Causal Inference for Multilevel Networks of Early Ethnographically Well-studied Populations

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Ethnographically well-studied cases have long been the concern and targets of attempts at causal inference that recognize network interdependencies (e.g., Dow, White and Burton 1982) – given that societies are spatially and historically interdependent. This paper uses methods for estimating Instrumental Variables (IV) for network effects of shared historical-linguistic and spatial proximities (i.e., Galton's problem). Using multiple linear regression, these methods combine with transformations of ordinal variables to make interval-level multiple regression-coefficient estimates. They also combine with multiple imputation of missing data. The results are used to make causal inference graphs for networks of causal relationships. For subsets of connected causal inference networks, estimation of direct and indirect causal effects (Pearl 2000) are illustrated, drawing from actual results from a sample of 186 cases. In more complex graphs, even when all variables are measured, it is often necessary to adjust for confounding variables when calculating the effect of a variable X on a dependent variable Y in a network after significant regression effects have been estimated.

Methods for valid statistical inferences drawn from samples of well-described ethnographic cases have become available in the last decade that may solve the problems of peer effects ("identification" endogeneity) and missing data for many different kinds of inference (Eff and Dow 2009). Here the goal is to draw causal-graph networks of causal inferences among variables using the multiple dependent variable regression method of Pearl (2000), taking peer effects into account by the use of Instrumental Variables (IVs), following Eff and Dow. Pearl (2009c) gives a succinct informal summary of what is needed to use the regression method for a causal graph:

> "Define the target quantity (dependent variable and short description).
> For each example with three or more variables it is essential that:
>
> > You are sure about the arrow directions.
> > You are sure about linearity.
> > You are sure there are no unobserved confounders between any pair."

The lack of confounders (measured or unmeasured variables that do not confound other effects) means that with full controls for peer effects, regression coefficients in a well-specified model can provide measurement of causal effects.

> "For three variables you are trying to estimate the direct effect c of X on Z given an indirect effect of Y. The causal diagram model gives you a license to do it by the regression method, where, for example,
>
> $$c = \frac{E(\mathrm{y}|\mathrm{x},\ \mathrm{z}) - E(\mathrm{y}|\mathrm{x}',\ \mathrm{z})}{\mathrm{x}-\mathrm{x}'} = \text{direct effect} = \text{total} - \text{indirect effect}, \qquad (1)$$
>
> x and x´ are the lower and higher values, respectively, in the empirical range of variable X.[(1)] Controlling for the change from x to x´, (y|x, z) and (y|x´, z) are the changes in variable Z due to unit changes in Y."[(2)] (email from Pearl; see Pearl 2000:368 and Chalak and White 2009).

Thus x→x´ changes y→y', which changes z through the x-y-z path, and allows us to use regression coefficients as causal estimates, assuming conditions above and below. For this to apply to larger graphs requires that one or both of two crucial structural criteria of the graph, "single door" or "back door", if satisfied, provide adjustments to block the effects of confounding variables (Pearl 2000:150-152; 79-80) along paths that are not necessarily directed in the DAG. Such adjustments as are required represent partial regression equations controlling for variables that have to be knocked out according to single or back door criteria. For **back door** causal estimates of X on Y, all other paths with arrows coming *into* X have to be blocked by a set of Z "adjustment" nodes for which there are partial-effect adjustments.(3) For **single door** the effect of X on Y is identifiable if there exists a set Z of nodes such that Z blocks all the indirect paths (i.e., d-separates) X from Y in the graph where the edge from X to Y is removed and no node in Z is a descendant of Y. Single door is stronger in that it implies the back door criteria.

Equation (1), expressed in probabilistic terms, is equivalent in terms of partial regression coefficients to total effect = direct effect + indirect effect = c + a•b where *a* is (partial) regression coefficient for x→y, *b* for y→z, and *c* for the direct effect x→z. Indirect effects are computed as products of path-specific regression coefficients. The back door criteria apply to this example where y blocks the indirect x→z path.

> "Causal diagrams are not a substitute for 2-stage regression usually employed to estimate causal connection when Instrumental Variables (IVs, or just "Instruments") are available. The IV is a causal notion and requires causal assumptions (e.g., a graph) to be thus identified. Causal models simply tell us what regression expression gives the right estimand (formulas for independent variable estimations of the target [2009b]). Given these understandings, the most neglected part of most studies (see my complaints in: 4.1 Defining the Target Quantity(4) http://ftp.cs.ucla.edu/pub/stat_ser/r355.pdf) is: What is the problem, what is given or assumed, what are we trying to estimate? Does it have a name? A mathematical expression?"

The estimates considered here, from coded ordinal variables for samples of well-described ethnographic cases (White et al. 2009), are those of direct and indirect (mediated) causal effects of sociocultural variables on one another, using Instrumental Variables to control for spatial and historical interdependence (Dow 1984, 1986, 2008; Dow and Eff 2009a, 2009b; Eff and Dow 2009). We compare our Eff-Dow results with results using a probit transformation of the ordinal variables in the dataset, leaving dichotomous and interval-level variables intact.

Arrows in (Pearl's) causal (asymmetric directed) graphs must not violate the unidirectionality of presupposed (time directed) causal effects. They require Bayesian inferences from independent knowledge of the domain of inference. Morgan and Winship (2007: 64) refer to three kinds of causal relations for three variables: mediation (A→C→B), mutual dependence (C→A, C→B) and common (mutual) causation (A→C, B→C). The sociocultural domains of the present study are drawn from the variables currently coded for the Standard Cross-Cultural Sample (Murdock and White 1969). A good illustration in this domain would be that, while money might be among the causes of evil eye beliefs considered as an expression of the envy that arises with unequal distribution of wealth, "belief in the evil eye" is not a plausible causality predicting the existence of money. Many other criteria must be satisfied as well to evaluate causal relationships (e.g., Pearl 1987, 2000, 2009a, 2009b, Avin, Shipster and Pearl 2005), only some of which are explored here.

To form a network from regression results, the domains of the dependent variables must correspond. When they do not, solutions much be found such as additional data that will fill in the components that are missing in order to have shared domains. An example would be those variables that were coded only for a selective subsample, such as prestate societies, e.g., Paige and Paige (1981) on fraternal interest groups, which also occur in regions of Afro-Eurasia (Old World). These variables would need to be coded for state societies in order to combine regression results into a single causal graph.

Pearl's causal graph methods assume that arrow directions are not reciprocal and do not form directed cycles. The methods of causal graph estimation are generalized by Chalak and White (2010) to include these two kinds of causal models. Good examples of reciprocal causality for the SCCS variables are the warfare codes for "attacking" and being attacked, each of which may affect the other, possibly in a runaway spiral. In economic markets, bids and asks interact reciprocally, often in terms of complex instabilities as well as other causes.

Identification problems in individual and societal level data. The basic distinction made in identifying the types of effects modeled using sample data (Manski 1995) is between *endogenous* effects ("peer effects" of social or network interaction among the units, see Evans, et al. 1992) and nonsocial or *exogenous* effects (impact of other variables pertaining to the units of study or their environments). The latter differentiate into two types (Manski 1993:532-533): *contextual effects* wherein the exogenous propensity of the individual or aggregate unit of study is to behave in a way that varies with the distribution of characteristics of a larger reference group to which they belong (e.g., ethnic provenience of individual or linguistic provenience of societal units); and *correlated effects* of other variables or their environment (i.e., units in the same group tend to behave similarly because they face similar environments or have similar characteristics). The latter (correlated effects) are typically measured in a regression model by fitted coefficients for the predictions of independent variables, while endogenous effects might be modeled by Instrumental Variables (Instruments), as explained below. If a model is not well specified, endogenous effects can show up as autocorrelated error terms from the fitted regression. *Contextual effects* can be specified by identification of spatial clusters of similar cases or specified regions with relatively homogeneous membership. There is ambiguity here because *contextual effects* may represent endogenous feedback (Erbring and Young 1979) when the sample within these larger units is composed of cases related through network interactions. There is also ambiguity in how the reference groups that set the context for endogenous effects are constituted. These ambiguities come to the fore in the *reflection problem* (Manski 1995:127-136), where "the researcher wishes to infer whether the average behavior in some group influences the behavior of the individuals that compose the group" (p.120). In a rather general model of this problem (p.132), identification of the parameters for different kinds of reflection problem effects "does not enable one to distinguish between endogenous and [exogenous] contextual effects, but it does permit one to learn whether some social effect is present." In a model where theoretical specification of equilibrium is well specified and well-fitted to an empirical (e.g., econometric) problem – and even where informed reference groups for social effects are specified in advance – "endogenous effects cannot be distinguished from contextual or from correlated effects" (p. 135).

Two-stage estimation methods for societal databases. Manski (1995:133-134) noted that pure endogenous effects in spatial (auto)correlation models typically use a two-stage method to estimate the parameters of "spatial correlation." Eff and Dow (2009) extend this type of two-stage least squares model to introduce open-source [R] software for estimating unbiased and efficient measures of regression effects in surveys in which the observations are not independent in the sense that they have affected one another in occupying spatial clusters of similar cases (where proximal interactions enhance similarities) or through shared histories, reflected, for example, in common ethnic, language family, or reference group memberships. Nonindependence in the two senses of spatial transmission or cultural heritage or social transmission is a virtually universal problem in observational and even experimental studies. (5) In regression analysis of predictions from a set of independent variables to a dependent variable, the term *unbiased* implies that the regression coefficients are maximum likelihood, and *efficient* that the significance tests are maximum likelihood.(6) Given that this is not generally the case when observations are interdependent, Eff and Dow's (2009) software offers an open resource for research classes and researchers worldwide to investigate, in ways that are potentially unbiased and efficient, regression models of interactive social units and related variables. This leaves the main research problems of whether the model's variables and regression coefficients are well specified and the model is properly identified.

Measuring endogenous "social effects." (7) The fact that survey research results in general and cross-societal studies in particular are subject to network interdependence may render significance tests nearly useless, even if samples are randomly selected. (8) If the number of "effectively independent" cases in a sample of N cases can be measured as the largest random subsample sample N_e that displays no spatial or other forms of autocorrelation,(9) then, as the ratio $N_e/N \rightarrow 0$, statistical significance will go toward the null hypothesis of no statistical significance, i.e., as the "effectively independent" cases go down. The effect of the magnitude of the N_e/N problem is difficult to identify with cross-tabulation statistics where significance tests are inflated by common histories or proximal interactions among the cases observed. The N_e/N problem is simpler to solve with multiple regression analysis for a dependent variable y, where the prediction is a weighted linear sum of independent variables in which spatial or network effects can be identified by type of process, measured by autocorrelation tests, and taken into account.

Model. We use the Instrumental Variables regression model of Eff and Dow (2009:12-14). Instruments are observed variables in regression and structural models, other than the cause or treatment of interest, that can play an instrumental role in identifying and estimating causal effects. One purpose of Instruments or IVs is to capture the kinds of potential endogenous social or network effects that, when not explicitly included in a regression model, will be reflected in autocorrelated errors in the error term of the regression. This may be done in a first stage of regressing $(Wy)_i$ – row normalized network matrixes multiplied by the dependent variable y thus identifying and measuring endogenous "social effects" on similarities among cases – that are then fitted as instruments for reducing autocorrelation in error terms:

$$(Wy)_i = a_0 + \Sigma_j a_j z_{ji} + \mu_i \tag{2}$$

Here the independent variables z_{ji} are weighted by regression coefficients and μ_i is the error term. This gives estimated coefficients that can be used to create a fitted value for $(Wy)_i$, as in equation (1) for causal graphs. It is this fitted value that is the Instrumental Variable for Eff and Dow (2009:15). It collects the potential endogenous or social effects created by interactions between the cases in the sample (but not the effects of social interactions *within* each individual case), estimated as Instruments:

$$(\widehat{Wy})_i = \hat{a}_0 + \sum_j \hat{a}_j z_{ji} \tag{3}$$

Each i Instrument from equation (3) is fitted (by the alpha coefficients) to the weighted sums of the independent variables z_{ji}. Then y is fitted in a second-stage regression containing these instruments, completing a 2-stage least squares (2SLS) regression analysis in which the second regression may be free of autocorrelation in the error term ε if there is correct specification of the exogenous independent variables X_i. For k of the W matrices,

$$y = \sum_{i=1}^{k} \rho_i (\widehat{Wy})_i + \beta_j X_j + \varepsilon \tag{4}$$

Where the $(\widehat{Wy})_i$ are the estimated left hand terms in (3). Wooldridge's (2006: 308, 280, 537) diagnostic tests show whether the model has correct functional form (RESET test), the appropriate variables are dropped (Wald test) and residuals are heteroskedastic (Breusch-Pagan test). The NCV (Non-Constant Variance) test checks whether the error terms are bunched, and the LM lag test checks whether residual autocorrelation in ε for spatial and linguistic clustering is independent of the $(Wy)_j$. If so the fitted regression error terms in (4) are likely to give unbiased estimates of the exogenous variables.

The β_j OLS regression coefficients in (4) are ideal for causal graph computation, as in estimating the direct effect, c, in equation (1), of X on Z.

Objective. Our objective for the use of causal graphs is to analyze as many directed causal relationships as possible in the Standard Cross-Cultural Sample (SCCS) database for 186 societies (White 2009b). Several thousand variables are currently available. The SCCS was created as the basis for a cumulative database for cross-cultural studies (White 2007) using a sample of the earliest best-described ethnographic cases in each of 186 major cultural provinces in the world.(10) The ethnographic cases for the sample are pinpointed in space and time (White 2009a) and chosen for maximum social diversity and historical depth in 186 world regions of intensive social interaction. Each ethnographic case was provided by Murdock and White (1969) with a rich inventory of available literature for purposes of coding ethnographic characteristics (White 1986). Approximately 670 of the 2000+ codes in the database as of 2010 were coded by researchers at the Cross-Cultural Cumulative Coding Center (CCCCC) funded by NSF (1968-1974). Other contributors coded about 1350 variables in subsequent years. The open-source [R] program contributed by Eff and Dow (2009) includes multiple imputation (MI) for missing data using 186x186 language and distance matrices in order to estimate spatial and linguistic peer effects and a rectangular data matrix in [R] (J. Dow 2004) of ethnographic variables for the 186 cases. The MI procedure creates multiple copies of the database with independent Bayesian estimates for missing data and combines them for reliable estimation using the formulas of Rubin (1987).

Goal. We aim at a causal graph analysis of all qualified variables in the SCCS.Rdata-base that will provide a basis for discovery and reevaluation of findings for which the SCCS sample can be used while taking peer effects into account. This motivates further research to correct misspecified models in the current cross-cultural literature. There are currently over a thousand published studies using the SCCS. The number of articles listed by Google Scholar for the "Standard Cross-Cultural Sample" is increasing by about one per day as of mid-2010 (see White 2009b for topical searches).

Practicalities. The goal here is practical using an adaptation of Eff and Dow's (2009) [R] software. Runs of peer-effects multiple regression models are easy to design and quick to execute. They can be automated for a series of qualified dependent variables. Our Statistical-Inference-In-SCCS Package, downloadable at http://github.com/drwhite/Statistical-Inference-In-SCCS, generalizes Eff and Dow

(2009). It uses their OLS with Instruments and our probit transformations of the variables after they are defined by the user, and is included on-line with this publication.

Preliminary results. Preliminary results building on these advances in modeling were created through a series of "learning through modification" (EduMod) pages on the open resource "InterSci" mediawiki at UC Irvine. Here, students worldwide or in a classroom lab download software and data, select variables for study, and edit existing examples of the R code to perform new analyses using new variables that each researcher might select for study along with ones already preselected for the student or for purposes of batch runs. One can also test the replication of prior analyses from the literature. The new regression software has now been used in 100s of wiki-based modeling projects that leave no doubt that the new software is working effectively. The preliminary results we give here result from the experiment carried out in UCI fall and winter undergraduate classes in 2009-2010. Each student was asked to try to explain a dependent variable of their choice from the SCCS database using the Eff and Dow (2009) software to estimate regression coefficients suitable for causal graphs of the independent variable effects.

Fig. 1 combines, from thirteen student studies, illustrative results for intra-society effects and network peer effects, put together for demonstration purposes to form a connected causal graph (Pearl 2000). Arrows in the figure are unidirectional and form a directed asymmetric graph according to Pearl's DAG criteria. Arrows go from independent (predictor) variables to the dependent variables in the ordered layers of the directed asymmetric graph. Solid black lines show positive and dotted red lines negative influences on the dependent variables.

Nodes in successive layers of Fig. 1 are colored green, yellow, red, and blue, going from purely independent variables to the purely dependent. Reciprocal effects are not considered here, an example being v892 (external war) which is in the graph and v891 (internal war), which is not, although they have reciprocal causality.

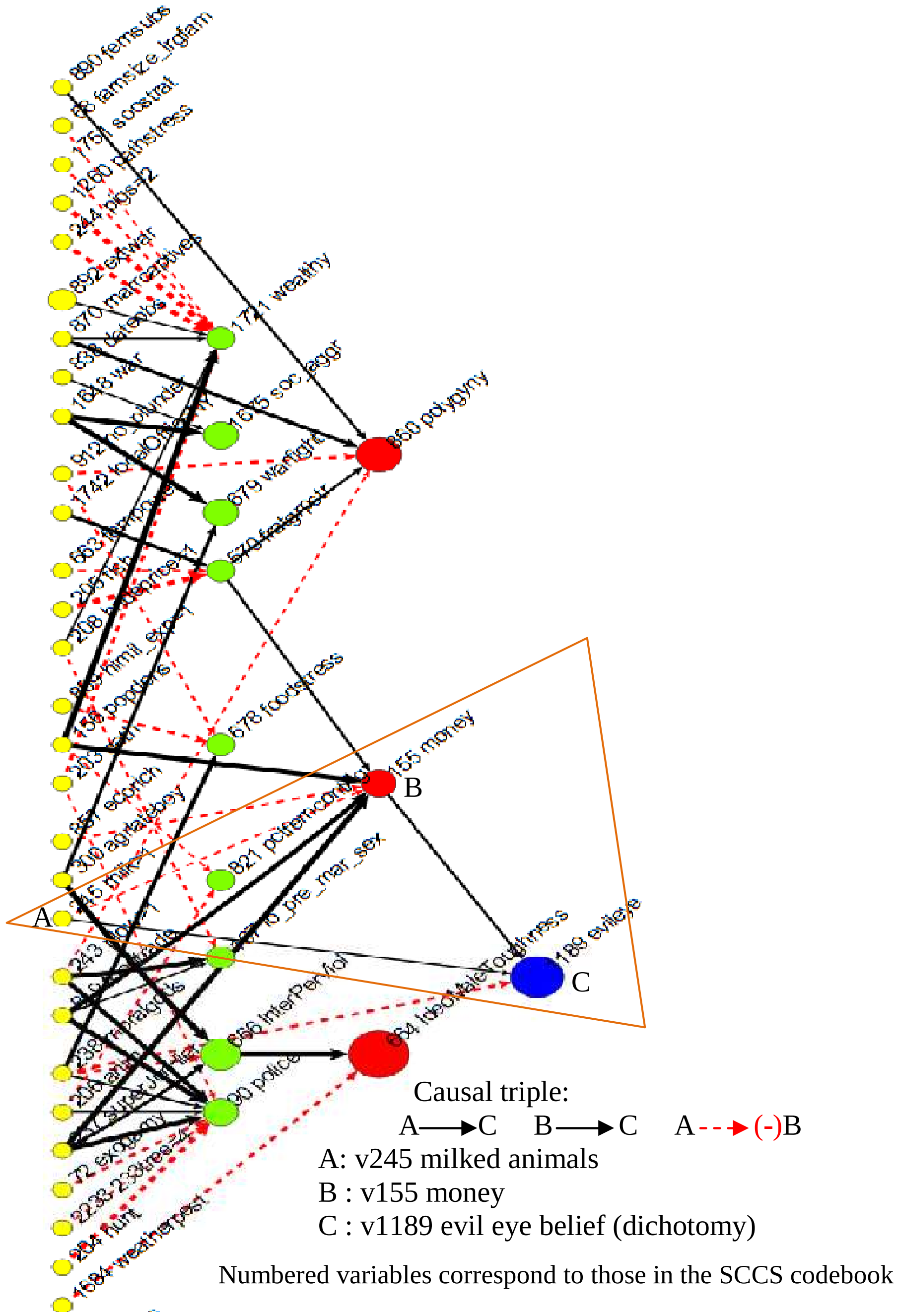
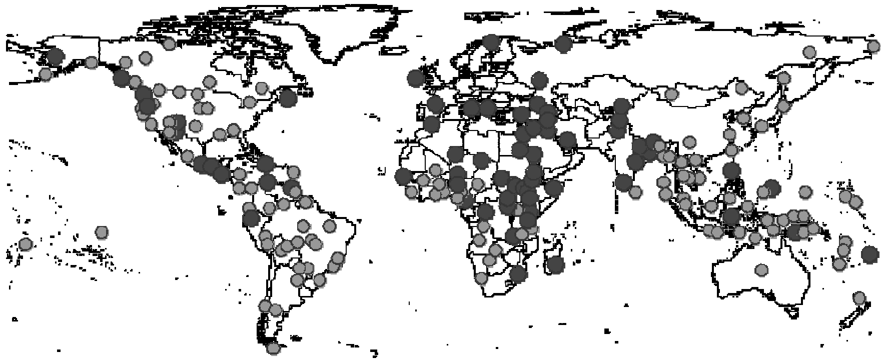


Fig. 1: ***A triangular regression effect within a causal graph.*** Two mutually exclusive causes of "Evil eye" (pastoral milked animals v245 vs. monetized economies v155) are found, significant at pvalue ≤ 0.0003 for their language network dissimilarity. Solid black lines show positive and dotted red lines negative influences. For societal attributes, regression slopes predicting Evil eye are positive for Money (0.25) and for Milked animals (1.01); both are sources of wealth, with significant pvalues. Spatial transmission effects for Evil eye are significant at pvalue ≤ 0. 0.00000015. The slope for Milked animals predicting Money is -0.42 (i.e., negative, with pvalue ≤ 0.06).



1189. Evil eye Belief
119 0 = Absent (gray nodes)
67 1 = Present (black nodes)

Fig. 2: Spatial clustering of Evil eye, spreading out from the Mediterranean to Europe and North and East African small states and pastoralists

Sizes of nodes for the dependent variables in Fig. 1 reflect the extent of "peer effects" of the spatial proximity Instrumental Variable from equation (3). The larger nodes have distance Instruments significant at pvalue ≤ 0.001. The effect of network autocorrelation weighted by neighbors' proximities, for example, are highly predictive for societies with evil eye, as shown by the size of the lowest (blue) node (pvalue ≤ 0.00001). Because the dependent variables were chosen for this diagram to produce a graph that is connected, we can see that many independent variables predict several dependent variables. There is a trend for variables that are predicted at deeper layers in the graph to have greater peer effects from proximity with similar neighbors, as shown by the distribution of sizes of the green, red and blue nodes.

Finding variables for estimating effects in causal graphs, both direct and indirect (i.e., mediation effects). To test Pearl's models of causal graphs with linked regression predictions the example in this paper uses variables in which the combination of transitive predictors ($X \rightarrow Y$, $X \rightarrow Z$, and $Z \rightarrow Y$) were not ruled out as implausible, but all of the reverse prediction arrows were judged as implausible. In Fig. 1 there is only one causal triple to serve as an example. Variable A (milking) predicts B (money) and C (evil eye) and B predicts C as well. In this case both the A→C and B→C regression slopes predicting C have significant positive coefficients while the A→ $^{(-)}$B regression slope is significantly negative. (In Fig. 1, red dotted lines show negative effects and solid black lines show positive influences). The IVs (Instruments) for the first two regression slopes are very significant for regional clusters (i.e., for pastoral societies versus monetized societies) while the significant IV *language* effects for milking animals and money are *negative*, which reflects the fact that the societies within these two types of economies not only come from significantly different language families, but are distinctive within their respective language groups.

The regression models 1-3: Evil eye. Money, and Moral gods. As examples of regression model predictors we use dependent variables coded for Evil eye, Money, and Moral gods. Table 1 (Model 1) shows the Instrumental regression for Evil eye, in its ordinal version (v1188). The map in Fig. 2 showed the same variable but dichotomized (v1189). Variable v1188 is used in the regression because it has a better R^2 (=0.505) than the dichotomy. The most significant predictor of Evil eye is spatial transmission of

Evil eye tendencies from neighboring societies, followed by Moral gods (v238), the log of Caste stratification (v272, Caststrat LGd, LGd meaning logged), Milking of animals (v245), and Degree of monetization squared (V155; Money^2). The LM test for spatial lag shows that the model cannot be improved by including a spatial transmission term based on the geographic proximity weight matrix (p > .24). The Brusch-Pagan test (p > .181) shows that the residuals are homoskedastic. The Wald test (p > .563) shows that appropriate variables were dropped, so that no significant variables remain among the independent variables. The problem with the RESET test (pvalue ≤ 0.04) is it shows that this model still does not have the correct functional form for some pairs of predictors (expected to be linear with the dependent variable, not squared or logged, etc.). The Shipiro-Wilk test (pvalue ≤ 0.001) shows that the residuals are not normally distributed.

For each independent variable in our Model 1, for Evil eye, Table 1 compares results for the ordinal and probit values. The probit coefficients and pvalues are given in the last two columns. The probit coefficients and pvalues are more uniform than the ordinal coefficients, and the R^2 is about 10% lower.

Table 1A: Restricted Model for Evil eye v1189 as the dependent variable, EduMod-78

```
1188. Evil eye Scaled Rating:
      1    1 = Absent, incontrovertibly
     45    2 = Absent, almost certainly
     46    3 = Absent, probably
     27    4 = Absent, possibly
      8    5 = Present, possibly
     13    6 = Present, probably
     16    7 = Present, almost certainly
     30    8 = Present, incontrovertibly
```

Model 1 Variables	Description Re: Evil eye	Eff-Dow coef	pvalue	VIF	Var.		Probit Coef	pvalue
(Intercept)		1.07	0.301	NA			0.174	0.672
Wy fydd	Spatial transmission	0.655	0.000001	2.230	NA	***	0.659	.0001
Wy fyll	Cultural transmission		n.s.		NA		-0.118	0.639
Milk	Milking of animals	0.688	0.075	2.382	v245	*	0.325	0.041
CaststratLDg	Degree of caste stratification	1.237	0.029	1.195	v272	* *	0.162	0.057
Money^2 (squared)	Degree of monetization	0.025	0.091	1.130	v155	*	0.128	0.043
Moral gods	Degree of morality of gods	0.347	0.007	1.629	v238	***	0.154	0.046
Diagnostics		Fstat	df	pvalue			Fstat	pvalue
RESET test. H0: model has correct functional form		4.369	3019.298	0.037			0.912	0.340
Wald test. H0: appropriate variables dropped		0.334	2554.504	0.563			0.436	0.509
Breusch-Pagan test. H0: residuals homoskedastic		1.791	6060.098	0.181			7.634	0.006
Shapiro-Wilk test. H0: residuals normal		18.752	209222.681	0.000			4.216	0.040
LM test. H0: Spatial lag (distance) not needed		1.671	5669.831	0.196			0.903	0.342
LM test. H0: Cultural lag (language) not needed		1.197	205983.081	0.274			1.937	0.164

Notes: R^2 = 0.505; Probit 0.456. N=186; number of imputations=3; standard errors and R^2 adjusted for two-stage least squares. "***" p-value ≤ 0.01, "**" p-value ≤ 0.05, "*" p-value ≤ 0.10. Language non-significant (p > .41). In this regression Wy fyll was computed and made similar predictions to Wy fydd but given fydd was nonsignificant at pvalue ≤ 0.30)

Our three variable model example, as shown in Fig. 1, involves two mutually exclusive causes of Evil eye: Milking of animals (v245) and Monetized economies (v155). Milking predicts Evil eye (Table 1) but monetized economies predict the absence of Evil eye (Table 2). The language network dissimilarity between the two causes is statistically significant at pvalue ≤ 0.0003 (Table 2). In looking at a triangle of variables such as Milking, Money, and Evil eye, how shall we treat Money (v157) when its effect is greater when squared? By dichotomizing v155 at >4, >3, >2, and >1 we hope to determine whether the effect of this variable is linear, nonlinear, or dichotomous. At these various thresholds, the significance rises from pvalue ≤ 0.48 to pvalue ≤ 0.16 to pvalue ≤ 0.12 to pvalue ≤ 0.03. Usually it is not valid to compare pvalues, but because the MI imputation is always for missing values of the dependent variables, such comparisons are valid within each of our tables although not between tables. Here the comparison tells us the real effect may be dichotomous, as between no money whatever versus any form of money, as defined in v155 below. There is, however, no separate effect of bridewealth, which often circulates opposite brides in North and East Africa.

Table 1B confirms that this dichotomy is actually a better predictor ($R^2 = 0.514$, a slight but significant increase) than money^2 (squared), which does not reflect the influence of true money only, but any form of money. For the map in Fig. 2, this implies that both the West Eurasian and North or East African regions of Evil eye are influence by the presence of valuables of exchange of any sort, including true money or domestic utilitarian exchange items.

Table 1B: Restricted Model for Evil eye as the dependent variable, changing the independent variable for Money

```
155. SCALE 7- MONEY (here, an independent variable)
     77    1 = None
     14    2 = Domestically usable articles
     43    3 = Alien currency
     27    4 = Elementary forms
     25    5 = True money
```

Variable	Description Re: Evil eye	Eff-Dow coef	pvalue	VIF	Var.	
(Intercept)		-0.738	0.229	NA		
Wy fydd	Spatial transmission	0.658	0.000	2.179	NA	***
Wy fyll	Cultural transmission			n.s.	NA	
Milk	Milking of animals	0.678	0.072	2.307	v245	*
CaststratLDg	Degree of caste stratification	1.217	0.028	1.177	v272	* *
MoneyDich>1	Degree of monetization	0.544	0.026	1.104	v155 ~v17	**
Moral gods	Degree of morality of gods	0.345	0.005	1.535	v238	***

Diagnostics	Fstat	df	Pvalue
RESET test. H0: model has correct functional form	4.442	87379.996	0.035
Wald test. H0: appropriate variables dropped	0.477	105.589	0.491
Breusch-Pagan test. H0: residuals homoskedastic	1.247	17074.685	0.264
Shapiro-Wilk test. H0: residuals normal	16.447	174240.424	0.000
LM test. H0: Spatial lag (distance) not needed	1.535	52244.213	0.215
LM test. H0: Cultural lag (language) not needed	1.455	858394.835	0.228

Notes: $R^2 = 0.514$; N=186; number of imputations=3; standard errors and R^2 adjusted for two-stage least squares. "***" p-value ≤ 0.01, "**" p-value ≤ 0.05, "*" p-value ≤ 0.10. Language non-significant (p > .33). In this regression Wy fyll was computed and made similar predictions to Wy fydd but given fydd was nonsignificant at pvalue ≤ 0.30)

Results are identical if the dichotomy >1 is tested from variable v17 (Money, in a slightly different set of ordinal categories. Changing the dichotomy from > 4 to >3, >2 and >1 results in increases of the R^2 over

that range and the significance of the independent variable effect increases from pvalue ≤ 0.25 to pvalue ≤ 0.03, exactly as earlier with v155.
A final adjustment of the model is made in Table 1C, using a recoding > 1 > 3 > 4 of the ordinal independent variable for Money, equating categories 2 and 3, and giving this variable slightly higher statistical significance.

Using the same recoding of the Money variable, now as the dependent variable, a second ordinal model is given in Table 2, along with a probit analysis of the same model, Model 2.

Table 1C: Restricted Model 1 for Evil eye as the dependent variable, Money >1 >3 >4, changing the independent variable for Money (EduMod-78: final model)

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17. MONEY (MEDIA OF EXCHANGE) AND CREDIT
      3    . = Missing Data
     77    1 = No media of exchange or money
     12    2 = Domestically usable articles as media of exchange
     26    3 = Tokens of conventional value as media of exchange
     42    4 = Foreign coinage or paper currency
     26    5 = Indigenous coinage or paper currency
```

Model 1	Description Re: Evil eye	Eff-Dow coef	pvalue	VIF	Var.		Probit Coef	pvalue
(Intercept)		-0.247	0.775	NA			1.1715	0.12
Wy fydd	Spatial transmission	0.763	.0000022	3.452	NA	***	0.6944	0.00004
Wy fyll	Cultural transmission	-0.228	0.362	2.329	NA		-0.2267	0.38
Milk	Milking of animals	0.664	0.080	2.328	245	*	0.3235	0.48
CaststratLDg	Degree of caste stratification	1.372	0.017	1.225	272	* *	0.5078	0.04
Money >1>3>4	Degree of monetization	0.597	0.017	1.152	155~v17	**	0.1011	0.05
Moral gods	Degree of morality of gods	0.294	0.020	1.664	238	**	0.1161	0.04
Diagnostics		Fstat	df	pvalue			Fstat	
RESET test. H0: model has right functional form		3.400	1801.470	0.065			0.717	0.397
Wald test. H0: appropriate variables dropped		0.476	308.949	0.491			0.431	0.512
Breusch-Pagan test. H0: residuals homoskedastic		1.193	3282.405	0.275			8.753	0.003
Shapiro-Wilk test. H0: residuals normal		16.146	9268.270	0.000			3.618	0.057
LM test. H0: Spatial lag (language) not needed		0.713	1877017.	0.398			1.086	0.297
LM test. H0: Spatial lag (distance) not needed		1.768	20982.58	0.184			2.214	0.137

Notes: R^2 = 0.513; N=186; number of imputations=3; standard errors and R^2 adjusted for two-stage least squares. "***" p-value ≤ 0.01, "**" p-value ≤ 0.05, "*" p-value ≤ 0.10. Language non-significant (p > .33).
Probit note: R^2 = 0.459; IV(distance)=0.9936; (language)=0.9946 see last two columns for coef and pvalue. (The single value of 1 is replaced for Evil eye).

Table 2: Restricted Models for Money dichotomized for v155 >1 >3 >4 as the dependent variable (EduMod-79). PC in this and following tables means Principal Component, as in Brown and Eff (2010). For PCsize, this combines a weighting of superjh (v237) and commsize (Community size v928). For Model 2, as opposed to results in Table 1, the probit R^2 outperforms the ordinal model.

Model 2	Description Re: Money	Eff-Dow coef	pvalue	VIF	Var.		Probit Coef	Pvalue
(Intercept)		-0.775	0.002	NA			0.2316	
Wy fydd	Spatial transmission	0.954	.0000279	3.644	NA	***	0.9057	3.758
Wy fyll	Cultural (language) transmission	-0.928	0.003	4.190	NA	***	-0.9220	4.309
Foodtrade	Imported food	0.430	0.134	1.219	819		0.1005	1.228
Fratgrpstr	Fraternal interest group strength+	0.120	0.092	1.840	570	*	0.1663	1.757
Milk	Milking of animals	-0.393	0.012	1.560	245	*	-0.2394	1.478
Caststrat LGd	Degree of caste stratification+,++	0.430	0.134	1.219	272			
Moral gods	Degree of morality of gods+.++	0.102	0.142	1.502	238		0.1021	0.142
Popdens	Population density	0.206	.0000053	1.552	156	***	0.3147	1.627
Superjh PCsize	Supra cmnty jurisdictional hier.	0.304	.0000002	1.633	237	***		
Diagnostics		Fstat	df	pvalue			Fstat	
RESET test. H0: model has right functional form		1.943	5301.617	0.163			2.187	0.139
Wald test. H0: appropriate variables dropped		15.266	17.503	0.001			13.332	0.000
Breusch-Pagan test. H0: residuals homoskedastic		13.833	950.560	0.000			4.995	0.027
Shapiro-Wilk test. H0: residuals normal		0.267	282.276	0.606			0.363	0.548
LM test. H0: Spatial lag (language) not needed		1.287	657642.	0.257			1.773	0.183
LM test. H0: Spatial lag (distance) not needed		1.352	991.504	0.245			1.902	0.168

+ Do not both enter model significantly, drop one or the other. ++Drop as 0.22 > p > .10
moralgods 0.075 0.215 1.498 (alone, R2=0.469)
caststrat LGd 0.403 0.164 1.203 (alone, R2=0.471)
Notes: R^2 = 0.490; N=186; number of imputations=3; standard errors and R^2 adjusted for two-stage least squares. "***" p-value ≤ 0.01, "**" p-value ≤ 0.05, "*" p-value ≤ 0.10. Language non-significant (p > .33).
Probit note: R^2 = 0.481; IV(distance)=0.9911; (language)=0.9957 see last two columns for coef and pvalue.

Table 3 shows the ordinal model for Moral gods as the dependent variable, along with a probit analysis. Although the probit analysis has a slightly lower R^2 with external war and interpersonal violence non-significant, it passes all the diagnostic tests.

Table 3: Restricted Models for Moral gods as the dependent variable (EduMod-80)

Model 3	Description Re: Moral gods	Eff-Dow coef	pvalue	VIF	Var.		Probit Coef	pvalue
(Intercept)		1.444	0.147	NA			2.010	0.015
Fydd	Spatial transmission	0.984	.00000001	2.499	NA	***	0.930	.0000002
Fyll	Cultural-language-transmission	-0.941	0.048	2.526	NA	**	-.972	0.050
PCAP	PC Agricultural potential	-0.034	0.105	1.123	921	*	-.104	0.041
PCsize	DROP PC Juris. Hierarchy	0.021	0.073	1.462	237	*	0.180	0.007
Milk	245 Milking of animals	0.466	0.032	2.230	245	**	0.274	0.075
Foodstress	Chronic food stress	0.237	0.038	1.096	1685	**	0.122	0.085
Eextwar	Frequency of external war	-0.032	0.005	1.117	1650	***	-.180	0.003
bridewealth	Bridewealth payments	0.309	0.049	1.225	208=1	**	0.209	0.064
caststratLgd	Log of Caste stratification	0.755	0.021	1.266	272	**	0.156	0.059
PCvioLntr+	Interpersonal violence		0 .08		666		-.164	0.128
pctFemPolyg+			> .75		972			
Anim2+			> .50		206			
Diagnostics		Fstat	Df	Pvalue			Fstat	
RESET test. H0: model has right functional form		0.257	460.947	0.612			0.116	0.733
Wald test. H0: appropriate variables dropped		0.840	24.219	0.369			1.900	0.175
Breusch-Pagan test. H0: residuals homoskedastic		2.931	347.656	0.088			-0.354	1.000
Shapiro-Wilk test. H0: residuals normal		7.388	143.820	0.007			0.758	0.386
LM test. H0: Spatial lag (language) not needed		1.359	3784497.	0.244			1.041	0.308
LM test. H0: Spatial lag (distance) not needed		0.922	14445354.	0.337			0.695	0.404

Notes: R^2 = 0.512; Probit R^2 = 0.483; N=168; number of imputations=3; standard errors and R^2 adjusted for two-stage least squares. "***" p-value ≤ 0.01, "**" p-value ≤ 0.05, "*" p-value ≤ 0.10. Language non-significant (p > .33).
Probit note: R^2 = 0.481; IV(distance)=0.9942; (language)=0.9861 see last two columns for coef and pvalue.

Judging from these results, probit does not always outperform the ordinal model but does as well on average as the ordinal model. Until other varieties of the probit algorithm are tested it is best at this juncture to use both and compare results. If probit were to outperform the ordinal model for Table 1, where one of the key independent variables (Money) needs adjustment here as well as in Model 2, where it is a dependent variable, it might overcome a limitation of the Eff and Dow (2009) linear regression software with Instruments, needing adjustments of the ordinal categories to obtain a better R^2. This limitation partially obstructs our main objective of a causal graph analysis in terms of how variables connect in combined DAG models as in Fig. 1. To do the causal graph analysis in a chain X→Y→ Z we require the intermediate variable Y to be identically measured as both a dependent variable of X and an independent variable of Z.

As shown in Table 4, the spatial transmission effects in our Models 1-3 are all positive, as in every model we have tested to date. They are the most significant effects in all three models. The cultural transmission effects (language phylogeny), however, are all negative, which is unusual.

Table 4: Transmission effects (Galton's problem)

Peer Effect	Variable	coef	pvalue
Spatial	Money	.960	.0000009
Transmission	Moral gods	.824	.0000014
(Distance)	Evil eye	.767	.000002
Cultural	Money	-.988	.002
Transmission	Moral gods	-.672	p > 0.14
(Language)	Evil eye	-.228	p > 0.36

The negative peer effects for language indicate that, for each of these dependent variables, there is a tendency, strong for Money and weak or nonexistent for the other two variables, NOT to be the result of cultural tradition but of innovation that differentiates the societies with Money, Moral gods and Evil eye from the norms in their respective language families. This tendency is nearly significant (pvalue ≤ 0.15) for societies with Moral gods.

Moral gods, Evil eye, and Inequality: John Roberts (1976). Evil eye and Moral gods have very similar distributions, significantly different from chance at 1/billion, so close they might seem to be coincident. It is implausible, however, that Evil eye is a cause of Moral gods, and our Model 1 (Table 1C) shows that Moral gods are a predictor of Evil eye (pvalue ≤ 0.02). Both are dependent on Milked animals, which is also a predictor of Money. Money is a predictor of Evil eye but not of Moral gods. Caste stratification – a measure of fixed inequalities – is a predictor of all three variables: it affects Moral gods and Evil eye strongly (pvalue ≤ 0.02) and Money weakly.[(11)]

> "Roberts sees stories and gossip about the evil eye as expressive forms related to conflict experienced during the process of enculturation. He assumes that there may be differences in the strength of belief in the evil eye within a given culture depending upon the strength of the antecedent conflicts at the individual level. The greater the conflict, the less representative of the "real" world the model needs to be to make it expressively satisfying. Roberts finds that, with few exceptions, the evil eye belief and its significant cluster of associated traits occur in such marked geographical patterns that he places its origin in the Mediterranean area with extensions into Europe, the Near East, and elsewhere." (Weidman 1980)

From Moral gods to Evil eye: Brown and Eff's model of Moral gods (2010). Our results show a close relation to Brown and Eff (2010), but ours extends their analysis to discover additional relationships such as bridewealth. Table 5 compares the independent variables predicting Moral gods from Brown and Eff (2010), and our Eff-Dow (2009) and probit regressions in Table 3.

Table 5: Comparison of Models with Moral gods as the dependent variable

Variable Name	Var. Number	Brown-Eff Coef	Pvalue		Eff-Dow OLS Coef	Pvalue		Probit Coef	Pvalue
PCAP	921	0.129	0.026	**	-0.038	0.075	*	-0.097	0.059
PCsize	63	0.226	0.002	***	0.554	0.035	**	0.212	0.002
PCsize^2	63^2	-0.114	0.006	***	-0.076	0.107		0.344	0.022
Milk	245	Anim. 0.83	Anim. 0.047	**	0.403	0.065	*	0.135	0.031
Foodstress	1685	Scarc 0.115	Scarc. 0.046	**	0.207	0.152		-0.190	0.003
Eextwar	1650	-0.039	0.000	***	-0.032	0.006	**	-0.187	0.024
Bridewealth	208=1	--	--		0.194	0.221		0.155	0.146
Caststrat LGd	272	0.209	0.043	**	0.704	0.030	**	0.183	0.035

Societies with Money (v155) do not seem to derive from those with Moral gods (v238), or be influenced by Moral gods (Table 2), or if so, only weakly (pvalue ≤ 0.15). Money is not a predictor of Moral gods in either our analyses (Table 3) or Brown and Eff (2010). Brown and Eff conclude from their study that societies with Moral gods are more likely in societies with small rather than large states, in resource-poor societies, societies *not* engaged in chronic external war, and in pastoral societies with milked animals. Our Model 3 (Table 3) further supports this view in finding marginal effects (close to significance) of the percentage of women married polygynously and interpersonal violence, which are common in societies which are common in such contexts. As the last variable added to Model 3, our prediction was that bridewealth exchange involving payments of cattle would be implicated in these contexts although the quantitative effect is not measurably strong. This proved to be correct in a weak sense of a probit pvalue ≤ 0.16. Other variables in the pastoral/polygynous small state complex such as Interpersonal violence (PCvioIntr), Percent female polygyny (pctFemPolyg) and Percent Animal husbandry (Anim^2, squared) reached levels (pvalue ≤ 0.20) close to significance.

While Roberts placed the origin of Evil eye "in the Mediterranean area with extensions into Europe, the Near East, and elsewhere," it might be more accurate to say that it is the pastoral and smaller states in this heartland of large state areas that gives rise to Evil eye beliefs. This would be consistent with our finding of negative peer effects within language groupings for Evil eye, Moral gods, and Money, concomitant with the differentiation of subsystems in large state/small state areas.

Causal graph computation of direct and indirect effects on dependent variables. After compiling results of the regression models 1-3 in Tables 1C, 2, and 3, the next steps are to assign the regression coefficients to the causal graph and then compute the direct and indirect effects.

Fig. 3 shows, in addition to the original triangular model involving variables A, B and C (Milking, Money, Evil eye) as extracted from Fig. 1, that we have discovered one additional variable, Moral gods, which mediates between Milking and Evil eye, and one additional and important independent variable, Caststrat, which was part of the Brown and Eff (2010) model for Moral gods. We found that Caststrat LGd (the log of Caste stratification) was a predictor of each of our other three dependent variables (significant in two cases at pvalue ≤ 0.02) and close to significant as a predictor of Money (pvalue ≤ 0.14).

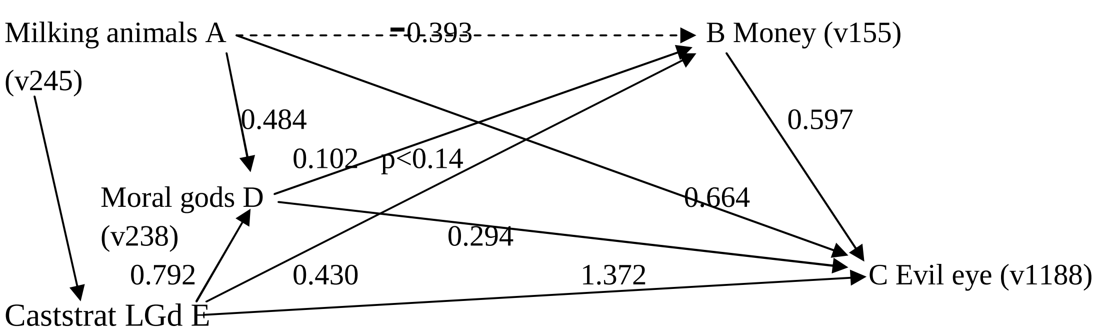
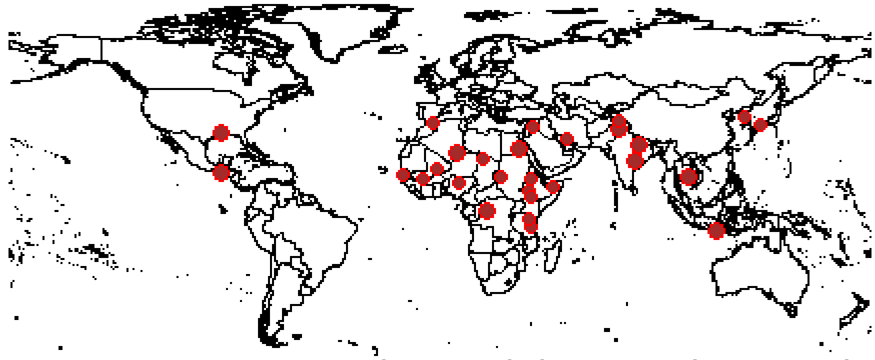


Fig. 3: **Causal graph with multiple triangular significant regression coefficients, after including peer effects and calculating regressions using equation (4)**

Fig. 4 shows the distribution of Caste stratification, which is primarily in those regions of Evil eye that are south and east of the Mediterranean (see Fig. 2).



272. CASTE STRATIFICATION (ENDOGAMY) (two cases have secondary castes)
5 . = Missing data
(154) 0 = (Omitted from map) Absent or insignificant
17 1 = Despised occupational group(s)
3 2 = Ethnic stratification
7 3 = Complex

Fig. 4: **Spatial clustering of Caste stratification, spreading from south of the Mediterranean**

Models for Caste stratification and Milking as dependent variables

When variable E (Log of Caste stratification) in Fig. 3 is taken as a dependent variable, a new link appears in this diagram: A Milking → E Caste stratification (pvalue ≤ 0.000001), with coef = 0.617, which alters the paths in Table 6. Similarly, when we took Milking as a dependent variable, we found a new dependent variable, “Foodstress”, which was also a predictor of Moral gods. Further independent variables might result if Foodstress was treated as a dependent variable.

In no case did the regression analysis with peer effect IVs for our five main (A E D B C) produce a reciprocal effect (X↔Y) or circular effects. This is consistent with our archaeological and historical interpretation that the order of temporal precedence of these variables, in spite of the mutually exclusive relation between pastoralism and fully monetized economies, with all the other effects being positive, is this:

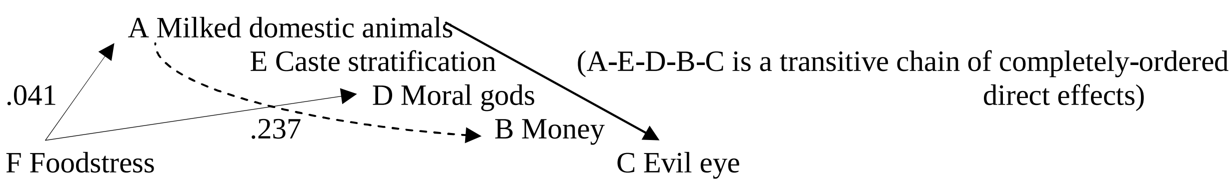


Fig. 5: **Causal graph with significant transitive direct regression effects A-E-D-B-C (after including peer effects), plus the additional confounder F.**

We interpret the central dynamic of the A-E-D-B-C transitive effects pattern as one where Evil eye, in each case, is a response to various forms of inequality: those produced by differential wealth production in pastoralism, encoded in caste stratification and regulated by moral gods, and a new form of maximization leading to inequality, monetized exchange. We did not check possible circularities with variable F so as not to enlongate the chains of successive regressions, but these act as confounders for the relationship between A and D.

The transitive chain A-E-D-B-C of direct effects satisfies Pearl's (2000:150-152; 79-80) back door and single door criteria which entails – under certain assumptions – that a direct effect measured by the (partial) regression coefficient in the linear model regression between any ordered pair of these variables, i.e., the total effect minus the sum of indirect or order path effects, or total = direct + indirect effects. This assumes that the independent-dependent regression relationships are *linear* and *independent*, e.g., as tested by further partial regressions of two or more variables at a time relative to the dependent variable. Here, we intend to study pairs of independent variables using the R code in appendix 1 to test these assumptions. We plan a further study of the effects of multiplicative interaction terms in modeling SCCS variables.

Estimating direct, indirect and total effects

Table 6 shows in the middle columns the net effects of direct and indirect causal graph effects from Fig. 3. We can estimate net or total effects on dependent variables B, C, D in Fig. 3 given relevant theorems and references regarding Pearl's backdoor criterion (e.g. Pearl, 2000) and Chalak and White's (2010) "exogenous causes" (XC) and "exogenous causes given conditioning instruments" (XC|I) cases. In the figure all potential backdoor paths are blocked by an observed variable. For example, if variable A was an unobserved effect this would not be true and the net causal effects on B and C could not be estimated.

Table 6: Causal graph effects and bivariate table regression slopes A-E-D-B-C and confounder F

Independent Variable	Dependent Variable	Arrow sequences	Total effect=Direct and Indirect Causal Graph Effects	Causal Graph	Fig. Slope
Milking	Evil eye	A E D B C Effect of F thru A thru D	0.664+(-.393*.597)+(.484*.294) +(.617*1.372) + (.484*.102*.597) +(.617*.792*.294) +(.617*.792*.102*.597) (.041*.664)+(.041*-.393*.597)+(.041*.484*.294) +(.041*.617*1.373) +.(.041*.484*.102*.597) +(.041*.617*.792*.294) +(.041*.617*.792*.102*.597) =(.237*.292)+(.237*.294)+(.237*.102*.597)	1.62 +.38 +.12 = 2.12 -0.66 =1.46	.810
Caste strat LGd	Evil eye	E D B C Control F	1.372+(.43*.597)+(.792*.294)+(.792*.102*.597)	1.910	
Moral gods	Evil eye	D B C Control F	=0.294+(0.102*.597)	0.355	.950
Money	Evil eye	B C Control F	0.597	0.597	.741
Milking	Money	A E D B Control F	=-.393+(0.484*.102)	-0.344	.244
Caste strat	Money	E D B Control F	=0.43+(.792*.102)	0.511	
Moral gods	Money	D B Control F	0.102	0.102	.482
Milking	Moral gods	A E D Control F	0.484	0.484	.270
Caste strat	Moral gods	E D	0.792	0.792	
Milking	Caste strat	A E Control F	0.617	0.617	

The last column in Table 6 gives a slope of the simple cross-tabulation of the independent variable. Note the discrepancy between the direct regression coefficient in Fig. 3 (-0.393) for variables A→B, which are negative, and the positive slope of the and total bivariate slope in the cross-tab of the two variables, which is positive (0.244). This discrepancy is due to the very strong effects (pvalues < .000005) of Popdens and Superjh on Money, which run opposite to the residual effect of Milking on Money, net also of spatial transmission. This highlights the fact that what shapes the bivariate contingency cross-tabs is very different from what shapes the causal graph coefficients, which are net of spatial and cultural transmission (Galton's problem) and the effects of other variables. Correlating the net causal graph effects and the bivariate slope of the cross-tab relations has not yet been done for the last two columns of the Table since the ratios of units for the first and last variables and intervening variables need adjustment.

The evidence of the peer effect regressions summarized in Table 6 give surprising results as to the directionality of causality among the variables studied. Not only do A→E→D→B→C form a causal chain but every ordered pair of variables has a direct causal effect, controlling for intermediaries, as for example the triangles A→E→D (where A→D), E→D→B (where E→B), and D→B→C (where D→C). That is, controlling for mediating variables (indirect effect) there is in every case a strong direct effect.

Conclusion. Causal graphs with Instruments for solving Galton's problem of peer effects or "identification" endogeneity, such as spatial or cultural transmission effects, is a vast improvement to testing hypotheses using significance tests (the norm in the comparative literature) showing that reliance on significant tests ought to be virtually forbidden by journal and book editors as unreliable. The example of effects of milking of animals on money is illustrative: the cross-tab correlation is positive and significant, while the causal graphs result is negative and significant. Fig. 1 – an illustrative graph of potential causes – shows a pattern of distributed links, might suggest that principal components and cluster analyses are unlikely to produce reliable results, although Fig. 3 might suggest otherwise.

The replicability of our results for the dependent variable of Moral gods, also investigated by Brown and Eff (2010) is illustrative of the validity of causal graphs with peer effects regression to control for "identification" endogeneity. Brown and Eff (2010) concluded that Moral gods are predicted by small states with pastoralism. Our results coincided (see Table 5) but went further to show that additional specific predictors like bridewealth support the validity of their inferences, which are based on the same methods we employ here. To counteract the criticism that the Eff and Dow (2009) methods use linear regression to model ordinal variables, we implemented a probit transformation of variables. Comparing these two variants of the methods showed closely equivalent results and no bias for the ordinal regressions to give inferior results in terms of R^2. We are still experimenting with better methods for probit renormalization.

The specificity of the results that are provided by regression with Instruments is extremely helpful in attaining well-specified models. The methods used include multiple imputation of missing data which retains sample sizes determined by the dependent variables. Problems may occur when dependent variables are coded for very different subsets of cases, which requires further coding effort to even out these subsample discrepancies.

Ethnographically well-studied and well-coded populations such as provided by the Standard Cross-Cultural Sample used in this study are a desideratum. Given that, cross-cultural research ought to be able to produce a reliable and replicable body of findings, but it has not done so. Many anthropologists regard the reigning standards of cross-cultural research as faulty, not just because of the difficulties of Galton's problem but as showing a disregard of sound scientific concern with the issues of Galton's problem, which we try to resolve here. In the cross-cultural literature, the use of small-size samples is often coupled with a denial that Galton's problem is relevant when a small number of cases are sampled randomly. Randomness of the selection of cases, however, is irrelevant to solving Galton's problem (see footnote 7), which is done by inclusion of peer-effects Instruments capable of correcting for the "identification" endogeneities of cultural and spatial transmission.

Our goal of providing and expanding baseline causal networks such as the one constructed for Fig. 1 has proven very useful in the employment of causal graphs. Instead of choosing variables to study on an arbitrary basis or because of our particular research interests, we took as our example a subset of the causal graphs in which a cohesive set of variables was found, in this case a triangular structure A→B→C and A→C, and then we reran the regression with Instruments for these dependent variables to collect a larger set of independent variables. Among these, we discovered a new variable D, Moral gods, that was also triangular with respect to our original variables, A, B, C. Investigating Moral gods as a dependent variable, we then discovered that one of our original variables, A had significant causal prediction for B, C, and D, and also discovered a new independent variable E (from the study of Moral gods by Brown and Eff 2001) that also connected to B, C, and D. This research strategy of expanding the focus of study by search for triangular or cohesive networks of variables led to a complex model that was still amenable to causal graph analysis. This strategy, then, by expanding the scope of study systematically, searches out the complex structures of relationships among the variables in a dataset, rather than choosing new variables on the basis of *a priori* assumptions. We conclude that our strategy, and the goal of aiming at a causal graph analysis of all qualified variables in the SCCS (the SCCS.Rdata-base of two thousand variables) will provide a basis for discovery and reevaluation of findings for which the SCCS sample can be used, taking peer effects into account.

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Declaration of Conflicting Interests

The author(s) declare no conflicts of interest with respect to the authorship and/or publication of this article.

Appendix 1: Partial regression plot (or added variable plot)

Source at http://zoonek2.free.fr/UNIX/48_R/11.html#2

Let us consider a regression situation with two predictive variables X1 and X2 and one variable to predict Y.

You can study the effect of X1 on Y after removing the (linear) effect of X2 on Y: simply regress Y against X2, X1 against X2 and plot the residuals of the former against those of the latter.

Those plots may help you spot influent observations.

```
partial.regression.plot <- function (y, x, n, ...) {
  m <- as.matrix(x[,-n])
  y1 <- lm(y ~ m)$res
  x1 <- lm(x[,n] ~ m)$res
  plot( y1 ~ x1, ... )
  abline(lm(y1~x1), col='red')
}

n <- 100
x1 <- rnorm(n)
x2 <- rnorm(n)
x3 <- x1+x2+rnorm(n)
x <- cbind(x1,x2,x3)
y <- x1+x2+x3+rnorm(n)
op <- par(mfrow=c(2,2))
partial.regression.plot(y, x, 1)
partial.regression.plot(y, x, 2)
partial.regression.plot(y, x, 3)
par(op)
```

R partial regression plots adapted to run after EduMod79

```
partial.regression.plot <- function (y, x, n, ...) {
  m <- as.matrix(x[,-n])
  y1 <- lm(y ~ m)$res
  x1 <- lm(x[,n] ~ m)$res
  plot( y1 ~ x1, ... )
  abline(lm(y1~x1), col='red')
}

Milking=sccs$v245
Moralgods=sccs$v238
Evileye=sccs$v1188
n <- 186
rnorm=rnorm(n)
```

```
x1 <- Milking
x2 <- Moralgods
x3 <- x1+x2+Evileye
x <- cbind(x1,x2,x3)#,rnorm)
y <- x1+x2+x3  #+rnorm(n)
op <- par(mfrow=c(2,2))
partial.regression.plot(y, x, 1)
partial.regression.plot(y, x, 2)
partial.regression.plot(y, x, 3)
par(op)
```

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If the paper requires use of software written by the author, the software must also be submitted with the manuscript.
Double spaced, with footnotes, references, tables, and charts on separate pages
The cover letter should contain all authors' names and contact information as well as the names of six possible reviewers, with their institutional affiliations and email addresses, excluding persons who are mentors, students, coauthors, or who have any other close connection to the author(s).
http://intersci.ss.uci.edu/wiki/index.php/Edu-Mod_2009-10:_The_Individual_Studies

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[1] For ordinal variables, we use the lower and upper values of the variables.

[2] Pearl (2009c): "Causal diagrams may also apply when you are not sure about the things listed above, where SEM (structural equation modeling) is dead silent about what are the direct and indirect effects. For example, if you are

not sure about linearity, the mediation formulas in section 6.2 of R-355 (Pearl 2009b) gives you definitions and estimands," i.e., the probabilistic formulas governing estimation of the dependent or target variable. "Whether the regression is single or 2-stage is up to the research but might depend on the structure of the model."
"The mathematical derivation of causal effect estimands, like Eqs. (25) and (27)" (Pearl 2009b: 35) "is merely a first step toward computing quantitative estimates of those effects from finite samples, using the rich traditions of statistical estimation and machine learning Bayesian as well as non-Bayesian."

[3] For a triangle, Z→aX→bY and Z→cY, for example, $P(y|\hat{x})=P(y|x,z)P(z)$, i.e., the direct effect of X on Y is the product of the total effect of X and Z on Y. In terms of regression coefficients, the sum of direct b effect and indirect ac effects. This is the same as a relabeling of x,y,z in equation (1), with z,x,y.

[4] Pearl (1990:34) "[B]efore specifying any aspect of the model," be it "causal effect", "mediated effect", "effect on the treated", or "probability of causation", "the structural modeling approach insists on defining the target quantity." "[T]he interventional distribution … [for example] is universally applicable to all models, parametric as well as non-parametric, through the formation of a submodel M_x. This definition remains the same regardless of whether X stands for treatment, gender, or the gravitational constant; manipulation restrictions do not enter the definitional phase of the study (Pearl 2009a, pp. 361; 375)."

[5] Morgan and Winship (2007), for example, develop causal inference models that treat endogenous effects in quasi-experimental studies.

[6] Typically, significance tests are highly inefficient (and departure from the null hypothesis highly overestimated) when endogenous "social effects" are operative, while correlations and regression coefficients may remain unbiased.

[7] Network interdependence in observational studies means, again, endogeneity: the cases observed have a past history in which they have influenced one another through past interaction, communication, diffusion, common ancestries, social or economic ties, and the like. This creates the problem of spatial or other kinds of clusters of similar cases (individuals in a sociological survey, social units in a comparative survey).

[8] It is claimed in Bernard (1998:678) that "Independence of cases means *only* that the choice of one case is not influenced by the choice of any other case (which random sampling guarantees)." This is patently untrue because Galton's problem of interdependence is due to social and historical interactions (e.g., diffusion and/or common origins) among sample cases.

[9] Autocorrelation may mean correlation among the data from different locations, time periods, or structural positions in a network, i.e.: Spatial, temporal or network autocorrelation. Murdock and White (1969), for example, use a shortest single route through the 186 society sample of the SCCS to compute samples at varying distances and then compute whether adjacent cases at each distance are significantly more similar than expected under the null hypothesis. The N_e estimates for "effectively independent" samples sizes calculated by Murdock and White are these, out of a possible largest score of 186: system of descent N_e=19 (10%), language N_e=20 (11%), economy N_e=46 (25%), and political integration N_e=61 (21%). In a HRAF probability samples these percentages would give N_e=6, 7, 15, and 19, absurdly low effective sample sizes for cross-cultural research. Even samples between 20 and 60 will suffer from endogenous "social interaction" effects that will lead to overestimated significance and false rejections of the null hypotheses.

[10] Several authors (Roes and Raymond 2003, Sanderson et al. 2005, among others) have printed a mistaken rumor that the SCCS was created as a subset of the Ethnographic Atlas (Murdock 1967) to minimize the effects of Galton's problem. Murdock and White (1969), to the contrary, showed Galton's problem to be a very serious problem and proposed a test of its extent for particular variables.

[11] The crosstab for the Evil eye dichotomy by moral gods is calculated in R as follows:

table(SCCS$v1189,SCCS$v238,useNA="ifany")
(Evil eye dichotomized cross-tabbed by Moral gods)

```
   1  2  3  4
 -+--+--+--+--+
 0|55 36  5  9|
 -+--+--+--+--+
 1|13 11  8 31| p =  0.0000000013
 -+--+--+--+--+
```