SUPPLEMENTAL MATERIAL

Analytic Strategy: Studies 1ab

My factorial research design yields panel data in which *i* vignettes (*i* = 1,…, 10) are nested within *j* individuals (*j* = 1,…, *J*). As a result, I estimated two-level correlated random-effects models to explore hypotheses 1 through 5.

The level-1 (or within-level) model takes the following form:

$$Y_{ij} = \beta_{0j} + \beta_{1j} X_{ij} + \delta_i V_i + e_{ij} \tag{1}$$

where Y_{ij} is a continuous measure of trust in the *i*th vignette for the *j*th individual, β_{0j} is a random intercept term capturing unobserved heterogeneity varying across individuals but not vignettes, β_{1j} is a non-random slope for X_{ij} (which is a vector of vignette dimensions treated as dummy variables that vary across both individuals and vignettes), δ_i is a non-random slope for V_i (which is the *i*th vignette treated as *i* – 1 dummy variables), and e_{ij} is a disturbance term that varies over the population of vignettes (assumed normal and *iid*).

I specify a level-2 model of between-individual variation in trust by modeling the random intercept, β_{0j}, from equation 1:

$$\beta_{0j} = \gamma_{00} + \gamma_{01} \bar{X}_j + \gamma_{02} W_j + u_{0j} \tag{2}$$

where β_{0j} is a random intercept term capturing individual-level variation in trust, γ_{00} is an overall population intercept for trust, γ_{01} is a non-random slope for $\bar{X}_j$ (which is a vector of individual-specific means for X_{ij} that vary across individuals but not vignettes), γ_{02} is a non-random slope for W_j (which is a vector of individual-level covariates), and u_{0j} is a random disturbance term that varies over the population of individuals (assumed normal and *iid*).

Because I randomly assigned levels of each dimension to vignettes, I can safely assume that X_{ij} are orthogonal to e_{ij}, the level-1 disturbance term. I cannot, however, safely assume that X_{ij} are orthogonal to u_{0j} even though I randomly assigned levels of each dimension to individuals: unbalanced distributions of levels of dimensions between individuals might correlate with u_{0j}. That is, individuals with greater (lower) proportions of certain levels of a dimension across the 10 vignettes may produce higher (lower) mean-levels of trust via learning and fatigue effects for instance. If X_{ij} and u_{0j} covary, then X_{ij} conflate within- and between-individual components, yielding inconsistent but efficient estimates of β_{1j}. Hausman specification tests estimating fixed- and random-effects econometric models for panel data support this conclusion (study 1a: $\chi^2(22) = 66.03$, $p < .001$; study 1b: $\chi^2(22) = 56.72$, $p < .001$).

As a result, I include $\bar{X}_j$ in equation 2 to decompose (or deconflate) the variances of X_{ij} into within- and between-individual components, yielding unbiased and consistent estimates of β_{1j}. Because $\bar{X}_j \neq 0$, equation 2 allows β_{0j} to be correlated with $\bar{X}_j$, which makes β_{1j} a within-individual between-vignette estimator (or fixed effect) and γ_{01} represents the difference between the within- and between-individual effect (or the unique contextual effect). In short, the inclusion of $\bar{X}_j$ in equation 2 coupled with the orthogonality assumption of X_{ij} and e_{ij} implies that I can interpret β_{1j} as causal and unbiased.

Model Assumptions. Tests revealed that the estimates presented in Table 1 were neither unduly influenced by outliers (results available upon request) nor first-order serial autocorrelation of the level-1 disturbance terms (Woolridge test for first-order autocorrelation, study 1a: $F(1, 1379) = 0.869$, $p > .10$; study 1b: $F(1, 1407) = 0.506$, $p > .10$), but that heteroscedastic level-1 errors were observed (Breusch-Pagan test for heteroscedasticity, study

1a: χ^2 (1) = 590.50, p < .001; study 1b: χ^2 (1) = 1139.13, p < .001). As a result, robust standard errors were used throughout.

Individual-Level Covariates: Studies 1ab

Since respondents vary with respect to when, where, and how they participated in studies 1a and 1b, I control for a number of individual-level covariates, W_j, intended to reduce model noise and address non-independence of observations (among others) that can arise from such unsystematic variation. First, it is possible for MTurk workers to participate in studies 1a or 1b from the same IP address. In this case, data are likely correlated and standard errors downwardly biased since clustered observations that violate the "stable unit treatment value assumption" contain less unique information. To address this issue, I include dummy variables where the referent category represents all IP addresses with a single partial or complete experiment and the indicator categories represent a vector of IP addresses with multiple partial or complete experiments (study 1a: 11% of participants from similar IP addresses; study 1b: 7% of participants from similar IP addresses). Second, my models contain a binary variable where the referent category represents complete experiments and the indicator category represents partial experiments (study 1a: 2% of participants were partials; study 1b: 4% of participants were partials). This is done to account for problems of attrition.

Third, as a manipulation check and to reduce overall model noise, I include two binary variables for each true-or-false screener question administered directly after the coversheet (and prior to the ten vignettes), where the referent category represents an incorrect answer and the indicator category represents a correct answer (study 1a: screener 1 = 96% correct, screener 2 = 98% correct; study 1b: screener 1 = 95% correct, screener 2 = 94% correct). Fourth, I further reduce model noise attributed to issues of attention by controlling for length of participation in a study (natural log time in minutes) (study 1a: *M* = 2.90, *SD* = 0.39, min = 0.31, max = 4.70; study 1b: *M* = 2.94, *SD* = 0.42, min = 0.41, max = 5.47). Fifth, to account for history effects, I include a binary variable where the referent category represents the first day of data collection and the indicator category represents the second day of data collection (data collection was completed in two days for study 1a and study 1b).

Analytic Strategy: Studies 2ab

To explore if and how gratitude and admiration mediate the relationship between perceived motivations and trust (i.e., hypotheses 6 through 8), I employed two-level correlated random-effects models with mediation in which lower level mediation (i.e., gratitude and admiration) of lower level effects (i.e., perceived motivations and trust) takes place.

The level-1 (or within-level) mediation model takes the following form:

$$\begin{aligned} M_{1ij} &= d_{1j} + a_{1j}X_{ij} + \delta_{1i}V_i + e_{1ij} \\ M_{2ij} &= d_{2j} + a_{2j}X_{ij} + \delta_{2i}V_i + e_{2ij} \\ Y_{ij} &= d_{3j} + b_{1j}M_{1ij} + b_{2j}M_{2ij} + c'_j X_{ij} + \delta_{3i}V_i + e_{3ij} \end{aligned} \tag{3}$$

where M_{1ij}, M_{2ij}, and Y_{ij} are continuous measures of gratitude, admiration, and trust, respectively, in the *i*th vignette for the *j*th individual. The random intercepts for M_{1ij}, M_{2ij}, and Y_{ij} are designated d_{1j}, d_{2j}, and d_{3j}, respectively, which capture unobserved heterogeneity varying across individuals but not vignettes. The effect of X_{ij} (which is a vector of vignette dimensions treated as dummy variables that vary across both individuals and vignettes) on M_{1ij} and M_{2ij} are designated as non-random slopes a_{1j} and a_{2j}, respectively; the effects of M_{1ij} and M_{2ij} on Y_{ij} are designated as non-random slopes b_{1j} and b_{2j}, respectively; and the direct effect of X_{ij} on Y_{ij} is designated as a non-random slope c'_j. The terms δ_{1i}, δ_{2i}, and δ_{3i} are non-random slopes for V_i (which is the *i*th vignette treated as *i* – 1 dummy variables), while e_{1ij}, e_{2ij}, and e_{3ij} are disturbances for M_{1ij}, M_{2ij}, and Y_{ij}, respectively, that vary over the population of vignettes (assumed normal and *idd*).

I specify a level-2 model of between-individual variation in gratitude, admiration, and trust by modeling the random intercepts d_{1j}, d_{2j}, and d_{3j} from equation 3:

$$d_{1j} = d_1 + \rho_{01}\bar{X}_j + \eta_{01}W_j + u_{1j}$$
$$d_{2j} = d_2 + \rho_{02}\bar{X}_j + \eta_{02}W_j + u_{2j} \qquad (4)$$
$$d_{3j} = d_3 + \rho_{03}\bar{X}_j + \theta_{01}\bar{M}_{1j} + \theta_{02}\bar{M}_{2j} + \eta_{03}W_j + u_{3j}$$

where d_{1j}, d_{2j}, and d_{3j} are random intercept terms capturing individual-level variation in gratitude, admiration, and trust, respectively; d_1, d_2, and d_3 are overall population intercepts for gratitude, admiration, and trust, respectively; ρ_{01}, ρ_{02}, and ρ_{03} are non-random slopes for $\bar{X}_j$ (which is a vector of individual-specific means for X_{ij} that vary across individuals but not vignettes); θ_{01} and θ_{02} are non-random slopes for $\bar{M}_{1j}$ and $\bar{M}_{2j}$, respectively (which are individual-specific means for M_{1ij} and M_{2ij}, respectively, that vary across individuals but not vignettes); η_{01}, η_{02}, and η_{03} are non-random slopes for W_j (which is a vector of individual-level covariates), and u_{1j}, u_{2j}, and u_{3j} are random disturbance terms that vary over the population of individuals (assumed normal and *iid*).

Following earlier specifications, I include $\bar{X}_j$ in equation 4 to decompose (or deconflate) the variances of X_{ij} into within- and between-individual components, yielding unbiased and consistent estimates of a_{1j} and a_{2j} (Hausman specification tests, study 2a: $\chi^2(22) = 60.14$, $p < .001$; study 2b: $\chi^2(22) = 16.45$, $p > .10$). Again, X_{ij} are orthogonal to e_{1ij}, e_{2ij}, and e_{3ij} because of randomization, which implies that I can interpret a_{1j}, a_{2j}, and c'_j as causal. However, because M_{1ij} and M_{2ij} were not randomly assigned, but instead are endogenous regressors, M_{1ij} and M_{2ij} may be correlated with e_{3ij}. Under these conditions, one can only assume that b_{1j} and b_{2j} are causal if e_{1ij} and e_{2ij} are uncorrelated with e_{3ij} or if X_{ij} captures all relevant confounding variables at the within-individual level. Yet, both of these assumptions are unfounded. As a result, even though I include $\bar{M}_{1j}$ and $\bar{M}_{2j}$ in equation 4 to decompose gratitude and admiration into within- and between-individual components, I do not interpret b_{1j} and b_{2j} as causal effects but as upwardly biased conditional associations that risk omitted variable bias and endogeneity bias.

Moreover, although I can interpret $c_j^{'}$ as causal, the estimate is downwardly biased since $c_j^{'}$ is the total effect of X_{ij} on Y_{ij} minus the indirect effects of $a_{1j}b_{1j}$ and $a_{2j}b_{2j}$ which are likely biased because of M_{1ij} and M_{2ij}. In other words, regressing Y_{ij} on post-treatment variables M_{1ij} and M_{2ij} in equation 3 yields downwardly biased estimates of $c_j^{'}$ for any treatments of X_{ij} with which M_{1ij} or M_{2ij} are correlated. In this case, M_{1ij} and M_{2ij} are likely correlated with X_{ij}. As a consequence, I interpret the estimate of $c_j^{'}$ as causal but with caution knowing it is likely downwardly biased.

Model Assumptions. Tests revealed that the estimates presented in Table 2 were neither unduly influenced by outliers (results available upon request) nor first-order serial autocorrelation of the level-1 disturbance terms (Woolridge test for first-order autocorrelation, study 2a: $F(1, 954) = 1.867$, $p > .10$; study 2b: $F(1, 923) = 0.519$, $p > .10$), but that heteroscedastic level-1 errors were observed (Breusch-Pagan test for heteroscedasticity, study 2a: $\chi^2(1) = 348.80$, $p < .001$; study 2b: $\chi^2(1) = 559.49$, $p < .001$). As a result, robust standard errors were used throughout.

Individual-Level Covariates: Studies 2ab

I include two additional individual-level covariates, W_j, beyond those outlined in studies 1a and 1b. First, in studies 2a and 2b it is not only possible to observe units from the same IP address but also units from the same survey token, which further downwardly biases standard errors. To address this additional clustering issue, I include dummy variables where the referent category represents all survey tokens with a single partial or complete experiment and the indicator categories represent a vector of survey tokens with multiple partial experiments or multiple partials and a complete experiment (study 2a: 17% of participants from similar survey tokens; study 2b: 17% of participants from similar survey tokens). Second, recruitment in studies 2a and 2b lasted approximately one academic quarter with one recruitment e-mail sent a week. To reduce model noise and account for individual-level variation in the number of recruitment e-mails required for respondents to participate, I include dummy variables where the referent category represents respondents who participated upon the initial recruitment e-mail and the indicator categories represent each additional recruitment e-mail sent before a respondent participated (study 2a: median = 2, min = 1, max = 8; study 2b: median = 2, min = 1, max = 8).

Following studies 1a and 1b, I include dummy variables for clustering around IP addresses (study 2a: 11% of participants from similar IP addresses; study 2b: 12% of participants from similar IP addresses), a binary variable for partial and complete experiments (study 2a: 10% of participants were partials; study 2b: 11% of participants were partials), two binary variables for each true-or-false screener question (study 2a: screener 1 = 90% correct, screener 2 = 96% correct; study 2b: screener 1 = 93% correct, screener 2 = 93% correct), a continuous variable for length of participation in a study (natural log time in minutes) (study 2a: $M = 2.96$, $SD = 0.53$, min = 0.34, max = 4.71; study 2b: $M = 2.97$, $SD = 0.51$, min = 0.56, max = 4.46), and dummy variables for the day in which participants partially or fully completed an experiment (study 2a: 50 unique date stamps; study 2b: 50 unique date stamps).

Table S1. Vignette Dimensions for Car Repair Scenario

Dimensions	Text with levels in **bold**
Age	The auto mechanic is a **20 year old**, The auto mechanic is a **30 year old**, The auto mechanic is a **40 year old**, The auto mechanic is a **50 year old**, The auto mechanic is a **60 year old**,
Race	**white**, **black**, **Hispanic**, **Asian**,
Gender	**male**. **female**.
Reputation	As far as you know, none of your friends have used the auto mechanic's services before (**no reputation**). Some of your friends have used the auto mechanic's services before and they were satisfied with the work (**positive reputation**).
Halo	Respondent shown nothing (**Blank**). The auto mechanic sold you a used computer before but you were dissatisfied with the computer (**bad used computer**). The auto mechanic sold you a used computer before and you were satisfied with the computer (**good used computer**).
Perceived Internal Motivations	The auto mechanic has never serviced or repaired your car before (**no prior interaction**). The auto mechanic has serviced your car before but provided fraudulent and costly repairs (**uncooperative**). The auto mechanic has serviced your car before and always provides justifiable repairs (**prior interaction**). The auto mechanic has serviced your car before and always provides justifiable repairs because the auto mechanic is interested in your future business (**encapsulated interests**). The auto mechanic has serviced your car before and always provides justifiable repairs because the auto mechanic genuinely cares for and is concerned about your interests. You know this since the auto mechanic has repaired your car for free when you couldn't afford the cost of repairs (**goodwill**). The auto mechanic has serviced your car before and always provides justifiable repairs because the auto mechanic genuinely cares for and is concerned about the interests of all customers. You know this since the auto mechanic has

	repaired your car and other customers' cars for free when customers couldn't afford the cost of repairs (**virtuous dispositions**).
Competence	Respondent shown nothing (**Blank**). [And or But], as best you can tell, is a competent machinist (**competent**).
Exertion	Respondent shown nothing (**Blank**). [And or But], as best you can tell, is a hard-working machinist (**hard-working**).
Contract	Respondent shown nothing (**Blank**). The auto mechanic verbally promises you that the repairs and new engine parts will last for at least 50,000 miles (**non-binding contract**). The auto mechanic signs a limited warranty outlining how the auto mechanic will be subject to costly professional penalties if the repairs and new engine parts do not last 50,000 miles (**binding contract**).
Regulations	An automotive agency does not regulate services at The Autoshop (**no regulations**). An automotive agency regulates services at The Autoshop by teaching auto mechanics who provide fraudulent services to their customers about business ethics and professional integrity (**non-monetary regulations**). An automotive agency regulates services at The Autoshop by fining auto mechanics who provide fraudulent services to their customers (**monetary regulations**).

Table S2. Vignette Dimensions for Group Project Scenario

Dimensions	Text with levels in **bold**
Age	The student is a **20 year old**, The student is a **30 year old**, The student is a **40 year old**, The student is a **50 year old**, The student is a **60 year old**,
Race	**white**, **black**, **Hispanic**, **Asian**,
Gender	**male**. **female**.
Reputation	As far as you know, none of your friends have worked on a group project with the student before (**no reputation**). Some of your friends have worked on a group project with the student before and they were satisfied with the student's contribution (**positive reputation**).
Halo	Respondent shown nothing (**Blank**). The student sold you a used computer before but you were dissatisfied with the computer (**bad used computer**). The student sold you a used computer before and you were satisfied with the computer (**good used computer**).
Perceived Internal Motivations	The student has never worked on a group project with you before (**no prior interaction**). The student has worked on a group project with you before but failed to complete the assigned data analysis task (**uncooperative**). The student has worked on group projects with you before and always completes the assigned data analysis task (**prior interaction**). The student has worked on group projects with you before and always completes the assigned data analysis task because the student is interested in working with you as a partner on future group projects (**encapsulated interests**). The student has worked on group projects with you before and always completes the assigned data analysis task because the student genuinely cares for and is concerned about your interests. You know this since the student has completed your assigned task when you were too overwhelmed with other obligations and commitments to finish it yourself (**goodwill**).

	The student has worked on group projects with you before and always completes the assigned data analysis task because the student genuinely cares for and is concerned about the interests of all group members. You know this since the student has completed your assigned task and tasks assigned to other group members when group members were too overwhelmed with other obligations and commitments to finish it themselves (**virtuous dispositions**).
Competence	Respondent shown nothing (**Blank**). [And or But], as best you can tell, is a competent data analyst (**competent**).
Exertion	Respondent shown nothing (**Blank**). [And or But], as best you can tell, is a hard-working data analyst (**hard-working**).
Contract	Respondent shown nothing (**Blank**). The student verbally promises you that the data analysis for the group project will be completed on time (**non-binding contract**). The student signs an academic honor pledge outlining how the student will be subject to costly academic penalties if the data analysis for the group project is not completed on time (**binding contract**).
Regulations	The college does not regulate contributions to group projects (**no regulations**). The college regulates contributions to group projects by teaching students who don’t turn in their assigned tasks about academic ethics and educational integrity (**non-monetary regulations**). The college regulates contributions to group projects by revoking financial aid and academic scholarships from students who don’t turn in their assigned tasks. And, as far as you know, the student receives financial aid (**monetary regulations**).