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CAUSAL NARRATIVES

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ABSTRACT

We study the generation, transmission, and effects of causal narratives - narratives which describe a (potentially incorrect) causal relationship between variables. In a controlled experiment, we show that exogenously generated causal narratives manipulate the beliefs and actions of subjects in ways predicted by theory. We then show how to ‘grow’ these types of narratives organically by asking subjects who observe a dataset of variables to advise future subjects on what actions to take. Subjects have a strict preference to share their homegrown narratives with other subjects, who are then persuaded by them. Finally, we show that factual, statistical information does not eliminate the power of causal narratives.

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Causal Narratives

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Abstract

We study the generation, transmission, and effects of causal narratives - narratives which describe a (potentially incorrect) causal relationship between variables. In a controlled experiment, we show that exogenously generated causal narratives manipulate the beliefs and actions of subjects in ways predicted by theory. We then show how to 'grow' these types of narratives organically by asking subjects who observe a dataset of variables to advise future subjects on what actions to take. Subjects have a strict preference to share their homegrown narratives with other subjects, who are then persuaded by them. Finally, we show that factual, statistical information does not eliminate the power of causal narratives.

1 Introduction

It is widely believed that people react to stories more than to facts or statistics. Journalists are trained to lead articles with captivating narratives and those who teach presentation skills emphasize the importance of telling a story.[1] However, we

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[1]Journalists call these leads, 'narrative leads': http://pablocalvi.com/?p=220. For an example of teaching presentation skills from the Harvard Business Review, see https://hbr.org/2014/07/how-to-tell-a-great-story.

have surprisingly little actual empirical evidence as to the power of narratives. What causes some narratives to go viral while others die away? Where do narratives come from? Can the persuasive power of false narratives be counteracted with factual information? If, as has been suggested (Shiller (2017, 2019)), narratives are critical for understanding economic issues from bubbles to political polarization, then we need answers to these questions in order to build economic models of these phenomena.

While narratives almost certainly impact people for various reasons (emotive content, an ability to relate, etc.), recent theoretical work has raised the intriguing possibility that narratives with a particular *structure* may affect people's actions by influencing the subjective beliefs they form from the data they observe (Spiegler (2016); Eliaz and Spiegler (2020)). Such narratives - which we call *causal narratives* - causally link an action variable to an outcome variable of interest by weaving in additional variables. For example, an anti-immigration politician may rally support for banning immigration by suggesting that increased immigration reduces job opportunities for locals and therefore lowers the living standards of the average American.[2] Taking the other side, a pro-immigration politician may argue that increased immigration stimulates innovation, thereby increasing living standards.[3] The theory of Eliaz and Spiegler (2020) posits that these different narratives, by incorporating different variables (job opportunities versus innovation), can cause decision-makers (DMs) to form different beliefs about the relationship between immigration policy and living standards *holding fixed* the true relationship observed in the data. Importantly, the theory makes precise predictions about the beliefs people will form, which in general differ from the beliefs a rational DM would form from the same data.

In this paper, through a series of controlled experiments, we study how causal narratives affect subjects' beliefs and actions, testing the predictions of standard, rational theory versus those of the theory in Eliaz and Spiegler (2020). Then, going beyond either theory, we ask whether people naturally create causal narratives, whether they have strict preferences for sharing them with others, and whether the effects of narratives can be counteracted with factual statistical information.

To understand how causal narratives can influence beliefs, consider a concerned

[2]e.g., https://time.com/4386240/donald-trump-immigration-arguments/.

[3]e.g., https://www.forbes.com/sites/washingtonbytes/2017/04/25/immigrants-can-help-boost-american-innovation-and-economic-growth/?sh=62378d145f5c.

parent that hears the narrative that social media causes depression in teenagers.[4] This narrative implies a causal chain from an action (parental ban on social media use), to an auxiliary variable (social media use), to an outcome (depression). Now suppose, as has been suggested, that this example represents a case of reverse causality - depression increases social media use and not the other way around (Hartanto et al. (2021)). Parents who understand this would realize that banning social media use would have no impact on the well-being of their children, and therefore rationally not impose such bans. But, parents who accept the narrative, and update their beliefs accordingly, will instead impose a ban.

The problem here is that the correlations in the data *together with* the narrative, distort parents' beliefs. Using the notation of directed acyclic graphs (DAGs), we can state the problem as follows (an arrow indicates a causal relationship between variables, pointing in the direction of causality). Rather than understanding the true model, *ban* $\rightarrow$ *social media use* $\leftarrow$ *depression*, from which it is clear that a ban has no effect on depression, the narrative implies the causal model, *ban* $\rightarrow$ *social media use* $\rightarrow$ *depression*, which, because of the positive correlation between social media use and depression in the data, induces parents to impose a ban.[5]

To take another example, those supporting gun rights may argue for arming citizens to improve public safety, using the argument that this will counteract the fact that criminals have guns[6], even if arming citizens is actually uncorrelated (or negatively correlated) with public safety. Comparing this example to the previous example illustrates two important dichotomies in causal narratives which we seek to understand. First, in the depression example, the narrative likely arises naturally out of the medical researchers' desire to explain the data they observe. On the other hand, those arguing for gun rights (or specific immigration policies) may intentionally construct the narrative to manipulate the public's beliefs.[7] We are interested in whether

[4] e.g., https://abcnews.go.com/Health/social-media-screen-time-linked-depression-teens-study/story?id=64399137.

[5] Suppose the potential ban (b), social media use (s), and depression (d) are all binary variables. The true relationship is $p(d|b) = p(d)$, so that b has no effect on d. But, the causal model implies $p(d|b) = p(d|s)p(s|b)$ which, given positive correlation between d and s and negative correlation between b and s, implies $b = 1$ will reduce the probability of d.

[6] See, for example, https://www.nytimes.com/2022/06/18/us/firearm-gun-sales.html.

[7] Stone (1989) argues compellingly that political actors deliberately associate events with *causal* stories in order to shape the political agenda and motivate partisan support for their side.

narratives have to be deliberately constructed to be effective, or whether narratives that arise naturally also have power.

The second dichotomy is with respect to the type of causal story the narrative presents. The depression example represents what Eliaz and Spiegler (2020) call a *lever* narrative, one which leverages an auxiliary variable to suggest a unidirectional causal chain from action to auxiliary variable to outcome. The gun rights narrative instead represents a *threat* narrative, a narrative which suggests that the action and auxiliary variable have opposing effects on the outcome (in this case, $arm\ citizens \rightarrow public\, safety \leftarrow criminals$). Given their different constructions, we are interested in which type of narrative is more effective, and which (if any) people generate naturally. Controlled experiments are ideal for answering these questions, allowing us to control both the data and narratives that subjects see.

In our first experimental treatment (CONSTRUCTED), subjects observe a dataset consisting of a history of observations of three binary variables: an action, an outcome, and an auxiliary variable (framed with neutral labels so that subjects are unlikely to have any preconceptions about their relationships). In the true data-generating process (DGP), the action and outcome are in fact unrelated, but we tell subjects only that they may or may not be related. In addition to the dataset, we present subjects with narratives that suggest a causal story by pointing out specific patterns in the dataset - carefully constructed narratives such as those that political actors may form. After forming beliefs about the relationship between actions and outcomes, subjects choose a policy - a probability distribution over the two actions. Subjects are paid more for good outcomes than bad, and pay a cost that increases for policies further from one-half. Thus, a rational subject, after studying the dataset, would understand the independence of actions and outcomes and therefore choose a policy of one-half (implying equal probabilities for each action). By contrast, according to the theory of Eliaz and Spiegler (2020), subjects will believe good outcomes are more likely under one of the actions (depending upon the narrative) and therefore choose policies different from one-half. We vary the datasets and causal narratives across subjects to test the comparative statics, as well as point predictions, of this theory.

We find that narratives have substantial persuasive effects - contrary to standard theoretical predictions, but very much in line with the predictions of the theory of Eliaz and Spiegler (2020). For the *same* underlying DGP (relationship between actions and outcomes), weaving different auxiliary variables into different causal narratives (as in the immigration examples above) results in costly deviations from the rational policy in opposite directions. Furthermore, fixing the DGP and the auxiliary variable, different narrative types (lever versus threat) also produce opposite deviations. Finally, we can reject the null hypothesis that subjects choose the rational policy, but we cannot reject the null hypothesis that both lever and threat narratives, on average, result in the point predictions of the behavioral theory (although heterogeneity in policy choices exists).

A plausible alternative to these results being driven by narratives changing subjects' beliefs is that they are driven by subjects blindly following narratives (perhaps due to inattention or experimenter demand). To test for this possibility, we designed the experiment so that subjects make policy choices for cases in which the narrative is easily falsified by looking at the dataset. Subjects that deviate from the rational policy of one-half in these cases are likely blindly following narratives. After removing them from the sample, we find that the effects of narratives are equally strong, demonstrating that some subjects are only convinced by narratives that they can reconcile with the data.

We also find that narratives have effects even when they are presented *after* subjects observe precise statistical information which clearly shows that the actions and outcomes are independent, thus invalidating the narrative. The effects of narratives diminish by 20 to 30 percent, but remain highly statistically significant. This result holds even among the subset of subjects that cannot be blindly following narratives and provides evidence that narratives are more convincing than statistical information.

These results demonstrate the power of causal narratives, but where do such narratives come from? Do they have to be carefully constructed or do people generate them naturally? To answer these questions, in our second experimental treatment (ELICIT), we provide subjects with datasets identical to those in the first condition. We again have them make policy choices, but instead of providing them with narratives, we incentivize them to construct their own. We ask them to give free-form advice to future subjects, and pay them according to how often their advice is rated as helpful by these subjects. In order to earn the right to share their advice, subjects have to win a first-price auction (be willing to pay the most for the opportunity to share).

We find that subjects produce all kinds of advice, including rational advice that describes the independence of actions and outcomes. But, strikingly, about 18 percent of the advice given weaves in the auxiliary variable to produce *causal* narratives almost identical to those we ourselves constructed, pointing out the same patterns in the data. Furthermore, subjects that generate these narratives are, on average, willing to bid more than other subjects, thereby demonstrating a stronger preference to share their narratives.[8] Almost all of the generated causal narratives are lever narratives, suggesting that they come more naturally to subjects than threat narratives.

Our third, and final, experimental treatment (NATURAL) is almost identical to the first except that instead of providing subjects with constructed narratives, we provide them with the narratives produced by subjects in the second experimental condition. Because these narratives contain causal narratives as well as other types of narratives, we are able to compare different types. We find that causal narratives produce the largest changes in beliefs and policy choices, significantly larger than those that correctly describe the actions and outcomes as being independent.[9] The results of the second and third experimental conditions, taken together, demonstrate how causal narratives can be generated and transmitted with the sole intent of being helpful, while ultimately misleading those who hear them.

Narratives have only recently begun to receive attention within economics (Shiller 2017, 2019). A growing literature has made important contributions in providing ways to think about narratives theoretically. For our purposes, Eliaz and Spiegler (2020), building on Spiegler (2016) is critical, as we test the predictions of their innovative conceptual framework which represents narratives as causal graphs that weave in auxiliary variables. Schwartzstein and Sunderam (2021) and Izzo, Martin, and Callander (2021) consider how a principal can persuade an agent through a narrative represented as a model of the underlying DGP.[10] Although we don't test

[8]Subjects that produce the causal narratives deviate more from the rational policy than other subjects. They are also more certain of their policy choices.

[9]Subjects also rate the causal narratives as being most helpful.

[10]See also Benabou, Falk, and Tirole (2018), who theoretically study narratives as they relate to morality norms.

these models explicitly, our experiment provides some of the first available evidence that persuasion via models (as opposed to signals or Bayesian persuasion experiments (Kamenica and Gentzkow (2011)) can be effective.

On the empirical side, in the paper closest to ours, Andre et al. (2022) survey people about the causes of recent inflation and map their responses to DAGs. They also test the power of narratives to influence (self-reported) inflation expectations. The paper complements ours in that it demonstrates that people generate causal narratives and can be influenced by these narratives in real-world settings. On the other hand, our control over the DGP allows us to more tightly connect the narratives to the DGP, to demonstrate how false narratives can arise, and to engage with the theory more tightly by testing precise theoretical predictions.[11]

Our work also connects to a recent experimental literature studying how people form and get stuck in mental models. Kendall and Oprea (2022) have an experimental task similar to ours in that subjects must form a mental model of a data-generating process. Their focus is on understanding what makes some models more difficult to infer than others, whereas we show that subjects can be attracted to some models (those corresponding to the lever and threat narratives) that are arguably more complex than the true model. Esponda, Vespa, and Yuksel (2021) show that subjects fail to learn that their mental models are incorrect even after extensive experience, similar to our finding that statistical information does not completely overcome the power of narratives. Graeber (2022) shows that people do not attend to all features of a DGP in statistical settings and Enke (2020) shows that people form incorrect mental models by focusing only on the immediate information at hand. In contrast, our results show that subjects 'overattend' to certain features of some datasets.

Neuroscientists have shown that narratives, through their appeal to emotion, cause the brain to more actively engage (e.g., Wallentin et al. (2011); Song, Finn, and Rosenberg (2021)). Our work complements this literature, demonstrating that narratives can have power, not only because of emotional responses or by making connections with those hearing them, but because they create a lens through which to

[11] Other narrative papers include Ash, Gauthier and Widmer (2021) and Flynn and Sastry (2022) who use textual analysis to classify narratives, and Morag and Loewenstein (2021) who show that people that tell stories about items they own, as opposed to simply describing them, ask for higher selling prices.

interpret data causally.

What it means for processes to be causal and how people think about causality is an active area of research outside of economics. Pearl (2009) is an important contribution, first suggesting the use of DAGs to represent causal relationships. Sloman (2009) provides psychological evidence that people form causal stories to make sense of uncertainty.

2 Theoretical Background

2.1 Causal Narratives and Beliefs

We focus on the 'short narratives' of Eliaz and Spiegler (2020) in which there are only three variables involved in the construction of a narrative: an action (a), an outcome of interest (y), and an auxiliary variable (z). All of the variables are binary, taking values 0 and 1, with $y = 1$ being the desirable outcome. The action, a, and the outcome, y, are statistically independent, with $p(y = 1) \equiv \mu$ exogenously given and $p(a = 1)$ to be determined endogenously.[12] We reserve the term DGP for describing the relationship between actions and outcomes. When we include the auxiliary variable, we instead refer to a *dataset*. Table 1 illustrates a pair of datasets which differ only in the auxiliary variables they include. Each consists of a series of observations of the three variables.

The two datasets in Table 1 are constructed with $\mu = \frac{1}{2}$, and the two auxiliary variables given by

$$z^+ = I(a = 1 \textit{ and } y = 1)$$

and

$$z^- = I(a = 0 \textit{ and } y = 1)$$

[12]Independence of a and y follows the setup in the short narratives section of Eliaz and Spiegler (2020), but, more importantly for our purposes, ensures that the belief of a rational DM will differ from that of a DM that fits a causal model to the data.

Table 1. Dataset Examples

a	z^+	y
0	0	0
0	0	1
1	0	0
1	1	1
1	1	1
0	0	1
1	0	0
0	0	0
$\vdots$	$\vdots$	$\vdots$

a	z^-	y
0	0	0
0	1	1
1	0	0
1	0	1
1	0	1
0	1	1
1	0	0
0	0	0
$\vdots$	$\vdots$	$\vdots$

respectively (where $I()$ is the indicator function).[13]

Given a large dataset with z^+ (left table) or z^- (right table), a rational DM would observe that y is equally likely to be 0 or 1 independent of a and therefore form the conditional belief, $p(y = 1|a) = p(y = 1) = \frac{1}{2}$. That is, a rational DM would realize that the auxiliary variable is irrelevant.

Suppose now a DM is presented with the following narrative when studying the dataset with z^+ (left table).

"$a = 1$ is needed to produce $z^+ = 1$. And, $z^+ = 1$ always leads to $y = 1$. So, choose $a = 1$ to produce $y = 1$ more often."

This narrative is completely factual - it can be verified with the data at hand. But, it suggests the false causal relationship in which a influences z^+, which in turn influences y. A DM that hears this narrative might come to believe that she can make $y = 1$ more likely by choosing $a = 1$. That is, she believes $p(y = 1|a = 1) > p(y = 1|a = 0)$.

Now, suppose that the DM is presented with the alternative narrative:

"If $z^+ = 0$, $a = 1$ always leads to $y = 0$. To counteract this, choose $a = 0$ to produce $y = 1$ even if $z^+ = 0$."

Again, this narrative is factual and can be verified in the data. But, unlike the first narrative, this one implies a different causal relationship: z^+ and a both influence y directly. A DM believing it will form the opposite belief, $p(y = 1|a = 1) < p(y =$

[13]These variables arise in the steady state of the competition between narratives in Eliaz and Spiegler (2020) (as $c \to 0$). For our purposes, we chose them because their deterministic nature makes their relationship to a and y easier to pick out in the data.

$1|a = 0)$. So, for the same dataset, different narratives can potentially cause DM's to take different actions.

To understand the importance of the auxiliary variable, consider the dataset with z^- (right table) and the narrative:

"$a = 0$ is needed to produce $z^- = 1$. And, $z^- = 1$ always leads to $y = 1$. So, choose $a = 0$ to produce $y = 1$ more often."

This narrative is very similar to the first narrative, except that a different auxiliary variable is woven into the same DGP. A DM hearing this narrative may come to believe she can make $y = 1$ more likely by choosing $a = 0$ (i.e., $p(y = 1|a = 1) < p(y = 1|a = 0)$). By choosing different auxiliary variables, narratives can potentially cause DM's to take different actions.

The key contribution of Eliaz and Spiegler (2020) is to formalize how these intuitive narratives can lead to mistaken beliefs. In addition to the directional predictions illustrated above, their behavioral theory makes precise point predictions about the beliefs people form.

Eliaz and Spiegler (2020), following Pearl (2009), use directed acyclical graphs (DAGs) to describe causal relationships. The first narrative above is an example of what Eliaz and Spiegler (2020) call a *lever* narrative, a narrative which describes the causal relationship, $a \to z \to y$. Eliaz and Spiegler (2020) assume that a DM, when faced with a causal narrative, will form conditional beliefs according to the Bayesian-network factorization formula associated with the DAG. Under a lever narrative, L, this formula results in the conditional beliefs $p_L(y|a) = \sum_{z=0,1} p(y|z)p(z|a)$. The beliefs follow intuitively from the DAG implied by the lever narrative: $p(z|a)$ captures how a affects z, and $p(y|z)$ captures how z then affects y. For example, for the dataset in Table 1 with z^+, we can calculate the conditional probability using Bayes' theorem:

$$\begin{aligned}
p_L(y = 1|a = 1) &= p(y = 1|z^+ = 1)p(z^+ = 1|a = 1) + p(y = 1|z^+ = 0)p(z^+ = 0|a = 1) \\
&= 1 \cdot \frac{1}{2} + \frac{1}{2} \cdot \frac{1}{2} \\
&= \frac{3}{4}
\end{aligned}$$

so that the DM believes that if she chooses $a = 1$, $y = 1$ will occur with probability three-quarters instead of the true probability of one-half.

The key reason that these mistaken beliefs can arise is that a and z^+, as well as z^+ and y, are in fact correlated in the data because the true DAG is $a \to z^+ \leftarrow y$. Mistaken beliefs arise when the causation between y and z^+ is reversed, much in the same way that reverse causation biases regression estimates.

The second example above is what Eliaz and Spiegler (2020) call a *threat* narrative, one which implies the causal relationship, $a \to y \leftarrow z$ (not to be confused with the true DAG). In this case, the conditional probability associated with the DAG is given by $p_T(y|a) = \sum_{z=0,1} p(y|a,z)$. Now, in addition to reversing the causality between y and z, the threat narrative also implies a direct effect of a on y (instead of on z). For the dataset with z^+ in Table 1, the conditional probability is:

$$\begin{aligned}
p_T(y=1|a=1) &= p(z^+=1)p(y=1|a=1,z^+=1) + p(z^+=0)p(y=1|a=1,z^+=0) \\
&= \frac{1}{4}\cdot 1 + \frac{3}{4}\cdot 0 \\
&= \frac{1}{4}
\end{aligned}$$

Thus, for the same dataset, the theory predicts that threat narratives and lever narratives move beliefs in opposite directions.

More generally, for the dataset with z^+, lever narratives generate beliefs

$$p_L(y=1|a=1) = \mu + (1-\mu)\frac{\mu(1-d)}{\mu(1-d)+1-\mu}$$

and

$$p_L(y=1|a=0) = \frac{\mu(1-d)}{\mu(1-d)+1-\mu}$$

while threat narratives generate beliefs

$$p_T(y=1|a=1) = d\mu$$

$$p_T(y=1|a=0) \quad = \quad d\mu\gamma + (1-d\mu)\mu$$

For threat narratives, we introduce $\gamma \in [0,1]$ as the subjective conditional probability $\gamma \equiv p_T(y=1|a=0,z^+=1)$, which is not pinned down by the data because $a=0$ and $z^+=1$ never occurs.[14]

2.2 From Beliefs to Actions

In our setup, a rational DM interested in maximizing $p(y=1)$ would be indifferent between $a=0$ and $a=1$, because the action does not affect the outcome. To generate point predictions that can be taken to the data, we make the action choice continuous by allowing the DM to choose the probability with which $a=1$ occurs. Furthermore, we associate different policies with different costs to break the indifference of a rational DM. Specifically, we incentivize subjects according to

$$u(y,d) = y - c(d-d^*)^2 \tag{1}$$

where d is the policy choice variable that determines the frequency at which $a=1$ is played (i.e., $d=p(a=1)$), d^* is a policy from which deviations are costly, and c is a scale variable that determines the cost of deviating from d^*. A rational DM would always choose the least costly policy, $d=d^*$, recognizing that d has no influence over outcomes.

Given subjective beliefs, $p_G(y|a)$ induced by a narrative, G, the DM chooses the policy, d, to maximize

$$\max_d d \cdot p_G(y=1|a=1) + (1-d)\cdot p_G(y=1|a=0) - c(d-d^*)^2 \tag{2}$$

Note that a change in d has the direct affect of changing the probability of a which, under the belief that a affects y, changes a DM's expected utility. But, it also has a more subtle indirect effect through learning - a change in d will change the frequency

[14]We could perturb the data-generating process in this case to ensure the conditional probability is well-defined. However, in the experiment, a small perturbation is going to be practically imperceptible so we prefer to allow for any subjective belief in deriving theoretical predictions.

of a and therefore can affect the DM's beliefs, $p_G(y=1|a=1)$ and $p_G(y=1|a=0)$ through changes in the new data generated. We assume the DM does not account for the indirect effect, an assumption we enforce in the experiment by providing subjects with no feedback. Specifically, beliefs are treated as fixed objects representing the beliefs of a DM that has observed a large dataset in which the policy has been held constant at some policy, $d=\delta$.

For a lever narrative with auxiliary variable, z^+, we can solve (2) by substituting the expressions for beliefs and taking the first-order condition. The optimal policy is

$$d = d^* + \frac{1}{2c}\left(\frac{\mu(1-\mu)}{\mu(1-\delta)+1-\mu}\right)$$

Because the causal narrative implies subjective beliefs different from the truth, it distorts policy choices away from what a DM would do if he or she understood the true DGP (choose $d=d^*$). We refer to datasets with auxiliary variable, z^+, as *positive* datasets because lever narratives imply positive policy distortions, $d>d^*$.

Under a threat narrative with z^+ we similarly obtain

$$d = d^* + \frac{1}{2c}\left(\delta\mu(1-\gamma)-\mu+\delta\mu^2\right)$$

which, in general, differs from the optimal policy in the lever narrative case. Thus, different narratives can induce different optimal policy choices for the *same* data, a key prediction we test in the experiment.

Lever and threat narratives with z^- are completely symmetric to the z^+ case because $a=1$ is swapped for $a=0$, resulting in symmetric optimal policies around d^*. We thus refer to datasets with auxiliary variable, z^-, as *negative* datasets because lever narratives imply negative policy distortions, $d<d^*$.

Finally, consider the case in which z is independent of a and y, and equally likely to be 0 or 1. We refer to these datasets as *neutral* datasets, because, in this case, it is simple to show that the optimal policy is the same as under the true DGP, $d=d^*$ for any μ and δ.

Table 2. Behavioral Theory Predictions

	Positive Dataset	Negative Dataset	Neutral Dataset
Lever	0.63	0.37	0.5
Threat	[0.36,0.45]	[0.55,0.64]	0.5

Notes: Predicted policy for each dataset (column) and narrative (row). For threat narratives, a range of policies is predicted because beliefs are not completely pinned down by the dataset.

2.3 Experimental Parameterization

For the experiment, we must choose μ, d^*, δ, and c. We do so with two goals in mind: (i) to be able to observe deviations from the d^* that would be chosen by a subject that understands the true DGP and (ii) to make deviations costly so that any deviation observed is not simply due to a lack of incentives. To satisfy the first goal, we set $d^* = \frac{1}{2}$ so that we can observe deviations in either direction. We then also choose $\delta = \frac{1}{2}$ because if $\delta \neq d^*$, policy choices different from $d^* = \frac{1}{2}$ may be due to subjects trying to match their policy choices to reflect the frequency of actions they observe in the data. Finally, we set $\mu = \frac{1}{2}$ and $c = \frac{4}{3}$. μ is not critical - it mostly determines the level of subject earnings which can be scaled independently. The choice of c is more important as it must strike a balance between goals (i) and (ii): a lower value for c will make deviations from the rational prediction easier to detect, but also reduce the cost from deviating. $c = \frac{4}{3}$ errs on the side of ensuring that deviations do not simply reflect a flat incentive structure.

With these parameter choices, the optimal policies under the lever and threat narratives with z^+ become $d = \frac{5}{8} \approx 0.63$ and $d = \frac{29}{64} - \frac{3}{32}\gamma$, respectively. With $\gamma \in [0, 1]$, the optimal policy under the threat narrative is in the range, $d \in [\frac{23}{64}, \frac{29}{64}] \approx [0.36, 0.45]$, so that the lever and threat narratives produce optimal policies on opposite sides of $d = \frac{1}{2}$. At the same time, the chosen parameters ensure that deviating from $d = \frac{1}{2}$ is costly: a subject that deviates to the most extreme policies (0 or 1) earns 66.7 percent less on average than a subject that chooses rationally. Table 2 summarizes the predictions of the behavioral theory.

Table 3. Datasets in the Experiment

a	z^+	y
GREEN	○	LOW
GREEN	○	HIGH
BLUE	○	LOW
BLUE	▲	HIGH
BLUE	▲	HIGH
GREEN	○	HIGH
BLUE	○	LOW
GREEN	○	LOW
⋮	⋮	⋮

a	z^-	y
GREEN	○	LOW
GREEN	▲	HIGH
BLUE	○	LOW
BLUE	○	HIGH
BLUE	○	HIGH
GREEN	▲	HIGH
BLUE	○	LOW
GREEN	○	LOW
⋮	⋮	⋮

Notes: The left dataset is an example of a positive dataset, and the right is an example of a negative dataset.

3 Experimental Design

We begin by describing the CONSTRUCTED treatment in detail. We then describe the differences for the ELICIT and NATURAL treatments.

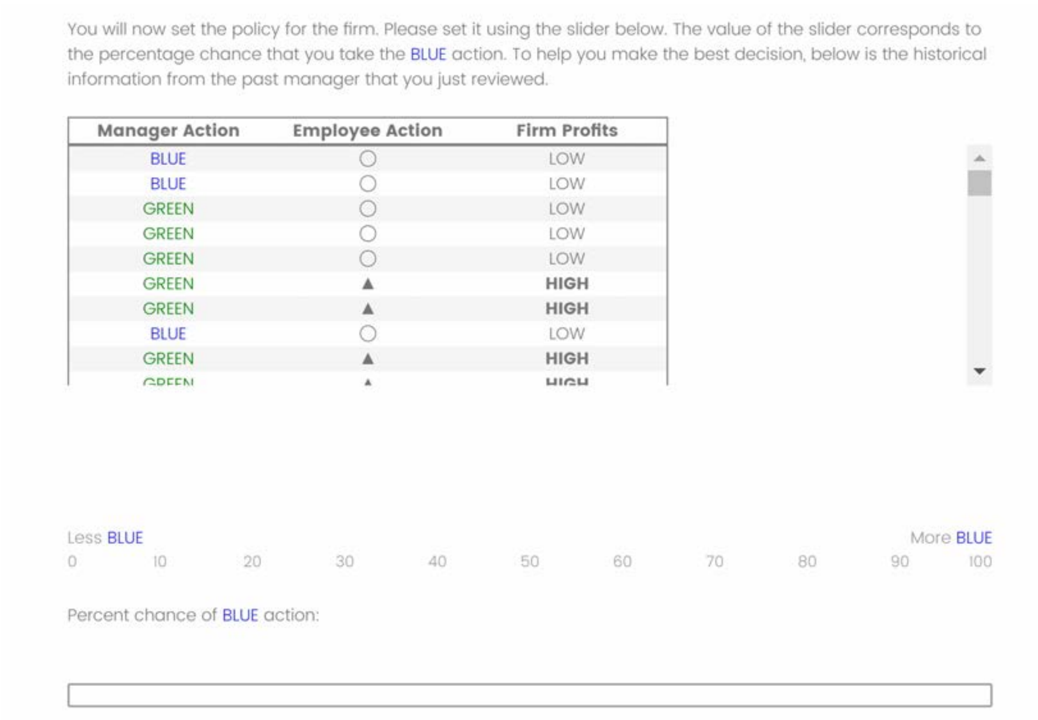
3.1 CONSTRUCTED Treatment

The experiment was designed to closely implement the environment described in the previous section. Subjects observed a dataset consisting of 120 rows of the variables of interest, as illustrated in Table 3 (mirroring the datasets presented in Table 1). We framed the problem as one of a manager choosing a policy, with the variables labeled as manager actions ($a \in \{BLUE(1), GREEN(0)\}$), employee actions ($z \in \left\{\blacktriangle(1), \bigcirc(0)\right\}$), and firm profits ($y \in \{HIGH(1), LOW(0)\}$). Figure 1 provides a screenshot of the step in which we asked subjects to make a policy choice. The screenshot shows a situation in which the subject saw a negative dataset.

Subjects in the CONSTRUCTED treatment observed three datasets: one positive, one negative, and one neutral, in randomized order. For each dataset, they were asked to complete the following tasks in order:

1. We first presented the dataset. To encourage subjects to engage with the dataset, we asked subjects to answer unincentivized questions about whether a particular realization of each variable occurred 'much more often', 'much less

Figure 1. Screenshot



often', or about 'equally as often' in the dataset. We told subjects little about how the dataset was generated, other than the fact that manager actions may or may not impact firm profits and that each row is independent from every other.

2. We asked subjects to choose a policy (the probability with which each action would be taken) using a slider as shown in Figure 1. The outcome, y, then realized and subjects received a payoff according to (1), in dollars. We gave subjects no feedback on the realization of y or their payoff to ensure that their beliefs remain fixed as assumed in the behavioral theory. We endowed subjects with \$0.33 so that their earnings could never be negative.
3. We asked subjects to rate (on a scale from 0-100) how certain they were that their chosen policy maximizes their earnings (these questions were not incentivized).
4. We provided subjects with either a narrative or a statistical summary framed as a consultant providing a policy recommendation. Subjects could review the dataset and the policy recommendation simultaneously, allowing them to form

subjective conditional expectations, $p_G(y|a)$. Subjects then made a second policy choice, rated how certain they were that their policy choice maximizes their bonus, and indicated whether they found the policy recommendation helpful or unhelpful.

5. In this step, we again provided subjects with either a narrative or a statistical summary. If subjects saw a narrative in step 4, we provided a statistical summary in this step, and vice versa. The order of narratives versus statistical summary in steps 4 and 5 was randomized across subjects. As in step 4, subjects could review the dataset and policy recommendation. They then made a third and final policy choice, rated how certain they were of their policy choice, and indicated whether they found the policy recommendation helpful.

A key component of the CONSTRUCTED treatment are the narratives we provided in steps 4 and 5. These narratives were carefully constructed causal narratives, i.e., lever and threat narratives. For each dataset, a subject saw either a lever or a threat narrative, which we randomized across subjects. The lever narrative for a positive dataset was

"The BLUE action is needed to produce an employee action of ▲*. And, an employee action of* ▲ *always leads to HIGH profits. So, choose the BLUE action more often."*

The corresponding threat narrative was

"If the employee action is ○*, the BLUE action always leads to LOW profits. To counteract this, choose the GREEN action more often so that profits can be HIGH even if employees chose* ○*."*

These narratives imply causal relationships between the variables, but, to avoid deception, are worded truthfully, pointing out exact patterns in the data. The narratives also gave policy recommendations, as many narratives do in practice (such as those regarding immigration and gun rights). The narratives for the negative dataset were identical except that BLUE and GREEN are reversed. For the neutral dataset, we presented subjects with a lever or threat narrative that was designed either for the positive or negative datasets (randomized across subjects), and so is easily falsified by looking at the data. We refer to such narratives as *incongruent* narratives and included them in order to identify subjects who blindly follow any narrative, even when it is inconsistent with the dataset. We also ensured that no subject ever saw the same narrative twice.

As described in steps 4 and 5, for each dataset we also presented subjects with a statistical summary that was framed as a policy recommendation. This statistical summary was a 2x2 table which summarized how often $y = 1$ and $y = 0$ occurred for each action in the dataset.[15] In addition to summarizing the data, the summary information explicitly told subjects to choose $d = 0.5$, arguing that the table shows that actions have no impact on firm profits.

Given three policy choices per dataset and three datasets, subjects made a total of nine incentivized policy choices. We paid for one randomly selected choice.

3.2 ELICIT Treatment

The goal of the ELICIT treatment is to elicit narratives. Subjects in this treatment completed steps 1, 2, and 3 described above. After completing step 3, subjects were given a free-form text box and asked to provide specific advice to future subjects. We endowed each subject with \$1.00 which they could use to bid in a first-price auction with nineteen other subjects. The winner's advice was provided to 40 future subjects (on average) and the winner was paid \$0.025 for each future subject that rated the advice as helpful. We broke ties for the highest bid in the auction randomly. We told subjects that if their advice was not specific (didn't explicitly or implicitly imply a policy choice), it would be excluded from the auction.

As in the CONSTRUCTED treatment, subjects completed these tasks for each of three datasets: positive, negative, and neutral, in randomized order. After completing all of the tasks for the third and final dataset, we gave subjects a policy recommendation consisting of a statistical summary table as in the CONSTRUCTED treatment. Subjects were then asked to make a second policy choice for the third dataset and to state how certain they were about their policy choice. We chose one of the four policy choices, and one of the three auctions randomly for payment.

[15] The summary table always showed that each action led to exactly the same frequency of $y = 1$ in order to ensure that it revealed the true DGP exactly. To do so, we generated the datasets by fixing the number of rows with each possible combination of variables and randomly ordered the rows across subjects.

3.3 NATURAL Treatment

The NATURAL treatment is identical to the CONSTRUCTED treatment except for the source of the narratives. In NATURAL, the narratives came from subjects that had bid the most in ELICIT for the right to share their advice (and subjects in NATURAL were made aware of this fact). The narratives for each of the positive and negative datasets came from a previous subject that saw a corresponding dataset. For the neutral dataset, we replaced the statistical summary with the advice from a subject that saw a neutral dataset. As in CONSTRUCTED, the narrative for a neutral dataset is one which we constructed for one of the other datasets.

3.4 Implementation

We ran all treatments online in June of 2022 using Qualtrics with custom Javascript coded by the authors. We recruited a sample of the U.S. population, balanced between men and women, using Prolific (average age of 38.7). All sessions began with detailed instructions (replicated in Appendix B), after which subjects had to successfully answer several comprehension questions before continuing. We recruited 201 subjects in ELICIT, who earned an average of \$3.80 for an average of 19.2 minutes of their time (\$11.88 per hour).[16] In NATURAL, we recruited 401 subjects, who earned an average of \$3.42 for an average of 18.4 minutes of their time (\$11.18 per hour). Finally, in CONSTRUCTED, we recruited 403 subjects who earned an average of \$3.42 for an average of 17.9 minutes of their time (\$11.45 per hour). These wage rates are almost 50% higher than the minimum Prolific requires (\$8 per hour).

3.5 Understanding the Design

The experimental design was intended to achieve a series of goals.

First, we wanted to compare naturally-occurring narratives to purposefully constructed narratives, a contrast provided by NATURAL and CONSTRUCTED. Constructed narratives correspond to the narratives that are purposefully designed (e.g., by politicians, political consultants, or advertising departments). Natural narratives

[16] We targeted 200 subjects, but ended up with 201 because Prolific recruited an extra subject after falsely indicating that another had timed out. The odd numbers in the other treatments arose similarly.

are instead those that arise endogenously with, at least in our case, the intention of being helpful.

Second, we wanted to test whether the effects of narratives can be overcome with factual statistical information that invalidates the narrative, which is the reason we provided this information to subjects in NATURAL and CONSTRUCTED. For each dataset, we randomized whether subjects saw this statistical information before or after they saw a narrative.

Third, we provided subjects with both positive and negative datasets so that we can test whether, for the same true DGP, narratives with different auxiliary variables can induce different choices. If so, it suggests that politicians and others that want to manipulate people can do so by choosing the auxiliary variable they weave into their narrative.[17]

Fourth, we wanted to see whether subjects would generate causal narratives on their own. The ELICIT treatment serves this purpose by incentivizing subjects to give advice to future participants. To the extent that not all naturally-generated narratives are the same, this treatment allows us to observe which types of narratives are most effective. Subjects were paid for their advice based on its perceived helpfulness instead of for the policy choices future subjects make. As such, subjects providing advice had no incentive to try to manipulate future subjects because their incentives were aligned. Future research should consider the effectiveness of narratives when a conflict of interest is present.

Fifth, we purposefully framed the environment in a particular way. We wanted subjects to understand that high profits are desirable, so labeled profits as $HIGH$ and LOW. But, for manager and employee actions, we did not want subjects to have any prior about how actions might map to profits and therefore gave them neutral labels.[18]

Sixth, we took seriously the possibility that subjects may respond to narratives regardless of whether or not they are coherent with the observed dataset. Such behavior could be interesting in the sense that narratives might work even when

[17] A key result of Eliaz and Spiegler (2020) is that, in equilibrium, a pair of narratives with different auxiliary variables co-exist.

[18] For example, if we had labeled manager actions as high and low effort, a likely prior would have been that high effort is more likely to lead to high profits.

inconsistent with data, but could also potentially reflect subjects simply not paying attention or trying to do what the experimentalist desires (a demand effect). In any case, to identify such subjects, we presented subjects with incongruent narratives in both the NATURAL and CONSTRUCTED treatments. Specifically, in neutral datasets, we presented subjects with either a lever or threat narrative constructed for one of the other datasets. Since these narratives are inconsistent with the neutral dataset, they can be easily falsified by looking at the dataset.

Lastly, we randomized the order of the rows in a dataset across subjects to prevent any idiosyncrasy of the dataset from driving the results.

4 Results

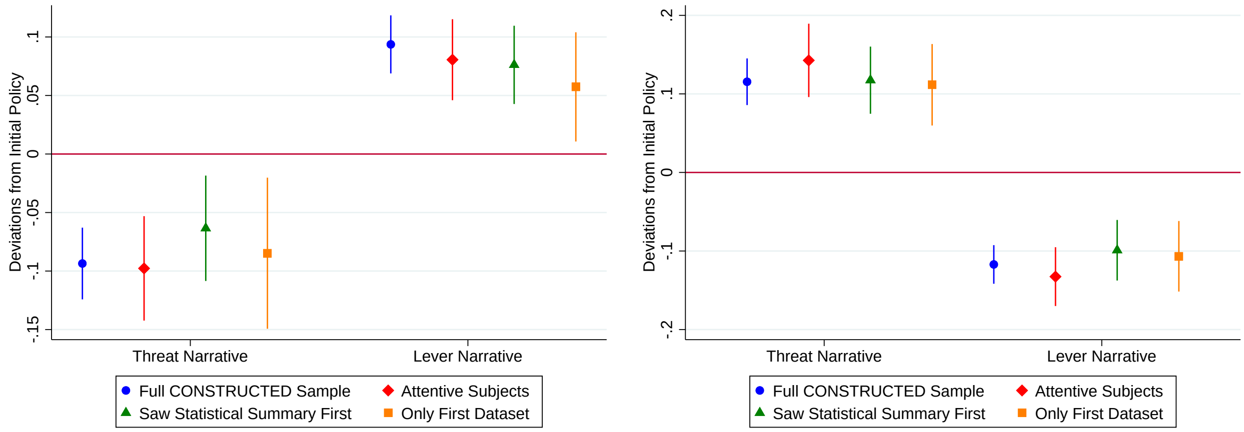
We present the results of the CONSTRUCTED treatment first, showing that carefully crafted narratives are capable of influencing actions. We then present the results of the ELICIT treatment, showing that subjects formulate a wide variety of narratives, including narratives very similar to the ones we constructed. Lastly, we compare the results of the NATURAL treatment to those of the CONSTRUCTED treatment. We find that, on average, homegrown narratives are not as effective as the narratives we constructed, but those most similar to ours are almost as influential.

4.1 CONSTRUCTED Treatment

4.1.1 Deviations from Initial Policies

In the CONSTRUCTED treatment, we study the effects of narratives that someone (e.g., a politician or consultant) might construct. We are interested in testing two predictions of the behavioral theory: (i) do different auxiliary variables, with their corresponding narratives, induce opposite deviations from the rational policy for the same underlying DGP, and (ii) do lever and threat narratives induce opposite deviations from the rational policy for the same dataset? To test these predictions, we compare the differences between subjects' chosen policies after they observe narratives and their initial policies for each combination of auxiliary variable (z^+ and z^-) and narrative. Here, we focus on deviations from initial policies to account for het-

Figure 2. Deviations from Initial Policies - CONSTRUCTED



Notes: Deviations from initial policies in the CONSTRUCTED treatment. The left panel is for positive datasets and the right for negative datasets. Attentive subjects refers to subjects who chose policies in the range $[0.48, 0.52]$ when the narrative was incongruent with the dataset. The bars show 95% confidence intervals using standard errors clustered by subject.

erogeneity in initial policies across subjects. In the following subsection, we compare final policies to the predictions of the rational and behavioral theories.

In the left panel of Figure 2, we plot the average deviation from the initial policy for subjects who saw a threat narrative (blue circle on the left) and for subjects who saw a lever narrative (blue circle on the right) for a positive dataset. In this dataset, the threat narrative supports a policy in the range $[0.36, 0.45]$, while the lever narrative supports a policy of 0.63. Therefore, we expect subjects who see a threat narrative to adjust their policies downwards and subjects who see a lever narrative to adjust their policies upwards, on average. Our results confirm this prediction: threat narratives push policies down by 0.094 and lever narratives push them up by the same amount.

In the right panel of Figure 2, we plot the same results for negative datasets. Recall that the only difference between positive and negative datasets is in the the auxiliary variable. In a negative dataset, the threat narrative supports a policy in the range $[0.55, 0.64]$, while the lever narrative supports a policy of 0.37. As predicted by theory, subjects now adjust their policies downwards if they see a lever narrative, and upwards if they see a threat narrative, with effect sizes very similar to those in the left panel. Overall, the results in Figure 1 show that narratives affect subjects' policies in the directions predicted by the behavioral theory, and that threat and lever narratives are equally effective. The fact that different auxiliary variables can be woven into narratives with opposite effects demonstrates how, given a rich variety of auxiliary variables to choose from, people can spin narratives that support either action. For instance, politicians with different partisan leanings can spin different stories, potentially polarizing their supporters.

Result 1: *Lever and threat narratives induce opposite responses for the same dataset. Different auxiliary variables for the same underlying DGP also induce opposite responses. Both results confirm the predictions of the behavioral theory.*

One potential concern with these results is that subjects might blindly follow any narrative – regardless of whether or not it makes any sense for the dataset – either because they are not paying attention or because they want to please the experimentalist. To address this concern, we identify such subjects and construct a subsample in which we remove them, leveraging the fact that subjects are presented with incongruent narratives in neutral datasets. These narratives can easily be falsified by looking at the dataset and should therefore not affect the policy choices of subjects who are paying attention and not responding to experimenter demand. We retain only subjects who choose a policy of $[0.48, 0.52]$ when faced with an incongruent narrative[19], re-estimate the effects for these *attentive* subjects, and plot the results using the red diamonds in Figure 2. We find that the effects of narratives are just as strong among subjects who do not blindly follow narratives, suggesting that neither experimenter demand nor inattention are driving our findings.

Result 2: *The effects of narratives are equally strong among subjects that do not respond to incongruent narratives, i.e., narratives that contradict the dataset.*

Having shown that narratives affect policies as predicted by the theory, a natural question is whether factual statistical information can curtail the persuasive power of these narratives. If subjects understand the true relationship between actions and outcomes, can narratives still have an effect? All subjects in our experiment see factual statistical information which clearly explains why the rational policy of 0.50

[19]The average deviation from the rational policy of 0.50 is -0.028 if the incongruent narrative supports a negative deviation, and +0.035 if it supports a positive deviation. By retaining only subjects who deviate by no more than +/- 0.02 from the rational policy, we remove 225 subjects, which corresponds to removing 56% of the sample. Our results are robust to using the more strict criterion of retaining only subjects who choose a policy of precisely 0.50.

is optimal, but whether subjects see this information before or after the narrative is randomized across subjects and datasets. We exploit this randomization and plot the effect for subjects who see the factual statistical information *before* the narrative using the green triangles in Figure 2.[20]

In this sample, the effect of narratives is reduced by 20-30% but remains strong and statistically significant. In fact, we cannot reject the hypothesis that the statistical information has no effect. Indeed, this result also holds, with a near identical magnitude, for the sample of attentive subjects who do not blindly follow narratives (not displayed in the graphs). These results are particularly striking, because, as we show in the following subsection, the statistical summaries are themselves quite effective in producing rational policy choices, suggesting that narratives can still have effects even after subjects appear to understand the true relationship in the data (recall that subjects make separate policy choices after receiving the narrative and the statistical summary). One interpretation of this result is that subjects narrowly frame each of their decisions. But to the extent that subjects consider both of the conflicting policy recommendations they have seen, another interpretation is that subjects adopt the more 'hopeful' one, as hypothesized in Eliaz and Spiegler (2020).[21]

Result 3: *Factual, statistical information reduces but does not eliminate the effect of narratives, even among attentive subjects who do not respond to incongruent narratives.*

Finally, we test whether the narrative that a subject sees in the first dataset has a stronger effect than narratives in later datasets. The idea behind this test is that subjects might learn over the course of the experiment. Since the three datasets that subjects see differ only in the auxiliary variable, it is possible that subjects are not misled by narratives once they have seen the statistical summary of the first

[20]For each dataset, we pool all subjects who saw the statistical information for that dataset before a narrative, regardless of the order in which subjects saw the three datasets. To the extent that there is learning across datasets, our test is conservative because subjects in the pooled sample will have seen at least one statistical summary, with some having seen two or three statistical summaries.

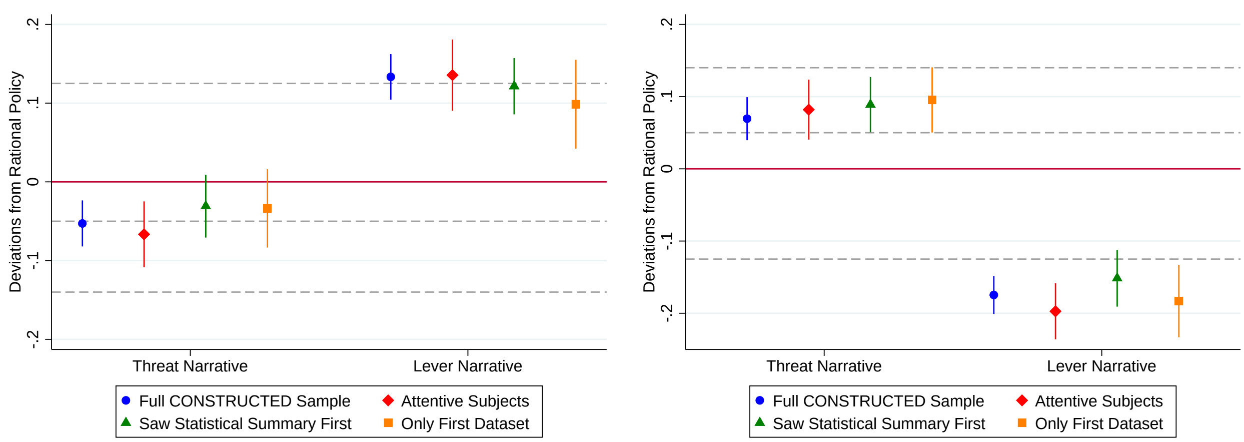
[21]The more hopeful recommendation is the one that induces beliefs that deliver the highest expected utility (what Eliaz and Spiegler call anticipatory utility). The statistical information induces rational beliefs so that the optimal policy delivers an expected utility of $0.5(0.5) + 0.5(0.5) = 0.5$. Both lever and threat narratives deliver higher expected utility. A lever narrative gives $0.63(0.75) + 0.37(0.25) - \frac{4}{3}(0.63 - 0.5)^2 = 0.55$, and a threat narrative gives $0.45(0.25) + 0.55(0.75) - \frac{4}{3}(0.45 - 0.5)^2 = 0.52$ or more, depending on the subject's subjective belief.

dataset. We use orange squares in Figure 2 to plot the effect for subjects who see the corresponding dataset as their first dataset. The effect size is very similar to the effect in the whole sample (blue circles), suggesting that narratives continue to have similar effects in later datasets.

4.1.2 Deviations from Rational Policies

In the tests thus far, we used deviations from subject's initial policies to estimate the effect of narratives. This approach has the advantage that we can flexibly account for initial policy variation across both subjects and datasets. However, to test the point predictions, we instead use deviations from the rational policy of 0.50.

Figure 3. Deviations from Rational Policies - CONSTRUCTED



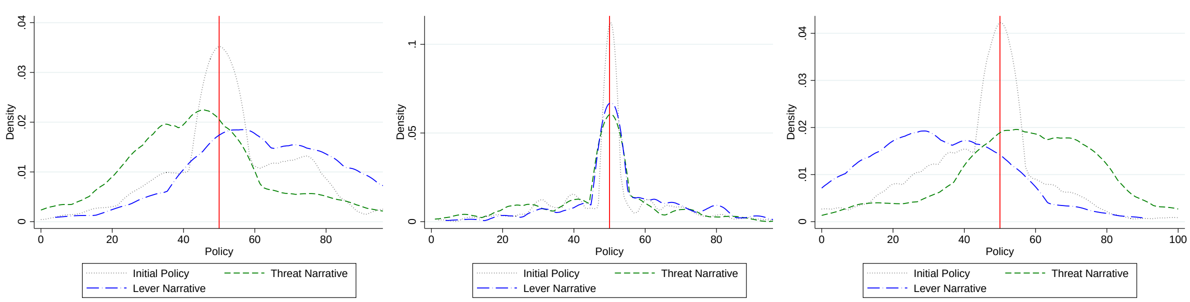
Notes: Deviations from rational policies in the CONSTRUCTED treatment. The left panel is for positive datasets and the right for negative datasets.. Attentive subjects refers to subjects who chose policies in the range $[48, 52]$ when the narrative was incongruent with the dataset. The bars show 95% confidence intervals using standard errors clustered by subject.

Figure 3 plots these deviations for the same subsets of the data as in Figure 2. The dashed gray lines in the graphs indicate the predictions of the behavioral theory for each type of narrative. Recall that this theory gives a point prediction for lever narratives, while it only gives a range of predictions for threat narratives. We find that, for the most part, subjects' policies are remarkably close to the predictions of the behavioral theory. Since the confidence intervals almost always contain the predictions of the theory, we cannot reject the null hypothesis that subjects choose the policies predicted by the theory, except for deviations that are slightly *larger* than predicted for lever narratives in negative datasets. In contrast, with the exception of two estimates in the positive dataset, we can reject the null hypothesis that subjects are choosing the rational policy.

Result 4: *On average, subjects' policies match the point predictions of the behavioral theory, except in one case in which subjects deviate more than predicted. We can reject the null hypothesis that subjects choose the rational policy in all but two cases.*

Figure 3 also shows that deviations from the rational policy are larger for lever narratives than for threat narratives. While this finding may seem at odds with our results from Figure 2, where we show that lever and threat narratives affect subjects equally, it foreshadows a result of Section 4.2: subjects tend to identify lever narratives from datasets without guidance, but fail to identify threat narratives. Thus, their initial policies tend to lean in the direction a lever narrative would imply so that, after responding to a lever or a threat narrative equally, lever narratives produce larger deviations from the rational policy of one-half. We explore this tendency in more detail in Section 4.2.

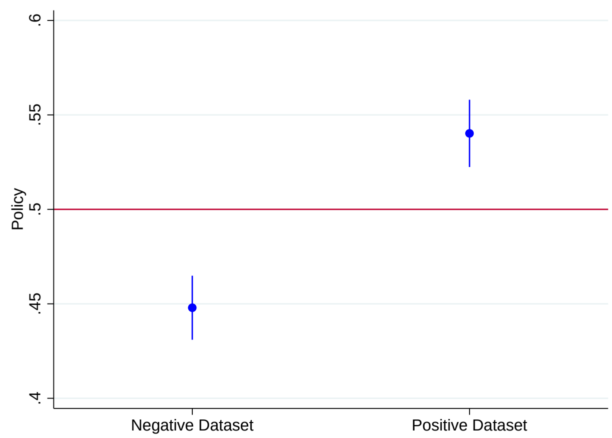
Figure 4. Heterogeneity in Policy Choices - CONSTRUCTED



Notes: Kernel density estimates of policy choices in the CONSTRUCTED treatment. The left panel is for positive datasets, the middle for neutral datasets, and the right for negative datasets.

The average effects shown in Figure 3 mask significant heterogeneity. Figure 4 plots kernel density estimates of subjects' policy choices in each of the three types of datasets. The most striking finding is that the distributions of policies in neutral datasets are quite tight, regardless of the type of narrative, suggesting that subjects do not respond strongly to incongruent narratives. On the other hand, we see much larger movements for narratives in the positive and negative datasets, consistent with the average effects. Further, the tendency for initial policies to lean in the direction implied by a lever narrative is also apparent in Figure 4: for positive datasets, the mass of initial policies is slightly right-skewed and conversely in negative datasets. We further confirm this tendency in Figure 5, which plots average initial policy choices, showing that they are smaller than 0.5 in the negative dataset and larger than 0.5 in the positive dataset.

Figure 5. Initial Policies - CONSTRUCTED



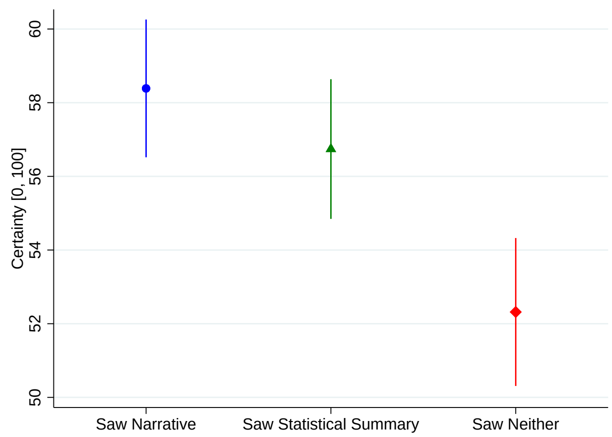
Notes: Initial policies in the CONSTRUCTED treatment. The bars show 95% confidence intervals using standard errors clustered by subject.

Lastly, we find that statistical information moves policy choices to the rational policy of 0.5: the average policy choices after observing the statistical information are 0.53, 0.47, and 0.51, in positive, negative, and neutral datasets, respectively (not shown in a figure). When combined with the results of the previous subsection, these results indicate that narratives can be effective even *after* subjects have comprehended the statistical information that contradicts the narrative: they make rational policy choices when seeing the statistical information, but then change their policy choices upon seeing the narrative.

4.1.3 Confidence

Recall that after each policy choice, we elicited subjects' confidence (certainty) that their chosen policy maximizes their bonus. As an alternative way of gauging the effectiveness of narratives, we test whether subjects are more confident in their policy after seeing a narrative. Figure 6 plots average certainty for policies chosen after a subject saw a narrative, after a subject saw the statistical summary, and before a subject saw either of them (i.e., representing confidence in initial policy choices). After seeing a statistical summary or a narrative, subjects are significantly more confident in their policies, and subjects are most confident after seeing a narrative. Thus, not only are narratives effective at changing beliefs, they also appear to be able to instill certainty in decisions.

Figure 6. Confidence - CONSTRUCTED



Notes: Average subject certainty in their policy choices in the CONSTRUCTED treatment. The bars show 95% confidence intervals using standard errors clustered by subject.

4.2 ELICIT Treatment

The results from the CONSTRUCTED treatment illustrate the persuasive power of narratives. Narratives can obviously be constructed but can they also arise naturally? Do subjects formulate narratives after studying a dataset, and, if so, what types of narratives? And, how does their willingness to pay to pass on any narratives they construct vary with the type of narrative? The design of the ELICIT treatment allows us to answer these questions.

Subjects in the ELICIT treatment observe the same three datasets as subjects in the CONSTRUCTED treatment. For each dataset, they give free-from advice, which can be passed on to future subjects by bidding for the right to pass it on in a first-price auction. We investigate how future subjects respond to this advice in Section 4.3 – here, we are primarily interested in analyzing which types of advice subjects produce and how they bid for the right to pass on that advice.

Subjects, for the most part, followed our instructions, providing advice that explicitly or implicitly recommended a policy choice. However, 36% of subjects provided generic advice such as "be attentive to every clue they give in the environment". As we told subjects we would do, we excluded such advice from the auction because it indicates a lack of attention to the instructions.[22]

We classify the remaining 64% of advice into three broad categories: causal narratives, other narratives, and neutral narratives. Causal narratives are those very similar to the narratives we constructed for the CONSTRUCTED treatment (e.g., "Blue management policy combined with the triangle action from the employees has historically always lead to high profits."). 'Other' narratives suggest a policy recommendation without a lever or threat construction (e.g., "It appears that mostly the blue has profits.").[23] Finally, neutral narratives are those created by subjects who were not misled by the auxiliary variable, but instead described the true DGP, sometimes perfectly (e.g., "It matters not whether the blue or green option is chosen. There's a 50/50 likelihood of one option being favorable with the other unfavorable.").

Of all the advice elicited for positive or negative datasets, we classified 18% as causal narratives, 31% as neutral narratives, and 51% as other narratives. Of the 18% causal narratives that subjects identified, the vast majority (89%) are lever narratives. This finding shows that subjects find it easier to identify lever narratives in the raw data, which is consistent with choosing initial policies that lean in the direction implied by them as we showed in the previous subsection. In Section 5, we discuss potential reasons for this strong imbalance across narrative types.

Result 5: *Subjects produce causal narratives after simply observing a dataset containing auxiliary variables.*

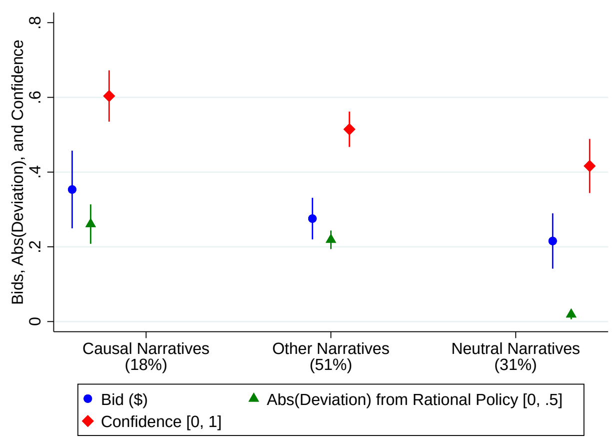
In Figure 7, we show that subjects who identify a causal narrative bid most for the right to pass on their narrative, deviate most from the rational policy, and are

[22]Each co-author independently decided whether each piece of advice provided an explicit or implicit recommendation, and we conservatively excluded only advice that both of us decided did not. In Appendix C, we provide the details of our classification procedure and provide all of the advice we elicited.

[23]One possible for reason for narratives that give a policy recommendation but don't give a causal story is that subjects may be picking up on a pattern corresponding to a causal narrative in the data, but may not be able to articulate it (Kendall and Oprea, 2022).

most confident about their policy choice, although not all of these differences are statistically significant at conventional levels. Overall, these results show that subjects who identify a causal narrative are more bullish about their narrative compared to subjects who identify non-causal narratives. As a result, causal narratives were more likely to be passed on than narratives that (correctly) describe the independence of actions and outcomes. Specifically, of the narratives that were passed on from positive or negative datasets, 25% are causal narratives, 20% are neutral narratives, and 55% are other narratives. The corresponding breakdown of narratives passed on from neutral datasets is: 10% (incongruent) causal narratives, 50% neutral narratives, and 40% (incongruent) other narratives.[24]

Figure 7. Bids, Policies, and Confidence - ELICIT



Notes: Bids, policies, and stated confidence for subjects in the ELICIT treatment. The bars show 95% confidence intervals using standard errors clustered by subject.

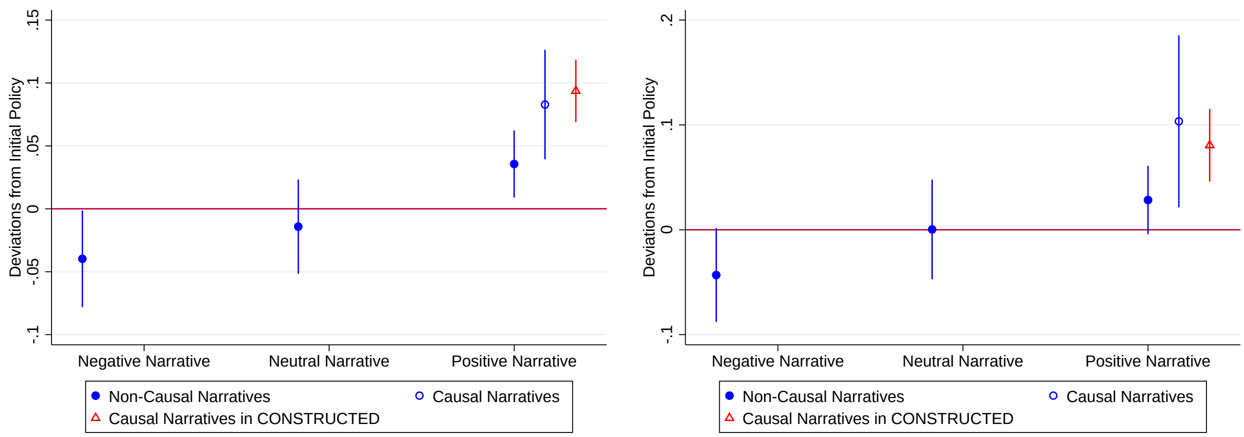
4.3 NATURAL Treatment

In the NATURAL treatment, we present subjects with the narratives produced by the subjects in the ELICIT treatment. These narratives contain both causal and non-causal narratives, allowing us to test whether causal narratives have a stronger effect. As in Section 4.1.1, we focus on deviations from initial policies to account for

[24]The causal narratives produced in the neutral dataset are surprising, but most likely reflect spillovers from previous datasets. In all cases in which a subject produced a causal narrative in the neutral dataset, that subject had already seen at least one of the other two datasets first.

different initial policies across subjects.[25] Figure 8 decomposes the effects of narratives by type. The filled markers show the effect of non-causal narratives (i.e., neutral and other narratives), while the hollow markers show the effect of causal narratives.

Figure 8. Deviations by Narrative Type - Positive Datasets



Notes: Deviations from initial policies in the NATURAL treatment by narrative type for positive datasets. The left panel is for the full sample and the right panel is for only those subjects that don't deviate when presented with incongruent narratives. The bars show 95% confidence intervals using standard errors clustered by subject.

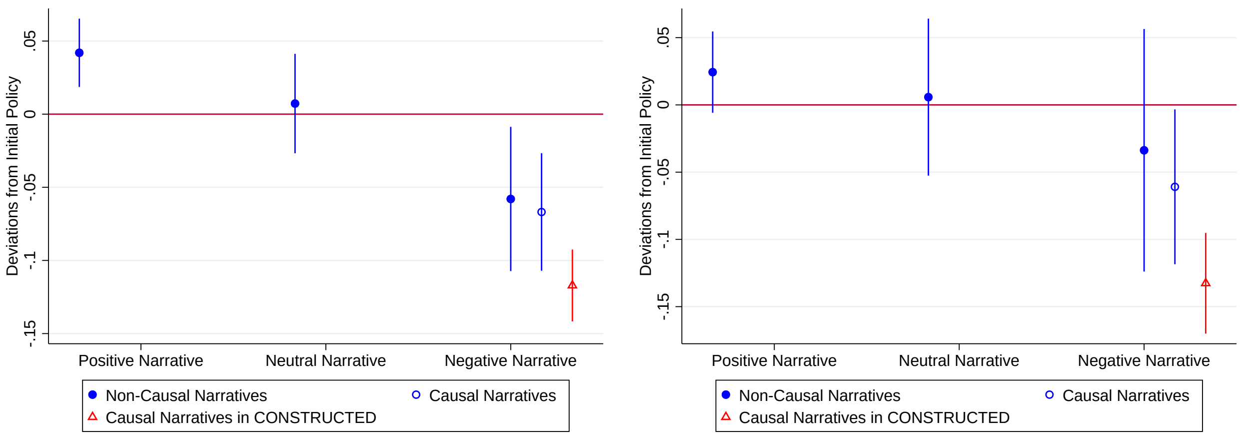
In the left panel of Figure 8 we first present the results of these tests for positive datasets. We find that causal narratives create the strongest deviations from initial policies, but the difference between positive causal and non-causal narratives is not statistically significant.[26] However, we also cannot reject that homegrown causal narratives (hollow blue circles) generate effects as large as the narratives we carefully constructed (hollow red triangles). In the right panel of Figure 8, we replicate these results using only attentive subjects - those that do not blindly follow narratives. The picture is very similar – in fact, causal narratives are the only narratives that result in significant deviations from the initial policy for these subjects. In Figure 9, we show similar results for negative datasets, although the difference between homegrown and

[25]For completeness, in Appendix A, Figures A1 and A2, we replicate Figures 1 and 2 using data from the NATURAL treatment. Overall, the results are similar but slightly weaker, because not all narratives in NATURAL are causal narratives.

[26]One reason subjects may follow non-causal narratives is that just the suggestion that one policy or another is better makes them discover the patterns corresponding to the causal narratives themselves.

constructed causal narratives is larger in this dataset.[27]

Figure 9. Deviations by Narrative Type - Negative Datasets



Notes: Deviations from initial policies in the NATURAL treatment by narrative type for negative datasets. The left panel is for the full sample and the right panel is for only those subjects that don't deviate when presented with incongruent narratives. The bars show 95% confidence intervals using standard errors clustered by subject.

Result 6: *Causal narratives lead to the strongest deviations. Causal narratives that subjects produce are almost as effective as carefully constructed causal narratives, and are the only endogenously grown narratives that have effects among attentive subjects.*

The above results show that causal narratives, even when endogenously grown, tend to perform better than non-causal narratives.[28] Another way to gauge the performance of causal narratives is to ask subjects directly which narratives they find most helpful. In Figure 10, we show that subjects find causal narratives significantly more helpful – even compared to the neutral narratives describing the true underlying DGP.

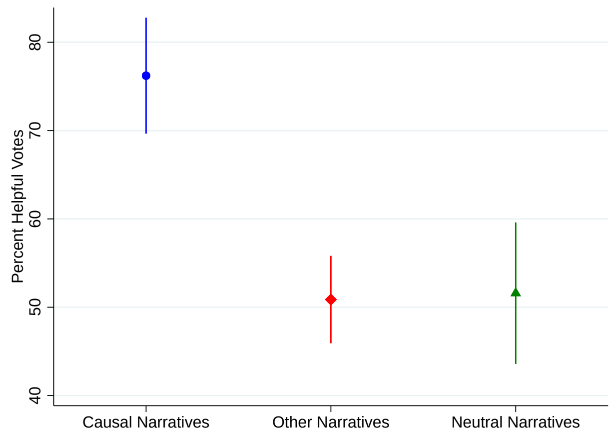
Finally, when we compare the expected value of winning the auction based on the average helpfulness rating ($0.57) to the average winning bid ($0.81), it is clear that subjects, on average, overbid in the auction. However, those that generated causal narratives, were more well-calibrated: the average winning bid was $0.73 which is

[27] In Appendix Figure A3, we show similar results using deviations from the rational policy.

[28] The fact that subjects respond to causal narratives generated by previous subjects is further evidence that responses to causal narratives are not driven by demand effects, because it's not clear why subjects would choose to follow the advice of previous subjects to please the experimentalist.

actually slightly less than the expected value of winning the auction ($0.76) with this type of narrative.

Figure 10. Rated Helpfulness - NATURAL



Notes: Percentage of narratives rated as ‘helpful’ (versus ‘unhelpful’). Pooled across the positive and negative datasets only.

5 Discussion

Taking a cue from recent theoretical advancements, we empirically study causal narratives, narratives which weave variables into a causal story. We find that these narratives affect people’s actions because of the way they manipulate people’s beliefs about the relationships between variables. Importantly, these results lend support to Eliaz and Spiegler’s (2020) theory of how people form beliefs and act upon them, allowing narratives to be incorporated into economic models in a tractable and meaningful way.

We then show that people construct causal narratives after simply observing patterns in the data, and are willing to pay to share them with others. The causal narratives people construct are more influential than other narratives, even those that describe the true DGP. Thus, while we certainly do not claim causal narratives are the only types of narratives with the potential to influence others, we do believe that causal stories make up an important part of why narratives are so influential.

Although narratives can undoubtedly be used for good, our results highlight how misspecified models of the world can arise, be transmitted as narratives, and mislead decision-makers, all with no malicious intent. These results obviously have troubling implications, raising the question as to what can be done to counteract their effects. We considered the possibility that, when confronted with overwhelming statistical information that invalidates the narrative, people will ignore the narrative. However, we find that such information only marginally diminishes the power of causal narratives.[29] Future work should consider other ways in which causal narratives might be overcome, perhaps by attempting to explain exactly why the narratives are misleading.

Our finding that lever narratives are generated much more often than threat narratives suggests that these types of narratives may be generated more often outside of the lab too.[30] Although we can't be certain why lever narratives are more popular, we consider two possibilities that future work should explore further. First, lever narratives may be simpler in that they involve a one-way causal chain ($a \to z \to y$) that may come more naturally to people because it only involves marginal distributions. Threat narratives, on the other hand, can only be constructed by understanding the joint effect of actions and auxiliary variables on outcomes ($a \to y \leftarrow z$), which requires understanding a more complex joint distribution. Second, Eliaz and Spiegler (2020) point out that threat narratives generically violate a desirable technical property of narratives they call "non status quo distortion".[31] Someone accepting a threat narrative has to accept the contradiction that the policy that was implemented in the past should have produced a distribution over outcomes different from the one observed, which may make the formation of such narratives less likely.[32]

We explored causal narratives in a particularly simple setting: (i) outcomes are uncorrelated so that the rational prediction stands in stark contrast to the predictions

[29] In our experiment, narratives and statistical information are exogenously assigned. If, as Bursztyn et al. (2022) find, people prefer opinion programs to straight news, people may select into hearing misleading narratives over statistics, exacerbating the problem.

[30] On the other hand, a very popular form of narrative - superstitions - take a threat form. For example, the advice to 'knock on wood' to counteract some malevolent force is a prototypical threat narrative.

[31] Lever narratives, on the other hand, satisfy non status quo distortion. It is easily verified that non status quo distortion is satisfied for the lever narratives we constructed, but not for the threat narratives.

[32] However, under this explanation, we might also expect threat narratives to also be less impactful, which we do not find.

of the narrative theory, and (ii) auxiliary variables are deterministic. It would be interesting to see whether causal narratives can influence beliefs when a true causal relationship exists, both when the narrative highlights the true relationship, but also when it contradicts it. To do so, one would likely have to introduce some randomness in the auxiliary variables and underlying DGP to avoid the problem from becoming completely trivial. It could be that, as with our results, the behavioral theory continues to predict well in noisy environments with some underlying relationship between actions and outcomes. But, ultimately, this is an empirical question, one which seems to be a natural next step in understanding the power of causal narratives.

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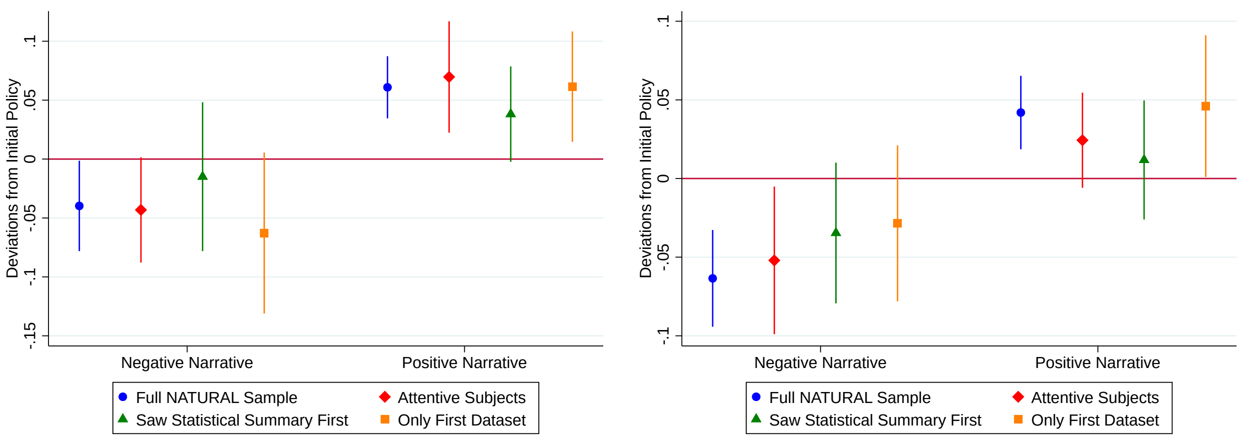
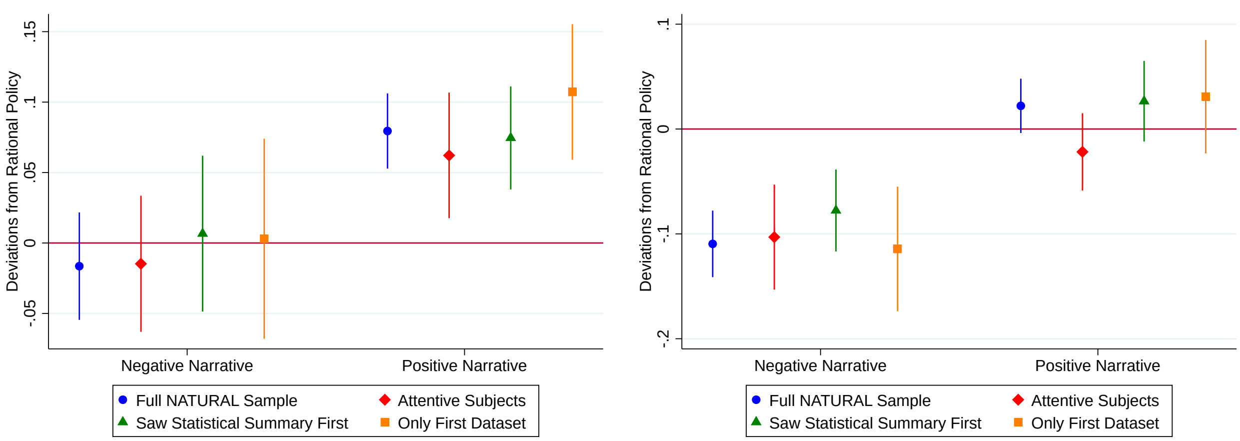
Appendix A: Additional Figures and Tables

Figure A1: Deviations from Initial Policies - NATURAL



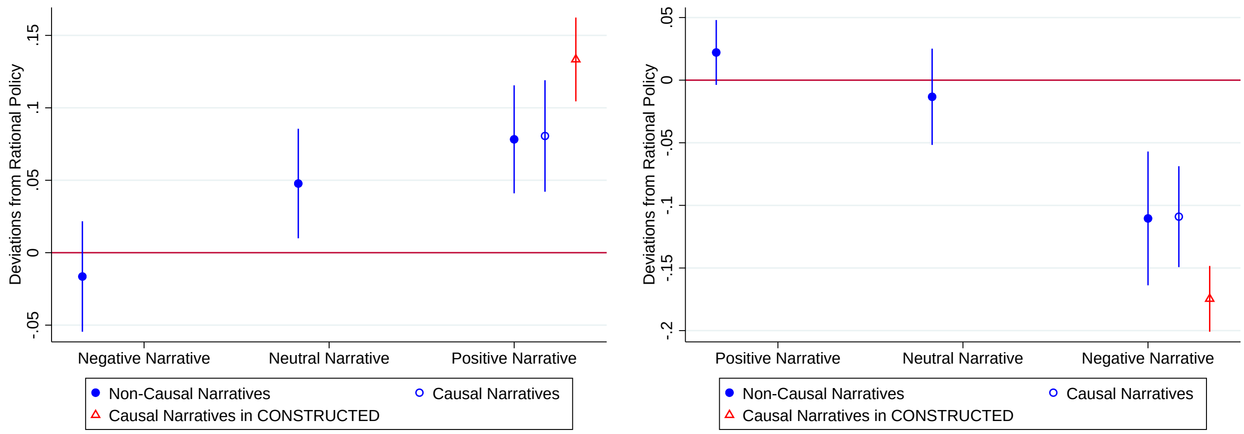
Notes: Deviations from initial policies in the NATURAL treatment. The left panel is for positive datasets and the right for negative datasets. The bars show 95% confidence intervals using standard errors clustered by subject.

Figure A2: Deviations from Rational Policies - NATURAL



Notes: Deviations from rational policies in the NATURAL treatment. The left panel is for positive datasets and the right for negative datasets. The bars show 95% confidence intervals using standard errors clustered by subject.

Figure A3: Deviations from Rational Policies by Narrative type - NATURAL



Notes: Deviations from rational policies in the NATURAL treatment by narrative type. The left panel is for positive datasets and the right for negative datasets. The bars show 95% confidence intervals using standard errors clustered by subject.

Appendix B: Instructions

The instructions for the CONSTRUCT treatment follow.

Restart Survey Place Bookmark Mobile view off Tools

Instructions (Overview)

In this experiment, you will take on the role of the manager of a firm. You will act as the manager of three different firms (in sequence). The three firms are not related in any way, so nothing that you learn about one firm applies to any of the other firms. For each firm, you should only use the information that is provided to you for that firm.

For each of the three firms, you will make three policy decisions. After each policy decision, you will report your confidence in your policy decision. For the second and third policy decisions of each firm, you will receive advice from a consultant before you make your decision. This advice may or may not help you in making your policy decisions -- you should always assess for yourself whether or not the advice makes sense! You will be asked whether or not you found each piece of advice helpful or not.

You will be paid the bonus that results from one of your policy decisions (chosen randomly with equal chance). We describe in more detail how your bonus will be determined on this and the following page.

As the manager, you will set the corporate policy for the firm. The policy determines the probability (percentage chance) you implement one of two actions: the BLUE action or the GREEN action. The policy you choose will have a cost associated with it, and may or may not affect the firm's profits. Your bonus will depend on the firm's profits and the cost of the policy you choose.

You are not sure how the policy you choose will affect the firm's employees or profits. Therefore, to help you choose the policy, you have received access to data on previous firm outcomes over the past 120 months. This data came from a previous manager. It shows the following information for each month:

- Which action was implemented: BLUE or GREEN.
- The action of employees. This action may or may not be related to the manager's action. The previous manager used a code to record the action of employees, but unfortunately did not leave a note stating what the code means. All you know is that the same code always means the same thing. The employee action was coded by the previous manager as ▲ or ◯.
- Whether the profits of the firm were **HIGH** or **LOW**.

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Instructions (Bonus)

Your bonus depends on the policy you choose and the firm's profits. When you choose the policy, you will choose the percentage chance that the BLUE action is implemented. Call this P. The GREEN action will be implemented with the remaining chance. The least costly policy is P=50: the policy in which you implement the BLUE action 50% of the time. If you choose a higher or lower chance of BLUE, the cost is higher.

Specifically, you will get a bonus from two parts (added together):

1. You will receive $1.00 if the firm's profits are HIGH and $0 if the firm's profits are LOW.
2. You will receive 0.33-0.000133x(P-50)^2 where P is the policy you choose. For example, you will receive $0.33 if you choose P=50 but $0 if you choose P=0 or P=100.

When choosing the policy, think carefully! A more expensive policy might be worth it if it increases the chance that the firm makes HIGH profits. When you have finished reading these instructions, please proceed to the next page.

The instructions for the ELICIT treatment follow.

Restart Survey Place Bookmark Mobile view off Tools

Instructions (Overview)

In this experiment, you will take on the role of the manager of a firm. You will act as the manager of three different firms (in sequence). The firms are not related in any way. For each firm, you will (i) make a policy decision, (ii) give advice to future participants in our study, and (iii) report your confidence in your policy decision. After doing these three things for each of the three firms, a consultant will give you additional information about the third firm and you will make one last policy choice. You will be paid the bonus that results from one of your four policy choices (chosen randomly with equal chance), and for one of the three pieces of advice you give (also chosen randomly with equal chance). We describe in more detail how your bonus will be determined in this and the following two pages.

As the manager, you will set the corporate policy for the firm. The policy determines the probability (percentage chance) you implement one of two actions: the BLUE action or the GREEN action. The policy you choose will have a cost associated with it, and may or may not affect the firm's profits. Your bonus will depend on the firm's profits and the cost of the policy you choose.

You are not sure how the policy you choose will affect the firm's employees or profits. Therefore, to help you choose the policy, you have received access to data on previous firm outcomes over the past 120 months. This data came from a previous manager. It shows the following information for each month:

- Which action was implemented: BLUE or GREEN.
- The action of employees. This action may or may not be related to the manager's action. The previous manager used a code to record the action of employees, but unfortunately did not leave a note stating what the code means. All you know is that the same code always means the same thing. The responses were coded by the previous manager as ▲ or ◯.
- Whether the profits of the firm were **HIGH** or **LOW**.

When you have read these instructions, please continue to the next page for further instructions.

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Instructions (Policy Choice)

Your bonus depends on the policy you choose and the firm's profits. When you choose the policy, you will choose the percentage chance that the BLUE action is implemented. Call this P. The GREEN action will be implemented with the remaining chance. The least costly policy is P=50: the policy in which you implement the BLUE action 50% of the time. If you choose a higher or lower chance of BLUE, the cost is higher.

Specifically, you will get a bonus from two parts (added together):

1. You will receive $1.00 if the firm's profits are HIGH and $0 if the firm's profits are LOW.
2. You will receive 0.33-0.000133x(P-50)^2 where P is the policy you choose. For example, you will receive $0.33 if you choose P=50 but $0 if you choose P=0 or P=100.

When choosing the policy, think carefully! A more expensive policy might be worth it if it increases the chance that the firm makes HIGH profits. After choosing the policy, you will be asked to give advice to future participants in our study about which policy to choose and why. When you have finished reading these instructions, please proceed to the next page for instructions on how this advice can increase your bonus.

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Instructions (Advice)

After making your policy choice, we will give you a text box to enter advice to give to future participants in our study. Giving good advice can increase your bonus, as we explain here.

After you enter your advice, you will participate in an auction to decide whether or not your advice will be given to future participants in our experiment. To participate in the auction, you will receive $1.00 that you can use to make a bid. You can bid any amount up to this amount and will get to keep the rest.

In the auction, you will be matched with 19 other participants based on the order in which we receive responses. The advice from the participant that bids the most in the auction will be given to an average of 40 future participants. The future participants will know that the advice came from the past participant that bid the most for their advice to be used.

If your advice is given to future participants, you will receive $0.025 for each future participant that says your advice was helpful (versus unhelpful), minus the cost of your bid.

So, for example, if you bid $0.50, and if your bid is accepted, and 30 future participants say it was helpful, you will earn $0.75 because your advice was helpful. But, you will have to pay the cost of your bid, $0.50. With the $1.00 you received initially, your bonus is then $1.00+$0.75-$0.50=$1.25. By contrast, if you bid $1.00, and your bid is accepted but no future participant says your advice was helpful, you will receive no bonus. If your bid is not accepted, you will simply keep the initial $1.00 you received. We will make these additional bonus payments after the future study is completed, which we expect will be within a week.

You will assist us in our research if your advice is specific - it tells future participants which policy you think they should choose either explicitly or implicitly (by telling them what to look for in the history). We will exclude your bid from the auction if it doesn't meet this requirement.

When you have understood these instructions, please proceed to the next page to answer a few quiz questions before the experiment starts. You will have to answer the

The instructions for the NATURAL treatment follow.

USC University of Southern California

Instructions (Overview)

In this experiment, you will take on the role of the manager of a firm. You will act as the manager of three different firms (in sequence). The three firms are not related in any way, so nothing that you learn about one firm applies to any of the other firms. For each firm, you should only use the information that is provided to you for that firm.

For each of the three firms, you will make three policy decisions. After each policy decision, you will report your confidence in your policy decision. For the second and third policy decisions of each firm, you will receive advice from a consultant before you make your decision. This advice may or may not help you in making your policy decisions -- you should always assess for yourself whether or not the advice makes sense! You will be asked whether or not you found each piece of advice helpful or not.

You will be paid the bonus that results from one of your policy decisions (chosen randomly with equal chance). We describe in more detail how your bonus will be determined on this and the following page.

As the manager, you will set the corporate policy for the firm. The policy determines the probability (percentage chance) you implement one of two actions: the BLUE action or the GREEN action. The policy you choose will have a cost associated with it, and may or may not affect the firm's profits. Your bonus will depend on the firm's profits and the cost of the policy you choose.

You are not sure how the policy you choose will affect the firm's employees or profits. Therefore, to help you choose the policy, you have received access to data on previous firm outcomes over the past 120 months. This data came from a previous manager. It shows the following information for each month:

- Which action was implemented: BLUE or GREEN.
- The action of employees. This action may or may not be related to the manager's action. The previous manager used a code to record the action of employees, but unfortunately did not

leave a note stating what the code means. All you know is that the same code always means the same thing. The employee action was coded by the previous manager as ▲ or ◯.

- Whether the profits of the firm were **HIGH** or **LOW**.

When you have read these instructions, please continue to the next page for further instructions.

Instructions (Bonus)

Your bonus depends on the policy you choose and the firm's profits. When you choose the policy, you will choose the percentage chance that the BLUE action is implemented. Call this P. The GREEN action will be implemented with the remaining chance. The least costly policy is P=50: the policy in which you implement the BLUE action 50% of the time. If you choose a higher or lower chance of BLUE, the cost is higher.

Specifically, you will get a bonus from two parts (added together):

1. You will receive $1.00 if the firm's profits are HIGH and $0 if the firm's profits are LOW.
2. You will receive 0.33-0.000133x(P-50)^2 where P is the policy you choose. For example, you will receive $0.33 if you choose P=50 but $0 if you choose P=0 or P=100.

When choosing the policy, think carefully! A more expensive policy might be worth it if it increases the chance that the firm makes HIGH profits. When you have finished reading these instructions, please proceed to the next page.

Instructions (Advice)

The consultant's advice will either be generated by us (the people running the experiment) or will come from the advice of previous a previous participant in the experiment. We will always tell you where the advice comes from.

If the advice was generated by a previous participant, they saw a history for the same firm and were then asked to choose a policy and to give advice to a future participant (yourself!) about how to choose the policy. The previous participant then participated in an auction with other previous participants. The advice you're seeing comes from one of the 5% of previous participants that was willing to pay the most to give you their advice. That previous participant will be paid $0.025 if you say their advice was helpful and nothing otherwise. The participants that provide advice for each firm could be the same or different participants.

When you have finished reading these instructions, please proceed to the next page.

Appendix C: Narrative Classification

Each of the two co-authors independently classified each narrative into one of the categories shown in Table C1. In the case of disagreement (4.8% of cases), we first erred on the side of keeping the narrative: if only one co-author rejected, we kept it with the classification assigned by the other. This procedure resolved the vast majority of disagreements, but when it did not, we discussed until reaching agreement.

Table C1: Classification Descriptions

Classification	Code	Description
Reject	REJ	Does not contain an explicit or implicit (describes pattern) policy recommendation
Green Other	GO	Suggests green (policy < 0.5) but does not describe causal pattern
Green Lever	GL	Suggests green (policy < 0.5) and describes pattern for lever narrative
Green Threat	GT	Suggests green (policy < 0.5) and describes pattern for threat narrative
Blue Other	BO	Suggests blue (policy > 0.5) but does not describe causal pattern
Blue Lever	BL	Suggests blue (policy > 0.5) and describes pattern for lever narrative
Blue Threat	BT	Suggests blue (policy > 0.5) and describes pattern for threat narrative
Neutral	N	Suggests a neutral policy either explicitly or by describing data as random

The following pages provide all 603 narratives elicited and their classifications. Those that were actually used in Natural are highlighted in yellow.

Positive Datasets	Classification	Negative Datasets	Classification	Neutral Datasets	Classification
Each choice has equal successes and failures based on the categories of performance or employee action. Either is a good chance.	N	Both BLUE and GREEN have their benefits. It is a nuanced choice and if you look at the employee action you can tip the scale accordingly.	REJ	Employee action did not always follow the profit level. Consistency and performance data makes the choice easier between BLUE and GREEN.	REJ
While Blue was chosen more often and did have HIGH profits, everytime Green was chosen, there was a HIGH profit that month.	GO	Looking at the data, Green and Blue both had HIGH months, but Blue was more frequent and had more recent HIGH months.	BO	There was a large amount of Blue with HIGH profits, and while there was a Green with a HIGH profit, the Blue seems to be very effective.	BO
Green seems to be high more often then blue, but not by a ton, I would lean towards green, maybe 20 or 30 percent.	GO	I didn't see a clear trend for green or blue being better, so I went for 50 percent and advise you do as well.	N	I couldn't tell if one was better, so I went for 50 percent and advise the same.	N
It appears that green action + the circle might produce a high profit, blue + triangle usually will produce a high profit, and blue + circle usually doesn't produce a profit.	BL	Blue action seems to be a higher chance for high profits. Green usually doesn't work out.. Blue isn't really a guarantee either, though.	BO	Blue and green actions come out about the same.	N
I would suggest to set your policy weighted towards green. Green seemed to provide a slightly higher rate of higher profits, although the employee actions did not seem to relate directly	GO	I would definitely set your policy heavily towards green in this firm. The rate of high profits with a green policy appeared to occur more often no matter the employee action, so green is better to achieve higher profits	GO	The outcome on this firm appears to be somewhat random. I could not deduce any specific pattern on the manager and employee actions and the profitability, so take your best guess	N
Try to feel it out and make the best decision they	REJ	I thin is smart to think it through	REJ	Try to think it through	REJ
Trust your instincts they are your most useful tool	REJ	Trust your employees they have been beneficial to profits	REJ	The blue policy appears more lucrative based on historical data	BO
look for patterns	REJ	look for patterns	REJ	determine which one was used more	REJ
See how many time each choice resulted in a higher profit and make your decision based on that.	REJ	I think you should compare the effects each choice had on profits to see which to choose because that will give you a good idea of how often you'll be successful.	REJ	See how often each choice resulted in high profits in the table you're given to make the best decision.	REJ
I would say go green, but I'm not positive.	GO	Go with green. It looks like blue does poorly.	GO	Everything looks pretty equal. It's hard to tell what to do.	REJ

Blue actions still apear to have a negative impact on profit in most cases. I believe this because the firms that perform blue actions usually immediately have lower profits.	GO	I think that Blue actions have the possibility to be positive if they are used only occasionally & infrequently, but it does appear that frequent green actions appear to lead to a higher profit margin.	GO	Blue actions appear to have a negative affect upon profit the majority of the time, but can bring high profits on occasion.	GO
One-half of the time either blue or green has high profits, and the split is even for both of them. It is also an equal split for low profits for the remaining half. The only difference is the employee action is a triangle for all the blue highs. For everything else it was a O. Unfortunately we don't know what the triangle and/or circle means. For these reasons, I selected 50% for blue.	N	I chose 50 percent for blue because both blue and green had an equal split on high profits. When Green had high profits, the triangle indicator shows, while it is a circle for blue. Since we don't know the meaning of these symbols, I chose a 50% split.	N	I chose to go with 50% because both green and blue had an equal number of high profits. Also, the employee action was equally divided between green and blue for both low and high income. It would appear there's a 50% chance of getting higher profits.	N
I feel like green was higher most of the time.	GO	I think you should go with the blue, it seems the best choice.	BO	I would go with green- I feel like they were higher more often.	GO
Pay attention to the numer of employee actions taken and how they affect the profits.	REJ	I paid attention to the amount of the color and the amount of profits associated.	REJ	I followed the amount of actions and the amount of high profits	REJ
There looks to be a correlation between Blue, the arrow, and high profits, so try and aim for blue	BL	Green seems to be associated with high profits, so avoid the blue action if possible.	GO	There does not seem to be a relationship between green and blue, so stay at 50%	N
Blue and green appear to occur equally as likely, so it helps to pick an average value.	N	Set the sliders about equal as the green and blue options are about equal.	N	Most of the profits were high, so both were equally good options.	N
Look at the past data and see if thee is any correlation between the employee action and profits when blue is chosen over green and vice versa.	REJ	Find a correlation between the employee action and the profits.	REJ	You should take the historical data into account as well as going with your gut instinct.	REJ
Blue is the clear winner here.	BO	Green is the safer choice, so I would go with that policy more often.	GO	Choosing a roughly equal mix of blue and green would be wise.	N
experiment with both options and then see which one gave you better results	REJ	experiment with both options and then see which one gave you better results	REJ	experiment with both options and then see which one gave you better results.	REJ
Historically, if Blue or Green is higher, there's a good chance it will be high again.	REJ	It all seems quite random to me, hust pick one that you think did well for the firm historically.	REJ	Honestly, just pick one. There's no way to really know. The outcome seems quite equal in most cases.	REJ

set chance at 30%. It seems like green is more likely to result in high profit if employee action is circle, which is most often	GT	Implement the Blue action about 60% of the time, as the distribution seems fairly even, but blue is slightly more successful	BO	50%, since there seems to be about an equal chance of each policy being successful	N
Green has more positive outcomes than blue	GO	Green has the best profit outcome	GO	Green seems to be the way to go. There are more profitable than nonprofitable.	GO
It seems the same blue or green.	N	Green is the only thing that works well for employees.	GO	Blue seems to get more HIGH results	BO
With the limited data, it appears that Blue choices have a slightly higher chance of similar employee response and of profitability	BO	The data suggests a Green decision with an employee response of "triangle" brought about profitability more often than other decision outcomes.	GL	It's your call. It seems anything can happen with this company.	REJ
read and count all data	REJ	follow directions, count and read all information	REJ	read and count all data	REJ
Blue seems better	BO	I just assumed it was 50/50, I have no clue.	REJ	Too much info, take the 50/50.	N
Based on the historical data, it seemed like the colors had no affect on the profits of the company. Both colors were chosen equally and the policy associated had no correlation with the profits either.	N	Based on the data, it seemd like blue had a slightly higher chance of increasing company profits.	BO	Based on the data, it seemed like Green had a slightly higher rate of getting a higher payout.	GO
You should look carefully at the data as this will guide your choices.	REJ	Read the data before making choices.	REJ	Read all data before making choices	REJ
Look for employee actions as they relate to the color of the policy. It seems that the high vs low profits are a result of the interaction between the two.	REJ	Employee action of triangle seems more important than blue or green action so motivating your employees to do triangle will be more important than the policy you choose, so pick 50% to reduce cost in that regard.	N	Seems to be equal chance of blue or green being high profit.	N
Managers action most important	REJ	Employees action is most important	REJ	Higher firm profits is most important.	REJ
Be sure and choose blue when the triangle as it give out a better payout	BL	Choosing equal amounts tends to benefit one the most with leaning towards the circle.	N	Leans towards blue with circle to get highest benefits	BO
I think an equal chance of either seems like the best choice because it seems like overall they are fairly equal.	N	I think you should choose the actions equally because it seems like both have an equal chance of high or low profits.	N	I think choosing blue more often would lead to a higher profit overall.	BO
It seems that profits were 50/50 when choosing blue or green.	N	The only time there was high profit was when the manager chose Green and the employee chose the triangle.	GL	I saw a lot of blue decision when employees chose triangle and received high profit.	BL

Choose 50% BLUE. It doesn't matter which policy is implemented because they both historically get the same amount of HIGH profit. Choosing 50% maximizes the bonus chance.	N	Choose BLUE 50%. There is no difference in profit historically between BLUE and GREEN, so choose 50% to maximize bonus chance.	N	Choose BLUE 50%. There is no difference historically between the two policies. 50% will maximize the bonus chance.	N
I would look at times the profit was high and mimic that decision.	REJ	IT seems that one employee activity was better at increasing profits. implement that policy	REJ	Choose either policy it won't matter	N
The answer that should be given is Blue. Blue is not only used more often but has been shown to equal higher profit historically.	BO	Based on the table data, though Blue and Green have been chosen a close to equal amount of times, the proifts on Green are High	GO	Blue and Green are failry equal, as are the High and Low profits.	N
Try to count them and turn it into percentages.	REJ	try to count them out and turn them into percentages.	REJ	try to count them out and turn them into percentages.	REJ
why not?	REJ	i chose 30% because the blue selections historically seemed to yield lower results this time.	GO	go 50% either way, its a 5050 chance the way i see it.	N
blue policy appears more effective	BO	Green policy appears more effective	GO	It does not appear that taking a blue action more frequently provides a better return than choosing green	N
Keep blue under 30%, as profits seem to stay high with this regular schedule of action re: blue/green ratio	GO	Blue appears wildly inconsistent and therefore unreliable; choosing green is a safer bet, though blue has some potential if you feel lucky	GO	This oneâ€™s tough; Hedging bets seems prudent here. Overall, profits were twice as likely to be high with more blue than green, so consider blue more lucrative than green but only moderately so.	BO
Blue with employee participation always leads to High profits.	BO	Green with employee high employee participation always ends with High profits	GO	This ones a crap shoot!	REJ
The blue action seemed to perform well whenever the employee action was a triangle, but it didn't lead to a high profit when the employee action was a circle. On the other hand, the green action seemed to fairly equally bounce between high and low profits, regardless of the employee action. I would lean toward the blue action somewhat, given that a triangle employee action seems to pretty much guarantee high profits.	BL	Blue generally has a better chance of leading to a good outcome compared to green, regardless of the employee action. That said, green seems to just about always perform well when the employee action is a triangle (conversely, when the employee action is a circle, it pretty much never performs well). Due to the uncertainty regarding the employee action, I recommend blue.	BO	Quite frankly, it seemed largely like a matter of luck as to whether the firm's profits would be high. Both blue and green showed fairly equal amounts of highs and lows, regardless of the employee action (though, perhaps, rows with a triangle were marginally more likely to be high?). I would leave it to chance and choose blue with 50% probability.	N

Pay attention to employee action	REJ	Pay attention to employee action and profit	REJ	Pay attention to firm profits	REJ
outcomes seem evenly split between both options so I think either option is acceptable	N	green is clearly the better option	GO	both outcomes seem to have equal profit so either option is good	N
Looking back it seems green had a little higher profits.	GO	I chose 20% because I think blue wasnâ€™t as profitable in the past history.	GO	Looking back over the past blue and green were about equal. I chose 51% for blue because of the past history.	N
If the manager did green and the employees did triangle, profit was always high. But employees didn't do triangle consistently.	GO	When green was in effect and the manager implemented the triangle, profit was always high.	GL	unable to discern a pattern	REJ

It is important to take your time but to also go with your gut or first instinct when making the choice around the percentage to bet for blue.	REJ	I think that something important to do is to take your time as you analyze the differences in highs and lows for blue and green. This can help you come to a decision when it comes to the percentages.	REJ	I think it is important for you to look and count the numbers of blues and greens. This way you can figure out which percentage is higher also which blues and greens are high versus low. I think this would be the most helpful in coming up with a choice for the firm.	REJ
Historically speaking there is an equal chance for each action to be successful or not.	N	Historically, green has resulted in an increase in profits.	GO	Historically both green and blue have done well.	N
Blue has the higher performance most of the time.	BO	Green has a greater expected value.	GO	Blue outperforms returns substantially	BO
Definitely trust your gut. Study the history data but donâ€™t try too hard to completely understand it. If you get it then great, if not, treat it like a process of elimination.	REJ	Try and figure out the correlation between the employee column and profits column. It could help you figure out which policy to do more.	REJ	To get more insight into what policies work, figure out the pattern within the previous managerâ€™s policy choices in relation to profits	REJ
Green has been more profitable and six in a row its the best choice	GO	blue has come out strong in profits last 3 times its on a roll i would go with current numbers	BO	Even thou in the longterm green and blue are about the same in profits in the recent blue has outformed green in the recent months	BO

I would recommend implementing the blue action 50% of the time because it is the least costly option and also because the previous data indicates that the blue action resulted in high profits approximately 50 percent of the time when implemented by previous managers.	N	I advise implementing Blue 50 percent of the time because this is the least costly option and because the historical data indicates that the Blue and Green policies both resulted in high profits approximately 50% of the time.	N	I advise implementing the blue policy 50% of the time because it is the least costly option and because the historical data indicates that both the blue and green actions resulted in high profits approximately 50% of the time.	N
There seems to be an equal amount of green and blue, so it might be a good idea to choose the middle.	N	The safe option seems to be 50% since blue and green are about equal.	N	Blue and Green seem equal, so I would say go with 50%	N
pick what makes the most sense for you	REJ	pick what seems best	REJ	pick what seems best	REJ
Look to see if you can identify a trend such as if it pays more or less more often or if it's just random then don't place as much certantity on it.	REJ	You should look at the historical data and see if you can identify a trend between whether or not green or blue was chosen more and if it did pay higher or not. This should help you narrow down a decision between the two as to which has a more likely chance of earning more.	REJ	Check if blue or green was chosen more on average and if a certain one pays more than the other more often	REJ
I believe blue is more likely to lead to high profits. It seemed to have a higher percentage of likelihood to end with high profits.	BO	I believe it is best to choose green. It seemed to result in a higher likelihood of high profits.	GO	I believe it's best to choose blue 50% of the time. It seemed to be equally likely that blue or green resulted in the highest profits.	N
Blue is unreliable and green seems to be the safer bet. Trust your gut and leave your doubts behind.	GO	Firm profits have little correlation to any choices you may make. Don't choose randomly, but try to be thoughtful in your actions.	N	Don't chase trends and try to remain level-headed in your decision making. Blue is generally the safer bet, but don't rest on your laurels and pay close attention.	BO
Mostly look at employee action to see how profits will be affected. A triangle always means HIGH profit. A triangle was also always associated with BLUE.	BL	Look at the Manager Decision to see a correlation between GREEN/BLUE and Profits. A triangle under employee action always means a high profit and corresponds with GREEN but it didn't seem to mean much in this scenario. I would lean more towards blue in this situation.	BO	Try to see if BLUE or GREEN causes a high or low profit and make your judgement from there. Employee action doesn't seem to mean much in this scenario. I would just choose a 50% split because there doesn't appear to be a set reason for HIGH or LOW profit.	N

Try to focus on the firm's profit	REJ	I would advise that you try to study the numbers well before making a decision	REJ	try to focus on manager's action and firm profits	REJ
Green has a better chance of success	GO	Pick blue because green has no chance of high profit.	BO	Pick green because it has a greater chance of success	GO
Even though green seemed to be used more, it appeared as though more of the higher earning fell on when blue was used rather than on green.	BO	There were no dominate patterns to what caused a high earnings.	N	Everything was about equal across the board, but it appeared blue triggered more earnings more often than the green did.	BO
Blue with a triangle action almost always will be high	BL	Green action almost always hit high	GO	Bid blue because it goes high more often than green	BO
high and low outcomes seemed to be relatively equal, as did the blue and green choices, so use 50% probablilty	N	High and Low profit outcomes seemed to be about 50% and so did the manager's actions between Blue and Green, so go for 50%	N	of the times that the firm had HIGH profits, 4 were during Blue and 2 were during Green - therefore, using those odds, select Blue 66% (2/3rds) of the time	BO
Focus on how many BLUE will lead to HIGH profits compared to LOW profits versus GREEN. From my judgment, the ratio was about the same for both color implementations. As a result, I chose a percentage closer to the middle ground 50%.	N	Estimate the ratio of low to high profits for BLUE. I estimate it to be higher than the ratio for GREEN, so I made the percentage higher for BLUE.	BO	GREEN clearly leads to more HIGH profits based on the data. So I minimized the percentage of choosing BLUE as much as possible.	GO
Check the color that has the highest percentage of High profits.	REJ	I examined the average percentage of High and Low and chose the blue based on its higher rate of High profits on the chart.	BO	Examine the chart and focus on the color with the highest amount of profits.	REJ
Blue action is likely to give a high firm profit.	BO	Choosing a higher or lower chance of blue makes the cost higher.	REJ	Blue action is likely to give a high firm profit.	BO
pick blue circles for better chance of profit	BO	Pick colors about 50% of the time and circles	N	pick more green and triangles	GL
When it's BLUE and triangle, profits are high.	BL	Seems rather random on circle or triangle, profit or not.	N	Seems to be a 50/50 chance for everything, irrespective of each variable. So my advice is to keep with 50%.	N
follow the directions look at the patterns	REJ	watch the patterns and follow the directions	REJ	Read the directions and pay attention the patterns	REJ

Looking at the data, it seemed like blue was more closely associated with higher profits.	BO	There was no correlation between policy, employee action and price. As such, it is safest to always choose a 50% chance for each policy.	N	Try to set it at 50% because that is the least risky option. If you set it differently, you could lose money. But with this, you are guaranteed at least a small return.	N
Go with your gut and choose 50% Blue to maximize profit.	N	Choose 50% Blue because it will help you to maximize profits.	N	Chose 50% Blue because all the profits were about the same regardless of policy.	N
it will be like the first just look at the information and you will be able to make your own judgemnent	REJ	They should just look at the information and it will clearly show the statistics.	REJ	well I dont know how much advice a person needs to do this i think their own judgement is good enough I dont know how much more guidance you can give someone to make a simple choice	REJ
The employee action matters much more than the manager action, if employee chooses triangle it will be a high profit, so by setting the manager decision to 50 percent we minimize costs.	N	The manager decision doesn't seem to influence much for this firm so I'd recommend setting blue to 50 percent to minimize costs.	N	It seems to be complete random whether profits are high or low so setting the decision to 50 percent minimizes costs.	N
None, sorry!	REJ	Make sure to carefully analyze all aspects and let that contribute	REJ	Make sure to scroll down because I didn't the first time lol	REJ
blue 60% seems to have higher profits especially when it has the triangle and also green at 40 % with the circle intertwined with blue seems to do well	BL	Green seemed to have higher profits more consistently than blue	GO	I went blue 30% historically green action had better odds of high profits	GO
I think the participant should evaluate the highs and lows in reference to the color policy	REJ	choose 50% because it looks as though the chance for high profits is equal	N	The participant should chose 50% because it looks like the profits of highs and lows were relatively equal	N
I think that this choice was mostly made with the green decision in mind.	REJ	I chose blue because it was the dominant choice and best one for the company	BO	I think the more used choice was green	REJ
try to look for any pattern u see, try to see if the symbols are related to high profits	REJ	look for pattern correlation	REJ	look for correlations with the symbol and profits	REJ
Green seemed to result in HIGH profits slightly more often than Blue.	GO	Stick with 50/50, or choose Blue slightly more often. The chances for HIGH profit seemed about equal.	N	Blue seemed to have HIGH profits slightly more often.	BO

In my opinion 50% on the blue option is safe and should help maximize the profits	N	Everything occurred equally so 50% seems to be the best option	N	everything is equal or almost equal so 50% should maximize your bonus	N
I would look at the data several times so you can try to identify patterns and relationships between blue/green options and high/low profits.	REJ	I advise you to focus on whether the blue action or green action leads to higher profits, which well help you determine if you should select the green option or blue option.	REJ	I would consider just doing a 50/50 for green vs. blue. It is really hard to detect patterns without using software, and I leaving it to change might be just as effective (unless there is an obvious pattern)	N
I dont know. It was so variational with no clear common denominator	REJ	I believe that the green policy is more successful. In those that the manager took action (the triangle) green policy was always chosen and had high profits. Blue had high profits too but not always	GL	More blue than green. Green rarely had high profits	BO
I, unsure	REJ	Animal care. Give a quiz about animal care	REJ	Parent quiz	REJ
There's not enough data to know which decision is better, though the blue decision resulted in high profits the one time it was made.	BO	The green action seems to result in high profits more often.	GO	The blue and green actions result in high earnings at similar frequency.	N
Try to choose GREEN	GO	Pick GREEN	GO	You should choose GREEN	GO
none	REJ	none	REJ	none	REJ
Well the chances are about the same but I really like that green was linked more to employees interjecting.	N	This one seems a little harder to gauge, mostly because the low profits on green mostly but since the workers didnt interact well, then it was mostly on managers	REJ	This time it seemed that green tanked things more. Overall this could be due to worker interaction but its just a guess	BO
Triangle actions seem to always lead to high profits. Employees seem to never pick triangle actions if the policy is green. They sometimes pick triangle actions if the policy is blue. Take a blue action as much as possible.	BL	It seems the employee picks the triangle action more frequently whenever the policy is green. Furthermore, triangle actions seem to have higher profits. The employee seems to pick the circle action more than the triangle action. So we should push for the employee to pick triangle actions with green policies.	GL	There does not seem to be any discrete or strict relationship between manager actions and employee actions. Employee actions do not seem to correspond to profits either. Pick 50/50 since it's reduces the risks and matches the existing firm history.	N
They seem to trend two colors back to back and make a profit	REJ	it looks like blue would trend next	BO	Looking at the trend i think blue would be the better option	BO

Mostly green but low profits so 60% to get higher profits with blue	BO	The green was higher than blue so I guessed 61% to keep it around there	REJ	Blue was low so I was leaving it low to get a better outcome	GO
When coosing the policies make sure you go through the whole graph. Look at the profits as well as what seemed to work.	REJ	I think you should pay close attention to the instructions first off. Then take your time looking at the graphs and make your decision based on what is given. Do not just guess.	REJ	This graph was much more equal so choose one in the middle. I would say don't just guess though.	N
Watch for patterns in the history.	REJ	Look for patterns with the action and the profits.	REJ	The history is the most informative.	REJ
The triangle response seems to be more correlated with low profits, and the triangles are much higher correlated with blue, so emphasize green.	GO	It seems that blue is more likely to correlate to higher profits independant of the employee response	BO	There's no correlation between any variable of action and the results shown, so I'd play it safe.	N
the bonus and pay isnt worth the time to seriously analyze this stuff.	REJ	dont listen to me	REJ	no ideA	REJ
My advice is look at the middle option and study it	REJ	Study hard and go with your instinct	REJ	I advise them to really study the table and go with their gut instinct	REJ
Based on historical profit data for the company it is more advantageous to select the Green option.	GO	Based on historical profit data on this company it is more advantageous to select the Green option.	GO	Based on historical firm profit data, it is more advantageous to select the Green option.	GO
Count the number of instances of Green and Blue action.	REJ	Analyze the data provided. Do a count of Blue actions and Green actions to determine a probability of future actions.	REJ	Count the number of Green and Blue actions and determine probability for future actions.	REJ
Looks about even	REJ	It is near a wash..guess	N	Looks like a wash..guess	N
Chose the green and the triangle. You may get better results	GO	I think the green should be chosen more often than blue.	GO	Choose green more than blue	GO
Every or almost every triangle indicates high profits. And triangles were only associated with blues.	BL	Green had more high profits than blue.	GO	See which policy choice is more popular and weigh their percentages when it comes to profits. Gauge the employee action by seeing a trend between the symbol and whether a profit was high or not.	REJ
none	REJ	none	REJ	none	REJ
Read the directions carefully	REJ	I would say read the directions very very carefully	REJ	Read the directions very carefully	REJ

Since the profits seemed to be high fairly equally between the blue and green actions, I set my bar around 50%.	N	I chose to implement the blue action less often because high profits seemed to happen more when a green action was taken.	GO	It looked like the firm had high profits more often when a green action was taken, so I made sure a blue action was taken less often.	GO
Look at changes in employee action based on color	REJ	Look at correlation of high or low based on colors	REJ	This is a gamble, go with your instinct	REJ
You should carefully notice the relationship between color and profit	REJ	The key it look at the employee action and the profit to see if it is high or low	REJ	looking at all 3 columns will allow you to see a pattern and relationship amongst the three	REJ
BLUE seems to lead to more triangle and higher profits compared to GREEN. Therefore I would go with BLUE a good majority of the time over GREEN since it will give you good odds.	BL	GREEN seems to lead to higher profits more than BLUE does. Therefore I went with BLUE happening not that often to maximize high profits by having a better chance of getting green.	GO	It seems that the firm did about equal amounts of BLUE and GREEN. From a quick glance I believe that GREEN might slightly outperform BLUE but not by tons. Therefore I would suggest doing BLUE slightly before 50%	GO
Pay attention	REJ	Pay attention	REJ	Pay attention	REJ
Try looking at the largest in the whole.	REJ	go fast but look for the most	REJ	Try to decide which of the options has the most.	REJ
Just go blue and O since there's no real difference between outcomes	BO	No reason to attempt a policy change since blue and green had low outcomes about equally the same	N	Go blue since it seemed to have the most high outcomes	BO
Again, it seems success between blue and green options was evenly distributed.	N	It seems as though the blue option gives the best chance for high profits given then information presented.	BO	It seems success with Blue or Green options is evenly distributed.	N
I would advise you to look at the profit closely. Try to identify if one policy produced a profit more often than the other, or if they were equally profitable.	REJ	Examine which policies are implemented more often, and determine which, if either, yielded more profit. It appears to me that both policies have been equally profitable, regardless of employee action.	N	Carefully examine the information provided in the charts, and determine which of the policies yielded a greater profit.	REJ
Look for possible trends. If a color appears more in profits, it may be worth considering putting on a higher percentage.	REJ	Employee actions affect the profit, so it is worth looking into.	REJ	Look for possible trends in the data given.	REJ
Use blue less often	GO	Blue has been used more often	REJ	Read carefully and play it safe	REJ

Now that you have more experience, still take your time but don't second guess yourself	REJ	I think now your choices are up to you since you have more experience	REJ	Study the graphs carefully. This isn't content we typically see so take that time to digest	REJ
It appears that the blue policy results in higher profits.	BO	It appears green had higher profits based on the chart.	GO	It looks like a pretty even mix between green and blue and the high and low profits.	N
The green is equally as likely as the blue though typically the profits are high	GO	Historically green was chosen and historically firm had higher profits0	GO	Choices in the past of green looks like it leadsmore often to higher profits	GO
half and half	N	I believe blue was chosen a bit less than green, so you should set it to 40%	GO	You should set the Blue option to around 50%, because it showed up about half as much as green did.	N
Looking at the data set the firm typically selects the blue and green option evenly. I chose to select the blue slightly more in the hopes of return some higher yields without taking too much undue risk.	BO	The Blue and the Green options were again fairly even with blue occuring slightly more frequently. When the High and Low options were also weighted they were also similar with the High options occuring a bit more frequently. Therefore I have more confidence in a High Blue will result, but I wanted to factor in a bit of protecting in my investment.	BO	Blue and Green were fairly evenly distributed with the blue option occuring a bit more frequently. I set the percentage at 52% to reflect the distribution as shown on the screen and also to promote some slight additional opportunities for higher yields. But I'm not as confident as I was in my assessment with firm 1.	BO
This data doesn't really help figure things out that much at all.	REJ	I really can't tell much from the data.	REJ	Green is the way to go. They are successful more of the time.	GO
calculate percent of highs that are blue.	REJ	You should choose to implement blue less because it costs more, and high profits occur about equally between green and blue.	GO	review and compare # of high profits with each.	REJ
Blue seemed to slighly edge out green in terms of profits, but it was almost equal.	BO	Blue seemed to do better overall. Green was 50/50, but blue appeared to have better success overall.	BO	When blue was implemented, the profits were always low. Green had a 50/50 chance and therefore seemed like the better chance to make higher profits.	GO

I would try to pay attention to what decisions previous managers made and make your best choice when making decisions.	REJ	I would pay attention to the options given when making your decision.	REJ	I would pay attention to the options given and take your time when selecting your answer.	REJ
Blue is better especially with employee action.	BO	I think you should go with green more often. It was much more likely to be profitable	GO	Overall in this case I think Green was much better. It seems high profits were associated with Green	GO
Green seems to have the action O more often, which also leads to low profits. I would increase the chance for blue	BL	Green option seems to result in action triangle more often, which seems to always result in high profits. Therefore, I would slightly lower percentage of blue	GL	Just leaving it at an equal change for either blue or green to be selected seems best because it doesn't seem to make a huge difference whether green or blue and which action is used	N
I would recommend blue as it is less costly. This seems the most risk averse option.	BO	I would recommend sticking with blue 50% of the time since it is the lower cost option.	N	I would recommend selecting blue 50% of the time. This is the lowest cost option. It seems like the best option because there are no guarantees for setting a more extreme measure here.	N
Both Green and Blue were chosen in the past, however Green had more high's than lows.	GO	Blue appeared to be chosen slightly more over green in the past, however it was rated higher more times the green so I chose blue for that reason.	BO	This was a 50/50 they both seemed to have a non streak of high's an lows.	N
read carefully the table of the firm profits	REJ	look into the employee action	REJ	look carefully in the table of the firm profits	REJ
Looked like blue was high half of the time	REJ	I would choose more green because it comes up more with high profits	GO	looked like blue was high half the time	REJ
Choosing blue 50% of the time seems to be a safe option.	N	Picking blue 50% of the time seems like the safest option to maximize profits.	N	Choosing blue at 50% seems to be the safest option.	N
Blue was chosen 50% and green as well but blue had more higher profit and more engagements so I would pick more blue and less green.	BL	It seems that if blue is chosen 50% and green 50% they each only make profit 50% of the time of that. I would chose more blue and less green as it would be cheaper but still seem to gain profit.	BO	Green was chosen more but had high profits less than Blue, so I would choose blue a little more than green.	BO

Go for a more stable option, especially since blue is risky and doesn't have a good past record.	GO	Go green for environmental friendly ... not. Simply go green because of less risk and more stable higher profit outcome.	GO	Go for the stable route. Risk is only worth if the result is up to chance, but here the end result is rigged by the researcher.	REJ
Green was more often chosen and seemed to come back with a decent rate of high profits. Blue wasn't a bad choice but didn't seem to have as high a profit margin.	GO	I feel the blue action comes out with high profits more often than the green action. It isn't a large or obvious difference but it seems the percentages give blue the better option.	BO	Green seems to have a slightly higher return depending on the action. It's not a large difference but the percentages seem to favor green.	GO
It seemed to me that blue and green are similarly likely but blue looked like it was more likely to be high.	BO	I'm not really sure what should be done with this one.	REJ	It seems to me that green is more likely to lead to high profits, especially if it's with the triangle action.	GL
It is clear from the table that Blue + Triangle always equals high profits, and Blue + Circle always equals low profits.	REJ	The results of the blue decision seems random, but you are always able to predict the profits with the green decision and employee action.	REJ	The manager decision does not seem to consistently result in the same employee action and amount of profit.	REJ
Green was a high profit more often than blue, both were used an equal amount	GO	Green looks to have high profits more often than blue	GO	Both green and blue were used evenly, and profits seemed evenly high and low on both	N
I chose 50% of the time because it all seemed like a gamble to me. I understood how it worked after reading the instructions in the survey, however I couldn't grasp my mind completely around it.	N	I think you should choose blue or green 50% of the time	N	I think you should split the decision 50/50 because it all seems like a game of chance	N
check the instructions very well	REJ	pay close attention to each symbol in the table	REJ	pay close attention to each symbol in the table	REJ
It looks like green would lead to more "green"	GO	It seems as if blue is more profitable.	BO	It looks as if green is more profitable.	GO
focus your policy on green for this firm	GO	Look for a pattern in switches from high to low. What changed (or specifically didn't) change month to month in the employee and policy decisions that led to a high or low profit. it seems like a change in behavior is what sparks a high to low profit and vice versa	REJ	go for blue if employee behavior is a circle, otherwise select green (it's probably a 50/50 split with employee behavior))	REJ
Look closely at the yeilds from the Green choices	REJ	Calculate the number of times Blue has been chosen and look at how likely it is to yeild high returns	REJ	Look closely at how often Blue was chosen and how likely it was to yeild high compared to green.	REJ

When green is selected, employees chose circle every time. Less than half the time did green, circle result in high profits. However when blue was chosen employees chose triangle over half the time and blue, triangle resulted in high profits almost every time.	BL	It appears as though picking mostly green will be beneficial because everytime green is picked and employees pick the triangle there is a high profit. However, part of the time when employees pick the circle and managers pick blue they are high. Therefore, I recommend keeping some blue in but mostly green so everytime triangle is picked you have a higher chance of high profits.	GL	There does not appear to be any correlation between what choices are made and the profits so may as well do the cheaper option most of the time.	N
You should choose to split, because high and low profits occur at about the same rate no matter what your choice is based on what I've seen.	N	You should choose to implement blue less because it costs more, and high profits occur about equally between green and blue.	GO	Choose blue less often than not, because when there are too many blue policies in a row the profits stay low.	GO
Blue yields high profits twice as often as green.	BO	Green was chosen less often but based on percentage yielded high profits equal times.	REJ	Green has yielded high profits 3 of 6 times while blue has yielded high profits 1 of 3 times.	GO
There are balances in the green versus blue and the profits.	N	Note a pattern in whether green or blue had more profit.	REJ	Make sure to note any patterns that can be seen and how they lead into a high profit month.	REJ
Both policies had a history of high and low profits. Blue started off strong but it's more recent uses had low profits so I implemented the blue policy 40% of the time	GO	Green has a greater history of having higher profits. Blue had some high profits as well, but green was more consistent and you should implement it more than the blue policy	GO	Based on the chart, it looks like blue has a slightly greater probability of having a high profit. You should implement the blue policy a little over half of the time	BO
You should estimate descriptive statistics of the data. If you have time, calculate the percentage of all blue actions that resulted in a profit. If you have less time, then randomly scroll and select three subsets of data and calculate the percentage of success of blue actions. Success is defined as high profit. When I did a random selection, it seemed like the blue action was successful about 50% of the time, which is what I put as the probability.	N	See if blue or green policies are associated with higher profit. Ignore the employee action symbol because you have no control over it. Bid on blue based on the percent of success of past blue actions, keeping in mind that they may be unrelated (e.g. if the policy doesn't affect profit at all, bid 50%).	N	Look to see if high or low profit occurs more often with blue or green policies. You can count all of the data, or scroll and take a random subset analysis of data. Doing this, however, I didn't see a clear pattern, so I only bid 50% for the blue policy.	N
Blue action plus traingle usually equals high profits	BL	Green plus triangle usually equals high profits	GL	The results seem random, so small bid	N

It helps to compare the number of times the profit was low compared to high and which color was picked for each one.	REJ	Its best to count all the high and low profits and see which color matches each.	REJ	Its worth it to take the time and study the table given before making a choice. Counting all the lows and highs along with what color was picked is very helpful even though it is time consuming.	REJ
If the employee action seems to always result in high profits and only occurs during a specific color, give that color a higher percentage (but be wary of how often the employees did this action)	BL	Pay close attention to if the employee action and profits always occur on the same color.	GL	If you aren't sure about the data you see, choose blue 50% of the time, since this has the lowest cost and will probably yield good results if the company seems equally split between all actions (blue/green, circle/arrow, high/low).	N
Study the data and make choices by using that. n	REJ	Make your choices based on the past data information.	REJ	You should study the data and make your choices keeping that in mind.	REJ
blue and green were pretty equal, as were profits.	N	The company has a few more blue than green so I went toward blue a bit more.	BO	The actions seemed similar across the board for blue and green, so I chose in the middle.	N
Look at the policy implemented and what outcome it generates. Both green and blue policy looks to generate low and high profits evenly.	N	I think the most important pieces of information is the policy implements and the outcome of the profits. I don't think the manager's action has much affect on the outcome. Just try to get an idea on which policy generates the better profits.	N	You should look at the policy implemented in place (blue or green) and the profits and just examine the outcomes.	REJ

For this firm, there seems to be a pattern with the employee action. When it is blue and triangle, the profits seems to be high, but always low when it is blue and circle. However, when it is green, employee actions seem to matter less. Since employee actions are more frequently a circle, leaning towards green seems to be the best option.	GT	For this firm, green seems to only have success when it is paired with a triangle employee action while blue is unaffected. Since circle actions are more frequent, going with more blue seems to be the best option.	BT	First, try to establish if there is any pattern. If the profits seem random, isolate either green or blue and double check to see if the profits look frequently higher or lower for that single option. If it still seems random, go with the middle. If you believe that one seems slightly more profitable, then slightly adjust towards that option. I think this method works better because the data can be overwhelming at a first glance, so singling out one option reduces the amount you have to look at, thus letting you make a more informed decision.	REJ
There didn't seem to be a pattern	N	It seems that green was associated with higher profits some of the time	GO	It seems that blue corresponds with higher profit more often	BO
Look at the employee action and how often it is up on good days.	REJ	I would count the blues and greens, then count the highs/lows of each. You can see how many times each were successful and choose your answer based on the average.	REJ	Don't stress too much about it.	REJ
The firm seems to get the best results when the blue decision is made and employees take a specific action represented by the triangle. I would suggest choosing a slightly higher percentage for blue.	BL	I would choose a low percentage for blue as green consistently seems to deliver the highest profits when paired with the triangle employee activity.	GL	I would set the percentage to 50 as the past performance seems to be fairly random in this situation.	N
You need to really read the chart	REJ	I failed economics so don't listen to me.	REJ	Read and count each item in every column on the chart.	REJ
The blue paired with the triangle employee action always yields high profits.	BL	There seems to be an equal chance of high or low profit across the board, however I did notice anytime the green was paired with the triangle employee action, the profit was always high.	GL	I'd go with 50/50 here. I can see no pattern	N

The best policy decision for Firm 3 would be to choose Green policy more often than not. Generally the Blue policy produces income when there is employee engagement and it appears that the employee engagement is much lower than anticipated. This would result in fewer chances that the Blue policy will outpace the Green policy from a profit standpoint.	GO	The correlation to high profits and low profits appears to be better for Green vs Blue. In addition, the more employee actions the higher the chance of High Profit. Likely due to the fact that employee engagement can increase profits due to the employee's feelings towards the employer and customers feelings on how they are treated by the employee and thus is representative of the company they are doing business with.	GO	Increased Blue activity with employee engagement correlates to higher profit approximately over half the time. It is recommended to review this data to come to your own conclusion.	BO
Look for which employee actions seemed to ensure high profit and which policy those tended to correspond with.	REJ	Look for which employee action and color pairs correspond with high profit. The employee actions seem to result from the policy chosen	REJ	Think about if any of the actions or policies occur more than the other and if the ones that do correlate with high or low profit.	REJ
More often than not the arrow provides a higher profit over the circle.	BL	Compare the Blue and Green policies to determine the averages of HIGHs and LOWs	REJ	Blue seems to provide higher profit outcomes more often than Green.	BO
The Blue action combined with the Triangle feature/action proved to result in high profits every time that combination was used. With any other combination it was a tossup as to what the profit margins were going to be.	BL	The Green Manager action combined with the Triangle Employer action always results in high profits. Every other combination is a tossup. I'd say go all in on green.	GL	There isn't really that much here to predict, the profit waves seem very random and it doesn't seem to matter what the manager actually chooses in terms of actions.	N
I think green has a better chance because their performance looks better. I would go with less of a percentage with blue because I do not think the profit will be as high because it looks like they did not always perform that well	GO	everything is kind of mix you can not go wrong with either choice i believe because looking at the chart there was a combination of both high and low profits	N	I think it looks like blue had a decent amount of consistant perormance which is why i think blue is a good choice	BO
The only instances of HIGH profits are associated with the BLUE action. I therefore recommend making the choice of taking the BLUE action 100% of the time.	BO	The BLUE and GREEN actions seem to have a random impact on the employee and the HIGH profit result. There are some patterns in the past history but they are hard to follow. I recommend using the BLUE and GREEN approach equally or 50% of the time.	N	It appears that the data shows GREEN being slightly more effective than BLUE at resulting in HIGH profits. Therefore I went with a 40% probability of BLUE to better my odds, but still account for a misinterpretation of the data.	GO
They are about equally the same	N	Choose blue	BO	Just look at the graphs and decide on your own	REJ

Percentage of blue should be higher because the employees and company profits will be higher	BL	The percentage of blue should be lower because it would make the profit higher.	GO	Percentage of both the green and blue should be equal because the company and the employees would make equal profits.	N
If you choose blue and the employees take action then the profits are always high	BL	If you choose green and the employee chooses triangle you will have high profits	GL	I did not see a difference	N
check the tab with past manager decisions as much as you need to make wise choices	REJ	my advice will be to pay attention to past decisions made by the manager to make wise decision	REJ	take your time no need to rush	REJ
This is becoming confusing now. If there was a way to take this data and put it in a graph	REJ	Look for the triangles- guarantees high profits. The Blue/ Green choice looks like a coin flip	N	Depends on how much you want to count. This looks like a coin flip to me	N
There is no edge. Basically a coin flip. Best to choose 50-50	N	There is no edge. It is basically a coin flip. Best to choose 50-50	N	There is no edge. It is random. Best to choose 50-50 like flipping a coin.	N
Try to look at the overall comparison of the manager action color and the employee action, and then compare it to which results in more high versus low.	REJ	Look at the table, compare the manager action color and employee action and see the result. Find the pattern in the different combinations, write it down to make it easier to see.	REJ	Pick the manager action color and employee action combination that results in the most highs versus lows.	REJ
I notice that Blue action has High profits only when Employee Action is a triangle, and that there are relatively few triangles. Therefore I propose that slanting toward Green is possibly the best choice?	GT	This seems to be the opposite of Firm 1. Green sees high profits only when employee action is also a triangle, and there are relatively few triangles. Blue profits are independent of the triangles, so I would slant toward blue?	BT	It looks like Employee Action is not a big factor in profits, and it looks like a toss-up between blue and green, so I would go with 50%.	N
Future participant should be fucus on firm fast report and make decision based on that.	REJ	Future participant should focus on the firm past report and make the decision based on that.	REJ	Future participant should focus on the firm past report and make the decision based on that.	REJ
Pay attention to which color is more likely to earn a HIGH profit.	REJ	You should carefully look through the data and think the decisions through.	REJ	You should figure out which color has a higher chance of getting a HIGH profit.	REJ

I think that looking at the chart and really looking it over and seeing where the triangles and o's are the blue or green and the high and low really take that all into account and add it up in your head and think of it in percentages.	REJ	its all about trying to get the percentage feeling for yourself at taking in the information blue and green, triangle and o's and the high and low and then form a percentage in your mind of what it feels like to you and what not.	REJ	just take into the consideration the blue and green and the triangle and o's and the high and low and think to yourself in percentage and put the percentage for blue at what you feel like it should be.	REJ
Profits and employee action are almost always high when choosing blue.	BL	Compare the number of times each color (blue and green) had "HIGH" profits to base your decision on.	REJ	Blue shows a slightly higher profit and positive employee action.	BL
The firm saw high profits half the time and there is a perfect even split between blue and green being chosen and each resulted in high profits the same amount of the time. As such it makes sense to pick a 50/50 allocation due to the equal success chance of both and choosing anything other than 50/50 resulting in extra costs.	N	Based on the provided information the green choice had high profits noticeably more often than blue. As such green should receive a higher percentage allocation as it has historically been the more likely to succeed.	GO	Both green and blue were chosen an equal number of times and resulted in an equal number of high and low profit months respectively. As both are equally likely to be successful and there is a cost associated with picking one over the other it makes the most sense to do a 50/50 allocation.	N
Check the amount of blue versus green then check which one has more high firm profits. This will tell you which you should pick.	REJ	Green has more profits to the firm than blue	GO	Checking blues profits to the firm and action of the employees, blue has the best chance.	BO
It seems there seems to be a higher correlation between profits coming to the firm and policy green rather than using policy blue, may be a better idea to implement policy green	GO	It seems that policy blue is not leading to more profits for the firm as there seems to be a correlation between profits coming in.	GO	I personally think you should follow Policy blue as there is a correlation between a higher number of it being implemented and much higher profits being reported.	BO
Blue management policy combined with the triangle action from the employees has historically always lead to high profits.	BL	Maintaining a 50% ratio between the two policies seems prudent. They were implemented equally and high profits occurred about equally between both policies in the historical data. There was no clearly superior policy that I could see.	N	Maintaining a balance between Blue and Green policies seems prudent as neither policy showed to be clearly superior in terms of high profits.	N

Blue and Green seemed to have equally high profits so pick 50%.	N	Blue had lower profits so use blue less.	GO	Pick higher percentage blue because higher profits usually are blue.	BO
It makes not difference whether the participant chooses a blue or green option. There's a 50/50 chance of either option being successful or unsuccessful.	N	There is little difference as to whether the participant should choose blue or green. Both options are pretty much equal and the best decision will be a matter of luck.	N	It matters not whether the blue or green option is chosen. There's a 50/50 likelihood of one option being favorable with the other unfavorable.	N
It appears that mostly the blue has profits.	BO	According to the data, blue has been chosen less often but just slightly than green. There have been slightly more profits as well.	GO	The mix from this data set was fairly equally distributed.	N
Keep it 50% chance. The results seem to be random with no clear pattern or preference.	N	Blue seems to yield high profits slightly more often. Raise the chance of blue slightly.	BO	I suggest playing it safe & keeping the chance of Blue near 50%. I could not detect a clear pattern in the historical information that favored any of the options disproportionately. This information has no relation to the current month, making it mostly useless.	N
Don't choose circle.	REJ	Try to avoid the circle action	REJ	I would try to find a pattern of the variables to see which combination most often resulted in high profts.	REJ
Keep an eye out for any pattern, particularly with how many times one color results in lower profits for the firm. Take your time and consider your answer, and don't be afraid to write anything down or work on a mental map to figure out what you want to go for.	REJ	Make sure to keep in mind of any patterns and to take notice of the symbols given in the instructions prior to looking at the firm's data, so you can make the best decision with the information in front of you. There might not be a pattern but generally there could be something, such as Blue getting higher profits more often, that might help with making your choice. Trust your instincts, too!	REJ	Do your best to count, if needed, to see which one shows up more often. Keep note of any patterns, as well, and see what you can glean from the data listed. Take your time and do your best not to rush.	REJ
blue seems more correlated with high profit, and all triangles are associated with blue, and all triangles are high profit	BL	go less on blue because triangle is only associated with green and triangle is always high profit	GL	go 50/50, there doesnt seem to be a clear pattern between color shape and profit	N
blue is good	BO	blue is better than green	BO	blue 50%	N

Manger action blue or green doesn't matter. Employee action triangle matters.	N	There are no significant differences between the manager implementing blue or green action. It appears that when the employee action is a triangle it almost always results in high profit.	N	It's pretty random. No actions matter.	N
You should keep in mind that the goal is to attain high profits. Because the manager's codes have not been deciphered, we cannot assume that the employee's actions actually have an effect on the firm's profits or the manager's actions. Try to pay attention to how often the GREEN and BLUE policies end up attaining high profits.	REJ	I think it is more likely that the GREEN action attains higher profits.	GO	This firm's profits are mainly high, and I do not think there is any relation to the policy implemented.	N
This one looked like it leaned more toward green, so choose slightly below 50.	GO	It appears to lean slightly more in the green directly, so keep your decision close to the 50 percent mark but slightly below.	GO	Do your best to scan the information and decipher a pattern, even with the little information presented. You will probably lean closely above or below 50% and you can use that as your decision.	N
I think by following my lead, you will do well. I have looked at the outcomes carefully.	REJ	Choosing blue 50% of the time is definitely better because that will increase the profits in this case.	N	Green is the way to go. It results in higher profits.	GO
The most reliable group is blue when the employee marking from the previous manager is a triangle. IT results in high profits every time. How ever if it is a blue circle it is always low profits. Green is less predictable and profits seem to fluctuate at random.	BL	In the past the firm has selected blue and green actions equally. This has resulted in ablaut equal low and high profits. Because of this you may want to put more emphasis on the arrow and "0" marks made by the previous manager to see which is more highly correlated to high profits.	N	There is almost a equal distribution among all different decision outcomes. Blue decisions with a triangle for employee decisions barely outperform the other categories so maybe lean slightly that direction.	BL
The blue action has a higher probability of being profitable based on the data if you review the last column and see that it was a lot higher than lower.	BO	Reviewing the firms profit column seemed that there was more times when it was higher profit than lower so I would go with that assumption.	REJ	Blue seemed to be set more often than green and the profits were higher than lower a greater percentage of the time.	BO

I believe that analyzing how stock patterns connect to the policies implemented is a useful tip to understand how profits are affected.	REJ	Sometimes the specific actions of employees show how certain policies more accurately affect the company's bottom line, a useful tip is to analyze employee actions and policies as a whole.	REJ	A very useful tip is to analyze how policy patterns affect the actions of employees and how this in turn affects the company's profits, it may be that certain actions are connected to a specific type of policy and this generates great profits.	REJ
Blue and green were chosen about an equal amount of time, and the profits were low more often than they were high, however the profits were high more times when the green choice was made over the blue. So both blue and green yield the possibility of high profits, but in my opinion statistically green offers a slightly higher chance of high profits. Based off of the date provided.	GO	Based off of the provided data, blue vs green as well as high vs low were about 50/50. However, employee behavior resulted in a triangle more often during green than blue.	N	there were no significant differences between blue and green. Employee action was the same across the board. 30 triangles for blue and green, 30 circles for blue and green. Green had 1 more low than high, blue was equal. So across the board it's essentially equal.	N
I think you should implement BLUE policies 50% of the time as they are typically followed by triangle employee actions that observably result in high company profit more consistently than GREEN policies. I say 50% because BLUE policies did not guarantee high profits and GREEN policies, although results are inconsistent, can still result in back-to-back high profit.	N	I think you should implement 50% BLUE policies, mainly because the previous manager seems to have done a half-and-half mix of BLUE and GREEN policies and was able to achieve high profits for what appears to be more than half of the 120 months.	N	I think you should implement 50% BLUE policies because there is no substantial evidence that either policies concretely resulted in high profit. Employees appeared to take triangle and circle actions in an uninfluenced manner regardless of policy and was still able to achieve high profit results for about half of the 120 months.	N
be attentive to every clue they give in the environment.	REJ	be attentive to every clue they give in the environment.	REJ	be attentive to every clue they give in the environment.	REJ
It seems that increase blue policy will increase profits.	BO	We will have to find out if changing to a more green policy will increase profits or not.	REJ	It seems that green policy is not working quite well to improve profits.	BO
Green had more high profits the low so despite Blue being more predictable. Having the higher chance at high profits is the better choice	GO	Green has a more predictable scenario. If the employee chooses Triangle itâ€™s always High profit. Circle is always low profit.	GL	Both are very even and there are no noticeable differences with the information presented	N
Neither choice is more likely to produce high profits, so minimize costs at 50%.	N	If neither choice leads to high profits a majority of the time, choose 50/50 to minimize cost.	N	No choice leads to higher profits more often, so minimize costs at 50%.	N