Appendix A: Details about the Learning Stimuli

This appendix provides additional details about the learning datasets. This appendix uses the $T_{gen}A_{gen}$ condition as an example, though the other three conditions have the same summary statistics, just negative values in the preventative conditions. Table A1 provides a summary of the unconditional and conditional metrics for the learning data.

Table A1. Summary of Unconditional and Conditional Metrics for the $T_{gen}A_{gen}$ Condition.

Statistical Relation	ΔP	PowerPC	Linear Regression	Logistic Regression (log odds)
T Unconditional	.00	.00	.00	.00
T Conditional $a = 1$	.33	1.00	.33	1.33
T Conditional $a = 0$	.33	.33		
A Unconditional	.50	.67	.50	2.20
A Conditional $t = 1$	.67	1.00	.67	2.50
A Conditional $t = 0$	.67	.67		

The ΔP column is the same as in Table 1. PowerPC (Cheng, 1997) is an alternative model of causal strength judgment that is equal to ΔP / $P(e = 0|t = 0)$, and versions of PowerPC controlling for $a = 1$ or $a = 0$ can be calculated with these subsets. For readers who are less familiar with probability notation and applying it to a dataset, the following three lines provide examples of how to calculate the unconditional ΔP relation between T and E, the conditional ΔP relation between T and E within the subset in which $a = 1$, and relation between T and E according to PowerPC conditioned on $a = 1$.

$$\Delta P_T = p(e = 1|t = 1) - p(e = 1|t = 0) = \frac{3+3}{3+0+3+6} - \frac{6+0}{6+3+0+3} = 0$$

$$\Delta P_{T,a=1} = p(e = 1|t = 1, a = 1) - p(e = 1|t = 0, a = 1) = \frac{3}{3+0} - \frac{6}{6+3} = 1/3$$

$$PowerPC_{T,a=1} = \frac{\Delta P_{T,a=1}}{P(e = 0|t = 0, a = 1)} = \frac{1/3}{3/(6+3)} = 1$$

In this dataset, the value of PowerPC for T is different conditional on $a = 1$ vs. $a = 0$, and the value of PowerPC for A is also different for when $t = 1$ vs. $t = 0$. Though these measures are different depending the level at which the other variable is held constant, otherwise known as a “focal set” (Cheng & Novick, 1992), an important aspect of the learning data is that the conditional influence of T on E is always positive in this dataset, and the conditional influence of A on E is always positive. This means that even if there is uncertainty about the exact value of the influence, the direction of the influence is clear.

Table A1 also shows the regression weights for linear regression, and log odds coefficients from logistic regression. Both types of regression were computed unconditionally ($E \sim T$, and $E \sim A$), and conditionally ($E \sim T + A$). Regression only gives one set of coefficients for the conditional regressions, not two different sets. Of course, logistic regression is more appropriate in this case given that E is binary; linear regression coefficients are included as well as it is useful to notice how they align with ΔP. For the logistic regression, because of the small dataset and the fact that some cells have no observations, maximum likelihood estimation did not work for the regression with both predictors, so exact logistic regression was implemented with the elrm version 1.2.5 package for R (Zamar et al., 2007).

The crucial point across all four methods of assessing the unconditional and conditional influence of T and A on E, is that they all come to same core conclusions: 1) T has zero influence on E unconditionally, 2) T has a positive influence on E controlling for A, 3) A has a positive influence on E unconditionally, and 3) A has a positive influence on E controlling for T. (In the other three datasets in which the conditional influence of T on E and A on E are preventative, the same analysis reveals negative coefficients.) Points 1 and 2 are what is necessary to test whether or not participants controll for A when assessing the influence of T (Spellman, 1996).

A final question is whether it is possible that T and A interact in influencing E. According to ΔP, the two different versions of the conditional influence are the same, which implies no interaction. Likewise, linear regression produces a coefficient of exactly 0 if the interaction is tested. According to PowerPC, the two conditional measures produce different values, which does imply an interaction (Novick & Cheng, 2004). When logistic regression was used to test for an interaction, even when exact logistic regression was used, the package could not calculate an interaction. In sum, though there are different ways to conceptualize whether or not there is an interaction, the critical four points in the prior paragraph hold.

Cheng, P. W. (1997). From covariation to causation: A causal power theory. *Psychological review*, *104*(2), 367.

Cheng, P. W., & Novick, L. R. (1992). Covariation in natural causal induction. *Psychological Review*, *99*(2), 365–382.

Novick, L. R., & Cheng, P. W. (2004). Assessing interactive causal influence. *Psychological Review*, *111*(2), 455.

Spellman, B. A. (1996). Acting as intuitive scientists: Contingency judgments are made while controlling for alternative potential causes. *Psychological Science*, *40*(3), 305–313.

Zamar, D., McNeney, B., & Graham, J. (2007). elrm: Software implementing exact-like inference for logistic regression models. *Journal of Statistical Software*, *21*, 1-18.

Appendix B: Task Order Effects in Experiment 1

In Experiment 1, participants completed a short and long version of the same task in a randomized order. To test for possible carryover or contrast effects, task order was included as an additional predictor for the analyses conducted in the main paper. Table B1 presents the results of interaction terms that were added on to the regressions run for Table 3. Findings with p-values < .05 or BFs > 3.0 are bolded.

None of the controlling findings appear to have any order effects; this is important because assessing controlling was the most important goal of this research. Though two of the Simple Learning findings have significant p-values, the BFs are weak. There are two Discounting findings that have significant p-values as well has strong BFs.

Table B1. Effect of Task Order on Findings in Experiment 1

Measure	**Controlling × Order**			**Simple Learning × Order**			**$A^{discounting}$ × Order**			**$T^{discounting}$ × Order**		
	b	***p***	***BF***	***b***	***p***	***BF***	***b***	***p***	***BF***	***b***	***p***	***BF***
Short												
Preds. in Learning	.03	.758	0.29	.16	.103	.35	.01	.899	.28	.06	.518	.12
Causal	.01	.907	0.23	.21	**.031**	1.05	-.18	.092	.88	-.01	.879	.11
Tallies	.04	.543	0.25	.19	**.011**	2.44	-.01	.942	.21	-.05	.468	.13
Long												
Preds. in Learning	-.04	.718	0.32	.01	.964	.15	-.39	**.001**	**61.40**	-.19	.104	.53
Causal	-.05	.692	0.29	.15	.214	.34	-.21	.095	.99	-.10	.407	.22
Tallies	-.04	.617	0.33	.06	.502	.20	-.19	**.034**	2.31	-.05	.594	.18
× Timeframe												
Preds. in Learning	.07	.619	.37	.15	.275	.52	.40	**.005**	**11.9**	.25	.071	1.34
Causal	.06	.682	.39	.06	.689	.35	.03	.826	.37	.09	.556	.38
Tallies	.09	.409	.43	.13	.217	.63	.19	.079	1.29	-.01	.960	.31

Because most of the tests of order effects were not significant, in order to utilize the data as fully as possible, Table B2 presents the within-subjects analysis of both tasks. Table B2 can be compared to Table 3. Some differences between the analysis of both tasks vs. only the first task are noted in the General Discussion.

Table B2. Regression Results for Judgments in Experiment 1 Analyzing Both Tasks

Measure	**Controlling**			**Simple Learning**			**$A^{discounting}$**			**$T^{discounting}$**		
	b	***p***	***BF***	***b***	***p***	***BF***	***b***	***p***	***BF***	***b***	***p***	***BF***
Short												
Preds. in Learning	.26	<.001	10^5	1.06	<.001	10^{50}	-.06	.185	.39	.07	.136	.17
Causal	.21	<.001	10^2	.95	<.001	10^{43}	-.35	<.001	10^7	-.14	.005	3.06
Tallies	.30	<.001	10^{12}	.78	<.001	10^{45}	-.06	.072	.61	.06	.102	.23
Long												
Preds. in Learning	.15	.008	5.79	.79	<.001	10^{26}	.02	.685	.23	.04	.500	.11
Causal	.17	.007	5.60	.75	<.001	10^{22}	-.31	<.001	10^4	.01	.851	.10
Tallies	.15	.001	33.45	.59	<.001	10^{23}	-.10	.027	2.06	.00	.944	.09
× Timeframe												
Preds. in Learning	.11	.128	.73	.27	<.001	10^2	-.09	.228	.47	.03	.633	.08
Causal	.04	.577	.20	.20	.006	4.19	-.04	.587	.20	-.15	.042	.76
Tallies	.15	.005	10.50	.20	<.001	63.9	.04	.467	.23	.07	.212	.16

Note: BFs greater than 10^2 are rounded to the nearest exponent.