Appendix A: Materials

German verb phrases used in Experiment 1

#	Category	Verb phrase	Translation (literal)	Translation (non-literal)
1	idiom	das Handtuch werfen	'to throw the towel'	'to give up'
2	idiom	den Garaus machen	'to make the GARAUS'	'to kill'
3	idiom	das Zeitliche segnen	'to bless the temporal'	'to die'
4	idiom	den Löffel abgeben	'to give away the spoon'	'to die'
5	idiom	die Leviten lesen	'to read the LEVITEN'	'to scold'
6	idiom	die Sau rauslassen	'to release the pig'	'to party excessively'
7	idiom	das Kriegbeil begraben	'to bury the hatchet'	'to end a conflict'
8	idiom	den Braten riechen	'to smell the roast'	'to become suspicious'
9	idiom	den Faden verlieren	'to lose the thread'	'to get lost (e.g., in a conversation)'
10	idiom	den Laufpass geben	'to give the LAUFPASS'	'to break up'
11	idiom	den Tiefpunkt erreichen	'to reach the lowest point'	'to be in the worst possible situation'
12	idiom	das Eis brechen	'to break the ice'	'to reduce the social tension'
13	non-idiom	den Bus verpassen	'to miss the bus'	–
14	non-idiom	den Manager verärgern	'to upset the manager'	–
15	non-idiom	die Fenster putzen	'to clean the windows'	–
16	non-idiom	den Hausschlüssel verlieren	'to lose the housekey'	–
17	non-idiom	den Rasen mähen	'to mow the lawn'	–
18	non-idiom	die Anlage ausmachen	'to turn off the stereo'	

English verb phrases used in Experiment 2

#	Idiom	Paraphrase of the figurative meaning
1	pop the question	'to propose to somebody'
2	lay down the law	'to give strict orders'
3	break the ice	'to reduce the social tension'
4	miss the boat	'to lose an opportunity'
5	hit the sauce	'to drink alcohol'
6	clear the air	'to reduce the social tension'
7	kick the bucket	'to die'
8	raise the roof	'to complain loudly and angrily'
9	shoot the breeze	'to chat aimlessly'
10	chew the fat	'to chat or gossip'
11	play the field	'to date a variety of people'
12	bite the bullet	'to party excessively'
13	forget the timer	–
14	eat the cake	–
15	cut down the hedges	–
16	reveal the trick	–
17	paint the car	–
18	throw away the cutlery	–

German verb phrases used in Experiment 3

#	Category	Verb phrase	Translation (lit.)	Translation (non-lit.)
1	idiom, def.	den Gürtel enger schnallen	'to tighten the belt'	'to limit one's budget'
2	idiom, def.	die Fliege machen	'to make the fly'	'to run away'
3	idiom, def.	die Klappe halten	'to hold the hatch'	'to be silent'
4	idiom, def.	die Wogen glätten	'to smooth the waves'	'to calm things down'
5	idiom, def.	den Bogen überspannen	'to overdraw the bow'	'to go too far'
6	idiom, def.	die zweite Geige spielen	'to play the second violin'	'to play a subordinated role'
7	idiom, def.	das Handwerk legen	'to lay down the craft'	'to stop someone's activities'
8	idiom, def.	den Kopf verdrehen	'to turn the head'	'to charm someone'
9	idiom, indef.	einen Denkzettel verpassen	'to attach a DENKZETTEL (think-note)'	'to teach someone a lesson'
10	idiom, indef.	Reißaus nehmen	'to take REIßAUS (tear-off)'	'to run away'
11	idiom, indef.	einen Bären aufbinden	'to tie on a bear'	'to trick someone'
12	idiom, indef.	kalte Füße bekommen	'to get cold feet'	'to have second thoughts'
13	idiom, indef.	Farbe bekennen	'to profess color'	'to reveal one's intentions'

14	idiom, indef.	eine dicke Lippe riskieren	'to risk a big lip'	'to say something cheeky'
15	idiom, indef.	eine Standpauke halten	'to hold a STANDPAUKE' (stand-sermon)	'to scold someone'
16	idiom, indef.	Süßholz raspeln	'to grate licorice'	'to make compliments'
17	non-idiom, def.	die Preise senken	'to lower the prices'	–
18	non-idiom, def.	die Couch wegwerfen	'to throw away the couch'	–
19	non-idiom, def.	den Job wechseln	'to change the job'	–
20	non-idiom, def.	die Haare schneiden	'to cut the hair'	–
21	non-idiom, indef.	eine Postkarte schicken	'to send a postcard'	–
22	non-idiom, indef.	einen Witz erzählen	'to tell a joke'	–
23	non-idiom, indef.	einen Spickzettel schreiben	'to write a cheat sheet'	–
24	non-idiom, indef.	eine Mahlzeit zubereiten	'to prepare a meal'	–
25	non-idiom, incorp.	Radio hören	'to listen radio'	'to listen to the radio'
26	non-idiom, incorp.	Zeitung lesen	'to read paper'	'to read the paper'
27	non-idiom, incorp.	Pause machen	'to make break'	'to take a break'
28	non-idiom, incorp.	Halt machen	'to make stop'	'to stop'
29	non-idiom, incorp.	Staub saugen	'to vacuum dust'	'to vacuum'
30	non-idiom, incorp.	Marathon laufen	'to run marathon'	'to run a marathon'
31	non-idiom, incorp.	Kuchen backen	'to bake a cake'	'to bake a/some cake'
32	non-idiom, incorp.	Pizza essen	'to eat pizza'	'to eat a/some pizza'

Appendix B: Methodological notes

B.1: Post-hoc observation: correlations in Experiment 1

An informal post-hoc observation about the results of Experiment 1 is that a subset of the tested structures seems to correlate with each other with respect to the acceptability of individual idioms. For example, visual inspection of Figure 4 in the paper suggests that the more acceptable an idioms is with prefield fronting, the better it works also with LD and scrambling: the items with particularly high mean ratings in the prefield structure (e.g., items #4, #10, #11) also tend to have high ratings in LD and scrambling, and a similar relationship seems to hold for items with particularly low ratings (e.g., #2, #3, #6). When we calculate simple linear correlations between the item means in these structures[1], all pairwise combinations show correlations with *Pearson's r* above 0.7; interestingly, they all also show a similarly high correlation with the anaphor structure, which differs from scrambling, LD, and prefield movement in that it is not a syntactic transformation in the same sense, but rather has to do with (co-)reference relations. Further descriptive details (plots) and a number of correlation-related hypotheses that we pre-registered based on this post-hoc observation can be found in our OFS repository. We have decided not to pursue these correlation-related hypotheses directly within this paper, as an in-depth, statistically sound inferential analysis of the correlations is beyond our scope here; we have to leave that to future research. However, the observation that there might be a connection between anaphoricity/pronominalization/reference and syntactic movement operations like scrambling contributed to our decision to focus on referentiality as an additional factor and to include materials there that vary in this aspect in Experiment 3.

B.2 Additional ordinal analyses

In addition to the linear mixed models (LMMs) reported in the paper, we also analyzed the data using cumulative link models (CLMs) for ordinal data (using the R package *ordinal* by R. H. B. Christensen) to make sure that our main conclusions are not based on artifacts of the analysis method. The full model specifications and results can be found in our OSF repository. Below, we will note and discuss deviations between the two model types.

According to our LMM analysis of Experiment 1 with respect to the factor idiomaticity, we found a larger contrast between idioms and non-idioms than in the canonical baseline for anaphor, prefield, LD, nominalization, and which-question. This was confirmed by the CLM analysis. In addition, a larger contrast between idiom and non-idioms was also found for scrambling and passive in the CLM. This suggests that we did not overestimate the gap between idioms and non-idioms in marked structures based on our LMM analysis.

Similarly, in our LMM analysis of Experiment 1 with respect to compositionality, we found a significant interaction between compositionality and structure in a number of structures (anaphor, prefield, LD, scrambling, and which-question). Again, this was confirmed by the CLM analysis, and in addition, a significant interaction was also found for nominalization.

1 More precisely, we do not look at *absolute acceptabilty* means per item, but rather *relative acceptability*, i.e., the difference between each item's mean rating in the baseline structure with canonical word order, and its means rating in the other structures; this way, we make sure to exclude any acceptability differences that are also present in canonical word order and are thus not relevant for questions of syntactic flexibility.

According to our LMM analysis of Experiment 2 with respect to the factor idiomaticity, we found a larger contrast between idioms and non-idioms than in the canonical baseline for passive and the cleft-like structure. This was confirmed by the CLM analysis. In the LMM, we found a significant deviance in the opposite direction (smaller contrast between idiom and non-idiom than in the canonical structure) for nominalization without "of". In the CLM, there was only a non-significant trend in the same direction.

In our LMM analysis of Experiment 2 with respect to compositionality, we found that the effect of compositionality did not differ from the one found in the canonical baseline for anaphor, passive, and the cleftlike structure. This was confirmed by the CLM analysis. The significant deviance towards a less positive effect of compositionality that was found in the LMM for both types of nominalization was also found in the CLM.

As for Experiment 3, the first LMM model concerned the effect of idiomaticity and definiteness. All significant effects that were found in the LMM were confirmed by the CLM. In the CLM, there were some additional effects/interactions that reached significance: a significant interaction between definiteness and structure not only reached a significant level for scrambling, but also for anaphor, LD, and which-question (for which only a trend in this direction was found in the LMM). As discussed in Section 5.2 of the paper, the semantic effect that we propose as an explanation for the scrambling data might also apply (in a weaker form) to other structures. Furthermore, an additional three-way between structure, idiomaticity, and DP type was found in the CLM: not only for which-question as in the LMM, but also for passive. Neither of these three-way interactions is directly relevant for our argumentation.

As for the second LMM model for Experiment 3 – concerning the effect of compositionality –, again, all significant effects that were found in the LMM were confirmed by the CLM, suggesting that we did not overestimate the positive effect of compositionality on syntactic flexibility. Again, there were some additional effects/interactions that reached significance in the CLM: in contrast to the LMM the interaction between compositionality and structure was even significant in all tested structures. Furthermore, the three-way interaction between structure, compositionality, and DP type was not only significant for anaphor and scrambling (which we discuss in detail in Section 5.2 of the main text), but also for LD and nominalization (indicating that these structures could also be worth a more detailed look in future work in this respect).

It also holds for the third model for Experiment 3 – concerning the effect of DP type within non-idioms – that all significant effects found in the LMM were confirmed by the CLM. There were two interaction effects that were additionally significant in the CLM: an interaction between structure and DP type towards lower ratings for definite than indefinite DPs for nominalization, and a towards lower ratings for incorporated than indefinite DPs for scrambling.

Overall, our main conclusions were all supported by both the LMM as well as the CLM analyses: a positive effect of compositionality on syntactic flexibility in German but not in English; definite-indefinite asymmetries for both idioms and non-idioms; an interaction between definiteness and compositionality which is strongest for anaphor and scrambling; and a tendency towards low flexibility for VPs with incorporated nouns.

B.3 Notes on compositionality judgments for the English idioms in Experiment 2

The compositionality judgments participants gave for the English idioms in our Experiment 2 do not fully line up with the categorization reported by Gibbs & Nayak (1989) and adopted by us in Wierzba et al. (2023). For example, while the idioms chew the fat and play the field are listed as non-decomposable in Gibbs & Nayak (1989), the majority of our participants in Experiment 2 who were familiar with the idiom stated that the idiom parts do have individual figurative meanings. In our view, it is plausible that the differences can be understood in terms of Maher's concern that presenting a paraphrase in the task might influence participants' judgments. For example, Gibbs & Nayak (1989) provided the verb+adverb paraphrase talk aimlessly for chew the fat, which might have biased participants towards judging it as non-compositional: in order to link each part of the idiom to the parts of the provided paraphrase, a mapping would need to be established where chew corresponds figuratively to talk, and the fat corresponds figuratively to aimlessly. This kind of mapping could be inhibited due to the different syntactic structures of the idiom and the paraphrase. In contrast, our participants provided verb(+preposition)+DP responses for this idioms, e.g., "chew stands for talk about/chat about/discuss" and "the fat stands for the details/a topic/the news", where the syntactic structures of the idiom and the paraphrase match. Thus, we think that we were successful in eliminating a potential bias present in the previously used compositionality categorization; however, even if this bias was present in our previous experiment, it was not the (sole) reason for the fact that we failed to find compositionality effect on syntactic flexibility, as our replication closely matches the results of Wierzba et al. (2023).

Appendix C: Models

All linear mixed model fit by maximum likelihood; t-tests use Satterthwaite's method. The exact specification of the determined parsimonious model is indicated by the list of random and fixed effects in the tables. For the treatment-coded factor syntactic structure, a description like "structure.can-wh" stands for the comparison between the baseline level "canonical word order" and the level "wh-question". For the sum-coded factor idiomaticity, "idiomaticity1" stands for the comparison between idioms and non-idioms. The contrast coding of definiteness/DP type is specified below for each model in which this factor was included.

Experiment 1, first model: the effect of idiomaticity

Data: whole dataset; fixed factors: structure (treatment coded, baseline: canonical), idiomaticity (sum coded)

AIC	BIC	logLik	deviance	df.resid
16340.4	16572.5	-8134.2	16268.4	4620

Scaled residuals:

Min	1Q	Median	3Q	Max
-3.4280	-0.5376	0.0868	0.6096	4.1586

Random effects:

Groups	Name	Variance	Std.Dev.
subject	structure.can-wh:idiomaticity1	0.177085	0.42081
subject.1	structure.can-passiv:idiomaticity1	0.036278	0.19047

subject.2	structure.can-anapho:idiomaticity1	0.172287	0.41508
subject.3	idiomaticity1	0.076521	0.27662
subject.4	structure.can-wh	0.843491	0.91842
subject.5	structure.can-nom	0.702463	0.83813
subject.6	structure.can-passiv	0.508429	0.71304
subject.7	structure.can-ld	0.578185	0.76038
subject.8	structure.can-prefie	0.009388	0.09689
subject.9	structure.can-anapho	0.376271	0.61341
subject.10	(Intercept)	0.794527	0.89136
item	structure.can-wh	0.556687	0.74611
item.1	structure.can-nom	0.482515	0.69463
item.2	structure.can-passiv	0.847427	0.92056
item.3	structure.can-scramb	0.537907	0.73342
item.4	structure.can-ld	0.045605	0.21355
item.5	structure.can-prefie	0.038879	0.19718
item.6	structure.can-anapho	0.159800	0.39975
item.7	(Intercept)	0.146664	0.38297
Residual	1.616497	1.27142	

Number of obs: 4656, groups: subject, 48; item, 18

Fixed effects:

	Estimate	Std. Error	df	t-value	p-value
(Intercept)	5.68481	0.16688	62.11518	34.066	<2e-16 ***
structure.can-anapho	-0.80465	0.18171	32.45850	-4.428	0.000101 ***
structure.can-prefie	-0.12159	0.08295	18.88751	-1.466	0.159179
structure.can-ld	-1.07745	0.13840	51.29866	-7.785	3.04e-10 ***
structure.can-scramb	-0.13594	0.20239	18.87968	-0.672	0.509910
structure.can-passiv	-1.87156	0.28538	29.92081	-6.558	3.00e-07 ***
structure.can-nom	-1.84336	0.25830	35.92256	-7.137	2.20e-08 ***
structure.can-wh	-1.65632	0.27791	36.62523	-5.960	7.38e-07 ***
idiomaticity1	0.01120	0.11353	26.59435	0.099	0.922155
structure.can-anapho:idiomaticity1	-0.39374	0.15515	27.79648	-2.538	0.017053 *
structure.can-prefie:idiomaticity1	-0.29867	0.08177	19.59087	-3.653	0.001625 **
structure.can-ld:idiomaticity1	-0.26495	0.08431	19.49621	-3.142	0.005241 **
structure.can-scramb:idiomaticity1	-0.39170	0.20129	18.47398	-1.946	0.067030 .
structure.can-passiv:idiomaticity1	-0.17136	0.24765	19.66413	-0.692	0.497065
structure.can-nom:idiomaticity1	-0.84454	0.19239	19.20004	-4.390	0.000308 ***
structure.can-wh:idiomaticity1	-1.15750	0.22142	24.62142	-5.228	2.17e-05 ***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Experiment 1, second model: the effect of compositionality

Data: only idioms, fixed factors: structure (treatment-coded), composionality (linear predictor)

AIC	BIC	logLik	deviance	df.resid
10907.0	11136.2	-5415.5	10831.0	3034

Scaled residuals:

Min	1Q	Median	3Q	Max
-3.3037	-0.5519	0.0699	0.6144	4.2413

Random effects:

Groups	Name	Variance	Std.Dev.
subject	structure.can-wh:comp	1.91825	1.3850
subject.1	structure.can-nom:comp	0.60331	0.7767
subject.2	structure.can-passiv:comp	0.69810	0.8355
subject.3	structure.can-ld:comp	0.14913	0.3862
subject.4	structure.can-anapho:comp	0.14317	0.3784
subject.5	comp	0.92570	0.9621
subject.6	structure.can-wh	0.71821	0.8475
subject.7	structure.can-nom	0.55287	0.7436
subject.8	structure.can-passiv	0.46346	0.6808
subject.9	structure.can-ld	0.55251	0.7433
subject.10	structure.can-prefie	0.02533	0.1592
subject.11	structure.can-anapho	0.72282	0.8502
subject.12	(Intercept)	0.62337	0.7895
item	structure.can-wh	0.60162	0.7756
item.1	structure.can-nom	0.60048	0.7749
item.2	structure.can-passiv	0.89002	0.9434
item.3	structure.can-scramb	0.51642	0.7186
item.4	structure.can-ld	0.08332	0.2887
item.5	structure.can-prefie	0.04400	0.2098
item.6	structure.can-anapho	0.03770	0.1942
item.7	(Intercept)	0.16459	0.4057
Residual	1.63837	1.2800	

Number of obs: 3072, groups: subject, 48; item, 12

Fixed effects:

	Estimate	Std. Error	df	t-value	p-value	
(Intercept)	6.1959	0.4469	15.5224	13.863	3.73e-10	***
structure.can-anapho	-2.8064	0.4131	19.8999	-6.794	1.36e-06	***
structure.can-prefie	-1.5011	0.3290	14.5241	-4.563	0.000405	***
structure.can-ld	-2.1824	0.3950	15.8664	-5.525	4.76e-05	***
structure.can-scramb	-2.7530	0.7656	12.5969	-3.596	0.003414	**
structure.can-passiv	-2.5049	0.9749	13.0301	-2.569	0.023294	*

structure.can-nom	-3.8630	0.8274	13.4730	-4.669	0.000400	***
structure.can-wh	-4.7461	0.8322	13.6803	-5.703	5.96e-05	***
comp	-1.0607	0.8937	14.2375	-1.187	0.254675	
structure.can-anapho:comp	3.4288	0.7643	13.7791	4.486	0.000532	***
structure.can-prefie:comp	2.3046	0.6688	14.2045	3.446	0.003864	**
structure.can-ld:comp	1.7886	0.7773	13.6320	2.301	0.037724	*
structure.can-scramb:comp	4.7527	1.5628	12.5059	3.041	0.009833	**
structure.can-passiv:comp	0.9893	1.9792	12.6633	0.500	0.625749	
structure.can-nom:comp	2.5151	1.6690	12.7779	1.507	0.156138	
structure.can-wh:comp	4.1377	1.6867	13.2040	2.453	0.028785	*

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Experiment 2, first model: the effect of idiomaticity

Data: whole dataset; fixed factors: structure (treatment coded, baseline: canonical), idiomaticity (sum coded).

AIC	BIC	logLik	deviance	df.resid
8528.7	8702.0	-4234.3	8468.7	2358

Scaled residuals:

Min	1Q	Median	3Q	Max
-3.4446	-0.5671	0.0803	0.6274	3.4597

Random effects:

Groups	Name	Variance	Std.Dev.
subject	structure.can-cleftl:idiomaticity1	0.1350352	0.36747
subject.1	structure.can-passiv:idiomaticity1	0.0638505	0.25269
subject.2	idiomaticity1	0.0639724	0.25293
subject.3	structure.can-cleftl	0.2958520	0.54392
subject.4	structure.can-passiv	0.4961964	0.70441
subject.5	structure.can-nom	0.8993550	0.94834
subject.6	structure.can-nom-of	0.6865792	0.82860
subject.7	structure.can-anapho	0.5525928	0.74337
subject.8	(Intercept)	0.6222574	0.78883
item	structure.can-cleftl:idiomaticity1	0.0426741	0.20658
item.1	structure.can-passiv:idiomaticity1	0.0297644	0.17252
item.2	structure.can-anapho:idiomaticity1	0.0002988	0.01728
item.3	idiomaticity1	0.1360860	0.36890
item.4	structure.can-cleftl	0.0061171	0.07821

item.5	structure.can-passiv	0.1984308	0.44546
item.6	structure.can-anapho	0.0459114	0.21427
item.7	(Intercept)	0.0045954	0.06779
Residual	1.7023343	1.30474	

Number of obs 2388: , groups: subject, 24; item, 18

Fixed effects:

	Estimate	Std. Error	df	t-value	p-value	
(Intercept)	5.35139	0.19843	39.08631	26.968	<2e-16	
structure.can-anapho	-0.25479	0.18767	29.12485	-1.358	0.185001	
structure.can-nom-of	-0.60409	0.19467	27.64524	-3.103	0.004382	**
structure.can-nom	-0.97149	0.21624	26.96259	-4.493	0.000119	***
structure.can-passiv	-1.74786	0.21043	34.96524	-8.306	8.65e-10	***
structure.can-cleftl	-1.02490	0.15713	29.26695	-6.523	3.68e-07	***
idiomaticity1	-0.31527	0.12694	40.93849	-2.484	0.017192	*
structure.can-anapho:idiomaticity1	-0.10201	0.11043	28.64724	-0.924	0.363326	
structure.can-nom-of:idiomaticity1	0.07647	0.09637	2092.76824	0.793	0.427600	
structure.can-nom:idiomaticity1	0.20213	0.09638	2092.27594	2.097	0.036090	*
structure.can-passiv:idiomaticity1	-0.40759	0.16206	25.96217	-2.515	0.018433	*
structure.can-cleftl:idiomaticity1	-0.67074	0.13413	33.08484	-5.001	1.83e-05	***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Experiment 2, second model: the effect of compositionality

Data: only idioms, fixed factors: structure (treatment-coded), composionality (linear predictor)

AIC	BIC	logLik	deviance	df.resid
5514.8	5658.7	-2730.4	5460.8	1497

Scaled residuals:

Min	1Q	Median	3Q	Max
-3.2798	-0.5985	0.0625	0.6317	3.4276

Random effects:

Groups	Name	Variance	Std.Dev.
subject	structure.can-anapho:comp	0.47596	0.6899
subject.1	mcomp	0.81953	0.9053
subject.2	structure.can-cleftl	0.35945	0.5995
subject.3	structure.can-passiv	0.36554	0.6046
subject.4	structure.can-nom	0.63548	0.7972

subject.5	structure.can-nom-of	0.49223	0.7016
subject.6	structure.can-anapho	0.15691	0.3961
subject.7	(Intercept)	0.54149	0.7359
item	structure.can-cleftl	0.01161	0.1078
item.1	structure.can-passiv	0.24817	0.4982
item.2	structure.can-nom	0.02174	0.1475
item.3	structure.can-nom-of	0.11366	0.3371
item.4	structure.can-anapho	0.07794	0.2792
item.5	(Intercept)	0.13788	0.3713
Residual	1.74824	1.3222	

Number of obs: 1524, groups: subject, 24 ; item, 12

Fixed effects:

	Estimate	Std. Error	df	t-value	p-value	
(Intercept)	3.20752	0.64934	21.82560	4.940	6.23e-05	***
structure.can-anapho	-0.08385	0.66180	17.20579	-0.127	0.900643	
structure.can-nom-of	1.10450	0.72019	19.34390	1.534	0.141316	
structure.can-nom	1.56987	0.59499	24.98850	2.638	0.014129	*
structure.can-passiv	-1.97727	0.87333	15.58701	-2.264	0.038218	*
structure.can-cleftl	-1.39533	0.56870	28.23972	-2.454	0.020571	*
comp	2.83543	0.97214	20.77592	2.917	0.008307	**
structure.can-anapho:comp	-0.42732	0.99900	16.83920	-0.428	0.674256	
structure.can-nom-of:comp	-2.51070	1.06355	17.49354	-2.361	0.030080	*
structure.can-nom:comp	-3.60107	0.85970	20.94549	-4.189	0.000416	***
structure.can-passiv:comp	-0.28118	1.30557	14.72362	-0.215	0.832433	
structure.can-cleftl:comp	-0.46313	0.83397	25.10598	-0.555	0.583580	

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Experiment 3, first model: the effect of idiomaticity and definiteness

Data: both idioms and non-idioms, but excluding incorporated nouns; fixed factors: structure (treatment coded, baseline: cancal), idiomaticity (sum-coded), definiteness (sum-coded, def vs. indef).

AIC	BIC	logLik	deviance	df.resid
18535.5	18898.4	-9212.7	18425.5	5369

Scaled residuals:

Min	1Q	Median	3Q	Max
-4.3876	-0.5462	0.0718	0.5979	4.4302

Random effects:

Groups	Name	Variance	Std.Dev.
subject	structure.can-wh:idiomaticity1	0.140147	0.37436
subject.1	structure.can-nom:idiomaticity1	0.200095	0.44732
subject.2	structure.can-scramb:idiomaticity1	0.126055	0.35504

subject.3	structure.can-ld:idiomaticity1	0.071979	0.26829
subject.4	structure.can-anapho:idiomaticity1	0.076141	0.27594
subject.5	idiomaticity1	0.010801	0.10393
subject.6	structure.can-wh	0.561662	0.74944
subject.7	structure.can-nom	0.535747	0.73195
subject.8	structure.can-passiv	0.270390	0.51999
subject.9	structure.can-scramb	0.216115	0.46488
subject.10	structure.can-ld	0.604016	0.77718
subject.11	structure.can-prefie	0.054689	0.23386
subject.12	structure.can-anapho	0.544445	0.73787
subject.13	(Intercept)	0.326041	0.57100
item	structure.can-wh	0.556114	0.74573
item.1	structure.can-nom	0.388298	0.62314
item.2	structure.can-passiv	0.468664	0.68459
item.3	structure.can-scramb	0.355531	0.59626
item.4	structure.can-ld	0.118525	0.34427
item.5	structure.can-prefie	0.005489	0.07409
item.6	structure.can-anapho	0.231225	0.48086
item.7	(Intercept)	0.079214	0.28145
Residual	1.401905	1.18402	

Number of obs : 5424, groups: subject, 60; item, 24

Fixed effects:

	Estimate	Std. Error	df	t-value	p-value	
(Intercept)	6.18591	0.10706	80.80938	57779	<2e-16	***
structure.can-anapho	-1.27778	0.15797	53.96002	-8.089	7.13e-11	***
structure.can-prefie	-0.27452	0.07763	39.58304	-3.536	0.001052	**
structure.can-ld	-1.41873	0.14769	62.52094	-9.606	6.33e-14	***
structure.can-scramb	-1.52810	0.16075	36.92461	-9.506	1.83e-11	***
structure.can-passiv	-0.70048	0.17626	34.93091	-3.974	0.000337	***
structure.can-nom	-2.10723	0.17993	45.56198	-11.711	2.45e-15	***
structure.can-wh	-2.38530	0.20015	40.87279	-11.918	7.01e-15	***
idiomaticity1	-0.06429	0.07978	41.06127	-0.806	0.424973	
def1	0.03878	0.07816	38.10465	0.496	0.622567	
structure.can-anapho:idiomaticity1	-0.49872	0.13298	32.78222	-3.750	0.000684	***
structure.can-prefie:idiomaticity1	-0.17343	0.07180	41.14728	-2.416	0.020233	*
structure.can-ld:idiomaticity1	-0.27377	0.10998	36.72496	-2.489	0.017456	*
structure.can-scramb:idiomaticity1	-0.43929	0.15792	34.51714	-2.782	0.008701	**
structure.can-passiv:idiomaticity1	-0.08779	0.16345	26.71586	-0.537	0.595643	
structure.can-nom:idiomaticity1	-0.91956	0.16371	34.49069	-5.617	2.59e-06	***
structure.can-wh:idiomaticity1	-0.63927	0.18228	29.71501	-3.507	0.001463	**
structure.can-anapho:def1	0.14606	0.12572	27.86898	1.162	0.255164	
structure.can-prefie:def1	-0.01735	0.07069	39.72479	-0.245	0.807341	
structure.can-ld:def1	0.10660	0.10441	31.49681	1.021	0.315049	
structure.can-scramb:def1	1.14649	0.14676	26.97980	7.812	2.13e-08	***
structure.can-passiv:def1	0.05024	0.16320	26.56638	0.308	0.760621	
structure.can-nom:def1	-0.39771	0.15400	27.77995	-2.582	0.015377	*

structure.can-wh:def1	-0.92701	0.17831	27.08027	-5.199	1.77e-05	***
idiomaticity1:def1	-0.10308	0.07776	37.29311	-1.326	0.193041	
structure.can-anapho:idiomaticity1:def1	0.10042	0.12515	27.59590	0.802	0.429157	
structure.can-prefie:idiomaticity1:def1	0.02451	0.06958	38.67160	0.352	0.726559	
structure.can-ld:idiomaticity1:def1	0.06061	0.10186	30.30615	0.595	0.556279	
structure.can-scramb:idiomaticity1:def1	0.03659	0.14676	26.96763	0.249	0.805014	
structure.can-passiv:idiomaticity1:def1	0.10460	0.16301	26.44703	0.642	0.526619	
structure.can-nom:idiomaticity1:def1	-0.06832	0.15767	29.26782	-0.433	0.667960	
structure.can-wh:idiomaticity1:def1	0.51658	0.17695	26.53093	20.919	0.007066	**

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Experiment 3, second model: the effect of compositionality

Data: only idioms, fixed factors: structure (treatment-coded), definiteness (sum-coded, def vs. indef), composionality (linear predictor)

AIC	BIC	logLik	deviance	df.resid
12352.9	12691.8	-6121.4	12242.9	3449

Scaled residuals:

Min	1Q	Median	3Q	Max
-4.1669	-0.5566	0.0494	0.6101	4.0136

Random effects:

Groups	Name	Variance	Std.Dev.
subject	structure.can-wh:comp	1.27965	1.1312
subject.1	structure.can-nom:comp	0.69235	0.8321
subject.2	structure.can-passiv:comp	0.09064	0.3011
subject.3	structure.can-ld:comp	0.73103	0.8550
subject.4	structure.can-anapho:comp	0.21371	0.4623
subject.5	comp	0.03420	0.1849
subject.6	structure.can-wh	0.49190	0.7014
subject.7	structure.can-nom	0.55930	0.7479
subject.8	structure.can-passiv	0.24822	0.4982
subject.9	structure.can-scramb	0.44243	0.6652
subject.10	structure.can-ld	0.56108	0.7491
subject.11	structure.can-prefie	0.06515	0.2553
subject.12	structure.can-anapho	0.66592	0.8160
subject.13	(Intercept)	0.33054	0.5749
item	structure.can-wh	0.53913	0.7343
item.1	structure.can-nom	0.26761	0.5173
item.2	structure.can-passiv	0.46503	0.6819
item.3	structure.can-scramb	0.26084	0.5107
item.4	structure.can-ld	0.15538	0.3942
item.5	structure.can-prefie	0.02299	0.1516

item.6	structure.can-anapho	0.25990	0.5098
item.7	(Intercept)	0.10434	0.3230
Residual	1.51944	1.2327	

Number of obs: 3504, groups: subject, 60 ; item, 16

Fixed effects:

	Estimate	Std. Error	df	t-value	p-value	
(Intercept)	6.53226	0.30775	26.50807	21.226	<2e-16	***
structure.can-anapho	-2.75727	0.47836	21.52761	-5.764	9.20e-06	***
structure.can-prefie	-1.21660	0.27500	24.69457	-4.424	0.000170	***
structure.can-ld	-2.40177	0.39644	21.77744	-6.058	4.44e-06	***
structure.can-scramb	-3.82934	0.46181	20.17271	-8.292	6.25e-08	***
structure.can-passiv	-1.97333	0.56900	18.52255	-3.468	0.002653	**
structure.can-nom	-4.28443	0.46957	19.67465	-9.124	1.67e-08	***
structure.can-wh	-4.44056	0.60702	17.80165	-7.315	9.14e-07	***
comp	-0.91342	0.55356	25.10196	-1.650	0.111381	
dptype1	0.06603	0.29982	23.97516	0.220	0.827560	
structure.can-anapho:comp	1.78954	0.87117	20.92181	2.054	0.052663	.
structure.can-prefie:comp	1.47743	0.50588	25.59164	2.921	0.007200	**
structure.can-ld:comp	1.40208	0.72164	21.40206	1.943	0.065297	.
structure.can-scramb:comp	3.54799	0.83511	19.44173	4.249	0.000415	***
structure.can-passiv:comp	2.72133	1.04123	18.65835	2.614	0.017249	*
structure.can-nom:comp	2.58176	0.85127	19.19635	3.033	0.006789	**
structure.can-wh:comp	2.92726	1.11363	18.10519	2.629	0.016987	*
structure.can-anapho:dptype1	-0.83814	0.46691	19.62767	-1.795	0.088055	.
structure.can-prefie:dptype1	-0.56100	0.28446	26.69772	-1.972	0.059035	.
structure.can-ld:dptype1	-0.40535	0.38908	20.03997	-1.042	0.309895	
structure.can-scramb:dptype1	-0.24651	0.46156	19.71458	-0.534	0.599266	
structure.can-passiv:dptype1	0.33997	0.56504	18.01985	0.602	0.554888	
structure.can-nom:dptype1	-0.95861	0.46897	19.08619	-2.044	0.054995	.
structure.can-wh:dptype1	-1.00231	0.60087	17.11301	-1.668	0.113491	
comp:dptype1	-0.07666	0.54863	24.22103	-0.140	0.890035	
structure.can-anapho:comp:dptype1	1.83029	0.83729	18.90526	2.186	0.041603	*
structure.can-prefie:comp:dptype1	0.83512	0.52069	27.39106	1.604	0.120215	
structure.can-ld:comp:dptype1	0.97924	0.73878	22.17206	1.325	0.198508	
structure.can-scramb:comp:dptype1	2.20113	0.83750	19.52499	2.628	0.016316	*
structure.can-passiv:comp:dptype1	-0.93726	1.03598	18.33907	-0.905	0.377349	
structure.can-nom:comp:dptype1	0.57521	0.84580	18.63297	0.680	0.504816	
structure.can-wh:comp:dptype1	0.63048	1.10025	17.33046	0.573	0.573985	

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Experiment 3, third model: the effect of DP/noun type

Data: only non-idioms, fixed factors: structure (treatment-coded), DP type (forward-difference coding, dptype2-1 = def vs. indef, dptype3-2 = indef vs. incorp)

AIC	BIC	logLik	deviance	df.resid
12949.8	13237.4	-6428.9	12857.8	3794

Scaled residuals:

Min	1Q	Median	3Q	Max
-4.6227	-0.5193	0.0794	0.5957	3.8268

Random effects:

Groups	Name	Variance	Std.Dev.
subject	structure.can-wh:dptype3-2	0.19513	0.4417
subject.1	structure.can-nom:dptype3-2	0.70734	0.8410
subject.2	structure.can-passiv:dptype3-2	0.32050	0.5661
subject.3	structure.can-scramb:dptype3-2	1.16207	1.0780
subject.4	structure.can-ld:dptype3-2	0.40271	0.6346
subject.5	dptype3-2	0.03304	0.1818
subject.6	structure.can-wh	0.58578	0.7654
subject.7	structure.can-nom	0.43838	0.6621
subject.8	structure.can-passiv	0.45097	0.6715
subject.9	structure.can-scramb	0.23992	0.4898
subject.10	structure.can-ld	0.68660	0.8286
subject.11	structure.can-prefie	0.05029	0.2243
subject.12	structure.can-anapho	0.57536	0.7585
subject.13	(Intercept)	0.34618	0.5884
item	structure.can-wh	0.57766	0.7600
item.1	structure.can-nom	0.58333	0.7638
item.2	structure.can-passiv	0.09572	0.3094
item.3	structure.can-scramb	0.14505	0.3809
item.4	structure.can-ld	0.01893	0.1376
item.5	structure.can-anapho	0.16243	0.4030
item.6	(Intercept)	0.08161	0.2857
Residual	1.28814	1.1350	

Number of obs: 3840, groups: subject, 60; item, 16

Fixed effects:

	Estimate	Std. Error	df	t-value	p-value	
(Intercept)	6.25473	0.12095	57.34913	51.712	<2e-16	***
structure.can-anapho	-0.92718	0.16626	39.16230	-5.577	1.98e-06	***
structure.can-prefie	-0.24334	0.08729	139.95659	-2.788	0.00605	**
structure.can-ld	-1.48904	0.14246	57.96158	-10.452	5.92e-15	***
structure.can-scramb	-1.67630	0.14959	33.16714	-11.206	8.12e-13	***
structure.can-passiv	-0.82638	0.14353	38.48174	-5.757	1.18e-06	***
structure.can-nom	-1.47630	0.23360	22.46507	-6.320	2.11e-06	***
structure.can-wh	-1.94707	0.23678	24.67320	-8.223	1.57e-08	***
dptype2-1	-0.34376	0.25214	26.41228	-1.363	0.18428	
dptype3-2	0.09543	0.21756	25.99021	0.439	0.66454	
structure.can-anapho:dptype2-1	-0.03124	0.35419	17.96345	-0.088	0.93069	

structure.can-prefie:dptype2-1	0.14376	0.21033	3150.72415	0.683	0.49436	
structure.can-ld:dptype2-1	-0.09693	0.23383	27.63820	-0.415	0.68169	
structure.can-scramb:dptype2-1	-2.18543	0.34242	20.52414	-6.382	2.80e-06	***
structure.can-passiv:dptype2-1	0.16876	0.30348	18.33097	0.556	0.58489	
structure.can-nom:dptype2-1	0.77325	0.58930	17.79210	1.312	0.20615	
structure.can-wh:dptype2-1	2.93828	0.58710	18.22860	5.005	8.86e-05	***
structure.can-anapho:dptype3-2	-0.36326	0.31076	18.35784	-1.169	0.25738	
structure.can-prefie:dptype3-2	-0.32616	0.17993	3066.85464	-1.813	0.06996	.
structure.can-ld:dptype3-2	-1.18612	0.21860	32.52143	-5.426	5.48e-06	***
structure.can-scramb:dptype3-2	-0.46422	0.33610	31.14298	-1.381	0.17706	
structure.can-passiv:dptype3-2	-0.63537	0.27455	21.12427	-2.314	0.03080	*
structure.can-nom:dptype3-2	-1.24412	0.52486	19.75226	-2.370	0.02807	*
structure.can-wh:dptype3-2	-1.98222	0.50322	17.68537	-3.939	0.00099	***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1