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Choice architects reveal a bias toward positivity and certainty☆

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ABSTRACT

Biases influence important decisions, but little is known about whether and how individuals try to exploit others' biases in strategic interactions. Choice architects—that is, people who present choices to others—must often decide between presenting choice sets with positive or certain options (influencing others toward safer options) versus presenting choice sets with negative or risky options (influencing others toward riskier options). We show that choice architects' influence strategies are distorted toward presenting choice sets with positive or certain options, across thirteen studies involving diverse samples (executives, law/business/medical students, adults) and contexts (public policy, business, medicine). These distortions appear to primarily reflect decision biases rather than social preferences, and they can cause choice architects to use influence strategies that backfire.

1. Introduction

Human decisions reveal a variety of biases that appear to violate standard economic models of rational choice (Bazerman & Moore, 2013; DellaVigna, 2009; Kahneman, 2003, 2011; Thaler & Sunstein, 2008; Tversky & Kahneman, 1981). Many of these biases can be used to influence people's choices in profound and often surprising ways. For instance, describing a choice between a risky option and a safe option using a gain frame (e.g., "number of lives saved") will nudge decision makers toward choosing the safe option, while describing the same two options using a loss frame (e.g., "number of lives lost") will nudge decision makers toward choosing the risky option (Kahneman & Tversky, 1979; Tversky & Kahneman, 1981). Social influence tactics that capitalize on these kinds of behavioral insights are increasingly recognized as powerful interventions that can be used to promote individual and social welfare (Thaler & Sunstein, 2008). However, surprisingly little is known about how good people are at strategically using nudges and biases to influence others, despite the fact that such influence opportunities are pervasive in social interactions (Bohns, 2016; Halevy, 2016; Johnson et al., 2012; Thaler & Sunstein, 2008; Zlatev, Daniels, Kim, & Neale, 2017). For example, negotiators nudge other negotiators, policymakers nudge citizens, managers nudge employees and consumers, and physicians nudge their patients (Zlatev et al., 2017).[1]

In existing theories across the behavioral sciences, it is widely assumed that decision makers understand others' biases and are capable of successfully exploiting them to influence others in desired directions (DellaVigna, 2009; Goldfarb et al., 2012). For instance, in economics, models of principal-agent interactions (e.g., interactions between

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[1] Generally, in this paper we will refer to nudges and biases in similar ways, because many prominent nudges leverage biases (e.g., framing effects, default effects); however, it is important to note that not all nudges leverage a bias, and not all biases can be easily leveraged using a nudge (Thaler & Sunstein, 2008).

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managers and their employees) assume that the principal will optimally exploit any biases the agent might have when designing a contract for the agent (for reviews, see DellaVigna, 2009; Köszegi, 2014), while models of firm-consumer interactions assume that managers will optimally exploit any biases that consumers might have (for reviews, see DellaVigna, 2009; Ellison, 2006). Similarly, in psychology, a review of the social influence literature suggests that "influence agents" often succeed when trying to influence "targets" in desired directions (Cialdini & Goldstein, 2004).

However, there is very little *empirical* work that examines whether and how individuals try to strategically exploit others' biases to influence them in desired directions. In fact, there is reason to suspect that individuals may often try to leverage nudges and biases in ways that are not always optimal (Camerer, 2003; Halevy, 2016; Kahneman, 2011; Zlatev et al., 2017). For instance, the vast majority of people do not have advanced training in psychology or behavioral economics. In addition, most people lack hard evidence about the effects of influence tactics on others' choices; for instance, a person does not usually conduct a randomized controlled trial before deciding whether to present a choice to others using a gain frame or a loss frame. Thus, while there is now a great deal of scientific evidence examining the impact of behavioral factors on decision making (Johnson et al., 2012), whether and how people strategically leverage such factors to influence others' decisions is a fundamental open question (Blount & Larrick, 2000; Bohns, 2016; DellaVigna, 2009; Frey & Eichenberger, 1994; McGinn & Nöth, 2012).

Biases and nudges can play an important role in influencing human behavior across a wide variety of important areas, including financial decision making (e.g., Madrian & Shea, 2001; Sonnemann, Camerer, Fox, & Langer, 2013), bargaining and negotiation (e.g., Blount & Larrick, 2000; Malhotra & Bazerman, 2008; McGinn, Milkman, & Nöth, 2012; Neale & Bazerman, 1985), management and organizational behavior (e.g., Bazerman & Sezer, 2016; Beshears & Gino, 2015; Daniels, Neale, & Greer, 2017; Nakashima, Daniels, & Laurin, 2017), marketing and consumer behavior (e.g., Basu & Savani, 2017; Gabaix & Laibson, 2006; Levav, Heitmann, Herrmann, & Iyengar, 2010; Mogilner & Norton, 2016; Simonson & Tversky, 1992), contracts (e.g., Hossain & List, 2012; Imas, Sadoff, & Samek, 2017), market design (e.g., Kessler & Roth, 2014; Lacetera, Larsen, Pope, & Sydnor, 2016), public policy and law (e.g., Madrian, 2014; Shu, Mazar, Gino, Ariely, & Bazerman, 2012; Thaler & Sunstein, 2008), politics (e.g., Nickerson & Rogers, 2010), public goods (e.g., Andreoni, 1995; Hsee, Zhang, Lu, & Xu, 2013), medicine and health (e.g., Johnson & Goldstein, 2003; Loewenstein, Brennan, & Volpp, 2007; Milkman, Beshears, Choi, Laibson, & Madrian, 2011; Tannenbaum et al., 2015), and beyond. Therefore, it is critically important to understand whether and how individuals try to use nudges and biases strategically to influence other people.

We examine this question in a series of thirteen studies, organized into six experiments.[2] We make use of a "Choice Architecture Game" that involves two players: Player 1 (the Choice Architect, or CA) selects a choice set from which Player 2 (the Choice Maker, or CM) makes a real or hypothetical choice. The Choice Architect is incentivized or directed to influence the Choice Maker to choose a randomly assigned, pre-determined target option. In Experiments 1 and 2, people are given the opportunity to act as Choice Architects and exploit either the reflection effect (Tversky & Kahneman, 1981) or the certainty effect (Kahneman & Tversky, 1979)—two Choice Maker biases that can be explained by prospect theory—to influence a Choice Maker's decision. We focus on these two prospect theory effects because they represent foundational and well-studied decision biases. In addition, both of these effects include a relatively "positive-valenced" choice set (i.e., choice sets including positive or certain options) and a relatively "negative-valenced" choice set (i.e., choice sets including negative or risky options) (e.g., Kuhnen & Knutson, 2005), allowing us to focus our investigation on potential valence-based biases in Choice Architect behavior. We find that Choice Architect influence strategies are systematically distorted toward presenting positive or certain options (as opposed to negative or risky options). In fact, in Experiment 1, a *majority* of Choice Architects choose to present positive or certain options even when this action is in direct opposition to their economic incentives.

Experiments 2–4 document the same qualitative pattern in Choice Architect behavior within the contexts of several important real-world domains: public policy, business, and medicine. We find that Choice Architect influence strategies are systematically distorted toward positive or certain options among business executives, law students, business students, and medical students. Experiment 5 demonstrates that the Choice Architect distortions toward positivity and certainty appear to primarily reflect decision biases rather than social preferences. Experiment 6 finds that Choice Architects' explicit judgments and feelings are generally not significant predictors of their influence strategies.

1.1. Related literature

To the best of our knowledge, the studies reported in this paper include a subset of the first incentivized experiments that investigate whether and how people strategically exploit others' individual decision biases. The most closely related paper is Zlatev et al. (2017), which investigates whether people are successful at using the default effect to influence others, using studies that were conducted contemporaneously with the studies that we report in this paper. Zlatev et al. (2017) find that people often fail to understand and/or use defaults, showing a kind of "default neglect" that persists over time and across contexts (Zlatev, Daniels, Kim, & Neale, 2018).

Other related work includes Blount and Larrick (2000), which studies how people use procedural framing effects in bargaining games, rather than individual decision biases; and Keren (2007) and Van Buiten and Keren (2009), which, respectively, study how people use attribute framing and the reflection effect but do not include experiments that are incentive-compatible. Our results for the reflection effect game are qualitatively similar to the results in Van Buiten and Keren (2009). More distantly, our paper is also related to work examining intrapersonal interactions regarding loss aversion (Imas et al., 2017) and present bias (O'Donoghue & Rabin, 1999); in contrast, our paper examines interpersonal interactions.

1.2. Structure of the paper

The remainder of the paper is organized as follows. In Section 2, we outline four simple theories of Choice Architect behavior and consider some of their key predictions. In Section 3, we describe the Choice Architecture Game used in our experiments. In Sections 4–7, we report our experimental results. In Section 8, we discuss implications and future directions.

2. Theories and hypotheses

We consider how individuals might try to exploit others' biases in a one-shot strategic interaction between a Choice Architect (CA) and a Choice Maker (CM). The CA, who wants to influence the CM toward a target option, selects one of two choice sets to give to the CM, with each choice set potentially influencing the CM toward a different option. The CM, upon receiving the choice set, selects one of two choices. If the CM does choose the target option, the CA receives extra utility (e.g., a monetary bonus payoff).

We next outline four simple theories that will make two additional types of assumptions about CAs. First, assumption **A1** will posit whether

[2] Data and code for all studies in this paper are available at https://osf.io/2dwv6/.

CA beliefs about CM biases are directionally correct (i.e., CAs are "sophisticated") or directionally incorrect (i.e., CAs are "naive"; see O'Donoghue & Rabin, 1999; Rogers & Milkman, 2016). In this paper, when we say that CA beliefs about CM biases are "directionally correct," we mean that CAs can correctly predict which of two influence strategies will be more likely to lead a CM to choose a pre-specified target option. Second, assumption **A2** will posit how CA beliefs translate into CA influence strategies (i.e., the nature of the CA's decision utility function).

The first theory we consider is the standard economic model, which assumes Choice Architects choose influence strategies so as to maximize their economic self-interest given their rational expectations (i.e., beliefs that are correct on average). The second, third, and fourth theories each emphasize one of three "deviations" away from the standard economic model: either incorrect beliefs, non-standard decision making (i.e., decision biases), or non-standard preferences (i.e., social preferences).

2.1. Economic theory of Choice Architects with correct beliefs

First, as both a normative benchmark and a baseline for other theories, we consider a "standard" economic theory of Choice Architects with correct beliefs about others' biases.

For assumption **A1**, CAs are assumed to hold beliefs about CMs' (i.e., other people's) biases that are directionally correct, following the majority of research in psychology and economics (e.g., Gneezy & Imas, 2014; Pronin, Gilovich, & Ross, 2004; Scopelliti et al., 2015; Van Boven, Dunning, & Loewenstein, 2000). Later, we will test this assumption in Experiment 6. For assumption **A2**, CA influence strategy decisions are assumed to maximize subjective expected utility (DellaVigna, 2009; Ellison, 2006; Köszegi, 2014). Together, these two assumptions imply that CAs will use optimal influence strategies.

In sum, when choosing an influence strategy, the CA will consult their (directionally correct) beliefs about the probability that each influence strategy will influence the CM in the desired direction. The CA will then choose the influence strategy with the highest expected value, which will be the optimal influence strategy.[3]

2.2. Economic theory of Choice Architects with incorrect beliefs

Second, we consider an economic theory of Choice Architects with incorrect beliefs about others' biases.

For assumption **A1**, CAs are assumed to hold beliefs about CMs' (i.e., other people's) biases that are directionally *incorrect*, perhaps as a result of erroneous lay theories about what factors influence others' behavior (e.g., Epley, Keysar, Van Boven, & Gilovich, 2004; Faro & Rottenstreich, 2006; Heath, 1999; Moore, 2004; Zlatev et al., 2017). For assumption **A2**, CA influence strategy decisions are again assumed to maximize subjective expected utility. Together, these two assumptions imply that CAs will actually use *suboptimal* influence strategies, because they are basing their decisions on beliefs that are incorrect.

In sum, when choosing an influence strategy, the CA will consult their (directionally *incorrect*) beliefs about the probability that each influence strategy will influence the CM in the desired direction. The CA will then choose the influence strategy with the highest expected value, which in this case will be the *suboptimal* influence strategy.

2.3. Behavioral theory of Choice Architects with decision biases

Third, we consider a behavioral theory of Choice Architects with correct beliefs about others' biases, but who are now also augmented with decision biases of their own.

For assumption **A1**, CAs are assumed to hold beliefs about CMs' (i.e., other people's) biases that are directionally correct. For assumption **A2**, however, CA influence strategy decisions may not follow expected utility theory, and thus CA influence strategies may systematically deviate from optimality. More specifically, we consider a behavioral theory of CA decision making in which biases analogous to classic prospect theory biases (Kahneman & Tversky, 1979; Tversky & Kahneman, 1991) could generate distortions in CAs' choices over choice sets, toward selecting choice sets that are more positive and more certain.

First, Choice Architects may reveal a bias toward positivity. Prospect theory predicts CM loss aversion (Kahneman & Tversky, 1979; Tversky & Kahneman, 1991): CMs may avoid selecting choices that can lead to losses even if those choices would likely lead to better economic outcomes for CMs. Analogously, we consider the possibility that CAs may also show a kind of *loss aversion for choice sets*. A choice set with options that appear to be losses from the CM's perspective—and are thus unattractive to the CM (Kahneman & Tversky, 1979)—may itself appear to be a kind of "loss" from the CA's perspective. As a result, CAs may avoid selecting such choice sets even when doing so would lead to better economic outcomes for CAs. Thus, CA influence strategies may be biased toward presenting gain options over presenting loss options.

Second, Choice Architects may reveal a bias toward certainty. Prospect theory predicts a CM certainty effect (Kahneman & Tversky, 1979; Tversky & Kahneman, 1991): outcomes that are certain and positive will be disproportionately attractive to CMs. Analogously, we consider the possibility that CAs may also show a kind of *certainty effect for choice sets*. A choice set with options that appear to be positive and certain from the CM's perspective—and are thus disproportionately attractive to the CM (Kahneman & Tversky, 1979)—may itself appear to be "positive" and "certain" from the CA's perspective. As a result, CAs may find such choice sets disproportionately attractive. Thus, CA influence strategies may be biased toward presenting choice sets that contain certain and positive options over choice sets that do not.

In sum, when choosing an influence strategy, the CA will consult their (directionally correct) beliefs about the probability that each influence strategy will influence the CM in the desired direction. The CA will then choose the influence strategy with the highest *potentially-distorted* expected value.

2.4. Behavioral theory of Choice Architects with social preferences

Fourth, we consider a behavioral theory of Choice Architects with correct beliefs about others' biases, but who are now also augmented with social preferences.

For assumption **A1**, CAs are again assumed to hold beliefs about CMs' (i.e., other people's) biases that are directionally correct. For assumption **A2**, CA influence strategy decisions may systematically deviate from behavior that maximizes their economic self-interest (i.e., wanting the CM to select the target option). In particular, we consider the possibility that CAs might also have concerns over CMs' economic or psychological outcomes. CAs might want CMs to experience greater economic payoffs (e.g., Charness & Rabin, 2002; De Dreu, Weingart, & Kwon, 2000), experience less economic risk, feel positive/good rather than negative/bad (e.g., Carnevale, 2008), or feel certain/safe rather than uncertain/unsafe.

In sum, when choosing an influence strategy, the CA will consult their (directionally correct) beliefs about the probability that each influence strategy will influence the CM in the desired direction. The CA will then receive decision utility both from choosing the influence strategy with the highest expected value (weighted by the importance of economic self-interest) and from choosing influence strategies that are "positive" or "certain" (weighted by the importance of social preferences).

2.5. Primary hypotheses

The primary question examined in this paper is whether CAs reveal a bias towards positivity or certainty in their influence strategies. Both the "decision bias" CA and the "social preference" CA will reveal a

[3] For simplicity, we abstract away from CA risk preferences here.

distortion toward "positive" and "certain" influence strategies (equivalently, away from "negative" and "uncertain" influence strategies), while "economic theory" CAs will not reveal such a distortion (regardless of whether their beliefs are correct or incorrect). After introducing our experimental methodology, we will test these two sets of competing hypotheses in Experiments 1–6.

Another important question is whether CA influence strategies are optimal on average (i.e., averaging CA performance across situations where the optimal choice set is "positive" or "certain" and situations where the optimal choice set is "negative" or "uncertain"). Most notably, "economic theory" CAs who have *correct* beliefs about CMs' biases will indeed choose influence strategies that are optimal on average. This property is also inherited by the "decision bias" and "social preference" theories that we have outlined here: such CAs will also choose influence strategies that are optimal on average. On the other hand, "economic theory" CAs who have *incorrect* beliefs about CMs' biases will not choose influence strategies that are optimal on average.

3. The Choice Architecture game

To experimentally investigate CA influence strategies, we developed a strategic decision problem we call the "Choice Architecture Game," inspired by similar games used in prior work (Blount & Larrick, 2000; Gneezy & Imas, 2014; Gneezy & Rustichini, 2000) and contemporaneously used by us in Zlatev et al. (2017). The experimental structure is based on the theoretical structure outlined in the previous section. There are two players, a Choice Architect and a Choice Maker, and typical play proceeds as follows. First, the CA selects one of two choice sets to give to the CM. Second, the CM receives a choice set and selects one of two options within that choice set. Third, the CA earns a monetary bonus payoff if and only if the CM chooses a randomly assigned target option.[4]

We use the Choice Architecture Game to test the aforementioned hypotheses derived from the four theories outlined in the previous section. We primarily focus on CA influence strategies that involve the CM reflection effect and the CM certainty effect.[5]

To study how CAs strategically use the reflection effect, we allow CAs to present either a gain-frame choice set or a loss-frame choice set to CMs. CMs act more risk seeking under loss frames and more risk averse under gain frames (Tversky & Kahneman, 1981). Therefore, if a CA wants to influence a CM toward choosing a safe option, the CA should present the gain-frame choice set to the CM; conversely, if a CA wants to influence a CM toward choosing a risky option, the CA should present the loss-frame choice set to the CM.

To study how CAs strategically use the certainty effect, we allow CAs to present either a choice set with one certain option and one risky option, or a choice set that includes two risky options, to CMs (with all options involving positive outcomes from the CM's perspective). CMs find outcomes that are certain and positive to be disproportionately attractive (Kahneman & Tversky, 1979). Therefore, if a CA wants to influence a CM toward choosing a safer option, the CA should present the choice set with one certain option and one risky option to the CM; conversely, if a CA wants to influence a CM toward choosing a riskier option, the CA should present the choice set with two risky options to the CM.

[4] Some experiments did not use monetary incentives for CAs; instead, CAs were simply instructed to influence CMs toward a randomly assigned target option.

[5] However, when we investigate a medical context in Experiment 5, we consider CA influence strategies that involve the CM mortality-frame/survival-frame effect instead of the CM reflection effect.

4. Experiments 1a-d: Choice Architect influence strategies

In the Choice Architecture Games in Experiments 1a-c, Choice Architects faced strategic choice tasks with real monetary outcomes, while Choice Makers faced nonstrategic choice tasks drawn from Tversky and Kahneman (1981) and Kahneman and Tversky (1979) with hypothetical outcomes. In Experiment 1d, both Choice Architects *and* Choice Makers faced choice tasks with real monetary outcomes.

4.1. Participants

To obtain Choice Architect responses, in Experiment 1a, we recruited 624 US-based adults from Amazon's Mechanical Turk (42% female, Mean age = 31.0, SD = 10.4; ethnicity 75% Caucasian, 5% African American, 7% Hispanic, 10% Asian, and 3% other; 15 participants did not respond to the postdecision questionnaire) to participate in an online experiment. Our target sample size was 600 participants.

In Experiment 1b, we recruited 300 Stanford undergraduate/graduate students to participate in a short survey. Participants were recruited in one of three ways: (1) 176 took the survey through an online participant pool operated by the Stanford Graduate School of Business Behavioral Lab; (2) 64 took the survey by responding to a post on one of two Stanford-University-related Facebook groups; (3) 60 took the survey on paper after being asked to participate by a research assistant. Our target sample size was 300 participants.

In Experiment 1c, we recruited 398 US-based adults from Amazon's Mechanical Turk (54% female, Mean age = 34.6, SD = 12.0; ethnicity 75% Caucasian, 8% African American, 6% Hispanic, 7% Asian, and 3% other) to participate in an online experiment. Our target sample size was 400 participants.

In Experiment 1d, we recruited 445 US-based adults from Amazon's Mechanical Turk (48% female, Mean age = 36.6, SD = 12.0; ethnicity 76% Caucasian, 7% African American, 6% Hispanic, 8% Asian, and 3% other; 3 participants did not respond to the postdecision questionnaire) to participate in an online experiment. Our target sample size was 400 participants.

We also recruited separate samples from Amazon's Mechanical Turk to obtain Choice Maker (CM) responses. Information about these samples is provided in the Appendix.

4.2. Procedure

First, we examined CA influence strategies involving the reflection effect (Tversky & Kahneman, 1981). Across Experiments 1a-c, CAs were shown both the gain frame and the loss frame adapted from the original reflection effect problem (Tversky & Kahneman, 1981):

> Imagine that your country is preparing for the outbreak of an unusual disease, which is expected to kill 600 people. Two alternative programs to combat the disease have been proposed. Assume that the exact scientific estimates of the consequences of the programs are as follows.

Option Set A.
Program 1 200 people will be saved.
Program 2 1/3 probability that all 600 people will be saved and 2/3 probability that no people will be saved.

Option Set B.
Program 1 400 people will die.
Program 2 2/3 probability that all 600 people will die and 1/3 probability that no people will die.

CAs were told that CMs would be given one of the two option sets above. In each case, the CM would decide whether they preferred to implement Program 1 or Program 2. CAs were randomly assigned to want the CM to choose one of the two options, with the target option being either the safe Program 1 or the risky Program 2. Then, CAs decided whether to be paired with a randomly- selected CM who had seen Option Set A (i.e., the gain frame) or with a randomly-selected CM who had seen Option Set B (i.e., the loss frame). We call the CA's decision an "influence strategy" since it can potentially exploit the CM's reflection effect bias. CAs received a bonus payoff if and only if the CM actually chose the randomly assigned target option. The bonus payoffs for the Choice Architects were $0.25 (in line with typical payments on MTurk (Amir, Rand, & Gal, 2012)), $4.00, $0.50, and $0.25 in Experiments 1a, 1b, 1c, and 1d respectively.[6]

Second, we examined CA influence strategies involving the certainty effect (Kahneman & Tversky, 1979). Across Experiments 1a-c, CAs were shown both scenarios from the original certainty effect problem (Kahneman & Tversky, 1979), reproduced below:

Scenario A.

Option 1	80% chance of 4000.
Option 2	100% chance of 3000.

Scenario B.

Option 1	20% chance of 4000.
Option 2	25% chance of 3000.

CAs were told that the CMs would be given one of the two scenarios above. In each case the CMs would decide whether they would choose Option 1 or Option 2. CAs were randomly assigned to want the CM to choose one of the two options, with the target option being either the riskier Option 1 or the safer Option 2. Then, CAs decided whether to be paired with a randomly-selected CM who had seen Scenario A (i.e., the scenario that included a certain option) or with a randomly- selected CM who had seen Scenario B (i.e., the scenario with no certain option). Again, we call the CA's decision an "influence strategy" since it can potentially exploit the CM's certainty effect bias. CAs received a bonus payoff if and only if the CM actually chose the (randomly assigned) target option. The bonus payoffs were the same as in the reflection effect scenarios.

In Experiment 1c, we included an additional feature in the experimental design. After CAs selected their influence strategy, we elicited their willingness to pay (WTP) for their influence strategy using the Becker-DeGroot-Marschak procedure (Becker, DeGroot, & Marschak, 1964), which provides an economic incentive for CAs to reveal their true valuations. CAs were told that they would receive an additional bonus of $0.50 and could choose how much of that money they were willing to pay to be paired with a CM who had seen the choice set the CA had previously selected. A number between 0 and 50 would then be randomly drawn and, if that number was greater than or equal to the amount that the CA was willing to pay (in cents), then the CA would be "sold" the ability to be paired with a CM who had received the choice set preferred by the CA. Otherwise, the CA would be paired with a CM at random.

Experiment 1d was similar to Experiments 1a-c, but included slightly different choice sets so that each option had real monetary payoffs for the Choice Makers (see Appendix), as well as $0.25 bonus payoffs for the Choice Architects if the Choice Maker chose the (randomly assigned) target option.

[6] We successfully replicated the reflection effect and certainty effect among Choice Makers, both with and without real monetary stakes; see Appendix for details.

4.3. Results

Table 1 presents a summary of results for all Experiments 1–4.

Fig. 1 displays results for Experiment 1a-c. First, we consider whether and how CAs strategically use the reflection effect. The two behavioral theories (but not the two standard economic theories) predict that CA influence strategies will be biased toward choice sets that include positive options over choice sets that include negative options. In line with the prediction of the two behavioral theories, across Experiments 1a-c, CA influence strategies were more likely to be optimal when the positive frame was optimal than when the negative frame was optimal. This difference was significant when the experiments were meta-analytically combined ($z = 8.59$, $p < 0.001$) and for each of the three experiments individually (Experiment 1a: $z = 6.55$, $p < 0.001$; Experiment 1b: $z = 3.37$, $p < 0.001$; Experiment 1c: $z = 5.57$, $p < 0.001$). CAs who wanted to influence CMs toward the safe program optimally chose to be paired with a CM who received the gain frame 76% of the time. This was significantly greater than chance when the experiments were meta-analytically combined (95% CI [71.4%, 80.6%]) and for each of the three experiments individually (Experiment 1a: 78.0% optimal, $\chi^2(1) = 50.49$, $p < 0.001$, 95% CI [70.8%, 84.0%]; Experiment 1b: 75.3% optimal, $\chi^2(1) = 17.75$, $p < 0.001$, 95% CI [63.6%, 84.4%]; Experiment 1c: 74.5% optimal, $\chi^2(1) = 22.54$, $p < 0.001$, 95% CI [64.5%, 82.5%]). CAs who wanted to influence CMs toward the risky program optimally chose to be paired with a CM who received the loss frame 40% of the time. This was significantly less than chance when the experiments were meta-analytically combined (95% CI [35.1%, 45.8%]) and for two of the three experiments individually (Experiment 1a: 40.3% optimal, $\chi^2(1) = 5.06$, $p = 0.02$, 95% CI [32.3%, 48.8%]; Experiment 1b: 48.1% optimal, $\chi^2(1) = 0.05$, $p = 0.82$, 95% CI [36.6%, 59.7%]; Experiment 1c: 34.0% optimal, $\chi^2(1) = 9.94$, $p = 0.002$, 95% CI [25.1%, 44.1%]).

We found a similar result in Experiment 1d when there were real monetary stakes for both the CA and the CM. Specifically, once again CA influence strategies were more likely to be optimal when the positive frame was optimal (59%) than when the negative frame was optimal (36%, $\chi^2(1) = 10.37$, $p = 0.001$).

Second, we consider whether and how CAs strategically use the certainty effect. The two behavioral theories (but not the two standard economic theories) predict that CA influence strategies will be biased toward choice sets that include certain options over choice sets that do not. In line with the prediction of the two behavioral theories, across Experiments 1a-c, CA influence strategies were more likely to be optimal when the choice set with the certain option was optimal than when the choice set without the certain option was optimal. This difference was significant when the experiments were meta-analytically combined ($z = 10.56$, $p < 0.001$) and for each of the three experiments individually (Experiment 1a: $z = 7.85$, $p < 0.001$; Experiment 1b: $z = 3.72$, $p < 0.001$; Experiment 1c: $z = 7.33$, $p < 0.001$). CAs who wanted to influence CMs toward the safer 3000-value option optimally chose to be paired with a CM who received the choice set with the certain option 87% of the time. This was significantly greater than chance when the experiments were meta-analytically combined (95% CI [83.4%, 90.5%]) and for each of the three experiments individually (Experiment 1a: 86.5% optimal, $\chi^2(1) = 85.42$, $p < 0.001$, 95% CI [80.1%, 91.2%]; Experiment 1b: 87.0% optimal, $\chi^2(1) = 40.73$, $p < 0.001$, 95% CI [77.0%, 93.3%]; Experiment 1c: 89.2% optimal, $\chi^2(1) = 61.19$, $p < 0.001$, 95% CI [81.1%, 94.2%]). CAs who wanted to influence CMs toward the riskier 4000-value option optimally chose to be paired with a CM who received the choice set without the certain option 43% of the time. This was significantly less than chance when the experiments were meta-analytically combined (95% CI [37.4%, 48.4%]) and for two of the three experiments individually (Experiment 1a: 41.2% optimal, $\chi^2(1) = 4.42$, $p = 0.04$, 95% CI [33.4%, 49.4%]; Experiment 1b: 58.9% optimal, $\chi^2(1) = 1.97$, $p = 0.16$ 95% CI [46.8%, 70.1%]; Experiment 1c: 32.6% optimal, $\chi^2(1) = 10.78$, $p = 0.001$, 95% CI [23.6%, 43.1%]).

Again, we found a similar result in Experiment 1d when there were

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Table 1
Summary of results for Experiments 1–4.

Experiment	N	Population	Context	CA Incentives	Reflection Effect Game*: % Optimal CA Influence Strategy Optimal Choice Set:		Certainty Effect Game: % Optimal CA Influence Strategy Optimal Choice Set:		CA Bias Towards Positivity/Certainty?	CA Influence Strategies Optimal on Average?
					Positive Frame	*Negative Frame*	*Certain Option*	*No Certain Option*		
1a	624	Online	Tversky & Kahneman	$0.25	78%	40%	87%	41%	Yes	Yes
1b	300	Undergrad./Grad. Students	Tversky & Kahneman	$4.00	75%	48%	87%	59%	Yes	Yes
1c	398	Online	Tversky & Kahneman	$0.50	74%	34%	89%	33%	Yes	Reflection: No, Certainty: Yes
1d	445	Online	Money	$0.25	59%	36%	85%	29%	Yes	Reflection: No, Certainty: Yes
2a	161	JD	Law	hypothetical	90%	41%	85%	49%	Yes	Yes
2b	405	Online	Law	hypothetical	88%	23%	90%	21%	Yes	Yes
3a	173	MBA	Business	hypothetical	76%	47%	86%	42%	Yes	Yes
3b	87	Executives	Business	hypothetical	91%	29%	93%	10%	Yes	No
3c	395	Online	Business	hypothetical	77%	26%	94%	10%	Yes	No
4a	314	MD	Medicine	$4.00	94%	64%	89%	63%	Yes	Yes
4b	400	Online	Medicine	hypothetical	89%	40%	94%	19%	Yes	Mortality: No, Certainty: Yes

N.B.: Participants in Experiments 1a, 1b, 1c, 1d played either the reflection effect game or the certainty effect game. Participants in Experiments 2a, 2b, 3a, 3b, 3c, 4a, and 4b played both the reflection effect game (*or the mortality-frame/survival-frame game) and the certainty effect game.

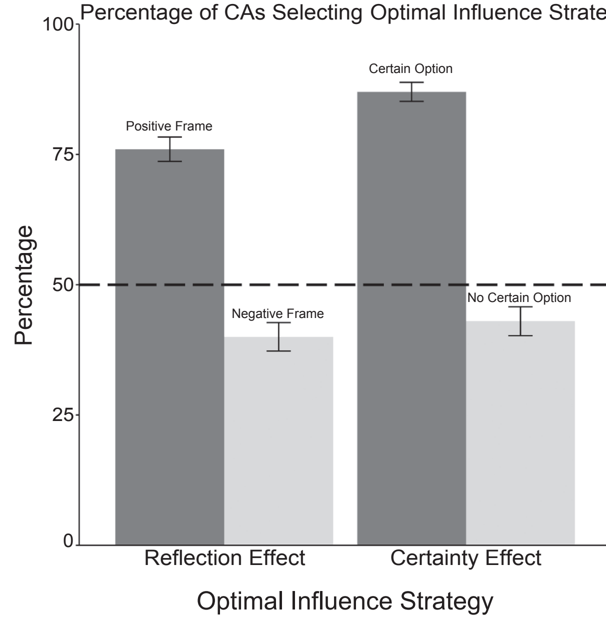

Fig. 1. Percentage of optimal CA influence strategies in the reflection effect and certainty effect games (Exp. 1a-c). Each bar label indicates the optimal influence strategy in the relevant condition. Error bars are SEs.

real monetary stakes for both the CA and the CM. CA influence strategies were more likely to be optimal when the choice set with the certain option was optimal (85%) than when the choice set without the certain option was optimal (29%, $\chi^2(1) = 72.09$, $p < 0.001$).

We note that pooling across all four bars in Fig. 1, most CA influence strategy decisions were optimal ($p < 0.001$). This result falsifies a key prediction of one of the four theories we considered—the economic theory of Choice Architects with incorrect beliefs, which predicted that CAs will overall use *suboptimal* influence strategies. Furthermore, this result is consistent with the hypothesis that CA beliefs about CMs' biases are directionally correct. (We will explore CA beliefs more directly in Experiment 6.)

Finally, for both the reflection effect game and the certainty effect game, Experiment 1c assessed CAs' willingness to pay for the ability to use their chosen influence strategy (as opposed to having an influence strategy be randomly selected for them) via the Becker-DeGroot-Marschak procedure (Becker et al., 1964). On average, CAs paid 34% of an additional endowment of $0.50 in order to use their chosen influence strategy. Overall, CAs were willing to pay significantly more than $0 ($p < 0.001$, by sign test); in fact, 76% of CAs were willing to pay a strictly positive amount of money to use their chosen influence strategy. This suggests that CAs were reasonably confident in their chosen influence strategies. This is particularly striking because many CAs who chose a suboptimal influence strategy were, by paying money to use their chosen influence strategy, actually paying to reduce their own expected pay.

5. Experiments 2–4: Influence Strategies of "Professional" Choice Architects

While people have opportunities to influence others in virtually all strategic interactions, understanding people's influence strategies can be especially important in domains such as public policy, business, and medicine. In our next set of experiments, we expanded our Choice Architect samples to include professional students in law, business, and medicine from Stanford University and Northwestern University—groups who are likely to include many important future decision makers in those domains (Fisman, Jakiela, Kariv, & Markovits, 2015). We also recruited business executives enrolled in an executive education program at Stanford Graduate

School of Business. This sample includes individuals who have extensive experience as leaders and managers, and thus represents a critical population for understanding influence strategies with potentially large consequences. For each sample of "professional" Choice Architects, we adapted the context of the games to the domains in which these groups were specialists—i.e., public policy, business, and medicine. Finally, for each of these domains, we recruited U.S. adults from an online pool to use as comparison Choice Architect samples.

5.1. Participants

For Experiment 2a, we recruited 161 students from Stanford Law School to participate in the experiment during class. Our target sample size was N = 150. In addition, for Experiment 2b, we recruited 405 US-based adults from Amazon's Mechanical Turk (51% female, Mean age = 35.9, SD = 12.3; ethnicity 76% Caucasian, 7% African American, 6% Hispanic, 9% Asian, and 3% other) to participate in a virtually identical experiment online. Our target sample size was N = 400.

For Experiment 3a, we recruited 173 MBA students from Stanford Graduate School of Business to participate in the experiment during class. Our target sample size was N = 150. For Experiment 3b, we recruited 87 executives enrolled in a one-year, full-time Master of Science degree program at Stanford Graduate School of Business to participate in the experiment during class. Our target sample was the entire class, which included 90 people (two people declined to participate and one person started the survey but did not answer the key dependent measures). In addition, for Experiment 3c, we recruited 395 US-based adults from Amazon's Mechanical Turk (48% female, Mean age = 35.5, SD = 12.2; ethnicity 75% Caucasian, 6% African American, 7% Hispanic, 9% Asian, and 3% other) to participate in a virtually identical experiment online. Our target sample size was N = 400.

For Experiment 4a, we recruited 314 students[7] from the Stanford University School of Medicine and the Northwestern University Feinberg School of Medicine (49% female, Mean age = 25.8, SD = 2.51; ethnicity 46% Caucasian, 2% African American, 6% Hispanic, 41% Asian, and 6% other; 40 participants did not respond to the postdecision questionnaire) to participate in the experiment online. Our target sample size was N = 300. In addition, for Experiment 4b, we recruited 400 US- based adults from Amazon's Mechanical Turk (49% female, Mean age = 33.6, SD = 11.8; ethnicity 74% Caucasian, 7% African American, 7% Hispanic, 8% Asian, and 3% other) to participate in a virtually identical experiment online. Our target sample size was N = 400.

5.2. Procedure

In Experiment 2, the reflection effect game and certainty effect game from Experiment 1 were adapted to a public policy setting. For the reflection effect game, participants assumed the role of a congressperson (i.e., a CA) who could present two different economic programs to the other members of Congress using either a gain frame or a loss frame. For the certainty effect game, participants also assumed the role of a congressperson who could present a report to the other members of Congress that either did or did not include a projected certain outcome.

In Experiment 3, the reflection effect game and certainty effect game from Experiment 1 were adapted to a business setting. For the reflection effect game, participants assumed the role of a CEO (i.e., a CA) who could present two different restructuring programs to one of the company's division heads using either a gain frame or a loss frame. For the certainty effect game, participants also assumed the role of a CEO who was choosing whether to enter a market that allowed managers to choose to develop a product with a certain outcome (vs. a market that only allowed risky outcomes).

In Experiment 4, the certainty effect game from Experiment 1 was adapted to a medical setting. For the certainty effect game, participants assumed the role of a physician (i.e., a CA) who was presenting case studies to the hospital's board of directors that either did or did not include a certain outcome. However, instead of using a reflection effect game as in previous experiments, we created a new mortality-frame/survival-frame game based on the mortality-frame/survival-frame effect widely studied in the medical decision making literature (McNeil, Pauker, Sox, & Tversky, 1982); participants also assumed the role of a physician who could present a choice between two different treatments to a patient using either a mortality frame (probability of dying) or a survival frame (probability of living). In contrast to the reflection effect, in which the gain frame nudges CMs toward risk aversion and the loss frame nudges CMs toward risk seeking, previous research on the mortality-frame/survival-frame effect has found that the mortality frame nudges CMs toward risk aversion while the survival frame nudges CMs towards risk seeking (see, e.g., McNeil et al., 1982).[8] In Experiment 4, we returned to using real monetary incentives for CAs who were MD students; in each game, these CAs received a bonus payoff of $4.00 if and only if the CM with whom they were matched actually chose the target option.

Unlike Experiments 1a-d, participants in Experiments 2–4 played *both* the reflection effect game (or mortality-frame/survival-frame game) and the certainty effect game. For more details on each of these experiments' procedures including experimental instructions, see the Appendix.

5.3. Results

See Figs. 2 and 3 for overall results.

5.3.1. Experiment 2: Influence strategies in public policy

As predicted by the two behavioral theories, among both samples who read the public policy scenarios, CAs selected the optimal influence strategy in the reflection effect game significantly more often when the positive frame was optimal than when the negative frame was optimal (JDs: $z = 5.90, p < 0.001$; U.S. Adults: $z = 11.69, p < 0.001$). CAs from both samples who were instructed to influence others toward the safe program optimally presented the gain frame at a rate significantly greater than chance (JDs: 89.5% optimal, $\chi^2(1) = 52.20$, $p < 0.001$, 95% CI [80.6%, 94.8%]; U.S. Adults: 87.6% optimal, $\chi^2(1) = 120.94, p < 0.001$, 95% CI [82.2%, 91.5%]). CAs from the JD sample who were instructed to influence others toward the risky program optimally presented the loss frame at a rate that was not significantly different from chance (41.3% optimal; $\chi^2(1) = 1.92$, $p = 0.17$, 95% CI [30.3%, 53.3%]). CAs from the U.S. online adult sample who were instructed to influence others toward the risky program optimally presented the loss frame at a rate that was significantly less than chance (23.4% optimal; $\chi^2(1) = 52.13$, $p < 0.001$, 95% CI [17.7%, 30.2%]).

Also as predicted by the two behavioral theories, among both samples, CAs selected the optimal influence strategy in the certainty effect game significantly more often when the choice set with the certain option was optimal than when the choice set without the certain option was optimal (JDs: $z = 4.48, p < 0.001$; U.S. Adults: $z = 12.23$, $p < 0.001$). CAs from both samples who were instructed to influence others toward the lower risk option optimally presented the choice set with the certain option at a rate significantly greater than chance (JDs: 84.9% optimal, $\chi^2(1) = 40.48$, $p < 0.001$, 95% CI [75.2%, 91.4%]; U.S. Adults: 89.9% optimal, $\chi^2(1) = 136.33$, $p < 0.001$, 95% CI

[7] A small proportion of participants in this experiment had already received their MD. For the sake of completeness, we report all responses.

[8] We successfully replicated the mortality-frame/survival-frame effect and certainty effect among Choice Makers; see Appendix for details.

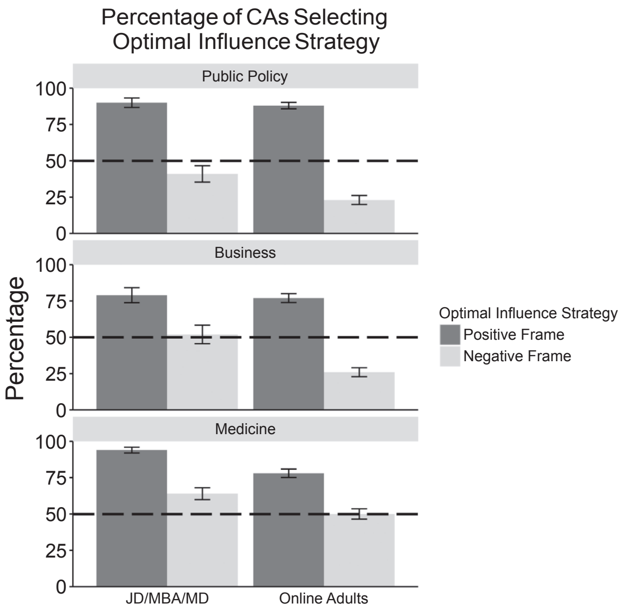

Fig. 2. Percentage of optimal CA influence strategies for the reflection effect and mortality-frame/survival-frame effect games (Exp. 2–4). Each bar label indicates the optimal influence strategy in the relevant condition. Error bars are SEs.

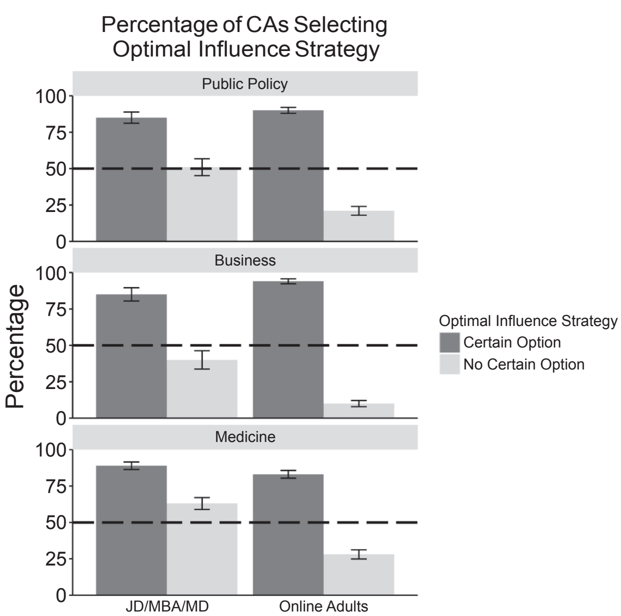

Fig. 3. Percentage of optimal CA influence strategies for the certainty effect games (Exp. 2–4). Each bar label indicates the optimal influence strategy in the relevant condition. Error bars are SEs.

[84.9%, 93.4%]). CAs from the JD sample who were instructed to influence others toward the higher risk option optimally presented the choice set without the certain option at a rate that was not significantly different from chance (50.7% optimal; $\chi^2(1) = 0$, $p = 1.00$, 95% CI [39.0%, 62.3%]). CAs from the U.S. online adult sample who were instructed to influence others toward the higher risk option optimally presented the choice set without the certain option at a rate that was significantly less than chance (20.7% optimal; $\chi^2(1) = 63.20$, $p < 0.001$, 95% CI [15.3%, 27.4%]).

5.3.2. *Experiment 3: Influence strategies in business*

As predicted by the two behavioral theories, among all three samples who read the business scenarios, CAs selected the optimal influence strategy in the reflection effect game significantly more often when the positive frame was optimal than when the negative frame was optimal (MBAs: $z = 3.86$, $p < 0.001$; Executives: $z = 5.19$, $p < 0.001$; U.S. Adults: $z = 9.61$, $p < 0.001$). CAs from all three samples who were instructed to influence others toward the safe program optimally presented the gain frame at a rate significantly greater than chance (MBAs: 76.5% optimal, $\chi^2(1) = 22.78$, $p < 0.001$, 95% CI [65.8%, 84.7%]; Executives: 91.1% optimal, $\chi^2(1) = 28.80$, $p < 0.001$, 95% CI [77.9%, 97.1%]; U.S. Adults: 76.7% optimal, $\chi^2(1) = 53.91$, $p < 0.001$, 95% CI [70.0%, 82.3%]). CAs from the MBA sample who were instructed to influence others toward the risky program optimally presented the loss frame at a rate that was not significantly different from chance (47.1% optimal; $\chi^2(1) = 0.19$, $p = 0.66$, 95% CI [36.3%, 58.1%]). CAs from the Executive and U.S. Adult samples who were instructed to influence others toward the risky program optimally presented the loss frame at a rate that was significantly less than chance (Executives: 28.6% optimal, $\chi^2(1) = 6.88$, $p = 0.009$, 95% CI [16.2%, 44.8%]; U.S. Adults: 25.7% optimal; $\chi^2(1) = 46.58$, $p < 0.001$, 95% CI [20.0%, 32.4%]).

Also as predicted by the two behavioral theories, among all three samples, CAs selected the optimal influence strategy in the certainty effect game significantly more often when the choice set with the certain option was optimal than when the choice set without the certain option was optimal (MBAs: $z = 5.46$, $p < 0.001$; Executives: $z = 6.14$, $p < 0.001$; U.S. Adults: $z = 12.92$, $p < 0.001$). CAs from all three samples who were instructed to influence others toward the lower risk option optimally presented the choice set with the certain option at a rate significantly greater than chance (MBAs: 85.5% optimal, $\chi^2(1) = 40.53$, $p < 0.001$, 95% CI [75.7%, 92.0%]; Executives: 93.3% optimal, $\chi^2(1) = 32.09$, $p < 0.001$, 95% CI [80.7%, 98.3%]; U.S. Adults: 93.8% optimal, $\chi^2(1) = 146.24$, $p < 0.001$, 95% CI [89.1%, 96.6%]). CAs from the MBA sample who were instructed to influence others toward the higher risk option optimally presented the choice set without the certain option at a rate that was not significantly different from chance (42.0% optimal; $\chi^2(1) = 1.78$, $p = 0.18$, 95% CI [31.3%, 53.4%]). CAs from the Executive and U.S. Adult samples who were instructed to influence others toward the higher risk program optimally presented the choice set without the certain option at a rate that was significantly less than chance (Executives: 9.5% optimal, $\chi^2(1) = 25.93$, $p < 0.001$, 95% CI [3.1%, 23.5%]; U.S. Adults: 10.4% optimal; $\chi^2(1) = 125.15$, $p < 0.001$, 95% CI [6.7%, 15.7%]).

5.3.3. *Experiment 4: Influence strategies in medicine*

As predicted by the two behavioral theories, among both samples who read the medicine scenarios, CAs selected the optimal influence strategy in the mortality-frame/survival-frame game significantly more often when the positive (survival) frame was optimal than when the negative (mortality) frame was optimal (MDs: $z = 5.42$, $p < 0.001$; U.S. Adults: $z = 9.30$, $p < 0.001$). CAs from both samples who were instructed to influence others toward Treatment 2 optimally presented the positive frame at a rate significantly greater than chance (MDs: 93.5% optimal, $\chi^2(1) = 103.60$, $p < 0.001$, 95% CI [87.7%, 96.8%]; U.S. Adults: 88.9% optimal, $\chi^2(1) = 123.67$, $p < 0.001$, 95% CI [83.6%, 92.7%]). CAs from the MD sample who were instructed to influence others toward Treatment 1 optimally presented the negative frame at a rate that was significantly greater than chance (64.1% optimal; $\chi^2(1) = 11.03$, $p < 0.001$, 95% CI [55.7%, 71.8%]). CAs from the U.S. Adult sample who were instructed to influence others toward Treatment 1 optimally presented the negative frame at a rate that was significantly less than chance (40.4% optimal; $\chi^2(1) = 6.72$, $p = 0.01$, 95% CI [33.5%, 47.7%]).

Also as predicted by the two behavioral theories, among both samples, CAs selected the optimal influence strategy in the certainty effect game significantly more often when the choice set with the certain option was optimal than when the choice set without the certain option was optimal (MDs: $z = 4.91, p < 0.001$; U.S. Adults: $z = 11.97, p < 0.001$). CAs from both samples who were instructed to influence others toward the lower risk option optimally presented the choice set with the certain option at a rate significantly greater than chance (MDs: 89.0% optimal, $\chi^2(1) = 87.46, p < 0.001$, 95% CI [82.5%, 93.4%]; U.S. Adults: 93.8% optimal, $\chi^2(1) = 146.24, p < 0.001$, 95% CI [89.1%, 96.6%]). CAs from the MD sample who were instructed to influence others toward the higher risk option optimally presented the choice set without the certain option at a rate that was significantly greater than chance (63.1% optimal; $\chi^2(1) = 9.19, p = 0.002$, 95% CI [54.5%, 71.0%]). CAs from the U.S. Adult sample who were instructed to influence others toward the higher risk program optimally presented the choice set without the certain option at a rate that was significantly less than chance (19.3% optimal; $\chi^2(1) = 76.70, p < 0.001$, 95% CI [14.3%, 25.5%]).

5.3.4. Were there differences between "Professional" and "Non-Professional" Choice Architects?

A notable feature of these findings is that CAs from some "professional" populations, although still far from achieving optimality, made significantly better CA decisions than CAs from "non-professional" populations. For example, in the medical games of Experiment 4, most (64.1%) CAs from the MD student sample presented the negative frame when it was optimal, but most (59.6%) CAs from the U.S. Adult sample did *not* present the negative frame when it was optimal. In this case, the MD students performed significantly better than the U.S. Adults ($\chi^2(1) = 17.71, p < 0.001$, 95% CI [12.7%, 34.8%])). Similarly, most (63.1%) CAs from the MD student sample presented the choice set without the certain option when it was optimal, but most (80.7%) CAs from the U.S. Adult sample did *not* present the choice set without the certain option when it was optimal. Once again, the MD students performed significantly better than the U.S. Adults ($\chi^2(1) = 67.10, p < 0.001$, 95% CI [33.6%, 54.0%])). (On the other hand, it was *not* always the case that "professional" CAs were better than "non-professional" CAs. For example, in the business games of Experiment 3, CAs from the executive sample did not perform significantly better than CAs from the U.S. Adult sample ($\chi^2(1) = 2.63, p = 0.11$, 95% CI [−1.8%, 22.4%]).) An interesting question for future research is whether these differences between CA samples are due to selection effects (e.g., some professions such as medicine might attract people who have better-than-average perspective-taking or critical thinking abilities that could lead to better CA influence strategies) or treatment effects (e.g., working or training in fields such as medicine that typically require extensive interpersonal interactions might give CAs better insight into the effects of various influence tactics on other people).

6. Experiment 5: Are Choice Architects revealing decision biases or social preferences?

Table 1 not only presents the results from Experiments 1–4, but also evaluates the implications of those results for our two primary research questions. First, do CAs reveal a bias toward positivity or certainty in their influence strategies? The answer is unambiguously yes: in *every* case, we find that CAs reveal a bias towards positivity or certainty. Second, are CA influence strategies optimal on average? The answer is in most cases yes, but in some cases no. Overall, we view this evidence as suggesting that while CAs do reveal at least some degree of sophistication in how they leverage CMs' biases to influence CMs (consistent with standard economic theory), decision biases and/or social preferences still have powerful and pervasive effects on CA behavior. Incorrect beliefs additionally seem to have an impact in at least some situations.

Perhaps the single most striking aspect of the results from Experiments 1–4 is that standard economic theory fails to predict the Choice Architect valence distortions observed in Experiments 1–4 toward "positive" influence strategies (equivalently, away from "negative" influence strategies) and toward "certain" influence strategies (equivalently, away from "uncertain" influence strategies). If Choice Architects are not maximizing their economic self-interest, this implies that at least one of two alternative explanations for the results of Experiments 1–4 must be correct (DellaVigna, 2009; Romer, 2006; Thaler, 2000). First, Choice Architects may be revealing the use of a non-standard decision process, i.e., a decision bias: CAs may be motivated solely by their economic self-interest, but use a decision rule that systematically deviates from subjective expected utility maximization. Second, Choice Architects may be revealing a type of non-standard preference, i.e., a social preference: CAs may use subjective expected utility maximization as a decision rule, but have concerns over CMs' economic or psychological outcomes.[9]

To distinguish between these possibilities, we conducted further Choice Architecture Games in which we randomly assigned Choice Architects to either play against human counterparts (as in Experiment 1a) or play against robot counterparts (Johnson, Camerer, Sen, & Rymon, 2002). If CAs' social preferences are driving the valence distortions observed in CAs' influence strategies, then CAs will select different choice sets if the CM is a human vs. a robot; specifically, the size of the valence distortions observed in CA influence strategies will decrease if the CM is a robot (vs. if the CA is a human). If, however, decision biases rather than social preferences are driving the valence distortions observed in CAs' influence strategies, then CAs will not select different choice sets if the CM is a human vs. a robot (Johnson et al., 2002); specifically, the size of the valence distortions observed in CA influence strategies will not change if the CM is a robot (vs. if the CA is a human).[10]

6.1. Participants

We recruited 1689 US-based adults from Amazon's Mechanical Turk (55% female, Mean age = 35.5, SD = 11.3; ethnicity 76% Caucasian, 8% African American, 6% Hispanic, 7% Asian, and 3% other; 47 participants did not respond to the postdecision questionnaire) to participate in an online experiment. Our target sample size was N = 1600.

6.2. Procedure

Choice Architects saw one of the following two sets of instructions:
Instructions for Human Counterpart condition:

"On the next few pages you will see some scenarios. You will choose one scenario that you want to give to a "responder".
The responder is a real person also recruited from Mechanical Turk who has seen the scenario that you choose to show them, and made a decision based on that scenario.
You will be paired up with a responder and will be paid a cash bonus based on how well you are able to predict their response.
Please click next to continue."

Instructions for Robot Counterpart condition[11]*:*

"On the next few pages you will see some scenarios. You will choose one scenario that you want to give to a "responder".
The responder is a computer, not a real person. When the computer makes a decision, it is done in the following way:
We recruited real people from Mechanical Turk who saw one of the two scenarios you will be choosing between. Using those people's decisions, we have calculated the probabilities that the computer must use to make decisions that "imitate" the behavior of a human who saw each scenario.
You will be paired up with this responder and will be paid a cash

[9] Of course, these two alternative explanations are not mutually exclusive; it is possible they both are operating simultaneously.
[10] This experiment was pre-registered at AsPredicted.org, AsPredicted #5294, https://aspredicted.org/29gp8.pdf.
[11] These instructions were adapted from Ellingsen, Johannesson, Mollerstrom, and Munkhammar (2012).

bonus based on how well you are able to predict its response. Please click next to continue."

CAs then played either the reflection effect game or the certainty effect game, with a bonus payoff of $0.25 if the CM chose the target option, as in Experiment 1a.

6.3. Results

Consistent with all previous experiments, CA influence strategies in the reflection effect game were more likely to be optimal when the positive frame was optimal (85%) than when the negative frame was optimal (32%, $\chi^2(1) = 237.34$, $p < 0.001$). In addition, CA influence strategies in the certainty effect game were more likely to be optimal when the choice set with the certain option was optimal (86%) than when the choice set without the certain option was optimal (27%, $\chi^2(1) = 287.77$, $p < 0.001$).

To test the hypothesis of primary interest in Experiment 5, we used logistic regressions to predict whether CA influence strategies were optimal—i.e., to predict a dummy outcome variable equal to 1 if CAs selected the optimal choice set in the Choice Architecture Game—using three predictor variables: a dummy for *valence* ("positive"/"certain" choice set optimal vs. "negative"/"uncertain" choice set optimal), a dummy for *counterpart* (human vs. robot), and their interaction. We found that valence distortions were not significantly different when CAs made decisions for a human player (i.e., the Human Counterpart condition) vs. when CAs made decisions for a computer player (i.e., the Robot Counterpart condition). This was the case both for the reflection effect game ($p = 0.48$, OR 95% CI [0.64, 2.55]) and for the certainty effect game ($p = 0.40$, OR 95% CI [0.67, 2.76]).

Thus, the findings of Experiment 5 suggest that the distortions observed in CA influence strategies appear to primarily reflect decision biases rather than social preferences.

7. Experiment 6: Do Choice Architects' explicit judgments and feelings predict their influence strategies?

To further investigate the psychology underlying Choice Architects' decision processes, we asked Choice Architects to indicate judgments and feelings related to the choice sets they could select. If Choice Architects use a deliberative decision process when choosing an influence strategy, we would expect their explicit judgments and feelings to be significant predictors of their strategies (Kahneman, 2003, 2011). However, we would not necessarily expect this to be the case if Choice Architects use an intuitive decision process when choosing an influence strategy.

7.1. Participants

We recruited 611 US-based adults from Amazon's Mechanical Turk (49% female, Mean age = 35.5, SD = 12.0; ethnicity 71% Caucasian, 10% African American, 6% Hispanic, 11% Asian, and 2% other; 10 participants did not respond to the postdecision questionnaire) to participate in an online experiment. Our target sample size was N = 600.

7.2. Procedure

The base design for this experiment was identical to the design of Experiment 1a, except CAs were not incentivized. However, in addition to deciding how which of two choice sets to present to CMs, CAs also made five judgments related to each of the choice sets (i.e., ten judgments in total).[12] For each choice set they could give to a CM, CAs were asked the following five questions:

1. "What percent of OTHER PEOPLE do you think chose each option?" (responses could range from 0 to 100, and had to sum to 100)
2. "How confident are you in the percentages you just indicated?" (1 = Not at all confident, 7 = Extremely confident)
3. "How do you think OTHER PEOPLE would feel if they read and responded to this scenario?" (1 = Extremely bad, 7 = Extremely good)
4. "How would YOU feel about asking other people to read and respond to this scenario?" (1 = Extremely bad, 7 = Extremely good)
5. "Do you think this scenario would effectively influence OTHER PEOPLE towards choosing [Program/Option] 1, towards choosing [Program/Option] 2, or neither?" (1 = Influence towards [Program/Option] 1, 7 = Influence towards [Program/Option] 2).

7.3. Results

7.3.1. Reflection effect game

First, we consider the reflection effect game. Table 2 reports summary statistics and significance tests regarding CAs' five judgments and feelings about each of the two possible choice sets, i.e., the choice set with the gain frame and the choice set with the loss frame. Across the five types of judgments/feelings, three were significantly different between the gain frame and the loss frame. CAs' beliefs about the reflection effect were directionally correct: CAs believed that CMs would be more likely to select the risky Program 2 under the loss frame than under the gain frame (equivalently, more likely to select the safe Program 1 under the gain frame than under the loss frame); this provides evidence for assumption **A1** in Section 2. CAs believed that CMs would feel slightly better if they were given the gain frame than if they were given the loss frame. Finally, CAs believed that the gain frame would be more likely to influence CMs toward the safe option (equivalently, that the loss frame would be more likely to influence CMs toward the risky option).

We next examined whether CA judgments/feelings were significant predictors of CA influence strategy optimality. Specifically, we employed linear regressions, with the outcome variable being a dummy variable equal to 1 if CAs selected the optimal choice set in the reflection effect game and equal to 0 otherwise (where, as before, the optimal choice set is the choice set in which CMs are more likely to select the randomly assigned target option).[13] We conducted a "valence predictor" OLS regression of CA influence strategy optimality on a dummy variable for valence that took a value of 1 if the optimal choice set was the positive choice set and took a value of 0 otherwise. Consistent with all previous experiments, valence was a significant predictor ($b = 0.51$, $p < 0.001$) of CA influence strategies; that is, CAs were 51 percentage points more likely to select the optimal choice set if the optimal choice set was the positive choice set. We then conducted 10 "judgment predictor" OLS regressions of CA influence strategy optimality on each of the 10 judgment items described previously. Nine judgments were not significant predictors of CA influence strategies; only one judgment—the extent to which the CA judged that the loss-frame choice set would effectively influence the CM toward Program 2 (vs. Program 1)—was a significant predictor ($b = 0.06$, $p = 0.003$). In an "all judgment predictors" OLS regression that predicted CA influence strategy optimality using all 10 judgments, again only one judgment—the extent to which the CA judged that the loss-frame choice set would effectively influence the CM toward Program 2 (vs. Program 1)—was a significant predictor ($b = 0.07$, $p = 0.015$).

Additionally, we used a Lasso regression analysis method from

[12] We counterbalanced whether CAs made judgments before or after playing the Choice Architecture Games.

[13] Using logistic regressions instead of OLS regressions leads to virtually identical results. Thus, for ease of interpretation, we report the results of OLS regressions.

Table 2
Average of CAs' judgments and feelings about choice sets, reflection effect game.

Item	Choice Set With Gain Frame	Choice Set With Loss Frame
"What percent of OTHER PEOPLE do you think chose each option?" (responses could range from 0 to 100, and had to sum to 100)	**58.76% Program 1 (Safe), 41.24% Program 2 (Risky)**	**44.40% Program 1 (Safe), 55.60% Program 2 (Risky)**
"How confident are you in the percentages you just indicated?" (1 = Not at all confident, 7 = Extremely confident)	5.30	5.28
"How do you think OTHER PEOPLE would feel if they read and responded to this scenario?" (1 = Extremely bad, 7 = Extremely good)	**3.54**	**3.31**
"How would YOU feel about asking other people to read and respond to this scenario?" (1 = Extremely bad, 7 = Extremely good)	3.80	3.67
"Do you think this scenario would effectively influence OTHER PEOPLE towards choosing Program 1, towards choosing Program 2, or neither?" (1 = Influence towards Program 1, 7 = Influence towards Program 2)	**3.56**	**4.35**

N.B.: CA responses within a row that are significantly different between choice sets are **bolded**. In the first row, responses to each choice set were significantly different (via *t*-tests and via Mann-Whitney *U* tests, *ps* < 0.001). In the second row, responses to each choice set were not significantly different (*t*-test $p = 0.836$, Mann-Whitney *U* test $p = 0.578$). In the third row, responses to each choice set were significantly different (*t*-test $p = 0.028$, Mann-Whitney *U* test $p = 0.010$). In the fourth row, responses to each choice set were not significantly different (*t*-test $p = 0.221$, Mann-Whitney *U* test $p = 0.123$). In the fifth row, responses to each choice set were significantly different (*t*-test $p < 0.001$, Mann-Whitney *U* test $p < 0.001$).

machine learning to examine which of 11 predictor variables (including valence and all 10 judgments) related to the reflection effect game should be selected for use as reliable predictors of CA influence strategy optimality in a linear regression model. We found that only valence was selected for use as a reliable predictor; that is, *no* judgments were selected as reliable predictors of CA influence strategy optimality (Belloni, Chernozhukov, & Hansen, 2011; Chernozhukov, Hansen, & Spindler, 2016). This suggests that CAs' explicit judgments are not reliable predictors of their influence strategies in the reflection effect game.

7.3.2. Certainty effect game

We next consider the certainty effect game. Table 3 reports summary statistics and significance tests regarding CAs' five judgments and feelings about each of the two possible choice sets, i.e., the choice set with the certain option and the choice set with no certain option. Across the five types of judgments/feelings, all five were significantly different between the two possible choice sets. CAs' beliefs about the certainty effect were directionally correct: on average, CAs believed that CMs are more likely to select the safer Option 2 if there is a certain option available (equivalently, more likely to select the riskier Option 1 if there is no certain option available); this provides evidence for assumption (A1) in Section 2. Furthermore, CAs were more confident about their predictions regarding the choice set with the certain option. CAs believed that both CMs *and* the CAs themselves would feel better if CAs gave CMs the choice set with the certain option (rather than the choice set with no certain option). Finally, CAs believed that the choice set with the certain option would be more likely to influence CMs toward the less risky option (equivalently, that the choice set with no certain option would be more likely to influence CMs toward the more risky option).

As with the reflection effect, we next examined whether CA judgments/feelings were significant predictors of CA influence strategy optimality. Once again, we employed OLS regressions, with the outcome variable being a dummy variable equal to 1 if CAs selected the optimal choice set in the certainty effect game and equal to 0 otherwise (where, as before, the optimal choice set is the choice set in which CMs

Table 3
Average of CAs' judgments and feelings about choice sets, certainty effect game.

Item	Choice Set With Certain Option	Choice Set With No Certain Option
"What percent of OTHER PEOPLE do you think chose each option?" (responses could range from 0 to 100, and had to sum to 100)	**30.43% Option 1 (More Risky), 69.57% Option 2 (Less Risky)**	**50.55% Option 1 (More Risky), 49.45% Option 2 (Less Risky)**
"How confident are you in the percentages you just indicated?" (1 = Not at all confident, 7 = Extremely confident)	**5.86**	**5.22**
"How do you think OTHER PEOPLE would feel if they read and responded to this scenario?" (1 = Extremely bad, 7 = Extremely good)	**5.16**	**4.42**
"How would YOU feel about asking other people to read and respond to this scenario?" (1 = Extremely bad, 7 = Extremely good)	**5.08**	**4.45**
"Do you think this scenario would effectively influence OTHER PEOPLE towards choosing Option 1, towards choosing Option 2, or neither?" (1 = Influence towards Option 1, 7 = Influence towards Option 2)	**5.17**	**4.09**

N.B.: CA responses within a row that are significantly different between choice sets are **bolded**. In all five rows, responses to each choice set were significantly different (via *t*-tests and via Mann-Whitney *U* tests, all *ps* < 0.001).

are more likely to select the randomly assigned target option). Consistent with all previous experiments, a "valence predictor" OLS regression showed that valence was a significant predictor ($b = 0.55$, $p < 0.001$) of CA influence strategy optimality; that is, CAs were 55 percentage points more likely to select the optimal choice set if the optimal choice set was the choice set with the certain option. We then conducted 10 "judgment predictor" OLS regressions of CA influence strategy optimality on each of the 10 judgment items described previously. Eight judgments were not significant predictors of CA influence strategy. Only two judgments were significant predictors of CA influence strategy: CA beliefs about the percentage of people who chose Option 2 (vs. Option 1) from the choice set with a certain option ($b = -0.002$, $p = 0.0175$) and the extent to which the CA judged that the choice set with a certain option would effectively influence the CM toward Option 2 (vs. Option 1) ($b = 0.048$, $p = 0.010$). In an "all judgment predictors" OLS regression that predicted CA influence strategy optimality using all 10 judgments, *no* judgment was a significant predictor.

As before, we used a Lasso regression to examine which of 11 predictor variables (including valence and all 10 judgments) related to the certainty effect game should be selected for use as reliable predictors of CA influence strategy optimality in a linear regression model. We again found that only valence was selected for use as a reliable predictor; that is, *no* judgments were selected as reliable predictors of CA influence strategy optimality. This suggests that CAs' explicit judgments are not reliable predictors of their influence strategies in the certainty effect game.

7.3.3. Discussion

Overall, in few cases (using OLS regressions) or no cases (using Lasso regressions) did CAs' explicit judgments reliably predict CA influence strategies. In our view, this suggests that Choice Architects are likely to be using an intuitive decision process, rather than a deliberative decision process, to choose an influence strategy (Kahneman, 2003, 2011). Of course, it is also possible that CAs are basing their influence strategy decisions on deliberative judgments that we did not measure. This would be an interesting direction for future research.

8. Conclusion

Whether and how people try to exploit other people's biases to influence their decisions is critical to understanding strategic interactions in social, political, and economic environments. In contrast to existing theoretical models, which widely assume that decision makers will optimally exploit others' biases (e.g., DellaVigna, 2009; Goldfarb et al., 2012), this paper documents profound and consistent distortions in how people try to strategically exploit others' biases to influence their choices. In six experiments, across diverse samples (including business executives; professional students in law, business, and medicine; and online adults), and multiple important contexts (including public policy, business, and medicine), we have shown that people's influence strategies are distorted toward selecting choice sets that emphasize positive or certain options. These distortions appear to primarily reflect decision biases rather than social preferences, and in some cases, they caused a majority of people to use an influence strategy that backfired.

Decades of research in the behavioral sciences have focused on the *effects* of nudges, framing, and biases on decision making (Kahneman, 2011); in contrast, the *causes* of these behavioral forces are much less well understood (Bohns, 2016; Frey & Eichenberger, 1994; Shleifer, 2012). Of course, in many social environments the causes of nudges are quite clear—they are chosen by other people (Halevy, 2016; Johnson et al., 2012; Thaler & Sunstein, 2008). And yet there is surprisingly little direct evidence about *whether and how people strategically create social contexts to influence other people by leveraging nudges and biases* (Blount & Larrick, 2000; DellaVigna, 2009; Frey & Eichenberger, 1994; Larrick, 2016; McGinn & Nöth, 2012). This fundamental question has been almost completely overlooked, despite its central importance for understanding negotiations, organizations, and markets, which are all social systems that not only influence human decisions, but are themselves shaped *by* human decisions (Camerer, 2003; DellaVigna, 2009; Powell, Lovallo, & Fox, 2011; Thau, Pitesa, & Pillutla, 2014). A systematic investigation of this question could shed light on longstanding puzzles in the literature. Consider two examples of such puzzles:

- *Why do people choose to design contracts and organizations characterized by positive valence (instead of negative valence)?* It is common for employers to offer compensation contracts that involve positive "rewards," but relatively rare for such contracts to involve negative "punishments" (Baker, Jensen, & Murphy, 1988). Similarly, people choose to build "reward institutions" rather than "punishment institutions" when attempting to induce cooperation in a social dilemma, even when punishment institutions are more effective (Sutter, Haigner, & Kocher, 2010). These asymmetries are not predicted by the economic theories of Choice Architect behavior, but they are predicted by both the "decision bias" and "social preference" behavioral theories.[14]
- *If risk preferences differ as a function of decision frame, why do people seem to be risk averse in most natural situations?* Risk preferences are famously malleable; gain frames reliably lead to risk averse behavior and loss frames reliably lead to risk seeking behavior (Kahneman, 2011; Kahneman & Tversky, 1979). Yet in most natural situations in the real world, people appear to be risk averse, and economic models designed to model natural situations typically assume people are risk averse (or risk neutral), not risk seeking (e.g., Fudenberg, 2006; Rabin, 2000). This difference seems puzzling at first, but we suggest it may have a simple explanation. In laboratory experiments, decision frames are given to decision makers by experimenters, who randomly choose to present, for example, a gain frame or a loss frame to a participant. But in the real world, decision frames are often given to decision makers by other people, who are significantly more likely to present gain frames rather than loss frames. In turn, this would nudge decision makers toward risk aversion in most natural situations.

Finally, future research could investigate whether and how people strategically deploy other "behavioral" tools, such as social norms or anchoring, to influence others' choices. This would not only further inform theories of strategic and interdependent human behavior (Camerer, 2003; Powell et al., 2011; Thau et al., 2014), but could also have important applications in understanding and improving multiagent systems such as negotiations, organizations, and markets. In particular, our analysis suggests that improving well-intentioned but suboptimal influence strategies appears to be a feasible objective which could lead to substantial benefits for both individuals

[14] Alternatively, some of these observed asymmetries (e.g., reward-based rather than punishment-based compensation contracts) may empirically arise in the context of repeated interactions rather than one-shot interactions, in which case additional theories our paper has not yet considered (due to our primary focus on one-shot interactions) may account for them. For example, while "punishment"-based compensation contracts might be more effective at inducing cooperation in a one-shot interaction, in a long-term *repeated* interaction Choice Makers under a "punishment"-based contract might come to feel resentment and ultimately choose to defect in the long run. Repeated interactions may also induce a greater focus on the interpersonal or relational benefits of presenting positive choice sets over negative ones. Therefore, wise Choice Architects who are anticipating a long-term interaction might opt to use "reward"-based contracts, anticipating that they may be better than "punishment"-based contracts at creating the trust and amicable relationships that can induce sustained cooperation over time. Future research should experimentally investigate the impact of anticipated time horizon (one-shot interaction vs. repeated interaction) on Choice Architect influence strategies.

and society. For example, rather than individually nudging thousands of employees, hospital patients, or students to be better Choice Makers, it may sometimes be more efficient to train a single manager, physician, or teacher to be a better Choice Architect. Overall, our research represents an initial investigation into an important but largely unexplored area of inquiry—how people use influence tactics and create choice architecture to strategically influence others—while also illuminating a novel path forward toward more effective applications of choice architecture to solve real-world problems.

Appendix for "Choice Architects reveal a bias toward positivity and certainty"

Experiments 1a–c

To obtain Choice Maker (CM) responses for Experiments 1a-c, we recruited 417 US-based adults from Amazon's Mechanical Turk (38% female, Mean age = 30.2, SD = 9.3; ethnicity 74% Caucasian, 6% African American, 9% Hispanic, 2% Asian, and 2% other; 9 participants did not respond to the postdecision questionnaire) to participate in an online experiment. Our target sample size was 400 participants.[15]

Among this sample of CMs, we successfully replicated the original reflection effect, $p < 0.001$, and certainty effect, $p < 0.001$. For the reflection problem, 68.3% (31.7%) of CMs chose the safe (risky) option in the gain frame, whereas 36.3% (63.7%) of CMs chose the safe (risky) option in the loss frame. For the certainty problem, 91.4% (8.6%) chose the lower (higher) expected value option in the choice set with the certain option, whereas 61.3% (38.7%) chose the lower (higher) expected value option in the choice set without the certain option.

Experiment 1d

To obtain Choice Maker responses for Experiment 1d, we recruited a new sample of 439 US-based adults from Amazon's Mechanical Turk (42% female, Mean age = 34.6, SD = 10.21; ethnicity 75% Caucasian, 6% African American, 4% Hispanic, 11% Asian, and 4% other; 2 participants did not respond to the postdecision questionnaire) to participate in an online experiment. Our target sample size was 400 participants. This study required a new sample of Choice Maker responses because the question they were being asked was different than the question that was asked in Experiments 1a–c (i.e., it involved real monetary stakes for the Choice Makers).

First, we examined Choice Architect (CA) influence strategies involving the reflection effect (Tversky & Kahneman, 1981). We used a simple binary choice with real stakes:

Scenario A.

Option 1	You get \$0. Then you have a 50% chance to win \$2 and 50% chance to win \$0.
Option 2	You get \$0. Then you win \$0.75.

Scenario B.

Option 1	You get \$2. Then you have a 50% chance to lose \$2 and 50% chance to lose \$0.
Option 2	You get \$2. Then you lose \$1.25.

CAs were told that CMs would be given one of the two choice sets above. In each case, the CMs would decide whether they preferred Option 1 or Option 2. Then, CAs decided whether to be paired with a randomly-selected CM who had seen Scenario A (the gain frame) or with a randomly-selected CM who had seen Scenario B (the loss frame). CAs received a bonus payoff of \$0.25 if and only if the CM actually chose the target option, which was randomly assigned to be either Option 1 or Option 2.

Second, we examined CA influence strategies involving the certainty effect (Kahneman & Tversky, 1979). We used a simple binary choice with real stakes:

Scenario A.

Option 1	80% chance of \$0.40.
Option 2	100% chance of \$0.30.

Scenario B.

Option 1	20% chance of \$0.40.
Option 2	25% chance of \$0.30.

CAs were told that CMs would be given one of the two choice sets above. In each case, the CMs would decide whether they preferred Option 1 or Option 2. Then, CAs decided whether to be paired with a randomly-selected CM who had seen Scenario A (the scenario that included a certain option) or with a randomly-selected CM who had seen Scenario B (the scenario with no certain option). CAs received a bonus payoff of \$0.25 if and only if the CM actually chose the target option, which was randomly assigned to be either Option 1 or Option 2.

Separately, an additional sample of U.S. adults from an online pool assumed the role of a Choice Maker. These CM participants were first

[15] This particular study also included a pilot test of the CA reflection effect game and CA certainty effect game described below. The CA results of this pilot were consistent with the other CA results but are not presented here due to the different way in which CA influence strategies were elicited in the pilot.

randomly assigned to either the reflection effect choice task or the certainty effect choice task. CMs who had been assigned to the reflection effect choice task were then further randomly assigned to view either the gain frame or the loss frame of the reflection effect choice task.[16] CMs who had been assigned to the certainty effect choice task were then further randomly assigned to view either the option set that included a certain option or the option set with no certain option of the certainty effect choice task. CAs were matched with these CM choices in order to determine CA bonus payoffs.

Experiment 2

Procedure

Participants who assumed the role of a CA were shown the following instructions:

> Imagine you are a member of congress. On this page (front AND back) are a number of decisions you will have to make. Please read them carefully and choose which option you would implement.

Influence strategies involving the reflection effect

CAs were shown both a gain frame and a loss frame of a "policymaker" variant of the reflection effect problem (Tversky & Kahneman, 1981):

> The economy has been doing very poorly in recent years, and 60,000 workers are expected to become unemployed in the near future. Two alternative economic programs to help save the jobs have been proposed. You can talk about these programs in your speech in one of the following two ways:

Description A.

Program 1	20,000 jobs will be saved.
Program 2	1/3 probability that all 60,000 jobs will be saved and 2/3 probability that no jobs will be saved.

Description B.

Program 1	40,000 jobs will be lost.
Program 2	2/3 probability that all 60,000 jobs will be lost and 1/3 probability that no jobs will be lost.

CAs were instructed to influence "voters" (hypothetical CMs) toward a target option, which was randomly assigned to be either Program 1 (i.e., the safer option) or Program 2 (i.e., the riskier option). Next, CAs decided which description to include in their speech—either Description A (i.e., the gain frame) or Description B (i.e., the loss frame).

Influence strategies involving the certainty effect

Next, CAs were shown both a certain-option scenario and a no-certain-option scenario for a "policymaker" variant of the certainty effect problem (Kahneman & Tversky, 1979):

> You are in charge of presenting a report comparing the results of two bills to the other members of congress. You have two reports from different think tanks that you can choose from to present:

Report A.

Bill 1	80% chance of a $4m boost to the economy.
Bill 2	100% chance of a $3m boost to the economy.

Report B.

Bill 1	20% chance of a $4m boost to the economy.
Bill 2	25% chance of a $3m boost to the economy.

CAs were instructed to influence other "members of congress" who "want to maximize the boost to the economy" (hypothetical CMs) toward a target option, which was randomly assigned to be either Bill 1 (i.e., the riskier option) or Bill 2 (i.e., the safer option). Next, CAs decided which report to present—either Report A (i.e., the certain-option scenario) or Report B (i.e., the no-certain-option scenario).

Experiment 3

Procedure

Participants who assumed the role of a CA were shown the following instructions:

[16] Among this sample of CMs, as expected, we found a reflection effect, $p < 0.01$, and a certainty effect, $p < 0.001$. For the reflection problem, 63.2% (36.8%) of CMs chose the safe (risky) option in the gain frame, whereas 42.3% (57.7%) of CMs chose the safe (risky) option in the loss frame. For the certainty problem, 78.6% (21.4%) chose the lower (higher) expected value option in the choice set with the certain option, whereas 54.7% (45.3%) chose the lower (higher) expected value option in the choice set without the certain option.

Imagine you are the CEO of a medium-sized company. On this page (front AND back) are a number of decisions you will have to make. Please read them carefully and choose which option you would implement.

Influence strategies involving the reflection effect

CAs were shown both a gain frame and a loss frame of a “business” variant of the reflection effect problem (Tversky & Kahneman, 1981):

One division of your company has been doing very poorly in recent years, and 60 employees from that division are expected to be laid off in the near future. Two alternative programs to help save the division have been proposed. These programs will be presented to the division head in one of the following two ways:

Option A.

Program 1	20 jobs will be saved.
Program 2	1/3 probability that all 60 jobs will be saved and 2/3 probability that no jobs will be saved.

Option B.

Program 1	40 jobs will be lost.
Program 2	2/3 probability that all 60 jobs will be lost and 1/3 probability that no jobs will be lost.

CAs were instructed to influence the manager of the division (the hypothetical CM) toward a target option, which was randomly assigned to be either Program 1 (i.e., the safer option) or Program 2 (i.e., the riskier option). Next, CAs decided which option to present to the manager of the division—either Option A (i.e., the gain frame) or Option B (i.e., the loss frame).

Influence strategies involving the certainty effect

Next, CAs were shown both a certain-option scenario and a no-certain-option scenario of a “business” variant of the certainty effect problem (Kahneman & Tversky, 1979):

As CEO, you will choose which market to enter; then, your managers will decide which product to release.

Market A.

Product 1	80% chance of 4000 units sold.
Product 2	100% chance of 3000 units sold.

Market B.

Product 1	20% chance of 4000 units sold.
Product 2	25% chance of 3000 units sold.

CAs were instructed to influence other “managers” who “want to maximize the number of units sold” (hypothetical CMs) toward a target option, which was randomly assigned to be either Product 1 (i.e., the riskier option) or Product 2 (i.e., the safer option). Next, CAs decided which market to enter—either Market A (i.e., the certain-option scenario) or Market B (i.e., the no-certain-option scenario).

Experiment 4

To obtain CM responses, we recruited 405 US-based adults from Amazon’s Mechanical Turk (39% female, Mean age = 33.1, SD = 10.7; ethnicity 78% Caucasian, 5% African American, 4% Hispanic, 12% Asian, and 2% other) to participate in an online experiment. Our target sample size was 400 participants.

Procedure

Participants who assumed the role of a CA were shown the following instructions:

Imagine you are a doctor in a medium-sized hospital. On the next page are a number of decisions you will have to make. Specifically, you will see some scenarios and will choose one scenario that someone else (called the “responder”) will see. Then, you will be randomly paired up with the actual response of a responder, who is a REAL person recruited from an online participant pool. You will be paid a bonus based on how well you are able to predict their response.

Influence strategies involving the mortality-frame/survival-frame effect

Choice Architect participants were shown both frames of the mortality-frame/survival-frame problem (McNeil et al., 1982):

One of your patients has been diagnosed with lung cancer. There are two treatments that the patient can decide between. You can present the treatments in one of the following two ways:

Option Set A.

Treatment 1	Of the patients who undergo this treatment, everyone survives the immediate post-treatment period. The life expectancy of the patients who undergo this treatment is 4.7 years.
Treatment 2	Of the patients who undergo this treatment, 90% survive the immediate post-treatment period. The life expectancy of the patients who survive the immediate post-treatment period is 6.8 years.

Option Set B.

Treatment 1	Of the patients who undergo this treatment, nobody dies during the immediate post-treatment period. The life expectancy of the patients who undergo this treatment is 4.7 years.
Treatment 2	Of the patients who undergo this treatment, 10% die during the immediate post-treatment period. The life expectancy of the patients who do not die during the immediate post-treatment period is 6.8 years.

CAs were told that the responders (CMs) would be given one of the two option sets above. In each case, the CMs would decide whether they preferred Treatment 1 or Treatment 2.

Then, CAs decided whether to be paired with a randomly-selected CM who had seen Option Set A (i.e., the survival frame) or with a randomly-selected CM who had seen Option Set B (i.e., the mortality frame). MD student CAs received a bonus payoff of $4.00 if the CM actually chose the target option, which was randomly assigned to be either Treatment 1 or Treatment 2.

Separately, an additional sample of U.S. adults from an online pool (N = 202) assumed the role of a Choice Maker. These CM participants were randomly assigned to view either the survival frame,

Imagine that you have been diagnosed with lung cancer. There are two treatments that you can decide between.

Treatment 1	Of the patients who undergo this treatment, everyone survives the immediate post-treatment period. The life expectancy of the patients who undergo this treatment is 4.7 years.
Treatment 2	Of the patients who undergo this treatment, 90% survive the immediate post-treatment period. The life expectancy of the patients who survive the immediate post-treatment period is 6.8 years.

or the mortality frame,

Imagine that you have been diagnosed with lung cancer. There are two treatments that you can decide between.

Treatment 1	Of the patients who undergo this treatment, nobody dies during the immediate post-treatment period. The life expectancy of the patients who undergo this treatment is 4.7 years.
Treatment 2	Of the patients who undergo this treatment, 10% die during the immediate post-treatment period. The life expectancy of the patients who do not die during the immediate post-treatment period is 6.8 years.

Then, CMs chose whichever treatment they preferred—either Treatment 1 or Treatment 2. CAs were matched with these CM choices in order to determine CA bonus payoffs.

Among this sample of CMs, we successfully replicated the mortality-frame/survival-frame effect, $p < 0.05$. Specifically, 68.8% (31.2%) of CMs chose the risky (safe) option in the gain frame, whereas 35.6% (64.4%) of CMs chose the risky (safe) option in the loss frame.

Influence strategies involving the certainty effect

Next, Choice Architect participants were shown both a certain-option scenario and a no-certain- option scenario of a "medical" variant of the certainty effect problem (Kahneman & Tversky, 1979):

You are in charge of presenting a case study comparing two treatments for a certain disease to the board of directors, who will decide which treatment to implement in the hospital. You have two case studies that you can choose from to present to the board:

Case A.

Treatment 1	80% chance of a normal life with an expected longevity of 20 years.
Treatment 2	100% chance of normal life with an expected longevity of 15 years.

Case B.

Treatment 1	20% chance of a normal life with an expected longevity of 20 years.
Treatment 2	25% chance of a normal life with an expected longevity of 15 years.

CAs were told that the responders (CMs) would be given one of the two option sets above. In each case, the CMs would decide whether they preferred Treatment 1 or Treatment 2.

Then, CAs decided whether to be paired with a randomly-selected CM who had seen Case A (i.e., the certain-option scenario) or with a randomly-selected CM who had seen Case B (i.e., the no-certain-option scenario). MD student CAs received a bonus payoff of $4.00 if the CM actually chose the target option, which was randomly assigned to be either Treatment 1 or Treatment 2.

Separately, an additional sample of U.S. adults from an online pool (N = 203) assumed the role of a Choice Maker. These CM participants were randomly assigned to view either the certain- option scenario,

Imagine that you have been diagnosed with a life threatening illness. There are two treatments that you can decide between.

Treatment 1	80% chance of a normal life with an expected longevity of 20 years.
Treatment 2	100% chance of normal life with an expected longevity of 15 years.

or the no-certain-option scenario,

Imagine that you have been diagnosed with a life threatening illness. There are two treatments that you can decide between.

Treatment 1	20% chance of a normal life with an expected longevity of 20 years.
Treatment 2	25% chance of a normal life with an expected longevity of 15 years.

Then, CMs chose whichever treatment they preferred—either Treatment 1 or Treatment 2. CAs were matched with these CM choices in order to determine CA bonus payoffs.

Among this sample of CMs, we successfully replicated the certainty effect, $p < 0.05$. Specifically, 60.2% (39.8%) chose the lower (higher) expected value option in the choice set with the certain option, whereas 46.3% (53.7%) chose the lower (higher) expected value option in the choice set without the certain option.

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