Supplementary Information

Contents

Kinship data

We collected kin terms from 45 languages for the following relations: B, D, F, M, MB, MZ, MZD, MZS, S, Z, collected from a combination of native speakers, ethnographies, and dictionaries in our 'Kinbank' database. Initially, the analyses used a broader set of kinship terms (e.g. FB, FZ), however we restricted the sample to form a comparable set of word frequencies. This is because most Indo-European languages do not have separate terms for e.g. MZD and MBD and separate terms for e.g. BW are exceedingly rare (both across languages as types and within languages as token). We have not included *husband* and *wife*, because these are often synonymous with *man* and *woman*, respectively.

Frequency data were collected from 34 corpora in 21 languages in three corpus types: spoken, written, and web-crawled. The list of corpora is in Table 1 below.

Table S1: Source of frequency data (source of words is Kinbank)

Language

Corpus name

Reference

Albanian

Albanian NC

(Morozova 2015)

Bulgarian

Bulgarian NC

(Koeva, Blagoeva, and Kolkovska 2010)

Bulgarian

Bulgarian Web 2012 (bgTenTen12)

(Kilgarriff et al. 2014)

Catalan

Catalan Web 2014 (caTenTen14)

(Kilgarriff et al. 2014)

English

CELEX

(Baayen, Piepenbrock, and H 1993)

German

CELEX

(Baayen, Piepenbrock, and H 1993)

Spanish

CoE

(Moreno-Sandoval et al. 2005)

Portuguese

CoP

(Craveiro, Macedo, and Madeira 2012)

Italian

CORIS

(Favretti, Tamburini, and De Santis 2002)

Czech

Czech Web 2012 (czTenTen12 v8)

(Kilgarriff et al. 2014)

Danish

Danish Web 2014 (daTenTen14)

(Kilgarriff et al. 2014)

Dutch

Dutch Instituut voor Nederlandse Lexicologie text corpora (written) Corpus Gesproken Nederlands (spoken)

(Kruyt and others 1997)

Dutch

Dutch Instituut voor Nederlandse Lexicologie text corpora (written) Corpus Gesproken Nederlands (spoken)

(Van Eerten 2007)

Dutch

Dutch Web 2014 (nlTenTen14)

(Kilgarriff et al. 2014)

French

French Web 2012 (frTenTen12)

(Kilgarriff et al. 2014)

German

German Web 2013 (deTenTen13)

(Kilgarriff et al. 2014)

Greek

Greek Web 2014 (elTenTen14)

(Kilgarriff et al. 2014)

Croatian

hrWaC

(Kilgarriff et al. 2014)

Italian

Italian Web 2010 (itTenTen)

(Kilgarriff et al. 2014)

French

lexique corpus

(New et al. 2001)

Norwegian

Norwegian Web 2015 (noTenTen15) Bokmal and Nynorsk

(Kilgarriff et al. 2014)

Polish

Polish NC written PELCRA spoken

(Przepiórkowski et al. 2008)

Polish

Polish NC written PELCRA spoken

(Przepiórkowski et al. 2010)

Polish

Polish Web 2012 (plTenTen12)

(Kilgarriff et al. 2014)

Portuguese

Portuguese Web 2011 (ptTenTen11, Freeling v3)

(Kilgarriff et al. 2014)

English

pukWaC (ukWaC parsed with MaltParser)

(Kilgarriff et al. 2014)

Romanian

Romanian Web (roWaC)

(Kilgarriff et al. 2014)

Romanian

ROMBAC

(Ion et al. 2012)

Russian

Russian NC via Leeds

(Lyashevskaya and Sharov 2009)

Russian

Russian Web 2011 (ruTenTen11)

(Kilgarriff et al. 2014)

Serbian

scWaC

(Kilgarriff et al. 2014)

Spanish

Spanish Web 2011 (esTenTen11, Eu + Am, Freeling v4)

(Kilgarriff et al. 2014)

Swedish

SUC

(Gustafson-Capková and Hartmann 2006)

Swedish

Swedish Web 2014 (svTenTen14)

(Kilgarriff et al. 2014)

Icelandic

textasafn

(Úlfarsdóttir and Bjarnadóttir 2017)

Czech

UCNK:SYN2015 (written) ORAL2013 (spoken)

(Čermák 1997)

Czech

UCNK:SYN2015 (written) ORAL2013 (spoken)

(Benešová, Kren, and Waclawicová 2013)

The analysis uses one term per language per kinterm. If it arises that a langauge has multiple words for a particular kinterm, we use which ever was more frequent in the corpus data. In the case where a language has multiple words for a single kinterm, and we do not have access to frequency data, we rely on expert judgement to select a term.

Supplementary data table

See the supplementary data csv file for the raw data used in this study.

Column description:

Table S2: Supplementary table column descriptions

Column name

Description

meaning

Code used for kinterm, see TS1 for a description

language

Common name for each language

word

Words used in the analysis

lingpy.cognate

Cognates as determined by lingpy, used as a first pass

expert.cognate

Cognates reviewed and corrected by expert reviewers, used in analysis

word.count

Frequency of each term in the given corpus

corpora.size

Total size of the corpus

corpora.type

Type of corpus used (either web, written, or spoken)

corpus

Name of the corpus

states

States

taxa

Taxa label in phylogeny

glottocode

Glottocode

source.ids

Standard deviation for the global rate of replacement

mean.roc

Mean global rate of replacement

sd.roc

Source of term (see source SM)

Data summary

We estimate rate of replacement and compare it with frequency of use for ten types of kin relations. Here we use MB, MZ, MZS, and MZD as shorthand for broader terms (uncle, aunt, male cousin, and female cousin, respectively). This is because commonly used terms in this set of languages do not distinguish terms according to the parent's gender.

Below is a table indicating the shorthand used for each kinterm, the number of languages for which we have data, and the number of states (or cognates) for that term.

We collected terms for a superset of the languages from which frequency data is available in order to have a more robust estimate of rate of replacement for each term.

Table S3: Each kinterm used, with counts for the number of languages we have data for and the number of cognates across our sample

Kinterm	Description	No. languages	States
F	Father	45	7
M	Mother	45	5
S	Son	43	7
D	Daughter	43	10
B	Brother	45	9
Z			

Sister

44

6

MB

Mother's brother (uncle)

39

7

MZ

Mother's sister (aunt)

39

10

MZS

Mother's sister's daughter (female cousin)

31

11

MZD

Mother's sisters son (male cousin)

31

11

Frequency data

Below are bar graphs of term frequency by langauge, across corpora types (web, written, or spoken).

Figure S1: Web frequencies of terms across languages

Figure S2: Written frequencies of terms across languages

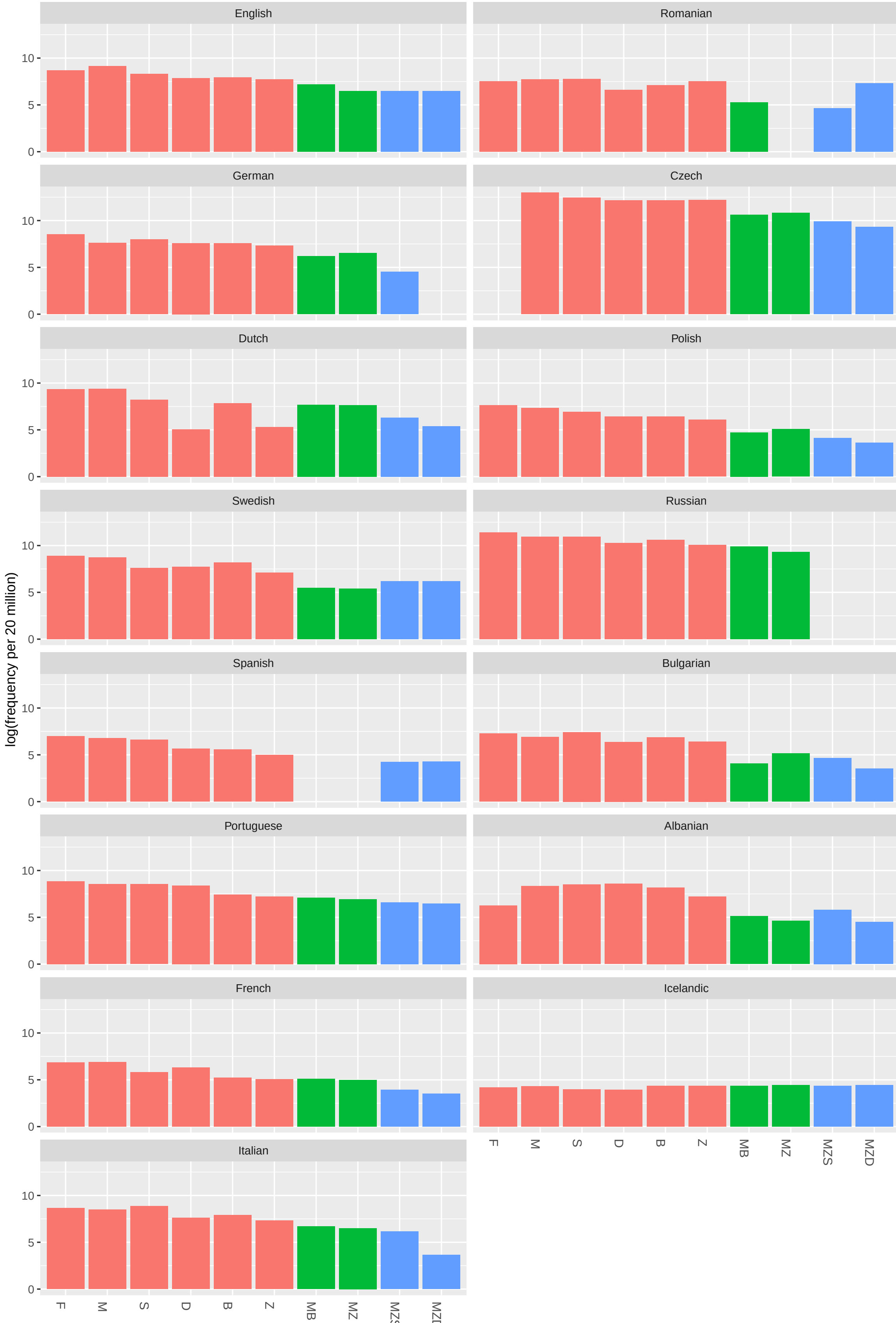
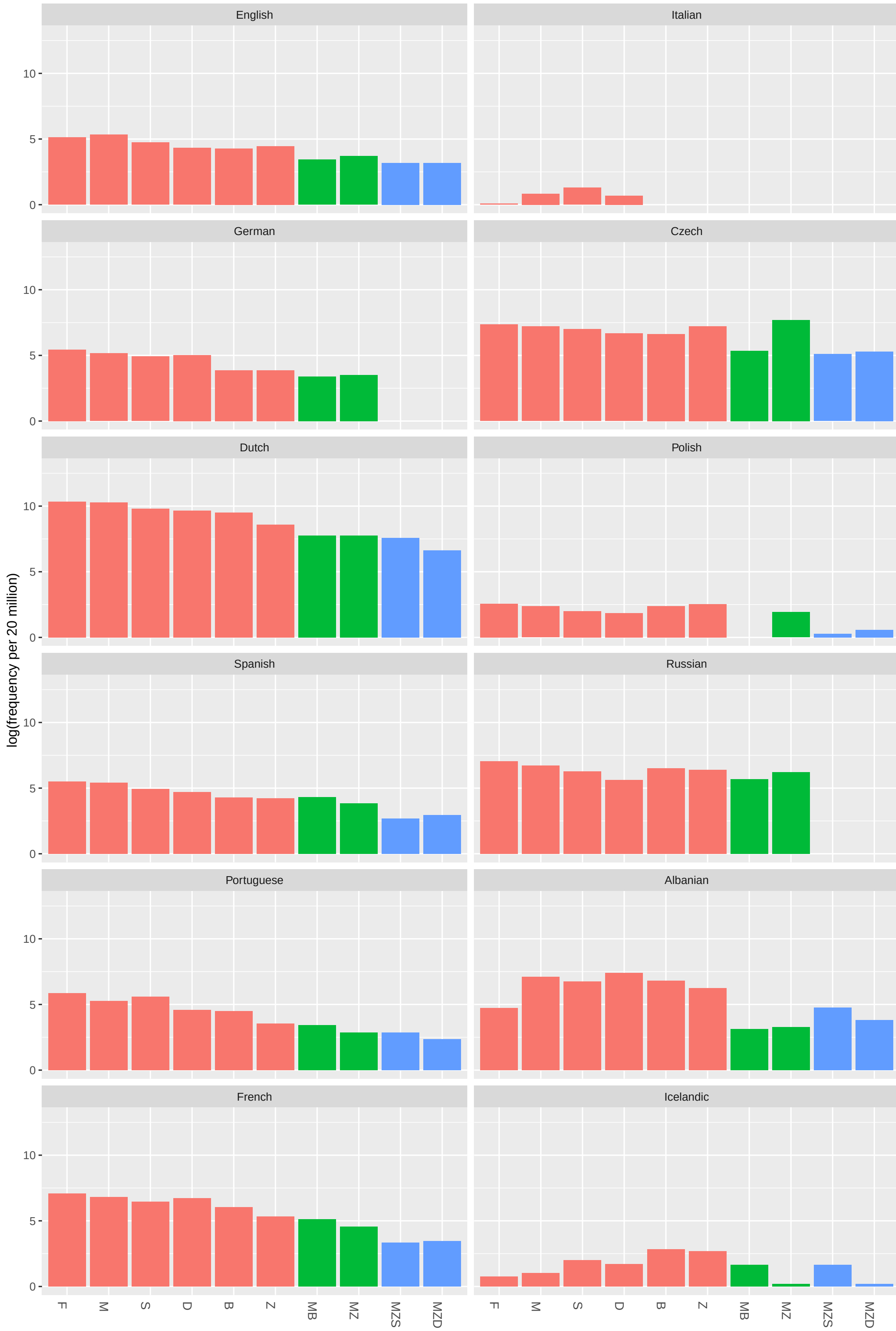


Figure S3: Spoken frequencies of terms across languages



Cognate data

We generated cognate classes using the Indo-European Etymological Dictionary (Buck 2008), LingPy (List, Greenhill, and Forkel 2018), and a panel of volunteer experts, recruited on Linguist List (all faults remain ours). All terms were automatically transcribed into the Speech Assessment Methods Phonetic Alphabet (SAMPA) through LingPy's `uni2sampa` function. Cognates were automatically allocated using LingPy's `cluster` function. Using the cognate-coded Swadesh list (subset to those languages for which we also have kinterms), we tested the appropriateness of edit distance, SCA, and turchin algorithms, alongside Phonemic and Phonetic transcriptions for cognate detection in our data, following the code examples from Lingpy.org. The F-score was highest for the edit-distance algorithm with a 0.4 threshold (see table S4) (List, Greenhill, and Forkel 2018). We then manually adjusted the results, followed by expert review which resulted in minor changes. Automatic decisions and the corrections are available in the supplementary data file.

Table S4: Precision, recall, & F-score for various LingPy cognate detection algorithms and their threshold settings.

transcription	threshold	method	precision	recall	fscore
Phonemic	0.4	edit	0.7792	0.4238	0.5490
Phonemic	0.6	edit	0.6259	0.4247	0.5060
Phonemic	0.4	turchin	0.5152	0.4271	0.4670
Phonemic	0.6				

turchin

0.5152

0.4271

0.4670

Phonetic

0.4

edit

0.8434

0.3194

0.4634

Phonemic

0.4

sca

0.4821

0.4273

0.4530

Phonemic

0.6

edit

0.6944

0.3204

0.4385

Romanised

0.4

edit

0.6930

0.2948

0.4136

Phonetic

0.4

turchin

0.4524

0.3213

0.3758

Phonetic

0.6

turchin

0.4524

0.3213

0.3758

Phonetic

0.6

turchin

0.4524

0.3213

0.3758

Romanised

0.6

edit

0.5079

0.2958

0.3739

Phonetic

0.4

sca

0.4418

0.3221

0.3726

Romanised

0.4

sca

0.4491

0.2962

0.3570

phoneMic

0.6

sca

0.3011

0.4294

0.3539

Romanised

0.4

turchin

0.4290

0.2963

0.3505

Romanised

0.6

turchin

0.4290

0.2963

0.3505

Phonetic

0.6

sca

0.2262

0.3244

0.2666

Romanised

0.6

sca

0.2227

0.2983

0.2550

Phylogeny

We used 1000 phylogenies from the most recent Bayesian posterior of Indo-European phylogenies (Bouckaert et al. 2012). Trees in the sample are rooted. Branch lengths are given in years and derived from statistical and historical calibration. The Indo-European posterior used has an approximate age of 8,700 years. Trees initially have 111 taxa, and these were pruned down for each kinterm dependent on available data. Counts for taxa for each kinterm can be found in table S3. By using a sample of likely phyloygenies and through using a Bayesian approach, we account for the phylogenetic uncertainty.

Rates of change

Table S3 shows the number of languages and states used to estimate rate of change for each kinterm. Each language is linked to a taxon in the Indo-European phylogeny. Following the methods in Pagel and Meade (2018) we use BayesTraits version 3.0.1 to implement a Bayesian MCMC approach to estimate the instantaneous global rate of change for each kin-term through Q-matrix normalisation. Probabilities of frequency were scaled to represent the empirical frequencies. We used a stepping-stone sampler, using 100 stones for 1000 iterations each. MCMC chains ran for a total of 10,010,000 iterations, with a burn-in of 10,000, sampling every 1000 iterations. This left a posterior sample of 10,000 iterations, which is approximately 10 samples per tree. To make the rates comparable to Pagel et al., we scale instantaneous rates to change per 10,000 years.

Each analysis was run 3 times to ensure the MCMC chain converged. Tables S5 - S14 display the marginal log-likelihood for each MCMC run, the mean global rate of change for each run, and the average across the three runs. For each kinterm, we also used the Gelman-Rubin diagnostic test for convergence (Gelman and Rubin 1992). This tests for MCMC convergence between multiple chains by analysing the differences between them. By estimating a ‘potential scale reduction factor’, which when multiplying across chains would remove the differences, we can quantify the differences between chains (a scale reduction factor 1 indicating no change needed). A rule of thumb suggests a point estimates of less than 1.1 is sufficient to claim convergence, and ensuring upper limits are also around these limits.

Table S5: B

	Marginal log-likelihood	Harmonic Mean global rate	Harmonic SD global rate
1	50.38400	0.0001267	5e-07
2	47.36400	0.0001240	4e-07
3	49.74900	0.0001219	4e-07
Mean	49.16567	0.0001242	4e-07

Table S6: D

	Marginal log-likelihood	Harmonic Mean global rate	Harmonic SD global rate
1	67.15900	0.0002732	8e-07
2			

66.91900

0.0002718

8e-07

3

70.64700

0.0002704

9e-07

Mean

68.24167

0.0002718

8e-07

Table S7: F

Marginal log-likelihood

Harmonic Mean global rate

Harmonic SD global rate

1

69.12500

0.0002581

8e-07

2

71.08600

0.0002657

9e-07

3

65.72500

0.0002615

9e-07

Mean

68.64533

0.0002618

8e-07

Table S8: M

Marginal log-likelihood

Harmonic Mean global rate

Harmonic SD global rate

1

57.339

0.0002995

1e-06

2

57.493

0.0002999

9e-07

3

59.432

0.0002995

1e-06

Mean

58.088

0.0002996

1e-06

Table S9: MB

Marginal log-likelihood

Harmonic Mean global rate

Harmonic SD global rate

1

57.44400

0.0003308

1.1e-06

2

57.04900

0.0003303

1.2e-06

3

57.78000

0.0003401

1.1e-06

Mean

57.42433

0.0003337

1.1e-06

Table S10: MZ

Marginal log-likelihood

Harmonic Mean global rate

Harmonic SD global rate

1

74.88300

0.0005056

1.8e-06

2

73.92900

0.0005090

1.8e-06

3

68.98400

0.0005106

1.7e-06

Mean

72.59867

0.0005084

1.7e-06

Table S11: MZD

Marginal log-likelihood

Harmonic Mean global rate

Harmonic SD global rate

1

63.392

0.0003877

1.3e-06

2

58.497

0.0003839

1.4e-06

3

57.940

0.0003916

1.3e-06

Mean

59.943

0.0003877

1.4e-06

Table S12: MZS

Marginal log-likelihood

Harmonic Mean global rate

Harmonic SD global rate

1

61.62400

0.0004162

1.3e-06

2

62.33400

0.0004158

1.3e-06

3

60.83500

0.0004151

1.4e-06

Mean

61.59767

0.0004157

1.4e-06

Table S13: S

Marginal log-likelihood

Harmonic Mean global rate

Harmonic SD global rate

1

47.75800

0.0001669

7e-07

2

50.56400

0.0001666

7e-07

3

48.46100

0.0001711

6e-07

Mean

48.92767

0.0001682

7e-07

Table S14: Z

Marginal log-likelihood

Harmonic Mean global rate

Harmonic SD global rate

1

42.31300

0.0001205

5e-07

2

44.06800

0.0001215

6e-07

3

44.12300

0.0001265

5e-07

Mean

43.50133

0.0001229

5e-07

Table S15: Point estimates and upper 95% confidence limits for Gelman-Rubin MCMC diagnostic tests

Point est.

Upper C.I.

Table S5: B

1.00

1.01

Table S6: D

1.00

1.00

Table S7: F

1.00

1.01

Table S8: M

1.00

1.00

Table S9: MB

1.00

1.00

Table S10: MZ

1.01

1.02

Table S11: MZD

1.00

1.02

Table S12: MZS

1.00

1.00

Table S13: S

1.00

1.00

Table S14: Z

1.00

1.00

Example BayesTraits script

```
BayesTraitsV3 tree.file data.file
1
2
NQM
Pis Emp
RevJump exp 10
Stones 100 1000
Iterations 10010000
Burnin 10000
Sample 10000
LogFile logs/file
run
```

Half-life

We calculate the half-life of each kinterm following methods from Pagel and Meade (2018). The half-life of a term estimates the expected amount of time before a 50% chance of a cognate change.

Table S16: Mean half-life for each kin code

Kin code	Half-life (years)
B	5471
D	2537
F	2686
M	2315
MB	2096
MZ	1371
MZD	1788
MZS	1666
S	4152
Z	5751

Frequency of use and rates of change: Swadesh words and kin terms

We want to see if

- Rate of change correlates with frequency of use for kin terms
- What the strength of this relationship is compared to Swadesh terms

The difficulty is that the two data sets are structured differently. A given **kin term** can have a written / spoken / web frequency as well as a word / lemma frequency. A given **Swadesh term** only has one frequency (though it may be written / spoken / etc. depending on the source corpus). Term **length** correlates with frequency of use in a way that's not directly relevant to our analysis either.

In order to create comparable kin- and Swadesh-datasets, we fit a linear mixed model as control on the kinterm data and use word random intercepts from this model in a second, predictive, model.

Control model: kin terms

Table S17: Summary of fixed effects for control model 1

	Estimate	Std. Error	t value
(Intercept)	-0.54	0.21	-2.56
genreweb	1.68	0.17	10.03
genrewritten	2.61	0.18	14.58
freq.typeword	-0.74	0.13	-5.50

The word-level random intercepts capture word frequency across data sources. The intercepts predict rate of change, even when controlling for word length.

Figure S4: correlation of frequency measure and raw frequencies in control model 1

Table S18: Summary of fixed effects for control model 1b

	Estimate	Std. Error	t value
(Intercept)	0.64	0.31	2.03
frequency.measure	-0.58	0.07	-8.72
word.length	-0.10	0.06	

-1.76

Predictive model: rate of change and frequency of use

We use the word intercepts from the control model as measures of frequency of use for kin terms, and centralised log frequency per million for the Swadesh terms. We restrict the dataset to languages for which we have kin term data.

Table S19: Summary of fixed effects for predictive model

	Estimate	Std. Error	t value
(Intercept)	0.12	0.12	1.01
frequency.measure	-0.44	0.08	-5.26
word.typeswadesh.word	-0.54	0.18	-2.91
frequency.measure:word.typeswadesh.word	0.18	0.09	2.02

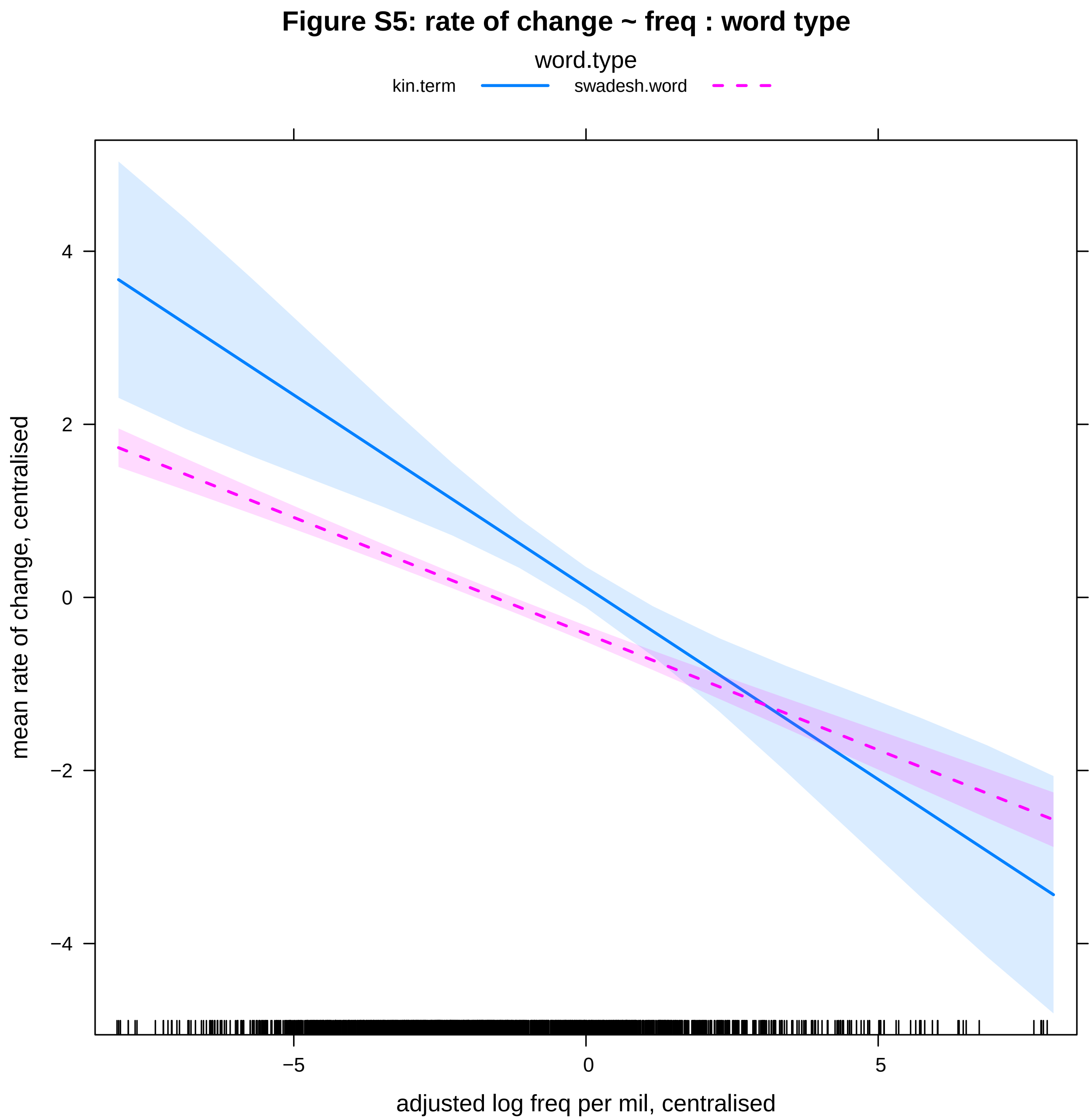
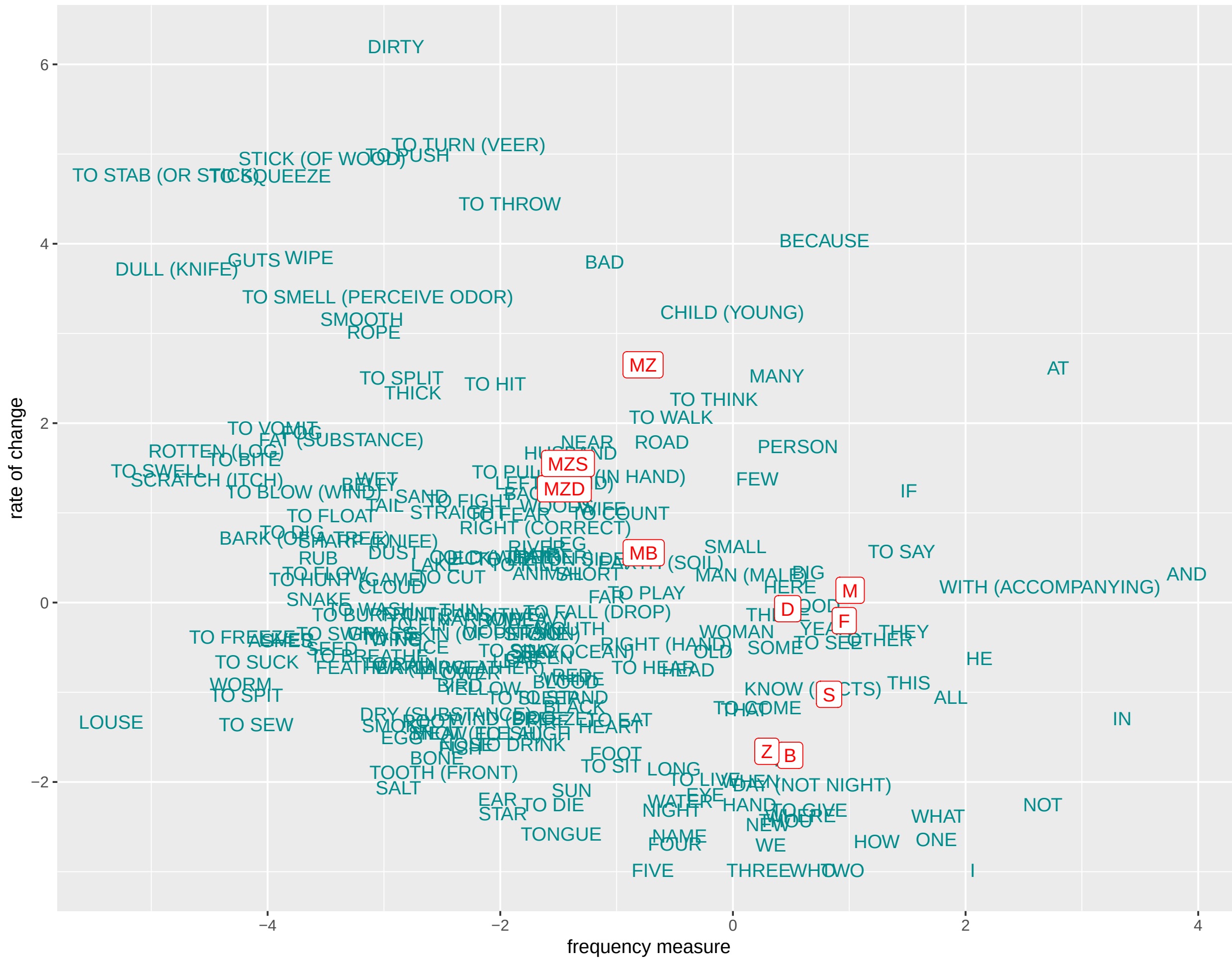


Figure S5: rate of change ~ freq : word type
word.type
kin.term
swadesh.word
4
2
0
−2
−4
mean rate of change, centralised
−5
0
5
adjusted log freq per mil, centralised

Figure S6: mean raw data correlation of rate of change and frequency measure in predictive model



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