Supplemental Materials for

Discerning Cultural Shifts in China? Commentary on Hamamura et al. (2021)

1. Target Article

Hamamura, T., Chen, Z., Chan, C. S., Chen, S. X., & Kobayashi, T. (2021). Individualism with Chinese characteristics? Discerning cultural shifts in China using 50 years of printed texts. *American Psychologist, 76*(6), 888–903. https://doi.org/10.1037/amp0000840

In the original article, Hamamura et al. (2021) investigated four Research Questions (RQ) on cultural associations between IND-COL and ten other concepts over five decades (from the 1950s to the 1990s) in China. To examine such cultural associations and their shifts, they tested the word similarities by using the *cosine similarity* between *word embeddings* (note: a word embedding is a vector of values on multiple dimensions to quantify a word's meaning, produced by machine learning). In particular, they utilized an established database of word embeddings (HistWords), which contains pre-trained word vectors for each decade across the 1950s~1990s based on the Google Ngram Chinese Corpus (Version 2).

Their four RQs and the corresponding pairs of concepts include:

RQ1: Is Chinese culture more positively disposed to individualism over time?

- *IND-COL words ↔ Positive and Negative words*

RQ2: Is achievement more closely associated with individualism over time?

- *IND-COL words ↔ Achievement words*

RQ3: Is collectivism continuing in China in some domains of life?

- *IND-COL words ↔ Work, Leisure, Home, Money, Religion, and Death words*

RQ4: How does Chinese culture associate individualism-collectivism and modernity?

- *IND-COL words ↔ Modernity words*

They tested hypotheses using Linear Mixed Models (LMM; aka. Multilevel Models), where they included *Decade*, *IND-COL*, and their interaction as predictors. They also used the

Word-Embedding Factual Association Test (WEFAT; Caliskan et al., 2017) to visualize the time trends. The main findings they reported include:

RQ1: Significantly higher similarity between IND (vs. COL) words and negative words (main effect).

RQ2: Significantly decreasing similarity between IND (vs. COL) words and achievement words over time (interaction).

RQ3: (1) Significantly lower similarity between IND (vs. COL) and work-related words (main effect). (2) Significantly increasing similarity between IND (vs. COL) and leisure words over time (interaction). (3) Significantly decreasing similarity between IND (vs. COL) and money words over time (interaction). (4) Nonsignificant, continuing similarity between IND (vs. COL) and words related to home, religion, and death (null effect).

RQ4: Nonsignificant, continuing similarity between IND (vs. COL) and modernity words (null effect).

In conclusion, they stated that their findings (1) did not support "*the hypothesized cultural shift toward individualism in China in the second half of the 20th century*" and (2) suggested "*continuing collectivism in contemporary China*" (p. 901). They also came to a conclusion that "*rising individualism is not a universal consequence of societal modernization*" (p. 888: *Abstract* and *Public Significance Statement*).

2. Misinterpretation of Simple Effects as Main Effects

The fixed effect (regression coefficient) of a predictor is not always its "main effect". When there is an interaction between two predictors X and Z, the fixed effect of X represents its *simple effect* on the outcome Y at $Z = 0$; however, the *main effect* of X actually refers to its "average effect" across all levels of Z (Cohen et al., 2003).

Cohen et al. (2003): "*In general, in a regression equation containing an interaction, the first-order regression coefficient for each predictor involved in the interaction represents the regression of Y on that predictor, only at the value of zero on all other individual predictors with which the predictor interacts.*" (p. 260)

Hox et al. (2018): "*Centering is also important if the multiple regression model includes interactions. For each of the two explanatory variables involved in an interaction, the interpretation of its slope is that it is the expected value of the slope when the other variable has the value zero. Again, since 'zero' may not even be a possible value, the value of the slope for the interaction term may not be interpretable at all. Since multilevel regression models often include cross-level interactions, this is a serious interpretation problem. When both variables in the interaction are centered on their grand mean, the problem disappears.*" (p. 49)

This is a basic statistical issue, albeit easy to be neglected (especially in R).

Hamamura et al. (2021), however, misinterpreted all fixed (simple) effects as main effects (see pp. 895–899). Below we demonstrate their LMM/multilevel-model equations. Their reported "main effect" of *IND-COL* actually denoted its "simple effect" at *Decade* = 0 (i.e., the 1950s, since they coded the decades as "1950s = 0, 1990s = 4"; see p. 895). Hence, all their conclusions derived from their misreported "main effects" are questionable (for details, see our reanalysis in the next section).

Level-1 equation:

$$Similarity_{ij} = \beta_{0j} + \beta_{1j} Decade_{ij} + e_{ij}$$

Level-2 equations ("intercept-as-outcome" and "slope-as-outcome" equations):

$$\begin{aligned} \beta_{0j} &= \gamma_{00} + \gamma_{01} INDCOL_j + u_{0j} && \text{(random intercepts)} \\ \beta_{1j} &= \gamma_{10} + \gamma_{11} INDCOL_j && \text{(fixed slopes)} \end{aligned}$$

Mixed-effect model equation:

$$\begin{aligned} Similarity_{ij} &= \gamma_{00} + \gamma_{10} Decade_{ij} + \gamma_{01} INDCOL_j + \gamma_{11} Decade_{ij} \times INDCOL_j + u_{0j} + e_{ij} \\ &= \gamma_{00} + (\gamma_{01} + \gamma_{11} Decade_{ij}) \times INDCOL_j + \gamma_{10} Decade_{ij} + u_{0j} + e_{ij} \end{aligned}$$

It is noteworthy that this problem is not attributable to the coding of variables. That is, using either Hamamura et al.'s (2021) coding or any other coding, the model fit of LMM does not change at all (see R Code File). The key point is that they misinterpreted simple effects as main effects. Indeed, in R programming, only `anova(model)`, rather than `summary(model)` (or other R functions of model summary), estimates real "main effects" (with the *F* statistics) regardless of the coding approach.

3. Reanalysis

With the data that Hamamura shared with us, we revisited their four research questions. First, we used the same analytic strategy as theirs (i.e., LMMs with only the random intercepts included and exactly the same model parameters specified in R). Nonetheless, besides their coding of decades (i.e., 1950s as the reference), we also coded it in four other approaches such that 1960s, 1970s, 1980s, and 1990s was treated as the reference, respectively (e.g., when 1990s was the reference, the coding became 1950s = –4, 1990s = 0). In this way, we can demonstrate how different coding approaches will produce different results of the *simple effect* of IND-COL but will not affect the real *main effect* and the model fit. We present these results in Table S1 (also see figures for each RQ in the R Code File).

Second, we aimed to utilize the WEAT algorithm (Caliskan et al., 2017) to examine the relative association between IND (vs. COL) and positive (vs. negative) concepts. Besides the positive and negative words in RQ1, we detected that achievement words (in RQ2) and money words (in RQ3) also involved both positive and negative words. For instance, there are **positive achievement** words like "*success*", "*able*", "*persist-in*" and **negative achievement** words like "*failure*", "*unable*", "*give-up*". Also, there are **positive money** words like "*income*", "*richness*" and **negative money** words like "*loss*", "*poverty*", "*bankrupt*", "*waste*". Thus, we distinguished between them based on valence ratings from 24 raters (for details, see the R Code File) and contrasted the positive ones against the negative ones (Caliskan et al., 2017). We present these results in Table S2 and Figures S1–S3.

3.1. RQ1: IND-COL ↔ Positive-Negative

There was no significant main effect of IND (vs. COL) on its association with either positive or negative words (ps > .19; cf. the misreported "main effect" p = .039 for the IND-negativity association in Hamamura et al., 2021). Moreover, simple-effect analyses showed that the association between IND (vs. COL) words and negative words was *only* significant in the 1950s but *not* significant in the 1960s~1990s (Table S1).

This finding was also supported by the WEAT analysis (Caliskan et al., 2017), where we calculated the differential association of the two sets of target words (IND vs. COL) with the two sets of attribute words (positive vs. negative). Results indicated that Chinese people held a (weakly) negative attitude toward IND (vs. COL) in the 1950s but a neutral attitude (i.e., neither positive nor negative) toward IND (vs. COL) in the next four decades (1960s~1990s) ($t_{\text{1960s-1990s vs. 1950s}} = 2.064$, $p = .043$; see Table S2 and Figure S1). All these findings are even consistent with the pattern shown in the Figure 2 in Hamamura et al. (2021, p. 896).

To summarize, these results suggest that individualism was increasingly accepted (or decreasingly rejected) over the past decades in China.

3.2. RQ2: IND-COL ↔ Achievement

The association between IND (vs. COL) words and achievement words varied across decades, with a nonlinear time trend. In the 1950s, neither IND nor COL was associated with achievement ($p = .76$). In the 1960s ($p = .025$) and the 1970s ($p = .086$), achievement was slightly more associated with COL than IND. This relative association was more salient in the 1980s ($p < .001$) but then dropped off (with the simple effect weakening from –.171 to –.080) in the 1990s ($p = .010$).

This result was not the final story because we identified both positive and negative achievement words in Hamamura et al.'s (2021) data. The differential association as revealed above suggests that positive and negative achievement words may be differentially associated with individualism and collectivism and therefore should be distinguished. Accordingly, we further distinguished these positive and negative words and calculated the associations using the WEAT algorithm (Caliskan et al., 2017). Results indicated that while IND (vs. COL) was weakly associated with negative (vs. positive) achievement words (e.g., *failure* vs. *success*) across the 1950s~1980s (ps < .10), this association was not significant in the 1990s ($p = .23$) ($t_{\text{1990s vs. 1950s-1980s}} = 1.200$, $p = .23$; see Table S2 and Figure S2).

To summarize, individualism was associated more with negative achievement words only in some previous decades but not in more recent decades in China.

3.3. RQ3: IND-COL ↔ Work, Leisure, Home, Money, Religion, and Death

Among these six life domains, we found neither the main effect of IND-COL nor its interaction with decade for three domains: home, religion, and death. This is consistent with

Hamamura et al.'s (2021) original findings. However, for the other three life domains, we had some concerns and obtained some different results.

IND-COL and Work. Our results are consistent with their original findings. It, however, is not a surprise because most of the "work" words in their data (e.g., *labor*, *cooperation*, *assignment*, *alliance*, *negotiation*, *government*, *institution*, *organization*) are apparently closer to the concept of collectivism.

IND-COL and Leisure. The main effect of IND (vs. COL) was significant (p = .013), showing that IND (vs. COL) words were more similar to words indicating leisure (e.g., *relax*, *interest*, *music*, *movie*, *sport*, *health*). More importantly, this association was not significant in the 1950s (p = .43) and 1960s (p = .10) but then became significant in the 1970s (p = .013), 1980s (p = .002), and 1990s (p = .001). This is largely in line with our new findings for RQ1 and RQ2, suggesting that individualism became increasingly associated with some positive aspects of life (e.g., time for enjoyment) over decades in China, especially since the 1970s.

IND-COL and Money. Again, we found both positive money words (e.g., *income*, *richness*) and negative money words (e.g., *loss*, *poverty*, *bankrupt*, *waste*) in Hamamura et al.'s (2021) wordlist. Hence, we distinguished between positive and negative money words, and utilized the WEAT algorithm (Caliskan et al., 2017) to calculate the relative cultural association between IND (vs. COL) and positive (vs. negative) money words. We found a strengthening association between IND (vs. COL) and positive (vs. negative) money words over the decades ($t_{\text{1990s vs. 1950s-1980s}}$ = 2.874, p = .005; see Table S2 and Figure S3).

Taken together, these findings suggest that individualism was increasingly associated with some positive aspects of life (e.g., earning money, time for enjoyment) over time in China.

3.4. RQ4: IND-COL ↔ Modernity

Consistent with Hamamura et al.'s (2021) findings, we found neither the main effect of IND-COL nor its interaction with decades on the association with modernity words. We totally agree with them that their dictionary of modernity was a major limitation (p. 899). It is also noteworthy that such null effects could not provide supportive evidence for the argument that "*rising individualism is not a universal consequence of societal modernization*" (p. 888).

Table S1. ***Reanalysis: IND-COL's Main Effect, Simple Effect, and Interaction with Decade.***

Outcome	Main Effect (*F* Statistics)	Simple Effect (Regression Coefficient)					Interaction with Decade
		1950s	1960s	1970s	1980s	1990s	
Positive	*F* = 0.03 (*F* = 0.06)	–.013 (–.018)	–.009 (.029)	–.005 (–.008)	–.001 ($–.065^{*}$)	.003 (.029)	*F* = 0.26 ($F = 3.88^{**}$)
Negative	*F* = 1.65 (*F* = 1.12)	**$.093^{*}$** **($.135^{**}$)**	$.070^{†}$ (.032)	.048 (.018)	.026 (–.041)	.003 (.054)	**$F = 3.26^{†}$** **($F = 3.67^{**}$)**
Achievement	**$F = 7.35^{**}$** **($F = 8.35^{**}$)**	–.016 (.010)	–.042 ($–.069^{*}$)	**$–.068^{**}$** **($–.053^{†}$)**	**$–.095^{***}$** **($–.171^{***}$)**	**$–.121^{***}$** **($–.080^{**}$)**	**$F = 12.58^{***}$** **($F = 10.27^{***}$)**
Work	**$F = 99.86^{***}$** **($F = 103.18^{***}$)**	**$–.189^{***}$** **($–.170^{***}$)**	**$–.199^{***}$** **($–.215^{***}$)**	**$–.209^{***}$** **($–.203^{***}$)**	**$–.219^{***}$** **($–.281^{***}$)**	**$–.229^{***}$** **($–.195^{***}$)**	**$F = 2.74^{†}$** **($F = 7.12^{***}$)**
Leisure	**$F = 6.21^{*}$** **($F = 6.00^{*}$)**	.048 (.077)	.087 (.006)	**$.126^{*}$** **($.169^{*}$)**	**$.166^{**}$** **($.162^{*}$)**	**$.205^{**}$** **($.208^{**}$)**	**$F = 5.55^{*}$** **($F = 2.77^{*}$)**
Home	*F* = 0.02 (*F* = 0.02)	–.090 (–.115)	–.052 (.059)	–.014 (.009)	.024 (–.120)	.062 (.092)	*F* = 1.29 (*F* = 1.84)
Money	*F* = 1.34 (*F* = 0.86)	**$.138^{**}$** **($.191^{***}$)**	$.093^{*}$ (.033)	.047 (–.016)	.002 (–.017)	–.043 (–.001)	**$F = 13.36^{***}$** **($F = 6.09^{***}$)**
Religion	*F* = 1.48 (*F* = 1.56)	–.114 (–.119)	–.111 (–.080)	–.107 (–.060)	–.103 ($–.217^{*}$)	–.099 (–.074)	*F* = 0.03 (*F* = 1.65)
Death	*F* = 0.86 (*F* = 0.75)	.132 (.157)	.114 (.135)	.097 (.033)	.079 (.017)	.061 (.110)	*F* = 0.34 (*F* = 0.50)
Modernity	*F* = 0.17 (*F* = 0.15)	.089 (.102)	.060 (.010)	.030 (.086)	.000 (–.036)	–.030 (–.022)	*F* = 2.05 (*F* = 1.34)

Note. In all these LMMs, we used the same model parameters as in Hamamura et al. (2021). The effects displayed **outside/inside** parentheses are from the LMMs with *Decade* as **continuous/discrete** predictors, which compare with the Tables and Figures in their article, respectively. COL = 0, IND = 1. For details (e.g., 95% CIs of simple effects, LMM model specifications), see the R Code File.

† $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Table S2. ***WEAT Analysis: IND-COL's Main Effect, Simple Effect, and Interaction with Decade.***

Target	Attribute (Pos. vs. Neg.)	Main Effect	WEAT Raw Effect (Mean Difference): IND (vs. COL) ↔ Positive (vs. Negative) Concept					Interaction with Decade
			1950s	1960s	1970s	1980s	1990s	
IND-COL	Valence	*F* = 0.47 *p* = .503	$–.153^{†}$ *p* = .089	–.004 *p* = .964	–.025 *p* = .770	–.024 *p* = .782	–.025 *p* = .772	*F* = 1.09 *p* = .368
	Achievement	**$F = 5.61^{*}$** **$p = .029$**	$–.328^{†}$ *p* = .052	**$–.427^{*}$** **$p = .014$**	$–.303^{†}$ *p* = .071	$–.274^{†}$ *p* = .099	–.197 *p* = .227	*F* = 0.69 *p* = .604
	Money	*F* = 1.91 *p* = .183	.015 *p* = .879	.060 *p* = .552	–.074 *p* = .464	.096 *p* = .348	**$.311^{**}$** **$p = .006$**	**$F = 2.57^{*}$** **$p = .045$**

Note. We used LMM to estimate the WEAT effects. For details, see the R Code File.

† $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

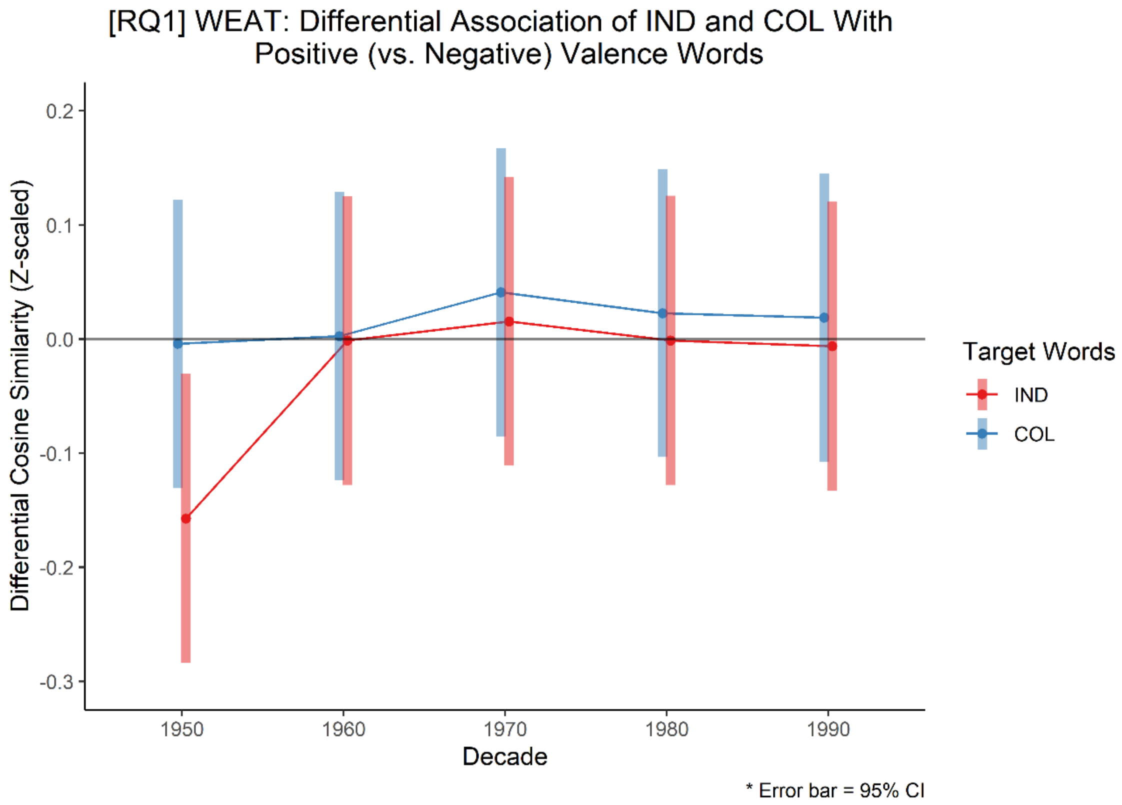

Figure S1. ***RQ1: IND (vs. COL) and Positive (vs. Negative) Valence Words*.**

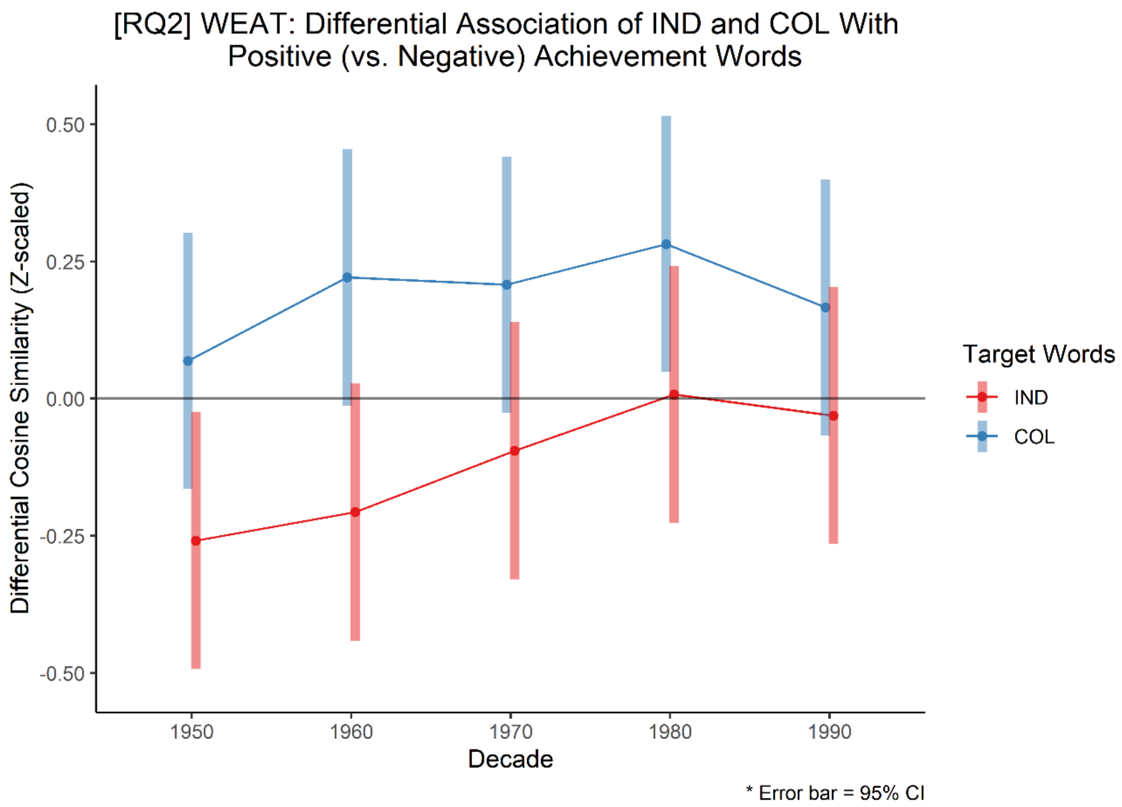

Figure S2. ***RQ2: IND (vs. COL) and Positive (vs. Negative) Achievement Words*.**

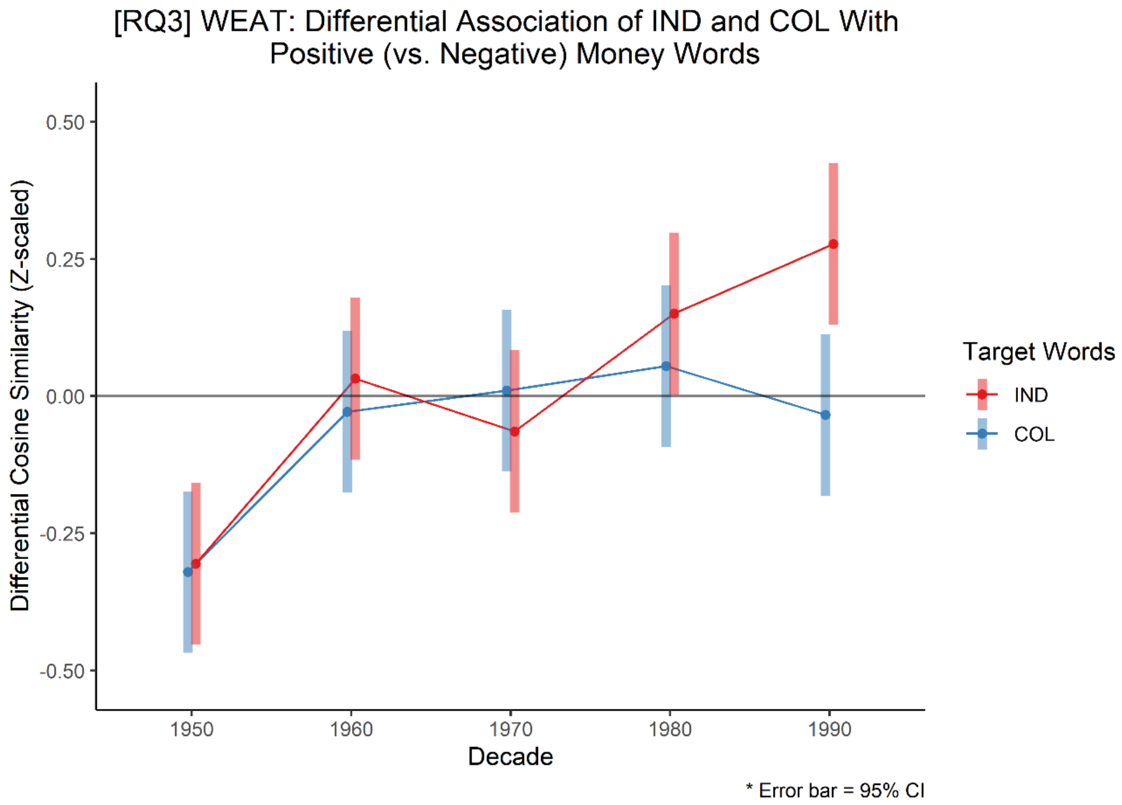

Figure S3. ***RQ3: IND (vs. COL) and Positive (vs. Negative) Money Words*.**

4. References

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