

1 **Syntactic probabilities affect pronunciation**
2 **variation in spontaneous speech**

3
4 HARRY TILY, SUSANNE GAHL, INBAL ARNON, NEAL SNIDER,
5 ANUBHA KOTHARI, AND JOAN BRESNAN*

6 *Stanford University*
7 *University of California, Berkeley*
8
9
10
11

12 *Abstract*

13
14 *Speakers frequently have a choice among multiple ways of expressing one*
15 *and the same thought. When choosing between syntactic constructions for*
16 *expressing a given meaning, speakers are sensitive to probabilistic tenden-*
17 *cies for syntactic, semantic or contextual properties of an utterance to favor*
18 *one construction or another. Taken together, such tendencies may align to*
19 *make one construction overwhelmingly more probable, marginally more*
20 *probable, or no more probable than another. Here, we present evidence*
21 *that acoustic features of spontaneous speech reflect these probabilities:*
22 *when speakers choose a less probable construction, they are more likely to*
23 *be disfluent, and their fluent words are likely to have a relatively longer du-*
24 *ration. Conversely, words in more probable constructions are shorter and*
25 *spoken more fluently. Our findings suggest that the differing probabilities*
26 *of a syntactic construction in context are not epiphenomenal, but reflect a*
27 *part of a speakers' knowledge of their language.*

28
29 *Keywords*

30 *pronunciation variation, gradience, disfluency, ditransitive, word duration,*
31 *speech production, syntactic alternation*
32
33

34 **1. Introduction**

35 Empirical methods have become ubiquitous in all subfields of Linguistics.
36 For example, the 2003 meeting of the Linguistic Society of America fea-
37 tured a symposium on “Probability theory and Linguistics”, but only a
38

39 * Correspondence address: Harry Tily, Linguistics, Margaret Jacks Hall, Stanford Univer-
40 sity, CA 94305, USA. E-mails: hjt@stanford.edu; gahl@berkeley.edu. This work was
41 supported by NSF grant BCS-9818077. We thank Dan Jurafsky, Tom Wasow, and the
42 audience at the 2007 AMLaP conference for useful comments and suggestions.

1 single regular session on psycholinguistics and none on corpus linguistics.
2 By contrast, the 2008 meeting had several sessions devoted to psycho-
3 linguistics and corpus linguistics, and, moreover, featured corpus-based
4 and experimental psycholinguistic research in practically every session,
5 on topics ranging from syntactic theory to morphology to lexical seman-
6 tics. This methodological change has gone hand in hand with the emer-
7 gence of new theoretical approaches. Most major models of grammar
8 until recently cast linguistic structure as discrete, static, and categorical.
9 Recent years, however, have seen the emergence of more and more
10 models that conceive of structure as gradient, malleable, and probabilistic
11 (see for example the papers in Barlow and Kemmer (2000); Bod et al.
12 (2003); Bybee and Hopper (2001); and Gahl and Yu (2006)). In these
13 models, knowledge of language includes not just knowledge of syntactic,
14 morphological, and phonological categories, but also knowledge of the
15 frequency and probability of use of these categories in speakers' experi-
16 ence. Families of frameworks such as "probabilistic linguistics", "usage-
17 based" and "exemplar-based" models all recognize gradient activation of
18 linguistic units and probabilistic and gradient effects of linguistic form
19 and meaning. The linguistic units in question include structures at all
20 levels of linguistic representation and varying degrees of abstraction (see
21 e.g. Borensztajn et al. 2009; Pierrehumbert 2001, 2002; Bybee 2002, 2006;
22 Johnson 1997). Taken together, these proposals constitute a major depart-
23 ure from a research tradition that imposed rigid boundaries between
24 competence and performance, sought to minimize redundancy in lexicon
25 and grammar, and assumed linguistic representations to be categorical
26 and discrete.

27 The development of these models has been possible in part thanks to
28 rich, large-scale corpora of naturalistic usage data and the availability of
29 statistical techniques for analyzing complex interactions of multiple fac-
30 tors. These tools have made it possible to build sophisticated models of
31 the many factors affecting how speakers encode meaning in linguistic
32 form. For example, Bresnan et al. (2007) examined what drives speakers'
33 choice of syntactic realization patterns in the so-called dative alternation.
34 A given scenario can be expressed with either of two syntactic patterns,
35 either NP NP or NP PP, exemplified in (1a) and (1b), respectively:

- 36 (1) a. They sent us two of our coach tickets (NP NP)
37 b. They sent two of our coach tickets to us (NP PP)
38

39 Attempts to account for speakers' choice between the dative alternants
40 have tended to invoke semantic differences between the forms (Green
41 1974; Gropen et al. 1989), or constraints on the pronominality (Green
42 1971), information structure (Erteschik-Shir 1979) or length of the two

1 arguments involved (Hawkins 1994). Each one of these generalizations
2 covers many cases—but each is subject to exceptions. Indeed, corpus
3 analysis shows the choice between the two constructions to be far more
4 flexible than first appears to intuition (Fellbaum 2005; Bresnan and
5 Nikitina 2007; Bresnan 2008). Analyzing a large corpus of such “dative”
6 sentences, Bresnan et al. (2007) showed that a multitude of such factors,
7 taken together, jointly predict speakers’ syntactic choice between NP NP
8 or NP PP alternants at very high accuracy. No analysis considering just
9 one factor at a time, be it semantic, phonological, or pragmatic, does
10 justice to the facts about the dative alternation. Grammatical models
11 seeking to describe syntactic realization patterns with any degree of accu-
12 racy must therefore take into account many factors at once.

13 Speakers’ syntactic choices can be accurately modeled using statistical
14 models incorporating interacting constraints that jointly estimate the
15 outcome probability. Moreover, (Bresnan 2008) found that acceptability
16 judgments reflect these factors, as well. However, the off-line judgment
17 task does not show whether the language production process is sensitive
18 to similar constraints as it unfolds: the models may achieve mere “de-
19 scriptive adequacy”. What constraints are speakers in fact sensitive to?
20 One means of investigating that question draws on observations about
21 pronunciation. Different tokens of one and the same word or phrase
22 typically sound slightly different. This variation may be random to some
23 degree; to some extent, however, it reflects planning processes during lan-
24 guage production: A large body of evidence suggests that the duration of
25 words and pauses provides a sensitive diagnostic revealing speakers’ sen-
26 sitivity to probabilities at various levels of linguistic structure, such as the
27 frequency and contextual predictability of words (Lieberman 1963; Bell
28 et al. 2009), morphemes (Pluymaekers et al. 2005; Kuperman et al. 2007),
29 and syntactic structures (Gahl and Garnsey 2004, 2006; Gahl et al. 2006).

30 Just as with research on syntactic alternations, research on pronuncia-
31 tion variation reveals speakers’ sensitivity to many probabilistic factors at
32 once. This point is firmly established in the study of word durations,
33 which simultaneously reflect static properties of single words such as or-
34 thographic regularity, and dynamically-changing properties related to the
35 speaker’s experience with that word: for example, its frequency, and its
36 likelihood of appearing in the context of the words before and after it
37 (Gahl 2008; Bell et al. 2009). Other things being equal, the production of
38 low-probability linguistic units—that is, low-frequency words and words
39 which are unlikely in a given context—tends to involve lengthening of
40 words and pauses. By contrast, the pronunciation of high-probability
41 linguistic units is characterized by phonetic reduction and durational
42 shortening.

1 Research on probabilistic pronunciation variation has often focused
 2 on “string probability” measures such as n-grams, or transitional proba-
 3 bilities, i.e. the probability of a word conditioned on the word(s) that
 4 precede or follow it (Jurafsky et al. 2001; Bell et al. 2009). However, if
 5 grammars are indeed probabilistic, one should expect to see similar pro-
 6 nunciation effects of more abstract syntactic probabilities, as pointed out
 7 in Gahl and Garnsey (2004). In our previous research, we have shown
 8 that syntactic probabilities can affect pronunciation. That research was
 9 based on the so-called subcategorization bias of a verb, or “verb bias”.
 10 Verb bias refers to the probability with which a given verb appears with
 11 each of the subcategorization frames it is compatible with, such as the
 12 sentential complement (SC) and double object (DO) frames shown in
 13 (2). Effects of verb bias, i.e. a syntactic property, on sentence comprehen-
 14 sion are well established (Trueswell et al. 1993; Garnsey et al. 1997).

- 15 (2) a. We confirmed the date was correct (SC)
 16 b. We confirmed the date (DO)
 17

18 In Gahl and Garnsey (2004), we examined pronunciation variation
 19 in these types of sentence, and showed that, among other things, the
 20 acoustic-phonetic realization of the clause boundary following “con-
 21 firmed” in the SC-variant was in part a function of the probability of
 22 encountering an SC following that verb. SCs after verbs that are highly
 23 likely to take direct objects (“DO-bias verbs”) are realized differently
 24 from SCs following verbs that are likely to take SCs (“SC-bias verbs”),
 25 independently of the specific words appearing in those structures. Import-
 26 tantly, this difference was not due to the real-life probability of scenarios
 27 described by sentences with high and low syntactic probability (cf. Gahl
 28 and Garnsey 2006, for discussion, and Gahl et al. 2006) for a similar
 29 effect in a different pair of constructions).

30 While the observations in Gahl and Garnsey (2004) suggest that pro-
 31 nunciation variation reflects probabilities associated with syntactic struc-
 32 ture, it is clear that the probability measure used there is overly simple.
 33 To look only at a verb’s subcategorization bias, estimated from corpus
 34 counts of various subcategorization frames in corpora, is to throw away
 35 the mass of rich information available in sentences which speakers’
 36 choices may be sensitive to. Subcategorization biases exist in tandem
 37 with (and in some part, result from) a host of local and discourse-level
 38 factors, as can be seen in the rich and detailed analyses in Bresnan et al.
 39 (2007), (Szmrecsanyi and Hinrichs 2008), and (Wasow 2002), among
 40 others.

41 The goal of the current study is to bring the tool of pronunciation vari-
 42 ation to bear on understanding the richness of speakers’ probabilistic

1 knowledge of language. The current examines pronunciation variation in
2 the dative alternation. If pronunciation variation is a sufficiently sensitive
3 reflection of the multiple probabilistic cues predicting the choice between
4 syntactic structures, then it can help show whether the human language
5 production system does indeed rely on the full range of available cues.

6 The current study also allows us to address serious questions left open
7 by previous research. Previous studies of syntactic probabilities (Gahl and
8 Garnsey 2004; Gahl et al. 2006) elicited speech from participants by asking
9 them to read sentences. That fact constitutes a limitation: For one
10 thing, the prosody of read speech differs from that of spontaneous speech
11 (Schafer et al. 2005). An even more serious problem is that the observed
12 effect may have resulted from comprehension difficulty, rather than directly
13 reflecting the workings of the language production system. Sentences
14 with local ambiguities often induce “garden-paths”, i.e. incorrect
15 parses that temporarily throw the comprehension system off-track. Gahl
16 and Garnsey (2004) excluded tokens from the analysis that showed self-
17 correction or marked overemphasis (“*we confirmed, no wait, oh now I get*
18 *it, . . . we conFIRMED the date was correct*”). Still, the possibility cannot
19 be ruled out that the subjects in those studies initially misunderstood
20 some of the sentences they were asked to read and then decided to
21 emphasize low-probability prosodic phrasings. In fact, to keep subjects
22 from feeling self-conscious knowing their speech would be analyzed, they
23 were falsely given the impression that the researchers needed the recordings
24 for a future comprehension experiment. Perhaps, then, speakers were
25 attempting to make the sentences easy to comprehend for an imaginary
26 listener. An analysis of spontaneous speech alleviates the problems caused
27 by possible garden-path effects experienced by the speakers, if it is assumed
28 that talkers are unlikely to induce garden-path effects in themselves
29 by their own speech. That assumption appears plausible, given that
30 talkers do not generally appear to be aware of local ambiguities in their
31 own speech here (Allbritton et al. 1996). In addition, though this is an
32 active area of research, it appears that speakers do not consistently
33 provide cues to listeners that would maximize ease of comprehension
34 (Ferreira and Dell 2000).

35 The dative alternation provides a particularly useful tool for an investigation
36 of syntactic probabilities in that the two alternants (*They sent us*
37 *two tickets* ~ *They sent two tickets to us*) denote identical real-life scenarios
38 (semantic differences between the alternants notwithstanding, cf.
39 Green 1974; Gropen et al. 1989). If the phonetic realization of dative
40 sentences indeed reflects probability of construction choice, then it does
41 not simply reflect probability of real-world scenarios. Speakers’ choices
42 of dative alternants are subject to a range of probabilistic constraints at

1 least some of which are based on linguistic facts alone, not on real-world
2 denotata. Therefore, differences in planning or processing difficulty be-
3 tween the two alternants must be due to speakers' store of linguistic ex-
4 periences, not to differences in the frequency of events in the world. Our
5 earlier studies controlled for real-life probability of denoted scenarios
6 (cf. the discussion in Gahl and Garnsey 2006), but they did so indirectly;
7 the dative alternation provides a direct means of teasing apart probability
8 of constructions and of real-world denotata.

10 **2. Background: The dative alternation**

11
12 In Bresnan et al. (2007), we used multivariate statistical analysis to inves-
13 tigate the many factors that have been claimed to influence speakers'
14 choice between the dative alternants. As mentioned above, previous ac-
15 counts explain the choice in terms of a single variable. Surprisingly per-
16 haps, all of these accounts work fairly well despite the different con-
17 straints they invoke. This is because the properties that have shown to be
18 relevant tend to pattern together: For instance, pronominal themes tend
19 to favour the NP PP construction and pronominal recipients the NP
20 NP construction; but pronouns also tend to be short, definite, concrete,
21 and given. Using a logistic regression model, however, Bresnan et al.
22 (2007) were able to include many such correlated factors and test whether
23 speakers' choices were influenced by each independently, controlling for
24 the others.

25 Bresnan et al.'s analysis used data from the Switchboard corpus of
26 spoken American English, which consists of recorded telephone conver-
27 sations between strangers (Godfrey et al. 1992). Bresnan et al. hand-
28 annotated each sentence containing one of the two dative alternants (NP
29 NP or NP PP; in a total of 2360 sentences), tracking a host of syntactic
30 and semantic variables that might have influenced the syntactic choice.
31 All of the variables were previously claimed to be relevant to the alter-
32 nation in the theoretical or experimental literature. All in all, fourteen
33 variables were chosen and annotated in the data: the semantic class of
34 the verb (coding the type of relationship held between the recipient and
35 theme); the givenness, pronominality, definiteness, animacy, person and
36 number of the recipient; the givenness, pronominality, definiteness, num-
37 ber and concreteness of the theme; the (log) difference in the number of
38 words of the recipient and theme; structural parallelism (whether there
39 had been instances of the same syntactic pattern in the preceding dia-
40 logue). A logistic regression model was then estimated which could pre-
41 dict the speaker's choice between NP NP and NP PP as a function of
42 these variables. Except for number and person of recipient, and concrete-

1 Table 1. Factors found by Bresnan et al. (2007) to favor the NP NP or NP PP constructions

2 NP NP more likely	NP PP more likely
4 given recipient or nongiven theme	given theme or nongiven recipient
5 pronominal recipient or nonpronominal theme	pronominal theme or nonpronominal recipient
6 animate recipient or inanimate theme	animate theme or inanimate recipient
7 definite recipient or indefinite theme	definite theme or indefinite recipient
8 short recipient or long theme	short theme or long recipient
9 singular theme	plural theme

10

11

12

13

14 ness of theme, all of the factors were found to have an effect on the choice
 15 of NP NP or NP PP: the nature of some of these effects is illustrated in
 16 Table 1. On previously unseen data, the model correctly predicted in
 17 94% of cases whether the NP NP or NP PP would be used.

18 The outcome variable in a logistic regression model is a continuous
 19 number ranging between 0 and 1. This number can be interpreted as the
 20 probability with which the model “expects” (or “predicts”) the NP PP
 21 construction—or equivalently, 1 minus the probability of the NP NP.
 22 For example, when all the cues converge to make the outcome very cer-
 23 tain, the output will be close to 1 or 0; in cases where the cues are more
 24 equivocal, the output will be closer to .5. We can consider this output as a
 25 measure of the probability of the construction choice, given the cues: for
 26 each NP NP or NP PP, was the speakers’ choice of that construction
 27 inevitable? Or was the choice more of coin flip between the two, or
 28 even—in a few cases—the *less* likely outcome?

29

30

31 **3. Methods**

32 The Bresnan et al. data and model give us a set of tokens of NP NP and
 33 NP PP sentences, along with an estimate of the probability of the alter-
 34 nant that was chosen: In some cases, the choice of the alternant that the
 35 speaker in fact chose received strong support from the various factors in
 36 the model. Other cases are assigned a lower probability by the model. For
 37 example, the two sentences below had predicted probabilities of 0.01 and
 38 0.99, respectively:

39

- 40 (3) a. Yeah. I haven’t given much thought to it. I’m kind of busy
 raising my kids (p = 0.01)
 41 b. if they can test the teachers, that gives them the full right to test
 42 the kids (p = 0.99)

1 With these probabilities in hand, we examined the effect of syntactic
 2 probability on the phonetic realization of dative sentences. We examined
 3 two aspects of phonetic realization: word duration and the presence of
 4 disfluencies. Word durations and the presence of disfluencies are two
 5 well established measures for fluctuations in processing speed and pro-
 6 cessing difficulty (Fox Tree and Clark 1997; Shriberg 2001; Clark and
 7 Fox Tree 2002; Bell et al. 2003).

8 To study word durations, we focused on the preposition *to* in the NP
 9 PP alternants, using durations extracted from the time-aligned transcript
 10 of the Switchboard corpus (Deshmukh et al. 1998). Our choice of the
 11 word *to* as our target was motivated largely by concerns about effect
 12 size: Previous studies of probabilistic pronunciation variation led us to ex-
 13 pect that the size of any effect of duration reduction would be quite small
 14 (Bell et al. 2003; Pluymaekers et al. 2005; Kuperman et al. 2007; Gahl
 15 2008; Bell et al. 2009), so it is important to minimize other effects that
 16 are not in the model, such as the length or frequency of other words in
 17 the dative constructions. Examining many instances of the same word is
 18 a way to control for word-specific information; hence we use the duration
 19 of this word in all of the NP PP outcomes as our dependent variable.

20 Our models also included the following other variables as controls:

- 21 – *Rate of speech*, measured in syllables per second, for the intonational
 22 phrase surrounding the word *to* (excluding the duration of *to* itself).
 23 Following (Bell et al. 2003), we define the intonational phrase as the
 24 longest region containing the word of interest that contains no sen-
 25 tence boundaries or pauses of 500ms or more.
- 26 – *Segmental context*, specifically the presence of a preceding and fol-
 27 lowing vowel, as this environment may favor flapping and other
 28 contextually-induced articulatory changes.
- 29 – Other measures of contextual probability:
 - 30 – *Verb bias*, i.e. the probability of NP NP or NP PP conditioned
 31 only on the verb,
 - 32 – *Forward and backward bigrams*, i.e. the probability of the word *to*
 33 given the immediately preceding or following word (Bell et al. 2009)
 34 obtained from the Web 1T ngram corpus (Brants and Franz 2006)
 35

36 We removed cases with disfluencies immediately preceding or following
 37 *to*. We consider the following to be disfluencies: a pause of 500ms or
 38 more; repetition of a word; a filled pause (“*uh*”, “*um*”); or a repair or
 39 restart (“*give thi- that to them*”).

40 We then built a multiple linear regression model to test the effects of
 41 these variables. A linear regression model relates a set of predictor vari-
 42 ables to an outcome variable, by considering the influence of all indepen-

1 dent variables simultaneously. The model determines a coefficient for
2 each independent variable which shows how strongly it correlates with
3 the outcome variable when all other variables in the model are controlled.
4 The outcome variable in our case was the duration of the word *to*. The
5 critical predictor variable of interest was syntactic probability, i.e. the
6 probability assigned a sentence in the Bresnan et al. model. The coeffi-
7 cient for probability showed the average difference, in milliseconds, of
8 the word *to* in high versus low probability instances of the construction,
9 after controlling for all other factors in the model. If this difference is
10 significantly different from zero, i.e. if it is large relative to the differ-
11 ence that would be expected due to random variation in the data, the
12 influence of syntactic probability on duration is considered to be statisti-
13 cally significant.

14 A second outcome variable of interest was the presence of disfluencies
15 in the dative sentences. A second regression model was constructed, this
16 time predicting the presence of disfluencies preceding or following the
17 verb or within either of its two arguments (the recipient or the theme) in
18 the NP NP and NP PP sentences. As this outcome variable is categorical,
19 we used logistic regression. Like linear regression, logistic regression re-
20 lates a set of predictor variables to an outcome variable. Unlike in the
21 case of linear regression, the outcome variable in a logistic regression
22 model is a probability estimate, namely the probability of observing par-
23 ticular values of a categorical variable, here, the probability that the ut-
24 terance contains a disfluency.

25 The only predictor variables in this model were verb bias, speech rate,
26 and the probability of the NP NP or NP PP variant, from the Bresnan
27 et al. database. Note that the other predictor variables in the model of
28 *to*-duration, such as the bigram probability measures, vary for each
29 word in a sentence. It would be possible to estimate the values of these
30 variables for every word in the sentences and to combine those measures
31 with the construction outcome probability to predict disfluency at each
32 point in the sentence. We are currently exploring this and other variants
33 of the disfluency model.

34 Data preparation and statistical analysis was carried out using the
35 statistical package R (R Development Core Team 2008) and in particular
36 the Design (Harrell 2007) and languageR (Baayen 2008) packages.

37

38 **4. Results**

39

40 We first turn to the model of the duration of the word *to* at the start of
41 the PP. Our dependent measure was the duration of this word in mili-
42 seconds. We removed datapoints with disfluencies adjacent to the word

Table 2. *Final model for to duration in the PP outcome*

	β	Std. Error	T	P
Intercept	0.17557	0.01220	14.397	0.000000
Outcome probability	-0.34147	0.13782	-2.478	0.013603
Backward bigram	-6.92303	2.12904	-3.252	0.001235
Previous vowel	0.02486	0.01038	2.396	0.017001

of interest, or with durations more than 2.5 standard deviations from the mean (8.4% of the data). 446 cases remained. A speech rate control variable was calculated by taking the duration of the intonational phrase containing the word *to* (i.e. the maximum period containing no pause of 500ms or more and no sentence boundaries). We excluded the word *to* itself from the region over which speech rate was calculated, to avoid collinearity with the dependent variable. The number of syllables in the region was divided by this duration, to determine the speaking rate, measured as syllables per second. The independent variable of interest, the probability of the actual outcome spoken, was calculated using the Bresnan et al. model. Together with the other controls described above, these variables were entered into a linear regression model. Regression inputs were standardized by subtracting the mean and dividing by two standard deviations, as recommended in Gelman (2008).

Although some of the predictor variables might be expected to co-vary, in fact collinearity turned out to be unproblematic. All VIFs were less than 1.2, meaning that the predictors were almost orthogonal. Because the number of datapoints from each speaker varied greatly and because speech rate accounted for much of the inter-speaker variability, we did not use any random or fixed effect for speaker.

The following controls were not significant, and were removed from the model during model comparison by fast backwards elimination of factors (Lawless and Singhal 1978): Forward bigram probability ($p = .43$), Speech rate of the surrounding region ($p = .27$) and Verb bias ($p = .95$).

The three factors shown in Table 2 were determined (by likelihood ratio tests) to improve model quality (at $p < .05$). Importantly, the probability of the PP outcome is a statistically significant predictor of the duration of *to*, with higher probability outcomes resulting in shorter pronunciations.

We now turn to our second variable of interest: disfluency. We coded sentences for whether they contained a disfluency in the intonational phrase surrounding the “dative” verb. Utterances were identified as disfluent if the longest stretch of pause-free speech surrounding the verb contained repetitions, filled pauses, repairs or restarts. Both NP PP and NP

1 Table 3. Final model for disfluency in the dative VP

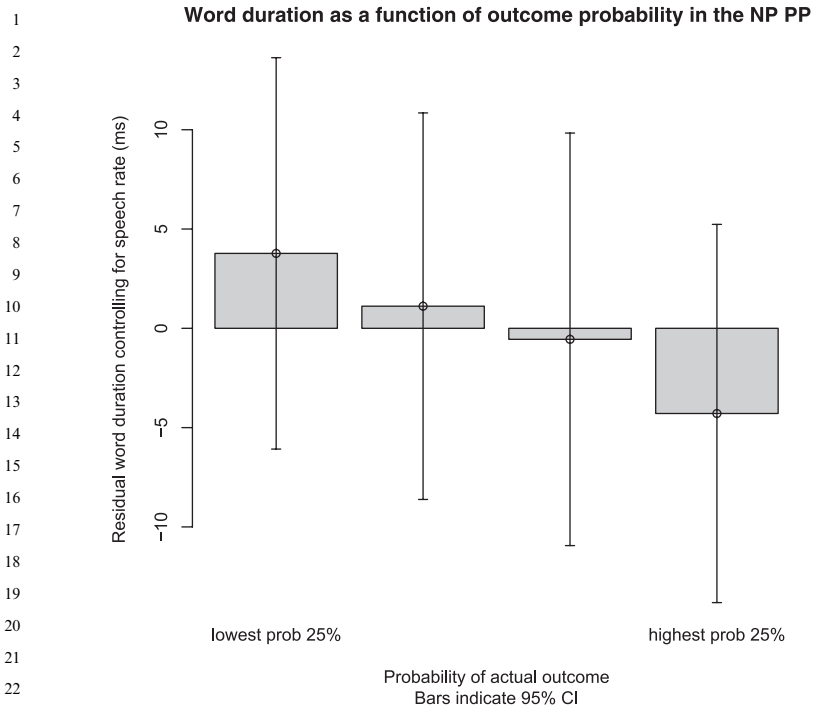
2	β	S.E.	Wald Z	p	
3					
4	Intercept	0.6782	0.27773	2.44	0.0146
5	speech rate	-0.8168	0.09997	-8.17	0.0000
6	outcome probability	-0.2020	0.09403	-2.15	0.0317

7
8 NP outcomes were included. We removed sentences with speech rate 2.5
9 standard deviations from the mean (0.43% of the data). This left 2061
10 cases, of which 594 contained a disfluency in the verb region. Again, our
11 independent variable of interest was calculated using the Bresnan et al.
12 model. This time, because both NP PP and NP NP outcomes were in-
13 cluded, and the variable was not the absolute probability of a NP PP,
14 but the probability of the actual outcome chosen (i.e. one minus the prob-
15 ability of the NP PP in the NP NP case). Collinearity between predictors
16 was found not to pose a problem: all VIFs were less than 1.3.

17 Verb bias proved non-significant by likelihood ratio tests during model
18 comparison ($p = .26$), and so was removed from the model.

19 The probability of the outcome (NP PP vs NP NP) is a significant pre-
20 dictor of disfluency: more probable NP PPs and more probable NP NPs
21 are less likely to contain disfluencies. Additionally, sentences that are
22 spoken more quickly are less likely to contain disfluencies.

23 The size of the effect of probability on duration is small. For the
24 *to*-model, the predicted difference between the least and most probable
25 outcome in the actual data is just over 20ms, but since the data is so
26 heavily skewed towards likely outcomes, most datapoints are predicted
27 to have much more similar durations. The difference between an utter-
28 ance at the 25th percentile (the probability value which is greater than
29 the least probable 25% of the data) and the 75th percentile, for instance,
30 is predicted to be 15ms. Figure 1 shows the distribution of durations for
31 each utterances falling in each quartile. It is not entirely surprising that
32 the effect on duration should be so small: the word *to* is very short
33 (mean duration of 129ms). Although standardizing the regression inputs
34 does make coefficients more comparable (see Gelman 2008), the proba-
35 bility measures used here have quite skewed distributions: In particular,
36 the bigram probabilities are much less evenly distributed than the out-
37 come probabilities, with roughly two thirds of the probabilities smaller
38 than 0.05. This skewed distribution exaggerates the standardized effect
39 size of the bigram relative to the outcome probability. As a result, we
40 cannot directly compare the bigram and outcome probability effect sizes.
41 Even so, it is safe to say that the bigram probability has a greater effect
42 on duration than the outcome probability.



24 Figure 1. *Duration of tokens of to as a function of outcome probability. Bars indicate one*
25 *standard deviation*

26
27 The size of the effect of probabilities on disfluency was slightly
28 stronger: The probability of a disfluency in an average speed utterance
29 jumps from .27 among the highest probability outcomes to .40 among
30 the lowest probability outcomes.

31 To explore the effect of syntactic probability further, we additionally
32 examined its effect on the duration of other words besides *to*. Recall that
33 we chose the word *to* in the PP for methodological, rather than theoretical
34 reasons: the within-item analyses allowed us to minimize noise, as well
35 as to avoid prosodic and structural confounds. Even more importantly,
36 we needed a word that was sufficiently frequent in our database to allow
37 this kind of statistical analysis. To supplement our analyses, we in addition
38 investigated the words which appear as the first word of the second
39 argument in the NP NP outcome. We extracted all words that appeared
40 in this position at least 30 times in the database, and used the entire
41 Switchboard corpus to determine the average duration for each of these
42 words overall, to control to some extent for differences between words.

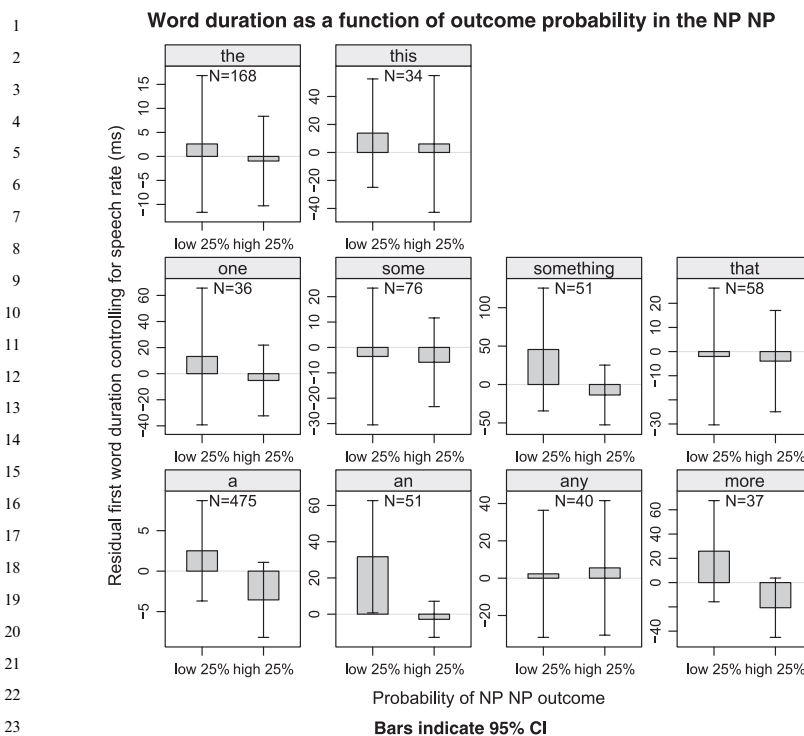


Figure 2. Average durations of words in initial position in the second argument of the NP NP construction. Bars indicate 95% confidence intervals

We do not report the resulting regression models here, except to note that a duration effect on the aggregated data is significant and similar to the model of *to*-duration. Figure 2 shows the durations for each of these words in low and high probability NP NP outcomes. It is clear that almost all the words show a similar effect: shorter duration when the actual outcome NP NP is more likely than the alternative. This suggests that the effect is not limited to the word *to* and that it shows up in both the NP NP and NP PP constructions.

5. Discussion

The goal of this study was to explore ways in which the probabilistic constraints on syntactic choice might be reflected in speakers' pronunciation of dative sentences. An additional goal was to ascertain whether this effect existed in spontaneous speech, or whether it was limited to the tightly-constrained artificial stimulus material used in previous studies.

1 Our crucial finding is that the probability of speakers' choice between
2 alternants is indeed reflected in pronunciation, in spontaneous speech.
3 While our previous findings on syntactic probabilities and pronunciation
4 variation in read speech might have arisen from garden-path effects, i.e.
5 a comprehension-based effect, the current results suggest that syntactic
6 probabilities affect language production. Several caveats are in order:
7 First, the observed effect on the duration of *to* was very small, and the
8 unexplained variability substantial. A related caveat concerns the fact
9 that the corpus data are heavily skewed towards likely syntactic choices:
10 low-probability outcomes are rare by their nature—a persistent problem
11 facing corpus-based research.

12 The small effect sizes and the sparseness of low-probability data raise
13 the question whether the observed effect was spurious. However, we
14 found the same probability estimate to be a significant predictor of dis-
15 fluency in both constructions. Moreover, the effect consistently seemed
16 to appear on other words in the NP NP construction. The pervasiveness
17 of these related patterns increase our confidence in their stability and
18 generalizability.

19 It may seem surprising that verb bias, a measure that had revealed itself
20 as a significant predictor of probabilistic pronunciation variation in pre-
21 vious research, did not emerge as a significant predictor in the current
22 data. On closer consideration, this fact is to be expected: verb bias is a
23 crude measure of the probability with which a speaker will choose each
24 construction. The detailed analysis in Bresnan et al. of the factors affect-
25 ing the dative alternation reveals that verb bias is overridden in many
26 cases by the host of other factors shown to play a role. Naturally, a crude
27 measure only reveals large effects—or small effects as long as other fac-
28 tors are tightly controlled, as was the case in the scripted stimuli in our
29 earlier work.

30 Our data do not enable us to say which of the many factors influencing
31 the choice of syntactic alternant carried the effect, or indeed whether any
32 single factor carried it. Our insistence that the dative choice is conditioned
33 on a multitude of factors might invite the objection that we only included
34 one summary measure in our models of phonetic variation, viz. the prob-
35 ability of the outcome conditioned on all of those factors. However, a
36 model including all factors as predictors of pronunciation variation
37 would be problematic, as it would unduly reflect phonetic properties of
38 particular words that tend to occur in one level of certain factors, rather
39 than the properties of those words that influence the syntactic outcome.
40 Hence, such a model would not have shed light on the role of syntactic
41 probabilities. Furthermore, the relatively small amount of data and the
42 large number of factors would have left us in danger of overfitting the

1 model to the specific data in our corpus; and the collinearity between
2 factors wouldn't have permitted us to see the importance of individual
3 factors with certainty.

4 The most promising way to tease apart the role of individual factors
5 probably lies in experimental research, for factorial manipulation of indi-
6 vidual factors. In this way, corpus studies and experimental research can
7 be mutually supportive. But again, it is possible that no single factor or
8 small set of factors would emerge as significant even then: the overall pat-
9 tern result from the entire collection of factors working in concert.

10 Our results add to the growing body of evidence that the acoustic real-
11 ization of words reflects higher-level linguistic information (Clark and
12 Wasow 1998; Gahl and Garnsey 2004). Taken together, these findings
13 argue for a model of language production in which high-level linguistic
14 representations of syntax and meaning are not strictly isolated from low-
15 level processes such as articulation and speech rate control, but where
16 information can flow between levels of representation. Computational
17 accounts that are consistent with the descriptive generalizations do exist.
18 For instance, *Uniform Information Density* (Aylett and Turk 2004; Levy
19 and Jaeger 2007) posits that speakers tend to make the rate at which
20 information is conveyed over the speech stream roughly constant, and
21 therefore more predictable words (which carry little information) should
22 be produced to take up a shorter duration than less predictable words.
23 This would be an efficient strategy for communication over the speech
24 channel, in that it makes utterances shorter without reducing the words
25 that the hearer would have the most difficulty reconstructing. While psy-
26 cholinguistic models of the language production system underlying these
27 effects that could accommodate these findings are not yet available, we
28 believe that current work on exemplar-based and usage-based models
29 may yield a useful formalization of the relevant processing units, thanks
30 to its ability to represent linguistic units at arbitrary levels of abstraction
31 and probabilistic tendencies between them.

32 Finally, our results add further evidence to the view that probabilistic
33 effects in language production are not due to probability of real-world
34 scenarios: There are multiple ways to express a given meaning. What we
35 have shown here is that meaning-equivalent alternants differ in pronun-
36 ciation, as a function of the syntactic probability.

37

38 **6. General conclusion**

39

40 Language production requires integrating many types of information.
41 The view of the mind that underlies this research is that language produc-
42 tion system is an adaptive system that comes to process those structures

1 most efficiently that it has processed most often in prior experience. But
 2 what aspects of prior language experience does the language production
 3 system keep track of? The present work supports the view that many fac-
 4 tors jointly shape speakers' probabilistic knowledge of language. We have
 5 arrived at this view based on corpus evidence, experimentation, and sta-
 6 tistical modeling. It is thanks to this methodological grounding that our
 7 theoretical models can explore the consequences of abandoning the sim-
 8 plifying assumptions of grammar as categorical and deterministic.

10 References

- 12 Allbritton, D. W., G. McKoon & R. Ratcliff. 1996. Reliability of prosodic cues for resolving
 13 syntactic ambiguity. *Journal of Experimental Psychology: Learning, Memory, & Cognition*
 14 22(3). 714–735.
- 15 Aylett, M. & A. Turk. 2004. The Smooth Signal Redundancy Hypothesis: A functional
 16 explanation for relationships between redundancy, prosodic prominence and duration in
 17 spontaneous speech. *Language and Speech* 47(1). 31–56.
- 18 Baayen, H. 2008. *Analyzing linguistic data: A practical introduction to Statistics using R*.
 19 Cambridge: Cambridge University Press.
- 20 Barlow, M. & S. Kemmer (eds.). 2000. *Usage-based models of language*. Chicago: CSLI.
- 21 Bell, A., J. Brenier, M. Gregory, C. Girand & D. Jurafsky. 2009. Predictability effects on
 22 durations of content and function words in conversational English. *Journal of Memory*
 23 *and Language* 60(1). 92–111.
- 24 Bell, A., D. Jurafsky, E. Fosler-Lussier, C. Girand, M. Gregory & D. Gildea. 2003. Effects
 25 of disfluencies, predictability, and utterance position on word form variation in English
 26 conversation. *Journal of the Acoustical Society of America* 113(2). 1001–1024.
- 27 Bod, R., J. Hay & S. Jannedy (eds.). 2003. *Probabilistic linguistics*. Cambridge, MA: MIT
 28 Press.
- 29 Borensztajn, G., W. Zuidema & R. Bod. 2009. Children's grammars grow more abstract
 30 with age—Evidence from an automatic procedure for identifying the productive units of
 31 language. *Topics in Cognitive Science* 1. 175–188.
- 32 Brants, T. & A. Franz. 2006. *Web 1T 5-gram*. Philadelphia, PA: LDC Data Consortium.
- 33 Bresnan, J. 2008. Is syntactic knowledge probabilistic? Experiments with the English dative
 34 alternation. In S. Featherston & W. Sternefeld (eds.), *Roots: Linguistics in search of its*
 35 *evidential base*, 75–96. Berlin & New York: Mouton de Gruyter.
- 36 Bresnan, J., A. Cueni, T. Nikitina & R. H. Baayen. 2007. Predicting the dative alternation.
 37 In G. Bourne, I. Kraemer & J. Zwarts (eds.), *Cognitive foundations of interpretation*, 69–
 38 94. Amsterdam: Royal Netherlands Academy of Science.
- 39 Bresnan, J. & T. Nikitina. 2007. The gradience of the dative alternation. In L. H. Wee &
 40 L. Uyechi (eds.), *Reality exploration and discovery: Pattern interaction in language and*
 41 *life*. Stanford: CSLI.
- 42 Bybee, J. & P. Hopper (eds.). 2001. *Frequency and the emergence of linguistic structure*
 (Typological studies in language 45). Amsterdam: John Benjamins.
- Bybee, J. 2002. Phonological evidence for exemplar storage of multiword sequences. *Studies*
in Second Language Acquisition 24(2). 215–222.
- Bybee, J. 2006. From usage to grammar: The mind's response to repetition. *Language* 82(4).
 529–551.

- 1 Clark, H. H. & T. Wasow. 1998. Repeating words in spontaneous speech. *Cognitive Psychology* 37(3). 201–242.
- 2 Clark, H. H. & J. E. Fox Tree. 2002. Using uh and um in spontaneous speaking. *Cognition*
- 3 84(1). 73–111.
- 4 Deshmukh, N., A. Ganapathiraju, A. Gleeson, J. Hamaker & J. Picone. 1998. Resegmentation
- 5 of Switchboard. International Conference on Spoken Language Processing, Sydney,
- 6 Australia, Australian Speech Science and Technology Association.
- 7 Erteschik-Shir, N. 1979. Discourse constraints on dative movement. In T. Givon (ed.), *Dis-*
- 8 *course and syntax*, 441–467. New York: Academic Press.
- 9 Fellbaum, C. 2005. Examining the constraints on the benefactive alternation by using the
- 10 World Wide Web as a corpus. In M. Reis & S. Kepser (eds.), *Linguistic evidence: Empiri-*
- 11 *cal, theoretical and computational perspectives*, 209–240. Berlin & New York: Mouton de
- 12 Gruyter.
- 13 Ferreira, V. S. & G. S. Dell. 2000. Effect of ambiguity and lexical availability on syntactic
- 14 and lexical production. *Cognitive Psychology* 40(4). 296–340.
- 15 Fox Tree, J. E. & H. H. Clark. 1997. Pronouncing “the” as “thee” to signal problems in
- 16 speaking. *Cognition* 62(2). 151–167.
- 17 Gahl, S. 2008. “Time” and “thyme” are not homophones: Word durations in spontaneous
- 18 speech. *Language* 84(3). 474–496.
- 19 Gahl, S. & S. M. Garnsey. 2004. Knowledge of grammar, knowledge of usage: Syntactic
- 20 probabilities affect pronunciation variation. *Language* 80(4). 748–775.
- 21 Gahl, S. & S. M. Garnsey. 2006. Syntactic probabilities affect pronunciation variation.
- 22 *Language* 82(2). 405–410.
- 23 Gahl, S., S. M. Garnsey, C. Fisher & L. Matzen. 2006. “That sounds unlikely”: Syntactic
- 24 probabilities affect pronunciation. 28th Annual Conference of the Cognitive Science Society,
- 25 CD-ROM.
- 26 Gahl, S. & A. C. L. Yu. (eds.). 2006. Special issue on Exemplar-based Models in Linguistics.
- 27 *The Linguistic Review* 23(3).
- 28 Garnsey, S. M., N. J. Pearlmutter, E. Myers & M. A. Lotocky. 1997. The contributions
- 29 of verb bias and plausibility to the comprehension of temporarily ambiguous sentences.
- 30 *Journal of Memory & Language* 37(1). 58–93.
- 31 Gelman, A. 2008. Scaling regression inputs by dividing by two standard deviations. *Statistics*
- 32 *in Medicine* 27. 2865–2873.
- 33 Godfrey, J., E. Holliman & J. McDaniel. 1992. Switchboard: Telephone speech corpus for
- 34 research and development. International Conference on Acoustics, Speech and Signal
- 35 Processing.
- 36 Green, G. 1971. Some implications of an interaction among constraints. In *Papers from the*
- 37 *seventh regional meeting*, 85–100. Chicago: Chicago Linguistic Society.
- 38 Green, G. 1974. *Semantics and syntactic regularity*. Bloomington: Indiana University
- 39 Press.
- 40 Gropen, J., S. Pinker, M. Hollander, R. Goldberg & R. Wilson. 1989. The learnability and
- 41 acquisition of the dative alternation in English. *Language* 65(2). 203–257.
- 42 Harrell, F. E. 2007. *Design*.
- Hawkins, J. 1994. *A performance theory of order and constituency*. Cambridge: Cambridge
- University Press.
- Johnson, K. 1997. Speech perception without speaker normalization: An exemplar model.
- In K. Johnson & Mullennix (eds.), *Talker variability in speech processing*, 145–165. San
- Diego: Academic Press.
- Jurafsky, D., A. Bell, M. Gregory & W. D. Raymond. 2001. Probabilistic relations between
- words: Evidence from reduction in lexical production [References]. In Joan Bybee and

- 1 Paul Hopper (eds.), *Frequency and the emergence of linguistic structure* (Typological
2 Studies in Language 45), 229–254. Amsterdam: John Benjamins.
- 3 Kuperman, V. & M. Pluymaekers, M. Ernestus & R. H. Baayen. 2007. Morphological predictability and acoustic duration of interfixes in Dutch compounds. *Journal of the Acoustical Society of America* 121(4). 2261–2271.
- 4 Lawless, J. & K. Singhal. 1978. Efficient screening on nonnormal regression models. *Biometrics* 34. 318–327.
- 5 Levy, R. & F. Jaeger. 2007. Speakers optimize information density through syntactic reduction. Twentieth annual conference on Neural Information Processing Systems.
- 6 Lieberman, P. 1963. Some effects of semantic and grammatical context on the production and perception of speech. *Language and Speech* 6. 172–187.
- 7 Pierrehumbert, J. B. 2001. Exemplar dynamics: Word frequency, lenition and contrast. [References]. In Joan Bybee and Paul Hopper (eds.), *Frequency and the emergence of linguistic structure* (Typological Studies in Language 45), 137–157. Amsterdam: John Benjamins.
- 8 Pierrehumbert, J. B. 2002. Word-specific phonetics. In C. Gussenhoven & N. Warner (eds.), *Laboratory phonology VII*, 101–140. Berlin: Mouton de Gruyter.
- 9 Pluymaekers, M., M. Ernestus & R. H. Baayen. 2005. Lexical frequency and acoustic reduction in spoken Dutch. *Journal of the Acoustical Society of America* 118(4). 2561–2569.
- 10 R Development Core Team. 2008. R: A language and environment for statistical computing. Vienna.
- 11 Schafer, A. J., S. R. Speer & P. Warren. 2005. Prosodic influences on the production and comprehension of syntactic ambiguity in a game-based conversation task. In J. C. Trueswell & M. K. Tanenhaus (eds.), *Approaches to studying world-situated language use*, 209–225. Cambridge, MA: MIT Press.
- 12 Shriberg, E. 2001. To ‘errrr’ is human: Ecology and acoustics of speech disfluencies. *Journal of the International Phonetic Association* 31(1). 153–169.
- 13 Szmrecsanyi, B. & L. Hinrichs. 2008. Probabilistic determinants of genitive variation in spoken and written English: A multivariate comparison across time, space, and genres. In T. Nevalainen, I. Taavitsainen, P. Pahta & M. Korhonen (eds.), *The dynamics of linguistic variation: Corpus evidence on English past and present*. Amsterdam: John Benjamins.
- 14 Trueswell, J. C., M. K. Tanenhaus & C. Kello. 1993. Verb-specific constraints in sentence processing: Separating effects of lexical preference from garden-paths. *Journal of Experimental Psychology: Learning, Memory & Cognition* 19(3). 528–553.
- 15 Wasow, T. 2002. *Postverbal behavior*. Stanford, CA: CSLI Publications.