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Effects of linguistic and usage-based factors on children's acquisition of English derivational morphology*

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Jun, Jongsup. 2014. Effects of linguistic and usage-based factors on children's acquisition of English derivational morphology. *Linguistic Research* 31(2), 325-356. Children must learn the variation in morphological productivity based on limited inputs. Previous studies have suggested several factors in the acquisition of derivational morphology. Some scholars have focused on semantic and phonological transparency, whereas others emphasize the role of input frequency. This paper explores the factors that influence children's acquisition and use of English derivational morphology. For this, we analyzed children's production of derived words in a million-word corpus taken from the CHILDES database. The data came from the voluntary production of derived words by 469 individuals at age 3-10. We extracted 7,234 derived words that were instances of 704 derivative types from the corpus, and conducted multiple regression analyses by using Baayen's (1993) *hapax-conditioned degree of productivity* as a function of several linguistic and usage-based factors. The results indicate that the family frequency of an affix in the input plays the most important role in the regression model, and that semantic and phonological transparency has only limited effects on the total variation. In particular, we discuss how a single principle can explain children's performance on derivational morphology at all ages, and how our new conception of *continuity* supports the view that language development should be constrained by both linguistic and usage-based factors. **(Hankuk University of Foreign Studies)**

Keywords productivity; derivational morphology; acquisition; CHILDES; usage-based grammar

* It took an unexpectedly long time to publish this paper. The data collection was done in the year of 2010 with the help of my graduate assistant Seung-ah Hong; the statistical analyses and the theoretical interpretation were carried out during my sabbatical leave at Carnegie Mellon University under the supervision of Brian MacWhinney in 2011; and I finally found time and funding to write up this paper. Naturally, my foremost gratitude goes to Seung-ah Hong for data collection and to Brian MacWhinney for discussion. I also thank Ray Jackendoff for many correspondences concerning earlier versions of this paper. Finally, I thank anonymous reviewers for critical comments and helpful suggestions for improvement. This work was supported by Hankuk University of Foreign Studies Research Fund of 2013.

1. Introduction

Children's acquisition of morphological productivity is a serious puzzle for linguistic theory (Jackendoff, 2010). Children must not only learn the regularity of a morphological process, but also determine the degree of productivity based on inputs. For instance, the agentive suffix *-er* is more productive than *-ist*, and English-speaking children at age 4 frequently substitute *-er* for *-ist*, not vice versa (Clark, 2003).[1] Certain generalizations do not hold for plausible candidates in many cases. For example, the morphological regularity found in '*create* → *creation*' or '*explore* → *exploration*' does not derive **incitation* from *incite*, or **ignoration* from *ignore*. As Jackendoff (2010, p. 33) points out, the degree of productivity "is not given in the data," but "everyone comes up with essentially the same answer."

The objective of this paper is to explore the factors that influence children's acquisition and use of English derivational morphology. In other words, we aim to explain children's use of derivational morphology at particular ages by using a quantitative model of productivity which is a function of linguistic and usage-based factors. To achieve this goal, we analyzed English-speaking children's production of derived words in a million-word corpus taken from the CHILDES database (MacWhinney and Snow, 1985, 1990)[2]. We extracted 7,234 derived words that were the instances of 704 derivative types from the corpus. The data came from the voluntary production of derived words by 469 individuals at age 3-10.[3]

In the corpus, preschool children used more derived words than previously reported. We adopted Baayen's (1993) *hapax-conditioned degree of productivity* as a quantitative measure of morphological productivity. The results of hierarchical multiple regression analyses indicate that various degrees of morphological productivity are well explained by a simple linear equation using the following

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1 In the same volume, Clark also introduces four-or-five-year-old children's rare innovations like *trumpetist* and *drummist*.

2 The target corpus of our study consists of two databases obtained from the CHILDES website: the HSLLD corpus (Dickinson and Tabors, 2001) and the Carterette and Jones corpus (Carterette and Jones, 1974; Jones and Carterette, 1963). For a detailed introduction of these databases, see 3.1.

3 Many children participated in the data collection at more than two age points. Because of the size and the inherent structure of the corpus, it is not possible to trace a particular subject's development of derivational morphology through a repeated measures design. For this reason, the 469 individuals do not represent 469 different subjects. We have considered a single subject as three individuals, if he/she participated in the data collection three times.

variables: children's age, the semantic transparency of derived words, the input frequency of the derivative types of a particular root, and the input family frequency of the derivative types of a particular affix. Most of all, the family frequency of an affix in caregivers' speech plays a critical role in the regression model, but the frequency of roots and the frequency of derived outputs are not significant factors in the acquisition of morphological productivity.

2. Previous studies on morphological productivity and the acquisition of derivational morphology

2.1 Problems of morphological productivity

As Bauer (2001) points out, defining *productivity* is a matter of dispute, although there is a general consensus among linguists that *productivity* refers to the property of language which allows us to produce what we have neither said nor heard before by applying the rules of grammar to novel instances. A classic demonstration of productivity is Berko Gleason's (1958) '*wug* test', in which children apply the productive rules of inflectional morphology to nonsense nouns like *wug*, and produce *wug-s* as the plural of *wug*. Clark and Hecht (1982) illustrate the same point with derivational morphology demonstrating that children use a more productive agentive suffix *-er* to express novel agents than less productive counterparts *-ist* and *-ian*. The term *productivity* sounds clear enough as long as we can find new coinages that share some regularity with existing words and phrases in controlled linguistic environments.

On the contrary, when we try to analyze large-scale data with reference to the standard definition of *productivity*, we immediately face the problem of emphasizing the potential for novel forms of language. The toughest problem is the presence of regularities that are not applied to plausible candidates. For instance, the morphological regularity found in '*create* → *creation*' or '*explore* → *exploration*' is not applied to the plausible candidates *incite* or *ignore* to produce **incitation* or **ignoration*. The English denominalization observed in *butter (the bread)* is blocked for **mustard (the bread)*. Jackendoff (1997, 2002, 2010) refers to these limited regularities as the *semiproductive* phenomena. To him, semiproductivity is governed by grammar, but the legitimate members that show semiproductivity must be listed in the lexicon. That is, the morphological regularity of suffixing -*(a)tion* to a verb stem is more or less confined to those cases that already exist in the lexicon, and hence such novel forms as **incitation* and **ignoration* are blocked.

Semiproductivity is a problem for language acquisition, since children have to learn essentially the same restrictions on morphological productivity. Jackendoff (2010, p. 33) proposed a plausible hypothesis for this puzzle: "children observing a regularity initially encode it as semiproductive, and later, if evidence warrants, upgrade it to productive." Nonetheless, we find children's overgeneralization errors in semiproductive processes. At the same time, children are conservative in applying existing generalizations to new items (Tomasello, 2003; recited from Jackendoff, 2010). In short, we need a more general theory of productivity to account for children's acquisition of derivational morphology.

2.2 Previous studies on the acquisition of derivational morphology[4]

Although derivational morphology plays an important role in theoretical linguistics (Anderson, 1992; Jackendoff, 2002, 2010), few studies have focused on the acquisition of derivational affixes.[5] One reason may be that children make limited use of derived words (Brown, 1973; Clark, 2003; de Villiers and de Villiers, 1973), and that the repertoire of their derivatives rarely shows the innovative use of derivational affixes.[6]

At the same time, there is a conceptual problem in assessing children's innovative uses of derivational morphology. Words like *runner* and *driver* may not

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4 This sub-section provides a critical overview of previous studies. Some part of the discussion overlaps with my own work (Author, 2011).

5 Preschool children's acquisition of English derivational morphology has been studied almost exclusively by Eve Clark and her colleagues in the 1980's (Clark, 1993, 2003; Clark and Berman, 1984; Clark, Carpenter and Deutsch, 1995; Clark and Cohen, 1984; Clark and Hecht, 1982). Clark observes that English-speaking children's first affixes are -*er*, -*ie*, and -*y*. These early suffixes occur in children's spontaneous speech around two-and-half years old.

6 Scholars tend to consider children's derivatives that do not exist in the adult lexicon as innovations. Clark (2003) reports such innovations as *brusher*, *gunner*, *clapper*, *reacher*, *sipper*, and *raker*. In general, one cannot learn much about the acquisition of derivational morphology from examining spontaneous innovations because preschool children strongly prefer compounds to derived words, and most innovative uses, if any, are restricted to derivatives of a few affixes like -*er*, -*ie*, -*ness* and *un*-.

be innovative uses to adult speakers. They may be fossilized lexical entries. On the other hand, the same words can be creative outputs of productive morphology to children. Although we generally have no evidence to determine whether a particular derivative produced by a child is a frozen expression or an innovation, we can indirectly access the problem by collecting data from controlled experiments.[7]

Clark and her colleagues have conducted several psycholinguistic experiments to examine children's acquisition of morphological productivity. Clark and Hecht (1982) tested preschool children's use of agentive suffixes with novel agents, and found that the *-er* suffix is more productive than *-ist* or *-ian*. In Clark and Cohen (1984), children were exposed to novel words ending in *-er*, *-ist*, or *-ian* with appropriate pictures, and later were asked to recall the correct word endings for the roots of the novel words. The result of the study was straightforward: the more productive the suffix, the better the recall.

At the end of the 1980's, there was a shift in research attention from preschool children to school-age children. Tyler and Nagy (1989) examined Grade 4, 6, and 8 students by using paper-and-pencil tests composed of multiple choice vocabulary questions; e.g. *You can* _______ *the effect by turning off the lights*. (Choices: *intensify*, *intensification*, *intensity*, *intensive*) (Tyler & Nagy's p. 656). They developed questions with specific designs to test children's relational, syntactic, and distributional knowledge. Overall, the higher the grade was, the better the child performed in the tests for the syntactic and distributional knowledge. They interpreted this as evidence for the late development of syntactic and distributional knowledge of English derivational morphology.

It is unclear whether Tyler and Nagy (1989) tested children's internal knowledge of the first language or their academic performance on a vocabulary exam.[8] They did

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7 A 3-year-old child in the HSLLD database (Dickinson and Tabors, 2001) produced *allegiance* by rote in the Pledge of Allegiance: *I pledge allegiance to the flag of the United States of America* ⋯ . Note that most of the derivatives spoken by children are not as clear cases as *allegiance* in terms of innovativeness.

8 Testing school-age children's academic performance to examine their knowledge of grammar should not be credited to Tyler and Nagy alone. Before Tyler and Nagy, Freyd and Baron (1982) tested Grade 8 and superior Grade 5 students by using a vocabulary exam, and concluded that superior students learned new words more efficiently because they were good at derivational morphology. Similarly, Templeton and Scarborough-Franks (1985) tested Grade 6 and 10 students, and concluded that children's capability of spelling was a good predictor to assess their knowledge of derivational morphological rules.

not include preschool children in the study. Their paper was entitled ‘The Acquisition of English Derivational Morphology’, but did not provide much information on the issue of acquisition except for Grade 4, 6, and 8 students' academic performance.

The tradition of testing school-age children’s academic performance continued in the 2000's. Deacon and Bryant (2006) tested whether school-age children used the knowledge of derivational morphology when they took the spelling test. Rabin and Deacon (2008) gave a fragment completion test to Grade 1-5 students, and used their exam scores to support the hypothesis that inflectional and derivational forms were similarly represented in the mental lexicon. In addition, Deacon et al. (2011) measured how fast and accurately Grade 4, 6, and 8 students read words on the screen, and found that students read high-frequency words faster and more accurately than low-frequency ones because they had access to the internal morphological structure of the high-frequency vocabulary.

Previous studies on the acquisition of derivational morphology have shown how difficult it is to obtain appropriate data and conduct a large-scale analysis that sheds light on the acquisition of morphological productivity. Clark’s studies were based on her longitudinal observation of a few children supplemented by psycholinguistic experiments. For this reason, her analysis was restricted to a small number of derived words produced by children at age 3-6. Previous studies considering school-age children have typically emphasized educational implications more than linguistic significance by interpreting elementary school students’ vocabulary exam scores as if they reflected linguistic knowledge.

A reasonable solution to this problem is to use a sufficiently large corpus in the CHILDES database (MacWhinney and Snow, 1985, 1990).[9] In this study, we combined the HSLLD corpus (Dickinson and Tabors, 2001) with the Carterette and Jones corpus (Carterette and Jones, 1974; Jones and Carterette, 1963) to obtain a million-word corpus. Thanks to the size of the combined corpus, we could extract 7,234 derived words that were instances of 704 derivative types. The data came from

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[9] MacWhinney (2000, p. 3) highlights this advantage of using the CHILDES database:

> In some cases, conclusions about individual differences in child language have been based on analysis of as few as two children, and rarely on groups larger than 25. ⋯ This problem arises in a particularly clear form when linguistic or psycholinguistic theory make predictions regarding the occurrence and distribution of rare events ⋯ Using the CHILDES database, a researcher can access data from a number of research projects.

the voluntary production of derived words by 469 individuals at age 3-10. Although we can overcome several limitations of previous studies by using a large-scale database, some conceptual problems remain in a corpus-based study. For instance, we still cannot determine whether a particular derivative produced by a child is a frozen expression or a real innovation. In this study, we assume that analyzing the 7,234 derived words through an elaborate statistical procedure would shed light on the acquisition of productive morphology.

3. Methods and procedures

3.1 The corpus and participants

We used a million-word corpus obtained from the CHILDES database (MacWhinney and Snow, 1985, 1990). In particular, we combined the HSLLD corpus (Dickinson and Tabors, 2001) with the Carterette and Jones corpus (Carterette and Jones, 1974; Jones and Carterette, 1963) because the two corpora included large samples of children in various age groups.

The HSLLD (Home-School Study of Language and Literacy Development) project was a decade-long study by researchers from the Harvard Graduate School of Education, Tufts University, Clark University, and the Education Development Center in Newton, Massachusetts. The primary investigators were Catherine E. Snow and David K. Dickinson. In the HSLLD project, speech transcripts were obtained from various modalities, i.e. discourse situations. The modalities included BR (Book Reading), ER (Elicited Report), MT (Mealtime), TP (Toy Play) among others.

The HSLLD corpus is a large-scale child language database tracing the language development of 83 American children from age 3 to 9. The project's original plan was to collect spontaneous speech data from the same children at different ages. However, because of the nature of a decade-long study, the numbers of participants varied over time. In particular, 74 of the 83 initial participants remained at age 5; but the number of children decreased to 68 by the time they were in the second grade.

The HSLLD corpus is originally organized in terms of the order of *home visits*. Because speech transcripts for each home visit do not precisely represent the same age group, we re-structured the data according to the age of each participant. Table 1 shows the number of participants in each age group.

Table 1. Number of participants by age in the HSLLD corpus

Age	3	4	5	6	7	8	9
# of Children	51	71	65	11	65	3	53

Most children belong to more than three age groups. In some cases, there were two home visits within one chronological year, and thus some children appeared twice in one age group. Note, however, that we are attempting to analyze a sizable corpus with a large number of participants, which is different from a controlled experiment with a fixed number of subjects. Some children may not appear in particular age groups, but we expect that losing several children will not significantly affect the result of the analysis. Because the corpus was large, and because the number of participants in each age group could not be controlled for thoroughly, we had to consider all participants in each age group as different individuals.

Because we do not have sufficient numbers of children at age 6 and 8 in Table 1, we supplemented the corpus with the Carterette and Jones corpus (Carterette and Jones, 1974; Jones and Carterette, 1963). The data in the Carterette and Jones corpus were collected from Grade 1, 3, and 5 school children as well as from adults, who engaged in casual conversation in groups of three individuals. In the present study, we used data from first-, third-, and fifth-grade students.[10] Table 2 summarizes the number of participants in the Carterette and Jones corpus.

Table 2. Number of participants by age in the Carterette and Jones corpus

Age	6	8	10
# of Children	54	48	48

We combined the HSLLD corpus with the Carterette and Jones corpus to obtain a

[10] We did not use the data from adults in the Carterette and Jones corpus because they had no social connections with the children. On the other hand, we employed the adult data in the HSLLD corpus because the data were collected from the children's caregivers' speech.

balanced number of children (total=469) for each age group (Table 3).

Table 3. Number of participants by age in the combined corpus

Age	3	4	5	6	7	8	9	10
# of Children (Total: 469)	51	71	65	65	65	51	53	48

3.2 Overview of the combined corpus

The combined database is a million-word corpus with 421,837 words in children's speech and 730,980 words in caregivers' utterances. In this corpus, children used 9,921 word types, and caregivers used 11,066 word types. Out of the 9,921 word types in children's speech, we extracted 704 derived words that were used 7,234 times.[11] [12] We then counted how many times each derived word was used by the children in each age group. In addition, we counted how many times the root of each derived word occurred in caregivers' speech (e.g. the frequency of *bake* for *baker*); how many times each derived word itself occurred in caregivers' speech (e.g. the frequency of *baker*); how many types of derived word each root generated in caregivers' speech (e.g. the number of derivatives of *bake*); and how many types of derived word each affix generated in caregivers' speech (e.g. the number of derivatives of -*er*). Finally, we classified the 704 derived words according to their syntactic, semantic, and phonological properties.

3.3 Data coding

We wanted to model the degree of productivity as a function of both linguistic and non-linguistic factors. We adopted Baayen's (1993) quantitative measure of productivity as an operational definition for the degree of productivity. Baayen (1989, 1992) originally measured the degree of productivity by calculating the ratio of morphological outputs (n_1) that occur in a corpus precisely once, i.e. *hapax*

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11 See Appendix 1 for a complete list of derived words that occur for the first time for each age group. We restricted this study to derived words resulting from affixation. That is, we did not consider denominalized verbs or other possible zero-derivations.

12 The type-token ratio is .097 (=704/7234).

legomena, to the total number of words (N) produced by that morphological operation, as shown in (1).

(1) $P = \frac{n_1}{N}$

One conceptual problem with this formula is that it does not take the type-frequency into consideration. Thus, Baayen (1993) proposed another measure of productivity, and labeled it somewhat confusingly as P^*, where the denominator (h_1) indicated the number of all hapax types.

(2) $P^* = \frac{n_1}{h_1}$

We calculated P^* values for all derivative types in our data to measure the degree of productivity. Let us illustrate how the equation (2) works with the suffix *-en*. In the combined corpus, one three-year-old child produced *blacken* just once. Hence, the numerator in (2) is 1. We examined all word types produced at age 3. The 51 three-year-old children in the combined corpus produced 2,500 word types in 48,988 tokens. Among the 2,500 word types, 892 words were used precisely once. Hence, 892 is the total number of hapax types. Therefore, the value of P^* for *-en* at age 3 is .0011 (=1/892). Here is another illustration from five-year-old children's data. Two derivatives of *-en* were produced in this age group: *smarten* and *tighten*. Of the two words, *smarten* was used twice, and *tighten* precisely once. Therefore, only *tighten* is the hapax, and the numerator in (2) is 1. We also examined the entire sub-corpus for five-year-old children, and found that the 65 children produced 3,768 word types in 96,723 tokens. Among the 3,768 word types, 1,398 were used precisely once. Therefore, the value of P^* for *-en* for this age group is .0007 (=1/1398).

This way, we calculated P^* values for all 704 derivative types for each group. In this paper, the P^* values make up a continuous variable ProdAGE (Productivity at each AGE). We have a technical problem of using ProdAGE as a dependent variable in the regression analysis. ProdAGE values are proportions or percents ranging from 0 to 1. Because multiple regression analyses make predictions that are less than 0 or greater than 1, we have to transform percentage values into their *natural logs*, so that they vary from minus infinity to plus infinity. This way, we log-transformed ProdAGE into LnProdAGE (Log of ProdAGE), and used it as the dependent variable.

The independent variables are straightforward and self-explanatory. Table 4 summarizes all the variables used in the regression analysis.

Table 4. Variables for data coding

Variable (Abbreviation)	**Values**	**Explanation**
SamePOS (POS)	0: Same 1: Different	Whether the root and its derivative match in the parts of speech
SemTran (S)	0: Transparent 1: Opaque	Whether the meaning of the derivative is transparent
PhonTran (PH)	0: No phonological change 1: Some phonological change	Whether the derivation carries some phonological change
AGE (A)	Continuous scale*	Range: 3-10
MOT1 (M1)	Continuous scale	How many times the root of each derived word occurs in caregivers' speech (e.g. the frequency of *bake* for *baker*)
MOT2 (M2)	Continuous scale	How many times each derived word itself occurs in caregivers' speech (e.g. the frequency of *baker*)
MOT3 (M3)	Continuous scale	How many types of derived word each root generates in caregivers' speech (e.g. the number of derivatives of *bake*)
MOT4 (M4)	Continuous scale	How many types of derived word each affix generates in caregivers' speech (e.g. the number of derivatives of *-er*)
LnProdAGE (P)	Continuous scale	Dependent variable, Log of ProdAGE

* We created several categorical variables for age, and used them as selection variables in appropriate contexts.

The first three variables are linguistic in nature. The SamePOS variable tests whether a child has access to the POS information on the root and its derivative. SemTran and PhonTran test a well-known hypothesis about the acquisition of derivational morphology. According to Clark (1993, p. 116), "speakers try to interpret and coin new words that are transparent in meaning". She also points out that children have difficulty in learning consonant alternations like *electric* and *electricity* because the phonological change violates the *simplicity of form* hypothesis. Similarly, Bauer (2001, p. 98) suggests possible factors for morphological productivity such as the frequency of appropriate bases, and phonological and semantic transparency. Thus far, the idea of semantic and phonological transparency has not been tested thoroughly, nor has it been challenged, partly because it is a reasonable hypothesis based on common knowledge. On the other hand, as we will see in the next section, semantic and phonological transparency accounts for only a small portion of the total variation (R^2 change of around 0.04), whereas the variables for input frequency explain more than 25% of the total variation.

In addition to Bauer (Ibid.), who suggested the frequency of appropriate bases as a factor that might influence morphological productivity, Ford et al. (2010) conducted lexical decision experiments to test the effect of base morpheme frequency on derivational morphology. Through multiple regression analyses, they separated the effects of *family size*, i.e. M4 in Table 4, from those of *base morpheme frequency*, i.e. M1 in Table 4. In what follows, we discuss the effects of caregivers' speech as well as other linguistic factors on children's acquisition of morphological productivity.

4. Results

4.1 Descriptive statistics: affixes in acquisition

One surprising result from the descriptive statistics is that young children produce more derivative types than have been reported in the literature. Appendix 2 summarizes all prefixes and suffixes with the number of derivative types produced by children for each age group. There are 24 prefixes and 41 suffixes in Appendix 2. Among three-year-old children's derived words, we find 11 of the 24 prefixes,[13] and 19 of the 41 suffixes.[14]

According to Clark (1993, 2003), English-speaking children produce a small number of derivatives with *-er*, *-ie* , and *-ness* at age 3, and add *-ist*, *-ment*, and *un-* at age 4. On the other hand, we found various derived words at age 3 such as *actually, allegiance*, *awesome*, *baker*, *beautiful*, *birdie*, *blacken*, *blueish*, *bracelet*, *Chinese*, *creamy*, *daily*, *department*, *different*, *goodness*, *indigestion*, *indivisible*, *Italian*, *mechanic*, *midnight*, *mistake*, *nonsense*, *outside*, *pastry*, *preschool*, *superman*, *Swish*, *telephone*, *triangle*, *underwear*, and *undone*.

Determining the category membership is a tough problem in any classification of the data from a sizable corpus. For instance, a three-year-old child produced *allegiance* and *indivisible* when reciting the Pledge of Allegiance from memory. Words like *business*, *department*, and *pastry* are truly controversial: they can be justified on some grounds, but cannot on others. Proper nouns like *Blacky* and *Jimmy* cannot be derivatives to many scholars. In fact, the larger the corpus, the more controversial cases we have in the classification of data. For this reason, empirical studies accept the presence of a certain amount of *noise* in empirical dat a.[15] We try to reduce the amount of noise as much as possible, but, in the end, we have to manage the noise by appropriate statistical analyses. As we discuss in sections 4.2 and 4.3, the total R^2 values of our regression models lie around .40 depending on the age group. From a purely statistical perspective, this is an impressive result. In normal situations, it would not be possible to achieve R^2 values of around .40 by virtue of noise. This suggests that young children know more about derivational morphology than we have expected so far.

Older children use more derivational affixes. At age 4, five more prefixes and 10 more suffixes appear in the transcripts.[16] At age 5, one prefix and six suffixes are added.[17] At age 6, three prefixes (*uni-*, *mono-*, and *fore-*) and one suffix *-ical* are

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13 *i(n/m/l)-*, *tele-*, *under-*, *tri-*, *out-*, *un-*, *pre-*, *super-*, *mis-*, *mid-*, and *non-*

14 *-(e/o/a)r*, *-y*, *-ie*, *-ly*, *-(a)(t)ion*, *-ful*, *-(i)(a)n*, *-ish*, *-ment*, *-ness*, *-ic*, *-(a/i)ble*, *-(a/e)ry* (Noun), *-(a/e)nt*, *-ance/ence*, *-en*, *-some*, *-ese*, and *-let*

15 Another type of *noise* can occur as a result of researchers' inconsistencies and mistakes. This is likely to happen when the organization of data is a laborious task that takes more than a year, and involves many revisions and updates. In the present study, we made substantial cross-validation efforts among colleagues. However, the more we revised the data, the more we were certain that we could never eliminate errors completely.

16 *re-*, *sub-*, *micro-*, *dis-*, and *trans-*; *-al*, *-en* (Adjectival), *-ist*, *-ous*, *-ity*, *-ine*, *-(a/e/an/en)cy*, *-less*, *-hood*, and *-age*

added. At age 7, two more suffixes *-ship* and *-(t)ive* appear. At age 8, the prefix *inter-* and the suffix *-(i)fy* appear. And at age 9, three more prefixes (*auto-*, *bi-*, and *hypo-*) are found in the transcripts. Appendix 1 shows a complete list of derived words for each age group. In the following sub-sections, we discuss a general model that explains children's production of derived words at all ages (→ 4.2), and age-specific models for each age group (→ 4.3).

4.2 A general regression model for the acquisition of derivational morphology

We conducted a hierarchical multiple regression analysis for all age groups. In this analysis, the dependent variable is LnProdAGE (P), and the independent variables are AGE (A), SamePOS (POS), SemTran (S), PhonTran (PH), MOT1 (M1), MOT2 (M2), MOT3 (M3), and MOT4 (M4). The variables are hierarchically entered in the following order.

(3) Hierarchically entered variables:[18]
a. Model 1: A
b. Model 2: A, POS
c. Model 3: A, POS, S, PH
d. Model 4: A, POS, S, PH, M1, M2, M3, M4

Table 5 is the model summary for this analysis.

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[17] *over-*; *-(s)ion*, *-ess*, *-ize*, *-ant* (Noun), *-al* (Noun), and *-ster*

[18] As in all regression analyses, we tested many hierarchical orderings for the data. Because input frequency (M1 through M4) explains the largest portion of the total variation, entering M1, M2, M3, and M4 at the beginning takes out possible effects of other linguistic factors. Therefore, we entered the linguistic variables before input frequency variables to determine the effects of POS, S, and PH on the dependent variable LnProdAGE.

Table 5. Model summary for (3)

	Newly Entered Variables	R^2	R^2 Change	F Change	df1	df2	Sig.
Model 1	A	.000	.000	.091	1	794	.762
Model 2	POS	.062	.062	52.560	1	793	.000
Model 3	S, PH	.096	.034	14.970	2	791	.000
Model 4	M1, M2, M3, M4	.349	.253	76.459	4	787	.000

According to Table 5, age (A) alone does not make any change to R^2, whereas entering POS, S, PH, M1, M2, M3, and M4 does. POS explains 6.2% of the total variation in LnProdAGE; S and PH an additional 3.4%; and input frequency variables (M1, M2, M3, and M4) an additional 25.3%. Based on this, we make an *initial guess* that age has no effect on LnProdAGE, and that POS, S, PH, and input frequency variables are significant predictors in the model. The R^2 in the last step is .349, indicating that the model explains about 35% of the variation in LnProdAGE. In the regression analysis, an R^2 value exceeding .25 is considered *quite respectable*, particularly after the transformation of the data.

Interestingly, a close examination of the coefficients shows different results from the *initial guess*. Table 6 summarizes the statistics for the coefficients in Model 4.

Table 6. Coefficients in Model 4

	Unstandardized B	Standardized Beta	t	Sig.	95% CI: Lower Bound	95% CI: Upper Bound	Tolerance
(Constant)	-7.784		-17.519	.000	-8.656	-6.911	
A	.084	.057	1.966	.050	.000	.168	.972
POS	.152	.022	.689	.491	-.280	.584	.813
S	-.574	-.081	-2.763	.006	-.981	-.166	.952
PH	.360	.036	1.183	.237	-.237	.957	.900
M1	.000	.016	.530	.596	.000	.000	.956
M2	.000	.003	.086	.931	-.002	.002	.942
M3	-.373	-.102	-3.318	.001	-.593	-.152	.874
M4	.015	.542	15.963	.000	.013	.017	.717

In contrast to the results from Table 5, the coefficient for age (A) in Table 6 is marginally significant (p=.050). In fact, A's coefficient was not significant until the previous step (p=.647 in Model 3); and thus, A's effect in Table 6 is due to the introduction of the input frequency variables, i.e. M1 through M4. This implies that we cannot see the effect of age until we take caregivers' speech into consideration.

The coefficients of POS and PH are not significant (p=.491 and .237 respectively). Note that the R^2 changes for Model 2 and Model 3 in Table 5 are significant. When we enter the input frequency variables, the effects of POS and PH disappear. This indicates that the apparent effects of POS and PH actually derive from input frequency, and that we cannot observe this crucial aspect of language until we control for input frequency. Let us illustrate this with a specific example. According to the regression results in Table 6, children have difficulty producing *electricity* not because it involves some phonological change, but because the input frequency, particularly M4, for *electricity* does not exceed a certain threshold for particular ages.

We examined the four input frequency variables in Table 6. Surprisingly, only the coefficients of M3 and M4 are significant (p=.001 and .000 respectively). In fact, M1 and M2 remain *non-significant* in all age-specific regression models, as we discuss in the next sub-section. We employed M1 for root frequency (e.g. the frequency of *bake* for *baker*), and M2 for the frequency of derived words (e.g. the frequency of *baker*). The regression model in Table 6 and the age-specific regression models in the next sub-section show that root frequency and the frequency of derived words do not make significant contributions to the productivity of a morphological process.

On the other hand, M3 and M4 are significant in Table 6.[19] We employed M3 to determine how many types of derived word each root generates in caregivers' speech; e.g. *bake* has *baker* and *bakery* as its derivatives. We also employed M4 to determine how many types of derived word each affix generates in caregivers'

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19 The effects of M3 are significant only in *some* age-specific models, whereas those of M4 are significant across *all* age-specific models. Whenever M3 counts significant, it has a negative effect on productivity. Concerning the negative effect of M3, one anonymous reviewer suggests a *neighborhood effect* as a possible explanation; i.e. the presence of other derivatives that share the same root in the input frequency may affect the productivity of the affix in a negative way. This is an interesting suggestion, but seems to be another research question that requires further study in the future. Finally, M4 always has a positive effect on productivity. See 4.3 for a detailed discussion.

speech; e.g. there are 301 derived word types of *-er* in caregivers' speech such as *driver*, *helper*, and *player*. According to Ford et al. (2010), M4 or *family frequency* is a key predictor of the response time for derived words in a lexical decision experiment.

We can summarize the discussion into a regression equation. Among the eight independent variables in Table 6, POS, M1, and M2 are eliminated because their coefficients are not significant. On the other hand, PH is not eliminated, partly because it entered the model with S, and it is significant for some age groups (→ 4.3). The following regression equation includes unstandardized coefficients of A, S, PH, M3, and M4.

(4) The general regression model for the acquisition of derivational morphology:

$$\ln(\text{ProdAGE}) = -7.784 + 0.084*A - 0.574*S + 0.36*PH - 0.373*M3 + 0.015*M4$$

Regression equations are generally interpreted in terms of their coefficients. For instance, the coefficient of M3 is -.373. If all other things remain constant, every one unit increase in M3 reduces the value of LnProdAGE by a multiple of .373. Because LnProdAGE is a log-transformed value with the base of *e*, the original ProdAGE value (Baayen's P^*) decreases by a multiple of '$e^{.373}$ = 1.45'. Similarly, if all other things remain constant, every one unit increase in M4 increases the value of LnProdAGE by a multiple of .015. In other words, the original ProdAGE value increases by a multiple of '$e^{.015}$ = 1.02'. Note that the increase in M3 has a negative effect on morphological productivity. M3 indicates the number of derived word types that each root generates in the input. Thus, the presence of *inside* and *upside* reduces the productivity score for *outside*. In some sense, the prefixation in *out-side* does not look like an outcome of the productivity of the prefix. Instead, the root *side* appears to get along well with several affixes regardless of their level of productivity.

4.3 Age-specific regression models for the morphological productivity of derived words

The general regression model in (4) is a generalization of the quantitative measure of productivity for all age groups. Because it is designed to explain the total variation for all age groups, its explanatory power for a particular age group tends to be weaker.[20] In the study of language development, we are interested in how language learners' grammar changes over time. This is why we want to test age-specific regression models. For this, we created a categorical variable for age, and used it as a selection variable in the multiple regression analysis. Table 7 presents the model summary of R^2 changes for each age group.

Table 7. Model summary of R^2 changes by age group

Age	**R^2 of the Final Model**	**R^2 Change for POS**	**R^2 Change for S and PH**	**R^2 Change for M1, M2, M3, and M4**
3	.530	.091*	.031	.408***
4	.357	.011	.036	.309***
5	.424	.061*	.127***	.236***
6	.420	.043	.135**	.242***
7	.346	.076*	.028	.242***
8	.421	.141*	.038	.242***
9-10	.414	.065*	.025†	.325***

* Significant at the model summary, but its coefficient in the last step is no longer significant.
** Significant at p<.05
*** Significant at p<.001
† Not significant at the model summary, but its coefficient becomes significant in the last step.

The R^2 values for the final models are impressive in Table 7. They range from .414 to .530 except for age 4 and 7. Because we obtain high R^2 values even after the log-transformation of the response variable, we can be positive that our analysis is quite robust. In addition, all R^2 changes for POS are either *not significant* or *significant with a non-significant coefficient*. As discussed in 4.2, we ignore the effects of POS because entering input frequency in the last step takes out the earlier effects of POS. The R^2 changes for S and PH are significant at age 5, 6, and 9. For five- and six-year-old children, the contributions of S and PH are .127 and .135

20 This is another reason why its R^2 value of .34 should be considered as an impressive result.

respectively, indicating that these children are sensitive to semantic and phonological transparency in producing derived words. This result contrasts with previous studies that consider semantic and phonological transparency as a key factor for learning derivational morphology at age 3 or 4.

The effect of input frequency is noteworthy. As in the general regression model, we entered input frequency variables in the last step. Nevertheless, their effects range from 0.236 to 0.408, indicating that caregivers' input is the most important factor in the acquisition of derivational morphology. Input frequency alone explains more than 40% of the total variation at age 3. It also explains more than 30% of the variation at age 4. This suggests that caregivers' speech influences three- and four-year-old children more than any other age group. The influence of caregivers' speech decreases to 0.23-0.24 after age 5. Because the R^2 changes for S and PH increase at age 5 and 6, we guess that children's learning strategy changes in this period.

Let us examine the coefficients in the final step of age-specific models. Table 8 summarizes the test results after eliminating non-significant variables (POS, M1, and M2).

Table 8. Unstandardized coefficients in age-specific models

Age	(Constant)	S	PH	M3	M4
3	-5.664***	-.8 (!)	-1.369	-1.485***	.022***
4	-7.204*** (!)	-.296 (!)	.619 (!)	-.106	.014*** (!)
5	-7.064*** (!)	-.283 (!)	-2.295**	-.341 (!)	.015*** (!)
6	-7.269*** (!)	-2.467**	3.186**	-.759	.018***
7	-8.355*** (!)	.07	-.333	-.123	.017*** (!)
8	-5.577***	-.406 (!)	.555 (!)	-.867***	.008***
9-10	-8.310*** (!)	-.661** (!)	.947** (!)	.216 (!)	.014*** (!)
95% CI of the General Model in <Table 6>	**-8.656 ~ -6.911**	**-.981 ~ -.166**	**-.237 ~ .957**	**-.593 ~ -.152**	**.013 ~ .017**

** Significant at p<.05

*** Significant at p≤.001

(!) The coefficient falls within the 95% Confidence Interval for the general model in Table 6

Half of the coefficients fall within the 95% confidence interval for each coefficient of the general regression model. When coefficients in an age-specific model fall within the 95% confidence interval for the general model, it is likely that the coefficients are not significantly different from those in the general model. If age-specific models are substantially different from the general model, we may question the validity of the analysis. On the other hand, if age-specific models are similar to the general model, we can be sure that these models cross-validate with one another. In inferential statistics, a null hypothesis is stated, such that two samples are not significantly different from each other. In this regard, the null hypothesis of our study is stated, such that the general model is not substantially different from age-specific models.

Using the unstandardized coefficients in Table 8, we can generate the following regression equations for each age group.

(5) Age-specific regression equations for the acquisition of derivational morphology:

a. Age 3: ln(ProdAGE) = – 5.664 – 0.8*S – 1.369*PH – 1.485*M3 + 0.022*M4

b. Age 4: ln(ProdAGE) = – 7.204 -0.296*S + 0.619*PH – 0.106*M3 + 0.014*M4

c. Age 5: ln(ProdAGE) = – 7.064 – 0.283*S – 2.295*PH – 0.341*M3 + 0.015*M4

d. Age 6: ln(ProdAGE) = – 7.269 – 2.467*S + 3.186*PH – 0.759*M3 + 0.018*M4

e. Age 7: ln(ProdAGE) = – 8.355 – 0.07*S – 0.333*PH – 0.123*M3 + 0.017*M4

f. Age 8: ln(ProdAGE) = – 5.577 – 0.406*S + 0.555*PH – 0.867*M3 + 0.008*M4

g. Age 9-10: ln(ProdAGE) = – 8.31 – 0.661*S + 0.947*PH + 0.216*M3 + 0.014*M4

We use these regression equations to predict the *degree of productivity* of each word for each age group. For instance, *dusty* is semantically and phonologically transparent, and thus S and PH are both 0. The values of M3 and M4 for *dusty* are

2 and 196 respectively. Plugging these figures into the equation for age 3 yields -4.322, as shown in (6).

(6) $\ln(\text{ProdAGE}) = -5.664 - 0.8*0 - 1.369*0 - 1.485*2 + 0.022*196$
$= -4.322$

The actual value of LnProdAGE for *dusty* is -4.214 at age 3. Thus, the prediction based on the regression equation in (5a) is surprisingly close to the real value.[21]

Another example is *electricity*, which is semantically and phonologically opaque. The values of M3 and M4 for *electricity* are 5 and 17 respectively. Plugging these figures into equation (5a) produces -14.884, as shown in (7).

(7) $\ln(\text{ProdAGE}) = -5.664 - 0.8*1 - 1.369*1 - 1.485*5 + 0.022*17$
$= -14.884$

The actual LnProdAGE value for *electricity* is -18.42 for nine-year-old children. To Clark (1993), children have more difficulty in learning *electricity* than *dusty*, since *electricity* involves a phonological change that *dusty* does not go through. In the present analysis, however, children learn *dusty* much more easily than *electricity*, since the quantitative measurement of productivity for *dusty* far exceeds that for *electricity*. The quantitative measure (LnProdAGE) is the function of semantics, phonology, and input frequency. In the case of derivational morphology, input frequency is the most important factor in the model.

5. Discussion

◎ The general model for the acquisition of morphological productivity

Unlike previous studies that focused on either linguistic or usage-based factors, we tested both factors in one regression analysis. In typical situations, it is rare that

21 There are many cases in which the differences between the actual and the predicted values, i.e. the residuals, exceed the expectation. Note that the regression equation in (5a) explains only 53% of the variation. Although the R^2 value of .53 is impressive, half the variation still remains unexplained due to *error* in statistical terms.

two factors, i.e. F1 and F2, account for an empirical phenomenon with a clear-cut boundary. Some effects of F1 and F2 may overlap, or the apparent effect of F1 may derive from F2 at a deeper level. Therefore, a comparison of F1 and F2 through appropriate statistical analyses can provide better understanding of the data.

In the regression analysis, we included such linguistic factors as SamePOS, S, and PH as well as input frequency variables. The significant effect of SamePOS disappeared when we entered the input frequency variables. This implies that the apparent effect of SamePOS may have derived from input frequency. In addition, the effects of S and PH were marginal when compared with the input frequency, as shown by the coefficients in Table 6.

Scholars have employed different measures of morpheme frequency. Some have focused on the base root frequency (M1). Others were interested in the whole-form frequency of derived words (M2), the frequency of morphological variants of a base word (M3), and the family frequency of affixes (M4). Among these measures, Ford et al. (2010) examined M1 and M4, whereas we compared all four measures of morpheme frequency in this study.

We found that M1 and M2 were not significant across age groups, whereas M3 and M4 played crucial roles in determining the morphological productivity of a word. In particular, M4 was the most important factors in the regression analysis. These results are consistent with the findings of Ford et al. (2010), who concluded that the family size of an affix (M4) facilitated the response time for derived words. They also pointed out that the base morpheme frequency (M1) facilitated responses for derivatives of highly productive affixes like *-er*, *-ly*, *-ness*, and *-ment*. Because we examined the spontaneous speech data, we could not obtain two similarly sized groups of *more* vs. *less productive* affixes. In this regard, testing the effects of M1 in a more controlled setting can be a promising topic for future research.

◎ Age-specific models for the acquisition of morphological productivity

A goal of statistical analyses in empirical science is to explain empirical data with parsimony. For this reason, *one model* is preferable to *two* or *three* models as long as their explanations do not differ from one another significantly. The results of the regression analyses in 4.3 indicate no substantial differences between the general model and age-specific models. More than half the coefficients in the age-specific models fall within the range expected by chance by the general model.

We also observed some age-specific effects. For example, S and PH contribute to morphological productivity for five- and six-year-old children. That is, the relative importance or *weight* of S and PH increases at age 5-6 compared with their importance for other age groups. In sum, the same principle governs all stages in the acquisition of morphological productivity, and children adjust the relative importance or *weight* of a particular factor in the model in each developmental stage.

◎ **Implications for the continuity hypothesis**

This study offers a new perspective on the strong/weak continuity hypothesis (Pinker, 1984; Lust, 1994).[22] The continuity hypothesis posits that children's grammar is not different from the adult grammar, and that children's language development is guided by UG's principles and representations from birth. The continuity hypothesis denies behaviorists' view of *stage changes* in language development.

The idea of *continuity* plays an important role in our study because we claim that a single principle of morphological productivity should guide language development for all age groups. However, the classical continuity hypothesis makes a number of assumptions and claims that are *not* consistent with our present view. The classical continuity hypothesis was proposed to address theory-internal issues in the Chomskyan view of language. Santelmann's (1997) discussion of Swedish data illustrates this point. Swedish children produce *wh*-less questions along with complex clauses that have overt complementizers in the same developmental stage. Both *wh*-questions and complex clauses need a full CP structure. Because Swedish children use complex clauses overtly in a full CP structure, they must have knowledge of the CP structure at early ages. Therefore, even *wh*-less questions must have a full CP structure in Swedish children's mind. In other words, children's early grammar is not different from mature grammar.

In the continuity hypothesis, grammar is a purely linguistic component that is not influenced by usage-based factors. The continuity hypothesis is not a generalization from empirical data, but a necessary tool enabling explanations of acquisition data in terms of the Chomskyan view of UG. On the contrary, the proposed view of

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22 See Ayoun (2005) for a detailed overview of the continuity hypothesis.

continuity in this paper is a generalized function of both linguistic and uage-based factors. In addition, at least for the area of derivational morphology, we have argued that input frequency is more important than linguistic factors. This view of continuity arises as a generalization based on statistical analyses of a million-word corpus. This view does not support the claim that grammar is a purely linguistic component.

The present proposal cannot be entertained in the original conception of the continuity hypothesis. Nevertheless, our proposal offers a plausible clue to the classical puzzle of the continuity hypothesis, i.e. the *triggering* problem. What triggers the onset of language acquisition? What triggers UG, such that it provides very young children with a full CP structure? Ayoun (2005, p. 42) points out that "Given its importance in a parameter-setting theory, it is surprising that we still know so little about it[=*continuity*]." The classical continuity hypothesis is part of the theory of UG. For this reason, the triggering problem has generally been explored in theoretical discussions leaving many empirical issues unaddressed. Nonetheless, if we re-examine continuity based on empirical data from a theory-neutral perspective, the triggering problem may no longer be a puzzle. This can be an interesting direction for future research on the classical continuity hypothesis.

6. Conclusion

By analyzing children's production of derived words for all age groups through a million-word corpus, we have shown that they produce more derived words at early ages than previously reported. In order to find out a linear combination of factors that influence the acquisition of productive morphology, we examined 7,234 derived words produced by 469 individuals at age 3-10. From these words, we extracted 704 derivative types, and organized the data based on their POS change, semantic and phonological transparency, and four measures of input frequency. We also adopted Baayen's (1993) hapax-conditioned degree of productivity as a response variable in the regression analysis.

Through hierarchical multiple regression analyses, we have found that the family frequency of affixes plays the most important role in determining the degree of morphological productivity. Linguistic factors like semantic and phonological transparency have only limited effects on the acquisition of derivational morphology.

In this study, we proposed a possible format of usage-based grammar, in which speakers' production of a particular form can be expressed as a linear function of both linguistic and non-linguistic factors like frequency. This view may not be welcomed by those who prefer to model grammar with purely linguistic elements. However, we expect that "the course of acquisition would follow from the distribution of the data in speech (Jackendoff 2010, p. 33)." The only way to explain the acquisition process by using the distribution of data seems to be the incorporation of usage-based factors like frequency into grammatical generalizations.

In the proposed analysis, a generalization that takes the form of a regression equation derives from the distribution of input data, i.e. frequency, as well as linguistic factors. A single principle holds for all age groups, and we can view the acquisition process, such that children determine the *weight* or relative importance of each factor in each developmental stage, and that they extend the input candidates of the function, i.e. the regression model, to novel instances. The general regression model in this paper can be used as a general rule of derivational morphology in adult grammar. In any such attempt to analyze adult language, the input frequency variables from caregivers' speech can be replaced with the frequency of relevant words in the language community or in a corpus of adult language.

Our study has some limitations. In a study of the present format, using the best quantitative measure of productivity is critical. We adopted Baayen's (1993) measure of productivity not because it is the perfect measure, but because it is the *only* measure that works reasonably well in most cases. Developing quantitative measures of productivity is still a new area in contemporary linguistics. We expect the quality of the model to improve through the use of improved measures of productivity. Also, we have focused only on children's spontaneous *production* in the corpus. We examined language development by using speech transcripts, and thus could not answer *what children knew but did not produce*. This is why researchers conduct specific experiments designed to understand children's comprehension or grammaticality judgment of language data. In fact, these limitations are already expressed in the regression model. Our regression models explain the data nicely with the R^2 values around .40, but still cannot explain a large portion of the total variation. In statistical terms, the unexplained portion is the *error*. In a critical evaluation of the proposal, the unexplained portion represents an urgent call for future research into more factors that we could not include in this study.

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Appendix

#1. Derived words that occur for the first time at particular ages

Age	New Occurrences
3	actually, adoption, allegiance, angry, apartment, auntie, awesome, baker, beautiful, birdie, blacken, Blacky, blueish, bracelet, buggie, bumper, business, buster, careful, carefully, Chinese, conditioner, counter, cracker, cranky, creamy, crispie, daddy, daily, department, different, dinner, dirty, doggie, drainer, dresser, driver, duckie, dusty, fishy, funky, funny, gently, goodie, goodness, helper, holder, hopper, horsie, hungry, hunter, indigestion, indivisible, Italian, Jackie, Jimmy, Johnny, kitty, lucky, maker, mechanic, merrily, midnight, mistake, mommy, muddy, nonsense, Norman, outside, pastry, pitcher, player, porter, potty, prayer, preschool, probably, really, recorder, refrigerator, rosy, ruler, safely, sailor, salty, scary, silky, sleepy, sneaker, soapy, softly, sparkler, spicy, sprinkler, Stephanie, superman, Swish, teacher, telephone, television, thirsty, thumper, topper, tractor, triangle, underwear, undone, vacation, wheelie, wrapper, yucky, yummy
4	activity, appointment, awful, bakery, basement, blower, bony, boxer, carriage, choppy, Christian, climber, cloudy, coaster, colorful, comfortable, cooker, corny, crumbly, cubbie, curly, cutie, darkness, dentist, difference, disappear, dollie, drawer, electronic, elevator, emergency, equipment, fallish, fally, fighter, filler, finally, flipper, foggy, foolish, foxy, Frankie, friendly, frosty, furry, golden, goody, goosie, governor, grumpy, illustration, imagination, important, Indian, insane, invention, invisible, jewelry, joker, Katie, kissy, kitten, lander, leader, library, locker, marker, medicine, messy, microphone, mighty, mouthie, nearly, neighborhood, nervous, operator, original, outdoor, outfit, piggy, pinkie, popper, porky, prehistoric, quietly, racer, recognize, reflector, remind, rewind, roller, saucy, scandral, scooter, seedless, sexist, shiny, shredder, skinny, skipper, slowly, snugglable, soggy, splinter, sticker, strainer, stuffy, submarine, sunny, sweetie, telescope, teller, thrasher, transform, transformer, tricky, triple, tropical, understand, untie, visible, walkie-talkie, warner, whoopsie, winner, wooden
5	African, allergic, artist, Asian, beaten, biker, builder, bumpy, buttery, certainly, chicky, commercial, computer, congratulation, container, contrary, cootie, crawly, creepy, Danish, decoration, definitely, delivery, differently, direction, dismissal, eater, electricity, eraser, especially, fattie, feeder, fertilizer, filthy, freezer, goldie, greasy, grocery, happily, highness, horner, illegal, imaginary, juicy, junky, killer, librarian, loudly, lovely, lumpy, magnetic, marriage, Maxie, microwave, missy, mostly, mover, mushy, musical, nectarine, noisy, officer, opener, overgrown, package, passage, patience, performance, permission, plumber, poster, princess, protector, quickly, rainy,

Age	New Occurrences
	remove, report, runny, saver, screechy, servant, slippery, smarten, snowy, Spanish, spotty, Stevie, sticky, stinger, stranger, sucker, suggestion, superhero, supervision, supervisor, tasty, tighten, toaster, totally, trickster, twisty, typewriter, usually, visitor, wiggly, windy, wiper, wonderful
6	accidentally, allowance, babysitter, bagly, bandage, bleedy, bloody, bouncy, combination, construction, crummy, dancer, easily, English, forehead, gardener, Hawaiian, horrible, magical, magically, manager, Mexican, microscope, monorail, nursery, O'clocker, operation, overcook, overnight, rusty, scientist, seater, shaker, signal, smokey, trailer, underground, underwater, unicycle, unlock, wheeler, whoopie, wowie
7	absolutely, American, assignment, assistant, barbaric, bashful, behavior, brainy, bringer, central, chunky, claymation, crappy, curvy, detector, disposal, estuary, evaporize, exactly, exclamation, famous, fisher, flutter, folder, friendship, fruity, goalie, grader, grassy, greedy, gruesome, heater, historical, homeless, icy, miserable, mixer, mouthful, negative, normal, nutcracker, nutritious, olden, outlandish, overflow, penmanship, prettiful, proudly, punctuation, punisher, raider, reader, realize, responsibility, return, scholarship, scorer, sensitive, sharpen, sharpener, simulator, stinky, suddenly, Superbowl, terminator, thankful, truthful, unbelievable, universal, writer
8	advertisement, archaeologist, badly, blackish, booster, bossy, breathy, carrier, carver, catcher, creeper, critic, cruiser, dangerous, designer, destroyer, dictionary, fantastic, glider, gravity, greenly, impression, international, invitation, Japanese, Jewish, jumper, kisser, magnetify, magnificent, meteorologist, mischievous, mystery, natural, naturally, naughty, nonfiction, partly, poisonous, positive, powerful, practically, primary, professional, prowler, pushy, robber, scenery, singer, stewardess, stocker, thrower, undress, unlike
9-10	accountant, actor, actress, adorable, alphabetical, alrighty, appliance, archeological, association, atomic, attachable, attractive, autobiography, automatically, basic, basically, batter, beggar, biplane, British, brutally, capitalize, causer, championship, cheater, checker, cheerful, classical, clearly, collection, collector, completely, conductor, Constitution, conversation, convertible, cooperative, crawler, creator, critical, customer, deadly, derringer, destruction, diagonally, directly, discussion, disputatious, dominator, dryer, education, electric, electrical, electromagnetic, endanger, engineer, enjoyable, entertainment, erasable, eventually, excellent, exclusive, expensive, explosion, expression, exterminator, fitness, fluffy, flyer, generator, geographic, girly, gradually, grouchy, Haitian, handedness, handful, headless, Himalayan, hopefully, hypothesis, identification, illustrator, imitation, immature, immediately, impossible, inaccurate, infection, instruction, insurance, kindergartener,

Age	New Occurrences
	lately, lawyer, layer, lightly, literacy, logical, lousy, lover, magnetical, magnetize, marcher, medical, miner, monologue, mysterious, national, necessarily, neutral, objective, outline, outstanding, overlap, oversea, particularly, penitentiary, personal, pinkish, playful, plunger, pollution, preacher, prevention, preview, quirky, recently, recharge, recital, refurnish, regrouping, reheat, removable, reversal, reverse, ringer, romantic, Russian, saltine, scaley, scrambler, selection, silent, sincerely, slipper, smelly, smiley, springy, squiggly, Stephie, stormy, straighten, styler, subatomic, sweater, thingy, threaten, tricycle, tripod, tuner, underline, underpant, undershirt, unicorn, uniform, unscrambler, unusual, various, vegetarian, volcanic, waiter, wilderness, woolly, wrestler

#2. Number of word types in each age group by affix

Suffix Type	Suffix	Examples	Age						
			3	4	5	6	7	8	9-10
Prefix	auto	autobiography	0	0	0	0	0	0	1
	bi	biplane	0	0	0	0	0	0	1
	dis	disappear	0	1	1	0	0	1	0
	en	endanger	0	0	0	0	0	0	1
	fore	forehead	0	0	0	1	0	0	0
	i(n/m/l)	illegal, impossible	2	2	2	1	1	0	3
	inter	international	0	0	0	0	0	1	0
	micro	microphone, microscope	0	1	1	1	2	1	1
	mid	midnight	1	1	0	0	0	0	1
	mis	mistake	1	0	1	0	0	0	1
	mono	monologue, monorail	0	0	0	1	0	0	1
	non	nonfiction, nonsense	1	0	0	0	0	1	0
	out	outline, outside	1	3	1	1	2	1	3
	over	overcook, oversea	0	0	1	2	1	0	3
	pre	preschool, preview	1	2	0	0	0	0	2
	re	refurnish, remind	0	3	4	1	2	2	11
	sub	subatomic, submarine	0	1	0	1	0	1	2
	super	superhero, supervise	1	1	3	0	1	1	1
	tele	telephone, television	2	3	3	2	0	1	2
	trans	transform	0	1	0	0	0	0	0

Suffix Type	Suffix	Examples	Age						
			3	4	5	6	7	8	9-10
	tri	triangle, tripod	1	2	1	0	0	1	4
	un	unlike, untie	1	1	0	1	1	4	2
	under	underground, underwear	1	2	1	2	0	2	6
	uni	unicorn, uniform	0	0	0	1	0	0	2
Suffix	(a)(t)ion	exclamation, invention	3	4	5	4	5	4	21
	(a/e)nt	excellent, magnificent	1	2	2	2	1	3	4
	(a/e)ry (Noun)	bakery, delivery	1	3	5	3	2	5	6
	(a/e/an/en)cy	emergency, literacy	0	1	0	0	0	0	2
	(a/i)ble	enjoyable, visible	1	3	2	2	4	1	8
	(e/o/a)r	driver, operator	31	47	50	20	37	29	75
	(i)(a)n	christian, librarian	2	2	4	2	3	3	9
	(i)fy	magnetify	0	0	0	0	0	1	0
	(s)ion	explosion, permission	0	0	1	0	0	1	4
	(t)ive	attractive, exclusive	0	0	0	0	2	1	7
	age	marriage, passage	0	1	3	1	0	0	0
	al	logical, personal	0	3	3	2	5	3	11
	al (Noun)	disposal, recital	0	0	1	0	1	0	2
	ance/ence	allowance, difference	1	1	2	1	1	0	4
	ant (Noun)	accoutant, servant	0	0	1	1	1	0	2
	ary	imaginary, primary	0	0	3	1	0	2	1
	en	sharpen, straighten	1	0	2	0	1	0	3
	en (Adjectival)	golden, wooden	0	3	4	1	3	3	2
	ese	Chinese, Japanese	1	0	1	1	1	1	1
	ess	actress, princess	0	0	1	0	0	1	2
	ful	colorful, thankful	2	4	4	3	8	3	10
	hood	neighborhood	0	1	0	0	0	0	1
	hypo	hypothesis	0	0	0	0	0	0	1
	ic	basic, volcanic	1	2	2	0	1	4	10
	ical	electrical, magnetical	0	0	0	1	1	0	9
	ie	birdie, daddy (in pronunciation)	17	27	24	11	14	7	16

Suffix Type	Suffix	Examples	Age						
			3	4	5	6	7	8	9-10
	ine	medicine, saltine	0	1	1	0	0	0	2
	ish	Danish, outlandish	2	3	2	2	2	3	6
	ist	artist, sexist	0	2	1	1	0	5	3
	ity	activity, electricity	0	1	2	0	3	1	2
	ize	evaporize, magnetize	0	0	1	0	2	0	2
	less	headless, homeless	0	1	0	0	1	0	1
	let	bracelet	1	1	1	1	0	0	1
	ly	badly, finally	8	9	17	12	14	12	37
	ment	advertisement, equipment	2	4	1	2	1	3	5
	ness	darkness, highness	2	3	3	0	1	0	4
	ous	dangerous, nutritious	0	1	1	0	2	4	7
	ship	friendship, scholarship	0	0	0	0	3	0	1
	some	awesome, gruesome	1	0	1	1	2	1	2
	ster	trickster	0	0	1	0	0	0	0
	y	cloudy, tasty	23	35	43	18	30	19	38

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