CHILD DEVELOPMENT

Child Development, March/April 2021, Volume 92, Number 2, Pages 609–625

The Longitudinal Relationship Between Conversational Turn-Taking and Vocabulary Growth in Early Language Development

Seamus Donnelly
The Australian National University and ARC Centre of Excellence for the Dynamics of Language

Evan Kidd
The Australian National University and ARC Centre of Excellence for the Dynamics of Language and Max Planck Institute for Psycholinguistics and Donders Institute for Brain, Cognition and Behaviour Radboud University

Children acquire language embedded within the rich social context of interaction. This paper reports on a longitudinal study investigating the developmental relationship between conversational turn-taking and vocabulary growth in English-acquiring children (*N* = 122) followed between 9 and 24 months. Daylong audio recordings obtained every 3 months provided several indices of the language environment, including the number of adult words children heard in their environment and their number of conversational turns. Vocabulary was measured independently via parental report. Growth curve analyses revealed a bidirectional relationship between conversational turns and vocabulary growth, controlling for the amount of words in children's environments. The results are consistent with theoretical approaches that identify social interaction as a core component of early language acquisition.

Language acquisition occurs within and is supported by a rich social context (Bruner, 1983; Clark, 2018; Nelson, 2007; Tomasello, 2003, 2019). Before they utter their first words, infants communicate using paralinguistic devices such as eye gaze, gesture, and vocalizations to engage others in protoconversations that enable the rudimentary exchange of meaning (Bruner, 1975; Snow, 1977). These emerging skills are supported and fostered by skilled others (e.g., caregivers; Che, Brooks, Alarcon, Yannaco, & Donnelly, 2018; Hoff-Ginsberg, 1994; Tamis-LeMonda, Kuchirko, & Song, 2014; Vygotsky, 1978), forming the basis of the *conversational duet* that lays the foundation for language and socio-cognitive development (Hirsh-Pasek et al., 2015; Song, Spier, & Tamis-LeMonda, 2014). In the current paper, we report on a longitudinal study that investigated the dynamic interplay between conversational turn-taking and vocabulary development in 122 infants aged 9–24 months. Specifically, we use daylong recording technology to probe the degree to which conversational turn-taking and vocabulary development mutually influence each other across infancy.

Socio-Communicative Interaction as a Foundation for Language

Socio-pragmatic approaches to language development identify joint interaction as the bedrock upon which a linguistic system is built (e.g., Bruner, 1983; Nelson, 2007; Tomasello, 2003). On such approaches, the child is an active yet still-maturing participant in communicative exchange, rapidly developing socio-cognitive skills that allow the comparatively longer process of language acquisition to proceed. Thus, at around 9 months of age children build upon earlier-developing skills to

This research was supported by the Australian Research Council (CE140100041: CI Evan Kidd). We thank all the families for participating, and Lauren Morrison and Amanda Piper for help with data collection, and Jay Verkuilen for statistical advice. Open Access funding enabled and organized by Projekt DEAL.
Our data and analysis code are available from: https://osf.io/v9fuq/.

Correspondence concerning this article should be addressed to Seamus Donnelly, Research School of Psychology, The Australian National University, Acton 2601, Canberra, Australia or Evan Kidd, Language Development Department, Max Planck Institute for Psycholinguistics, PO Box 310, 6500 AH Nijmegen, The Netherlands.
Electronic mail may be sent to seamus.donnelly@anu.edu.au or evan.kidd@mpi.nl.

 0009-3920/2021/9202-0011
DOI: 10.1111/cdev.13511

engage in processes like triadic joint attention (Carpenter, Nagell, & Tomasello, 1998; Striano & Stahl, 2005) and deictic pointing (Bates, Camaioni, & Volterra, 1975; Tomasello, Carpenter, & Liszkowski, 2007). Tomasello (1999, 2008; see also Tomasello, Carpenter, Call, Behne, & Moll, 2005) suggested that such behaviors coalesce in a "9-month revolution," whereby children begin to understand others as intentional agents, heralding a step change in their capacity to engage in collaborative activities that promote vocabulary development (Tomasello & Farrar, 1986). Thus, equipped with these skills, children can engage in what Bruner (1977) referred to as the "joint enterprise," which "sets the deictic limits that govern joint reference, determines the need for a referential taxonomy, establishes the need for signalling intent, and eventually provides a context for the development of explicit predication" (p. 287). Consistent with this suggestion, vocabulary development has been shown to be a mutually-driven dyadic process, where *both* infants' and caregivers' behavior contribute to lexical development (Donnellan, Bannard, McGillion, Slocombe, & Matthews, 2019; Dunham & Dunham, 1992; see also Tamis-LeMonda et al., 2014).

A fundamental component of communicative interaction is the notion of a linguistic or conversational turn. Levinson's (2006, 2016) *interaction engine hypothesis* argues that turn-taking is a universal property of human language, and may have placed important constraints on the evolution of language because the processes underlying spoken language likely adapted to the intense time pressure conversational structure places on speakers. Consistent with its status as a universal, turn-taking emerges early in ontogeny (Bateson, 1975; Bruner, 1975; Hilbrink, Gattid, & Levinson, 2015; Murray & Trevarthen, 1985), with its development appearing to significantly influence and be influenced by spoken language development. Thus, there is evidence that turn-taking predicts spoken language development concurrently and longitudinally (Gilkerson et al., 2018; Romeo et al., 2018; Zimmerman et al., 2009), and evidence that turn-taking changes across early development as a function of linguistic and cognitive development. On the latter point, Hilbrink et al. (2015) reported on a longitudinal study of turn-taking in infant–mother dyads followed from age 3 to 18 months, focusing on turn gap timing and the degree to which infants reciprocally structure their interaction jointly with their mothers. They found that, while infants aged 6 months and under typically take the same time to initiate turns as their mothers, from 9 months onwards those initiation times slow down and continue to lag behind mature language users until they are 18 months. Thus, around the time children are developing greater socio-cognitive skills (i.e., the 9 month "revolution," Tomasello, 1999), and beginning to build a lexicon (e.g., Bergelson & Swingley, 2012; Kidd, Junge, Spokes, Morrison, & Cutler, 2018), their turn-timings slow down, which Levinson (2016) interprets to reflect the greater pressure placed on the infant to coordinate several new cognitive processes within the pressures of conversation. Consistent with this conclusion, turn length is also positively associated with syntactic complexity in older children's utterances (Casillas, Bobb, & Clark, 2016). The suggestion is that turn-taking tests the limits of human cognitive performance; there is a pressure to produce conversational turns within a narrow time window, which necessitates significant speech planning while a conversational partner is still completing their turn (see Levinson, 2016). Importantly, Hilbrink et al. (2015) also showed that infants play a reciprocal role in communicative exchange: their turn transitions were not randomly distributed, but instead were indicative of being an active participant in the conversation.

While dyadic interaction plays a central role in socio-pragmatic approaches to language development (e.g., Bruner, 1983; Nelson, 2007; Tomasello, 2003; Vygotsky, 1978), research investigating the developmental dynamics connecting turn-taking and spoken language development is relatively rare. Recent advances in automated analysis of spoken language recordings have suggested a key role for turn-taking in language development, to which we now turn.

The Language Environment Analysis (LENA®) technology is a composite recording and analysis package that records up to 16 hr of a child's language environment across one day (Greenwood, Thiemann-Bourque, Walker, Buzhardt, & Gilkerson, 2011). In addition to providing estimates of the number of adult words a child hears, it also computes the number of conversational turns in which a child engages, the number of child vocalizations, and the amount of extraneous background noise a child hears due to electronic media such as television and radio. Data from several studies have consistently shown that children's conversational turn count (CTC), and to a lesser extent the adult word count (AWC), is associated with language outcomes. For instance, in a cross-sectional study of children aged 2–48 months, Gilkerson et al. (2014) reported that both were significantly correlated with several outcome measures of language and cognitive development. Gilkerson et al. (2018) tested a subset of the children on language outcome measures 10 years later, finding that only conversational turn measurements at 18–24 months were consistently related to language outcomes. Romeo et al. (2018) showed that the number of conversational turns measured from daylong LENA® recordings significantly predicted 4- to 6-year-old children's language proficiency over and above measures of input quantity, and was associated with greater activation in the Left Inferior Frontal Gyrus in Broca's Area during a separate language processing task conducted in an MRI scanner. These effects appear robust: in a recent meta-analysis synthesizing effect sizes across 13 studies, Wang, Willimas, Dilley, and Houston (2020) reported an average mean weighted effect size of $r = .32$ between LENA® CTCs and language proficiency. The relationship between AWC and language proficiency was also robust, albeit lower ($r = .21$).

While there is an attested relationship between language development and conversational turns, the causal direction of this relationship is less clear. Three possibilities exist. First, there could be a unidirectional relationship between language development and conversational turns, such that children who have better language skills procure more interaction. Second, there could be a unidirectional relationship between conversational turns and language, such that children acquire more language within joint interaction. Finally, the relationship could be bidirectional, such that developmental gains in one variable lead to gains in the other, and vice versa.

Zimmerman et al. (2009) examined this question in a study that investigated the relationship between CTC, as measured by LENA®, and language development, as measured by age normalized scores from the Preschool Language Scale, 4th ed. (PLS-4, a standardized measure of language proficiency; Zimmerman, Steiner, & Pond, 2002) in a sample aged 2–36 months. The relationships were investigated concurrently and again 18 months later. In the longitudinal analysis, they found that conversational turns predicted later language over and above Time 1 language scores, but that language at Time 1 did not predict conversational turns over and above prior turn-taking. They concluded that the most likely developmental relationship between turn-taking and language was one in which conversational turns predicted language proficiency, but not vice versa.

Some details of Zimmerman et al.'s (2009) design and analysis complicate this interpretation. First, the age range of the sample was wide and included children who likely had a wide range of socio-cognitive skills that directly influence turn-taking. Second, the PLS-4 is a broad measure of language development, which includes non-verbal communication skills that may also be affected by turn-taking. Third, while the effect of PLS on conversational turns over and above prior conversational turns was non-significant, the confidence interval on this coefficient ranged from −.01 to .06, suggesting a near-significant effect, which could have been masked by either of the two issues. Overall, the absence of a bidirectional effect is surprising if, as argued by socio-pragmatic theory (e.g., Bruner, 1977, 1983; Carpenter et al., 1998; Dunham & Dunham, 1992; Tomasello, 2003), acquisition in context is jointly determined (as also indicated by Hilbrink et al., 2015). That is, we should see an influence of children's language level on conversational dynamics because their developing proficiency is indicative of and a consequence of a mastery of language use *in toto*. In other words, greater levels of language knowledge should beget more conversation, and more conversation provides the exact conditions under which young children should become more proficient.

The Current Study

The present study aimed to test the directionality of the relationship between turn-taking and early language development. We report on a longitudinal study where we collected LENA® and vocabulary measurements every 3 months between the ages of 9 and 24 months. Crucially, we model growth in each of these variables across time to determine the developmental relationship between the two. Following socio-pragmatic approaches to language development (Bruner, 1983; Nelson, 2007; Tomasello, 2003; Vygotsky, 1978), and research suggesting that turn-taking is influenced by language development (Casillas et al., 2016; Hilbrink et al., 2015), we predicted a bidirectional relationship between turn-taking and language, such that growth in one variable positively predicts growth in the other.

Method

Participants

Participants were part of a larger longitudinal project tracking language development from 9 months to 5 years (see Kidd, Junge, et al., 2018), run from 2015 to 2020 (with all participants completing the 24 month sessions by the end of 2017).

One-hundred and twenty-four (N = 124) families were recruited from Canberra, Australia. Inclusion criteria for the longitudinal study were as follows: (a) full-term (at least 37 weeks of gestation) babies born with a typical birth weight (> 2.5 kg), (b) a predominantly monolingual language environment (i.e., miminal exposure to a language other than English–in all but two cases, 20% or less exposure to another language, thus the children were acquiring Australian English as a first language), and (c) no history of medical conditions that would affect typical language development, such as repeated ear infections, visual or hearing impairment, or diagnosed developmental disabilities. Two participants were later diagnosed with developmental difficulties and were removed from the analyses. Therefore, these analyses contained a maximum of 122 participants (55 females). The research was approved by the human research ethics committee of the Australian National University and followed the National Health and Medical Research Council of Australia guidelines.

Consistent with the demographics of the city, the sample was drawn from families high in socio-economic status, as indicated by caregiver education measured on a 7-point scale: 0 = *some high school*, 6 = *PhD*). Median education was 4 (bachelor degree) for Caregiver 1 (SD = 1.12, range = 0–6) and 4 for Caregiver 2 (SD = 1.12, range = 0–6). Since socioeconomic status (SES) has been shown to be associated with both variation in input and vocabulary development (Bergelson et al., 2019; Hart & Risley, 1995; Hoff, 2003; Rowe, 2012), it is important to acknowledge that our results may not generalize fully to other populations. Interestingly, however, we note that even *within* more narrow SES bands we see large individual differences in both input and vocabulary development (Donnelly & Kidd, 2020; Weisleder & Fernald, 2013). Data on participant ethnicity were not collected, although the sample was representative of the Canberra population, which is predominantly of white, Anglo-Celtic origin (approx. 90%), and contains a range of other ethnicities based on different waves of migration since the mid-20th century (Australian Bureau of Statistics, 2016).

Methods and Procedure

Families visited the laboratory every 3 months between the ages of 9 and 24 months, when they were given (a) a LENA® recorder, (b) an item of clothing in which the recorder could be placed, and (c) MacArthur-Bates Communicative Development Inventories (MBCDIs).

LENA® Home Recording

Caregivers were given the LENA® recorder, the item of clothing, and an information sheet on how to use the system. They were asked to record their child for a full day (i.e., 16 hr) at the next possible and convenient day, with the additional request that the day be representative of a typical day in the family's life. While families were free to fit data collection around other activities, most families designated recording days when the child and primary caregiver were predominantly at home. Once the recording was completed, parents returned the device to the laboratory via post, along with the completed MBCDI. The number of available LENA® recordings at each time point, as well as descriptive statistics for the age in weeks at which the recording was taken, are presented in Table 1.

The recordings were processed using the LENA® proprietary software, which provides several estimates of the child's language environment, including (a) AWC, defined as the number of words spoken in the vicinity of the child, (b) Child Vocalization Count (CVC), defined as the number of vocalizations (including words and non-words, such as babbling or exclamatives, e.g., *ah!*), (c) the child's exposure to non-social electronic media (e.g., TV, radio, music, henceforth "TV PCT"), and (d) child–adult CTC, defined as two discrete utterances between child–adult pairs that contain a pause no longer than 5 s.

Several past studies have reported on the reliability of the LENA® indices by comparing the output of the algorithm to human coders, with a main focus on those variables that likely influence language development: AWC, CVC, and CTC. Zimmerman et al. (2009) reported high concordance rates for a subset of their sample in which they compared LENA® output to human transcription and coding of the same recording, in most cases exceeding 70% overlap for AWC and CVC. These numbers have by and large replicated across

Table 1
Number of LENA Recordings and Age of Participants at Each Time Point

Session time point	N	M_{weeks}	SD_{weeks}	$\text{Range}_{\text{weeks}}$
9 months	120	42.9	1.4	40–47
12 months	119	56.7	1.6	54–64
15 months	105	69.1	1.7	66–81
18 months	109	82.2	1.4	78–87
21 months	107	95.2	1.6	93–103
24 months	101	108.0	1.4	104–113

several other studies. In a recent meta-analysis, Cristia, Bulgarelli, and Bergelson (2020) reported average Pearson correlation coefficients between LENA® outputs and human coders for AWC as $r = .79$, and for CVC as $r = .77$. The correlation was lower for CTC ($r = .36$), but seems to have been significantly influenced by outliers in some studies (see Wang et al., 2020). A difficulty in assessing the accuracy stems from the small amount of human transcribed data that is compared with LENA® outputs, which is often as low as 1-min segments of recordings (for a thorough assessment along these lines, see Cristia, Lavechin, et al., 2020). Thus, extrapolating from small transcribed segments requires the assumption that error rates are constant across a full recording. Suffice it to say, while there is no doubt much room for improvement, the LENA® system provides one fairly well-scrutinized way to measure features of children's linguistic environment. To preface some of our results, in our sample we find very good longitudinal correlations within variables, especially AWC and CTC (see Tables S1–S4 for correlations across time points for all four LENA® measures), suggesting that the system reliably captures variability in these concepts across individual children between the ages of 9 and 24 months. That these variables have predictive validity is also notable (Wang et al., 2020).

Recordings that were less than 16 hr were not included in the analyses to ensure counts were over a uniform period of time ($n = 12$).

MacArthur-Bates Communicative Development Inventories

Children's language was measured using the MBCDI—Words and Gestures form (Fenson et al., 2007) between 9 and 15 months, and the MBCDI—Words and Sentences form between 18 and 24 months. The MBCDI—Words and Gestures form contains 396 words; caregivers are asked to indicate whether their child understands and/or produces them. The form was designed to measure language and communicative development in children aged 8–18 months. The MBCDI—Words and Sentences form contains 682 words; caregivers are asked to indicate whether their child produces them. Following Reilly et al. (2007), some minor changes were made to a small number of words to better capture the Australian dialect, resulting in a total of 678 items. The form is designed to measure vocabulary and early morphosyntactic development between 16 and 30 months. Both forms have excellent reliability and validity (see Fenson et al., 2007).

The two forms were used at the appropriate age point to ensure accurate estimation of the children's productive vocabulary. This amounts to assuming that children between 9 and 15 months did not know any words on the Words and Sentences form that were not on the Words and Gestures form. Given the relatively small productive vocabulary sizes at these time points (see Table 8), we argue that this is a plausible assumption.

As Mayor and Plunkett (2011) point out, MBCDI scores are not linearly related to vocabulary size. The MBCDI represents a sample of overall vocabulary. As the proportion of words that children know on the MBCDI increases, so does the probability that they know words that are not on the MBCDI. Therefore, the difference between an MBCDI score of 0 and 1 likely reflects a much smaller gain in total vocabulary size than a difference between 300 and 301. Accordingly, Mayor and Plunkett derived a transformation to map from MBCDI scores to true vocabulary scores. The difference between the MBCDI scores and transformed scores is small at low MBCDI scores but increases as MBCDI scores increase. While this transformed score is a potentially more accurate measure of vocabulary size, it is not widely used. We therefore report all analyses using the transformed MBCDI and raw MBCDI.

Statistical Approach

For our primary analyses, we fit sets of growth curve models predicting (a) CTC from change in vocabulary from the prior time point and (b) vocabulary from change in CTC from the prior time point. For both sets of analyses, we first fit baseline growth curve models predicting the relevant dependent variable from a time variable and a set of control variables (the choice of control variables was different across the two models and are, therefore, explained for each dependent variable separately). We then added a change score in the relevant independent variable between time t and time $t - 1$ as a predictor variable (which we call time-specific change) to determine whether this change score predicted variability in the relevant DV over and above its growth trajectory. One potential problem with this approach is that when time-varying predictor variables are entered into a growth curve model on their own they conflate within and between subject effects. For example, when predicting CTC growth over time from a time-varying vocabulary change score, the coefficient for this variable will reflect both (a) how time-specific variability in vocabulary change predicts time-specific variability in CTC growth within participants and (b) how variability in total vocabulary growth predicts variability in total CTC growth across participants. These two effects can be disaggregated by explicitly accounting for between-subject variability. To do this, we averaged the time-specific growth variables for each participant, which we call *participant-average change*. The specifics of how these models were implemented are different for the analyses of vocabulary and CTCs, and therefore we consider each separately below.

Vocabulary Change Scores

Vocabulary change between time t and $t-1$ was calculated for each time point t. For 9-month sessions, we used 0 as the vocabulary size at time $t-1$, based on the assumption that a 6-month-old child would be very unlikely to produce words. We calculated change scores using both transformed and raw MBCDI scores. Moreover, in some cases, vocabulary at time t was smaller than at time $t-1$, so we considered both change scores and change scores where negative scores were converted to 0. This led to four operational definitions of the time-specific change score: (a) transformed change scores with no negatives, (b) transformed change scores with negatives, (c) raw change scores with no negatives, and (d) raw change scores with negatives. In addition to these time-varying change scores, we included participant-average change (i.e., average change over the 15-month duration of the study), to account for between-subject effects, as explained earlier.

CTC Change Scores

Taking raw difference scores in CTC between time t and time $t-1$ is problematic because the number of conversational turns depends on the amount of language the child heard and produced at each time point, both of which are time-varying. That is, within individuals, there will be random fluctuations in CTC that will reflect the relative social intensity, or "talkativeness," of the recording day. Note also that LENA® captures adult words inside and outside of conversation. Thus, we needed to control for language use to isolate growth in CTC over and above the number of words a child uses or hears on a particular day. To do this, we residualized CTC on AWC, CVC, and TV PCT. Specifically, we fit six negative binomial regressions, one at each time point (9–24 months), predicting CTC from AWC, CVC, TV PCT as well AWC Squared and CVC Squared, to account for nonlinear effects of AWC and CVC on CTC. Models that only included linear effects of CVC and AWC exhibited poor fit according to plots of residuals versus fitted values and adding the squared terms for these variables improved the pattern of residuals versus fitted values and both produced significant coefficients. Coefficients for each of these models are presented in Supporting Information (Tables S5). In one of these models (18 months), we removed one observation because it produced a very large Cook's distance and was strongly affecting the estimates of the residuals for all other data points.

We used negative binomial regression rather than linear regression because CTC is a count variable and estimation of residuals is quite sensitive to the choice of model. Count variables deviate from normally distributed variables in two key respects: (a) they have floors of 0 and (b) their variance tends to increase with their mean. Negative binomial regression better accommodates these two properties than linear regression. We considered two types of residuals: response and Pearson residuals. Response residuals are the observed value minus the predicted value. Pearson residuals are the response minus the predicted value divided by the model-implied standard deviation for that predicted value. These two residuals differ in an important way. The negative binomial distribution assumes that the dependent variable's standard deviation increases with its mean; therefore, for larger predicted values, it expects greater deviations from the predicted value. Response residuals do not account for this, whereas Pearson's residuals do. For example, if two participants had predicted values of 500 and 600 conversational turns and both exceeded their predicted value by 100, the response residuals for the two participants would be the same. However, because the expected standard deviation for a participant with a predicted value of 600 would be larger than that of a participant with a predicted value of 500, the participant with a larger predicted value would have a smaller residual. We also performed these analyses using Gaussian residuals and raw CTC change scores as exploratory analyses, although we do not endorse this approach. Results from these analyses are in Supporting Information (see Tables S6 and S7).

Correlation matrices for each type of residual across the time points are presented in Tables 2 and 3. These correlations were generally significant and

Table 2
Correlations Between Pearson Residuals From Models Predicting Conversational Turn Count at Each Time Point

	9 months	12 months	15 months	18 months	21 months	24 months
9 month	1					
12 months	.44***	1				
15 months	.32**	.39**	1			
18 months	.05	.21*	.32**	1		
21 months	.41***	.51***	.42***	.31***	1	
24 months	.30**	.37**	.24*	.29**	.63***	1

*p < .05. **p < .01. ***p < .001.

Table 3
Correlations Between Response Residuals From Models Predicting Conversational Turn Count at Each Time Point

	9 months	12 months	15 months	18 months	21 months	24 months
9 month	1					
12 months	.38***	1				
15 months	.22*	.32**	1			
18 months	.10	.32**	.19[a]	1		
21 months	.40***	.43***	.30*	.31*	1	
24 months	.23*	.32**	.13	.33*	.52***	1

[a]p < .06. *p < .05. ** p < .01. *** p < .001.

of moderate magnitude. This pattern of results reveals stable and measurable individual differences in CTC that are independent of the amount of language the dyad experiences in a day, thereby justifying our use of these residualized scores. In other words, these variables are quantifying a unique and stable aspect of the linguistic interaction between parents and children, independent of frequency of input.

We calculated change scores on each residual type between time t and $t-1$ (again subtracting 0 from the 9-month residual) and calculated each participant's average change score (to de-confound within- and between-subject effects).

Confirmatory and Exploratory Analyses

Our primary analyses are confirmatory tests of the hypothesized bidirectional relationship between vocabulary and conversational turns: (a) the models predicting growth in conversational turns from changes in vocabulary and (b) the models predicting growth in vocabulary from changes in conversational turns, when conversational turns were residualized using the negative binomial models. All additional analyses should be considered exploratory.

Results

Descriptive Statistics of LENA® Variables and MBCDI

Our data and analysis code are available from https://osf.io/v9fuq/. Descriptive statistics for each variable at each time point are presented in Tables 4–8. Correlations between LENA® variables across time are reported in Supporting Information (Tables S1–S4). Prior to addressing our main research questions, we examined whether the four LENA® variables (AWC, CVC, CTC, and TV) increased over time. For AWC, CVC, and CTC, we fit both linear growth curve models and negative binomial distributed growth curve models. For TV, we fit both linear and beta-distributed growth curve models (Smithson & Verkuilen, 2006). For all models, we included uncorrelated random intercepts and random slopes, as several models with correlated random effects produced implausible random effects estimates (random effects correlations of 1). Parameters of all models are presented in Table 9. All four variables increased over time.

The Effect of Vocabulary Growth on CTCs

To determine the effect of vocabulary growth on CTC, we first fit a baseline linear growth curve

Table 4
Descriptive Statistics for Adult Word Count

	M	*SD*	Range
9 months	14,362	6,179	3,266–33,465
12 months	14,572	6,826	3,234–35,323
15 months	15,230	8,388	2,551–51,616
18 months	15,920	7,088	4,340–38,097
21 months	15,919	6,297	2,986–34,006
24 months	16,827	7,237	2,491–37,453

Table 5
Descriptive Statistics for Child Vocalization Count

	M	*SD*	Range
9 months	1,373	569	289–3,331
12 months	1,639	666	202–3,611
15 months	1,929	863	29–5,343
18 months	2,265	980	629–5,336
21 months	2,825	1,222	80–7,649
24 months	3,030	1,343	378–7,221

Table 6
Descriptive Statistics for Conversational Turn Count

	M	*SD*	Range
9 months	366	172	49–902
12 months	433	196	44–1,062
15 months	523	267	12–1,586
18 months	614	299	112–2,000
21 months	733	346	25–1,764
24 months	811	404	57–1,985

Table 7
Descriptive Statistics for TV PCT

	M	*SD*	Range
9 months	0.05	0.08	0.01–0.45
12 months	0.06	0.06	0.01–0.34
15 months	0.05	0.06	0.01–0.42
18 months	0.06	0.06	0.01–0.31
21 months	0.07	0.07	0.01–0.51
24 months	0.07	0.07	0.01–0.41

Note. TV PCT = TV, radio, music.

model predicting CTC growth from time (as single continuous variable with 0 for 9 months and 5 for 24 months) and the set of control variables (AWC, CVC, TV Percentage, and Parental Education). Raw coefficients of this model are presented in Table 8.

Table 8
Descriptive Statistics for MBCDI

	N	Raw MBCDI prod	Transformed MBCDI prod
9 months	120	0 (0–24)	0 (0–26)
12 months	122	5 (0–102)	5 (0–124)
15 months	115	18 (0–173)	19 (0–235)
18 months	115	67 (0–412)	77 (0–781)
21 months	114	201.5 (7–662)	285 (7–2,292)
24 months	113	357 (17–678)	626 (18–2,971)

Note. Median in cells. Range in parentheses. MBCDI = MacArthur-Bates Communicative Development Inventories.

See Figure 1 for an illustration of the growth trajectory. While a negative binomial growth curve model would have arguably been more appropriate as CTC is a count variable, these models did not converge.

We then fit four models examining the effect of each of the four operationalizations of time-specific vocabulary change. All reported models include random intercepts and random slopes for time. We considered models with random slopes for vocabulary change scores, but they frequently produced convergence warnings and did not produce qualitatively different results. We do not report these models here; however, the relevant code and output is available in the script associated with this publication. As can be seen in Figure 1, one value of CTC at 18 months was much larger than the rest. All models were fit with and without this data point, which also produced a very large residual (> 4 across all models). However, results did not qualitatively differ, so we report models with all data points here. See accompanying script for results with and without this observation. Examination of qq plots did not reveal any other problematic residuals. Parameter estimates for all four final models are presented in Table 10. As can be seen, in all four models, the effect of time-specific vocabulary change between time t and $t - 1$ on CTC is positive and significant. These results suggest that individual increases in vocabulary size over 3-month periods predict individual conversational turn growth.

The Effect of CTC Growth on Vocabulary

To determine the effect of CTC growth on vocabulary growth, we first fit two baseline negative binomial growth curve models, one for the transformed vocabulary score and one for the raw

Table 9
Models of Growth in LENA Measures Across Time

	AWC		CVC		CTC		TV	
	Linear	N Binom	Linear	N Binom	Linear	N Binom	Linear	Beta
Fixed								
Intercept	14,339 (13,027 to 15,486)***	9.50 (9.41 to 9.57)***	1,318 (1,211 to 1,420)***	7.20 (7.13 to 7.26)***	353 (322 to 384)***	5.86 (5.77 to 5.93)***	0.05 (0.04 to 0.06)***	−3.09 (−3.23 to −2.96)***
Time	497 (276 to 724)***	0.03 (0.02 to 0.05)***	340 (292 to 391)***	0.16 (0.14 to 0.18)***	90 (76 to 104)***	0.16 (0.14 to 0.18)***	0.00 (0.00 to 0.01)***	0.07 (0.04 to 0.10)***
AIC	13,239	13,187	10,727	10,721	9,051	9,001	−1,949	−2,591

Note. Unstandardized regression coefficients with confidence intervals in parentheses. CIs for beta-distributed errors are Wald CIs. CIs for other models are bootstrapped. LENA = Language Environment Analysis; AWC = Adult Word Count; CVC = Child Vocalization Count; CTC = conversational turn count; AIC = Akaike information criterion.
***p < .001.

vocabulary score. These models included time coded as a second-order orthogonal polynomial (to account for the well-established nonlinear relationship between time and vocabulary size; McMurray, 2007), and parental education. We did not include AWC, CVC, and TV PCT in these models as these variables were used to create the residualized CTC Change variables (as an exploratory analysis, we considered models with AWC, CVC, and TV PCT as control variables but these did not reliably converge, so we do not report them here. However, inferences did not qualitatively differ from those reported in the tables). The models included uncorrelated random slopes for both time terms and a random intercept. Parameter estimates for the two measures are presented in Tables 11 and 12. Growth trajectories for each model are presented in Figures 2a and 2b.

We added the time-specific CTC change scores to our baseline models. We first considered models with random slopes for time-specific CTC change scores (which we call full models). However, when we fit models without these random slopes (reduced models) for time-specific CTC change scores, they fit better. Since the results differed across the two models, we report both. There are two points in Figure 2a that are much larger than the others at 21 and 24 months. We fit all models with and without these points. Results did not qualitatively differ. Moreover, these observations, while large, did not produce problematic residuals, suggesting they were not unexpectedly large given the models' parameters. We, therefore, report on analyses with all data points. As can be seen in Tables 11 and 12, the time-specific CTC change scores were significant and positively related to vocabulary in all models, except for when response residuals were used in the reduced models. These results suggest that time-specific increases in CTC predict growth in vocabulary.

Discussion

In the current paper, we followed a group of 122 monolingual English-acquiring infants from 9 to 24 months, measuring their language environment using daylong recordings, and their vocabulary knowledge, every 3 months. Specifically, we investigated the relationship between growth in infant conversational turn-taking and growth in vocabulary. Following socio-pragmatic approaches to language development (e.g., Bruner, 1983; Clark, 2018; Dunham & Dunham, 1992; Nelson, 2007; Tomasello, 2003; Vygotsky, 1978) and results that suggest turn-taking is affected by developing language and cognitive abilities (Casillas et al., 2016; Hilbrink et al., 2015), we predicted a bidirectional relationship between the two such that growth in conversational turns would predict growth in vocabulary (as reported by Zimmerman et al., 2009) and vice-versa (pace Zimmerman et al.). Our hypothesis was supported: controlling for the number of adult words in the child's environment, we found evidence that the two variables mutually influence each other across early development.

The results support arguments for a strong social basis to early language development, which is likely to operate at multiple levels. Following Kuhl (2007), early acquisition of language-specific speech patterns may be socially gated (see Garcia-Sierra, Ramírez-Esparza, & Kuhl, 2016). Once children become capable of sustained joint attention, interaction affords caregivers opportunities to scaffold

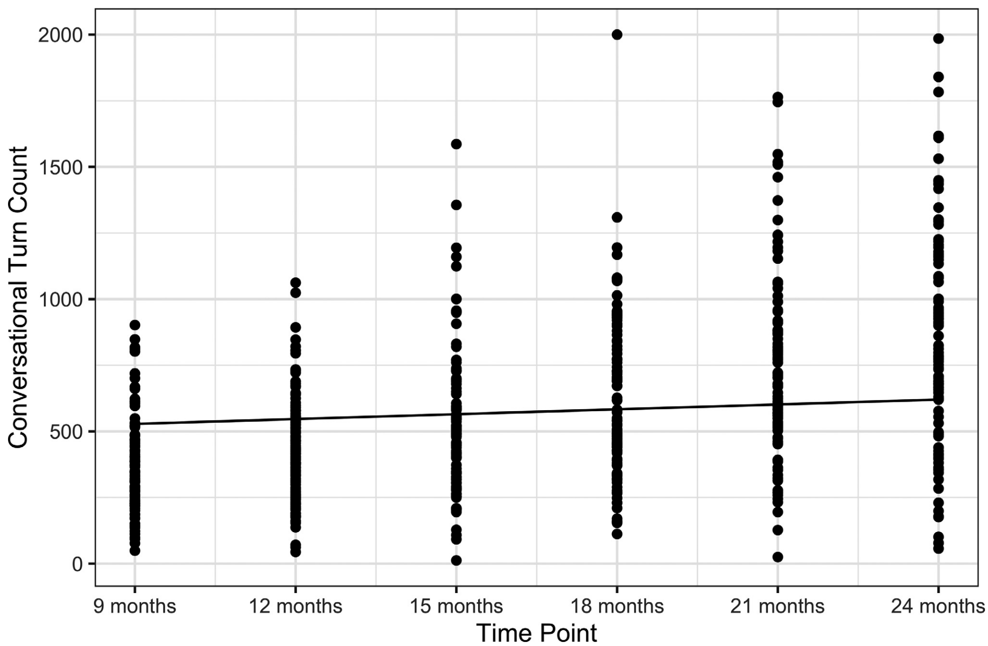

Figure 1. Growth in CTC over time. Line represents the slope for time (from baseline mode), holding other variables in the model constant. Note that because other variables are held constant, this model suggests greater heteroskedasticity than would plots of residuals. CTC = conversational turn count.

Table 10
Models Predicting CTC Growth From Vocabulary

		Transformed vocab		Raw vocab	
Parameter	Baseline model	Model 1 No negatives	Model 2 Negatives	Model 3 No negatives	Model 4 Negatives
Intercept	−135.6 (−177 to −84)***	−139.1 (−186 to −88)***	−139 (−185 to −90)***	−133.7 (−186 to −83)***	−133.6 (−181 to −80)***
Control variables					
Time	18.4 (11.8 to 25.5)***	14.2 (6.4 to 21.4)***	14.3 (6.8 to 22.0)***	11.7 (3.79 to 18.78)**	11.7 (3.81 to 19.6)***
AWC	0.02 (0.02 to 0.02)***	0.02 (0.02 to 0.02)***	0.02 (0.02 to 0.02)***	0.02 (0.02 to 0.02)***	0.02 (0.02 to 0.02)***
CVC	0.19 (0.18 to 0.20)***	0.18 (0.17 to 0.20)***	0.18 (0.17 to 0.19)***	0.18 (0.17 to 0.19)***	0.18 (0.17 to 0.19)***
TV PCT	50.43 (−90.8 to 192.8)	44.3 (−85 to 168)	44.3 (−91.7 to 180.7)	42.5 (−76.5 to 159.1)	42.6 (−93.71 to 174.0)
Parental education	−5.55 (−16.5 to 5.0)	−5.4 (−16.9 to 4.78)	−5.4 (−15.5 to 4.8)	−5.4 (−15.8 to 5.0)	−5.4 (−15.6 to 4.19)
Avg MBCDI change		0.09 (−0.05 to 0.24)	0.09 (−0.07 to 0.25)	0.11 (−0.29 to 0.48)	0.11 (−0.29 to 0.51)
Predictor variable					
MBCDI change		0.07 (0.01 to 0.13)*	0.07 (0.01 to 0.13)*	0.28 (0.16 to 0.42)***	0.28 (0.14 to 0.42)***

Note. Unstandardized regression coefficients with bootstrapped confidence intervals in parentheses. AWC = Adult Word Count; CVC = Child Vocalization Count; CTC = conversational turn count; MBCDI = MacArthur-Bates Communicative Development Inventories; TV PCT = TV, radio, music.
$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

language via engagement in objects and shared communicative routines (Bruner, 1983). Such interaction allows competent others to calibrate their input to children's developmental level, forming a feedback loop that provides a fertile context for language acquisition (Hirsh-Pasek et al., 2015; Romeo et al., 2018; Tamis-LeMonda et al., 2014; Vygotsky, 1978; Zimmerman et al., 2009). This is consistent with a unidirectional relationship from turn-taking to language; however, our data also show the opposite relation. We suggest that this result reflects the *active involvement* of the child in the acquisition process. That is, the fact that vocabulary growth positively predicted turn-taking

Table 11
Models Predicting Transformed Vocabulary From CTC

		NB Pearson residuals		NB response residuals	
	Baseline model	Full	Reduced	Full	Reduced
Intercept	3.63 (2.87 to 4.29)***	3.66 (3.01 to 4.31)***	3.66 (2.90 to 4.40)***	3.65 (2.95 to 4.27)***	3.68 (2.97 to 4.33)***
Control variables					
Time	59.82 (57.24 to 62.22)***	59.86 (57.48 to 61.86)***	59.85 (57.32 to 62.28)***	60.14 (57.73 to 62.81)***	59.82 (57.18 to 62.19)***
Time^2	−7.77 (−9.53 to −6.36)***	−7.79 (−9.56 to −6.15)***	−7.78 (−9.63 to 6.29)***	−7.81 (−9.46 to −6.18)***	−7.77 (−9.38 to −6.46)***
Parental education	−0.10 (−0.28 to 0.08)	−0.11 (−0.27 to 0.05)	−0.11 (−0.31 to 0.08)	−0.12 (−0.28 to 0.07)	−0.12 (−0.29 to 0.09)
Mean change residual		−0.52 (−1.31 to 0.19)	−0.51 (−1.36 to 0.22)	−0.68 (−1.40 to 0.02)[a]	−0.68 (−1.45 to −0.00)[a]
Predictor variables					
Change residual		0.04 (0.01 to 0.07)*	0.04 (0.00 to 0.07)*	0.04 (0.00 to 0.07)**	0.02 (−0.01 to 0.05)
AIC	5,673	5,672	5,670	5,762	5,672

Note. Unstandardized regression coefficients with bootstrapped confidence intervals in parentheses. CTC = conversational turn count; AIC = Akaike information criterion.
[a]$p < .10$. *$p < .05$. **$p < .01$. ***$p < .001$.

suggests that children increasingly influence their own development as their linguistic competence increases. In other words, the infant jointly controls the *interaction engine* (Levinson, 2016).

More broadly, the data are consistent with accounts of development that argue learning is grounded within temporally contingent social interaction that is scaffolded by a competent other (Gergely & Csibra, 2009, 2011; Rogoff, 1990; Tomasello, 1999; Vygotsky, 1978). Recent neurophysiological work by Leong et al. (2018) reported evidence for neural coupling between 8-month-old infants and adult interlocutors in joint attention contexts. An adult experimenter sang nursery rhymes to infants while both participants' brain oscillations were recorded across two conditions: a gaze-direct condition, in which the experimenter looked directly at the infant, and a gaze-indirect condition, in which she fixated on an object 20° to the left or right. The strongest coupling was observed in the direct gaze condition, suggesting that ostensive social signals to joint attention serve to bring brains into mutual temporal alignment. Interestingly, the effect was moderated by infant vocalization, with infants who vocalized more showing greater neural coupling with an adult partner. The authors suggested that the latter result could reflect a social feedback mechanism, in which infant vocalizations reinforced and sustained dyadic synchronicity.

The Leong et al. (2018) data fit nicely with the bidirectional relationship between conversational turns and vocabulary development that we observed in the current study. If direct social interaction, as indexed by CTC, increases neural alignment between infant–adult dyads, then this provides optimum conditions for early vocabulary learning. Subsequent increases in vocabulary likely lead to greater procurement of and complexity in conversation, thus completing a virtuous developmental circle.

The suggestion that early language acquisition has a strong social basis is consistent with arguments that input quality plays an important role in early language development over and above the role of input quantity. Input quality has been operationalized in many different ways in the literature, from the diversity of vocabulary and grammatical phrases in the input (e.g., Huttenlocher, Vasilyeva, Waterfall, Vevea, & Hedges, 2010; Jones & Rowland, 2017), decontextualized language use (Rowe, 2012), referential transparency (Cartmill et al., 2013), and as constellations of socio-communicative behaviors related to joint communication, shared routines, and connectedness of the exchange (Hirsh-Pasek et al., 2015). We suggest that our measure most likely captures the social end of this continuum and the qualitatively important behaviors that occur within joint attentional frames, since we removed variance associated AWCs and children's

Table 12
Models Predicting Raw Vocabulary From CTC

		NB Pearson residuals		NB Response residuals	
	Baseline model	Full	Reduced	Full	Reduced
Intercept	3.38 (2.73 to 4.08)***	3.41 (2.75 to 4.09)***	3.43 (2.75 to 4.03)***	3.42 (2.76 to 4.10)***	3.45 (2.77 to 4.07)***
Control variables					
Time	54.56 (52.03 to 56.71)***	55.03 (52.84 to 57.23)***	54.41 (52.08 to 56.77)***	55.01 (52.49 to 57.44)***	54.39 (52.13 to 56.58)***
Time^2	−9.75 (−10.96 to −8.84)***	−9.62 (−11.02 to −8.10)***	−9.26 (−10.73 to −7.90)***	−9.52 (−11.07 to −7.86)***	−9.24 (−10.89 to −7.93)***
Parental education	−0.08 (−0.29 to 0.08)	−0.10 (−0.27 to 0.07)	−0.10 (−0.25 to 0.07)	−0.10 (−0.28 to 0.06)	−0.10 (−0.26 to 0.06)
Mean change residual		−0.48 (−1.25 to 0.28)	−0.47 (−1.17 to 0.11)	−0.64 (−1.28 to 0.07)*	−0.61 (−1.29 to 0.04)[a]
Predictor variables					
Change residual		0.04 (0.01 to 0.08)**	0.04 (0.01 to 0.06)**	0.05 (0.02 to 0.08)**	0.02 (−0.00 to 0.04)
AIC	NA	5,417	5,327	5,619	5,330

Note. Unstandardized regression coefficients with bootstrapped confidence intervals in parentheses. Note that the baseline model only contains a random effect for a first-order polynomial and we do not report AIC because it differs from other models in its random effects structure. CTC = conversational turn count; AIC = Akaike information criterion.
[a]$p < .10$. *$p < .05$. **$p < .01$. ***$p < .001$.

vocalizations from the conversational turn variable. Moreover, the fact that these residuals were correlated across time suggests that this is a mostly stable property of dyads, and our growth curve models of CTC found growth in conversational turns over time which is not attributable to AWC or child vocalizations. Considerable effort has been invested in reducing poor language outcomes associated with variables such as SES (e.g., Hart & Risley, 1995) by focusing on input quantity (the "30-million-word gap," see Golinkoff, Hoff, Rowe, Tamis-LeMonda, & Hirsh-Pasek, 2019). Input quantity is no doubt predictive of children's acquisition, particularly at young ages (Rowe, 2012), but like others before us (e.g., Golinkoff, Can, Soderstrom, & Hirsh-Pasek, 2015; Hirsh-Pasek et al., 2015), we suggest that focusing on bridging gaps in language outcomes also requires a focus on the social basis of language use.

Our results were inconsistent with Zimmerman et al. (2009), who reported a unidirectional relationship between conversational turns and language. In fact, when we analyzed our data using an unresidualized measure of conversational turns, we did not replicate their finding (see Supporting Information). Several differences between the two studies could explain the results. Whereas the current study had tightly controlled age bands, Zimmerman et al. recruited children between the ages of 2 and 36 months, and so were sampling a range of abilities at their first time point. This no doubt spans an age range in which the mechanics and socio-communicative content of the conversational turn changes in many ways (see Hilbrink et al., 2015). Additionally, our language measure, vocabulary, was a more narrowly defined linguistic domain than Zimmerman et al.'s (2009) more holistic measure. Finally, our analytical strategy, modeling growth over several time points, was likely more sensitive to developmental effects. One notable strength of our modeling approach is that it allows us to make claims about individual dyads and individual children's vocabulary growth independent of between-participant effects. That is, we have isolated the effects at the level of the individual, an important next step if we are to build more accurate theories that capture processes that explain the pervasive individual variability characteristic of language acquisition (Kidd & Donnelly, 2020; Kidd, Donnelly, & Christiansen, 2018). This has not typically been a feature of past research, where a reliance on traditional analytic approaches like correlation and multiple regression conflates within- and between-participant variance (e.g., Dunham & Dunham, 1992; Gilkerson et al., 2014, 2018; Romeo et al., 2018;).

Our study also has several limitations. First, we are limited to the LENA® software's definition of a

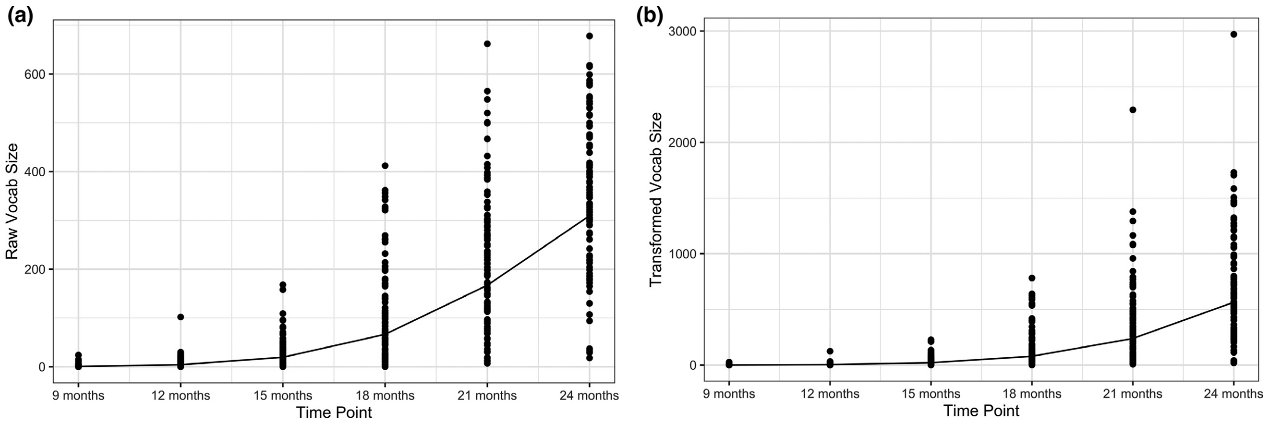

Figure 2. Growth in (a) raw vocabulary over time and (b) transformed vocabulary over time. Line represents slope of time holding other variables constant. Note that this is the slope of a negative binomial growth curve model, which explicitly models the heteroskedastcitiy.

conversational turn, and it is likely that there will be instances where turns are not identified (Cristia, Lavechin, et al., 2020), such as when speakers partially overlap (Hilbrink et al., 2015). Despite this, it is encouraging to find that, consistent with meta-analytic evidence reported by Wang et al. (2020), the relation between CTC and language proficiency is robust. We are also encouraged by converging evidence from a separate study in our laboratory, which found the same relationship in a separate group of infants and in which the CTCs were hand-coded (Creaghe, Quinn, & Kidd, 2020). In that study, CTC at 18 months (the beginning of the study) was significantly associated with vocabulary both concurrently and 6 months later, controlling for the amount of adult words in the input. The longitudinal relationship held after controlling for children's vocabulary at 18 months.

Second, the coarseness of the method means that we lack understanding of what happens within turns. We assume that the importance of turn-taking reflects how interaction within joint attentional frames supports language (e.g., Bruner, 1983; Donnellan et al., 2019; Tamis-LeMonda et al., 2014; Tomasello & Farrar, 1986). However, we suggest that our finding of a bidirectional relation between turn-taking and vocabulary growth highlights the importance of focusing on dialogical patterns of interaction that concentrates on both caregivers and children as intentional agents that co-construct meaning (Bruner, 1983; Sameroff, 2010; Vygotsky, 1978). Understanding the full richness of this process will require a mixed-methods approach that combines large-scale studies such as ours with micro-analytic studies that focus on the moment-by-moment features of interaction. Relatedly, it is also likely that children are engaging in joint attention in contexts where conversational turn-taking is minimal, and such contexts are no doubt important for acquisition. Several past studies have enriched the LENA® recordings by transcribing or hand-coding subsets of the daylong recordings, with good results (e.g., Garcia-Sierra et al., 2016; Weisleder & Fernald, 2013), and it would be instructive to know more about the frequency and distribution of different forms of input and interaction throughout the day. However, for the current data set that would be difficult, as transcribing and coding even a small representative sample of approximately 10,000 hr of data would be no small task.

Finally, although our sample was largely representative of the demographics of the city where the study was conducted, it fits firmly into the WEIRD (Western, Educated, Industrialised, Rich, Democratic; Henrich, Heine, & Norenzayan, 2010), which is overrepresented in studies of child development (Nielsen, Haun, Kärtner, & Legare, 2017). Whether the current data generalize beyond WEIRD contexts remains an open question, since there is large cultural diversity in child-rearing practices and beliefs regarding what it means to be a competent speaker of a language, thus affecting child-centered interaction. Cross-cultural studies of children's language environment show several instances where children growing up in small-scale traditional cultures hear a lower quantity of child-directed speech, particularly in non-child centered cultures (e.g., Brown, 2014; Casillas, Brown, & Levinson, 2019; Shneidman & Goldin-Meadow, 2012). Importantly, however, entholinguistic studies show that a key component of language socialization involves the use of social routines (Ochs & Schieffelin, 1984). These, according to socio-pragmatic theory, constitute the locus of language acquisition, rather than child-directed speech alone (de León, 2011). Thus, we suggest that our finding of a bidirectional link between interaction and development is likely to find an analogue cross-culturally.

Conclusion

In the current study, we reported on a comparatively large and intensive longitudinal data set of daylong language recordings of children acquiring Australian English, followed between 9 and 24 months. While such recordings provide a range of indices that describe the child's linguistic environment, we tested a specific hypothesis deriving from the socio-pragmatic theoretical approach to language development (Bruner, 1983; Dunham & Dunham, 1992; Tomasello, 2003); namely, there would be a bidirectional relationship between growth in independently measured vocabulary and growth in conversational turn-taking, under the assumption that infants and caregivers jointly determine meaningful social exchange that provides the foundation for language development. The hypothesis was supported, highlighting both the importance of social interaction in early language development, and the active role infants play in the process.

References

Australian Bureau of Statistics. (2016). *2016 census community profiles: Australian Capital Territory*. Canberra: Australian Bureau of Statistics. Retrieved from https://quickstats.censusdata.abs.gov.au/census_services/getproduct/census/2016/communityprofile/8ACTE.

Bates, E., Camaioni, L., & Volterra, V. (1975). The acquisition of performatives prior to speech. *Merrill-Palmer Quarterly*, *21*, 205–226. http://www.jstor.org/stable/23084619

Bateson, M. C. (1975). Mother-infant exchanges: The epigenesis of conversational interaction. *Annals of the New York Academy of Sciences*, *263*, 101–113. https://doi.org/10.1111/j.1749-6632.1975.tb41575.x

Bergelson, E., Casillas, M., Soderstrom, M., Seidl, A., Warlaumont, A. S., & Amatuni, A. (2019). What do North American babies hear? A large-scale cross-corpus analysis. *Developmental Science*, *22*, e12724. https://doi.org/10.1111/desc.12724

Bergelson, E., & Swingley, D. (2012). At 6–9 months, human infants know the meanings of many common nouns. *Proceedings of the National Academy of Sciences of the United States of America*, *109*, 3253–3258. https://doi.org/10.1073/pnas.1113380109

Brown, P. (2014). The interactional context of language learning in Tzeltal. In I. Arnon, M. Casillas, C. Kurumada, & B. Estigarribia (Eds.), *Language in interaction: Studies in honor of Eve V. Clark* (pp. 51–82). Amsterdam, Netherland: John Benjamins.

Bruner, J. S. (1975). The ontogensis of speech acts. *Journal of Child Language*, *2*, 1–19. https://doi.org/10.1017/S0305000900000866

Bruner, J. (1977). Early social interaction and language acquisition. In H. R. Schaffer (Ed.), *Studies in mother–infant interaction* (pp. 271–289). San Diego, CA: Academic Press.

Bruner, J. (1983). *Child's talk: Learning to use language*. New York: NY: W.W. Norton.

Carpenter, M., Nagell, K., & Tomasello, M. (1998). Social cognition, joint attention, and communicative competence from 9 to 15 months of age. *Monographs for the Society of Research in Child Development*, *63*, 1–143. https://doi.org/10.2307/1166214

Cartmill, E. A., Armstrong, B. F., Gleitman, L. R., Goldin-Meadow, S., Medina, T. N., & Trueswell, J. C. (2013). Quality of early parent input predicts child vocabulary 3 years later. *Proceedings of the National Academy of Sciences*, *110*, 11278–11283. https://doi.org/10.1073/pnas.1309518110

Casillas, M., Bobb, S. C., & Clark, E. V. (2016). Turn taking, timing, and planning in early language acquisition. *Journal of Child Language*, *43*, 1310–1337. https://doi.org/10.1017/S0305000915000689

Casillas, M., Brown, P., & Levinson, S. C. (2019). Early language experience in a Tseltal Mayan village. *Child Development*. https://doi.org/10.1111/cdev.13349

Che, E., Brooks, P. J., Alarcon, M., Yannaco, F. D., & Donnelly, S. (2018). Assessing the impact of conversational overlap in content on child language growth. *Journal of Child Language*, *45*, 72–96. https://doi.org/10.1017/S0305000917000083

Clark, E. V. (2018). Conversation and langauge development: A pragmatic approach. *Language Learning and Development*, *14*, 170–185. https://doi.org/10.1080/15475441.2017.1340843

Creaghe, N., Quinn, S., & Kidd, E. (2020). *Symbolic play provides a fertile context for language development*. https://doi.org/10.31234/osf.io/eg8yz

Cristia, A., Bulgarelli, F., & Bergelson, E. (2020). Accuracy of the Language Environment Analysis (LENATM) system segmentation and metrics: A systematic review. *Journal of Speech, Language, and Hearing Research*, *63*, 1093–1105. https://doi.org/10.1044/2020_JSLHR-19-00017

Cristia, A., Lavechin, M., Scaff, C., Soderstrom, M., Rowland, C., Räsänen, O., . . . Bergelson, E. (2020). A thorough evaluation of the Language Environment Analysis (LENA) system. *Behavior Research Methods*. https://doi.org/10.3758/s13428-020-01393-5

de León, L. (2011). Language socialization and multiparty participation frameworks. In A. Duranti, E. Ochs, & B. B. Schieffelin (Eds.), *Handbook of language socialization* (pp. 81–111). Malden, MA: Wiley-Blackwell. https://doi.org/10.1002/9781444342901.ch4

Donnellan, E., Bannard, C., McGillion, M., Slocombe, K., & Matthews, D. (2019). Infants' intentionally communicative vocalisations elicit responses from caregivers and are the best predictors of the transitions to language: A longitudinal investigation of infants' vocalisations, gestures, and word production. *Developmental Science*, e12843. https://doi.org/10.1111/desc.12843

Donnelly, S., & Kidd, E. (2020). Individual differences in lexical processing efficiency and vocabulary in toddlers: A longitudinal investigation. *Journal of Experimental Child Psychology*, *192*, 104781. https://doi.org/10.1016/j.jecp.2019.104781

Dunham, P., & Dunham, F. (1992). Lexical development during middle infancy: a mutually- driven infant-caregiver process. *Developmental Psychology*, *28*, 414–420. https://doi.org/10.1037/0012-1649.28.3.414

Fenson, L., Bates, E., Dale, P. S., Marchman, V. A., Reznick, J. S., & Thal, D. J. (2007). *MacArthur-Bates communicative development inventories* (2nd ed.). Baltimire, MD: Brookes.

Garcia-Sierra, A., Ramírez-Esparza, N., & Kuhl, P. K. (2016). Relationships between quantity of language input and brain responses in bilingual and monolingual infants. *International Journal of Psychophysiology*, *110*, 1–17. https://doi.org/10.1016/j.ijpsycho.2016.10.004

Gergely, G., & Csibra, G. (2009). Natural pedagogy. *Trends in Cognitive Sciences*, *13*, 148–153. https://doi.org/10.1016/j.tics.2009.01.005

Gergely, G., & Csibra, G. (2011). Natural pedagogy as an evolutionary adaptation. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *366*, 1149–1157. https://doi.org/10.1098/rstb.2010.0319

Gilkerson, J., Richards, J. A., Warren, S. F., Montgomery, J. K., Greenwood, C. R., Oller, K., & Paul, T. D. (2014). Mapping the language environment using all-day and automated analysis. *American Journal of Speech-Language Pathology*, *26*, 248–265. https://doi.org/10.1044/2016_AJSLP-15-0169

Gilkerson, J., Richards, J. A., Warren, S. F., Oller, K., Ruddo, R., & Vohr, B. (2018). Language experience in the second year of life and language outcomes in late childhood. *Pediatrics*, *142*, e20174276. https://doi.org/10.1542/peds.2017-4276

Golinkoff, R. M., Can, D. D., Soderstrom, M., & Hirsh-Pasek, K. (2015). (Baby) talk to me: The social context of infant-directed speech and its effects on early language acquisition. *Current Directions in Psychological Science*, *24*, 339–344. https://doi.org/10.1177/0963721415595345

Golinkoff, R. M., Hoff, E., Rowe, M. L., Tamis-LeMonda, C., & Hirsh-Pasek, K. (2019). Language matters: Denying the existence of the 30-million-word gap has serious consequences. *Child Development*, *90*, 985–992. https://doi.org/10.1111/cdev.13128

Greenwood, C. R., Thiemann-Bourque, K., Walker, D., Buzhardt, J., & Gilkerson, J. (2011). Assessing children's home language environments using automatic speech recognition technology. *Communication Disorders Quarterly*, *32*, 83–92. https://doi.org/10.1177/1525740110367826

Hart, B., & Risley, T. (1995). *Meaningful differences in the everyday experience of young American children*. Baltimore, MD: Paul. H. Brookes.

Henrich, J., Heine, S. J., & Norenzayan, A. (2010). The weirdest people in the world? *Behavorial and Brain Sciences*, *33*, 61–83. https://doi.org/10.1017/S0140525X0999152X

Hilbrink, E. E., Gattid, M., & Levinson, S. C. (2015). Early developmental changes in the timing of turn-taking: A longitudinal study of mother-child interaction. *Frontiers in Psychology*, *6*, 1492. https://doi.org/10.3389/fpsyg.2015.01492

Hirsh-Pasek, K., Adamson, L. B., Bakeman, R., Owen, M. T., Golinkoff, R. M., Pace, A., . . . Suma, K. (2015). The contribution of early communication quality to low-income children's language success. *Psychological Science*, *26*, 1071–1089. https://doi.org/10.1177/0956797615581493

Hoff, E. (2003). The specificity of environmental influence: Socioeconomic status affects early vocabulary development via maternal speech. *Child Development*, *74*, 1368–1378. https://doi.org/10.1111/1467-8624.00612

Hoff-Ginsberg, E. (1994). Influences of mother and child on maternal talkativeness. *Discourse Processes*, *18*, 105–117. https://doi.org/10.1080/01638539409544886

Huttenlocher, J., Vasilyeva, M., Waterfall, H., Vevea, J., & Hedges, L. V. (2010). Sources of variability in children's language growth. *Cognitive Psychology*, *61*, 343–365. https://doi.org/10.1016/j.cogpsych.2010.08.002

Jones, G., & Rowland, C. F. (2017). Diversity not quantity in caregiver speech: Using computational modelling to isolate the effects of the quantity and the diversity of the input on vocabulary growth. *Cognitive Psychology*, *98*, 1–21. https://doi.org/10.1016/j.cogpsych.2017.07.002

Kidd, E., & Donnelly, S. (2020). Individual Differences in First Language Acquisition. *Annual Review of Linguistics*, *6*, 319–340. https://doi.org/10.1146/annurev-linguistics-011619-030326

Kidd, E., Donnelly, S., & Christiansen, M. H. (2018). Individual differences in language acquisition and processing. *Trends in Cognitive Sciences*, *22*, 154–169. https://doi.org/10.1016/j.tics.2017.11.006

Kidd, E., Junge, C., Spokes, T., Morrison, L., & Cutler, A. (2018). Individual differences in infant speech segmentation: Achieving the lexical shift. *Infancy*, *23*, 770–794. https://doi.org/10.1111/infa.12256

Kuhl, P. K. (2007). Is speech 'gated' by the social brain? *Developmental Science*, *10*, 110–120. https://doi.org/10.1111/j.1467-7687.2007.00572.x

Leong, V., Byrne, E., Clackson, K., Georgieva, S., Lam, S., & Wass, S. (2018). Speaker gaze increases information coupling between infant and adult brains. *Proceedings of the National Academy of Sciences of the United States of America*, *115*, 13290–13295. https://doi.org/10.1073/pnas.1702493114

Levinson, S. C. (2006). On the human "interaction engine". In N. J. Enfield & S. C. Levinson (Eds.), *Roots of human sociality: Culture, cognition and interaction* (pp. 39–69). Oxford, UK: Berg.

Levinson, S. C. (2016). Turn-taking in human communication—Origins and implications for language processing. *Trends in Cognitive Sciences*, *20*, 6–14. https://doi.org/10.1016/j.tics.2015.10.010

Mayor, J., & Plunkett, K. (2011). A statistical estimate of infant and toddler vocabulary size from CDI analysis. *Developmental Science*, *14*, 769–785. https://doi.org/10.1111/j.1467-7687.2010.01024.x

McMurray, B. (2007). Defusing the childhood vocabulary explosion. *Science*, *317*, 631. https://doi.org/10.1126/science.1144073

Murray, L., & Trevarthen, C. (1985). Emotional regulation of interactions between two- month-olds and their mothers. In T. M. Field & N. A. Fox (Eds.), *Speech perception in infants* (pp. 177–197). Norwood, NJ: Alex.

Nelson, K. (2007). *Young minds in social worlds: Experience, meaning, and memory*. Cambridge, MA: Harvard University Press.

Nielsen, M., Haun, D., Kärtner, J., & Legare, C. H. (2017). The persistent sampling bias in developmental psychology: A call to action. *Journal of Experimental Child Psychology*, *162*, 31–38. https://doi.org/10.1016/j.jecp.2017.04.017

Ochs, E., & Schieffelin, B. (1984). Language acquisition and socialization: Three developmental stories and their implications. In R. A. Schweder & R. A. LeVine (Eds.), *Culture theory: Essays on mind, self, and emotion* (pp. 276–322). Cambridge, UK: Cambridge University Press.

Reilly, S., Wake, M., Bavin, E. L., Prior, M., Williams, J., Bretherton, L., . . . Ukoumunne, O. C. (2007). Predicting language at 2 years of age: A prospective community study. *Pediatrics*, *120*, e1441–e1449. https://doi.org/10.1542/peds.2007-0045

Rogoff, B. (1990). *Apprenticeship in thinking: Cognitive development in social context*. New York, NY: Oxford University Press.

Romeo, R. R., Leonard, J. A., Robinson, S. T., West, M. R., Mackey, A. P., Rowe, M. L., & Gabrieli, J. D. (2018). Beyond the 300-million-word gap: Children's conversational exposure is associated with language-related brain function. *Psychological Science*, *29*, 700–710. https://doi.org/10.1177/0956797617742725

Rowe, M. L. (2012). A longitudinal investigation of the role of quantity and quality of child-directed speech in vocabulary development. *Child Development*, *83*, 1762–1774. https://doi.org/10.1111/j.1467-8624.2012.01805.x

Sameroff, A. (2010). A unified theory of development: A dialectic integration of nature and nurture. *Child Development*, *83*, 1762–1774. https://doi.org/10.1111/j.1467-8624.2009.01378.x

Shneidman, L. A., & Goldin-Meadow, S. (2012). Language input and acquisition in a Mayan village: How important is directed speech? *Developmental Science*, *15*, 659–673. https://doi.org/10.1111/j.1467-7687.2012.01168.x

Smithson, M., & Verkuilen, J. (2006). A better lemon squeezer? Maximum-likelihood regression with beta-distributed dependent variables. *Psychological Methods*, *11*(1), 54–71. https://doi.org/10.1037/1082-989X.11.1.54

Snow, C. E. (1977). Development of conversation between mothers and babies. *Journal of Child Language*, *4*, 1–22. https://doi.org/10.1017/S0305000900000453

Song, L., Spier, E. T., & Tamis-LeMonda, C. S. (2014). Reciprocal influences between maternal language and children's language and cognitive development. *Journal of Child Language*, *41*, 305–326. https://doi.org/10.1017/S0305000912000700

Striano, T., & Stahl, D. (2005). Sensitivity to triadic attention in early infancy. *Developmental Science*, *8*, 333–343. https://doi.org/10.1111/j.1467-7687.2005.00421.x

Tamis-LeMonda, C. S., Kuchirko, Y., & Song, L. (2014). Why is infant language learning facilitated by parental responsiveness? *Current Directions in Psychological Science*, *23*, 121–126. https://doi.org/10.1177/0963721414522813

Tomasello, M. (1999). *The cultural origins of human cognition*. Harvard, MA: Harvard University Press.

Tomasello, M. (2003). *Constructing a language: A usage-based theory of language acquisition*. Harvard, MA: Harvard University Press.

Tomasello, M. (2008). *Origins of human communication*. Cambridge, MA: MIT Press.

Tomasello, M. (2019). *Becoming human: A theory of ontogeny*. Cambridge, MA: Harvard University Press.

Tomasello, M., Carpenter, M., Call, J., Behne, T., & Moll, H. (2005). Understanding and sharing intentions: The origins of cultural cognition. *Behavioral and Brain Sciences*, *28*, 675–691. https://doi.org/10.1017/S0140525X05000129

Tomasello, M., Carpenter, M., & Liszkowski, U. (2007). A new look at infant pointing. *Child Development*, *78*, 705–722. https://doi.org/10.1111/j.1467-8624.2007.01025.x

Tomasello, M., & Farrar, M. J. (1986). Joint attention and early language. *Child Development*, *57*, 1454–1463. https://doi.org/10.2307/1130423

Vygotsky, L. (1978). *Mind in Society: The development of higher psychological processes*. Cambridge, MA: Harvard University Press.

Wang, Y., Willimas, R., Dilley, L., & Houston, D. M. (2020). A meta-analysis of the predictability of LENATM automated measures for child language development. *Developmental Review*, *57*, 100921. https://doi.org/10.1016/j.dr.2020.100921

Weisleder, A., & Fernald, A. (2013). Talking to children matters: Early language experience strengthens processing and builds vocabulary. *Psychological Science*, *24*, 2143–2152. https://doi.org/10.1177/0956797613488145

Zimmerman, F. J., Gilkerson, J., Richards, J. A., Christakis, D. A., Xu, D., Gray, S., & Yapenel, U. (2009). Teaching by listening: The importance of adult-child conversations to langauge development. *Pediatrics*, *124*, 342–349. https://doi.org/10.1542/peds.2008-2267

Zimmerman, I., Steiner, V., & Pond, E. (2002). *Pearson Language Scale* (4th ed.). San Antonio, TX: Pearson.

Supporting Information

Additional supporting information may be found in the online version of this article at the publisher's website:

Table S1. Correlation Coefficients Across Time for AWC

Table S2. Correlation Coefficients Across Time for CVC

Table S3. Correlation Coefficients Across Time for CTC

Table S4. Correlation Coefficients Across Time for TV PCT

Table S5. Negative Binomial Regressions Predicting CTC From AWC

Table S6. Linear Regressions Predicting CTC From AWC

Table S7. Additional Results