Material Scarcity and Unethical Economic Behavior: A Systematic Review and Meta-Analysis

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Material Scarcity and Unethical Economic Behavior: A Systematic Review and Meta-Analysis

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Abstract

Individuals around the globe experience different forms of material resource scarcity in terms of aspects such as hunger, thirst, or financial strains. As experiences of material scarcity have been found to make individuals more risk-taking, impulsive, and focused on regaining resources in the short-term, a growing body of research has investigated how such scarcity affects moral economic behavior. Yet, findings remain mixed and at times contradictory, thus calling for a systematic meta-analytical review on this overarching topic. In this pre-registered systematic review and meta-analysis, we evaluate qualitatively and quantitatively how material resource scarcity affects moral economic behavior. We analyze a comprehensive dataset including 44 published and unpublished studies comprising a total of 6,921 respondents across four distinct types of material scarcity: financial scarcity, physiological scarcity, scarcity reminders, and lower social class. Our findings show that acute scarcity significantly increases the propensity to engage in unethical economic behavior ($g_{\text{financial}} = .24$, $g_{\text{physiological}} = .39$, $g_{\text{reminders}} = .32$). Importantly, we find no evidence that chronic experiences of scarcity in the form of low social class affect unethical economic behavior ($g_{\text{social class}} = .02$). These results appear robust to the influence of publication bias and contextual sensitivity. We discuss how these findings advance our understanding of the psychological and moral consequences of scarcity and elaborate on implications for public policy.

Keywords: resource scarcity, socioeconomic status, morality, unethical economic behavior, meta-analysis

Unethical economic behaviors, such as fraud, theft, corruption, and embezzlement, cost societies billions of dollars every year (Gee & Button, 2019). Albeit big scandals, like the Volkswagen Dieselgate emissions scandal, the Siemens corruption scandal, and Danske Bank's involvement in money laundering for some of the world's worst criminals, are often the examples that make it to the news headlines, the aggregated effects of small-scale unethical economic behavior can have equally or even more detrimental consequences for the societies and stakeholders. For instance, only in the U.S., misreporting liable income was estimated to cost the tax authorities \$458 billion dollars in 2019 (United States Government Accountability Office, 2019). Whether large or small in scale, unethical economic behavior has destructive consequences for individuals, businesses, and societies in general, underscoring the importance of understanding the human motivation to engage in such behavior crucial for policy makers (Ayal et al., 2015; Babakus et al., 2004; Gerlach et al., 2019; Mazar & Ariely, 2006; Mitchell et al., 2009; Transparency International, 2019).

Unethical economic behavior can be conceptualized as any sort of economic outcome that occurs through immoral actions. Due to the endemic nature of unethical economic behavior (Transparency International, 2019), studies within psychology, neuroscience, management, marketing, and behavioral economics have investigated which factors might affect the propensity to engage in such morally questionable behavior (Fischbacher & Föllmi-Heusi, 2013; Gino et al., 2009; Greene & Paxton, 2009; Kajackaite & Gneezy, 2017; Kocher et al., 2018; Mazar et al., 2008; Shalvi et al., 2015). Importantly, as the last two decades have seen a rapid rise across disciplines in empirical work addressing the causes and consequences of material resource scarcity (Dhurandhar, 2016; Griskevicius et al., 2013; Hamilton et al., 2019; Huppert et al., 2020; Lee & Zietsch, 2011; Nelson & Morrison, 2005; Prediger et al., 2014; Roux et al., 2015), an emerging body of research has started to investigate whether and how experiences of material resource scarcity (such as hunger, thirst, or financial poverty) may

influence people's propensity to engage in unethical economic behavior (DeWall et al., 2008; Gino et al., 2011; Mead et al., 2009; Wang et al., 2017).

However, the evidence on the impact of material scarcity on unethical economic behavior is characterized by seemingly mixed findings. Some studies suggest that material scarcity increases unethical behavior (Birkelund & Cherry, 2020; Goldsmith et al., 2018; Prediger et al., 2014; Sharma et al., 2014; Yam et al., 2014) while other studies indicate that material scarcity increases prosocial behavior (Bartos, 2016; DeWall et al., 2008; Häusser et al., 2019; Herzenstein & Posavac, 2019; Huppert et al., 2020). These mixed findings have also spurred a new debate on how material scarcity affects decision-making more generally (Hall et al., 2014; Mani et al., 2013; Mullainathan & Shafir, 2014; Shah et al., 2012)

Here, we present the first pre-registered systematic review and meta-analysis on the relationship between experiences of material scarcity and unethical economic behavior. Based on the systematic review, we argue that it is important to distinguish between different types of acute and chronic experiences of material scarcity to understand their impact on financial outcomes. Specifically, we identify financial and physiological scarcity as well as reminders of scarcity as three fundamental forms of acute scarcity, whereas social class constitutes a key indicator of chronic scarcity.

Using this typology, we then provide the first meta-analysis on how material resource scarcity might affect individuals' propensity to engage in unethical economic behavior. Analyzing 44 published and unpublished studies including 6921 respondents, we find that acute financial and physiological scarcity as well as reminders of scarcity significantly increase individuals' propensity to engage in unethical economic behavior. Importantly, we find no evidence that more chronic material scarcity, in the form of lower social class, impacts unethical economic behavior. Thus, based on the extant body of published research, the propensity to engage in dishonest behavior for direct monetary gains appears to operate

irrespective of social class and is equally likely to occur among individuals from lower and higher social classes.

Overall, the findings from the systematic review and the meta-analysis do not support the general claim that scarcity increases the propensity to engage in unethical economic behavior. Instead, our results highlight the importance of distinguishing between different types of material scarcity, where only temporary or acute experiences of scarcity seem to impact people's moral decision-making in the financial realm. Sensitivity analyses conducted as part of our meta-analysis indicate that the results are not strongly impacted by contextual sensitivity (cf. Van Bavel et al., 2016) and robust to the existence of publication bias (cf. Mathur & VanderWeele, 2020; Simonsohn et al., 2015).

Together, the results from the qualitative systematic review and the quantitative meta-analysis highlight that the seemingly mixed findings on the relationship between material resource scarcity and unethical economic behavior can be disentangled by distinguishing between different types of temporary and acute versus more chronic forms of scarcity. Consequently, rather than focusing on consequences of "the scarcity mindset," scholars may benefit from theorizing on the psychological architecture and consequences of different forms of material scarcity. As acute experiences of material resource scarcity can in effect apply to individuals around the globe, we argue that the current review has important implications for the theoretical understanding of how material scarcity can distort human moral judgment and decision-making and how policy initiatives aimed at hindering unethical behavior should incorporate such considerations.

Scarcity Effects on Decision-Making

Research over the last decade has found robust evidence that scarcity in the form of hunger, thirst, or financial strains induces myopic decision-making, where present, short-term gains are

overvalued, while future possible gains are discounted (Loewenstein, 1996; Mani et al., 2013; Mullainathan & Shafir, 2014; Shah et al., 2012; Skrynka & Vincent, 2019). Scholars have suggested that scarcity taxes the mind, reducing “mental bandwidth” – an umbrella term used to cover the cognitive functions associated with executive control and fluid intelligence – leading scarcity-constricted individuals to “tunnel” attention (Mani et al., 2020; Mani et al., 2013; Mullainathan & Shafir, 2014; Shah et al., 2012). While this tunneling of cognitive resources might increase the likelihood of obtaining material resources to balance the scarcity (i.e., what is known as “the focus dividend”), it usually comes with a cost. Importantly, because scarcity-constricted individuals tunnel attention towards the options that might best satisfy their current needs, other resources and obligations are repeatedly neglected, leading to sub-optimal prospective decision-making outcomes (Mani et al., 2013; Mullainathan & Shafir, 2014; Piech et al., 2010; Shah et al., 2012). Consistent with this notion, scholars have shown that individuals who have matured in environments characterized by resource scarcity (i.e., low childhood socioeconomic status) perform worse in tasks requiring cognitive inhibition, but are better able to shift attention, because such behavior is considered particularly useful in unpredictable environments (Mittal et al., 2015). Furthermore, research has provided evidence that scarcity significantly increases risk-taking and impulsive behavior in individuals (Griskevicius et al., 2013; Hamilton et al., 2019; Payne et al., 2017; Simpson et al., 2012), again pointing to potentially problematic decision-making due to scarcity.

Importantly, some research on how material scarcity affects decision-making argues that the “scarcity-mindset” is induced independent of the resource in question. That is, whether the current scarcity is experienced as a lack of food, water, or financial resources, the effect of this lack of necessary resources will lead to similar cognitive and behavioral outcomes across different types of material resource scarcity (Mullainathan & Shafir, 2014). It should be noted that this conceptualization of scarcity does not entail that poor individuals are worse decision-

makers (Mullainathan & Shafir, 2014). Instead, it prescribes to the idea that cognizant experiences of relative scarcity make the individual focus on regaining the lack of resources in the short-term, regardless of the individual's social class or demographic profile.

Material Scarcity and Unethical Economic Behavior: A Systematic Review

The findings that material scarcity increases risk-taking, impulsiveness, and future discounting have led scholars to hypothesize that scarcity increases unethical economic behavior based on the argument that individuals constricted of resources exhibit an increased focus on regaining the experienced lack of resources in the short term (Birkelund & Cherry, 2020; Gino & Pierce, 2010; Sharma et al., 2014; Yam et al., 2014). In what follows, we present a systematic review of extant scientific studies on this topic, which aligned with the inclusion criteria for the subsequent meta-analysis. The aim of this section is threefold: (1) to provide an in-depth overview of the different types of material scarcity that have been studied, (2) to delineate the types of manipulations and research designs that have been used in this overarching topic domain, and (3) to critically summarize the mixed nature of the existing findings. The contribution of this qualitative review is hence to provide a comprehensive theoretical overview of the current literature in this specific domain of moral psychology, in order to structure and increase the interpretability of the subsequent quantitative meta-analysis.

Physiological Scarcity

Some studies focus on food deprivation, indexed by self-reported hunger or physiological levels of blood glucose, to test how this specific form of scarcity affects unethical economic behavior. Across five laboratory experiments, Yam et al. (2014) found that individuals experiencing physiological deprivation, either in the form of hunger or thirst, were more prone to engage in unethical behaviors that could alleviate these aversive experiences, but that such

scarcity made individuals less prone to exhibit unethical behavior in unrelated consumption domains. Williams et al. (2016) demonstrated a similar relationship by showing that individuals restricted of food or water were more likely to engage in unethical behavior to increase their chances of winning a prize, but only if the prize could alleviate their current lack of resources. Hence, scarcity did not create a generalized spillover effect in unethical behavior across domains, as has been shown to exist when it comes to prosocial behavior (Briers et al., 2006). On the developmental level, results have indicated that scarcity in the form of hunger might affect moral behavior. Koenig et al. (2004) found that experiences of resource scarcity, indexed by maltreatment, significantly affected moral development in 5-year-old children. Specifically, these authors' experimental results revealed that maltreated children engaged in significantly more cheating and stealing behaviors compared to non-maltreated children, indicating that resource scarcity can have detrimental consequences for the development of moral behavior early on in an individual's life.

Financial Scarcity

While research on scarcity points towards a unified framework of effects, where any form of material scarcity (be it thirst, hunger, or a lack of financial resources) exerts similar decision-making effects across domains (Mullainathan & Shafir, 2014; Shah et al., 2012), a majority of research on material scarcity and unethical behavior has examined specifically how a relative lack of financial resources affects decision-making. A possible reason for this could be that relative scarcity in economic resources has received wide-spread attention beyond academia, in politics and the media, due to the alarming and increasing levels of economic inequality across the world (Alvaredo et al., 2018; Piketty, 2020).

Gino and Pierce (2010), investigated how economic inequality, as manipulated by resource allocation (allocated randomly or subjectively), affected moral behavior in the form

of either helping or hurting others. Results showed that inequality significantly predicted increased levels of dishonest behavior for individuals with less resources and a follow-up experiment indicated that people behaved unethically to restore the perceived inequality. Also, Sharma et al. (2014) showed that manipulating resource scarcity in the form of financial deprivation lead individuals to cheat more for economic gains, and to judge such behavior as being less immoral. This effect was mediated by whether individuals considered the experienced deprivation as an acceptable reason for engaging in unethical behavior and if they were made aware of that the unethical behavior could not alleviate the experienced scarcity, in which case the effect no longer emerged (Sharma et al., 2014).

More recently, Birkelund and Cherry (2020) found that individuals experiencing financial inequality (vs. equality) cheated significantly more for monetary resources in an experimental dishonesty task and justified such behavior as result of the experienced scarcity. Relatedly, Gino and Pierce (2009b) investigated the influence of relative resource scarcity, indexed by inequity in endowments between individuals, on unethical economic behavior in a laboratory setting. Albeit the incentives for dishonest behavior varied, results consistently showed that inequity between partners in the experiment increased cheating and, importantly, that pure self-interest was not the prime mechanism in the causal chain; rather, individuals engaged in cheating due to emotional reactions (i.e., envy) elicited by the perceived resource scarcity. Results also indicated that dishonest behavior triggered by inequity made individuals more inclined to engage in dishonest helping due to empathy with the less fortunate partner (Gino & Pierce, 2009b). The tendency to justify unethical behavior under scarcity as a part of helping other resource deprived individuals was also supported in the work by Dubois et al. (2015), who showed that individuals with lower social class were more likely to engage in unethical behavior, only if such behavior could benefit their in-group. These findings suggest two important psychological mechanisms regarding scarcity; (1) that reminders of one's

relative lack of economic resources (compared to others) can increase the individuals' tendency to engage in unethical economic behavior, and (2) that such behavior finds justification on the basis of in-group altruism.

Reminders of Scarcity

Several studies have also examined how reminders and primes of scarcity might affect cognition and behaviors related to morality. Within this research tradition, scholars have demonstrated that individuals who exhibit a maximizing mindset (vs. a neutral mindset) regarding resource acquisition engage in significantly more immoral behaviors, and that the adoption of a maximizing mindset occurs due to cognitions related to scarcity (Goldsmith et al., 2018). Seuntjens et al. (2019) showed that greedy individuals (with greed conceptualized as a form of competitive orientation) were more likely to engage in and justify unethical behavior, while simultaneously being more prone to accept bribes due to the temptation of monetary gains being higher for such individuals. Moreover, activating cognitions related to scarcity through conceptually congruent reminders has been shown to increase competitive orientation in individuals, leading to more selfish behavior by guarding monetary resources instead of donating to charity, unless such charity is self-beneficial (Roux et al., 2015).

Notably, Roux et al. (2015) provided evidence for the thesis that exposure to scarcity cues can both increase selfish or prosocial behavior but only if such behavior is self-beneficial and advances personal welfare. However, results from experimental work on moral behavior have repeatedly shown that selfish behavior is a robust predictor of unethical behavior (Dubois et al., 2015; Engelmann & Fehr, 2016; Gino & Galinsky, 2012; Mead et al., 2009). Using reminders of scarcity in the form of visual exposure to inequality, Gino and Pierce (2009a) demonstrated that the presence (vs. absence) of visual proximity to money increased economic cheating among individuals with smaller (vs. larger) monetary endowments. Specifically, by

1 creating an environment where one's current relative financial scarcity was visually
2 emphasized, the authors documented that participants cheated more to alleviate this state, with
3 the cheating also provoking emotions of envy towards wealthy others. In a similar vein, an
4 experiment by John et al. (2014) used performance-based pay-rates, and found that dishonesty
5 emerged in individuals with lower pay-rates, but only when it was salient to them that there
6 was an opportunity of gaining a higher pay-rate (relative to their own rate), again emphasizing
7 the effects that *relative* scarcity has on activating a competitive orientation and a maximizing
8 mindset (Goldsmith et al., 2018; Roux et al., 2015).

9 In relation to specific cognitions and behaviors stemming from scarcity, scholars have
10 argued that such cognitive and behavioral responses could be the result of an evolutionary
11 response to harsh environments. Notably, the use of fast life history strategies (i.e., short-term
12 mating, low group altruism, higher criminal record, and higher risk taking) have been shown
13 to emerge more frequently when resources are scarce (Griskevicius, Delton, et al., 2011;
14 Griskevicius, Tybur, et al., 2011). Reynolds and McCrea (2015) employed a series of
15 laboratory experiments to test if faster (vs. slower) life history strategies, as well as primes of
16 faster (vs. slower) life history contingencies, would lead to exploitative and deceptive resource
17 acquisition strategies. Their findings indicated that individuals with a fast life history strategy
18 cheated more than individuals with a slow life history strategy, and that priming individuals
19 with fast life history contingencies further increased cheating. There results provide evidence
20 that experiences of resource scarcity, as indexed by life history strategies, increase unethical
21 economic behavior, and that being reminded of one's lack of resources, by fast life history
22 primes, can further increase the propensity to engage in unethical economic behavior to acquire
23 resources.

24

25

Field Evidence

While laboratory experiments represent a major source of scientific knowledge in the social sciences, providing rigor and control (Falk & Heckman, 2009), lab-based results might not always be generalizable to naturally occurring environments or the real-world (Levitt & List, 2007; Otterbring et al., 2020; Potters & Stoop, 2016; Roe & Just, 2009; Shadish et al., 2002). Consequently, a series of studies have utilized lab-in-the-field experiments and field experiments to study the effects of resource scarcity on unethical behavior among targeted relevant populations in naturalistic settings (Gneezy & Imas, 2017). Attending to this form of work, Gatiso et al. (2015) conducted a dynamic lab-in-the-field experiment in a communally managed forest in Ethiopia, finding that individuals exposed to resource scarcity engaged in significantly more unethical behavior by overharvesting forest, thus leaving less available resources to other individuals. Furthermore, men were particularly prone to develop a competitive orientation during such circumstances, in line with previous research (Hamilton et al., 2019; Roux et al., 2015), which made them overharvest resources even more. The results additionally indicated that resource scarcity decreased cooperation between individuals for the common good (Gatiso et al., 2015).

Prediger et al. (2014) employed a lab-in-the-field experiment in Namibia, providing evidence that individuals subjected to exposure of biomass resource scarcity were twice as likely to engage in unethical behavior in the form reducing other individuals' income. Contrary to such findings, though, recent results from a lab-in-the-field experiment in Thailand have provided evidence that unethical behavior might *not* increase through scarcity (Boonmanunt et al., 2020). Based on the argument that unethical behavior, such as corruption or tax evasion, is widespread in developing countries, Boonmanunt et al. (2020) investigated whether low-income rice farmers in Thailand would be more inclined to cheat for monetary gains when experiencing resource scarcity. Unethical behavior was not found to increase by experiences

of scarcity; however, reminders of social-norms of morality cut cheating behaviors for richer individuals, while it had no effect for individuals experiencing resource scarcity (Boonmanunt et al., 2020).

Aksoy and Palma (2019) investigated the effects of scarcity on cheating and in-group favoritism, using a lab-in-the-field experiment in Guatemala. While the authors found no effect of scarcity on cheating for economic gains in a well-validated cheating task (Fischbacher & Föllmi-Heusi, 2013), they did find that affluency (vs. scarcity) increased cheating behaviors directed towards one's in-group. The mixed evidence of these findings taps into the ongoing academic debate on how psychological constructs developed primarily in WEIRD (Western, Educated, Industrialized, Rich and Democratic) contexts might not generalize to non-WEIRD contexts (Henrich et al., 2010; Mitkidis et al., 2017; Muthukrishna et al., 2020; Xygalatas et al., 2013).

Andreoni et al. (2017) used a natural field experiment in the Netherlands (i.e., a WEIRD culture) to test whether resource scarcity, as indexed by household income, could predict moral economic behavior. Specifically, the authors tested to what degree poor versus rich households would return "misdelayed" envelopes containing varying amounts of cash or a bank transfer card. Their findings showed that the rich (vs poor) acted significantly more prosocial by returning the misdelayed envelopes more often. While the specific study was framed around differences in prosocial economic behavior, these results show that individuals from poorer households to a lesser degree returned misdelayed envelopes with a monetary value for which they were not entitled, indicating that such individuals acted significantly more unethical than their wealthier counterparts (Andreoni et al., 2017).

However, other researchers have reached different conclusions, even in the same cultural context. Using objective measures of social class from a large Dutch population in a survey and an experiment, Trautmann et al. (2013) investigated differences in unethical

behavior between individuals experiencing varying levels of resource scarcity. They found that wealthier individuals (i.e., a trait of high social class) viewed cheating on taxes more acceptable, while individuals with low employment status (i.e., a trait of low social class) viewed such cheating as less acceptable. On the contrary, lying and accepting bribes was considered less of an ethical violation by individuals' with lower social class (Trautmann et al., 2013). Results like these highlight the current inconsistencies in the literature.

Opposing Evidence

While a relatively large part of the above cited evidence suggests a causal link between a lack of financial resources and an increased inclination to engage in unethical behavior, other studies have failed to provide evidence for this relationship and sometimes argued that the association might not be as linear as expected. For instance, in a series of six laboratory experiments, Dubois et al. (2015) showed that relative resource scarcity, indexed by social class, negatively predicted unethical behavior, such that lower class individuals were more likely to participate in acts of unethical behavior, but only when such behavior was carried out to benefit others. However, if the unethical behavior was instead aimed at benefitting the individuals themselves, social class positively predicted the likelihood of engaging in unethical behavior (Dubois et al., 2015).

Grundmann and Lambsdorff (2017) found no effect of relative resource scarcity on unethical behavior in a task where participants could earn different levels of income based on skill and luck, and then rolled a die (either privately or in public) that would determine their tax-rate of the earned income. Resource scarcity was manipulated by how much money individuals earned in the task, while participants had the opportunity to cheat in the experiment by reporting a lower tax rate (i.e., a lower die roll) in the private die-roll. In contrast to the thesis that resource scarcity increases unethical behavior, Grundmann and Lambsdorff (2017)

found that individuals with higher incomes cheated marginally *more* to gain a lower tax rate. Similarly, Piff et al. (2012) showed that individuals with higher social class were *more* likely to cheat to win a prize, steal goods from other people, and engage in other non-economic acts of immorality, such as breaking the law while driving. Yet, recent direct replications of this study have provided mixed results, as some scholars have been able to successfully replicate the original findings (Clerke et al., 2018), while others have failed to do so (Balakrishnan et al., 2017; Nowlin et al., 2018).

Aoki et al. (2010) investigated if deceptive behavior would be dependent on socioeconomic status. Although they found a series of situational factors influencing the propensity to engage in deceptive lying resembling previous findings in the area (for a review, see Gerlach et al., 2019), no effect of socioeconomic status on lying was found. Likewise, a recent study by Liu et al. (2019) showed that experiences of scarcity, in the form of low childhood socioeconomic status, was positively associated with dispositional greed, a well-known antecedent of unethical behavior (Hilbig & Zettler, 2015). Findings like these contribute to the mixed evidence of how scarcity can affect moral behavior by showing that scarcity, indexed by social class, can both increase and decrease unethical behavior.

Taken together, most prior research points to the possibility that experiences of material scarcity could *increase* individuals' tendencies to engage in unethical economic behavior. Nevertheless, a notable chunk of the reviewed literature has produced conflicting evidence, where this relationship either cannot be robustly established, is not sufficiently controlled for, or where the direction of the effect follows the opposite pattern (i.e., affluency increases unethical economic behavior or scarcity decreases unethical behavior). Consequently, a meta-analysis on the topic is desirable to statistically establish and quantify the accumulated evidence that material resource scarcity exerts on unethical economic behavior.

Method

Search

In August 2020, we performed a search across the academic databases Web of Science, ScienceDirect, Scopus, and Google Scholar for all scientific works that investigated a relationship between material resource scarcity and unethical economic behavior. A detailed overview of the search terms, keywords, and subject areas used in the search process can be found in our pre-registered review protocol (<http://bit.ly/3t1zd8z>). Additionally, we sent out calls for unpublished literature on the subject to the mailing lists of the following research communities: *Society for Personality and Social Psychology (SPSP)*, *Society for Judgment and Decision Making (JDM)*, *Society for Advancement of Behavioral Economics (SABE)*, *The European Marketing Academy (EMAC)*, *Association for Consumer Research (ACR)*, *Academy of Marketing Science (AMS)*, *American Marketing Association (AMA)*, *Human Behavior and Evolution Society (HBES)* and *European Human Behavior and Evolution Association (EHBEA)*. Our database search and the calls for unpublished research covered all types of academic work on the subject (i.e., journal articles, working papers, pre-prints, book chapters, academic theses, etc.) to minimize the possibility of solely obtaining published research, which often tends to favor statistically significant results (Atkinson et al., 1982; Sterling, 1959; Sterling et al., 1995). In the remainder of this paper, we refer to each included piece of academic work as an article. **Figure 1** depicts the search and selection process following the PRISMA statements (Moher et al., 2009; Moher et al., 2015; Page, McKenzie, et al., 2020; Page, Moher, et al., 2020). A detailed overview of all included articles can be found in Appendix A.

Notably, while the inclusion criteria of our pre-registered review protocol concerned research on how material resource scarcity might affect unethical economic behavior, our literature search, resulted in a series of articles which either investigated how scarcity might affect both unethical and prosocial behavior or which purely sought to investigate how scarcity

might affect prosocial behavior. In theory, such articles should have been excluded, since prosocial behavior cannot be considered a direct opposite of unethical behavior (Curry et al., 2019; Graham et al., 2013; Tomasello & Vaish, 2013). Nevertheless, we decided to include such studies in a separate meta-analysis, reported in Appendix B, to further strengthen our theoretical contribution of how resource scarcity might affect moral behavior in general, and to aid future research on this overarching topic.

Figure 1. Process chart depicting the article search and inclusion process following the PRISMA standards (preferred reporting items for systematic reviews and meta-analyses). All articles were retrieved by the end of August 2020, with n = number of articles, k = number of studies, and g = number of relevant effects sizes. Dotted lines represent articles included for the supplementary meta-analysis on the relationship between resource scarcity and prosocial economic behavior (see Appendix B).

Coding procedure

The studies identified as eligible for inclusion were coded with respect to the dependent and the independent variable. The coding procedure was carried out by two trained student coders, with backgrounds in economics and cognitive science, and all coded information was verified subsequently in correspondence with the first author. Specifically, we extracted information on the dependent variable, independent variable(s), mediators, moderators, population type (e.g., students, children, etc.), location, site of the study (i.e., onsite vs. online), research design (e.g., lab experiment, lab-in-the-field experiment, etc.), and participant compensation from all the included articles. Independent variables were divided into four sub-groups: Financial scarcity (i.e., poverty and economic inequality), Social class (socioeconomic status), Physiological scarcity (i.e., hunger and thirst), and Reminders of scarcity (i.e., the activation of cognitions related to scarcity).

The coders also extracted the appropriate information from the reported test statistics in the articles to compute the effect size (Hedges g) and standard error of all reported statistical tests (See section, *Effect Size Computation*). All effect sizes and standard errors were checked and verified by both coders and the first author. In articles where the reported information was not sufficient to calculate the specific effect statistic ($N = 18$), we contacted the corresponding authors to obtain the relevant data needed for these calculations. All included articles as well as articles where it was not possible to obtain this information are listed in Appendix A.

Lastly, to examine whether variability in contextual sensitivity might moderate the generalizability and validity of our findings, we had three expert coders (PhD candidates) evaluate all included articles for differences in contextual sensitivity (See section, *Contextual Sensitivity Assessment*) following the recommendations from Van Bavel et al. (2016). Here, contextual sensitivity indicates the degree to which the findings of any given article included

in this meta-analysis is perceived to be particularly sensitive to contextual differences in site, location, time, and population. Following the ratings from the expert coders, the contextual sensitivity means of the included articles were computed and coded into the dataset. Our inclusion criteria resulted in a final dataset consisting of 28 articles (with a total of $N = 6921$ observations) covering 44 studies.

Effect Size Computation

In order to pool the effects of the results in the included articles, we followed the approach suggested by Borenstein et al. (2011) by standardizing the mean difference of all results to the Hedges' g effect size statistic. Here g expresses the difference of the means (M_1 and M_2) in units of the pooled standard deviation (SD_{pooled}) (Hedges, 1981):

$$g = \frac{M_1 - M_2}{SD_{pooled}}$$

$$SD_{pooled} = \sqrt{\frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{(n_1 - 1) + (n_2 - 1)}}$$

While Hedges' g is similar to the more commonly used Cohen's d in the way that both assume equal population variances and thus can be interpreted in the same way (Grissom & Kim, 2005; Hedges, 1981; Rosenthal et al., 1994), Cohen's d has been shown to overestimate the size of the actual effect in studies using smaller sample sizes. Hedges' g controls for this bias by pooling standard deviations using $n-1$ (vs. n for Cohens d) and can be further bias-corrected for very small sample sizes ($n < 50$) (Hedges, 1981). Thus, it provides a more robust and conservative estimate of the effect size than Cohen's d (Hedges & Olkin, 2014) and is considered the preferred effect size statistic for use in meta-analyses (Harrer et al., 2019; Hedges & Olkin, 2014).

All effect sizes were computed and coded individually in the dataset using the *R*-package *esc* for meta-analytic effect size computation (Lüdtke, 2018). Wherever possible, effect sizes were calculated based on means, standard deviations, *F*-statistics, *t*-statistics, *r*-statistics, and *p*-values. All reported tests of a given article concerning the relationship between resource scarcity and moral behavior were coded in the dataset and the main test of each study was dummy coded (1 = main study result on unethical behavior, 2 = additional test of unethical behavior) to clarify the main findings of each article, while still preserving individual tests of the relationship based on different sub-group analyses (e.g., gender differences, physiological differences, etc.). Studies reporting significant as well as insignificant statistical tests were included in the dataset.

Contextual Sensitivity Assessment

Following the approach by Van Bavel et al. (2016), we recruited three expert coders (PhD candidates) to evaluate the included articles for contextual sensitivity. Due to the interdisciplinary nature of the included works, the three coders were recruited from three distinct disciplines instead of only one, like in the original article. The three coders had graduate training in Social Psychology, Economics, and Marketing. All coders were rewarded for their work and their professional credentials are publicly available at OSF (<http://bit.ly/3t1zd8z>).

To ensure consistency in the coding, and following previous procedures, all coders were asked to practice their rating scheme on four studies, which were not included in the dataset, prior to coding the included articles for contextual sensitivity (Van Bavel et al., 2016). Subsequently, after verifying that the coders rated the studies in a similar and consistent fashion, they rated the 28 articles included in the main meta-analysis. Expectedly, due to the large number of studies ($N = 100$) to be evaluated in the original article by Van Bavel et al. (2016), the authors randomly picked 25 articles to be rated by all three coders, while 25 articles

were randomly assigned between the three coders. As our sample of articles was smaller ($N = 28$), all three coders evaluated each of the included articles, but in a randomized order. Vitrally, this process still allowed us to calculate interrater reliability between the coders through intraclass correlation coefficients (Bartko, 1966; Fleiss & Cohen, 1973).

In the rating of the articles, the three coders assessed how likely the findings of the individual articles were to vary by context, which could be in terms of location (i.e., WEIRD vs. non-WEIRD countries/regions, cf. Heinrich et al., 2010), sample type (i.e., student vs. non-student populations, differences in racial characteristics, etc.), time (i.e., before vs. after large political changes, before vs. after recessions, etc.). Thus, the coding scheme aimed to capture a selection of macrolevel contextual effects that could be expected to influence the generalizability of the included research on scarcity and unethical economic behavior (Van Bavel et al., 2016). Importantly, the three coders were specifically instructed to only assess the contextual sensitivity of the included findings, while disregarding possible concerns on the quality of the research or the reputation of specific researchers or laboratories. The coders were only asked to evaluate the possibility that a given result might vary if the research was replicated directly in a different context than that of the original article. In practice, the coders read the title and abstract of a given article and replied to a Likert-type scaled item reading: “To what extent do you think context (culture, time, place, etc. in which study is conducted) could affect the results of the study?”, with scale points at 1 (“context is not at all likely to affect results”), 3 (“context is somewhat likely to affect the results”) and 5 (“context is very likely to affect results”) ($M = 2.95$, $SD = .63$) (Van Bavel et al., 2016).

When the three coders had finished their individual assessment of the 28 articles, we calculated interrater reliability, which revealed sufficient reliability ($ICC = .479$). Notably, while we closely followed the approach of Van Bavel et al. (2016), our measure of interrater reliability was considerably lower. We believe that this inconsistency exists because: (1) we

used a much smaller sample of studies ($N = 28$ vs. $N = 100$), which led to a more sensitive measure of interrater reliability (Mehta et al., 2018), and (2) our expert coders had training in three distinct disciplines within the social sciences, which should allow for a much more robust perspective of contextual sensitivity for studies stemming from more than one discipline, contrary to that of the original article by Van Bavel et al. (2016). Furthermore, recent work on interrater reliability in academic assessment on aspects such as grant proposals have found much lower agreement among expert reviewer assessments, highlighting the complicated nature of comparing scores across reviewers (Pier et al., 2018). Thus, we deemed our coders' contextual sensitivity assessments to be sufficiently reliable and, consequently, calculated the mean value of contextual sensitivity for each article, which was subsequently used as a measure in our analyses.

Analysis

Firstly, following our pre-registered analysis outline (<http://bit.ly/3t1zd8z>) we employed a random-effects model meta-analysis to pool the effect sizes of the included studies. This model was chosen a priori based on the assumption of exchangeability; that is, we assumed the individual results not only to deviate from the true intervention effect due to sampling error, but further assumed that additional variation would be present due to the studies stemming from a series of different populations rather than a single population (Harrer et al., 2019; Schwarzer et al., 2015). Hence, the formula for our random-effects model meta-analysis is as follows:

$$\widehat{\theta}_k = \theta_F + \epsilon_k + \zeta_k$$

where $\widehat{\theta}_k$ denotes the observed effect size of an individual study k , θ_F denotes the true effect size, ϵ_k denotes the sampling error estimate, and ζ_k denotes the second source of error which

1 is assumed to be present due to the effect size θ_k being a part of the distribution of true effect
2 sizes (Borenstein et al., 2011; Harrer et al., 2019).

3 To estimate the variance of the distribution of true effects sizes, denoted τ^2 , we used
4 the Hartung-Knapp-Sidik-Jonkman (HKSJ) method, as this estimation algorithm has been
5 shown to provide more robust estimates of the variance of the pooled effect than the widely
6 used DerSimonian-Laird method (IntHout et al., 2014). Utilizing this estimator provides more
7 conservative results of τ^2 and decreases the possibility of obtaining false positives due to small
8 sample sizes or heterogeneity (Hartung, 1999; Hartung & Knapp, 2001a, 2001b; Makambi,
9 2004). Furthermore, to estimate the amount of heterogeneity in the effect sizes, we computed
10 I^2 , estimating the percentage of variability in the included effect sizes, which can be determined
11 not to be caused by sampling error (Higgins & Thompson, 2002). As a robustness check, to
12 address scholarly concerns on residual variance when using the HKSJ method (Jackson et al.,
13 2017; Wiksten et al., 2016), we also conducted a sensitivity analysis comparing the HKSJ
14 method to the DerSimonian-Laird method (See Appendix C). This analysis confirmed that the
15 HKSJ method provided a more robust and conservative estimate of the overall effect size in
16 the form of narrower confidence intervals. All analyses were performed using the *dmeter*
17 package in R (Harrer et al., 2019).

18 Still sticking to our pre-registered analysis outline, we then employed a novel approach
19 to analyze publication bias in the included articles by the use of sensitivity analysis, as
20 suggested by Mathur and VanderWeele (2020). This method is inherently different from the
21 more classic methods, such as assessing funnel plot asymmetry using Egger's test (Egger et
22 al., 1997) and then using the Trim-and-Fill procedure (Duval & Tweedie, 2000) to adjust the
23 meta-analysis, in which it is assumed that publication bias does not operate on very large
24 studies and where said bias is determined based on the size of the point estimates rather than
25 the p -values (Mathur & VanderWeele, 2020). The use of this sensitivity analysis instead allows

for a relaxation of various statistical assumptions concerning the distributions and population effects and simply requires the specification of a weighting function for which studies are more (vs. less) likely to be published, making such an analysis much more robust to individual study influences than more classic approaches (Mathur & VanderWeele, 2020). In our case of a random-effects model meta-analysis, publication bias was calculated using a numerical grid search, tested with varying levels of this weighting function. The biggest advantage of this method is that it allows for very intuitive classifications of the level of publication bias, as the sensitivity analysis provides a direct quantification of the publication likelihood of affirmative studies if such studies were to attenuate the population effects of the meta-analysis to null (Mathur & VanderWeele, 2020). All sensitivity analyses on publication bias in the meta-analytic results were performed using the *PublicationBias* package in *R* (Mathur & VanderWeele, 2020).

Finally, we performed our pre-registered analysis of contextual sensitivity, in which we computed Pearson's correlation coefficients (r) and Bayes Factor (BF) between our marker of contextual sensitivity and the effect sizes, p -values, and sample sizes from the included articles to examine the relationship between contextual sensitivity and these metrics. All correlation analyses were performed using the *correlation* package in *R* (Makowski et al., 2020).

Results

Inspired by previous meta-analytic work (Orquin & Kurzban, 2016), our analysis followed a hierarchical breakdown strategy, in which we initially analyzed a global model of all included studies before breaking them down to the subgroup level, as defined by the independent variables. The results are presented in **Table 1**. The key variables of interest in this analysis is the Standardized Mean Difference (SMD) in the form of Hedges' g , the percentage of variability in effect sizes I^2 , and the between study variance in the form of τ^2 .

1 The analysis of all included studies revealed a significant overall effect size of 0.2237,
2 corresponding to a medium effect of resource scarcity on unethical economic behavior by
3 current standards (Funder & Ozer, 2019). The results of the global model, however, also
4 revealed substantial heterogeneity $I^2 = 82\%$, comparable to what has been observed in recent
5 meta-analytic work on unethical behavior (Gerlach et al., 2019).

6 Grouping the analysis by the subgroup defined by the main independent variable
7 strongly reduced the degree of heterogeneity for studies on social class, $I^2 = 47.2\%$ and studies
8 on physiological scarcity, $I^2 = 23.3\%$, although the subgroup of articles on financial scarcity
9 accounted for a large degree of the observed heterogeneity in the overall model, $I^2 = 89.2\%$.
10 The second-level subgroup analysis revealed a marginally significant effect size estimate of
11 0.2606 for the studies on financial scarcity, statistically significant effect sizes of 0.3207 and
12 0.3893 for studies on reminders of scarcity and physiological scarcity, respectively, and an
13 insignificant effect size estimate of 0.0185 for studies on social class.

14

Table 1
Main Results of the Effect of Resource Scarcity on Unethical Behavior

<i>Results prior to heterogeneity adjustment</i>							
Group	<i>k</i>	<i>N</i>	SMD	95% CI	<i>p</i>	<i>I</i> ²	<i>τ</i> ²
All studies	44	6921	0.2237	[0.0793; 0.3680]	0.0032	82.0%	0.1931
Financial Scarcity	21	3136	0.2606	[-0.0227; 0.5440]	0.0694	89.2%	0.3508
Reminders of Scarcity	3	575	0.3207	[0.1435; 0.4980]	0.0161	0.0%	0.0006
Physiological Scarcity	9	686	0.3893	[0.1710; 0.6076]	0.0034	23.3%	0.0494
Social Class	11	2524	0.0185	[-0.1422; 0.1792]	0.8030	47.2%	0.0419
<i>Results post heterogeneity adjustment</i>							
Group	<i>k</i>	<i>N</i>	SMD	95% CI	<i>p</i>	<i>I</i> ²	<i>τ</i> ²
All studies	38	6037	0.2073	[0.0981; 0.3165]	0.0005	65.5%	0.0850
Financial Scarcity	15	2252	0.2376	[0.0219; 0.4532]	0.0331	73.5%	0.1237
Reminders of Scarcity	3	575	0.3207	[0.1435; 0.4980]	0.0161	0.0%	0.0006
Physiological Scarcity	9	686	0.3893	[0.1710; 0.6076]	0.0034	23.3%	0.0494
Social Class	11	2524	0.0185	[-0.1422; 0.1792]	0.8030	47.2%	0.0419

Note. *k* = number of studies, *N* = sample size, SMD = Standardized Mean Difference by Hedges' *g*, 95% CI = 95% confidence interval, *p* = *p*-value, *I*² = percentage of variability in effect sizes, *τ*² = between-study variance.

To explore the observed heterogeneity, we conducted a GOSH (Graphical-Display-of-Heterogeneity) analysis (Olkin et al., 2012), a more sophisticated method to asses individual study influence in meta-analysis than the commonly used Leave-One-Out analysis (Viechtbauer & Cheung, 2010). In this analysis, we fitted our global model and subgroup model to all possible subsets, 2^{k-1} , of the data, by the use of a supervised machine learning algorithm, known as three clustering, to detect any specific heterogeneity clusters in our data (Harrer et al., 2019). The analysis revealed that four articles ($k = 6$; Andreoni et al., 2017; Gatiso et al., 2015; Gino & Pierce, 2009a; Gino & Pierce, 2010) accounted for 16.5% of the observed heterogeneity in the global model as well as 15.7% of the observed heterogeneity in the subgroup of financial scarcity. Rerunning the analysis without these studies reduced the

1 heterogeneity of the global model to $I^2 = 65.5\%$ and yielded a revised statistically significant
2 pooled effect size estimate of 0.2073. Furthermore, the heterogeneity of the three subgroups
3 (social class, reminders of scarcity, and physiological scarcity) remained unchanged, while the
4 heterogeneity of the subgroup of studies on financial scarcity was reduced to $I^2 = 73.5\%$,
5 resulting in a statistically significant pooled effect size of 0.2376 for this subgroup. A forest
6 plot based on the heterogeneity adjusted subgroup analysis is presented in **Figure 2**.

Figure 2. Forest plot, adjusted for heterogeneity, of the effect sizes for each of the four subgroups as well as the overall effect. Error bars represent 95% confidence intervals. Grey diamonds depict the pooled effect for the subgroups. The grey diamond connected to the dotted line depicts the overall effect of the model. The black line depicts the prediction interval of the overall model. Articles marked with (R) denotes replication attempts of Piff et al. (2012).

Overall, the second-level model adjusted for heterogeneity supports an analysis of the included data at the subgroup level. Specifically, our model shows that resource scarcity in the form of (1) financial scarcity, (2) reminders of scarcity, and (3) physiological scarcity significantly affects individuals' propensity to engage in unethical economic behavior. Social class, however, does not affect individuals' tendency to engage in unethical behavior. On the global level, our model results in a medium effect size (.21) on the relationship between material resource scarcity and unethical economic behavior.

As a robustness check, and to further assess the relationship between resource scarcity and unethical behavior, we fitted a model with every extracted effect size from all included studies (See Appendix C). While this resulted in a model in which one study was represented by several effect sizes, and thus a redundancy in sample sizes, the model confirmed our main model's pooled estimate of a medium-effect sizes estimate (.20) across 135 effects and 26,901 individuals.

Sensitivity to Publication Bias

To assess the validity and robustness of the derived effects in the meta-analysis, it is essential to evaluate the sensitivity of the result to publication bias. A widespread way to do this is to evaluate funnel plot asymmetry by the use of Egger's test (Egger et al., 1997) and if funnel

1 asymmetry exists, to correct the meta-analytic results by the use of the Trim-and-Fill procedure
2 (Duval & Tweedie, 2000). However, these methods rely on the assumption that publication
3 bias does not exist in studies with large point estimates because publication bias is evaluated
4 based on the point estimate instead of the level of statistical significance (Mathur &
5 VanderWeele, 2020). This means that such methods provide an inaccurate estimation of
6 publication bias if the included articles contain studies with small effect sizes, because these
7 effect sizes would distort the symmetry of the funnel plot (Debray et al., 2018; Zwetsloot et
8 al., 2017).

9 To circumvent the limitations linked to the above methods, we conducted a sensitivity
10 analysis of publication bias, as recommended by Mathur and VanderWeele (2020). This
11 sensitivity analysis estimates the amount of publication bias that is required to shift the meta-
12 analytic estimate to zero. In our case, the sensitivity analysis estimates the n -fold times, referred
13 to as the S -value, that studies with significant point estimates (affirmative studies) would need
14 to be published compared to studies with insignificant point estimates (non-affirmative studies)
15 in order to shift the model point estimate to null (Mathur & VanderWeele, 2020). A
16 significance funnel plot of the analysis is depicted in **Figure 3**. Our analysis showed that for
17 publication bias to shift the result of our meta-analytic estimate to null, affirmative studies (in
18 our case $N = 18$) would need to be close to 7-fold ($S = 6.98$) more likely to be published than
19 non-affirmative studies (in our case $N = 26$), hence indicating that considerable amounts of
20 publication bias would be required to distort our findings. These findings indicate that the
21 results of the meta-analysis are fairly robust to the influence of publication bias, at least by
22 means of conventional tests to detect this bias source (Mathur & VanderWeele, 2020).

23

24

Figure 3. Significance funnel plot of the meta-analysis, based on the sensitivity analysis of publication bias in the included studies. Diagonal line indicates $p = .05$. Grey dots indicate non-affirmative studies. Black dots indicate affirmative studies. Black diamond indicates meta-analytic estimate of the random-effects model (0.22). Grey diamond indicates worst-case meta-analytic estimate (-0.0607).

1

2 As a further robustness check of publication bias, we carried out a P-curve analysis to
 3 detect to what degree the included literature would be sensitive to data mining (i.e., p -hacking)
 4 (Simonsohn et al., 2014a, 2014b; Simonsohn et al., 2015). The P-curve for statistically
 5 significant studies ($\alpha = .05$) is depicted in **Figure 4**.

Figure 4. P-curve of all included studies with significant p -values ($p < .05$). P-curve analysis shows no visible signs of data mining (i.e. p -hacking) in the included literature, as measured by a test of skewedness.

The results of the P-curve analysis revealed that the curve was significantly right-skewed ($z = -6.049$, $p < 0.001$), while the test of curve flatness was insignificant ($z = 2.612$, $p > 0.999$). The mean post-hoc statistical power for the significant studies was 69%, with a 95% confidence interval ranging from 47.3% to 84.2%. These results suggest that a “true” effect is present in the included studies, meaning that the findings cannot easily be explained through publication bias or p -hacking (Harrer et al., 2019; Simonsohn et al., 2014b). Thus, the results from the sensitivity analysis and the P-curve analysis indicate that, even under the assumption

of some level of publication bias, our meta-analysis still provides a fairly robust estimate of the pooled effect of resource scarcity on unethical economic behavior.

Contextual Sensitivity

The results of our analysis of contextual sensitivity of the included studies disproved the prediction that individual study characteristics would be correlated with the rated level of contextual sensitivity in a (Bayesian) Pearson’s correlation. Results are reported in **Table 2**.

Table 2
Main Results of the Contextual Sensitivity Analysis

	Effect Sizes <i>r</i> (BF) [95% CI]	Standard Errors <i>r</i> (BF) [95% CI]	P-Values <i>r</i> (BF) [95% CI]	Sample Sizes <i>r</i> (BF) [95% CI]
Contextual Sensitivity	0.09 (0.389) [-0.22, 0.37]	-0.19 (0.671) [-0.46, 0.11]	0.06 (0.361) [-0.24, 0.35]	0.07 (0.365) [-0.24, 0.36]

Note. *r* = Pearson’s correlation coefficient, BF = Bayes Factor, 95% CI = 95% confidence interval.

Following the guidelines for interpretation of Bayes Factor from Kass and Raftery (1995), our results show moderate evidence of the null hypothesis that no correlation exist between our contextual sensitivity variable and the sample sizes, *p*-values, effect sizes, and standard errors of the included studies, because all of such values of the Bayes Factor fall below 1. Importantly, the use of this dual-framework approach allows us to establish that the hypothesized correlations are in favor of the null, something that would not have been possible in a purely frequentist framework, without utilizing additional analytic techniques in the form of equivalence testing (Lakens et al., 2018).

In sum, contrary to what we hypothesized in our pre-registration, the results of our contextual sensitivity analysis indicate no statistically significant relationship between how contextually sensitive the included studies were rated and the magnitude of the extracted effect sizes, standard errors, sample sizes, and *p*-values. Hence, our analysis of contextual sensitivity

conveys two main messages: (1) that findings on the relationship between resource scarcity and unethical economic behavior can be considered fairly generalizable across contexts, and (2) that the influence of contextual sensitivity in general might not be as predictive of study outcomes and future replication success, supporting Inbar (2016) concerns for this metric in response to Van Bavel et al. (2016).

Intended as a further exploration and robustness check of our measure of contextual sensitivity, we evaluated how ratings of contextual sensitivity were distributed across research designs, experimental sites, and countries in which the studies were carried out. Our analysis showed no significant difference in contextual sensitivity between research designs ($F(3, 40) = 0.16, p = 0.920; \eta_p^2 = 0.01, 90\% \text{ CI } [0.00, 0.03]$), experimental sites ($F(1, 42) = 0.03, p = 0.871; \eta_p^2 = 6.36\text{e-}04, 90\% \text{ CI } [0.00, 0.05]$) or countries ($F(11, 32) = 0.76, p = 0.674; \eta_p^2 = 0.21, 90\% \text{ CI } [0.00, 0.21]$). Accordingly, contextual sensitivity is not significantly associated with any of these outcomes in the included studies.

Discussion

Material resource scarcity is a key challenge experienced by individuals around the globe and the implication of these experiences for unethical behavior remains a key issue of debate in moral psychology. Different approaches have been applied to theorize the relationship between material resource scarcity and moral economic behavior and various research designs have been utilized to investigate this relationship empirically. Importantly, general conclusions have been lacking due to mixed and, at times, contradictory findings. This pre-registered systematic review and meta-analysis sought to synthesize existing studies and establish the current known aggregate effect of whether resource scarcity influences individuals' propensity to engage in unethical economic behavior. Overall, our results show that acute experiences of financial

1 scarcity and physiological scarcity can shift people's propensity to engage in unethical
2 economic behavior. We also show that scarcity reminders exert the same impact. Importantly,
3 our results show that more chronic experiences of scarcity, in the form of lower social class,
4 do not have this effect. Thus, when studying the relationship between scarcity and direct
5 cheating for monetary gains, our findings indicate that it may not be sufficient to rely on "the
6 scarcity mindset" account. Rather, the present results imply that scholars may gain a deeper
7 and more nuanced understanding into this relationship by distinguishing between different
8 types of acute and chronic experiences of material scarcity.

9 A crucial distinction to make based on the present research is that social class is not a
10 predictor of unethical economic behavior: individuals from lower social classes are *not* more
11 inclined to engage in unethical economic behavior compared to their wealthier counterparts.
12 Instead, our results suggest that more acute experiences of relative material scarcity can
13 increase individuals' tendency to engage in unethical economic behavior to counteract and
14 alleviate the experienced lack of resources.

15 These results have important implications and suggest that economic decision-making
16 in a context of experienced acute resource scarcity, whether a lack of food, water, or monetary
17 resources, can increase individuals' inclination to engage in unethical economic behaviors. As
18 such, the current findings align with previous studies on scarcity and decision-making, which
19 have argued that different types of material resource scarcity affect behavior in similar ways
20 by making individuals more risk-seeking, impulsive, and focused on regaining resources
21 (Griskevicius et al., 2013; Hamilton et al., 2019; Payne et al., 2017; Shah et al., 2012).

22 Notably, the observed difference between acute and more chronic forms of scarcity
23 regarding unethical economic behavior might be explained by findings on how scarcity affects
24 behavior at a more general level. Specifically, this difference might be explained by research
25 which has shown that scarcity does not necessarily affect decision-making until individuals

1 have been reminded of their relative lack of resources (Shah et al., 2012), especially in
2 comparison to others (Goldsmith et al., 2018; Roux et al., 2015). Our findings support this
3 notion; individuals who experience a lack of financial or physiological resources are more
4 inclined to engage in unethical behavior to alleviate this state, and reminders of scarcity
5 activates the same behavioral pattern.

6 Concerning social class, the results of the meta-analysis converge with previous
7 paradigms showing that individuals with a lower (vs. higher) social class, if anything, might
8 exhibit less immoral behavior (Clerke et al., 2018; Piff et al., 2012). While our results do not
9 indicate that individuals constricted by lower social class act more moral than others, our
10 findings clearly reject the idea that lower social class increases the propensity to engage in
11 unethical economic behavior.

12 As a large portion of the included studies were conducted in very specific contexts, we
13 initially suspected that the generalizability of these findings should vary considerably,
14 consistent with previous research (Van Bavel et al., 2016). However, our results suggest that
15 the difference in contextual sensitivity of the included findings is not associated with the
16 strength of the point estimate or statistical significance of our studied relationships. In
17 particular, we found no significant correlations between the reported sample sizes, effect sizes,
18 standard errors, and *p*-values, on the one hand, and our measure of contextual sensitivity, on
19 the other hand. By the use of Bayes Factor, our analysis instead provided substantial support
20 of the null hypothesis that contextual sensitivity is not significantly correlated with the findings
21 of the included studies. These results indicate that the findings on the relationship between
22 resource scarcity and unethical economic behavior might be relatively generalizable across
23 contexts, to a greater degree than initially expected. Moreover, our sensitivity analysis did not
24 reveal any clear signs of publication bias, with no evidence of data mining either.

1 Our meta-analysis showed substantial heterogeneity both in the overall model and
2 across subgroups, except for reminders of scarcity. Such heterogeneity was also documented
3 in a recent meta-analysis on general dishonesty paradigms (Gerlach et al., 2019) and indicates
4 that the decision of whether to engage in unethical economic behavior depends on other
5 relevant factors beyond scarcity.

6 Across all sub-groups except social class, our results suggest a small-to-moderate effect
7 of resource scarcity on unethical economic behavior according to updated conventional
8 standards (Funder & Ozer, 2019). It is important to emphasize that while such an effect might
9 be small at the level of single events, the accumulated effect of this relationship can have
10 detrimental consequences when aggregated over time and across populations (Funder & Ozer,
11 2019). Nevertheless, together with the substantial heterogeneity in our models, this also points
12 towards a more complicated interpretation of what motivates individuals to engage in unethical
13 economic behavior. Specifically, the size of our documented effects and the degree of
14 heterogeneity in our models indicate that individual differences (traits) and situational factors
15 (states) are crucial to consider when evaluating whether and when material resource scarcity
16 increases unethical economic behavior (cf. Gerlach et al., 2019).

17 Practically, our findings have important societal implications. Economic inequality has
18 been rising around the world for decades (Piketty, 2020) and has destructive consequences for
19 general well-being, incarceration rates, political polarization, and mortality (Wilkinson &
20 Pickett, 2011; Wilkinson & Pickett, 2006). Policy debates often highlight economic inequality,
21 specifically in the Western world, in order to generate increased awareness of the problem.
22 Furthermore, the rise of social media and digital technology increases the dissemination of the
23 immediate affluence of certain segments of the population. Our results suggest that such policy
24 debates and portrays in popular culture might trigger unintended side effects by making relative

resource scarcity salient, thereby acting as scarcity reminders with negative downstream effects on people's propensity to engage in unethical economic behaviors across social classes.

Limitations

Certain limitations of our analysis should be noted. First, the pooled estimate from our meta-analysis needs to be interpreted against the assumption of potential biases. While our meta-analysis was found to be robust to the impact of publication bias, at least based on conventional tests to detect this bias source, the possibility of publication bias cannot be excluded. Our analysis indicated that significant (vs. non-significant) studies would need to be close to 7 times more likely to be published, which is not unlikely to be true considering previous research on publication bias (Sterling, 1959; Sterling et al., 1995). Nevertheless, considering the number of studies that reported non-significant results and were still published, we consider it unlikely that publication bias should have a material impact on our results.

Second, as is often the case in the social sciences (Muthukrishna et al., 2020; Pollet & Saxton, 2019; Rad et al., 2018), the majority of our included studies originated from student samples and online panels. Whether such samples enable generalizability claims is still highly debated (Falk et al., 2013; Fosgaard, 2020; Henrich et al., 2010; Muthukrishna et al., 2020), but it is beyond the scope of this article to engage in such meta-scientific discussions.

Third, our meta-analysis resulted in substantial levels of heterogeneity in both our global model and as well as our second-level analysis. These levels of heterogeneity is comparable to what has been observed in a recent meta-analysis of studies on unethical behavior (Gerlach et al., 2019). However, this heterogeneity is indicative of larger differences in effect sizes between studies, which in turn could indicate differences in precision of the true estimate between studies. While we employed advanced analyses to adjust for this level of

heterogeneity, it remained relatively high. Hence, our pooled estimate should be interpreted with appropriate caution.

Fourth, our measure of contextual sensitivity did not achieve the same level of reliability as in the original work presented by Van Bavel et al. (2016). While we argue that this discrepancy largely stems from the fact that we used expert raters from three distinct disciplines, which should be a more robust measure of contextual sensitivity, future research could aim to assess this construct with different methods, such as crowd-sourced academic rating schemes (Tierney et al., 2021).

Finally, it should be noted that this article has focused specifically on unethical economic behavior. When discussing the larger topic of the relationship between scarcity and morality, it is important to be aware of the sensitivity of the issue and the multiple dimensions of ethical behavior. Hence, while it may be unethical economic behavior if hungry individuals steal money to feed their starving children, a different philosophical perspective could emphasize that such behavior could also reflect a humanitarian and parental action made to protect innocent children. Thus, while a given behavior might be considered immoral from one perspective, it may be perceived as defensible and even altruistic from other perspectives.

Directions for Future Research

The present work is the first of its kind to provide a generalizable quantification of the relationship between material resource scarcity and unethical economic behavior. Furthermore, our results suggest that more chronic forms of scarcity (i.e., lower social class) do not make individuals more inclined to engage in such financially fraudulent actions. However, it remains unknown whether individuals with lower (vs. higher) social class may experience acute influences of relative material scarcity differently with respect to moral judgment and decision-making. Given that such an investigation could have important implications for structuring

1 policy initiatives aimed at helping individuals experiencing chronic resource scarcity, future
2 empirical work should examine this possibility.

3 We acknowledge that the meta-analysis is based on a relatively small sample ($k = 44$),
4 highlighting the rather narrow set of existing studies in this domain. Although the results of the
5 sensitivity analysis indicate that the findings from the meta-analysis are robust by conventional
6 standards, future research should aim to further test how different forms of material scarcity,
7 both acute and chronic, affect moral economic behavior across populations, contexts, and study
8 paradigms.

9 While our pre-registered work focused on the impact of material scarcity on
10 individuals' inclination to engage in unethical economic behavior, our review protocol also
11 resulted in a series of articles investigating how this form of scarcity may affect both unethical
12 and prosocial behaviors or prosocial behaviors alone. As a supplement, we included the articles
13 that focused on prosocial behavior but not unethical behavior in a separate meta-analysis
14 reported in Appendix B. It is likely that we did not identify all studies on the relationship
15 between material scarcity and prosocial economic behavior, given that our review protocol was
16 not designed to do so. Nevertheless, the findings from this supplementary analysis showed a
17 small positive and significant effect between material resource scarcity and prosocial economic
18 behaviors. Again, this adds to the inconsistencies in the literature on how resource scarcity
19 affects moral behaviors, and future research is needed to investigate these relationships further.

21 **Conclusion**

22 The results of this systematic review and meta-analysis show that acute experiences of relative
23 resource scarcity in the form of financial scarcity, physiological scarcity, and scarcity
24 reminders increase individuals' inclination to engage in unethical economic behavior. In
25 contrast, more chronic experiences of scarcity in the form of lower socioeconomic status do

not increase the propensity to engage in such behavior. Thus, our investigation highlights that individuals from lower social classes are not more immoral economic decision-makers than their wealthier counterparts. Instead, our findings suggest that acute experiences of relative resource scarcity make individuals more inclined to engage in unethical economic behavior, regardless of their social class. Thus, this meta-analysis emphasizes the benefits of complementing “the scarcity mindset” by distinguishing between different types of acute and chronic experiences of material scarcity to enrich our understanding of scarcity effects in the moral psychology domain.

Data Availability

The data that support the findings of this study are openly available on the Open Science Framework: <http://bit.ly/3t1zd8z>

Code Availability

All programming codes used to perform the analysis in this study, are available openly available on the Open Science Framework: <http://bit.ly/3t1zd8z>

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5 **Author Contributions**

6 C.T.E., P.M., L.A. and T.O. designed the study; C.T.E. collected the data; C.T.E. analyzed the
7 data; C.T.E., P.M., L.A. and T.O. wrote the final paper.

9 **Competing Interests**

10 The authors declare no competing interest.

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Appendix A

Inclusion Criteria and Integrated Scientific Works

This section provides more detail on the article selection process. First, we only included articles which concerned material resource scarcity. Some articles from our database search concerned cognitive depletion and cognitive scarcity, but such studies were not included based on our pre-registered research rationale. Second, our database search resulted in several studies that only dealt with material resource scarcity but not unethical behavior or vice versa. Because such studies did not investigate the relationship between these two factors, they were also excluded. Third, we excluded review articles as they did not abide to empirically test the relationship between resource scarcity and unethical behavior. If the criteria specified in our pre-registration were fulfilled, we extracted the effect size(s) from the available test statistics in the articles. In cases where such information was not available, we contacted the authors to retrieve the necessary data used in the chosen effect size calculation(s) (Hedges' g). Two articles had to be excluded, because the authors did not respond to requests about data sharing (Gino & Pierce, 2009b; Nie et al., 2020). The following tables list all included articles in chronological order. **Table A1** represents all studies and conditions on the relationship between resource scarcity and unethical behavior, while **Table A2** represents all studies and conditions on the relationship between resource scarcity and prosocial behavior. Each row represents an extracted effect size.

Table A1

Resource Scarcity and Unethical Behavior

Study: Condition	n	g	Data
Koenig et al., 2004: Cheat, abused and neglected	54	-0.1585	yes
Koenig et al., 2004: Cheat, abused and nonmaltreated	56	0.4051	yes
Koenig et al., 2004: Cheat, neglected and nonmaltreated	54	0.6843	yes
Koenig et al., 2004: Steal, abused and neglected	54	0.3631	yes
Koenig et al., 2004: Steal, abused and nonmaltreated	56	0.1771	yes
Koenig et al., 2004: Steal, neglected and nonmaltreated	54	-0.2412	yes
Koenig et al., 2004: Rule compatible, abused and neglected	54	0.5507	yes
Koenig et al., 2004: Rule compatible, abused and nonmaltreated	56	-0.0746	yes

Koenig et al., 2004: Rule compatible, neglected and nonmaltreated	54	-0.6078	yes
Gino et al., 2009: Wealth abundance and overstating performance	53	1.359	yes
Gino et al., 2009: Wealth vs. poor and overstated rounds	99	1.1059	yes
Gino et al., 2009: Wealth vs. weal. bys. and overstated	99	0.3172	yes
Gino et al., 2009: Weal. bys. vs. poor and overstated	102	0.8265	yes
Gino et al., 2009: Weal. bys. vs. poor and overstated, other sample	74	1.415	yes
Gino et al., 2009: Weal. bys. vs. poor at least one overstated round	74	0.9674	yes
Gino et al., 2009: Wealthy vs. poor, at least one overstated round	74	1.25	yes
Gino & Pierce 2010a: Weal. judge, poor judge, and poor solver	168	-0.6211	yes
Gino & Pierce 2010a: Weal. judge, poor judge, and weal. solver	168	0.7822	yes
Gino & Pierce 2010a: Weal. judge + solver vs. poor judge + solver	168	0.4637	yes
Gino & Pierce 2010b: (Dis)honest reporting	178		n.r.
Gino & Pierce 2010b: (Dis)honest reporting, financial cost	164		n.r.
Aoki et al., 2010: Students vs. non-students, payoff 1000	193	-0.2808	yes
Aoki et al., 2010: Students vs. non-students, payoff 100	139	-0.02	yes
Piff et al., 2012: Cars cutting off other vehicles	274	-0.2411	yes
Piff et al., 2012: Cars cutting off pedestrians	152	-0.3641	yes
Piff et al., 2012: SES and unethical decision-making	105	-0.4692	yes
Piff et al., 2012: SES and unethical behaviour	129	-0.5567	yes
Piff et al., 2012: SES and unethical decision other sample	129	-0.4044	yes
Piff et al., 2012: SES and attitude towards greed	108	-0.7663	yes
Piff et al., 2012: SES and truth telling	108	0.4909	yes
Piff et al., 2012: SES and attitude towards greed, other sample	195	-0.3437	yes
Piff et al., 2012: SES and cheating	195	-0.2817	yes
Piff et al., 2012: Features of greed and attitude towards greed	90	0.5685	yes
Neville, 2012: State inequality and academically dishonest search	50	0.992	yes
Daubman et al., 2013: SES, unethical decision making	80	0.4892	yes
John et al., 2013: Rep. score, aware earning less, and unaware	118	0.487	yes
John et al., 2013: Rep. score, aware earning more, unaware	118	0.1937	yes
John et al., 2013: Rep. score, aware earn. less, unaware, sample 2	172	0.3902	yes
John et al., 2013: Rep. score, aware earn. more, unaware, sample 2	172	0.2095	yes
Sharma et al., 2013: Deprivation and dishonesty rate	89	0.7302	yes
Sharma et al., 2013: Deprivation and evolution of dishonesty rate	89	0.5767	yes
Sharma et al., 2013: Deprivation and dishonesty rate, sample 2	50	0.5692	yes
Sharma et al., 2013: Dishonesty rate, hypothetical vs. real gain	50	1.0026	yes
Sharma et al., 2013: Unfairly deprived and cheating	201	0.237	yes
Sharma et al., 2013: Unfairly vs. fairly deprived and cheating	201	0.295	yes
Sharma et al., 2013: Leniency for immoral behaviour	96	0.7774	yes
Sharma et al., 2013: Lenient sentences, deprived vs. non-deprived	235	0.3091	yes
Trautmann et al., 2013: Propensity to betray	470	0.0839	yes
Yam et al., 2014: Cheating and edible prize	56	0.2345	yes
Yam et al., 2014: Cheating and drinkable prize	56	-0.2335	yes
Yam et al., 2014: Cheating, edible prize, thoughts of hunger	56	0.2532	yes
Yam et al., 2014: Cheating, drinkable prize, thoughts of hunger	56	-0.2532	yes
Yam et al., 2014: Cheating and edible prize, sample 2	88	0.51	yes
Yam et al., 2014: Cheating and drinkable prize, sample 2	88	-0.9134	yes
Yam et al., 2014: Cheating and edible prize, sample 3	146	0.3326	yes
Yam et al., 2014: Cheating and non-edible prize	146	-0.7739	yes
Yam et al., 2014: Cheating, drinkable prize and thirst	124	0.3748	yes
Yam et al., 2014: Cheating, non-drinkable prize and thirst	124	-0.3695	yes
Prediger et al., 2014: Low-yield area, JoD, Table 2, reg. 1	120	0.2049	yes
Prediger et al., 2014: Low-yield area, JoD, Table 2, reg. 2	120	0.285	yes
Prediger et al., 2014: Low-yield area, JoD, Table 2, reg. 3	120	0.1956	yes
Prediger et al., 2014: Low-yield area, JoD, Table 2, reg. 4	120	0.1968	yes
Prediger et al., 2014: Low-yield area, JoD, Table 2, reg. 5	120	-0.0618	yes
Prediger et al., 2014: Low-yield area, JoD, Table 2, reg. 6	120	0.1646	yes
Prediger et al., 2014: Low-yield area, JoD, Table 2, reg. 7	120	0.1685	yes
Prediger et al., 2014: Poor pasture quality, JoD, Table 2, reg 8	120	0.2342	yes
Gatiso et al., 2015: Scarcity, cooperative behaviour	130	-0.8052	yes
Reynolds et al., 2015: Cheating, FLHC	181	0.3735	yes

Reynolds et al., 2015: Cheating, SLHC	181	-0.2711	yes
Reynolds et al., 2015: EDRASS factor 1, FLHC	187	0.1619	yes
Reynolds et al., 2015: EDRASS factor 1, SLHC	187	-0.1868	yes
Reynolds et al., 2015: EDRASS factor 2, FLHC	187	-0.2664	yes
Reynolds et al., 2015: EDRASS factor 2, SLHC	187	0.0455	yes
Reynolds et al., 2015: EDRASS factor 3, FLHC	187	-0.0145	yes
Reynolds et al., 2015: EDRASS factor 3, SLHC	187	-0.1274	yes
Reynolds et al., 2015: EDRASS factor 4, FLHC	187	0.0085	yes
Reynolds et al., 2015: EDRASS factor 4, SLHC	187	-0.1049	yes
Roux et al., 2015: Recognizing words related to competition	142	0.42	yes
Roux et al., 2015: Higher competitive orientation	52	0.7416	yes
Roux et al., 2015: Choosing absolute maximum gain	69	0.2769	yes
Roux et al., 2015: Choosing relative maximum gain	69	0.3085	yes
Roux et al., 2015: Allocating less money to other player, dictator	157	0.3355	yes
Williams et al., 2016: Lying for water bottle, thirsty vs. not thirsty	62	0.787	yes
Williams et al., 2016: Lying for water bottle, sample 2	72	0.459	yes
Williams et al., 2016: Lying for a pen, thirsty vs. not thirsty	46	0.58	yes
Williams et al., 2016: Lying for water bottle, sample 3	45	0.425	yes
Williams et al., 2016: Lying for water bottle, (sample 1+2+3)	179	0.56	yes
Balakrishna et al., 2017: Greed attitude and unethical	264	0.4432	yes
Balakrishna et al., 2017: Low SES and behaviour	264	0.1108	yes
Balakrishna et al., 2017: Greed attitude, behaviour and sample 2	257	0.2636	yes
Balakrishna et al., 2017: Low SES, behaviour and sample 2	257	0.0145	yes
Balakrishna et al., 2017: Greed attitude, behaviour, sample 3	306	0.2879	yes
Balakrishna et al., 2017: Low SES, behaviour, sample 3	306	0.0272	yes
Balakrishna et al., 2017: Greed attitude, behaviour and sample 4	114	0.4521	yes
Balakrishna et al., 2017: Low SES, behaviour and sample 4	114	0.0219	yes
Andreoni et al., 2017: Return misdelivered envelope	360	-0.4638	yes
Andreoni et al., 2017: Return rate, cash treatment	360	-0.4752	yes
Andreoni et al., 2017: Return rate, bank transfer treatment	360	-0.3114	yes
Goldsmith et al., 2017: Moral disengagement	590	0.0693	yes
Goldsmith et al., 2017: Economic cheating	304	0.2727	yes
Goldsmith et al., 2017: Economic cheating, threat to self-concept	304	0.1429	yes
Goldsmith et al., 2017: Immoral behaviour, housing	90	0.4091	yes
Goldsmith et al., 2017: Acceptance of immoral behaviour	559	0.1756	yes
Mitkidis et al., 2018: Die roll cheating, poor vs. affluent	101	-0.3001	yes
Mitkidis et al., 2018: Die roll cheating, poor SES vs. affluent	84	0.0174	yes
Mitkidis et al., 2018: Die roll cheat., low affluent and pov.	79	0.004	yes
Mitkidis et al., 2018: Die roll cheat., affluence high and pov. low	79	-0.052	yes
Mitkidis et al., 2018: Die roll cheat., pov. low and neutral low	80	-0.0803	yes
Mitkidis et al., 2018: Die roll cheat., neutral high and pov. low	78	-0.1483	yes
Mitkidis et al., 2018: Die roll cheat., affluence low and pov. high	81	0.1793	yes
Mitkidis et al., 2018: Die roll cheat., high affluent and pov.	80	0.1123	yes
Mitkidis et al., 2018: Die roll cheat., neutral low and pov. high	80	0.1944	yes
Mitkidis et al., 2018: Die roll cheat., neutral high and pov. high	79	-0.0188	yes
Nowlin et al., 2018: SES and unethical behaviour	96	0.3535	yes
Nowlin et al., 2018: Greed attitude and behaviour	96	0.0114	yes
Clerke et al., 2018: SES and lying	317	-0.0399	yes
Clerke et al., 2018: SES and greed attitude	317	-0.14	yes
Clerke et al., 2018: SES and lying, sample 2	320	0.0399	yes
Clerke et al., 2018: SES and greed attitude, sample 2	320	-0.3442	yes
Aksoy et al., 2019: Cheating for themselves	250	-0.0455	yes
Aksoy et al., 2019: Cheating for in-group	250	-0.1032	yes
Aksoy et al., 2019: Cheating for out-of-group	250	0.1132	yes
Seuntjens et al., 2019: Dispositional greed, behaviour, American	304	0.6045	yes
Seuntjens et al., 2019: Dispositional greed, behaviour, Belgian	1000	0.6285	yes
Seuntjens et al., 2019: Dispositional greed, behaviour, Dutch	1018	0.4079	yes
Seuntjens et al., 2019: Dispositional greed, justifiable to engage	269	0.7943	yes
Seuntjens et al., 2019: Dispositional greed, transgressions accept	822	0.5828	yes
Seuntjens et al., 2019: Greed, accepting a bribe	172	0.389	yes

Seuntjens et al., 2019: DGS, bribe	172	0.5129	yes
Seuntjens et al., 2019: DGS, wallet	302	0.6496	yes
Seuntjens et al., 2019: DGS, cheat	302	0.6068	yes
Liu et al., 2019: Greed, childhood SES	3200	0.0734	yes
Birkelund et al., 2020: Cheat, no adv. + unequal, no adv. + equal	192	0.9105	yes
Birkelund et al., 2020: Cheat, no adv. + unequal, adv. + equal	192	1.4455	yes
Birkelund et al., 2020: Cheat, no adv. + unequal, adv. + unequal	192	1.4674	yes
Boonmanunt et al., 2020: Baseline cheating game	284	0.0119	yes
Boonmanunt et al., 2020: Norm-reminder game	274	0.1058	yes

Note. *n* = number of participants; *g* = Hedges' *g* effect size; data = data available in original article or by request to authors (with yes = data obtained; n.r. = no response from authors)

Table A2

Resource Scarcity and Prosocial Behavior

Study: Condition	<i>n</i>	<i>g</i>	Data
Koenig et al., 2004: Helping gesture, abused and neglected	54	-0.2956	yes
Koenig et al., 2004: Helping gesture, abused and nonmaltreated	56	-0.069	yes
Koenig et al., 2004: Helping gesture, neglected and nonmaltreated	54	0.2151	yes
Koenig et al., 2004: Comfort gesture, abused and neglected	54	0.2981	yes
Koenig et al., 2004: Comfort gesture, abused and nonmaltreated	56	0.2304	yes
Koenig et al., 2004: Comfort gesture, neglected and nonmaltreated	54	-0.0946	yes
Koenig et al., 2004: Donation, abused and neglected	54	-0.3077	yes
Koenig et al., 2004: Donation, abused and nonmaltreated	56	-0.4005	yes
Koenig et al., 2004: Donation, neglected and nonmaltreated	54	-0.0844	yes
Koenig et al., 2004: Guilt, abused and neglected	54	-0.1184	yes
Koenig et al., 2004: Guilt, abused and nonmaltreated	56	-0.0748	yes
Koenig et al., 2004: Guilt, neglected and nonmaltreated	54	0.057	yes
Koenig et al., 2004: Empathy, abused and neglected	54	-0.0519	yes
Koenig et al., 2004: Empathy, abused and nonmaltreated	56	-0.2335	yes
Koenig et al., 2004: Empathy, neglected and nonmaltreated	54	-0.1762	yes
Briers et al., 2006: Hunger and willingness to pay to charity	66	0.19	yes
Briers et al., 2006: Food scent and willingness to pay to charity	58	0.5297	yes
DeWall et al., 2008: Self-regulation and helping others	19	0.9869	yes
Dewall et al., 2008: Self-regulation, helping strangers vs. family	291	2.19	yes
DeWall et al., 2008: Self-regulation and helping strangers	291	0.2095	yes
Harel & Kohut, 2014: Willing to donate, experienced hunger	108	0.3282	yes
Harel & Kohut, 2014: Willing to donate, hungry vs. satiated	196	0.244	yes
Roux et al., 2015: Wanting to donate	52	0.5614	yes
Roux et al., 2015: Choosing joint maximum gain	69	-0.4946	yes
Roux et al., 2015: Likelihood of donating, private donation	360	0.3466	yes
Roux et al., 2015: Likelihood of donating, public donation	360	0.214	yes
Bartos et al., 2018: Generosity, one-shot dictator game	136	-0.0702	yes
Bartos et al., 2018: Generosity, third-party punishment game	136	-0.0729	yes
Bartos et al., 2018: Fairness, third-party punishment game	136	-0.4631	yes
Herzenstein et al., 2019: Willingness to donate (donation rate)	107	-0.2102	yes
Herzenstein et al., 2019: Willingness to donate (charity size)	107	-0.0241	yes
Herzenstein et al., 2019: Donation size to UNICEF US	107	0.2176	yes
Herzenstein et al., 2019: Donation size to UNICEF Africa	107	-0.2803	yes
Herzenstein et al., 2019: Donation, someone else's money	229	0.2996	yes
Herzenstein et al., 2019: Donation size to local charity	158	0.4514	yes
Herzenstein et al., 2019: Donation size to far away charity	158	-0.1834	yes
Herzenstein et al., 2019: Donation size to East Coast	94	0.425	yes
Herzenstein et al., 2019: Asian origin, scarcity, donation	405	-0.586	yes
Herzenstein et al., 2019: Asian origin, abundance, donation	405	0.0094	yes
Herzenstein et al., 2019: Donation size, experience, scarcity	803	0.2738	yes
Herzenstein et al., 2019: Donation size, experience, abundance	803	0.687	yes

Herzenstein et al., 2019: Donation size, lifesaving, scarcity	803	0.2682	yes
Herzenstein et al., 2019: Donation size, lifesaving, abundance	803	0.1191	yes
Häusser et al., 2019: Contribution to common pool in PGG	62	0.0502	yes
Häusser et al., 2019: Stag hunt game	62	0.47	yes
Häusser et al., 2019: Stag hunt game (larger sample size)	103	-0.1044	yes
Häusser et al., 2019: Social mindfulness	103	-0.2481	yes
Häusser et al., 2019: Willingness to accept unfair offers in UG	103	-0.1937	yes
Häusser et al., 2019: Scarcity, SVO scores	267	0.071	yes
Huppert et al., 2019: Generosity, dictator game	203	0.2975	yes
Birkelund et al., 2020: Offer, no adv. + unequal, no adv. + equal	192	-0.4305	yes
Birkelund et al., 2020: Offer, no adv. + unequal, adv. + equal	192	-0.7415	yes
Birkelund et al., 2020: Offer, no adv. + unequal, adv. + unequal	192	-1.0321	yes
Nie et al., 2020: Water scarcity, farmer's willingness to cooperate	312		n.r.

Note. *n* = number of participants; *g* = Hedges' *g* effect size; data = data available in original article or by request to authors (with yes = data obtained; n.r. = no response from authors)

Appendix B

Supplementary Review and Meta-Analysis on Prosocial Behavior

As noted in our methods section (see sub-section, *Search*), our pre-registered review protocol (<https://bit.ly/3t1zd8z>) restricted our search terms and inclusion criteria to research that had investigated the relationship between resource scarcity and unethical behavior. However, as previously noted, our database search resulted in a series of articles that either investigated how scarcity might affect both unethical and prosocial behavior or which purely sought to investigate how scarcity might affect prosocial behavior. While considered irrelevant to the main body of the systematic review and meta-analysis, we decided that it would still be relevant to outline the results of such studies in connection with our main focus on unethical behavior. Consequently, the below section outlines the meta-analytical results on how resource scarcity might affect prosocial behavior.

Meta-analysis

As with the main analysis presented in the paper, the meta-analysis of the relationship between resource scarcity and prosocial behavior followed a hierarchical approach, in which we firstly analyzed a global model on all the included studies, before breaking the analysis down to the subgroup level. Here, it should be noted that this supplementary analysis only included three subgroups: *Financial Scarcity*, *Reminders of Scarcity*, and *Physiological Scarcity*. The results are presented in **Table B1**. Again, the key variables of interest in this analysis is the Standardized Mean Difference (SMD) in the form of Hedges' g , the percentage of variability in effect sizes I^2 , and the between study variance in the form of τ^2 .

Table B1

Supplementary analysis of the relationship between resource scarcity and prosocial behavior

<i>Results prior to heterogeneity adjustment</i>							
Group	<i>k</i>	<i>N</i>	SMD	95% CI	<i>p</i>	<i>I</i> ²	τ^2
All studies	21	3307	0.0823	[-0.0693; 0.2338]	0.2708	66.4%	0.0872
Financial Scarcity	8	1457	-0.0311	[-0.3531; 0.2909]	0.8261	78.4%	0.1180
Reminders of Scarcity	3	481	0.0794	[-1.2674; 1.4262]	0.0219	80.6%	0.4561
Physiological Scarcity	10	1369	0.1751	[0.0319; 0.3184]	0.8235	0.0%	0.1872
<i>Results post heterogeneity adjustment</i>							
Group	<i>k</i>	<i>N</i>	SMD	95% CI	<i>p</i>	<i>I</i> ²	τ^2
All studies	17	2622	0.1672	[0.0646; 0.2697]	0.0033	21.9%	0.0247
Financial Scarcity	6	860	0.1274	[-0.1673; 0.4222]	0.3169	56.2%	0.0534
Reminders of Scarcity	2	412	0.3550	[-0.1738; 0.8838]	0.0743	0.0%	0.0015
Physiological Scarcity	9	1350	0.1622	[0.0552; 0.2693]	0.0081	0.0%	0.0092

Note. *k* = number of studies, *N* = sample size, SMD = Standardized Mean Difference by Hedges' *g*, 95% CI = 95% confidence interval, *p* = *p*-value, *I*² = percentage of variability in effect sizes, τ^2 = between-study variance.

The analysis of all supplementary studies on the relationship between resource scarcity and prosocial behavior revealed an insignificant pooled effect size of 0.0823. The results of the global model also revealed substantial heterogeneity $I^2 = 66.4\%$. Grouping the analysis by the subgroup defined by the main independent variables strongly reduced the degree of heterogeneity for studies on physiological scarcity, $I^2 = 0.0\%$, while revealing that studies on financial scarcity ($I^2 = 78.4\%$) and reminders of scarcity ($I^2 = 80.6\%$) accounted for a large degree of the observed heterogeneity in the overall model. Consequently, the second-level subgroup analysis revealed insignificant and very small effects sizes for the subgroups with high-levels of heterogeneity. On the contrary, the subgroup on physiological scarcity yielded a statistically significant small effect size of 0.1751.

A GOSH-analysis of heterogeneity revealed that 4 articles ($k = 4$) accounted for a large degree of the observed heterogeneity (Birkelund & Cherry, 2020) (DeWall et al., 2008) (Herzenstein & Posavac, 2019) (Roux et al., 2015). Rerunning the analysis without these

studies reduced the heterogeneity of the global model to $I^2 = 21.9\%$ and yielded a revised statistically significant pooled effect size estimate of 0.1672. Furthermore, this analysis reduced the heterogeneity of the two subgroups financial scarcity and reminders of scarcity to $I^2 = 56.2\%$ and $I^2 = 0.00\%$, respectively. The heterogeneity adjusted subgroup analysis yielded a significant effect size estimate of 0.1622, while still leaving the pooled estimate for the two other subgroups insignificant. A forest plot based on the heterogeneity adjusted subgroup analysis is presented in **Figure B1**.

Figure B1. Forest plot, adjusted for heterogeneity, of the effect sizes for each of the three subgroups as well as the overall effect of resource scarcity on prosocial behavior. Error bars

represent 95% confidence intervals. Grey diamonds depict the pooled effect for the subgroups. The grey diamond connected to the dotted line depicts the overall effect of the model. The black line depicts the prediction interval of the overall model.

In sum, the second-level model adjusted for heterogeneity supports an analysis of the included data at the subgroup level. Our supplementary analysis shows that resource scarcity in the form of physiological scarcity has a positive significant effect on individuals' propensity to engage in prosocial behaviors, but that such an effect does not exist for the subgroups on financial scarcity or reminders of scarcity. On the global level, our model results in a small-to-medium effect size (.17) on the relationship between material resource scarcity and prosocial behavior, largely driven by the results in the subgroup on physiological scarcity.

Appendix C

Supplementary Robustness Analyses

Sensitivity Analysis of Estimation Algorithm

Estimating the variance of the pooled effect in a random-effects model meta-analysis using the Hartung-Knapp-Sidik-Jonkman (HKSJ) method has been shown to provide more robust estimates of the variance than the widely used DerSimonian-Laird estimator (IntHout et al., 2014). However, to address recent work on residual concerns when using the (HKSJ) method (Jackson et al., 2017), we followed recommendations from Wiksten et al. (2016) and conducted a sensitivity analysis of the derived variance of the meta-analytic effects by applying the widely used DerSimonian-Laird estimator (DerSimonian & Laird, 1986).

Our analysis showed no difference in effect size estimates between the two methods. The results of the sensitivity analysis are presented in **Figure C1**. This analysis hence supports our initial prediction that the main results of our meta-analysis is robust to the use of different estimation algorithms.

Figure C1. Sensitivity analysis of the difference between the Hartung-Knapp-Sidik-Jonkman estimation algorithm and the DerSimonian-Laird estimation algorithm. The algorithm used in the main meta-analysis is robust due to the extremely small difference in pooled estimates.

Meta-analysis of all extracted effect sizes

To further assess the robustness of our main findings on the relationship between resource scarcity and unethical behavior, we carried out a random-effect model meta-analysis by the use of every single extracted effect size from the included articles. While this entailed a redundancy in sample sizes (i.e., multiple tests for the same sample size) and, consequently, high levels of heterogeneity, we argue that such an analysis provides further validity and robustness of our main findings, given that this analysis was conducted on a much larger data set than that of the original. **Table C1** reports the results this analysis.

Table C1

Supplementary analysis of the relationship between resource scarcity and unethical behavior

<i>Results prior to heterogeneity adjustment</i>							
Group	<i>k</i>	<i>N</i>	SMD	95% CI	<i>p</i>	<i>I</i> ²	τ^2
All studies	135	26,901	0.1973	[0.1202; 0.2743]	< 0.0001	84.7%	0.4192
Financial Scarcity	55	7927	0.2959	[0.1539; 0.4379]	< 0.0001	86.2%	0.2429
Reminders of Scarcity	29	8555	0.2851	[0.1701; 0.4000]	< 0.0001	79.8%	0.0719
Physiological Scarcity	24	1836	0.1241	[-0.0778; 0.3259]	< 0.0001	78.8%	0.1784
Social Class	27	8583	-0.0127	[-0.1501; 0.1248]	< 0.0001	78.2%	0.1006
<i>Results post heterogeneity adjustment</i>							
Group	<i>k</i>	<i>N</i>	SMD	95% CI	<i>p</i>	<i>I</i> ²	τ^2
All studies	75	11,810	0.1784	[0.1071; 0.2497]	< 0.0001	65.7%	0.1797
Financial Scarcity	31	3223	0.1784	[0.0649; 0.2920]	0.0032	65.6%	0.0737
Reminders of Scarcity	15	5336	0.2045	[0.0669; 0.3422]	0.0066	62.0%	0.0422
Physiological Scarcity	16	634	0.2374	[0.0291; 0.4457]	0.0282	64.8%	0.1081
Social Class	13	5898	0.0925	[-0.0917; 0.2768]	0.2952	69.6%	0.0703

Note. *k* = number of studies, *N* = sample size, SMD = Standardized Mean Difference by Hedges' *g*, 95% CI = 95% confidence interval, *p* = *p*-value, *I*² = percentage of variability in effect sizes, τ^2 = between-study variance.

The robustness analysis of all included effect sizes revealed a significant overall effect of 0.1973, close to, but lower than that of the main findings. As expected, the global model also

revealed substantial heterogeneity $I^2 = 84.7\%$. An identical pattern emerged in the subgroup analysis. Here, all estimates for the subgroups were highly significant and yielded positive effect sizes for all groups except that of social class.

Following previous procedures, we conducted a GOSH analysis (Olkin et al., 2012) to explore the observed heterogeneity in our models. As expected, due to the redundancy in sample sizes, this analysis revealed that 60 effect sizes accounted for the cluster of observed heterogeneity in the model. Excluding such studies in a subsequent analysis reduced the heterogeneity of the global model to $I^2 = 65.7\%$ (close to that of the main model) and revealed a revised statistically significant pooled effect size estimate of 0.1784. Moreover, the revision of the model reduced the heterogeneity for all subgroups and hence yielded revised effect estimates. Specifically, the heterogeneity adjusted model lowered the effect size estimates for the subgroups of financial scarcity (0.1784) and reminders of scarcity (0.2045), while increasing the pooled estimate for the subgroup on physiological scarcity (0.2374). All of these three subgroups, however, still yielded statistically significant estimates in the revised model. On the contrary, while the effect size estimate for the subgroup on social class increased to become positive, this estimate was no longer significant in the revised model, which again mimics the relationship found in our main analysis.

In sum, our supplementary analysis adds further robustness to our main findings by showing a largely identical relationship, wherein resource scarcity increases individuals' propensity to engage in unethical behavior. Again, our models support an analysis at the subgroup level by showing that resource scarcity in the form of (1) financial scarcity, (2) reminders of scarcity, and (3) physiological scarcity significantly affects individuals' propensity to engage in unethical behavior, while social class does not.