INFLECTION VS. DERIVATION IN A DISTRIBUTIONAL VECTOR SPACE

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ABSTRACT: This paper is an attempt to assess empirically whether, as often stated in the literature, inflection is "semantically more regular" than derivation. We reformulate the observation in terms of the *stability of syntactic and semantic contrasts* within a morphological relation: inflectional contrasts are hypothesized to be more stable than derivational contrasts. We then propose an operational definition of contrasts between words as offset vectors in a distributional vector space of the kind familiar from distributional semantics. In the empirical part of the paper, we show that French data does validate the hypothesis for all pairings of an inflectional and a derivational relation that we were able to investigate.

KEYWORDS: inflection, derivation, distributional semantics.

1. INTRODUCTION[1]

The literature is divided on the relationship between inflection and derivation. Many morphologists, of various theoretical inclinations, hold that inflection and derivation are essentially the same thing (Robins, 1959; Di Sciullo & Williams, 1987; Bochner, 1993; Booij, 1996; Kœnig, 1999), or that there is at most a gradient distinction between canonical inflection and canonical derivation (Dressler, 1989; Corbett, 2010; Spencer, 2013). Many others on the contrary hold that there is an irreducible difference between the

[1] Aspects of this work were presented at the Paradigmo conference (Toulouse, June 2017), at LingLunch Paris Diderot (Paris, July 2017), at the Autumn School on Experimental Grammar (Cargèse, November 2017), and at the 18th International Morphology Meeting (Budapest, May 2018). We thank audiences at these events for their feedback, and two anonymous reviewers for detailed comments. This work was partially supported by a public grant overseen by the French National Research Agency (ANR) as part of the "Investissements d'Avenir" program (reference: ANR-10-LABX-0083), and by ANR project *Démonext* (reference: ANR-17-CE23-0005).

two (Matthews 1965, 1974; Anderson 1982; Perlmutter 1988; Aronoff 1994; Stump 2001).

It is striking how little empirical evidence is brought to bear on this issue: most of the discussions focus on conceptual arguments to the effect that inflection and derivation must or can't be similar. A family of empirical criteria for distinguishing the two has been elaborated, starting with Bloomfield (1933:224–226), and challenging cases are identified, but there are few if any attempts to operationalize such criteria on a larger scale to study the nature of the inflection-derivation divide.

We focus on one of the criteria that are discussed in the literature, sometimes called 'semantic regularity', and which we term **stability of contrast**. In a nutshell, inflection is supposed to be stable in its syntactic and semantic effects across lexemes (*books* is to *book* as *cats* is to *cat*), while derivation is expected to be less so (*delegation* is not to *delegate* as *election* is to *elect*).[2] The idea that inflection and derivation differ in this way is intuitively compelling, and has been stated repeatedly (Robins 1959: 125-126; Matthews 1974, 49-52; Wurzel 1989, 36; Stump 1998). However, to our knowledge, no previous study has attempted to define stability of contrast in an operational fashion, and to test on a large scale the validity of a difference between inflection and derivation: rather, all studies discuss intuitive semantic contrasts between hand-picked series of pairs of words.

In this paper we propose an operational definition of stability of contrast building on the distributional hypothesis in semantics: a series of pairs of words contrast in a stable way if their contexts of occurrence differ in a systematic, rather than a haphazard fashion. We can thus explore stability of contrasts using standard tools from distributional semantics (cf. Lenci 2008), by setting up a distributional vector space and examining how variegated are distributional differences between pairs of morphologically related words.

The main empirical contribution of the paper is a distributional study of stability of contrast in morphological families consisting of all inflected forms of a French verb and the forms of various other lexemes derived from that verb. We show that, across various morphological relations, inflectional contrasts are systematically significantly more stable than derivational contrasts.

2. CONCEPTUAL MOTIVATION

2.1 Inflection and derivation as two kinds of morphology

[2] Example from Matthews 1974, p. 51.

Implicit consensus within what Stump (2001) terms inferential-realizational approaches to inflection (starting with Chomsky 1965 and Matthews 1965, and including Anderson 1992, Zwicky 1985, Stump 2001, *inter alia*) is that an adequate description of inflection takes the form of a specification of how a lexeme's paradigm cells are filled. On the other hand, many authors are skeptical about the idea that the logic of paradigmatic organization be extended to derivation. First, while inflectional paradigms are finite and normally complete (defectiveness is exceptional), derivational families are unbounded (some combinations of derivational processes are recursive) and often have fuzzy fringes. Second, lexicalization seems to interact with derivation in a fashion that is not normally found for inflection: derived words tend to take on a life of their own, and are subject to shifts in meaning or usage independently of their base; while the content of inflectionally related words normally do not drift apart (again, there are interesting exceptions, but these are taken to be too rare to affect the design of the inflectional component). This has led many researchers to adopt what Fradin (2003) calls the *Lexeme and Paradigm* view, which essentially combines a Word and Paradigm view of inflection (describing the inflection of a lexeme is describing the makeup and structure of its paradigm) with an Item and Process view of derivation (describing derivation is describing processes deriving one lexeme from another lexeme).

Although this view of the respective role of inflection and derivation has never been completely agreed upon, with some authors highlighting the occurrence of essentially paradigmatic phenomena within derivational families (e.g. van Marle, 1984; Becker, 1993; Bochner, 1993; Booij, 1996; Bauer, 1997), it has long served as a central conceptual motivation for assuming a strict divide between inflection and derivation, despite the lack of clear-cut empirical criteria for telling them apart.

2.2 Empirical criteria

Many morphologists, starting with Bloomfield (1933), have provided lists of criteria for distinguishing inflection from derivation, which are typically accompanied by examples of problematic cases highlighting the unreliability of individual criteria and the empirically fuzzy nature of the distinction. For concreteness, we briefly outline Stump's (1998) carefully formulated list.

(1) a. **Change in lexical meaning or part of speech**: if two morphologically-related words have distinct lexical meaning or part of speech, they must be related by derivation.

b. **Syntactic determination**: if the syntactic context determines which of two morphological types of words must be used, the distinction between these two types must be inflectional.

c. **Productivity**: inflection is generally more productive than derivation.
d. **Semantic regularity**: inflection is semantically more regular than derivation.
e. **Closure**: inflected words cannot be subject to further derivation, while derived words can be subject to further inflection.

A few remarks are in order about these criteria. First, (1a), (1b) and (1e) have only partial applicability. For instance, (1a) does not help decide the status of pairs of words with the same part of speech and lexical meaning. Second, conversely, (1c) and (1d) are gradient, and hence by nature cannot provide a sharp divide between inflection and derivation. Third and most importantly, the criteria are formulated in terms of high-level morphological notions that are not easy to operationalize, such as 'having distinct lexical meaning' (how does one decide what is lexical vs. non-lexical within meaning?), 'morphological type of word' (how does one decide the appropriate granularity for belonging to the same type?), or 'semantic regularity'.[3] As a result, even if the criteria were fully satisfactory from a conceptual point of view, they would not help directly decide whether a particular morphological relation should be classified as inflectional or derivational.

2.3. Stability of contrasts

Our goal in this paper is to propose an explicit operationalization of (1d) and test its validity. However, we prefer to avoid the term 'regularity', which suggests either a normative or a psycholinguistic distinction between regular and irregular. We suggest instead the more explicit notion of 'stability of contrast':

(2) **Stability of contrast**: the morphosyntactic and semantic contrasts between pairs of words related by the same *inflectional* relation are more similar to one another than the contrasts between pairs of words related by the same *derivational* relation.

A number of remarks are necessary to make sense of the proposal in (2). First, stability of contrast is based on the notion of a morphological *relation* rather than that of a morphological *category*: we will be comparing e.g.

[3] The one exception here is productivity, for which there are relatively good operationalizations (see e.g. Baayen 2001). However, as Gaeta (2007) shows, such operationalizations do not provide a categorical cut-off point between "fully productive" inflection and "partially productive" derivation. On the contrary, some derivational processes are more productive than some inflectional processes.

the relation between singular and plural nouns and the relation between infinitive verbs and singular action nouns. Second, morphological relations are defined in terms of content, not form (Štekauer, 2014; Bonami & Strnadová, 2018): to decide whether two words are related by relation *R*, we examine how their meanings and syntactic properties relate to one another, not what the exact alternation between their forms is.[4] This allows us to abstract away from inflection classes and derivational affix rivalry.[5] Third, the notion of contrast lumps together semantic and possible morphosyntactic differences between pairs of words. This is motivated by the fact that it is often conceptually unclear whether some morphologically relevant contrast should be considered semantically potent: contextual inflection such as agreement or case is usually assumed not to convey a difference in meaning; in derivation, it is often claimed that action nouns and their verbal bases, manner adverbs and their adjectival bases, or relational adjectives and their nominal bases, are synonymous. Fourth, (2) is not formulated in terms of syntactic/semantic similarity between pairs of related words: we are not claiming that two words resemble each other more if they are related by inflection than if they are related by derivation. This might well be the case (see Wauquier 2015 for relevant evidence), but is conceptually distinct from semantic regularity. We claim instead that inflectionally related words differ from each other in a more stable fashion.

In the remainder of this paper, we propose a computational method based on distributional semantics to test empirically the validity of the stability of contrast conjecture.

3 METHOD

We propose here to employ the tools of distributional semantics in the study of the stability of contrasts in derivation and inflection. Distributional se-

[4] Note the implicit distinction between *morphological relatedness*, which relies on both form and content, and *morphological relations*, which are particular sets of pairs of morphologically related words meeting some syntactic or semantic criterion. For instance, both ⟨*eat*, *eater*⟩ and ⟨*salt*, *salty*⟩ are pairs of morphlogically related words, but they are not related by the same morphological relation. On the other hand, ⟨*state*, *statement*⟩ and ⟨*assert*, *assertion*⟩ instantiate the same verb-action noun morphological relation, despite the fact that they are linked by distinct formal alternations.

[5] Note that we presuppose that there is consensus on what the relevant morphological relations are for one system. This is not a trivial issue, since different levels of granularity could be adopted. For instance, should the Verb-Agent and Verb-Instrument relations be considered distinct? Such decisions do have an incidence on our calculations, since more fine-grained relations will lead to less distributional diversity. We leave the exploration of such issues for future research.

mantics encodes statistical patterns of usage of a word-form in a vector representation. Such representations for different words can be compared using numerical measures. Since distributional vectors are created for all word forms at once on a large scale, they allow us to perform a systematic study of word pairs in any given relation, morphological or semantic, provided the relevant word forms are sufficiently frequent in corpora.

3.1 Distributional Hypothesis

Distributional semantics is a computational approach to representing information about words based on the distributional hypothesis. In a nutshell, the underlying assumption here is that properties of a word, including semantic properties that are otherwise notoriously hard if not impossible to characterize systematically, are reflected in and can be inferred from the distribution of the word in texts. The philosophical underpinnings are aptly summarized in the famous quote by the British linguist and philosopher of language John R. Firth: "You shall know a word by the company it keeps" (Firth 1951/1957).

Exact formulations of the distributional hypothesis vary. Most important empirical support of distributional models comes from modeling of semantic similarity and relatedness of words. Distributional properties of a word can be encoded in a numeric vector (see more details below), and vector similarity measures such as the cosine of the angle between the vectors strongly correlate with human judgements on lexical similarity and relatedness. As the result of this overwhelming attention to semantic similarity in empirical work, the distributional hypothesis itself is sometimes formulated in terms of similarity, e.g.:

> "The degree of semantic similarity between two linguistic expressions A and B is a function of the similarity of the linguistic contexts in which A and B can appear." (Lenci 2008: 3)

Our focus here, however, is on word-to-word relations rather than on similarity.

3.2 Vector space models as a computational realization of the distributional hypothesis

Before we apply the distributional machinery to morphological relations, a few words are in place on the exact nature of distributional representations. We adopt a common formalization of relations as *vector offsets* representing the difference between two word vectors. The word vectors themselves, embedded in a multidimensional semantic space, realize an interpretation of the distributional hypothesis. Namely, "the company a word keeps" is formalized as a statistical pattern of the word's association with various contexts. The kinds of contexts that are taken into account vary across different models. For example, in Latent Semantic Analysis (LSA, Landauer and Dumais 1997) and Topic Models (Griffiths et al. 2007) contexts are defined as the documents a word occurs in, as exemplified in Table 1.

	doc1	doc2	doc3	doc4	doc5	doc6	...
jury	17	0	4	0	0	0	...
election	14	0	3	0	4	5	...
bill	0	18	0	0	0	0	...
bills	0	2	5	0	0	0	...

TABLE 1. WORD-DOCUMENT COOCCURRENCE MATRIX

In other approaches, contexts are defined as other words occurring within a proximity to a given one, for example within a window of 2 words to the right or to the left. In this case the rows of the cooccurrence matrix are words rather than documents, as shown in Table 2.[6]

	the	, (comma)	*be*	*owner*	*walk*	...
dog	5176	4628	3195	245	237	...

TABLE 2. WORD COOCCURRENCE FREQUENCIES OF THE WORD *DOG*[7]

As the last example shows, raw cooccurrence counts are not always informative about the word's meaning. It is typical to normalize the counts converting them into association scores using various weighting schemes. One popular weighting method is pointwise mutual information (PMI), which highlights the word's association with rare contexts (Church and Hanks 1990):

	the	, (comma)	*be*	*owner*	*walk*	...

[6] One can think of the context words as defining a virtual 'document' with all words occurring next to it in the corpus.
[7] Frequency counts from the UKWAC web corpus (Baroni et al. 2009).

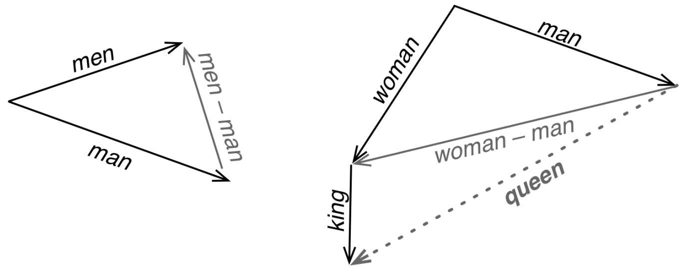
dog	1.6	1.52	1.56	3.05	2.73	...

TABLE 3. PMI ASSOCIATION SCORES BASED ON WORD COOCCURRENCE

Machine-readable corpora are now very large, leading to contexts consisting of millions of words or documents; the data in cooccurrence matrices is typically very sparse, with information in many of the cells missing. A common further step is hence to overcome data sparsity by applying a dimensionality reduction technique such as Singular Value Decomposition (SVD) or one of its numerous alternatives. Under dimensionality reduction, a small fixed-size vector is estimated for each word and each context, such that it allows to approximately reconstruct the association score of the word and the context, ass(w,c) ≈ vector(w) * vector(c). Recently, methods involving artificial neural networks have been proposed to efficiently estimate word and context vectors (Mikolov et al. 2013, Pennington et al. 2014, Bojanowksi et al. 2016), showing impressive performance on various tasks. At the heart, however, neural models are doing the same task as the previous generation dimensionality reduction techniques such as SVD, estimating word and context vectors that allow to approximate the association between them (see Levy and Goldberg 2014).

3.3 Relations as vector offsets in distributional semantics

If word forms are represented as vectors, relations between them can in turn be represented as shifts in the vector space. For example, if *man* and *men* are vectors for corresponding words, the difference vector *men* – *man* encodes the relation between the distribution of the plural and singular forms of the noun. This is represented schematically, in a two-dimensional vector space, in Figure 1a. Indeed, many approaches in computational semantics have adopted this formalization of the semantic shift between word forms as a word vector difference. For example, Mikolov et al. (2013) proposed a method of solving semantic analogies based on difference vectors, or vector offsets. Their model assumes that in cases of lexical analogy (such as *king* : *queen* :: *man* : *woman*), pairs of words in analogical relations have similar vector offsets. It follows that a missing member of the analogy can be estimated using vector offset from another pair, as shown in Figure 1b: the vector for *queen* can be approximated by the vector for *king* summed with the *woman* – *man* offset vector. The offset vector $x - y$ has also been used as the input representation in various approaches to the identification of lexical relations, in particular hypernymy (Roller et al., 2014; Weeds et al., 2014; Fu et al., 2014).



(a) plural ≈ men – man (b) queen ≈ king + (woman – man)

FIGURE 1: TOY EXAMPLES OF VECTOR ARITHMETICS

Without sharing the strong assumptions behind the semantic-analogy-as-offset-identity method, we rely here on distributional vector differences as a characterization of relations between words. Specifically, we measure the consistency of semantic vector offset as an operationalization of contrast predictability. For every type of relation (e.g. singular vs. plural form of a noun, verb vs. action noun) we can compute how consistent the shift is. We do this by calculating the variance of the offset vector, i.e. the mean Euclidian distance between individual offset vectors and the average offset for the relation.[8] The average relation offsets were calculated separately for each sample of triples. If derivational relations tend to be less semantically consistent, we also expect the variance of the derivational offset vectors to be greater than in the case of inflectional ones. We describe below in more detail how we test this hypothesis on French morphological data.

3.4 Distributional Implementation adopted

For the experiments reported in this paper, we trained a distributional semantic model on the FRWAC corpus, a large corpus of the French language collected using the WaCKy methodology (Baroni et al. 2009). The corpus was collected by web crawling pages from the .fr domain, with medium-frequency words from the *Le Monde Diplomatique* corpus and basic French vocabulary lists as seeds.

For the distributional model, we chose among many possible options the one identified as the best according to the thorough evaluation by Baroni et al. (2014): a continuous bag of words (CBOW) model with negative sampling (10 negative samples), subsampling, window size 5 and vector size of 400. Simplifying for expository purposes, one can say that the CBOW model estimates vectors for words matching them with contexts in which they oc-

[8] Another measure, cosine similarity between individual offset vectors and the average offset for the relation, gives similar results when applied to our data.

cur, in full accordance with the distributional hypothesis. For any occurrence of the word w, the context is represented by the surrounding words (e.g. 5 tokens around the given word occurrence). The average of the vectors of these context words *c* surrounding *w* is computed as the representation of the context average(vector(*c*)). This context representation is also referred to as the Continuous Bag of Words, meaning that the representations are vectors of continuous values and the order information is lost ("bag of words"). Vector dimension values are adjusted so that average(vector(*c*)) is most similar to vector(*w*). At the same time the model makes sure that different words get contrasting representations. This is achieved by the technique called negative sampling: the objectives of the model include that the CBOW representation average(vector(*c*)) be as distinct as possible from the vectors of randomly chosen words *w'*, so called negative samples. The model uses standard techniques of gradient descent to search for the best values of word and context vector dimensions. See Mikolov et al. (2013) for details on the model architecture and a further explanation of the parameters.

Having estimated CBOW vectors for French tokens, we compute the vector offsets for word pairs of interest. As the next step, we average the offset vector for word pairs in any specific relation (e.g. 3sg Present vs. 3pl Present forms). This gives us a numeric representation of the mean shift in usage for the word pairs instantiating the relation, e.g. the mean shift in usage between singular and plural forms of verbs in the Present tense.

Relying on offset vectors, we can immediately assess the issue of stability of content in derivational and inflectional relations. Note that word vectors in different instantiations of the same relation can be quite different (*laver* vs. *dormir*, *lavait* vs. *dormait*), but corresponding vector offsets (vector(*laver*) – vector(*lavait*) and vector(*dormir*) – vector(*dormait*)) are expected to be similar to each other. Note that we are not examining the distance between word meanings but the distance between *shifts* in meaning; the units of comparison are word pairs as represented by offset vectors rather than individual words.

As a methodological clarification, we need to emphasize that all the linguistic units that we use to compute vectors are word forms rather than lexemes. It is possible to obtain distributional vector for a lexeme (abstracting away from the specific morphological forms in which it is attested in texts), and some distributional models do just that, e.g. replacing all word forms in corpora by the vocabulary form (this procedure is known as lemmatization). Our task, however, includes comparing inflectional forms of the same lexeme, so we did not apply any lemmatization when training the distributional model. By extension, although derivation is often seen as a relation between lexemes rather than word forms, in our experiments we effectively compare word forms as derivationally related entities (e.g. the verb infinitive and the singular form of the action noun). This is necessary to make meaningful comparison of derivational and inflectional relations, and also has the advantage of not committing us to any hypothesis on the nature of abstract lexical items.

4 EMPIRICAL RESULTS

4.1. Outline of our method

Different semantic relations, be they derivational or inflectional, cannot be compared without preliminary data selection. Relations will differ in the frequency and the semantic classes of words typically instantiating them, as illustrated by the examples in Table 4. A verb's aktionsart influences the likelihood of it being found in different inflectional aspectual variants: atelic verbs such as *dormir* 'sleep' are more commonly found in imperfective forms, while telic verbs such as *endormir* 'fall asleep/put asleep' are more commonly found in perfective forms. Similar contrasts are found for derivational relations, and tend to be more extreme because of the effects of lexicalization.

(a) Sample inflectional relation

PST.IPFV.3SG		PST.PFV.3SG	
dormait	2103	*dormit*	224
endormait	210	*endormit*	600

(b) Sample derivational relation

Verb		Agent noun	
confesser	1305	*confesseur*	702
professer	357	*professeur*	113105

TABLE 4: FREQUENCY IN FRWAC OF A SAMPLE OF INFLECTIONALLY OR DERIVATIONALLY RELATED WORDS.

To test stability of contrasts as discussed in sections 1 and 2, we construct word form triples involving a first *pivot* word that stands in an inflectional relation with the second, and a derivational relation with the third word. For each triple, we compute vector offsets between the pivot and the other two forms. To best isolate the factor of inflectional vs derivational relation, we make sure that the two forms compared to the pivot have similar frequencies.

By hypothesis, we expect the vector offsets for derivationally-related pairs to be more diverse than those for inflectionally-related pairs. We employ the Euclidian distance between the vector offsets and the mean vector for the same relation as our main measure of diversity. This is illustrated schematically in Figure 2. The null hypothesis in *t*-test analysis is that the means of the two paired samples are identical. The contrast stability hypothesis will be confirmed if the deviation from average is greater for derivational relations than for inflectional ones with a significant *t*-test value. The paired samples for relations R_1 and R_2 in our case consist of pairs $\langle w_0,w_1\rangle$ and $\langle w_0,w_2\rangle$, where $\langle w_0,w_1\rangle$ stand in relation R_1 and $\langle w_0,w_2\rangle$ are in relation R_2. Since w_0 is shared between the two relations, the relation samples are paired. Essentially, we look at triples of morphologically related forms, one of which w_0 is used as the pivot for comparison.

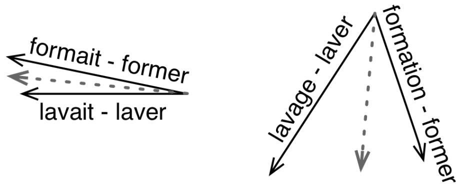


FIGURE 2: GRAPHICAL ILLUSTRATION OF THE CONTRAST STABILITY HYPOTHESIS. The distance between individual offset vectors (solid black lines) and their respective average vectors (dotted grey lines) is larger for derivationally-related words than for inflectionally related words.

Our data include samples from 174 systems of triples identified by a pair of an inflectional and a derivational relation (see below on data selection). These sets of triples constitute *paradigmatic systems* in the sense of Bonami & Strnadová (2018): collections of partial morphological families structured by the same set of syntactic/semantic contrasts.

For each of the 174 systems, we compute the vector offset averages for the two relations. Then, we compute the Euclidian distance between each individual vector offset and the average vector. Lastly, we perform a paired *t*-test to assess whether there is a significant difference in distance to the average between the vector offsets for the two compared classes.[9]

4.2. Data selection

We selected data using existing derivational and inflectional resources for French. We first extracted all derivational families documented in the *Démonette* database (Hathout and Namer, 2014), consisting of citation forms for at least two lexemes among (i) a verb, (ii) a masculine agent and/or instrument noun in *-eur*, (iii) an action noun. Families with multiple members of the same category were excluded. We expanded these partial derivational

[9] We used the paired sample two-tailed Student's *t*-test as implemented in the SciPy package (scipy.stats.ttest_rel).

paradigms by adding 1298 hand-validated deverbal adjectives in *-able* selected in the GLÀFF lexicon (Hathout et al., 2014), a large inflectional lexicon derived from the French version of Wiktionary. Finally, we used the GLÀFF to tabulate all inflected forms of all relevant lexemes; only those lexemes with inflected forms documented in the GLÀFF were kept, and all words that have a homograph in the GLÀFF were discarded. The resulting dataset hence forms a table of 6576 rows each documenting a partial morphological family and 59 columns documenting distinct morphological categories of words.[10] The average size of families is of 11.8 words.

We then used this full dataset to extract relevant collections of triples of words. We explored all combinations of three columns in the table $\langle p,i,d\rangle$, where p, the *pivot*, and i, the *inflectional comparandum*, correspond to two paradigm cells of the same lexeme, and d, the *derivational comparandum*, corresponds to a paradigm cell of a distinct, derivationally related lexeme. For each of the 16,878 such combinations, we determined whether one could find a collection of 100 triples $\{\langle x_1,y_1,z_1\rangle, \langle x_2,y_2,z_2\rangle, \ldots, \langle x_{100},y_{100},z_{100}\rangle\}$ such that, (i) all 300 words have an absolute frequency of at least 50 in FRWAC; (ii) the frequency ratio between each pair $\langle y_i,z_i\rangle$ is between 0.2 and 5.[11] Only 174 triples of columns (1% of the total possibilities) survived this selection process.

When a triple of columns met our criteria, we selected the 100 word triples with a median frequency ratio as close to 1 as possible and minimal dispersion of frequencies. We thus worked with 174 distinct sets of 100 carefully selected triples that were as consistent in their frequencies as possible. Each of these collections of triples forms a small paradigmatic system combining an inflectional relation and a derivational relation. Table 5 exhibits one of these systems.

[10] 53 forms for each verb, 2 for each *-eur* noun, 2 for each action noun, 2 for each *-able* adjective. Note that all *-able* adjectives have syncretic masculine and feminine forms; hence we included only two, gender-neutralized form per adjectival paradigm.

[11] The first filter ensures that each word has enough occurrences for vectors to capture some aspects of its distribution. The second filter is necessary because the quality of vectors is heavily dependent on frequency. We compensate for this by making sure that we compare words of similar frequency.

Pivot: Verb infinitive	Inflectional comparandum: Verb PST.IPFV.3SG	Derivational comparandum: SG *-eur* noun	Frequency ratio
posséder	*possédait*	*possesseur*	0.349
changer	*changeait*	*changeur*	0.356
prolonger	*prolongeait*	*prolongateur*	0.380
entendre	*entendait*	*entendeur*	0.389
sonner	*sonnait*	*sonneur*	0.390
…	…	…	…
pronostiquer	*pronostiquait*	*pronostiqueur*	0.931
mettre	*mettait*	*metteur*	0.935
régler	*réglait*	*régleur*	0.940
effacer	*effaçait*	*effaceur*	0.950
baigner	*baignait*	*baigneur*	0.964
contenir	*contenait*	*conteneur*	1.002
allumer	*allumait*	*allumeur*	1.003
brûler	*brûlait*	*brûleur*	1.009
afficher	*affichait*	*afficheur*	1.027
ramasser	*ramassait*	*ramasseur*	1.055
…	…	…	
livrer	*livrait*	*livreur*	2.047
reprendre	*reprenait*	*repreneur*	2.074
écumer	*écumait*	*écumeur*	2.127
demander	*demandait*	*demandeur*	2.169
envahir	*envahissait*	*envahisseur*	2.184

TABLE 5: A SAMPLE PARADIGMATIC SYSTEM CONTRASTING INFLECTION AND DERIVATION. We show only the 10 triples with extreme frequency ratios and the 10 triples closest to the median.

4.3. Empirical results

In all 174 systems, we found a higher dispersion around the average for vector offsets between derivationally related words than for vector offsets between inflectionally related words. This difference is statistically highly significant ($p < 0.001$) in all but 2 cases.[12] The effect of derivational vs. inflectional contrast on variance is typically medium in size (average Cohen's d of 58%). Table 3 presents a sample of these results, illustrating the diversity of triples that were explored. In particular, we have triples comparing two finite forms, two nonfinite forms, or a finite and a nonfinite form of a verb to a derived agent/instrument noun in *-eur*, an action noun, or an adjective; or two forms of a noun to a finite or nonfinite form of a verb. Note that we have triples that differ only in the choice of the pivot (e.g. ⟨Infinitive, IPFV.3SG, SG action noun⟩ vs. ⟨IPFV.3SG, Infinitive, SG action noun⟩) although this rep-

[12] Interestingly, both of these cases represent borderline instances of the inflection-derivation divide, including an infinitive, a participle, and an action noun.

resents only a small portion of the systems under examination, as it is seldom the case that the frequency distribution of 3 morphological series are similar enough for this. The full results can be found in the appendix.

Pivot	Inflectional comp.	Variance	Derivational comp.	Variance	*t* statistic	*p*-value	Cohen's *d*
Infinitive	IPFV.3SG	2.8612	SG *-eur* N	3.2856	-9.6358	6.82E-16	0.8495
Infinitive	IPFV.3SG	2.8433	PL action N	3.1698	-8.1474	1.16E-12	0.7
Infinitive	PRS.PTCP	2.5703	PL action N	2.9170	-8.7947	4.63E-14	0.6042
Infinitive	PRS.3PL	2.8916	M.SG *-able* A	3.2872	-8.2444	7.17E-13	0.7095
IPFV.3SG	Infinitive	2.8246	PL action N	3.3884	-14.8729	5.58E-27	1.0358
IPFV.3PL	PRS.3PL	2.6169	PL action N	3.2839	-14.6943	1.28E-26	1.595
PRS.1PL	PRS.3PL	2.6859	PL action N	3.1643	-11.1871	2.87E-19	0.8024
FUT/3SG	PRS.2PL	2.5398	SG *-eur* N	2.9572	-9.4050	2.17E-15	0.476
SG action N	PL action N	2.9924	IPFV.3SG	3.2036	-6.8934	5.14E-10	0.3783
PL *-eur* N	SG *-eur* N	2.2573	PRS.PTCP	2.6185	-8.7404	6.07E-14	0.4036

TABLE 3: SELECTED RESULTS

Our study thereby brings about strong distributional evidence that derivational relations are less stable semantically than inflectional ones.

5 DISCUSSION

Our experiment compares different kinds of relations between word forms in a controlled, paired-sample setting. The results support the existence of a systematic contrast between derivational and inflectional relations. This finding fully agrees with existing theoretical literature and is meant to inform the ongoing debate on the status of derivation and inflection in language and cognition.

At the same time, while strongly supporting a difference between inflection and derivation in terms of stability of contrasts, our results do not necessarily entail that there is a categorical distinction. Our findings are in principle compatible with an alternative, less discrete view. It could be, for instance, that typical derivational contrasts and typical inflectional contrasts cluster around distinct points on the stability scale, but the scale itself is continuous and contains intermediate points and more subtle contrasts between relations. To assess this, we can look at the offset variance for collections of pairs of words related by inflectional vs. derivational relations. Figure 3 outlines the results of such an exploration, for the 190 derivational relations and 281 inflectional relations in our database instantiated by at least 10 pairs of words and meeting the same frequency criteria discussed in section 3. Although this should be confirmed by a more detailed investigation, Figure 3 strongly suggests that, while inflectional relations are more stable on average, no categorical cut-off point between inflection and derivation can be found.

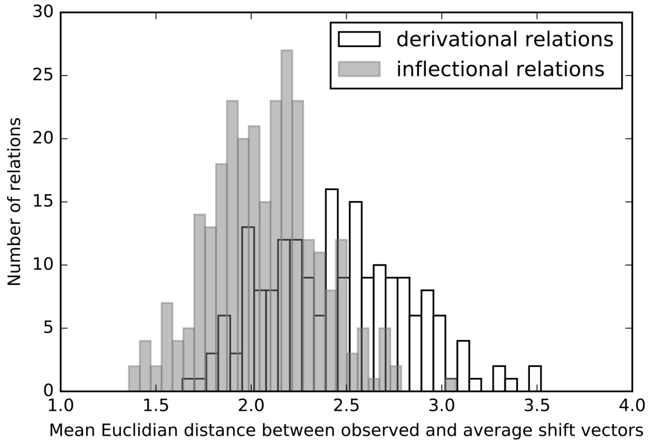


FIGURE 3 — HISTOGRAMS OF THE DISTRIBUTIONS OF OFFSET VARIANCE FOR DERIVATIONAL (WHITE) AND INFLECTIONAL (GREY) RELATIONS.

This observation leads to new open questions for future research. First of all, can we rank morphosyntactic features in terms of semantic predictability? It would be interesting to establish an objective ranking of morphological relations, and to get a firmer empirical grip on the idea (Dressler, 1989) that some morphological relations are non-prototypical inflection (e.g. plural) or non-prototypical derivation (e.g. diminutives). Second, if such a ranking can be established based on the distributional data for one language, does the ranking vary across languages? Linguistic literature suggests that the same relation can be inflectional in one language and derivational in the other, the prime example being aspect (e.g. Dahl, 1985); it would be interesting to test whether the more or less grammaticalized status of these phenomena in different languages is reflected in terms of semantic (and distributional) predictability.

Third, could we establish in such a ranking that distinctions of dubious status on the inflection-derivation divide (finiteness, voice, etc.) fall in the middle ground in terms of semantic predictability?

To summarize, the experiments reported in this paper both introduce new evidence that bears on important issues in theoretical morphology, and allow us to raise new questions. We hope to shed new light on these exciting questions in our future research.

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APPENDIX

The following table shows full results for 174 sets of 100 ⟨pivot, inflectional comparandum, derivational comparandum⟩ triples. The two cases where no statistically significant difference between the offset vector variances was observed are highlighted in boldface.

Pivot	Inflectional comparandum	Variance	Derivational comparandum	Variance	*t* statistic	*p*-value
ACT_pl	ACT_sg	2.9151	V_pst.ptcp.m.sg	3.2428	-8.4799	2.22E-13
ACT_pl	ACT_sg	2.8393	V_inf	3.1693	-8.2097	8.51E-13
ACT_sg	ACT_pl	3.1155	V_prs.2pl	3.4002	-7.2699	8.48E-11

Pivot	Inflectional comparandum	Variance	Derivational comparandum	Variance	*t* statistic	*p*-value
ACT_sg	ACT_pl	3.1154	V_pst.ptcp.m.pl	3.2238	-3.9715	1.36E-04
ACT_sg	ACT_pl	3.0960	V_pst.ptcp.f.pl	3.2668	-6.6198	1.87E-09
ACT_sg	ACT_pl	3.0280	V_pst.ptcp.f.sg	3.1770	-5.4388	3.88E-07
ACT_sg	ACT_pl	3.0177	V_prs.3pl	3.2192	-5.6228	1.74E-07
ACT_sg	ACT_pl	2.9924	V_ipfv.3sg	3.2036	-6.8934	5.14E-10
ACT_sg	ACT_pl	2.9257	V_inf	3.0779	-4.4658	2.12E-05
ACT_sg	ACT_pl	2.9094	V_prs.ptcp	3.0394	-4.6576	9.97E-06
ACT_sg	ACT_pl	2.9073	V_pst.ptcp.m.sg	3.1258	-6.6500	1.62E-09
AGM_pl	AGM_sg	2.3385	V_prs.3pl	2.6764	-7.4271	3.96E-11
AGM_pl	AGM_sg	2.2947	V_pst.ptcp.m.sg	2.6685	-7.5981	1.72E-11
AGM_pl	AGM_sg	2.2752	V_prs.2pl	2.7614	-10.6799	4.07E-18
AGM_pl	AGM_sg	2.2573	V_prs.ptcp	2.6185	-8.7404	6.07E-14
AGM_pl	AGM_sg	2.1981	V_ipfv.3sg	2.6409	-10.7058	3.17E-18
AGM_sg	AGM_pl	2.4110	V_prs.3pl	2.8690	-11.3905	1.05E-19
AGM_sg	AGM_pl	2.3532	V_prs.2pl	2.8918	-12.2752	1.33E-21
AGM_sg	AGM_pl	2.3263	V_prs.ptcp	2.7554	-9.8384	2.46E-16
AGM_sg	AGM_pl	2.2492	V_ipfv.3sg	2.7290	-13.1700	1.72E-23
V_cond.3sg	V_inf	2.8216	ACT_sg	3.1431	-8.1671	1.05E-12
V_cond.3sg	V_prs.3pl	2.7103	ACT_pl	3.3366	-16.1690	1.56E-29
V_fut.3pl	V_inf	2.8537	ACT_pl	3.4788	-18.5239	6.11E-34
V_fut.3pl	V_inf	2.8321	ACT_sg	3.2051	-10.4078	1.41E-17
V_fut.3pl	V_prs.3pl	2.6292	ACT_pl	3.2910	-14.5800	2.17E-26
V_fut.3sg	V_inf	2.9145	ACT_pl	3.6317	-15.7866	8.64E-29
V_fut.3sg	V_pst.ptcp.m.sg	2.8997	ACT_pl	3.3854	-9.7909	3.13E-16
V_fut.3sg	V_inf	2.8960	ACT_sg	3.2170	-7.9466	3.12E-12
V_fut.3sg	V_pst.ptcp.m.pl	2.7192	ACT_pl	3.0206	-6.2520	1.03E-08
V_fut.3sg	V_prs.3pl	2.5821	ACT_pl	3.1895	-12.8203	9.32E-23
V_fut.3sg	V_prs.2pl	2.5398	AGM_sg	2.9572	-9.4050	2.17E-15
V_fut.3sg	V_prs.ptcp	2.4611	ACT_pl	2.9716	-10.2823	2.65E-17
V_fut.3sg	V_prs.1pl	2.3630	ABLE_m.sg	2.5993	-5.1079	1.58E-06
V_fut.3sg	V_ipfv.3sg	2.3196	AGM_sg	2.8899	-11.1343	3.74E-19
V_fut.3sg	V_ipfv.3sg	2.2582	AGM_pl	2.8592	-11.4229	8.90E-20
V_fut.3sg	V_ipfv.3sg	2.1892	ABLE_m.sg	2.4993	-6.4184	4.78E-09
V_inf	V_prs.2pl	2.9956	ACT_pl	3.2991	-8.4250	2.92E-13
V_inf	V_prs.2pl	2.9740	ABLE_m.sg	3.1892	-5.6339	1.66E-07
V_inf	V_prs.2pl	2.9592	AGM_sg	3.3366	-8.7870	4.81E-14
V_inf	V_prs.2pl	2.9439	AGM_pl	3.3349	-9.0132	1.55E-14
V_inf	V_pst.3sg	2.9401	AGM_sg	3.2301	-6.4891	3.44E-09
V_inf	V_ipfv.3sg	2.9364	ABLE_m.pl	3.1920	-5.9209	4.63E-08
V_inf	V_ipfv.3sg	2.9173	ABLE_m.sg	3.1513	-5.6793	1.36E-07
V_inf	V_prs.3pl	2.8916	ABLE_m.sg	3.2872	-8.2444	7.17E-13
V_inf	V_prs.1pl	2.8827	ABLE_m.sg	3.0795	-4.8775	4.11E-06
V_inf	V_fut.3sg	2.8717	ACT_pl	3.2799	-9.9885	1.28E-16
V_inf	V_ipfv.3sg	2.8612	AGM_sg	3.2856	-9.6358	6.82E-16
V_inf	V_fut.3sg	2.8548	ABLE_m.sg	3.1302	-7.2764	8.22E-11

Pivot	Inflectional comparandum	Variance	Derivational comparandum	Variance	*t* statistic	*p*-value
V_inf	V_ipfv.3sg	2.8500	AGM_pl	3.2507	-8.8043	4.41E-14
V_inf	V_ipfv.3sg	2.8433	ACT_pl	3.1698	-8.1474	1.16E-12
V_inf	V_pst.ptcp.f.pl	2.8001	AGM_sg	3.0467	-7.8960	4.01E-12
V_inf	V_prs.3pl	2.7573	AGM_sg	3.2469	-10.1427	5.34E-17
V_inf	V_prs.3pl	2.7352	AGM_pl	3.2459	-10.3489	1.90E-17
V_inf	V_prs.ptcp	2.6978	AGM_pl	3.1933	-9.7835	3.25E-16
V_inf	V_pst.ptcp.f.pl	2.6970	ACT_pl	2.8708	-5.9765	3.61E-08
V_inf	V_pst.ptcp.m.pl	2.6669	ACT_pl	2.8730	-7.2353	1.00E-10
V_inf	V_prs.ptcp	2.6391	AGM_sg	3.1391	-10.5093	8.49E-18
V_inf	V_pst.ptcp.f.sg	2.6377	ACT_pl	2.8711	-7.0496	2.44E-10
V_inf	V_pst.ptcp.m.pl	2.6370	AGM_sg	2.8708	-6.9205	4.52E-10
V_inf	V_prs.3pl	2.6231	ACT_sg	2.9174	-4.8510	4.57E-06
V_inf	**V_pst.ptcp.f.sg**	**2.6027**	**ACT_sg**	**2.6399**	**-1.1011**	**0.274**
V_inf	V_prs.3pl	2.5962	ACT_pl	2.9635	-8.7821	4.93E-14
V_inf	V_pst.ptcp.m.sg	2.5901	ACT_pl	2.9375	-8.4864	2.15E-13
V_inf	V_prs.ptcp	2.5703	ACT_pl	2.9170	-8.7947	4.63E-14
V_inf	**V_pst.ptcp.m.sg**	**2.5597**	**ACT_sg**	**2.6213**	**-1.7906**	**0.07641**
V_inf	V_pst.ptcp.m.sg	2.4540	AGM_sg	2.8494	-8.4984	2.03E-13
V_ipfv.3pl	V_inf	2.8802	ACT_pl	3.4474	-14.0081	3.17E-25
V_ipfv.3pl	V_inf	2.8487	ACT_sg	3.1124	-6.6007	2.05E-09
V_ipfv.3pl	V_prs.3pl	2.6169	ACT_pl	3.2839	-14.6943	1.28E-26
V_ipfv.3pl	V_prs.ptcp	2.4812	ACT_pl	2.9857	-10.1608	4.88E-17
V_ipfv.3pl	V_prs.2pl	2.4683	AGM_sg	2.8178	-6.8335	6.83E-10
V_ipfv.3pl	V_ipfv.3sg	1.9892	AGM_sg	2.6551	-12.1681	2.25E-21
V_ipfv.3sg	V_inf	2.9071	ACT_sg	3.1740	-6.3333	7.09E-09
V_ipfv.3sg	V_inf	2.8246	ACT_pl	3.3884	-14.8729	5.58E-27
V_ipfv.3sg	V_pst.ptcp.m.sg	2.7441	ACT_pl	3.2081	-9.9091	1.73E-16
V_ipfv.3sg	V_pst.ptcp.m.sg	2.7333	ACT_sg	3.0527	-7.0345	2.63E-10
V_ipfv.3sg	V_pst.ptcp.f.sg	2.6146	ACT_pl	2.9203	-5.8303	6.95E-08
V_ipfv.3sg	V_pst.ptcp.m.pl	2.5874	ACT_pl	2.8023	-4.7250	7.61E-06
V_ipfv.3sg	V_prs.2pl	2.5420	AGM_sg	2.8652	-7.9161	3.63E-12
V_ipfv.3sg	V_prs.3pl	2.4720	ACT_pl	3.0377	-12.3926	7.48E-22
V_ipfv.3sg	V_prs.3pl	2.3287	AGM_sg	2.9388	-10.6253	4.75E-18
V_ipfv.3sg	V_prs.ptcp	2.2899	ACT_pl	2.7569	-9.7971	3.03E-16
V_ipfv.3sg	V_prs.1pl	2.2750	ABLE_m.sg	2.4905	-4.3631	3.15E-05
V_ipfv.3sg	V_pst.3sg	2.1650	AGM_sg	2.6811	-10.7117	3.48E-18
V_prs.1pl	V_inf	2.9675	ACT_pl	3.5385	-13.5638	2.61E-24
V_prs.1pl	V_inf	2.9229	ACT_sg	3.2145	-8.2203	8.08E-13
V_prs.1pl	V_prs.3pl	2.6859	ACT_pl	3.1643	-11.1871	2.87E-19
V_prs.1pl	V_prs.ptcp	2.6376	ACT_pl	3.0600	-9.4962	1.37E-15
V_prs.2pl	V_pst.ptcp.m.sg	3.0607	ACT_pl	3.4807	-10.2022	3.96E-17
V_prs.2pl	V_inf	3.0353	ACT_pl	3.6523	-13.3982	5.76E-24
V_prs.2pl	V_inf	2.9417	ACT_sg	3.2933	-8.2988	5.47E-13
V_prs.2pl	V_pst.ptcp.m.pl	2.8751	ACT_pl	3.1203	-5.0610	1.93E-06
V_prs.2pl	V_prs.3pl	2.7007	ACT_pl	3.1640	-11.3263	1.44E-19

Pivot	Inflectional comparandum	Variance	Derivational comparandum	Variance	*t* statistic	*p*-value
V_prs.2pl	V_prs.ptcp	2.6312	ACT_pl	3.0776	-10.6752	3.70E-18
V_prs.2pl	V_prs.3pl	2.6117	AGM_sg	3.0377	-8.9354	2.29E-14
V_prs.2pl	V_prs.1pl	2.5397	ABLE_m.sg	2.8025	-5.3326	6.12E-07
V_prs.2pl	V_ipfv.3sg	2.5255	AGM_sg	2.9041	-8.2600	6.63E-13
V_prs.2pl	V_ipfv.3sg	2.4811	AGM_pl	2.8824	-8.5146	1.87E-13
V_prs.3pl	V_prs.2pl	2.7885	ABLE_m.sg	2.9698	-4.9952	2.56E-06
V_prs.3pl	V_inf	2.7714	ACT_sg	3.1909	-10.0255	9.62E-17
V_prs.3pl	V_prs.2pl	2.7157	AGM_pl	2.9993	-5.9782	3.58E-08
V_prs.3pl	V_prs.1pl	2.7098	ABLE_m.sg	2.9827	-6.8244	7.13E-10
V_prs.3pl	V_prs.2pl	2.7072	ACT_pl	2.8810	-4.0112	1.17E-04
V_prs.3pl	V_pst.ptcp.m.sg	2.7071	ACT_sg	3.0022	-5.9853	3.47E-08
V_prs.3pl	V_prs.2pl	2.6788	AGM_sg	3.0315	-8.8630	3.29E-14
V_prs.3pl	V_pst.3sg	2.6589	AGM_sg	3.0196	-7.6968	1.06E-11
V_prs.3pl	V_fut.3sg	2.6584	AGM_sg	3.2199	-10.7537	2.50E-18
V_prs.3pl	V_fut.3sg	2.6239	ABLE_m.sg	2.9649	-7.9205	3.55E-12
V_prs.3pl	V_pst.ptcp.m.sg	2.6033	ACT_pl	3.0241	-9.0794	1.11E-14
V_prs.3pl	V_inf	2.6011	ACT_pl	3.1738	-11.6160	3.42E-20
V_prs.3pl	V_ipfv.3sg	2.5746	ABLE_m.sg	2.9673	-9.2537	4.64E-15
V_prs.3pl	V_pst.ptcp.m.pl	2.5407	ACT_pl	2.8189	-7.2923	7.61E-11
V_prs.3pl	V_pst.ptcp.f.sg	2.5036	ACT_pl	2.8208	-7.2103	1.13E-10
V_prs.3pl	V_ipfv.3sg	2.4688	AGM_pl	2.9807	-10.2855	2.61E-17
V_prs.3pl	V_ipfv.3sg	2.4288	AGM_sg	2.9701	-10.7422	2.65E-18
V_prs.3pl	V_pst.ptcp.f.pl	2.2952	ACT_pl	2.5671	-7.7637	7.67E-12
V_prs.3pl	V_prs.ptcp	2.2161	AGM_pl	2.7814	-10.6192	4.90E-18
V_prs.3pl	V_prs.ptcp	2.1239	AGM_sg	2.6826	-10.9669	8.61E-19
V_prs.3pl	V_prs.ptcp	2.1048	ACT_pl	2.5127	-9.5160	1.24E-15
V_prs.ptcp	V_inf	2.7024	ACT_sg	2.9926	-8.4737	2.29E-13
V_prs.ptcp	V_pst.ptcp.m.sg	2.6591	ACT_sg	2.8656	-4.5948	1.28E-05
V_prs.ptcp	V_inf	2.6005	ACT_pl	3.1130	-10.6890	3.45E-18
V_prs.ptcp	V_pst.ptcp.m.pl	2.4695	ACT_pl	2.6687	-5.1460	1.35E-06
V_prs.ptcp	V_pst.ptcp.m.sg	2.4691	ACT_pl	2.8091	-7.9285	3.41E-12
V_prs.ptcp	V_pst.ptcp.f.sg	2.3777	ACT_pl	2.6533	-6.9050	4.87E-10
V_prs.ptcp	V_pst.ptcp.f.pl	2.2522	ACT_pl	2.4619	-6.0813	2.25E-08
V_prs.ptcp	V_prs.3pl	2.1174	AGM_pl	2.6567	-10.6421	4.37E-18
V_prs.ptcp	V_prs.3pl	2.1114	ACT_pl	2.5406	-9.6279	7.10E-16
V_prs.ptcp	V_prs.3pl	2.0231	AGM_sg	2.4499	-9.2055	5.92E-15
V_pst.3sg	V_inf	2.9150	ACT_pl	3.4377	-12.4436	5.83E-22
V_pst.3sg	V_inf	2.8710	ACT_sg	3.1172	-6.7146	1.20E-09
V_pst.3sg	V_pst.ptcp.m.sg	2.8189	ACT_pl	3.3221	-10.2620	2.94E-17
V_pst.3sg	V_prs.3pl	2.6386	ACT_pl	3.1304	-11.8594	1.03E-20
V_pst.3sg	V_prs.2pl	2.5646	AGM_sg	2.8876	-7.2054	1.16E-10
V_pst.3sg	V_prs.ptcp	2.4162	ACT_pl	2.8350	-9.4171	2.04E-15
V_pst.3sg	V_ipfv.3sg	2.1881	AGM_sg	2.7765	-11.2914	1.71E-19
V_pst.ptcp.f.pl	V_inf	2.9345	ACT_sg	3.0751	-4.5051	1.82E-05
V_pst.ptcp.f.pl	V_inf	2.6280	ACT_pl	2.9153	-7.2202	1.08E-10

Pivot	Inflectional comparandum	Variance	Derivational com-parandum	Variance	*t* statistic	*p*-value
V_pst.ptcp.f.pl	V_pst.ptcp.m.sg	2.5619	ACT_sg	2.7720	-4.6840	8.97E-06
V_pst.ptcp.f.pl	V_prs.3pl	2.4660	ACT_pl	2.7573	-7.0697	2.22E-10
V_pst.ptcp.f.pl	V_pst.ptcp.m.sg	2.4650	ACT_pl	2.7615	-7.3891	4.76E-11
V_pst.ptcp.f.pl	V_prs.ptcp	2.3550	ACT_pl	2.6050	-6.8718	5.70E-10
V_pst.ptcp.f.pl	V_pst.ptcp.f.sg	2.2032	ACT_pl	2.5536	-9.7201	4.46E-16
V_pst.ptcp.f.pl	V_pst.ptcp.m.pl	2.1762	ACT_pl	2.5812	-11.1998	2.70E-19
V_pst.ptcp.f.sg	V_inf	2.8088	ACT_sg	2.9443	-4.5001	1.85E-05
V_pst.ptcp.f.sg	V_prs.3pl	2.5510	ACT_pl	2.8714	-7.8572	4.85E-12
V_pst.ptcp.f.sg	V_inf	2.4237	ACT_pl	2.7726	-9.2245	5.38E-15
V_pst.ptcp.f.sg	V_prs.ptcp	2.3736	ACT_pl	2.6294	-6.8137	7.50E-10
V_pst.ptcp.f.sg	V_pst.ptcp.m.pl	2.3279	ACT_pl	2.7214	-10.9137	1.12E-18
V_pst.ptcp.f.sg	V_pst.ptcp.m.sg	2.2750	ACT_sg	2.5646	-6.6263	1.81E-09
V_pst.ptcp.f.sg	V_pst.ptcp.m.sg	2.2295	ACT_pl	2.7364	-11.0971	4.50E-19
V_pst.ptcp.f.sg	V_pst.ptcp.f.pl	2.1667	ACT_pl	2.5859	-10.3257	2.13E-17
V_pst.ptcp.f.sg	V_pst.ptcp.f.pl	2.1286	AGM_sg	2.6028	-11.8174	1.26E-20
V_pst.ptcp.m.pl	V_inf	2.7898	ACT_sg	2.9238	-4.1116	8.12E-05
V_pst.ptcp.m.pl	V_inf	2.5952	ACT_pl	2.8483	-6.6030	2.02E-09
V_pst.ptcp.m.pl	V_prs.3pl	2.5165	ACT_pl	2.7772	-7.1315	1.65E-10
V_pst.ptcp.m.pl	V_pst.ptcp.m.sg	2.3994	ACT_sg	2.6385	-7.0951	1.96E-10
V_pst.ptcp.m.pl	V_prs.ptcp	2.3514	ACT_pl	2.5343	-5.7666	9.23E-08
V_pst.ptcp.m.pl	V_pst.ptcp.m.sg	2.3251	ACT_pl	2.7018	-9.0252	1.46E-14
V_pst.ptcp.m.pl	V_pst.ptcp.f.sg	2.2746	ACT_pl	2.5502	-8.5597	1.50E-13
V_pst.ptcp.m.pl	V_pst.ptcp.f.pl	2.0960	ACT_pl	2.4751	-9.3951	2.28E-15
V_pst.ptcp.m.sg	V_prs.3pl	2.7801	ABLE_m.sg	3.1488	-8.4155	3.07E-13
V_pst.ptcp.m.sg	V_inf	2.6752	ACT_sg	2.9110	-8.4832	2.19E-13
V_pst.ptcp.m.sg	V_inf	2.6499	ACT_pl	3.1101	-11.0552	5.54E-19
V_pst.ptcp.m.sg	V_prs.3pl	2.5738	ACT_pl	2.9678	-8.3668	3.91E-13
V_pst.ptcp.m.sg	V_prs.3pl	2.5493	AGM_pl	2.9760	-9.9219	1.62E-16
V_pst.ptcp.m.sg	V_prs.3pl	2.5246	AGM_sg	2.9583	-8.9731	1.90E-14
V_pst.ptcp.m.sg	V_prs.ptcp	2.4769	AGM_sg	2.8583	-9.5109	1.28E-15
V_pst.ptcp.m.sg	V_pst.ptcp.f.pl	2.4558	ACT_pl	2.7854	-9.5695	9.51E-16
V_pst.ptcp.m.sg	V_prs.ptcp	2.4437	ACT_pl	2.7215	-7.6717	1.20E-11
V_pst.ptcp.m.sg	V_pst.ptcp.m.pl	2.4081	ACT_pl	2.8502	-11.2180	2.46E-19
V_pst.ptcp.m.sg	V_pst.ptcp.m.pl	2.2851	AGM_sg	2.7234	-10.7005	3.26E-18
V_pst.ptcp.m.sg	V_pst.ptcp.f.sg	2.2803	ACT_sg	2.5860	-7.0762	2.24E-10
V_pst.ptcp.m.sg	V_pst.ptcp.f.sg	2.2718	ACT_pl	2.7389	-10.9644	8.72E-19