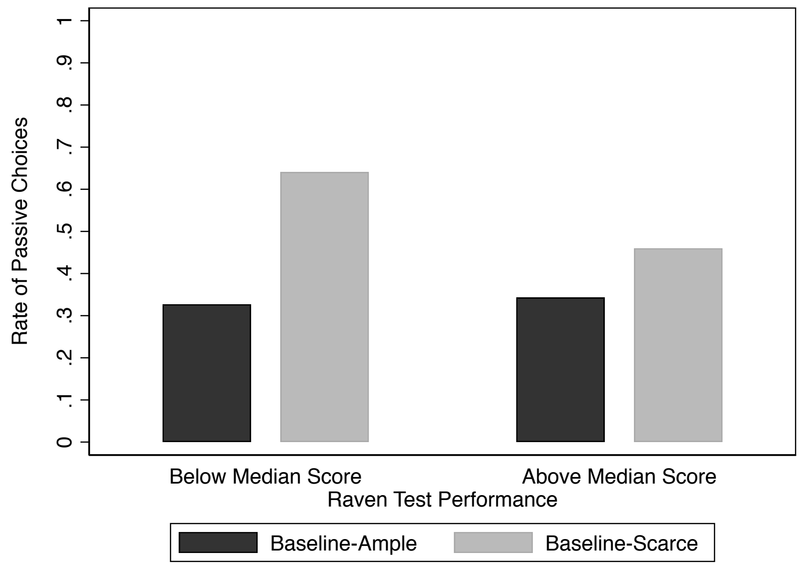
The strong overall treatment difference raises the question whether certain groups of participants exhibit stronger increases in passivity than others. A natural source of heterogeneity to consider in this respect is individuals' "stock" of cognitive resources. Intuitively, subjects with abundant cognitive resources might be less affected by the exogenously induced scarcity in Baseline-Scarce than subjects with lower cognitive capacity. This is indeed what we observe. As a proxy for participants' stock of cognitive resources, we use their performance in a short test for fluid intelligence that was administered as part of the post-experimental questionnaire for a random subset of participants.[9] Among subjects whose test score lies below the median in our sample, the likelihood to follow defaults is 31.4 percentage points higher in Baseline-Ample than in Baseline-Scarce (see Figure 3). In contrast, the size of the treatment effect is only 11.7 percentage points for subjects with an above-median test score. The treatment difference for subjects with above-median test scores is significantly smaller than the difference for those with below median test scores (t-test, $p = 0.022$).[10] In fact, treatment differences in passivity rates even vanish entirely for subjects in the

[9] Specifically, our measure is based on a 10-item version of Raven's Progressive Matrices, in which 50% of participants in both the Baseline-Ample and Baseline-Scarce condition participated.

[10] The reported p-value for the "diff-in-diff" effect is obtained from a regression framework in which a treatment dummy is interacted with a dummy that is one if the subject's score in the Raven test lies above the sample median and zero otherwise. Standard errors account for potential clustering at the subject level.

top quartile of the test-score distribution (37.3% default adherence in Baseline-Ample vs. 33.6% Baseline-Scarce, Mann-Whitney-U test, $p = 0.8661$).

Figure 3: Passive Behavior by Raven scores



Note: The figure depicts default adherence rates in Baseline-Scarce and Baseline-Ample, separately for subjects whose performance in a Raven matrices test lies above / below the median test score.

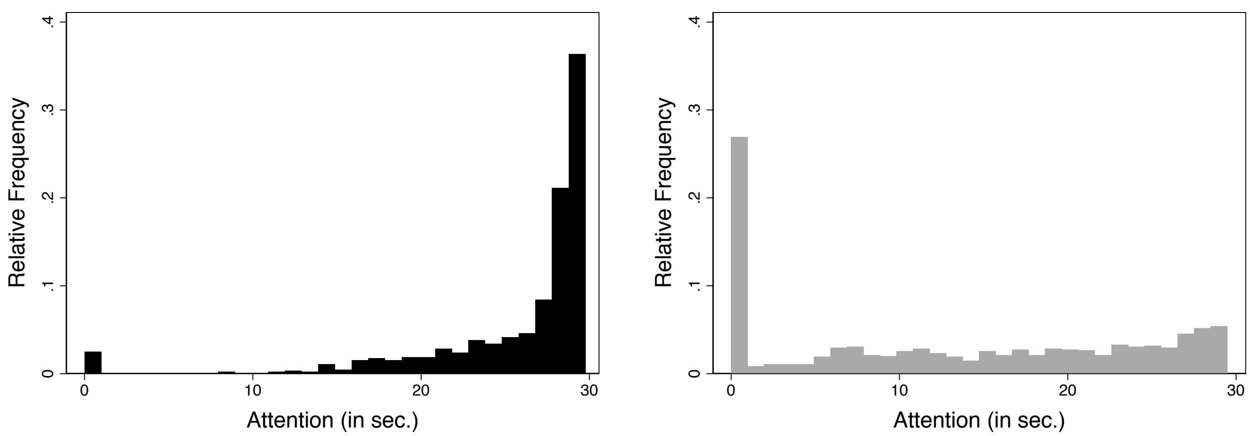
4.2 Re-allocation of cognitive resources

The differences in passive behavior between Baseline-Ample and Baseline-Scarce are consistent with the hypothesized consequences of cognitive resource scarcity. In a next step, we analyze whether the underlying mechanisms are also in line with those discussed in Section 3. In particular, we study whether the observed behavioral effects can be linked to treatment differences in how subjects' allocate their cognitive resources across tasks.

As our first measure of cognitive resource allocation, we examine how much visual attention subjects devote to the decision task. In particular, we consider the total number of seconds that a subject dedicates to the decision task in a given round of the experiment. Figure 4 depicts histograms of the attention spans in Baseline-Ample and Baseline-Scarce. The figure demonstrates strong, systematic, and statistically significant treatment differences in how subjects allocate their attention (Kolmogorov-Smirnov test on subject-round level, $p < 0.01$). The difference between treatments is particularly striking when considering the modes of the distributions: while the modal behavior in Baseline-Ample is paying maximal attention, subjects most frequently devote zero attention to the decision task when cognitive resources are scarce. On average, the amount of time dedicated to the decision task decreases from 25.76 seconds in Baseline-Ample to 13.15 seconds in Baseline-Scarce (t-test, $p < 0.01$).

Figure 4: Attention spans in Baseline

(a) Baseline-Ample (b) Baseline-Scarce



Note: The figure plots distributions of attention spans devoted to the decision task, as measured by the total number of seconds devoted to the task in a given period. Histograms for Baseline-Ample (left panel) and Baseline-Scarce (right panel).

The documented effect on average attention spans can be decomposed into an extensive-margin and an intensive-margin effect. Subjects completely ignore the decision task in 32.1% of cases in Baseline-Scarce, whereas they do so in only 2.5% of cases in Baseline-Ample ($p < 0.01$, Fisher-exact test).[11] Two points are worth noting about this result. First, paying zero attention to the decision task directly implies that subjects devote no cognitive resources to solving the task. Hence, in line with the first part of Hypothesis 1, subjects are more likely not to devote any resources to the decision task when cognitive resources are scarce. Second, complete inattention to the decision task automatically translates into passive acceptance of the stipulated default option. The extensive-margin reduction in cognitive resources thus accounts for a considerable share of the overall treatment difference in the frequency of passive choices. In particular, both the treatment difference in passive choices as well as the treatment difference in completely inattentive choices are approximately 30 percentage points. At first glance, this observation might suggest that the extensive-margin reduction in attention accounts for the entire increase in passivity across treatments. Note, however, that even if subjects attend to the task, they follow the default in roughly

[11] The reported numbers are based on the full sample of the Baseline environment and therefore differ slightly from the values in Figure 4 (recall that the exact length of attention spans depicted in Figure 4 was recorded only for a 50% subsample in both treatments). The corresponding figures in the sample underlying Figure 4 are 26.3% (Baseline-Scarce) and 2.5% (Baseline-Ample), respectively ($p < 0.01$, Fisher-exact test).

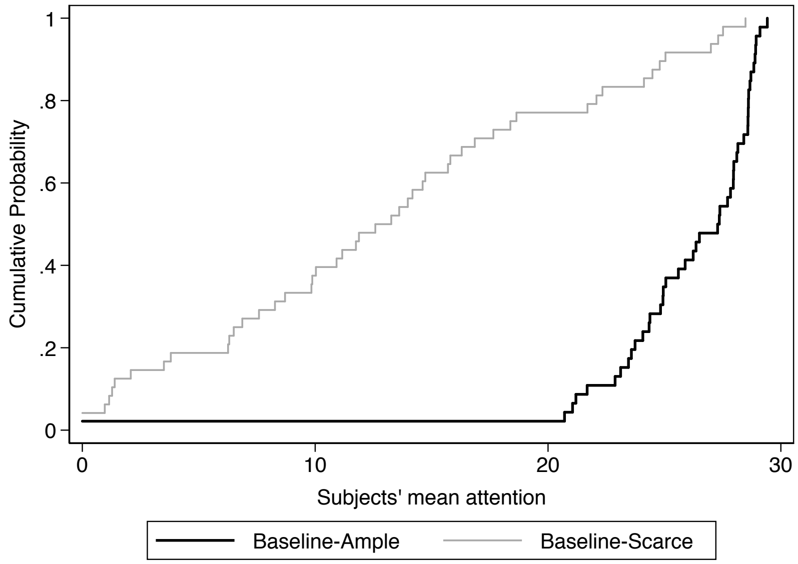
one third of the cases. Hence, about one third of the decisions that are taken under complete inattention in Baseline-Scarce would also have resulted in a "default choice" in Baseline-Ample. The extensive-margin effect therefore accounts for approximately two thirds of the observed increase in passivity. An Oaxaca-Blinder decomposition (Oaxaca 1973, Blinder 1973, Fortin et al. 2011), presented in more detail in Appendix C.3, confirms this observation: the extensive-margin reduction is estimated to account for approximately 70% of the overall treatment difference in passive behavior.

The second part of Hypothesis 1 predicts that the amount of cognitive resources devoted to the decision task should also decrease at the intensive margin. To examine whether this is the case, we first analyze differences in the amount of attention that subjects devote to the decision task conditional on paying any attention to the task (i.e., conditional on entering the decision task at least once in a given round of the experiment). In line with our hypothesis, we observe that the conditional average attention span in Baseline-Scarce is significantly shorter than in Baseline-Ample (17.8 vs. 26.4 seconds; t-test, $p < 0.01$). This shift in attention spans is driven by the entire population of subjects. Figure 5 depicts the cumulative distribution of mean attention spans that subjects devote to the decision task. The cumulative distribution in Baseline-Ample first-order stochastically dominates its counterpart in Baseline-Scarce, corroborating the second part of Hypothesis 1.[12] Hence, scarcity of cognitive resources causes subjects to shift their attention away from the decision task at both the intensive and the extensive margin.

In sum, our findings on how individuals allocate their attention in Baseline-Ample and Baseline-Scarce are consistent with our behavioral hypotheses. While the attention data provide valuable insights into subjects' allocation of cognitive resources, they have to be treated with some caution. Specifically, it is a priori not clear that attention spans provide a precise measure for the allocation of cognitive resources at the intensive margin. For example, it could be the case that subjects in Baseline-Scarce attend to the decision task, but are not able to effectively deploy cognitive resources to solve the task, as the background task simply takes up too much of their bandwidth. Conversely, subjects could still devote some cognitive resources to the task at times where they do not visually attend to it. We therefore consider a second measure for treatment differences in cognitive resource allocation at the intensive margin: the quality of individuals' choices in the decision task. Since the decision task requires cognitive resources to be solved correctly, and since more resources devoted to the task will translate into better decisions, the decision quality

[12] First-order stochastic dominance is also observed when considering the CDFs of decision-level data instead of subject-level averages (see Figure C.1 in the appendix).

Figure 5: Individuals' attention levels in BASELINE



Note: The figure depicts the cumulative distribution of subjects' mean attention levels in BASELINE-AMPLE and BASELINE-SCARCE

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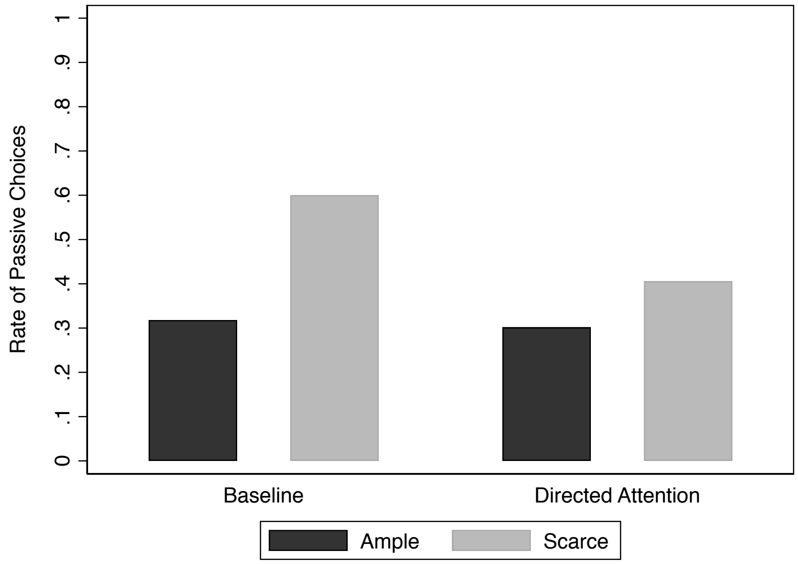
constitutes a natural "outcome-based" measure of the resources allocated to the decision task. To examine intensive-margin treatment differences based on this measure, we compare the quality of subjects' choices for all cases in which subjects entered the decision task at all. On average, subjects in BASELINE-AMPLE correctly solve the decision task in 85.0% of these cases. The corresponding number for BASELINE-SCARCE is 12.1 percentage points lower (t-test, $p < 0.01$). The data on decision quality thus ascertain that subjects do not only react at the extensive margin, but also reduce the cognitive resources allocated to the decision task at the intensive margin.

Result 2. *Under cognitive resource scarcity, subjects devote fewer resources to the decision task, as measured by the amount of attention devoted to the task as well as the quality of individuals' choices.*

4.3 How choice-promoting interventions affect passivity

The observed differences between BASELINE-AMPLE and BASELINE-SCARCE demonstrate that scarce cognitive resources can be an important source of passive behavior. This insight raises two interesting questions regarding the effects of policies that aim at encouraging active decision-making. First, do the consequences of such choice-promoting policies depend on whether decision makers act under cognitive resource scarcity or with abundant cognitive resources? Second, how does fostering active choice in one domain affect individuals' decisions in other tasks or choice domains?

Figure 6: Passive Behavior Across Choice Environments



Note: The figure shows the average default adherence rates for Baseline and Directed Attention.

To shed light on these questions, we analyze the behavior of subjects in the two additional decision environments (cp. Table 1). Figure 6 compares default adherence rates between the Baseline and Directed Attention environment. In line with Hypothesis 3, the frequency of passive behavior is very similar in Baseline-Ample and Directed-Ample in which the background task puts little strain on individuals' cognitive resources (31.8% vs. 30.2% in Baseline-Ample and Directed-Ample, respectively; Mann-Whitney-U test, $p = 0.243$). This finding corroborates our previous observation that subjects in Baseline-Ample essentially devote all of their cognitive resources to the decision task (cp. Figure 4 and Figure 5). An intervention that aims at steering individuals' attention to the decision task thus has only negligible effects on the allocation of cognitive resources, and the resulting choices.

Under cognitive resources scarcity, this picture changes substantially. Comparing the frequency of passive choices between Baseline-Scarce and Directed-Scarce reveals strong treatment differences. Default adherence rates drop from 60.0% to 40.6% when individuals' attention is directed to the decision task, by simply displaying the task permanently on their screens. The difference in the frequency of passive choices is statistically significant (Mann-Whitney-U test, $p < 0.01$). At the same time, however, the rate of passive choices in Directed-Scarce still lies significantly above the one in Directed-Ample (Mann-Whitney-U test, $p < 0.01$). Directing attention to the decision task thus fosters active decision making, but it does not fully eliminate the passivity caused by cognitive resource scarcity.

It is also informative to compare default adherence in BASELINE-SCARCE and DIRECTED-SCARCE to the frequency with which subjects choose the corresponding decision alternative in ACTIVE-SCARCE (that featured no defaults), i.e., to the rate at which subjects in ACTIVE-SCARCE choose the option that happened to be the default in the *exact same version* of the decision task in BASELINE-SCARCE and DIRECTED-SCARCE. In ACTIVE-SCARCE, subjects choose this option in 33.8% of cases. This number lies significantly below the rate of passive choices in both BASELINE-SCARCE and DIRECTED-SCARCE (Mann-Whitney-U test, $p < 0.01$ for ACTIVE-SCARCE vs. BASELINE-SCARCE; $p = 0.018$ for ACTIVE-SCARCE vs. DIRECTED-SCARCE), corroborating the second part of Hypothesis 3.[13]

Result 3. *Encouraging active decision-making through an active-choice intervention or by directing individuals' attention to a task reduces passivity if cognitive resources are scarce. Directing subjects' attention to a specific decision, however, does not fully eliminate passive behavior relative to an active-choice environment. Both interventions do not affect passivity if subjects have ample cognitive resources.*

4.4 Consequences for choice quality

The increase in active decision making in response to choice-promoting interventions also leads subjects in DIRECTED-SCARCE and ACTIVE-SCARCE to make *better* decisions. As the first row of Table 2 shows, subjects in BASELINE-SCARCE on average solve 59.1% of decision tasks correctly. This number increases to 68.8% and 72.0% in ACTIVE-SCARCE and DIRECTED-SCARCE, respectively. The observed increase in decision quality is statistically significant for both ACTIVE-SCARCE and DIRECTED-SCARCE (Mann-Whitney-U test, $p < 0.01$ in both cases), whereas the latter two treatments do not differ significantly from each other ($p = 0.338$). Hence, when cognitive resources are scarce, both choice-promoting interventions succeed in their primary goal: they help individuals to make better decisions by encouraging them to choose actively.

In the three conditions with AMPLE cognitive resources, we observe only minor differences in the quality of choices in the decision task (see row (4) in the bottom panel of Table 2).[14] This is

[13] A question of detail concerns the evaluation of cases in which subjects failed to make a decision in the ACTIVE CHOICE environment (cp. Footnote 4). For sake of comparability, the numbers reported above treat these cases as "passive choices"—since the same behavior of ignoring the decision task entirely would result in a default choice in the BASELINE and DIRECTED ATTENTION environments. If we instead drop the corresponding cases from our calculations, the passive-choice frequencies slightly change to 27.5% (ACTIVE-SCARCE) and 28.5% (ACTIVE-AMPLE), respectively.

[14] The difference in choice quality between BASELINE-AMPLE and DIRECTED-AMPLE turns out to be statistically significant (Mann-Whitney-U test, $p = 0.035$), but is relatively small in magnitude. The corresponding differences for

not surprising, as we would expect subjects in Baseline-Ample to devote essentially all of their cognitive resources to the decision task. Hence, policies that direct attention to this task or force subjects to make an active decision should not yield improvements in choices.

Table 2: Decision Quality and Payoffs

			Baseline	Directed Attention	Active Choice
				Scarce	
(1)	Decision Task	% correct	59.11 (21.47)	71.98 (18.45)	68.76 (21.92)
(2)	Background Task	% correct	77.89 (20.30)	73.33 (20.82)	74.44 (18.47)
(3)	Total Payoff	Earnings per round	37.07 (8.15)	36.53 (8.65)	36.65 (7.58)
				Ample	
(4)	Decision Task	% correct	83.56 (14.00)	87.45 (11.98)	85.47 (14.05)
(5)	Background Task	% correct	97.98 (3.46)	98.78 (2.40)	96.93 (10.87)
(6)	Total Payoff	Earnings per round	47.55 (2.16)	48.26 (1.68)	47.32 (5.34)

Note: The table presents proportions of correctly solved tasks in the decision task and background task, as well as the average total payoff of subjects in one round of the experiment. The reported standard deviations (in parentheses) are calculated based on subject-level averages in decision qualities and payoffs, respectively (i.e., they refer to the between-subject SDs).

While reductions in passivity and the potential gains resulting from more deliberate, active decisions are typically the core criteria to evaluate choice-promoting interventions, our experiment is designed to also shed light on potential cognitive spillovers to other domains or tasks that decision makers have to handle simultaneously. Specifically, we can investigate how encouraging active decision making in the decision task affects individuals' performance in the background task. The second row of Table 2 indicates that the interventions have a negative effect on the quality of subjects' decisions in the background task. The likelihood to correctly recall the number decreases from 77.9% in Baseline-Scarce to 73.3% in Directed-Scarce and 74.4% in Active-Scarce. In both cases, the differences relative to Baseline-Scarce are (weakly) significant (Mann-Whitney-U tests, $p = 0.071$ for Baseline-Scarce vs. Directed-Scarce, $p = 0.086$ for Baseline-Scarce vs. Active-Scarce).

Baseline-Ample vs. Active-Ample and Directed-Ample vs. Active-Ample are both statistically insignificant ($p = 0.265$ and $p = 0.300$, respectively).

The results show that the studied choice-promoting interventions cause two countervailing effects. On the one hand, they reduce passivity and thereby improve decisions in the targeted choice domain. On the other hand, they encourage subjects to withdraw scarce cognitive resources from other choice domains, which in turn deteriorates the quality of their decisions in these domains. To evaluate the overall consequences of the Directed Attention and Active Choice intervention, it is therefore crucial to assess whether the increase in payoffs in the targeted domain is "worth" the accompanying negative cognitive spillovers on other decisions. We address this question by comparing treatment differences in subjects' average total payoff from solving the decision task and the background task.[15] Notably, individuals' average total payoff (reported in the third row of Table 2) is essentially identical for all three decision environments. If anything, payoffs are slightly higher in Baseline-Scarce compared to Directed-Scarce and Active-Scarce. All pairwise treatment comparisons turn out to be statistically insignificant (Mann-Whitney-U tests, $p = 0.659$ for Baseline-Scarce vs. Directed-Scarce, $p = 0.415$ for Baseline-Scarce vs. Active-Scarce, and $p = 0.791$ for Directed-Scarce vs. Active-Scarce). Hence, the positive impact on the quality of choices in the decision task and the negative spillovers on the background task cancel each other out, such that the resulting net effect on subjects' overall payoffs is essentially zero.

Result 4. *Compared to* Baseline-Scarce*, the quality of choices in the decision task increases in* Directed-Scarce *and* Active-Scarce*. At the same time, choice quality in the background task decreases from* Baseline-Scarce *to* Directed-Scarce *and* Active-Scarce*. The resulting overall payoffs do not differ significantly across decision environments.*

5 Conclusion

We conclude by discussing practical implications of our findings for institutions that design or evaluate default rules and choice-promoting policies. Typically, the success of such policies is examined solely with respect to the outcomes in the decision domain that is the subject of the intervention. This approach presumes that the policies do not trigger negative spillovers to other domains. Our results indicate that this assumption might frequently be violated. Whenever different tasks or decisions compete for people's scarce cognitive resources, interventions that foster active choice in one domain can induce negative cognitive spillovers to others, which may dilute or even fully offset the policies' positive effects. While for some interventions the net effects may still be positive—

[15]Recall that the payoff for solving the background task correctly is relatively high (see Section 2). Hence, while the percentage change in the decision quality of this task may appear to be small, the observed differences can be relatively high for subjects' overall payoffs.

e.g., in the case of high-quality personalized recommendations (Kling et al. 2012, Kaufmann et al. 2018)—examining the existence and magnitude of cognitive spillovers is crucial in order not to systematically overestimate the benefits of choice-promoting policies.

Our findings also shed new light on the question of which "types" of decision makers are especially prone to stick to defaults, and under which conditions default specifications might be beneficial for consumers. The fact that passive decision making is more pronounced under cognitive resources scarcity implies that default specifications have particularly strong consequences for subgroups of the population that face scarce cognitive resources. To the extent that poverty is a driver of such resource scarcity (see for example Mani et al. 2013), the group that remains passive will be relatively more likely to be poor. When stipulating defaults, policy makers should account for these differences in the incidence of default effects, and their potential distributional consequences. In the context of defaults that are set by firms to sell preconfigured goods, the same reasoning implies that decision makers with scarce cognitive resources will be particularly susceptible to exploitation. On a more positive note, our findings also suggest that high-quality defaults can generate positive cognitive spillovers to choices in other domains of decision makers' lives. In particular, defaults in our experiment were chosen at random and, therefore, passive behavior resulted in relatively poor choices in the decision task. Well-chosen defaults, in contrast, might yield a double dividend when cognitive resources are scarce: they do not only improve outcomes for passive decision makers, but also "free up" scarce cognitive resources, allowing people to focus on other particularly pressing tasks or decisions.

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Appendix A Formal Derivation of Hypotheses

This section presents the formal arguments underlying the behavioral predictions discussed in Section 3. To fix ideas, we present a simple theoretical framework reflecting the key ideas of our experiment design. Within this framework, we describe a set of sufficient conditions for the hypotheses discussed in Section 3. We base our analysis upon the premise that agents have a limited stock of cognitive resources and optimally allocate these resources across tasks. While both of these assumptions represent significant simplifications, this approach is valuable for deriving qualitative predictions on how we should expect behavior to differ across treatments. We build upon a simplified version of the framework proposed by Alonso et al. (2014) to analyze resource allocation in the brain.[16] The main idea of Alonso et al.'s model is that different cognitive tasks are executed by different systems of neurons. These systems simultaneously demand resources, which are allocated by a central executive system. For more details on the underlying research in neuroscience, we refer the reader to the literature review in Alonso et al. (2014) and Brocas (2012).

To understand how the allocation of cognitive resources affects outcomes across treatments, we incorporate two key features of our experiment. First, we assume that subjects face two tasks that simultaneously require resources—the decision task and the background task. Second, the decision task features three options, one of which is randomly preselected as the default. Formally, suppose that every individual j is equipped with a stock of cognitive resources X^j and faces a background task B and a decision task D to which she can allocate resources $x_i,\ i \in \{B, D\}$, such that $x_B + x_D \leq X^j$. Allocating resources x_B to a background task of difficulty $\theta \in \{\theta_L, \theta_H\}$ results in a likelihood of $\pi_B(x_B, \theta)$ to correctly solve the background task and obtain utility u_B. $\pi_B(x_B, \theta_H)$ is increasing, strictly concave, and continuously differentiable in x_B. Moreover, we assume that $\pi_B(x_B, \theta_L) = 1 \quad \forall x_B \in \mathbb{R}^+$, in line with the idea that keeping in mind a two-digit number essentially requires no cognitive resources. Allocating resources x_D to the decision task results in a likelihood $\pi_D(x_D, d)$ to solve the task and obtain utility u_D, where $d \in \{c, inc, no\}$ specifies whether the stipulated default option is correct, incorrect, or nonexistent (as in the Active Choice environment). If the default is specified at random, a subject's expected probability to solve the task correctly is thus $\frac{1}{3}\pi_D(x_D, c) + \frac{2}{3}\pi_D(x_D, inc)$, which we assume to be strictly increasing, differentiable, and concave in x_D. If $x_D = 0$, the individual stays passive and automatically follows the default option (if there is one). Making use of the above notation we can now state the subjects' decision problem. Since it is ex ante unknown to subject j whether the default is correct, she

[16] We deviate from Alonso et al. (2014) in two respects. First, we abstract from asymmetric information across different regions of the brain and revert to the case of perfect knowledge. Second, we impose slightly more structure on payoffs, in line with our experimental setup.

allocates her cognitive resources in the BASELINE environment according to:

$$\max_{x_B, x_D} u(x_B, x_D) = \pi_B(x_B, \theta)u_B + \left(\frac{1}{3}\pi_D(x_D, c) + \frac{2}{3}\pi_D(x_D, inc)\right) u_D \tag{2}$$
$$s.t. \;\; x_B + x_D \leq X^j$$

The optimal allocation of cognitive resources thus depends on the shape of the functions $\pi_B(\cdot)$ and $\pi_D(\cdot)$ as well as the payoffs obtained from each of the tasks. In a next step, we discuss a set of plausible sufficient conditions on the shape of $\pi_D(x_D, d)$, under which the hypotheses from Section 3 hold.

Condition 1. *For all x_D, the probabilities $\pi_D(x_D, d)$ satisfy the following conditions:*
(i) $\pi_D(x_D, c) > \pi_D(x_D, no) > \pi_D(x_D, inc)$
(ii) $\frac{\partial \pi_D(x_D, c)}{\partial x_D} < \frac{\partial \pi_D(x_D, inc)}{\partial x_D}$
(iii) $\pi_D(x_D, no) = \frac{1}{3}\pi_D(x_D, c) + \frac{2}{3}\pi_D(x_D, inc)$

Condition 1 imposes three restrictions. First, correct default options catalyze correct choices and incorrect default options catalyze incorrect choices. Hence, holding x_D constant, the probability to make a correct choice is highest if the default option is correct and lowest if it is incorrect. This feature captures the intuition and widespread observation that people tend to stick to defaults disproportionally often, even if these are specified at random (see, e.g., de Haan and Linde 2017, Altmann et al. 2019).[17] Second, there is more to be gained from allocating cognitive resources to the decision task if the default option is incorrect, i.e., if the baseline probability to make a mistake is relatively high. Third, for a given amount of cognitive resources, subjects are equally likely to solve the decision task correctly irrespectively of whether there is a random default option or no default option. This condition implies that there is no arbitrage opportunity in terms of decision qualities if a random default instead of no default is established.

Derivation of Hypothesis 1

We start by deriving the optimal allocation of cognitive resources. If a subject faces a background task with difficulty θ_L, all cognitive resources will be allocated to the decision task since $\pi_B(x_B, \theta_L) = 1 \;\; \forall x_B \in \mathbb{R}^+$. Consider now a subject who faces a background task with difficulty θ_H. Since $\pi_B(x_B, \theta_H)$ is strictly increasing, all cognitive resources will be used in any optimum. The maximization problem can then be rewritten as

$$\max_{x_D} \pi_B(X_j - x_D, \theta_H)u_B + \pi_D(x_D)u_D,$$

[17] We abstract from explicitly modeling the potential sources of this attraction, such as a status quo bias, omission/commission biases, etc. (see Sunstein 2013 for a comprehensive overview).

where $\pi_D(x_D) \equiv \frac{1}{3}\pi_D(x_D, c) + \frac{2}{3}\pi_D(x_D, inc)$. This objective function is strictly concave in x_D. The derivative with respect to x_D yields

$$-\pi_B'(X_j - x_D, \theta_H)u_B + \pi_D'(x_D)u_D.$$

As a consequence, the optimal solution (x_D^*, x_B^*) will satisfy $x_D^* = 0$ if and only if:

$$\pi_D'(0)\frac{u_D}{u_B} \leq \pi_B'(X^j, \theta_H).$$

To solve the optimization problem we have to consider two cases.

Case I: $\pi_D'(0)\frac{u_D}{u_B} < \pi_B'(0, \theta_H)$

Due to the concavity of π_B and π_D, there exists a threshold $\bar{X} \in \mathbb{R}^+$ such that subjects with $X^j \leq \bar{X}$ will abstain from devoting cognitive resources to the decision task in Baseline-Scarce. In Case I, $\bar{X}$ will be strictly positive, because subjects with a minimal stock of cognitive resources have a higher marginal incentive to allocate cognitive resources to the background task compared to the decision task. We should therefore observe an effect at the extensive margin of attention: More subjects in Baseline-Scarce completely ignore the decision task than in Baseline-Ample, where subjects should spend all their resources on the decision task.

For all subjects with $X^j > \bar{X}$, $x_D^* > 0$ holds. Furthermore, x_B^* will also be strictly positive for these subjects by construction of $\bar{X}$. Hence, we expect subjects with $X^j > \bar{X}$ to react at the intensive margin: They dedicate less resources to the decision task in Baseline-Scarce than in Baseline-Ample but they attend to the decision task in both conditions. If the population of participants is heterogeneous enough in terms of X^j, we should therefore observe extensive-margin as well as intensive-margin effects. As a consequence, the cumulative distribution over cognitive resources dedicated to the decision task in Baseline-Scarce first order stochastically dominates the corresponding cumulative distribution in Baseline-Ample, yielding Hypothesis 1.

Note that we chose parameters in the experiment to ensure treatment take-up, i.e., we choose incentives to ensure that subject try to solve the background task in all treatments (see Section 2 for details). We therefore derive all our hypotheses for the experiment from Case I only. For sake of completeness, we also solve the optimization problem if the condition does not hold.

Case II: $\pi_D'(0)\frac{u_D}{u_B} \geq \pi_B'(0, \theta_H)$

In this case, subjects always dedicate positive amounts of cognitive resources to the decision task. Then, there exists a threshold $\tilde{X}$ such that subjects dedicate all resources to the decision task if $X^j \leq \tilde{X}$ and distribute their resources across both tasks otherwise. Hence, subjects with $X^j \leq \tilde{X}$

do not react to the treatment and subjects with $X^j > \tilde{X}$ react at the intensive margin. Again, if the population of participants is heterogeneous enough in terms of X^j, we should observe the cumulative distribution over cognitive resources dedicated to the decision task in Baseline-Scarce to first-order stochastically dominate the corresponding cumulative distribution in Baseline-Ample.

Derivation of Hypothesis 2

Recall that subjects who completely ignore the decision task in Baseline-Scarce automatically stay passive. Passivity rates for subjects with a small stock of cognitive resources $X^j \leq \bar{X}$ are therefore higher in Baseline-Scarce compared to Baseline-Ample. Second, consider subjects with larger stocks of cognitive resources, who react at the intensive margin. Let ρ denote the probability of default adherence for $x_D > 0$, conditional on the default being incorrect and the subject choosing either the default or the other incorrect option. As indicated in Section 3, our hypotheses hold as long as individuals who dedicate fewer resources to a task are more likely to follow an incorrect default option than to actively opt for another wrong option, i.e., as long as $\rho \geq \frac{1}{2}$. In this case, a subject with $x_D > 0$ will stick to the default with probability

$$\frac{1}{3}\pi_D(x_D, c) + \frac{2}{3}\rho(1 - \pi_D(x_D, inc)).$$

To determine the direction of the effect of a reduction in cognitive resources at the intensive margin on default adherence, it suffices to consider the derivative of the above expression with respect to x_D, which is given by:

$$\frac{1}{3}\pi'_D(x_D, c) - \frac{2}{3}\rho\pi'_D(x_D, inc) \leq \frac{1}{3}[\pi'_D(x_D, c) - \pi'_D(x_D, inc)] \leq 0,$$

where the last inequality holds because there is more to be gained from allocating cognitive resources to the decision task if the default option is incorrect than if it is correct (part (ii) of Condition 1). Both the extensive and intensive margin effects therefore imply that default adherence is lower in Baseline-Ample than in Baseline-Scarce, yielding the first part of Hypothesis 2.

Focusing only on cases in which the default option is incorrect yields a likelihood to stick to the default of $\rho(1 - \pi_D(x_D, inc))$ for subjects who choose a strictly positive x_D^*. This probability decreases in x_D, because $\pi_D(x_D)$ increases with x_D and the second part of Condition 1. For this case, extensive- and intensive-margin effects are thus aligned and default adherence unambiguously increases from Baseline-Ample to Baseline-Scarce. Focusing instead on cases in which the default option is correct yields a default adherence probability of $\pi_D(x_D, c)$ for subjects with strictly positive x_D. Hence, subjects with $X^j \geq \bar{X}$ may follow the default more often in Baseline-Ample than in Baseline-Scarce, because they make fewer mistakes. However, there is a countervailing extensive-margin effect: more subjects choose $x_D^* = 0$ in Baseline-Scarce, which in turn leads to higher default adherence in Baseline-Scarce relative to Baseline-Ample. If the default option coincides with the correct solution, the net effect is thus ambiguous. These insights establish the second part of Hypothesis 2.

Derivation of Hypothesis 3

Our theoretical framework also provides a natural setting to examine how the choice-promoting interventions in the Directed Attention and Active Choice environments affect the allocation of cognitive resources, and the resulting decisions. We assume that, as a result of the interventions, some strictly positive amount of cognitive resources $0 < x_T < X^j \;\; \forall j$—which depends on treatment $T \in \{Directed, Active\}$—is exogenously directed towards the decision task. Given an amount of cognitive resources x_D, the expected rate of correct choices in the decision task is identical in Active Choice and Directed Attention because of the no-arbitrage condition (part (iii) of Condition 1). A subject thus faces the following decision problem in both treatments:

$$\begin{aligned} &\max_{x_B, x_D} u(x_B, x_D) = \pi_B(x_B, \theta)u_B + \left(\frac{1}{3}\pi_D(x_D, c) + \frac{2}{3}\pi_D(x_D, inc)\right) u_D \\ &s.t. \quad x_D \geq x_T \qquad \text{and} \qquad x_B + x_D \leq X^j \end{aligned} \tag{3}$$

In all environments with Ample resources, the constraint will not be binding since $x_T < X^j = x_D^* \;\; \forall j$. Hence, there will be no behavioral reaction to the treatment interventions and thus no differences in the quality of subjects' decisions, yielding the first part of Hypothesis 3. Directing individuals' attention to the decision task under cognitive resource scarcity (Directed-Scarce), however, increases the amount of resources allocated to the decision task for subjects with $X^j \leq \bar{X}$, relative to Baseline-Scarce. Following the same arguments as above, this increase implies lower default adherence. Nevertheless, individuals in Directed-Scarce will in expectation stick to the default in more than one third of cases. To see this, note that, for $\rho \geq \frac{1}{2}$,

$$\frac{1}{3}\pi_D(x_D, c) + \frac{2}{3}\rho(1 - \pi_D(x_D, inc)) \geq \frac{1}{3}[\pi_D(x_D, c) + (1 - \pi_D(x_D, inc))] \geq \frac{1}{3},$$

where the last inequality holds as a consequence of part (i) of Condition 1. Hence, options that are (randomly) preselected as default will, in expectation, be chosen more often in Directed-Scarce compared to the same (non-default) options in Active-Scarce.

Derivation of Hypothesis 4

In all environments with Ample resources, the constraint of devoting x_T to the decision task will not be binding since $x_T < X_j \;\; \forall j$. Hence, there will be no behavioral reaction to the treatment interventions, which yields the first part of Hypothesis 4. Since the optimization problem in (3) is a constrained version of the optimization in (2), it is clear that overall profits should be weakly higher in Baseline-Scarce compared to Directed-Scarce and Active-Scarce, which yields the second part of Hypothesis 4.

As stated in the derivation of Hypothesis 3, directing individuals' attention to the decision task under cognitive resource scarcity (Directed-Scarce), increases the amount of resources allocated to the decision task for subjects with $X^j \leq \bar{X}$, relative to Baseline-Scarce. As $\pi_D(x_D)$ is increasing in x_D, the increase in cognitive resources also implies an increase in the likelihood of making correct choices in the decision task. As the cognitive-resource constraint is binding in Directed-Scarce and Active-Scarce, the increase in resources devoted to the decision task implies a reduction of resources devoted to the background task and, hence, a lower likelihood of correctly solving this task (last part of Hypothesis 4).

Appendix B Supplementary Information about the Experiment

Appendix B.1 Instructions

First Part

The first part of the experiment consists of a total of 10 rounds. The sequence of events in each round is as follows:

- First, a number is displayed on your screen.
- Your task is to memorize this number.
- After 10 seconds, the number will not be displayed anymore and you face a blank screen for 30 seconds.
- After 30 seconds have elapsed, a screen with an input field appears. In this field you can enter the number you have memorized at the beginning of the round. You have 20 seconds to enter the number.
- If you enter the correct number, you will receive a payoff of **40 cents**.
- If you enter nothing or a wrong number, you will receive **0 cents**.
- After you entered the number, the round is over and the next round begins.

Second Part

The second part of the experiment consists of a total of 10 rounds. The sequence of events in each round is as follows:

- In each round you will see three options, as illustrated in the figure below. Each option corresponds to a calculation task.
- Your task is to select the option that yields the **highest sum**.
- To select an option, please click the box in front of the respective option. You have 30 seconds to do so.
- If the selected option is the correct choice, you will receive a payoff of **10 cents** for this round.
- If the option you selected is not correct or you did not select any option, you will receive **0 cents** for this round.

Third Part

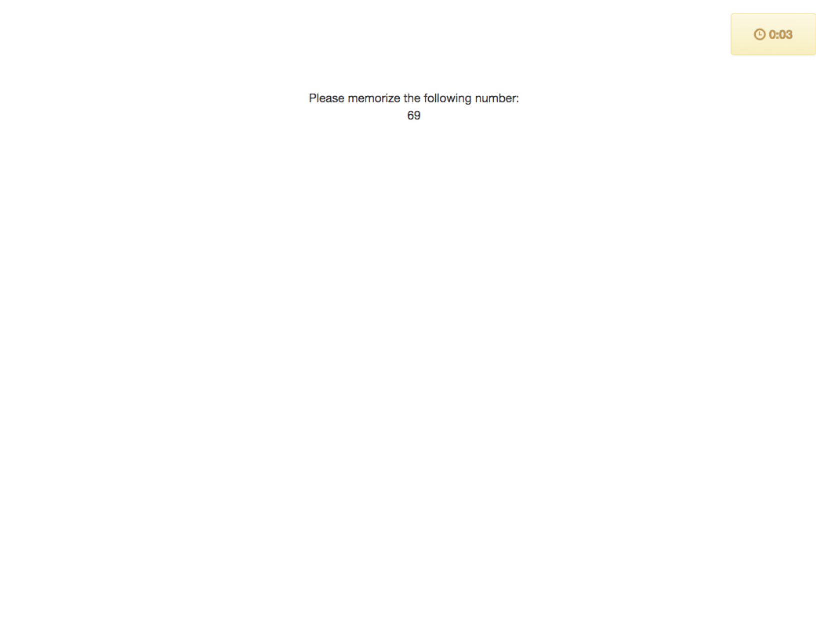
The third part of the experiment consists of a total of 20 rounds. In each round you can work on the task from Part 1 and the task from Part 2. The sequence of events in each round is as follows:

- First, a number is displayed on the screen for 10 seconds. As in Part 1, your task is to memorize this number.
- Following this screen, the number will not be displayed for 30 seconds. During this time, you can work on a calculation task as in Part 2. [Only in BASELINE] *To work on the task from Part 2, you have to press and hold a key on the keyboard. The key you need to press will be displayed on the screen.*
- [Only in BASELINE and DIRECTED] *In the task from Part 2, one of the three options is preselected in each round. If you do not work on the task, this option will be considered as your choice. The preselected option is determined randomly. This means that in about one third of the cases, the preselected option also corresponds to the correct option.*
- After 30 seconds have elapsed, a screen with an input field appears. As in Part 1, you can enter the number you have memorized at the beginning of the round in this field. You have 20 seconds to enter the number.
- If you enter the correct number in the task from Part 1, you will receive a payoff of **40 cents** for this task. Otherwise, you will receive **0 cents** for this task.
- If the chosen option in the task from Part 2 is correct, you will receive a payoff of **10 cents** for this task. If the chosen option is not correct, you will receive **0 cents** for this task.
- The payoff in one round is the sum of the payoffs from both tasks.

Appendix B.2 Screenshots

Figure B.1: Screenshots

(a) Screen 1: Background Task



(b) Screen 2: Decision Task (only in Baseline)

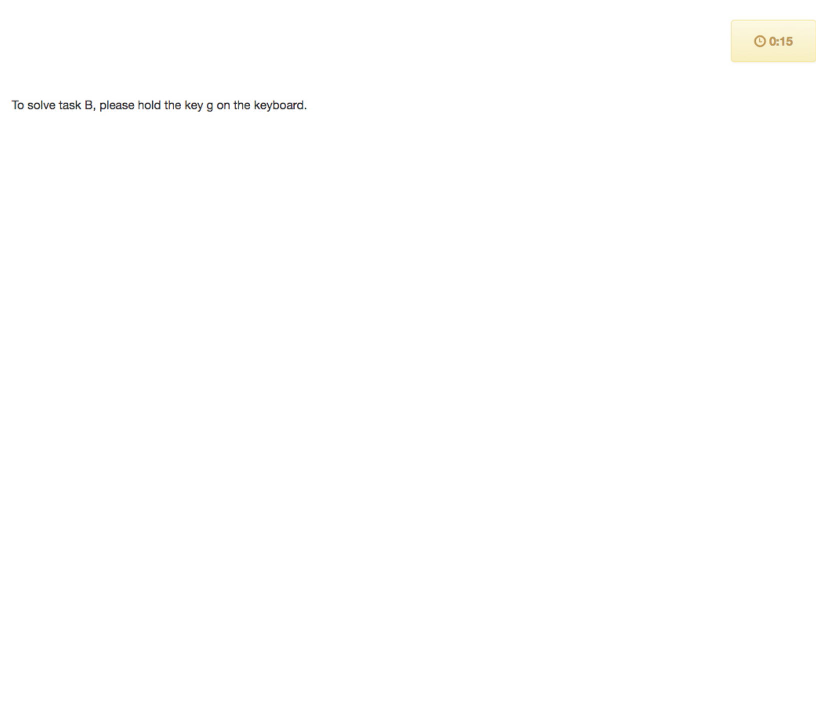
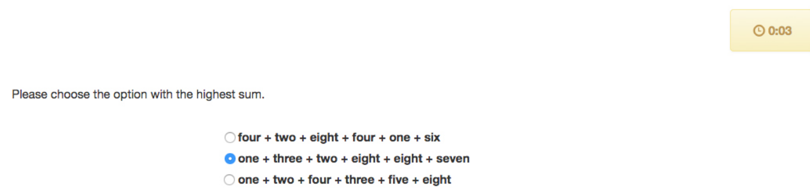
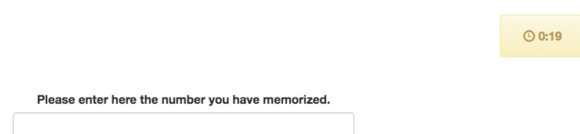


Figure B.1: Screenshots

(c) Screen 3: Decision Task



(d) Screen 4: Background Task



Appendix C Supplementary Analysis

Appendix C.1 Sample Descriptives

In the following table, we provide an overview of baseline characteristics for our sample. The first two rows in Table C.1 depict treatment-level averages for the ability measures from Part 1 and Part 2 of the experiment (see Section 2 for details). The remaining rows depict average values of sociodemographic characteristics across treatments. The last column of Table C.1 reports p-values of Kruskal-Wallis tests for the identity of means across treatments. We do not find any significant differences across treatments.

Table C.1: Descriptives

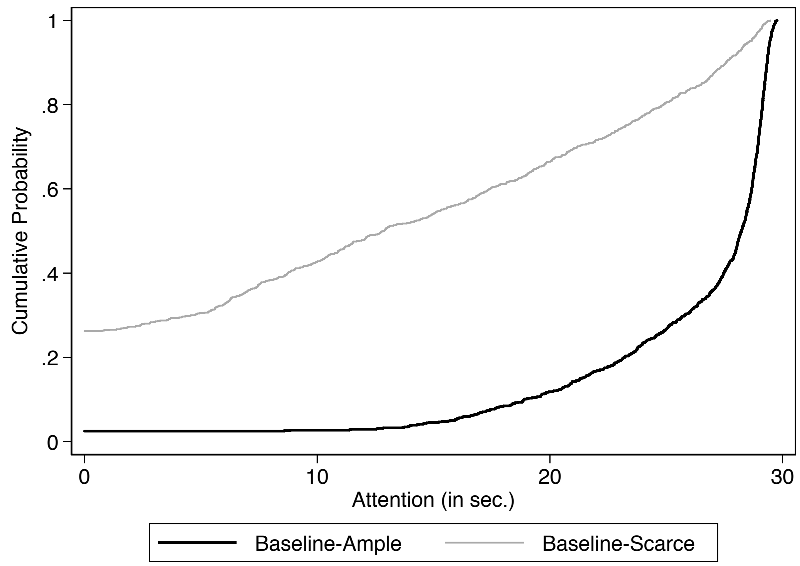
	Baseline		Directed Attention		Active Choice		Kruskal-Wallis
	Ample	Scarce	Ample	Scarce	Ample	Scarce	p-value
Decision Task ability	0.86	0.85	0.86	0.84	0.83	0.84	0.38
	(0.13)	(0.14)	(0.12)	(0.13)	(0.14)	(0.14)	
Background Task ability	0.83	0.81	0.79	0.81	0.80	0.81	0.64
	(0.12)	(0.14)	(0.14)	(0.15)	(0.16)	(0.14)	
Age	23.13	23.36	23.33	23.90	24.74	23.48	0.20
	(4.30)	(4.10)	(3.54)	(4.11)	(6.09)	(4.08)	
% Female	0.59	0.62	0.62	0.57	0.55	0.53	0.82
	(0.50)	(0.49)	(0.49)	(0.50)	(0.50)	(0.50)	
% Economists	0.18	0.16	0.13	0.15	0.16	0.18	0.92
	(0.39)	(0.37)	(0.34)	(0.35)	(0.36)	(0.39)	
Raven Score[18]	6.09	6.35	6.20	6.35	6.06	5.83	0.55
	(1.87)	(1.67)	(1.63)	(1.47)	(1.97)	(1.46)	
N	94	95	94	96	96	89	

Note: The table shows the average for basic characteristics of our sample in each treatment. Standard deviations are reported in parentheses.

[18]Number of correct answers in a 10-item version of Raven's Progressive Matrices. Raven scores were only elicited for 50% of participants in each treatment.

Appendix C.2 Attention and re-allocation of cognitive resources

Figure C.1: Attention levels in Baseline-Ample and Baseline-Scarce



Note: The figure depicts CDFs of subjects' attention devoted to the decision task in Baseline-Ample and Baseline-Scarce. Calculations are based on individual attention spans at the subject-round level.

Appendix C.3 Blinder-Oaxaca Decomposition

Using an Oaxaca-Blinder decomposition (Oaxaca 1973, Blinder 1973, Fortin et al. 2011), we can decompose the average treatment effect between Baseline-Ample and Baseline-Scarce. This approach provides a descriptive estimate of the extent to which the differences in passive choices between Baseline-Ample and Baseline-Scarce are accounted for by the differences in decisions that are taken without even entering the decision task.

Given the standard assumptions of the decomposition, the difference in the dependent variable Y, i.e., the treatment difference in the rate of passive choices, can be decomposed in three components. Denote by $I_{Attention=0}$ the dummy variable that takes the value of 1 if a subject does not enter the decision task in a given round of the experiment. Then, rewriting the overall difference in outcomes yields

$$\begin{aligned} E[Y_S] - E[Y_A] =& \beta_0^{\mathrm{S}} - \beta_0^{\mathrm{A}} \;+\; E[I_{Attention=0}|T = \mathrm{S}]\; (\beta_1^{\mathrm{S}} - \beta_1^{\mathrm{A}}) \\ &+\; (E[I_{Attention=0}|T = \mathrm{S}] - E[I_{Attention=0}|T = \mathrm{A}])\beta_1^{\mathrm{A}}, \end{aligned}$$

where β_0^T and β_1^T are the coefficients from treatment specific linear regression models of Y on $I_{Attention=0}$, with $T \in \{S(carce); A(mple)\}$. The first two summands represent the effect due to changes in β_0 and β_1. The last part is the composition effect, i.e., the part of the treatment effect which is due to the change of the fraction of decisions that are taken by completely inattentive subjects. All components of the decomposition can be estimated using OLS regressions, replacing the expected values by the sample averages (see Table C.2 for the corresponding numbers). The overall treatment difference in passivity is 28.19 percentage points. The decomposition reveals that 73.32% of this effect can be accounted for by the change in the fraction of decisions that are taken without entering the decision task. The effect at the extensive margin, therefore, accounts for a difference in passivity rates of 20.67 percentage points.

Table C.2: Attention and passive choices

	Means		Coef.	
	(1)	(2)	(3)	(4)
	Ample	Scarce	Ample	Scarce
$E[I_{Attention=0}\|T]$	0.0250	0.3205		
	(0.0036)	(0.0107)		
Attention = 0, β_1			0.6994	0.5887
			(0.0077)	(0.0221)
Constant, β_0			0.3006	0.4113
			(0.0077)	(0.0221)
Observations	1880	1900	1880	1900

Note: The first two columns present the fraction of subjects in the Baseline-Ample *and* Baseline-Scarce *treatment who devote no attention to the decision task. Columns (3) and (4) present OLS estimates using default adherence as the outcome variable. Robust standard errors (in parentheses) account for potential clustering on subject level.*