Dominance is necessary to explain human status hierarchies

Extended Online Version and Supplemental

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Introduction

Durkee et al. (2020) (hereafter, DLB) conducted a cross-cultural investigation of people's beliefs about how traits, behaviors, and practices that enhance an individual's perceived ability to generate benefits (prestige) or inflict costs (dominance) promote perceived social status in humans. Here, we identify multicollinearity in DLB's statistical analyses and explain how this statistical problem renders their results inconclusive as to how benefit-delivery and cost-infliction contribute to status allocation. In particular, this statistical error severely undermines DLB's conclusion that dominance has little to no impact on status. In closing, we briefly survey the broader empirical record on actual status relations among real people (rather than people's beliefs about what leads to status), conducted both in the lab and in naturalistic settings; these studies consistently yield opposite conclusions to those offered

by DLB and demonstrate that both prestige and dominance govern human status hierarchies.

DLB's original data and code are available here: <https://osf.io/57yu8/>. Code and data for reproducing the analyses in this reply can be found at: <https://github.com/joeytcheng/Dominance-Necessary-to-Explain-Status>.

S1. Collinearity limits inferences about the importance of dominance

Here, we discuss the problem of collinearity in DLB's analyses and the implications of this limitation for the authors' results. We then report results from a more appropriate alternative analysis of DLB's data that partially addresses collinearity, and show that even minor re-specifications produce a different conclusion.

S1.1 The problem of collinearity

In their critical main test, DLB regressed status-impact ratings on four simultaneous predictors that capture the extent to which a given trait or behavior is inferred to signal the displayer's (a) benefit-generation ability (BGA), (b) benefit-generation willingness (BGW), (c) cost-infliction ability (CIA), and (d) cost-infliction willingness (CIW). This approach aimed to isolate the unique contribution of each of these four predictors, and therefore should, in principle, address whether status differences arise from benefit conferral (prestige) or cost infliction (dominance) or both. However, DLB overlooked the problem of multicollinearity that plagues the suite of predictors. To see the extent of this issue, consider the strong positive associations among all four predictors:

Figure 1 | A pairs plot showing pairwise associations between the four predictors in DLB data. Benefit-generation ability (BGA) and willingness (BGW), and cost-infliction ability (CIA) and willingness (CIW), are each strongly positively correlated both within and across benefit and cost domains. In particular, within domain predictors—BGA and BGW, and CIA and CIW—are so strongly correlated that they are, for practical purposes, redundant. Across domains (such as BGA with CIA), collinearity is especially high among female targets.

Furthermore, two commonly used indices indicate serious collinearity problems. First, the exceptionally strong positive associations among predictors—particularly between ability and willingness (BGA & BGW, $r_s = 0.87 - 0.91$; CIA & CIW, $r_s = 0.80 - 0.84$)—exceed the conventional cut-offs for diagnosing collinearity ($r < 0.80$; Berry et al., 1985). Second, the variance inflation factor (VIF) on all four predictors exceed the 2.5 threshold that warrants collinearity concern (Johnston et al., 2018; Vatcheva et al., 2016):

```
fit.4.predictors <- lm(Status ~
  BGA + BGW + CIA + CIW,
  data = agg_df)

library(car)
vif(fit.4.predictors)

##      BGA      BGW      CIA      CIW
## 4.854797 5.763175 3.680333 3.345738
```

The profound impact of ignoring collinearity on statistical inference is widely recognized and well documented (Cohen et al., 2013; Kutner et al., 2005). Multicollinearity creates a range of interpretational challenges but the crux of the problem, as applied to DLB’s paper, is that the collinearity among predictors obscures the identification of important predictors. With such

exceptionally strong associations between BGA and BGW ($r > 0.87$) and between CIA and CIW ($r > 0.80$), these predictors contain almost perfectly redundant information. Regression models reveal how much each predictor adds to the *unique* prediction of the outcome. As such, while any one of these predictors may be in truth an important predictor of Status, the effect of each may not be shown to matter in the regression model *once the effect of any one predictor is already known*. Regardless of their true contribution to Status, the collinearity among predictors guarantees that each will be shown to be unimportant in the model estimates (Kutner et al., 2005). This means that any conclusions from DLB'S models are misleading because the data, as modeled, are ill suited for investigating how benefit-delivery and cost-infliction each contribute to status.

S1.2 Simulating collinearity

To illustrate how collinearity undermines DLB's conclusions, we conducted a series of simulations. We simulate five datasets with increasingly large correlations among four predictors: BGA, BGW, CIA, and CIW. Across all scenarios, the true association of Status (the outcome) with BGA and BGW are each fixed at $r = 0.50$, while the associations with CIA and CIW are fixed at $r = 0.40$. These chosen associations represent moderate to large effect sizes. In each, we simulate data for 240 behavioral items or events, as in DLB. Across these 5 cases, we begin with data absent of any collinearity (Case 1), and progressively increase the correlation among predictors to ultimately approximate the severe collinearity observed in DLB's data (Case 5)

In Case 1, we first consider a situation free of any collinearity. The correlation among all four predictors is zero:

```
set.seed(48096325)

library(faux)
cmatCase1 <-
  c(1, .5, .5, .4, .4, # corrs between DV & 4 predictors
    .5, 1, 0, 0, 0,
    .5, 0, 1, 0, 0,
    .4, 0, 0, 1, 0,
    .4, 0, 0, 0, 1)
```

```
Case1.df <- # sim 240 samples, 5 vars, M = 0, SD = 1
```

```
  rnorm_multi(
    240,
    5,
    0,
    1,

    cmatCase1,
    varnames = c( # variable names
      "Status",
      "BGA",
      "BGW",
      "CIA",
      "CIW"),
    empirical = TRUE
  )
```

```
library(GGally)
ggpairs(Case1.df, # get scatterplot matrix
  lower = list(continuous = wrap(ggally_points,
    alpha = .2)))
```

Case 1. No collinearity

In Case 2, we move to a low collinearity situation with weak correlations among predictors. Ability and willingness variables *within* benefits or costs domains, $r = 0.20$. *Across* domains, benefits and costs predictors $r = 0.10$.

```
cmatCase2 <- c(1, .5, .5, .4, .4,
               .5, 1, .2, .1, .1,
               .5, .2, 1, .1, .1,
               .4, .1, .1, 1, .2,
               .4, .1, .1, .2, 1)
Case2.df <- rnorm_multi(240, 5, 0, 1,
  cmatCase2,
  varnames = c("Status", "BGA", "BGW", "CIA", "CIW"),
  empirical = TRUE)

ggpairs(Case2.df,
  lower = list(continuous = wrap(ggally_points,
    alpha = .2)))
```

Case 2. Low collinearity

Case 3 exhibits moderate collinearity, with moderate correlations among predictors. *Within* domains, ability and willingness predictors $r = 0.60$. *Across* domains, benefits and costs predictors $r = 0.50$.

```
cmatCase3 <- c(1, .5, .5, .4, .4,
               .5, 1, .6, .5, .5,
               .5, .6, 1, .5, .5,
```

```

      .4, .5, .5, 1, .6,
      .4, .5, .5, .6, 1)
Case3.df <- rnorm_multi(240, 5, 0, 1,
  cmatCase3,
  varnames = c("Status", "BGA", "BGW", "CIA", "CIW"),
  empirical = TRUE)

ggpairs(Case3.df,
  lower = list(continuous = wrap(ggally_points,
    alpha = .2)))

```

Case 3. Moderate collinearity

Case 4 presents high collinearity created by strong correlations among predictors. *Within* domains, ability and willingness predictors $r = 0.80$. *Across* domains, benefits and costs predictors $r = 0.70$.

```

cmatCase4 <- c(1, .5, .5, .4, .4,
      .5, 1, .8, .7, .7,
      .5, .8, 1, .7, .7,
      .4, .7, .7, 1, .8,
      .4, .7, .7, .8, 1)
Case4.df <- rnorm_multi(240, 5, 0, 1,
  cmatCase4,
  varnames = c("Status", "BGA", "BGW", "CIA", "CIW"),
  empirical = TRUE)

ggpairs(Case4.df,
  lower = list(continuous = wrap(ggally_points,
    alpha = .2)))

```

Case 4. High collinearity

Case 5 exhibits severe collinearity. *Within* domains, ability and willingness predictors $r = 0.90$. *Across* domains, benefits and costs predictors $r = 0.80$. These exceptionally strong associations most closely approximate the strong intercorrelations among DLB's predictor variables.

```

cmatCase5 <- c(1, .5, .5, .4, .4,
      .5, 1, .9, .8, .8,
      .5, .9, 1, .8, .8,
      .4, .8, .8, 1, .9,
      .4, .8, .8, .9, 1)
Case5.df <- rnorm_multi(240, 5, 0, 1,
  cmatCase5,
  varnames = c("Status", "BGA", "BGW", "CIA", "CIW"),
  empirical = TRUE)

ggpairs(Case5.df,
  lower = list(continuous = wrap(ggally_points,
    alpha = .2)))

```

Case 5. Severe collinearity

Next, to compare the impact of these differing degrees of collinearity, we regress *Status* on all 4 predictors simultaneously—BGA, BGW, CIA, and CIW—in Bayesian models using each of the 5 simulated datasets. In all five cases, for which the true association is known, the expected standardized beta coefficient, β , that measures the association of *Status* with benefit-generation and cost-infliction is expected to be $\beta = 0.50$ and 0.40 , respectively. As in DLB, we used default noninformative priors for all model parameters.

Table 1 displays the model estimates for benefit-generation and cost-infliction ability and willingness. First, note the difference across cases in the β parameter. For the β s on BGA and BGW, which have a true value of 0.50 (as accurately captured by Case 1 results), as collinearity increases the estimated coefficients *decrease*. In fact, under severe collinearity (Case 5), the coefficients become roughly half of its true value at β s = $0.29 - 0.30$. For the β s on CIA and CIW, which have a true value of 0.40 , the decrease in magnitude as collinearity increases is even more striking, as it even becomes *negative*, $\beta = -0.04$, under severe collinearity (Case 5).

Second, consider the increased variance of the model estimates under collinearity. The standard errors of the β s increase in magnitude as collinearity increases from Case 1 to Case 5, first slowly and then more rapidly as collinearity becomes high or severe. Under severe collinearity, where r s among predictors = $0.80 - 0.90$ (Case 5), the standard errors of the β s have a 4-5 fold increase compared to when collinearity is completely absent (Case 1). Along with the increase in these standard errors, of course, are widened confidence intervals (*CI*s) around each estimate as collinearity increases.

Note, this exercise decisively demonstrates that DLB's data and analysis are not suitable for making the inferences that they in fact made regarding the relative and absolute effect sizes of the impacts of costs and benefits on status.

These adverse effects of collinearity on parameter estimates and their standard errors have been similarly observed in many datasets and across a range of disciplines (Cohen et al., 2013; Gordon, 1968; Hoffmann, 2010; Kleinbaum et al., 2013; Kutner et

al., 2005; McElreath, 2020).

Table 1 | Data simulations show that model estimates are severely negatively biased and imprecisely estimated under high collinearity (Bayesian linear regression).

	<i>Case.1</i>	<i>Case.2</i>	<i>Case.3</i>	<i>Case.4</i>	<i>Case.5</i>
BGA	0.50 (0.44 – 0.56) (0.03)	0.37 (0.29 – 0.45) (0.04)	0.26 (0.11 – 0.39) (0.07)	0.26 (0.07 – 0.46) (0.10)	0.30 (0.03 – 0.56) (0.14)
BGW	0.50 (0.45 – 0.55) (0.03)	0.37 (0.29 – 0.46) (0.04)	0.26 (0.12 – 0.39) (0.07)	0.27 (0.07 – 0.46) (0.10)	0.29 (0.03 – 0.56) (0.14)
CIA	0.40 (0.35 – 0.45) (0.03)	0.27 (0.19 – 0.36) (0.04)	0.09 (-0.04 – 0.23) (0.07)	0.02 (-0.18 – 0.22) (0.10)	-0.04 (-0.30 – 0.22) (0.13)
CIW	0.40 (0.34 – 0.45) (0.03)	0.27 (0.19 – 0.36) (0.04)	0.09 (-0.05 – 0.23) (0.07)	0.01 (-0.18 – 0.21) (0.10)	-0.04 (-0.30 – 0.22) (0.13)
Intercept	-0.00 (-0.05 – 0.05) (0.03)	0.00 (-0.08 – 0.08) (0.04)	0.00 (-0.10 – 0.10) (0.05)	0.00 (-0.10 – 0.11) (0.06)	0.00 (-0.11 – 0.11) (0.06)
Observations	240	240	240	240	240
R ² Bayes	0.819	0.587	0.331	0.281	0.268

Paralleling the results above derived from a Bayesian approach, we obtain qualitatively similar results with a frequentist approach using ordinary least squares regressions. As shown in Table 2 below, we again observe that as collinearity increases, the estimated β s decrease in magnitude (and the decline is especially sharp for CIA and CIW) and their $\mathcal{C}$ s widen.

Table 2 | Data simulations show that model estimates are severely negatively biased and imprecisely estimated under high collinearity (ordinary least squares regression).

	Simulated Dataset				
	Case.1	Case.2	Case.3	Case.4	Case.5
Benefit-Generation Ability (BGA)	0.50*** (0.03)	0.37*** (0.04)	0.26*** (0.07)	0.27*** (0.10)	0.30** (0.14)
Benefit-Generation Willingness (BGW)	0.50*** (0.03)	0.37*** (0.04)	0.26*** (0.07)	0.27*** (0.10)	0.30** (0.14)
Cost-Infliction Ability (CIA)	0.40*** (0.03)	0.27*** (0.04)	0.09 (0.07)	0.02 (0.10)	-0.04 (0.14)
Cost-Infliction Willingness (CIW)	0.40*** (0.03)	0.27*** (0.04)	0.09 (0.07)	0.02 (0.10)	-0.04 (0.14)
Intercept	-0.00 (0.03)	0.00 (0.04)	-0.00 (0.05)	-0.00 (0.06)	0.00 (0.06)
Observations	240	240	240	240	240

R ²	0.82	0.59	0.33	0.28	0.26
Adjusted R ²	0.82	0.58	0.32	0.27	0.25
Residual Std. Error (df = 235)	0.43	0.65	0.83	0.86	0.86
F Statistic (df = 4; 235)	267.64***	84.05***	28.70***	22.64***	21.16***

Note:

$p < 0.1$; **$p < 0.05$** ; $p < 0.01$

OLS, standard errors in parentheses

Results of these simulations illustrate the adverse impact of collinearity on inferences made from DLB's results. DLB's analyses purportedly show large positive effects of BGA and BGW on status allocation, but weak or non-existent effects for CIA and CIW. These results and conclusions, however, ignore the severe collinearity among predictors (similar in degree to our Case 5). These predictors provide almost perfectly redundant information, particularly the ability and willingness predictors (BGA & BGW, CIA & CIW, where r s = 0.80 - 0.91). As we illustrate above, such high levels of collinearity have a serious adverse impact on the parameter estimates—underestimating the effects of the collinear variables (especially the cost-infliction predictors) and increasing their standard errors. This statistical problem thus obscures the identification of key independent predictors of Status, as any important predictors may be erroneously revealed to be unimportant in their models. DLB's results are thus uninformative regarding how benefit-delivery and cost-infliction contribute to status allocation.

S1.3 Partially correcting for collinearity in Durkee et al.'s models

Fully correcting for collinearity would entail reducing the correlation among predictors substantially to below $r = 0.10$. Other simulation studies reveal that even modest correlations among predictors in the range of $r = 0.20$ can produce changes in coefficient estimates and standard errors (Cohen et al., 2013; Vatcheva et al., 2016). Given the severe collinearity among all four predictors in DLB's models (r s = 0.45 - 0.91), a full correction—which necessitates dropping all but one of DLB's predictors—is untenable since this would make their central question unanswerable.¹

Although a full correction of collinearity in DLB's models is not possible, here we partially correct for it through a series of

¹ Note, however, that similar analyses conducted in other existing work (including our own; Cheng et al., 2010, 2013), which deploy measures of prestige and dominance that are uncorrelated or only weakly negatively

model re-specifications.² These alternative analyses reveal that even a small partial correction produces different conclusions to those claimed by DLB.

As discussed above and shown in Figure 1, the collinearity problem is most severe among predictors BGA and BGW ($r = 0.87 - 0.91$), and between CIA and CIW ($r = 0.80 - 0.84$). As a first approach to reduce collinearity among these predictors, we combined each of these pairs of variables into a single aggregated index, labeled BGcomposite and CImposite. This approach is justified by (1) the strong empirical overlap among these variables, and (2) the lack of clear theoretically driven rationale for expecting a strong theoretical differentiation between *ability* and *willingness*. In fact, DLB and other researchers (Cheng et al., 2013; Henrich & Gil-White, 2001) premise their conclusions on benefit-delivery and cost-infliction broadly, without distinguishing between the empirically indistinguishable ability and willingness. To examine the effect of this re-specification, we use the same analytic approach as deployed by DLB but here include only these two composite indices as predictors.

Our results are displayed in Table 3, to the right of DLB’s original results from models that include all four collinear predictors (that is, columns ‘All.Predictors’), which we reproduce here using the authors’ analysis code (their findings are reported in their Fig. 3). Our model estimates now show that, for male targets, both BGcomposite and CImposite positively predict Status projections—in contrast to DLB’s finding of a weak or null effect of cost-infliction for men. For female targets, however, we find that while BGcomposite positively predicts Status, CImposite remains a null predictor.

correlated, are free of this collinearity problem. These uncorrelated or weakly correlated measures of the same concepts are thus better suited for investigations like the present one, aimed at identifying the determinants of status.

² Model re-specification, such as by combining collinear variables or dropping redundant variables, is one of the first lines of remedy for collinearity problems (Cohen et al., 2013; McElreath, 2020). It is particularly well suited for data (such as DLB’s) in which collinearity stems from overlapping conceptual content of the highly correlated variables (here, for example, a person seen as *able* to generate benefits for others is also regarded as more *willing* to provide those benefits). A range of other methods have been developed to address collinearity—from clustering or the use of latent methods to extract a subset of variables, to alternative modeling techniques such as ridge regressions—but these methods vary in effectiveness and each have unique limitations (see: Dormann et al., 2013; Kiers & Smilde, 2007).

Table 3 | Perceived status impact is unrelated or weakly related to cost-infliction when all four collinear predictors are included, but is positively predicted by cost-infliction when benefits and costs composites are included as predictors instead.

	All.Predictors: Men	All.Predictors: Women	Composites: Men	Composites: Women
Predictors	Estimates	Estimates	Estimates	Estimates
BGA	0.38 (0.29 – 0.47) (0.05)	0.61 (0.52 – 0.69) (0.04)		

BGW	0.43 (0.32 – 0.54) (0.05)	0.28 (0.19 – 0.37) (0.04)		
CIA	0.11 (0.03 – 0.19) (0.04)	0.06 (-0.04 – 0.15) (0.05)		
CIW	0.06 (-0.03 – 0.15) (0.05)	-0.01 (-0.07 – 0.06) (0.03)		
BGcomposite			0.78 (0.73 – 0.84) (0.03)	0.86 (0.80 – 0.93) (0.03)
CIcomposite			0.18 (0.11 – 0.24) (0.03)	0.04 (-0.03 – 0.11) (0.03)
Intercept	-0.01 (-0.04 – 0.03) (0.02)	0.00 (-0.04 – 0.04) (0.02)	-0.01 (-0.04 – 0.03) (0.02)	-0.00 (-0.04 – 0.04) (0.02)
N	14 Country 240 item_id	14 Country 240 item_id	14 Country 240 item_id	14 Country 240 item_id
Observations	3069	3069	3069	3069
Marginal R ² / Conditional R ²	0.824 / 0.900	0.823 / 0.902	0.824 / 0.899	0.816 / 0.902

Why CIcomposite does not reliably predict Status in women targets is a puzzle worth considering. Recall our results above (and illustrated in Figure 1) revealing higher collinearity between benefit generation and cost-infliction in female targets relative to males (e.g., r between BGA and CIA = 0.81 for females vs. 0.45 for males). This raises the possibility that the two composite indices may still suffer from collinearity in female targets, compared to males. Confirming this expectation, the correlation between BGcomposite and CIcomposite is much stronger for female targets than male targets, and the VIFs in females (but not in males) exceed the 2.5 threshold:

Particularly strong correlations among benefits and costs composite predictors in women.

```
library(car)

ols.composite.men <-
  lm(Status ~ BGcomposite + CIcomposite,
      data = agg_df %>% filter(TargetSex == "Man"))
vif(ols.composite.men) # get vif in male targets

## BGcomposite CIcomposite
## 1.707661 1.707661

ols.composite.women <-
  lm(Status ~ BGcomposite + CIcomposite,
      data = agg_df %>% filter(TargetSex == "Woman"))
vif(ols.composite.women) # get vif in female targets

## BGcomposite CIcomposite
## 2.647302 2.647302
```

Having identified this persisting collinearity issue in the composite indices among female targets leads us to a second re-specification approach, in which we included only one benefits and one costs predictor, rather than composites.³ Using this second approach, we found a positive significant effect of cost-infliction among women (as well as in men). In their respective models, CIA and CIW each reliably predict higher Status projections in both female and male targets.

Table 4 | Perceived status impact increases with cost-infliction for both male and female targets.

	Ability: Men	Ability: Women	Willingness: Men	Willingness: Women
Predictors	Estimates	Estimates	Estimates	Estimates

³ Although the two predictors included in these models—BGA and CIA or BGW and CIW—are, on average, less strongly correlated with each other compared to BGcomposite and CIcomposite, their associations are nevertheless still too strong ($r_s = 0.45 - 0.81$) to consider these models free of collinearity issues. Thus, while we consider our re-specifications to partially reduce collinearity, this issue remains pervasive in DLB's original data and continues to severely limit any inferences from these data. As our simulations above suggest,

BGA	0.74 (0.69 – 0.79) (0.03)	0.77 (0.71 – 0.85) (0.04)		
CIA	0.26 (0.21 – 0.32) (0.03)	0.14 (0.07 – 0.21) (0.04)		
BGW			0.79 (0.72 – 0.87) (0.04)	0.77 (0.70 – 0.84) (0.03)
CIW			0.13 (0.05 – 0.21) (0.04)	0.14 (0.07 – 0.20) (0.03)
Intercept	-0.00 (-0.05 – 0.04) (0.02)	-0.00 (-0.04 – 0.04) (0.02)	-0.00 (-0.05 – 0.04) (0.02)	-0.00 (-0.05 – 0.05) (0.03)
N	14 Country 240 item_id	14 Country 240 item_id	14 Country 240 item_id	14 Country 240 item_id
Observations	3069	3069	3069	3069
Marginal R ² / Conditional R ²	0.800 / 0.898	0.808 / 0.901	0.799 / 0.899	0.737 / 0.902

even in these re-specified models where collinearity exists, the effects of cost-infliction are still likely to be severely underestimated.

Together, these simulation and re-analysis results reveal the sensitivity of DLB's results to collinearity. Their misleading claims are heavily driven by collinearity among predictors. As our simulations above highlight, CIA and CIW are nearly perfectly redundant predictors. Although both have strong positive relations with *Status* projections, neither CIA nor CIW helps to explain this outcome *once you already know the impact of the other*. When we apply even a small correction for the problem of collinearity through model re-specification, DLB's main conclusions are overturned and *both* benefits and costs emerge as reliable predictors of *Status*.

Nevertheless, one might be tempted to conclude from these re-analyses that even after partially correcting for collinearity in re-specified models, the effect of dominance is estimated to be much weaker than that of prestige (by a factor of 3-6). However, a crucial consideration (as noted above) is that even in our re-specifications, associations among predictors are only somewhat ameliorated and collinearity remains high ($r_s > 0.64$ in composite models, > 0.45 in ability models, and > 0.61 in willingness models). Our simulations above indicate that at these levels of collinearity (Cases 4 and 5), the effect of dominance may still be *underestimated* by 4-40 times. Similar

efforts by statisticians have led to similar conclusions (Vatcheva et al., 2016), revealing that even with $r = 0.25$ among predictors, significant multicollinearity effects may lead to unstable coefficient estimates. Given the severe collinearity in DLB's data, then, the contribution of dominance to status projections in these partially corrected models is still seriously underestimated.

In light of these new conclusions, it is worth noting that a large body of existing research demonstrates the importance of cost-infliction (i.e., dominance), along with benefit-generation (i.e., prestige), in shaping status outcomes. Below, we provide a brief overview of this work.

S2. Existing evidence consistently reveals that dominance (i.e., cost-infliction) contributes to status

Studies that have examined actual status relations among real people, in the lab and naturalistic settings, consistently find that both prestige (i.e., benefit-generation) and dominance (i.e., cost-infliction) contribute to status, and can have a similarly large impact across a broad range of contexts and groups:

1. In Cheng et al. (2013), we tested in small 'minimal' laboratory groups whether prestige and dominance (each measured using reliable 8-item peer-rating scales) each result in greater deference, measured as (1) demonstrated behavioral impact over group decision-making, (2) amount of visual attention received (assessed by eye-tracking), and (3) group member ratings of who "led the task", "was paid attention", and "had high status".
2. In subsequent work, these same measures were used to evaluate group members' relative influence in the field among sports clubs, volunteer groups, businesses, bands, and chess clubs (Brand & Mesoudi, 2019), as well as collaborative student project teams (Redhead et al., 2019).

3. In Anderson et al. (2020)'s study of status and power in the workplace, status was measured using self- and coworker-reports on items that indicate an individual's "influence over important decisions", "influence in the everyday activities of the organization", and ability to "get my [his/her] way" and "get others to listen to what I [he/she] say(s)".

In all of these prior studies, dominance and prestige were found to have similarly large effects on influence (Brand & Mesoudi, 2019; Cheng et al., 2013; Garfield & Hagen, 2020). This is a striking departure from the substantially weaker effect of dominance observed by DLB. DLB's is also the only study in this larger body of work that measured status on the basis of people's subjective beliefs rather than actual deference or influence; it is also the only study that found little to no effect of dominance on status.⁴

Nonetheless, one might wonder whether dominance is universally present and important across populations. After all, the people sampled in the studies described above are primarily from Western, Educated, Industrialized, Rich and Democratic (WEIRD) societies (Henrich et al., 2010), whereas DLB sampled across a number of nations and states, and this difference might be assumed to explain the divergent findings. However, emerging evidence from small-scale foragers and horticulturalists confirm the importance of dominance-based status in these diverse populations. For example, in Von Rueden et al. (2014)'s study of Tsimane' forager-horticulturalists of Bolivia, physically dominant men are more likely to rise to and maintain leadership positions and exercise community-wide influence (also see Von Rueden et al. (2008) for similar findings). In Garfield & Hagen (2020)'s study on the traits and attributes of elected officials in Chabu, a small-scale society with a long history of egalitarianism, men who intimidate and are feared—a prime index of dominance—were over-represented in leadership positions; importantly, as in the WEIRD findings surveyed above, this status-enhancing effect of dominance was obtained after accounting for any effects of prestige on status, ruling out DLB's core assertion that the association between

⁴ By confirming the status-enhancing effects of both prestige and dominance, the prior field studies contradict DLB's claim that "most evidence supporting the dual-pathway account, for example, is derived from laboratory-based interactions among previously unacquainted temporary groups, which may not function in the same way as real-world human groups" (p. 21236). For additional evidence from real-world social relations and groups, see Garfield & Hagen (2020) and Von Rueden et al. (2008).

cost-infliction ability and status is mediated by perceptions of others' ability to supply group benefits.⁵ Thus, even within the most egalitarian societies, dominants appear able to dominate and gain deference despite strong cultural emphases on equality and respect for individual autonomy. Although more work is needed, the existing evidence of dominance- and prestige-based political leadership in small, kin-based societies with highly egalitarian social norms tentatively suggests the universality of these two avenues to status.

Dovetailing with this work, evidence from developmental psychology consistently points to the importance of dominance early in development. Children as young as 3-5 years old can, for example, track which of two agents has relatively greater dominance from cues of physical size (who is physically larger) or domineering behavior (who forcefully imposes their will on others), and then spontaneously defers to these more dominant individuals by yielding resources or obeying their decisions (Charafeddine et al., 2016; Grueneisen & Tomasello, 2017; Kajanus et al., 2020). Even 12-month-old preverbal infants can mentally represent dominance relations, and use these cues to predict that the larger or more aggressive agent will prevail and be obeyed in conflicts (Margoni et al., 2018; Thomsen et al., 2011). The tendency to take dominance into account when navigating social relations thus appears to develop early without extensive learning and requires relatively little complex conscious reasoning.

⁵ This finding from Garfield & Hagen (2020), which goes unmentioned by DLB, is especially important as it suggests that the contribution of dominance to status in diverse societies *cannot be explained by perceived ability to supply group benefits*. This is because these researchers tested and confirmed the independent contribution of dominance, after accounting for a host of other traits and attributes that may increase one's ability to deliver benefits. These control variables included peers' rankings on perceived prestige (measured using rankings of expertise, respect, and likeability), intelligence, spousal quality, mentor salience, and other characteristics that pertain strictly to physical formidability such as upper-body strength and fighting involvement.

Conclusion

DLB's cross-cultural investigation of the perceived determinants of status in 14 countries is laudable. However, their findings are undermined by collinearity concerns, which prohibit any clear conclusions about the foundations of human status.

For reproducibility, below we list the packages used in our analyses:

```
devtools::session_info()
```



```
## - Session info -----
## setting value
## version R version 4.0.2 (2020-06-22)
## os Windows 10 x64
## system x86_64, mingw32
## ui RTerm
## language (EN)
## collate English_Canada.1252
## ctype English_Canada.1252
## tz America/New_York
## date 2021-02-24
##
## - Packages -----
## package * version date lib source
## abind 1.4-5 2016-07-21 [1] CRAN (R 4.0.
## assertthat 0.2.1 2019-03-21 [1] CRAN (R 4.0.
## backports 1.1.10 2020-09-15 [1] CRAN (R 4.0.
## base64enc 0.1-3 2015-07-28 [1] CRAN (R 4.0.
## bayesplot 1.7.2 2020-05-28 [1] CRAN (R 4.0.
## bayestestR 0.7.2 2020-07-20 [1] CRAN (R 4.0.
## boot 1.3-25 2020-04-26 [2] CRAN (R 4.0.
## bridgesampling 1.0-0 2020-02-26 [1] CRAN (R 4.0.
## brms * 2.14.0 2020-10-08 [1] CRAN (R 4.0.
## Brodbingnag 1.2-6 2018-08-13 [1] CRAN (R 4.0.
## broom 0.7.1 2020-10-02 [1] CRAN (R 4.0.
## callr 3.5.1 2020-10-13 [1] CRAN (R 4.0.
## car * 3.0-10 2020-09-29 [1] CRAN (R 4.0.
## carData * 3.0-4 2020-05-22 [1] CRAN (R 4.0.
## cellranger 1.1.0 2016-07-27 [1] CRAN (R 4.0.
## cli 2.1.0 2020-10-12 [1] CRAN (R 4.0.
## coda 0.19-4 2020-09-30 [1] CRAN (R 4.0.
## codetools 0.2-16 2018-12-24 [2] CRAN (R 4.0.
## colorspace 1.4-1 2019-03-18 [1] CRAN (R 4.0.
## colourpicker 1.1.0 2020-09-14 [1] CRAN (R 4.0.
## conflicted * 1.0.4 2019-06-21 [1] CRAN (R 4.0.
## crayon 1.3.4 2017-09-16 [1] CRAN (R 4.0.
## crosstalk 1.1.0.1 2020-03-13 [1] CRAN (R 4.0.
## curl 4.3 2019-12-02 [1] CRAN (R 4.0.
## data.table 1.13.0 2020-07-24 [1] CRAN (R 4.0.
## desc 1.2.0 2018-05-01 [1] CRAN (R 4.0.
## devtools 2.3.2 2020-09-18 [1] CRAN (R 4.0.
## digest 0.6.25 2020-02-23 [1] CRAN (R 4.0.
## dplyr * 1.0.2 2020-08-18 [1] CRAN (R 4.0.
## DT 0.16 2020-10-13 [1] CRAN (R 4.0.
## dygraphs 1.1.1.6 2018-07-11 [1] CRAN (R 4.0.
## effectsize 0.3.3 2020-09-17 [1] CRAN (R 4.0.
## ellipsis 0.3.1 2020-05-15 [1] CRAN (R 4.0.
## emmeans 1.5.1 2020-09-18 [1] CRAN (R 4.0.
## estimability 1.3 2018-02-11 [1] CRAN (R 4.0.
## evaluate 0.14 2019-05-28 [1] CRAN (R 4.0.
## fansi 0.4.1 2020-01-08 [1] CRAN (R 4.0.
```

## farver	2.0.3	2020-01-16	[1]	CRAN	(R 4.0.
## fastmap	1.0.1	2019-10-08	[1]	CRAN	(R 4.0.
## faux	* 0.0.1.5	2020-09-22	[1]	CRAN	(R 4.0.
## forcats	0.5.0	2020-03-01	[1]	CRAN	(R 4.0.
## foreign	0.8-80	2020-05-24	[2]	CRAN	(R 4.0.
## fs	1.5.0	2020-07-31	[1]	CRAN	(R 4.0.
## generics	0.0.2	2018-11-29	[1]	CRAN	(R 4.0.
## GGally	* 2.0.0	2020-06-06	[1]	CRAN	(R 4.0.
## ggeffects	0.16.0	2020-09-13	[1]	CRAN	(R 4.0.
## ggplot2	* 3.3.2	2020-06-19	[1]	CRAN	(R 4.0.
## ggridges	0.5.2	2020-01-12	[1]	CRAN	(R 4.0.
## glue	1.4.2	2020-08-27	[1]	CRAN	(R 4.0.
## gridExtra	2.3	2017-09-09	[1]	CRAN	(R 4.0.
## gtable	0.3.0	2019-03-25	[1]	CRAN	(R 4.0.
## gtools	3.8.2	2020-03-31	[1]	CRAN	(R 4.0.
## haven	2.3.1	2020-06-01	[1]	CRAN	(R 4.0.
## here	* 0.1	2017-05-28	[1]	CRAN	(R 4.0.
## highr	0.8	2019-03-20	[1]	CRAN	(R 4.0.
## hms	0.5.3	2020-01-08	[1]	CRAN	(R 4.0.
## htmltools	0.5.0	2020-06-16	[1]	CRAN	(R 4.0.
## htmlwidgets	1.5.2	2020-10-03	[1]	CRAN	(R 4.0.
## httpuv	1.5.4	2020-06-06	[1]	CRAN	(R 4.0.
## httr	1.4.2	2020-07-20	[1]	CRAN	(R 4.0.
## igraph	1.2.6	2020-10-06	[1]	CRAN	(R 4.0.
## inline	0.3.16	2020-09-06	[1]	CRAN	(R 4.0.
## insight	0.9.6	2020-09-20	[1]	CRAN	(R 4.0.
## jsonlite	1.7.1	2020-09-07	[1]	CRAN	(R 4.0.
## jtools	* 2.1.0	2020-06-23	[1]	CRAN	(R 4.0.
## kableExtra	1.2.1	2020-08-27	[1]	CRAN	(R 4.0.
## knitr	1.30	2020-09-22	[1]	CRAN	(R 4.0.
## labeling	0.3	2014-08-23	[1]	CRAN	(R 4.0.
## later	1.1.0.1	2020-06-05	[1]	CRAN	(R 4.0.
## lattice	0.20-41	2020-04-02	[2]	CRAN	(R 4.0.
## lifecycle	0.2.0	2020-03-06	[1]	CRAN	(R 4.0.
## lme4	1.1-23	2020-04-07	[1]	CRAN	(R 4.0.
## loo	2.3.1	2020-07-14	[1]	CRAN	(R 4.0.
## magrittr	1.5	2014-11-22	[1]	CRAN	(R 4.0.
## markdown	1.1	2019-08-07	[1]	CRAN	(R 4.0.
## MASS	7.3-51.6	2020-04-26	[2]	CRAN	(R 4.0.
## Matrix	1.2-18	2019-11-27	[2]	CRAN	(R 4.0.
## matrixStats	0.57.0	2020-09-25	[1]	CRAN	(R 4.0.
## memoise	1.1.0	2017-04-21	[1]	CRAN	(R 4.0.
## mime	0.9	2020-02-04	[1]	CRAN	(R 4.0.
## miniUI	0.1.1.1	2018-05-18	[1]	CRAN	(R 4.0.
## minqa	1.2.4	2014-10-09	[1]	CRAN	(R 4.0.
## modelr	0.1.8	2020-05-19	[1]	CRAN	(R 4.0.
## munsell	0.5.0	2018-06-12	[1]	CRAN	(R 4.0.
## mvtnorm	1.1-1	2020-06-09	[1]	CRAN	(R 4.0.
## nlme	3.1-148	2020-05-24	[2]	CRAN	(R 4.0.
## nloptr	1.2.2.2	2020-07-02	[1]	CRAN	(R 4.0.
## openxlsx	4.2.2	2020-09-17	[1]	CRAN	(R 4.0.

##	pander	0.6.3	2018-11-06	[1]	CRAN	(R 4.0.
##	parameters	0.8.6	2020-09-21	[1]	CRAN	(R 4.0.
##	performance	0.5.0	2020-09-12	[1]	CRAN	(R 4.0.
##	pillar	1.4.6	2020-07-10	[1]	CRAN	(R 4.0.
##	pkgbuild	1.1.0	2020-07-13	[1]	CRAN	(R 4.0.
##	pkgconfig	2.0.3	2019-09-22	[1]	CRAN	(R 4.0.
##	pkgload	1.1.0	2020-05-29	[1]	CRAN	(R 4.0.
##	plyr	1.8.6	2020-03-03	[1]	CRAN	(R 4.0.
##	prettyunits	1.1.1	2020-01-24	[1]	CRAN	(R 4.0.
##	processx	3.4.4	2020-09-03	[1]	CRAN	(R 4.0.
##	promises	1.1.1	2020-06-09	[1]	CRAN	(R 4.0.
##	ps	1.4.0	2020-10-07	[1]	CRAN	(R 4.0.
##	purrr	0.3.4	2020-04-17	[1]	CRAN	(R 4.0.
##	R6	2.4.1	2019-11-12	[1]	CRAN	(R 4.0.
##	RColorBrewer	1.1-2	2014-12-07	[1]	CRAN	(R 4.0.
##	Rcpp	* 1.0.5	2020-07-06	[1]	CRAN	(R 4.0.
##	RcppParallel	5.0.2	2020-06-24	[1]	CRAN	(R 4.0.
##	readxl	1.3.1	2019-03-13	[1]	CRAN	(R 4.0.
##	remotes	2.2.0	2020-07-21	[1]	CRAN	(R 4.0.
##	reshape	0.8.8	2018-10-23	[1]	CRAN	(R 4.0.
##	reshape2	1.4.4	2020-04-09	[1]	CRAN	(R 4.0.
##	rio	0.5.16	2018-11-26	[1]	CRAN	(R 4.0.
##	rlang	0.4.7	2020-07-09	[1]	CRAN	(R 4.0.
##	rmarkdown	2.4	2020-09-30	[1]	CRAN	(R 4.0.
##	rprojroot	1.3-2	2018-01-03	[1]	CRAN	(R 4.0.
##	rsconnect	0.8.16	2019-12-13	[1]	CRAN	(R 4.0.
##	rstan	2.21.2	2020-07-27	[1]	CRAN	(R 4.0.
##	rstantools	2.1.1	2020-07-06	[1]	CRAN	(R 4.0.
##	rstudioapi	0.11	2020-02-07	[1]	CRAN	(R 4.0.
##	rvest	0.3.6	2020-07-25	[1]	CRAN	(R 4.0.
##	scales	1.1.1	2020-05-11	[1]	CRAN	(R 4.0.
##	sessioninfo	1.1.1	2018-11-05	[1]	CRAN	(R 4.0.
##	shiny	1.5.0	2020-06-23	[1]	CRAN	(R 4.0.
##	shinyjs	2.0.0	2020-09-09	[1]	CRAN	(R 4.0.
##	shinytan	2.5.0	2018-05-01	[1]	CRAN	(R 4.0.
##	shinythemes	1.1.2	2018-11-06	[1]	CRAN	(R 4.0.
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##	sjmisc	2.8.5	2020-05-28	[1]	CRAN	(R 4.0.
##	sjPlot	* 2.8.5	2020-09-24	[1]	CRAN	(R 4.0.
##	sjstats	0.18.0	2020-05-06	[1]	CRAN	(R 4.0.
##	StanHeaders	2.21.0-6	2020-08-16	[1]	CRAN	(R 4.0.
##	stargazer	* 5.2.2	2018-05-30	[1]	CRAN	(R 4.0.
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##	stringi	1.5.3	2020-09-09	[1]	CRAN	(R 4.0.
##	stringr	1.4.0	2019-02-10	[1]	CRAN	(R 4.0.
##	testthat	2.3.2	2020-03-02	[1]	CRAN	(R 4.0.
##	threejs	0.3.3	2020-01-21	[1]	CRAN	(R 4.0.
##	tibble	3.0.4	2020-10-12	[1]	CRAN	(R 4.0.
##	tidyr	* 1.1.2	2020-08-27	[1]	CRAN	(R 4.0.
##	tidyselect	1.1.0	2020-05-11	[1]	CRAN	(R 4.0.
##	tint	* 0.1.3	2020-07-18	[1]	CRAN	(R 4.0.

```
## usethis          1.6.3      2020-09-17 [1] CRAN (R 4.0.
## utf8             1.1.4      2018-05-24 [1] CRAN (R 4.0.
## V8               3.2.0      2020-06-19 [1] CRAN (R 4.0.
## vctrs            0.3.4      2020-08-29 [1] CRAN (R 4.0.
## viridisLite      0.3.0      2018-02-01 [1] CRAN (R 4.0.
## webshot          0.5.2      2019-11-22 [1] CRAN (R 4.0.
## withr            2.3.0      2020-09-22 [1] CRAN (R 4.0.
## xfun             0.18       2020-09-29 [1] CRAN (R 4.0.
## xml2             1.3.2      2020-04-23 [1] CRAN (R 4.0.
## xtable           1.8-4       2019-04-21 [1] CRAN (R 4.0.
## xts              0.12.1     2020-09-09 [1] CRAN (R 4.0.
## yaml            2.2.1      2020-02-01 [1] CRAN (R 4.0.
## zip              2.1.1      2020-08-27 [1] CRAN (R 4.0.
## zoo              1.8-8       2020-05-02 [1] CRAN (R 4.0.
##
## [1] C:/Users/chengjt/Documents/R/win-library/4.0
## [2] C:/Program Files/R/R-4.0.2/library
```

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