

# Environmental shaping of the bacterial and fungal community in infant bed dust and correlations with the airway microbiota

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## Research

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## 17 **ABSTRACT**

### 18 **Background**

19 From early life, children are exposed to a multitude of environmental exposures, which may be of  
20 crucial importance for healthy development. Here, the environmental microbiota may be of  
21 particular interest as it represents the interface between environmental factors and the child. As  
22 infants in modern societies spend a considerable amount of time indoors, we hypothesize that the  
23 indoor bed dust microbiota might be an important factor for the child and for the early colonization  
24 of the airway microbiome. To explore this hypothesis, we analysed the influence of environmental  
25 exposures on 577 dust samples from the beds of infants together with 542 airway samples from  
26 the Copenhagen Prospective Studies on Asthma in Childhood<sub>2010</sub> cohort.

### 27 **Results**

28 Both bacterial and fungal community was profiled from the bed dust. Bacterial and fungal diversity  
29 in the bed dust was positively correlated with each other. Bacterial bed dust microbiota was  
30 influenced by multiple environmental factors, such as type of home (house or apartment), living  
31 environment (rural or urban), sex of siblings and presence of pets (cat and/or dog), whereas fungal  
32 bed dust microbiota was majorly influenced by the type of home (house or apartment) and  
33 sampling season. We further observed minor correlation between bed dust and airway microbiota  
34 compositions among infants. We also analysed the transfer of microbiota from bed dust to the  
35 airway, but we did not find evidence of transfer of individual taxa.

### 36 **Conclusions**

37 Current study explores the influence of environmental factors on bed dust microbiota (both  
38 bacterial and fungal) and its correlation with airway microbiota (bacterial) in early life using high-  
39 throughput sequencing. Our findings demonstrate that bed dust microbiota is influenced by

40 multiple environmental exposures and could represent an interface between environment and  
41 child.

42

43 **KEYWORDS**

44 House dust – bacterial microbiome – fungal microbiome – airway microbiome – infant  
45 microbiome

## 46 **BACKGROUND**

47 As societies become more modernized, people tend to spend an increasing amount of time indoors,  
48 especially within their homes [1]. Here humans are exposed to a large number of microbes, which  
49 can have important implications for health and disease. With the advancement of sequencing  
50 technologies, it is now possible to study the indoor microbiome [2–4], and how microbes therein  
51 affect the inhabitants [5, 6]. Most studies to date have characterized the indoor microbiome in  
52 schools, homes, offices, hospitals, or kindergarten classrooms [5, 7–10]. In homes, studies were  
53 mostly done on floors, kitchen sinks, and bathrooms [5, 11]. However, very little is known about  
54 microbial communities present in beds with which humans have extended daily exposure [12].

55 Environmental factors such as pets, type of housing, and land use of the surrounding area have  
56 been associated with the microbiota of homes [2, 13, 14]. As many published studies have looked  
57 at the influence of pets in homes, but none have addressed a pet’s influence on the bed microbiome.  
58 Many pet owners share their bedroom space with their pets [15], therefore the pets may influence  
59 the bed dust composition, including health relevant taxa, as microbes can be airborne and get  
60 enriched in closed systems. Some studies reported that the exposure to pets (e.g. dogs and cats)  
61 decreases the risk of allergic diseases [16–18], where another has shown increased risk [19]. With  
62 the reasonably consistent findings across studies, exposure to pets, specifically dogs, remains a  
63 promising approach for identifying a prevention strategy for allergic diseases in early life.

64 Furthermore, especially among young infants, the bed dust is a highly relevant place of sampling  
65 for capturing the indoor dust microbiota, which can serve as a proxy for many environmental  
66 exposures and act as a seeding source for the microbiota colonizing the child. Early infancy  
67 characterizes a rapid developmental phase of the airway microbial colonization [20] but also with  
68 regards to immune function [21]. Elucidating the relationship between the indoor and infant airway

69 microbiome in early life could be important in understanding human development, especially as  
70 the early-life airway microbiota has been associated with later asthma development [22, 23]. The  
71 relationship between microbial exposures from surroundings and the composition of the infant  
72 airway microbiota is still poorly understood [24, 25].

73 In this study, we evaluate which environmental factors influence the bacterial and fungal  
74 composition of the infants' beds at 6 months after birth. Additionally, we compare bed dust to the  
75 bacterial composition of the airways at age three months. All samples were collected in the  
76 Copenhagen Prospective Studies on Asthma in Childhood<sub>2010</sub> (COPSAC<sub>2010</sub>) cohort [26]. Through  
77 a comprehensive analysis of the microbiomes in bed dust and early life airways, we aim to  
78 elucidate the interactions between the two and secondarily identify the external factors that affect  
79 the microbial interactions between bacterial and fungal microbiome. To our knowledge, this is the  
80 first study to provide detailed qualitative and quantitative descriptions of microbial taxa and  
81 diversity in bed dust.

82

## 83 **RESULTS**

### 84 **Characteristics of the cohort**

85 In this study, we included 584 bed dust samples collected from the infants' beds at 6 months after  
86 birth and 658 airway samples collected from the infants 3 months after birth. The demographic  
87 information about the study population in this study is summarized in Table S1.

## 88 **Sequencing results and quality control**

89 In total, for the 584 dust samples and 70 controls (including negative and positive controls)  
90 obtained from the bed of the cohort children at age six months, we had 65,183,188 and 57,936,573  
91 raw reads, from 16S ribosomal RNA gene (16S rRNA gene) (V3-V4 region) and Internal  
92 transcribed spacer (ITS) amplicon (ITS2 region) sequencing including controls, respectively. After  
93 quality filtering and chimera detection, amplicon sequences were clustered into 79,347 and 24,474  
94 amplicon sequence variants (ASVs) for 16S rRNA gene and ITS data. The coverage of our  
95 sequencing was assessed by rarefaction curves, showing a beginning plateau at 10,000 reads per  
96 sample (Fig. S1a and b). After removing the negative controls and the samples that did not reach  
97 a satisfactory read depth (minimum 3000 reads), we were left with 577 samples, representing  
98 49,371 and 20,211 unique bacterial and fungal ASVs.

99 In the total 658 airway samples obtained from the cohort from children at age three, 34,319,874  
100 raw reads passed quality filtering. After quality filtering and chimera detection, amplicon  
101 sequences were clustered into 3,692 ASVs for 16S rRNA gene (V4 region) data. We removed  
102 airway samples without a matching bed dust sample from the downstream analysis, ending up with  
103 542 samples that contained a total of 2,272 ASVs.

## 104 **Microbial community composition in bed dust**

105 A total of 930 bacterial genera from 31 phyla were detected in the beds of six month old infants.  
106 The most abundant phyla were Firmicutes (43.05%), Proteobacteria (25.69%), Actinobacteria  
107 (19.27%), Cyanobacteria (6.89%), Bacteroidetes (2.17%) and Fusobacteria (1.85%) (Fig. 1a, Fig.  
108 S3a, Table S2). The remaining 25 phyla combined represented 1% of the relative abundance.  
109 Taxonomic identification at the class, family and genus levels (Fig. S3b, c, and d, respectively)  
110 revealed that most of the Firmicutes belonged to the class Bacilli, with varying amounts of the

111 families Streptococcaceae and Staphylococcaceae. Among these, the most abundant genera were  
112 *Streptococcus* (23.6%), *Staphylococcus* (12.43%), *Rothia* (6.17%), *Haemophilus* (4.15%),  
113 *Paracoccus* (4.12%), and *Corynebacterium* (4.09%) (Table S3).

114 A total of 102 fungal genera from 6 phyla were detected. The most abundant phyla were  
115 Ascomycota (82.47%) and Basidiomycota (6.60%) (Fig. S4a, Table S4). The remaining four phyla  
116 represented less than 1% of the overall abundance with an additional 10.53% of the sequences not  
117 classified at the phylum level (Fig. S4b, Table S4). A similar trend was observed at the family  
118 level (Fig. S4c) and class level (Table S5). The most abundant genera were *Spegazzinia* (9.61%),  
119 *Aureobasidium* (5.34%), *Sphaerellopsis* (4.99%), *Curvularia* (4.83%), *Saccharomyces* (4.50%)  
120 and *Penicillium* (3.55%) (Fig. S4d, Table S6), with 44.1% of reads being unclassified Ascomycota.

## 121 **Correlations between the bacteria and fungi in bed dust**

122 We explored the relationship between the bacterial and fungal members in the bed dust microbiota  
123 of the children at six months. Bacterial and fungal alpha diversity values were positively correlated  
124 ( $r_{\text{observed}}=0.17$ ,  $r_{\text{shannon}}=0.24$ ), when assessed by linear regression ( $p_{\text{observed}}=2.9e-05$ ,  $p_{\text{shannon}}=8.8e-$   
125  $09$ ) (Fig. 1 b). We further looked at the correlation both within and between the fungal and bacterial  
126 microbiomes for the genera present in at least 30% of the samples ( $n=173$ ). For fungal-fungal  
127 correlation, most of the significant correlations ( $p<0.01$ ) were positive, while correlations between  
128 *Saccharomyces* with *Spegazzinia* (Spearman correlation coefficient,  $r=-0.15$ ), *Curvularia*  
129 (Spearman correlation coefficient,  $r=-0.23$ ), *Sphaerellopsis* (Spearman correlation coefficient,  $r=-$   
130  $0.19$ ), and *Neophaeosphaeria* (Spearman correlation coefficient,  $r=-0.13$ ) were negative (Fig. S5).  
131 The strongest positive correlation occurred between *Spegazzinia* and *Curvularia* (Spearman  
132 correlation coefficient,  $r=0.54$ ), while *Curvularia* and *Saccharomyces* (Spearman correlation  
133 coefficient,  $r=-0.23$ ) exhibited the strongest negative correlation.

134 A higher number of significant correlations were found for bacteria-bacteria correlation compared  
135 to fungal-fungal correlation. The strength of negative correlation is very low in bacteria-bacteria  
136 correlation (Spearman correlation coefficient, (r) range from -0.12 to -0.28). For example, the  
137 genera *Sphingomonas* was significantly correlated ( $p < 0.01$ ) with more than 30 genera, most  
138 correlations were positive (Spearman correlation coefficient, (r) range from 0.15 to 0.72), and  
139 showed negative correlations with 10 genera (Spearman correlation coefficient, (r) range from -  
140 0.12 to -0.16). *Peptoniphilus* genera showed the strongest positive correlation with *Finogoldia*  
141 (Spearman correlation coefficient,  $r = 0.75$ ). We also observed many clinically relevant genera, that  
142 were significantly correlating with many other genera, for example, *Moraxella* showed strongest  
143 positive correlation with *Abiotrophia* genus (Spearman correlation coefficient,  $r = 0.32$ ), whereas,  
144 *Staphylococcus* showed the strongest positive correlation with *Corynebacterium* (Spearman  
145 correlation coefficient,  $r = 0.6$ ) and strongest negative correlation with *Streptococcus* (Spearman  
146 correlation coefficient,  $r = -0.27$ ). On the other hand, *Streptococcus* shows significantly positive  
147 correlation with *Gemella* (Spearman correlation coefficient,  $r = 0.64$ ) (Fig. S6).

148 We next assessed the correlations between the fungal and bacterial microbiota at the genus level.  
149 Comparing the relative abundances, both positive and negative correlations existed between fungal  
150 and bacterial taxa (Fig. 2). *Cutibacterium* and *Malassezia* showed the strongest inter-domain  
151 positive correlation (Spearman correlation coefficient,  $r = 0.43$ ), whereas *Prevotella* with  
152 *Erythrobasidium* (Spearman correlation coefficient,  $r = -0.25$ ) exhibited the strongest negative  
153 correlation.

#### 154 **Environmental factors shaping the bed dust microbiome**

155 The effect of environmental factors on the bed dust microbiome, i.e., income level, type of home,  
156 type of living environment, pets, season of dust sample collection, race, number of male or female

157 siblings were evaluated (Table 1). The bacterial richness in the bed dust was significantly affected  
158 by the type of home (house or apartment, median richness 294 and 269, respectively), type of  
159 living environment (rural or urban, median richness 298 and 267, respectively) and pets (cat and  
160 dog vs no pets, median richness 346 and 273, respectively) (Wilcoxon test, adjusted  $p=0.0089$ ,  
161 adjusted  $p=0.0004$ , and adjusted  $p=0.00045$ , respectively). We investigated the bacterial richness  
162 in the apartment and house locating either in the rural and urban areas. Apartments in rural areas  
163 showed significantly higher bacterial richness compared to apartments in urban areas (apartments  
164 in rural vs urban, median richness 302 vs 263) (Wilcoxon test, adjusted  $p=0.024$ ) while houses had  
165 no significant differences between rural and urban areas (Fig. S7a). On the other hand, bacterial  
166 richness between houses and apartments in rural and urban areas were not significantly different  
167 (Fig. S7b).

168 The fungal richness was significantly affected by the type of home (house or apartment, median  
169 richness 251 and 230, respectively) and the season of sampling (median richness for summer: 262,  
170 winter: 233, spring: 266, and autumn: 229) (Kruskal-Wallis test, adjusted  $p=1.3e-05$ ). The samples  
171 collected in spring and summer showed a higher fungal diversity. We further investigated the  
172 fungal richness into the apartment and house present in the rural and urban areas, and we did not  
173 observe any significant differences (Fig. S8a). On the other hand, fungal richness between house  
174 and apartment in urban areas were significantly different (house vs apartment in urban areas,  
175 median richness 255 vs 228) (Wilcoxon test,  $p=0.003$ ) (Fig. S8b), whereas the houses and  
176 apartments present in rural areas were not.

177 Moreover, siblings correlated with an increased bacterial (no vs yes, median richness 265 vs 298)  
178 (Wilcoxon test, adjusted  $p=0.03$ ) and fungal richness (no vs yes, median richness 226 vs 255)  
179 (Wilcoxon test, adjusted  $p=0.0023$ ). We further observed that homes that had only male siblings

180 showed significantly higher bacterial richness compared to homes that had no siblings (median  
181 richness 311 vs 265) (Wilcoxon test, adjusted  $p=0.0079$ ). However, homes that had only female  
182 siblings did not show any significant difference (median richness 265 vs 284) (Wilcoxon test,  
183 adjusted  $p=0.4$ ). Moreover, fungal richness correlated with male and/or female siblings (median  
184 richness for no siblings: 225, male only: 258, female only: 251, both male and female: 273)  
185 (Kruskal-Wallis test, adjusted  $p=0.0093$ ). We further observed that number of male siblings  
186 correlated with an increase in bacterial (none vs two or more, median richness 265 vs 330)  
187 (Wilcoxon test, adjusted  $p=0.0004$ ) and fungal richness (none vs two or more, median richness  
188 225 vs 267) (Wilcoxon test, adjusted  $p=0.0047$ ). On the other hand, we did not observe any  
189 significant changes in bacterial (none vs two or more, median richness 265 vs 321) (Wilcoxon test,  
190 adjusted  $p=0.1$ ) or fungal richness (none vs two or more, median richness 225 vs 257) (Wilcoxon  
191 test, adjusted  $p=0.073$ ) in relation to increase in female siblings.

192 The bacterial microbial community (beta diversity) was significantly affected by the type of living  
193 environment, pets, the season of dust samples collection and presence of siblings (PERMANOVA  
194 for weighted Unifrac,  $p=0.001$ ,  $R^2=0.008$ ;  $p=0.005$ ,  $R^2=0.007$ ;  $p=0.001$ ,  $R^2=0.01$ ; and  $p=0.026$ ,  
195  $R^2=0.003$ , respectively). With the exception of pets and siblings, this was also the case for the  
196 fungal microbial community (PERMANOVA for weighted Unifrac,  $p=0.001$ ,  $R^2=0.014$  and  
197  $p=0.001$ ,  $R^2=0.105$ , respectively) (Table 1). We next investigated the interaction between all the  
198 significant factors and look for the marginal effects. We performed PERMANOVA for weighted  
199 Unifrac distance, environmental factors namely season had the largest interaction with bacterial  
200 and fungal bed dust microbiome composition ( $p=0.001$ ,  $R^2=0.021$ ;  $p=0.001$ ,  $R^2=0.084$ ,  
201 respectively) (Table S15).

202 **Table 1.** The effects of environmental factors on alpha and beta-diversity on the bed dust  
203 microbiome. ^Alpha diversity were calculated based on observed richness and significance were

204 calculated using the Wilcoxon test (for two groups) and Kruskal-Wallis test (for three or more  
 205 groups), FDR corrected. #Effects were quantified with R2, and p-values, as determined by  
 206 PERMANOVA on weighted UniFrac distances. Significant adjusted p-values (p<0.05) are shown  
 207 in bold. ↑ represents the significant increase in alpha diversity of bacterial and/or fungal  
 208 microbiome. \*Income level is categorized into Low (<€50,000/year), medium (€50,000–  
 209 €110,000/year), high (>€110,000/year).

Category	Variable	Overall n (%)	Bacterial Alpha Diversity (median richness)	Bacterial Alpha Diversity^ Adjusted p-value	Bacterial Beta Diversity# R2 / p-value	Fungal Alpha Diversity (median richness)	Fungal Alpha Diversity^ Adjusted p-value	Fungal Beta Diversity# R2 / p-value
	n	577						
Sex	Male	301 (52.2)						
Income level*	Low	52 (9)	308	0.46	0.004 / 0.132	228	0.51	0.003 / 0.417
	Medium	302 (52.3)	285			246		
	High	222 (38.5)	274			246		
Type of home	House ↑	316 (54.8)	294	<b>0.0089</b>	0.003 / 0.076	251	<b>0.0016</b>	0.003 / 0.139
	Apartment	231 (40)	269			230		
Type of living environment	Rural ↑	251 (43.5)	298	<b>0.0004</b>	<b>0.008 / 0.001</b>	246	0.14	<b>0.014 / 0.001</b>
	Urban	295 (51.1)	266			242		
Pets	Cat	87 (15.1)	292	<b>0.0039</b>	<b>0.007 / 0.005</b>	255	0.52	0.004 / 0.468
	Dog	69 (11.9)	294			252		
	Both ↑	32 (5.5)	346			247		
Season of dust sample collection	Winter (Dec, Jan, Feb)	140 (24.5)	272	0.97	<b>0.01 / 0.001</b>	233	<b>1.3e-05</b>	<b>0.105 / 0.001</b>
	Spring ↑ (March, April, May)	115 (20.1)	288			266		
	Summer ↑ (June, July, August)	149 (26)	283			262		

	Autumn (Sep, Oct, Nov)	168 (29.4)	277			229		
Race	Caucasian	552 (95.7)	281	0.12	0.002 / 0.054	243	0.9	0.001 / 0.442
Siblings	No	132 (22.87)	265	<b>0.03</b>	<b>0.003 / 0.026</b>	225	<b>0.0023</b>	0.0023 / 0.329
	Yes ↑	329 (57.02)	298			255		
Siblings	No	132 (22.87)	265	<b>0.049</b>	<b>0.009 / 0.003</b>	225	<b>0.0093</b>	0.011 / 0.053
	Male only	140 (24.26)	311 ↑			258 ↑		
	Female only	121 (20.97)	284			251 ↑		
	Both male and female	68 (11.78)	290			273 ↑		
Number of male siblings	None	132 (22.87)	265	<b>0.0015</b>	0.007/0.33	225	<b>0.0062</b>	0.0003/0.99
	One	114 (19.75)	308			255		
	Two or more ↑	26 (4.5)	330			267		
Number of female siblings	None	132 (22.87)	265	0.29	0.008/0.33	225	0.11	0.003/0.95
	One	97 (16.81)	274			248		
	Two or more	24 (4.16)	321			257		

210 **Influence of pets on bed dust microbiome**

211 Various environmental factors influenced the bed dust microbiome composition (Table 1), and we  
212 performed in-depth evaluations of the effects of pets. Among the families, 87/577 (15.1%) had cat  
213 only, 69/577 (11.9%) had dogs only and 32/577 (5.5%) had both cat and dog. We observed that  
214 the bacterial alpha diversity were not significantly associated with the presence of either a cat or a  
215 dog only, but significantly higher in homes with both cat and dog (Kruskal-Wallis test,  
216  $p_{\text{observed}}=0.0039$ ,  $p_{\text{shannon}}=0.066$ ,  $p_{\text{chao1}}=0.0021$ ) (Fig. 3), whereas fungal alpha diversity was not

217 influenced by the pet ownerships (Kruskal-Wallis test,  $p_{\text{observed}}=0.52$ ,  $p_{\text{shannon}}=0.92$ ,  $p_{\text{chao1}}=0.46$ )  
218 (Fig. S9).

219 We used the phylogeny-based weighted UniFrac method to assess the relatedness between samples  
220 from homes that had dogs and/or cats using principal coordinate analysis (PCoA). We found a  
221 small, but significant, effect on the bacterial community composition ( $p_{\text{permonova}}=0.003$ ,  $R^2=0.007$ ),  
222 but no significant effect on the fungal community composition ( $p_{\text{permonova}}=0.9$ ,  $R^2=0.004$ ) (Fig.  
223 S10). Compared to homes without cats or dogs, we found that homes that had both cat and dog  
224 had over-representation of 19 taxa in infant beds, belonging to the phyla Firmicutes, and  
225 Proteobacteria (Fig. 4, Table S7) and under-representation of 6 taxa, belonging to Cyanobacteria,  
226 and Proteobacteria. Among these phyla, genera such as *Gemella*, *Staphylococcus*, and  
227 *Sphingomonas* were significantly over-represented ( $\log_{10}(\text{LDA score}) > 4$ ,  $p < 0.05$ ), and  
228 *Enhydrobacter* genera were significantly under-represented ( $\log_{10}(\text{LDA score}) > 4$ ,  $p < 0.05$ ).

229 In homes with either a cat or a dog, the bacterial microbiota appeared to be less influenced than  
230 homes with both (Fig. 3). Homes with a dog had over-representation of 21 taxa compared to homes  
231 that had no pets, belonging to the phyla Firmicutes, Fusobacteria, Proteobacteria, Cyanobacteria,  
232 and Actinobacteria, whereas, homes with a cat had over-representation of 3 taxa, belonging to  
233 phylum Actinobacteria (Table S8). Genera belonging to *Paeniclostridium*, *Atopobium*,  
234 *Tychonema*, and *Acinetobacter* ( $\log_{10}(\text{LDA score}) > 3.5$ ,  $p < 0.05$ ) were significantly more abundant  
235 in the homes that have only dog, whereas, *Turicella* ( $\log_{10}(\text{LDA score}) > 3.5$ ,  $p < 0.05$ ) was  
236 significantly more abundant in the homes that have only cat (Table S9).

237 Furthermore, homes with both cat and dog had over-representation of 38 taxa, belonging to the  
238 phyla Ascomycota, Basidiomycota, Chytridiomycota, and Mortierellomycota. Genera belonging  
239 to *Neophaeosphaeria*, *Mortierella*, *Preussia*, *Tylospora*, *Spizellomyces*, *Oleoguttula*, and  
240 *Monilochaetes* ( $\log_{10}(\text{LDA score}) > 3.5$ ,  $p < 0.05$ ) were the significant ones that were over-

241 represented in the homes that had both cat and dog (Table S10). Genera belonging to *Setosphaeria*,  
242 *Peziza*, *Melanogaster*, *Lodderomyces*, *Preussia*, *Curvularia*, and *Dirkmeia* ( $\log_{10}(\text{LDA}$   
243  $\text{score}) > 3.5$ ,  $p < 0.05$ ) (Table S11) were significantly more abundant in the homes that have only  
244 dog, whereas *Oleoguttula*, *Curvularia*, and *Caloplaca* ( $\log_{10}(\text{LDA score}) > 3.5$ ,  $p < 0.05$ ) were  
245 significantly more abundant in the homes that have an only cat (Table S12).

#### 246 **Influence of living environment (rural or urban) on bed dust microbiome**

247 Bacterial richness and composition of the bed dust were highly influenced by the living  
248 environment (rural or urban) (Table 1). We further investigated and identified the taxa at genus  
249 level between rural and urban living environments. We found 353 genera in the bed dust from rural  
250 environment that were not present in the bed dust from urban environment (Table S13, Fig. S11a).  
251 In addition, we performed differentially abundant analysis using Wilcoxon tests to identify the  
252 taxa with significantly different abundance between the two groups (Fig. S11b). *Paracoccus*,  
253 *Micrococcus*, and *Sphingomonas* were the top three significantly more abundant taxa in the rural  
254 environment (adjusted p-value  $< 0.05$ ). Moreover, genera belonging to order *Rickettsiales* were  
255 significantly more abundant in the urban environment (adjusted p-value  $< 0.05$ ).

#### 256 **Seasonal effect on other environmental factors**

257 To test for interactions between the season of sampling and the effect of environmental variables  
258 in the bed dust, we stratified the significant variables from Table 1 by the season of sampling. The  
259 effect of "type of living environment", and "type of home" on microbial diversity was consistent  
260 across seasons. However, the homes with both cat and dog only had a higher bacterial diversity in  
261 their bed dust when sampled in the fall and winter (Table S14).

## 262 **Correlations between the dust and airway microbiota**

263 Next, we evaluated whether associations existed between the two microbial compartments (beds  
264 dust when infants were 6 months old and airways at 3 months), possibly alluding to the importance  
265 of the dust microbiota on the infant airway composition. We observed significantly higher bacterial  
266 alpha diversity in bed dust compared to infant airways (Wilcoxon test, adjusted  $p < 1e-15$ ) (Fig. 5a).  
267 Furthermore, bed dust and airway microbiota separated well by Bray-Curtis distance measures  
268 ( $P_{\text{permonova}} < 0.001$ ) (Fig. 5b).

269 We applied several methods to identify relationships between bed dust and airway microbiota.  
270 Based on the Spearman correlations, we did not observe any significant correlations in alpha  
271 diversity ( $p = 0.9$ ) (Fig. 5d). Furthermore, we tested for transfer between the dust and airway  
272 bacteria using presence-absence of shared genera and odds ratio analysis. Interestingly, we did not  
273 identify any significant sharing of genera using this method (Fig. S12). In addition, bed dust and  
274 airway samples from the same child were not more similar to each other than randomly paired dust  
275 and airway samples using Bray-Curtis distance (Wilcoxon test, adjusted  $p = 0.3$ ) (Fig. 5c).

276 When taking into account the relative abundance and looking for correlations, we found that the  
277 fungal community composition in bed dust did not show significant correlations with the airway  
278 bacterial community. However, we observed several bacterial genera in the bed dust that correlated  
279 significantly with bacterial abundances in the infant airways ( $p < 0.01$ ) (Fig. 6). For example,  
280 *Youngiibacter*, and *Pseudolabrys* in dust samples had many positive correlations with genera from  
281 the airway samples. Moreover, multiple genera in the bed dust samples such as *Arachidicoccus*,  
282 *Pseudosphingobacterium*, *Calothrix*, and *Syntrophaceticus* showed positive correlations with  
283 *Luteibacter* among airway samples.

## 284 **DISCUSSION**

285 In this study, we determined that bacterial and fungal communities in bed dust are related to each  
286 other with positive correlations in alpha diversity and that they are both influenced by  
287 environmental factors. The presence of pets and type of living environment (rural or urban) are the  
288 dominant factors among those studied that most affect microbial communities.

289 We observed that the fungal microbiota composition of bed dust samples were dominated by fungi  
290 from the phyla Ascomycota and Basidiomycota (Fig. S4a). In accordance with previous work,  
291 *Aureobasidium* and *Penicillium* genera have commonly been identified in homes [27] at several  
292 sites such as floors [28] and kitchen sinks [29]. These shared features in community composition  
293 indicate that common taxa present elsewhere in homes are likely to be discovered in beds also.

294 Moreover, the bed dust samples were dominated by Gram-positive bacteria, including genera  
295 known to be associated with human sources such as *Staphylococcus*, *Streptococcus*, and  
296 *Corynebacterium* (Fig. S3d). These bacterial genera, which are commonly found on human skin  
297 [30], have been documented in other studies of the home microbiomes as well [31, 32]. The human  
298 contribution to bacteria within the home is further confirmed in a study [5] showing the abundance  
299 patterns of bacterial taxa in samples from homes that closely resemble the microbial profiles of its  
300 human residents.

301 Environmental factors such as pets had a significant influence in shaping the bed dust  
302 microbiomes. Studies have shown that bacterial diversity increases significantly by the presence  
303 of a dog (but not by a cat) in a household [4, 14]. We observed that bacterial diversity was increased  
304 significantly by the presence of both cat and dog in the home (Fig. 3) but not if either one was  
305 present alone. Many taxa associated with pet ownership have previously been associated with  
306 human health outcomes. For example, *Corynebacterium* and *Staphylococcus* genera were  
307 associated with the homes that have both dog and cat. These genera are found mostly on skin and

308 nose and may play an active role in host defense [33]. *Acinetobacter* was associated with homes  
309 that have only a dog. These genera, part of the human skin microbiota, may protect against allergic  
310 sensitization and inflammation [34].

311 Some studies have reported that the living environment (rural or urban) has little to no significant  
312 effect on bacterial or fungal diversity [35], whereas others have shown significant changes in the  
313 microbial diversity [36]. In our study, the effect of urbanization showed a significant effect on both  
314 bacterial and fungal diversity on the bed dust microbiome. Approximately 30% of bacterial genera  
315 present in the bed dust from rural areas were not found in bed dust samples collected from an urban  
316 living environment (Fig. S11). While a wide range of factors can influence the risk of developing  
317 asthma, rates of allergic asthma are higher for children living in more urbanized areas than in rural  
318 areas [37]. It has been hypothesized that these geographic differences in allergy rates can be  
319 attributed to people living in more urbanized areas being exposed to lower levels of microbial  
320 diversity [38], and our study supports the hypothesis.

321 Furthermore, we observed that having siblings in the household correlated with increased bacterial  
322 and fungal richness, similar to the data from Weikl *et al* (2016) who found that households with  
323 more than three occupants had higher bacterial richness [39]. Earlier studies showed that fewer  
324 siblings in early life are associated with increased risks of developing asthma and other atopic  
325 diseases later in life [40]. Moreover, higher microbial diversity in the environment has been found  
326 to be inversely associated with asthma [25]. Together with our results, these suggest that siblings  
327 protect against asthma and atopic disease by increasing the bacterial and fungal richness, but  
328 further studies are needed to confirm this.

329 As no study we know of have investigated how the sex or siblings affect the bacterial or fungal  
330 richness, we stratified for the sex of siblings. Interestingly, we found that only male siblings

331 significantly increased bacterial and fungal richness and correlated with the number of male  
332 siblings. In homes with only female siblings, fungal richness were significant increased, but we  
333 did not have the statistical power to determine if the trend towards higher bacterial richness were  
334 significant. Additionally, we did not find any significant differences in the richness when  
335 comparing homes with either female or male siblings. While not directly comparable to our study  
336 population, it has been suggested that men shed more bacteria to their environment [7] and a study  
337 by Raju et al. found higher bacterial richness in saliva of boys compared to girls [41].

338 Interestingly, alpha diversity of the bacterial and fungal microbiome of the bed dust was  
339 significantly and positively correlated (Fig. 1c). To further understand the association between the  
340 bacterial and fungal microbiome in the bed dust samples, we observed numerous significant  
341 correlations at the genus level. In the fungal-fungal correlations, we observed mostly positive  
342 correlations with only *Saccharomyces* having negative correlations (to *Spegazzinia*, *Curvularia*,  
343 and *Sphaerellopsis*). *Saccharomyces* is a common genus in home dust and usually associated with  
344 humans [42]. For bacteria-bacteria correlations, the most abundant genera *Staphylococcus* and  
345 *Streptococcus* showed both positive and negative correlations with other genera. *Staphylococcus*  
346 and *Streptococcus* are a typical part of the human microbiome and constantly interact with each  
347 other [30]. Moreover, we also observed an inter-domain correlation between bacteria and fungi  
348 and most of these correlations were positive, pointing at synergistic relationships or that they were  
349 transported to the bed dust together from the same source.

350 Not surprisingly, the bed dust bacterial microbiota was different from the airway bacterial  
351 microbiota. While both airway and bed dust samples harboured diverse microbial communities,  
352 the diversity of bacteria was higher in bed dust samples (Fig. 5a). The airway samples were  
353 dominated by genera from the families Streptococcaceae and Staphylococcaceae, as well as the  
354 genus *Moraxella*, which are mainly observed in the upper respiratory tracts of healthy children

355 [43]. In our comparisons of bed dust and airway microbiota, based on OR, we did not observe any  
356 significant taxa that were shared between bed dust and infants' airway. However, based on the  
357 microbial relative abundance, we observed several positive correlations between airway bacterial  
358 and bed dust bacterial and fungal microbiomes. The biological significance of these positive  
359 correlations remains unknown, but as we found limited evidence of transfer, shared exposure  
360 reservoirs may be the cause. However, we cannot exclude the possibility that the difference in  
361 sampling time between the bed dust and airway samples might have caused this lack of evidence  
362 for transfer.

363 Our study has some limitations. We have used different DNA extraction kits for the airway and  
364 dust samples. Different types of extraction kits may have different biases in extraction efficiency,  
365 which in turn may affect the bacterial composition results. Moreover, we have used different  
366 sequencing primers for dust and airway microbiome (V3-V4 region for the bed dust samples and  
367 V4 region for the airway samples), and different PCR primers preferentially amplify different sets  
368 of taxa [44, 45]. This may hamper the identification of transfer events on the ASV level. However,  
369 this should not affect the correlation analysis between the two compartments. Furthermore, we  
370 have collected the children's airway samples at 3 months of age whereas and the bed dust samples  
371 3 months later. Collecting the samples at the same time point would have provided a stronger  
372 premise for association analyses, especially as seasonal differences in the microbiomes was found.  
373 However, we also observed that the sampling season did not seem to interact with the effect of  
374 other environmental variables, with the exception of the effect of pet ownership that was only  
375 found in the fall and winter. During fall and winter months Danish people are likely to spend less  
376 time outdoors, but as pets need to visit there regularly during every season, they can act as vectors  
377 of bacteria from the outside. However, the stratification results in groups with quite low numbers,  
378 which can result in spurious findings, and should thus be interpreted with caution. Lastly, many of

379 the fungal sequencing reads could not be assigned to specific taxa (10.53% unclassified at the  
380 phylum level, 47.25% of reads being unclassified class level), this did limit our analysis and  
381 indicate that it might be relevant to revisit our analysis when better fungal reference databases are  
382 available.

## 383 **CONCLUSION**

384 In summary, our study finds evidence of interplay between bacterial and fungal diversity in the  
385 bed dust of young infants and that both bacterial and fungal composition are affected by  
386 environmental variables. We find limited evidence of transfer between the dust and developing  
387 airway microbiota. From early life, children are exposed to a multitude of environmental  
388 exposures, which may impact a healthy development perhaps through the microbiome of home  
389 dust, which may act as the interface between environment and child.

## 390 **METHODS**

### 391 **Study design and sample collection**

392 The study was embedded in the population-based COPSAC<sub>2010</sub> prospective mother-child cohort  
393 of 736 women and their children followed from week 24 of pregnancy [26].

394 Beds dust was sampled by the parents when the infants were 6 months old. This was done using  
395 an external filter kit (DUSTREAM® Collector, Indoor Biotechnologies, or Dust Collecting Device  
396 from ALK-Abello) attached to the family's vacuum cleaner with instructions to vacuum the sheets  
397 and pillow for 5 minutes. Filters were then kept in the freezer for 3 days to kill dust mites and  
398 shipped to COPSAC where they were kept at -20 °C until DNA extraction. The infant airway was  
399 sampled using hypopharyngeal aspirates obtained at 3-months of age, using a soft suction catheter  
400 passed through the nose and stored at -80 °C until DNA extraction [23].

401 **Covariates**

402 Information on educational level, household income, pet ownership, race, type of home, and home  
403 address was obtained during the scheduled visits to the research clinic. Living environment  
404 (rural/urban) was defined based on the land cover in a three-kilometer radius based on children's  
405 birth address as previously described (Lehtimäki et. al., under review).

406 **DNA extraction and amplification**

407 Dust was released from the filter boxes, and 250 mg were used for DNA extraction using the  
408 NucleoSpin® 96 Soil DNA Isolation Kit optimized for epMotion® (MO-BIO Laboratories, Inc.,  
409 Carlsberg, CA, USA) using the epMotion® robotic platform model (Eppendorf) under  
410 manufacturer's protocol. The bed dust samples were profiled with bacterial as well as fungal  
411 community using amplicon sequencing, using a two-step protocol. In the first step, we amplified  
412 the community specific rRNA target using general primers and in the second step, we used primers  
413 with sequencing adaptors, barcodes, and the target sequence, so each sample could be uniquely  
414 identified post-sequencing. For fungi, we targeted the internal transcribed spacer, region 2 (ITS2),  
415 with the primers gITS7F (5'- GTGARTCATCGARTCTTTG-3') and ITS4ngs (5'-  
416 TTCCTSCGCTTATTGATATGC-3'). For bacteria we targeted variable region V3-V4 of the 16S  
417 rRNA gene, using forward primer 341f (5'- CCTAYGGGRBGCASCAG-3') and reverse primer  
418 806r (5- GGACTACHVGGGTWTCTAAT-3). Negative controls were included for the extraction  
419 and PCR amplification procedures. All final PCR products were purified using HighPrep™ PCR  
420 (MAGBIO, USA), based on paramagnetic beads technology. Then it was normalized using  
421 SequalPrep™ Normalization plate kit (Invitrogen, USA). Further cleaning and concentration were  
422 done by using the DNA Clean & Concentrator™-5 Kit (Zymo Research, Irvine, CA, USA).

423 Concentrations were then determined using the Quant-iT™ High-Sensitivity DNA Assay Kit (Life  
424 Technologies).

425 The airway samples from the children at 3 months of age used in this study was a part of  
426 COPSAC<sub>2010</sub> cohort that was already published in Mortensen et al. 2016 [20] and Gupta et al. 2019  
427 [43]. Genomic DNA was extracted for airway samples using the PowerMag® Soil DNA Isolation  
428 Kit optimized for epMotion® (MO-BIO Laboratories, Inc., Carlsberg, CA, USA) using the  
429 epMotion® robotic platform model (Eppendorf) under manufacturer's protocol. The airway  
430 microbiota were profiled with the same method, but only for bacteria, targeting variable region v4  
431 of the 16S rRNA gene, using forward primer 515f (5'-GTGCCAGCMGCCGCGGTAA-3') and  
432 806r (5'-GGACTACHVGGGTWTCTAAT-3'). Rest of the steps were the same as mentioned  
433 above for dust samples.

#### 434 **Sequencing**

435 Paired-end sequencing was performed on the Illumina MiSeq System (Illumina Inc., CA, USA),  
436 including 5% PhiX as an internal control. All reagents used were from the MiSeq Reagent Kits v3  
437 (Illumina Inc., CA, USA) for bed dust samples and MiSeq Reagent Kits v2 for airway samples.  
438 Automated cluster generation and paired-end sequencing with dual-index reads were performed  
439 with 2x300bp for bed dust samples and 2x250bp for airway samples. The sequencing output was  
440 generated as demultiplexed fastq-files for downstream analysis.

#### 441 **Sequence Analysis**

442 Primers were removed from the raw paired-end FASTQ files generated via MiSeq using  
443 “cutadapt” [46]. Further, reads were analyzed by QIIME2 [47] (qiime2-2018.11) pipeline through  
444 dada2 [39] to infer the ASVs present and their relative abundances across the samples. For bed  
445 dust samples, using read quality scores for the dataset, forward and reverse reads were truncated

446 at 270bp and 220bp, followed by trimming the 5` end till 8bp for both forward and reverse reads,  
447 respectively; other quality parameters used dada2 default values for both 16S rRNA gene and ITS  
448 sequencing. For airway samples, forward and reverse reads were truncated at 180bp and 160bp,  
449 other parameters remain the same as mentioned above. For 16S rRNA gene sequencing, taxonomy  
450 was assigned using a pre-trained Naïve Bayes classifier (Silva database, release 132, 99%ASV)  
451 [48] and for ITS sequencing, UNITE database (dynamic-2017-12-01) [49] were used.

## 452 **Quality control**

453 To ensure that our analyses were not confounded by spurious results, we first analyzed the alpha  
454 diversity of negative control samples (including PCR negative, extraction control) that produced  
455 sequencing reads and dust samples (Fig. S1). The DNA extraction and other negative controls had  
456 significantly lower observed richness than all dust samples (analysis of variance (ANOVA),  
457  $p < 0.05$ ) for both fungal and bacterial data. Furthermore, profiles were significantly different for  
458 both bacterial and fungal microbiome by sample type (Fig. S2a, b). Sequencing contaminants (75  
459 of 79,347 bacterial and 141 of 24,474 fungal ASVs) were identified based on the prevalence of  
460 ASVs in the negative control and removed using the decontam package (default parameters); this  
461 did not measurably affect the microbiota structure (Fig. S2c, d). We then removed the PCR and  
462 sequencing controls before downstream analysis. Moreover, samples that did not have a  
463 satisfactory sequencing of both 16S rRNA gene (minimum 3,000 reads per sample) and ITS  
464 (minimum 3,000 reads per sample) were removed. For airway samples, sequencing contaminants  
465 (14 of 3,692 bacterial ASVs) were identified based on the prevalence of ASVs in the negative  
466 control and removed using the decontam package (default parameters). The DNA extraction and  
467 other negative controls had significantly lower observed richness than all dust samples (analysis  
468 of variance (ANOVA),  $p < 0.05$ ) (Fig. S2e).

469 **Statistical analysis**

470 Data analysis was conducted in R (R Core Team, 2017). Initial preprocessing of the ASV table  
471 was conducted using the phyloseq package (v1.20.0) [50]. Further filtering was done by removing  
472 ASVs classified as archaea, chloroplast, or without phylum-level classification, from 16S rRNA  
473 gene sequencing data as well as Rhizaria from ITS sequencing data. Sequencing contaminants  
474 were identified and removed using the decontam package [51]. To avoid the bias due to sampling  
475 depth, the ASVs table was multiple rarefied [43] to 6,774 high-quality sequences per bed dust  
476 sample for 16S rRNA gene, 9,942 per bed dust sample for ITS, and 1,957 per sample for airway  
477 16S rRNA gene.

478 All downstream analyses were performed on this rarefied ASVs table unless mentioned. We used  
479 three alpha diversity indices i.e., observed richness, Shannon diversity index, and Chao1 index.  
480 Furthermore, beta diversity were calculated using weighted and unweighted UniFrac metric and  
481 visualized by Principal Coordinates Analysis (PCoA). Alpha and beta diversity was calculated  
482 using phyloseq v1.20.0 and visualized with ggplot2 v2.2.1 [52] in R v3.4.1. Comparison of  
483 community richness and diversity was assessed by the Kruskal–Wallis test between all the groups  
484 and comparison between the two groups were done by Wilcoxon test with Benjamini-Hochberg  
485 FDR multiple test correction. Significance testing between the groups for beta diversity was  
486 assessed using permutational multivariate analysis of variance (PERMANOVA) using the “vegan”  
487 package [53]. Marginal effect were calculated using the PERMANOVA analysis (for each  
488 significant environmental factor) using the following formula: `adonis2(dist ~`  
489 `Type_of_Environment + Pet + Type_of_home + Siblings + Season, by = "margin")` for beta  
490 diversity.

## 491 **Microbial correlation and differentially abundant analysis**

492 Considering the variable nature of 16S compositional data, we estimated the core microbial group  
493 of ASVs within the samples with a presence in at least 30% of the study samples. The correlation  
494 analyses were performed at the genus level of the bed dust and airway samples. To better  
495 understand the dust community structure, characterize intra-community interactions and identify  
496 potentially shared niches, the co-occurrence network analysis was performed and visualized by R.  
497 Spearman correlation analysis built into the function “rcorr” from the package “Hmisc” [54] was  
498 used to calculate the association at the genus level. p-values were adjusted for comparisons with  
499 the false discovery rate (FDR) algorithm after compositional transformation. The significance of  
500 the correlation adjusted p-value<0.01 was the threshold to define significant correlations. The  
501 correlation matrix of genera was visualized by the function “corrplot” in the package “corrplot”  
502 [55]. The linear regression analysis was visualized by the function “ggscatter” in the package  
503 “ggpubr” [56]. We analyzed the transfer of bacteria from bed dust to airway microbiome using  
504 Fisher’s exact test by comparing the presence/absence of bacteria (at genus level) and calculated  
505 the odds ratio for transfer with a one-sided p-value. Only bacteria (at genus level) showing  
506 presence/absence in both the bed dust as well as the airway were included in the analysis. Inference  
507 for transfer of single bacteria (at genus level) was evaluated using Benjamin & Hochberg FDR  
508 correction. Furthermore, LEfSe [57] was used to identify the microbiological markers associated  
509 with a pet by linear discriminant analysis (LDA) effect size of cut off 3.5. Other parameters were  
510 kept default. For rural and urban living environment, we have used the Wilcoxon tests.

511

## 512 **DECLARATIONS**

513

### 514 **Ethics**

515 This study followed the principles of the Declaration of Helsinki, and was approved by the Ethics  
516 Committee for Copenhagen (The Danish National Committee on Health Research Ethics) (H-B-

517 2008-093) and the Danish Data Protection Agency (2008-41-2599). Written informed consent was  
518 obtained from all participants.

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521 Research) - 0603-00280B and Ministeriet Sundhed Forebyggelse (Ministry of Health) - 903516

### 522 **Consent for Publication**

523 Written consent for publication has been obtained from the parents or legal guardians of all  
524 participants.

### 525 526 **Availability of data and materials**

527 The dataset analyzed during the current study will be available, upon publication, in the Sequence  
528 Read Archive (SRA) repository under project id PRJNA605085 for bed dust samples (both  
529 bacterial and fungal raw sequencing reads). Airway samples was already published in our previous  
530 article and it is available in the Sequence Read Archive (SRA) repository,  
531 <http://www.ncbi.nlm.nih.gov/bioproject/340273>. All other data is available from the  
532 corresponding author.

### 533 **Conflict of Interest**

534 The authors declare no conflict of interest.

### 535 **Authors' contributions**

536 S.G. is the main author of this paper. S.G. and M.S.M performed the DNA extraction, construction  
537 of the ITS and 16S rRNA gene amplicon libraries, and sequencing. S.G. and X.L. performed the  
538 bioinformatics analysis. M.H. and J.L. helped in the dust sample processing. J.S. sampled the  
539 infants. S.G., M.H., J.L., M.S.M., M.A.R., U.T. and J.R. helped interpret the data. S.G wrote the  
540 manuscript. This project was conceived and designed by S.J.S. and H.B. All authors have read,  
541 revised, and approved the manuscript.

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544 all their support and commitment. We acknowledge and appreciate the unique efforts of the  
545 COPSAC research team.

546 **ADDITIONAL FILES**

547 Additional file1: **Fig. S1.** Rarefaction curves of the (a) Bacteria (16S rRNA gene), and (b) Fungi  
548 (ITS) samples, generated from the amplicon sequencing. The rarefaction curves were calculated  
549 using the richness and Shannon diversity index at increasing sequencing depth. Error bars  
550 represent standard deviation. **Fig. S2.** Data quality. (a)  $\beta$  diversity by sample type prior to removal  
551 of potential contaminant ASVs using the decontam package for 16S rRNA samples. (b)  $\beta$  diversity  
552 by sample type prior to removal of potential contaminant ASVs using the decontam package for  
553 ITS samples.  $\beta$  diversity was assessed on Bray-Curtis dissimilarity and tested by PERMANOVA.  
554 There was a significant difference based on the sample type. (c) Composition of the ASVs before  
555 and after contaminant removal at class level (>1% mean relative abundance) for 16S rRNA  
556 samples. (d) Composition of the ASVs before and after contaminant removal at class level (>1%  
557 mean relative abundance) for ITS samples. (e)  $\beta$  diversity by sample type prior to removal of  
558 potential contaminant ASVs using the decontam package for airway samples.  $\beta$  diversity was  
559 assessed on Bray-Curtis dissimilarity and tested by PERMANOVA. There was a significant  
560 difference based on the sample type. **Fig. S3.** Bacterial microbiome by 16S rRNA gene (panels a–  
561 d) at four taxonomic levels (a) phylum (b) class (c) family, and (d) genus. Each of the above-  
562 stacked bar plots illustrates the average relative abundance (y-axis) of the microbiota at different  
563 taxonomic levels. Taxa with a mean abundance of at least 1% across all samples are represented  
564 in colors; those with < 1% abundance are not shown. Each column represents one individual. The  
565 taxonomy for bacterial ASVs was assigned from the SILVA database. **Fig. S4.** Fungal microbiome  
566 by ITS (panels a–d) at four taxonomic levels (a) phylum (b) class (c) family, and (d) genus. Each  
567 of the above-stacked bar plots illustrates the average relative abundance (y-axis) of the microbiota  
568 at different taxonomic levels. Taxa with a mean abundance of at least 1% across all samples are  
569 represented in colors; those with <1% abundance are not shown. Each column represents one  
570 individual. The taxonomy for bacterial ASVs was assigned from the UNITE database. **Fig. S5.**  
571 Spearman correlation by genus abundance. Only significant values ( $p < 0.05$  after FDR adjustment)

572 are shown. Correlation inferred for the home dust microbiome based on fungi only. Orange and  
573 blue represents significant negative correlations and positive correlations. Darker color represents  
574 stronger correlations. **Fig. S6.** Spearman correlation by genus abundance in the dust. Only  
575 significant values ( $p < 0.05$  after FDR adjustment) are shown. Correlation inferred for the home  
576 dust microbiome based on bacteria only. Orange and blue represents significant negative  
577 correlations and positive correlations. Darker color represents stronger correlations. **Fig. S7.** Box  
578 plots of the bacterial richness (a) differences between apartment and house in the rural and urban  
579 areas, (b) differences between rural and urban in the house and apartment. **Fig. S8.** Box plots of  
580 the fungal richness (a) differences between apartment and house in the rural and urban areas, (b)  
581 differences between rural and urban in the house and apartment. **Fig. S9.** Box plots of the three  
582 diversity metrics for fungal (a) Observed, (b) Shannon diversity, and (d) Chao1 diversity with  
583 homes categorized according to pet ownership. **Fig. S10.** Visualization of differences in (a)  
584 bacterial and (b) fungal community composition based on weighted Unifrac distance. Principal  
585 coordinates plot showing the relationship among samples belongs to a home that owns a pet. **Fig.**  
586 **S11.** Differentially abundant analysis between rural and urban living environment. (a) Venn  
587 diagram depicting the microbial genera constantly present in the rural and urban living  
588 environment. (b) Relative abundances in the bed dust samples associate with living environment  
589 (rural or urban). Comparison among the 30 most significantly abundant bacterial genera. P-values  
590 correspond to Wilcoxon rank-sum tests of the relative abundances, with significant values  
591 ( $p < 0.05$ ) bolded with FDR correction. A pseudocount ( $+1e-06$ ) was added to all abundances for  
592 the log-scale presentation. The black dots indicate median values and the abundances are colored  
593 according to the rural (red) ( $N = 251$ ) or urban (blue) ( $N = 295$ ) living environment. **Fig. S12.** The  
594 odds for transfer of taxa (at genus level) from dust to airway microbiota of children. Top panel  
595 shows the odds ratio (x-axis) and the strength (p-value). Of particular interest is the distribution of  
596 positive- (odds ratio  $> 1$ ) compared to negative odds (odds ratio  $< 1$ ). Lower panel shows odds ratio  
597 (y-axis) versus the population-wide dust abundance (x-axis). Odds larger (or smaller) than 100  
598 fold are truncated to 100 (or 0.01). Colors indicate the top 15 overall most abundant taxonomic  
599 families. **Table S1.** Characteristics of the study population ( $n = 584$  infants). \*Income level is  
600 categorize into Low ( $< €50,000/\text{year}$ ), medium ( $€50,000 - €110,000/\text{year}$ ), high ( $> €110,000/\text{year}$ ).  
601 \*\*Education level is categorize into Low (primary school, secondary school, or college graduate),  
602 medium (tradesman or bachelor degree), high (master's degree). **Table S2.** Abundances of  
603 bacterial phyla in percentage among home dust samples. **Table S3.** Abundances of bacterial genera

604 in percentage among home dust samples. **Table S4.** Abundances of fungal phyla in percentage  
605 among home dust samples. **Table S5.** Abundances of fungal class in percentage among home dust  
606 samples. **Table S6.** Abundances of fungal genera in percentage among home dust samples. **Table**  
607 **S7.** Table showing differentially abundant bacterial taxa detected by LEfSe for bed dust samples.  
608 †Column labeled “Pet ownership” represents the home that have dog and cat both in which the  
609 corresponding taxa (as presented in column labeled “Differentially abundant Taxa”), was found to  
610 be significantly differentially abundant by LEfSe. ‡ Differentially abundant taxa is described using  
611 the following hierarchy: Phylum|Class|Order|Family|Genus|species. **Table S8.** Table showing  
612 differentially abundant bacterial taxa detected by LEfSe for bed dust samples. †Column labeled  
613 “Pet ownership” represents the home that have dog in which the corresponding taxa (as presented  
614 in column labeled “Differentially abundant Taxa”), was found to be significantly differentially  
615 abundant by LEfSe. ‡ Differentially abundant taxa is described using the following hierarchy:  
616 Phylum|Class|Order|Family|Genus|species. **Table S9.** Table showing differentially abundant  
617 bacterial taxa detected by LEfSe for bed dust samples. †Column labeled “Pet ownership”  
618 represents the home that have cat in which the corresponding taxa (as presented in column labeled  
619 “Differentially abundant Taxa”), was found to be significantly differentially abundant by LEfSe.  
620 ‡ Differentially abundant taxa is described using the following hierarchy:  
621 Phylum|Class|Order|Family|Genus|species. **Table S10.** Table showing differentially abundant  
622 fungal taxa detected by LEfSe for bed dust samples. †Column labeled “Pet ownership” represents  
623 the home that have dog and cat both in which the corresponding taxa (as presented in column  
624 labeled “Differentially abundant Taxa”), was found to be significantly differentially abundant by  
625 LEfSe. ‡ Differentially abundant taxa is described using the following hierarchy:  
626 Phylum|Class|Order|Family|Genus|species. **Table S11.** Table showing differentially abundant  
627 fungal taxa detected by LEfSe for bed dust samples. †Column labeled “Pet ownership” represents  
628 the home that have dog in which the corresponding taxa (as presented in column labeled  
629 “Differentially abundant Taxa”), was found to be significantly differentially abundant by LEfSe.  
630 ‡ Differentially abundant taxa is described using the following hierarchy:  
631 Phylum|Class|Order|Family|Genus|species. **Table S12.** Table showing differentially abundant  
632 fungal taxa detected by LEfSe for bed dust samples. †Column labeled “Pet ownership” represents  
633 the home that have cat in which the corresponding taxa (as presented in column labeled  
634 “Differentially abundant Taxa”), was found to be significantly differentially abundant by LEfSe.  
635 ‡ Differentially abundant taxa is described using the following hierarchy:

636 Phylum|Class|Order|Family|Genus|species. **Table S13.** List of bacteria present in rural and urban  
637 environment at genus level. **Table S14.** The effects of season on environmental factors on alpha  
638 and beta-diversity on the bed dust microbiome. ^Alpha diversity were calculated based on  
639 observed richness and significance were calculated using the Wilcoxon test (for two groups) and  
640 Kruskal-Wallis test (for three or more groups), FDR corrected. #Effects were quantified with R<sup>2</sup>,  
641 and p-values, as determined by PERMANOVA on weighted UniFrac distances. Significant  
642 adjusted p-values (p<0.05) are shown in bold. Abbreviations - R: Rural, U: Urban, H: House, A:  
643 Apartment, C: Cat, D: Dog, B: both cat and dog. **Table S15.** The adjusted (marginal) effects of  
644 environmental factors on alpha and beta-diversity on the bed dust microbiome. ^Alpha diversity  
645 were calculated based on observed richness and significance were calculated using the ANOVA.  
646 #Effects were quantified with R<sup>2</sup>, and p-values, as determined by PERMANOVA on weighted  
647 UniFrac distances. Significant adjusted p-values (p<0.05) are shown in bold.

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797 **Figure Legends**

798 **Fig. 1.** (a) Relative abundance of bacterial phyla in bed dust and airway samples. Phyla with a  
799 mean abundance of at least 1% abundance across bed dust samples are represented in colors. (b)  
800 Associations between fungal and bacterial alpha diversity (observed richness and Shannon  
801 diversity index values) for a given sample. The shaded grey region represents 95% confidence  
802 intervals. Linear regression analysis:  $p=2.9e-05$ ,  $R=0.17$  for observed richness and  $p=8.8e-09$ ,  
803  $R=0.25$  for Shannon diversity.

804 **Fig. 2.** Spearman correlation by genus abundance. Only significant values ( $p<0.05$  after FDR  
805 adjustment) are shown. Correlation inferred for the home dust microbiome based on bacteria and  
806 fungi combined. Orange and blue represents significant negative correlations and positive  
807 correlations. Darker color represents stronger correlations.

808 **Fig. 3.** Box plots of the three diversity metrics for bacteria [(a) observed, (b) Shannon diversity,  
809 and (d) Chao1 diversity] with homes categorized according to pet ownership. Alpha diversity were  
810 tested using the Kruskal-Wallis test and Benjamin & Hochberg FDR method was used for p value  
811 correction. After the global test was significant, a Wilcoxon test was performed to determine which  
812 group of the independent variable differ from each other group.

813 **Fig. 4.** Different abundances of bacterial communities between homes with both cat and dog and  
814 no pets. With LEfSe for data analysis and visualization key ASVs were identified as differentiating  
815 between homes with both cat and dog and no pets. The threshold for the logarithmic LDA score  
816 was 4 and  $p<0.05$  for the factorial Kruskal-Wallis test among classes.

817 **Fig. 5.** Alpha and beta diversity comparison of airway and bed dust samples. (a) Box plot showing  
818 the shannon diversity. Highly significant differences were observed in the diversity (Wilcoxon  
819 test,  $p<2.2e-16$ ) between airway and bed dust samples. (b) Distances shown in the PCoA plot are  
820 based on Bray Curtis diversity metrics. The bacterial microbiome of each sample is indicated with  
821 one dot. (c) Bray Curtis distance between the dust-airway sample pairs for a specific child  
822 compared to the other random sample pair. "Own" represents the distance between specific  
823 children bed dust with their own airway samples. "Others" represents the distance between random  
824 pairs of children bed dust with random airway samples. (d) Associations between fungal and  
825 bacterial alpha diversity (observed richness) for a given sample. The shaded grey region represents  
826 95% confidence intervals. Linear regression analysis:  $p=0.99$ ,  $R=-0.00057$  for observed richness.

827 **Fig. 6.** Spearman correlation by genus abundance. Only significant values ( $p<0.05$  after FDR  
828 adjustment) are shown. Correlation inferred for bacterial bed dust microbiome with bacterial

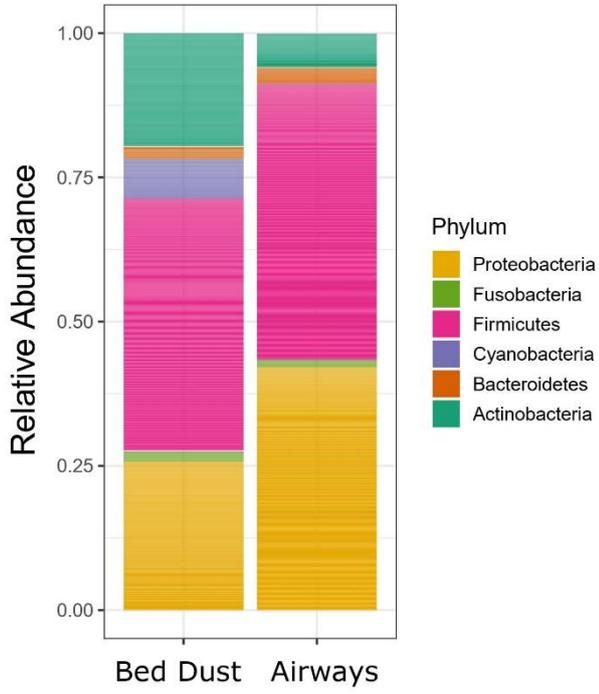
829 airway microbiome. Orange and blue colors represent significant negative correlations and  
830 positive correlations. Darker color represents stronger correlations.

831 **Fig. 1.**

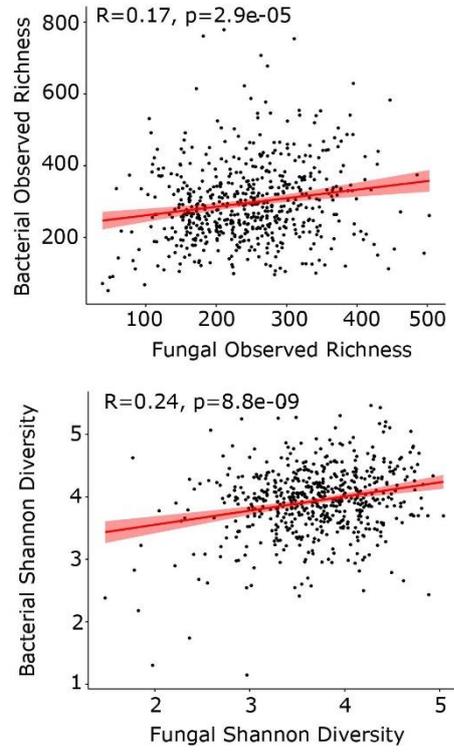
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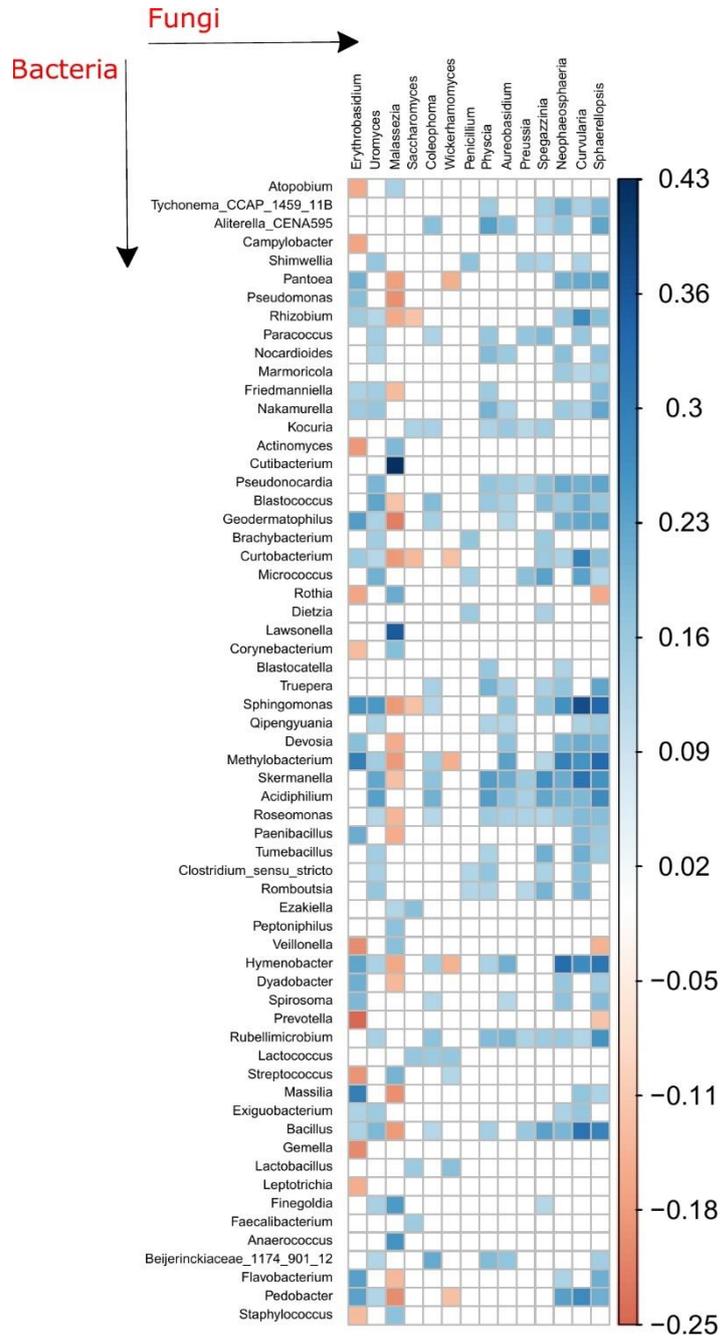
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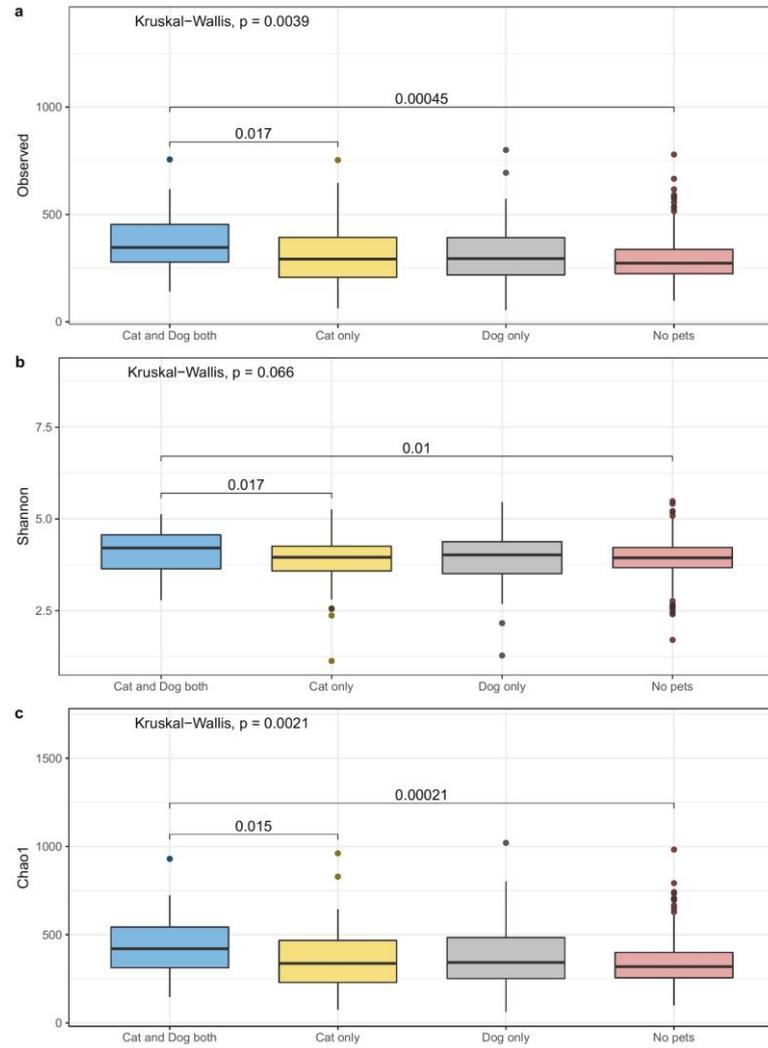
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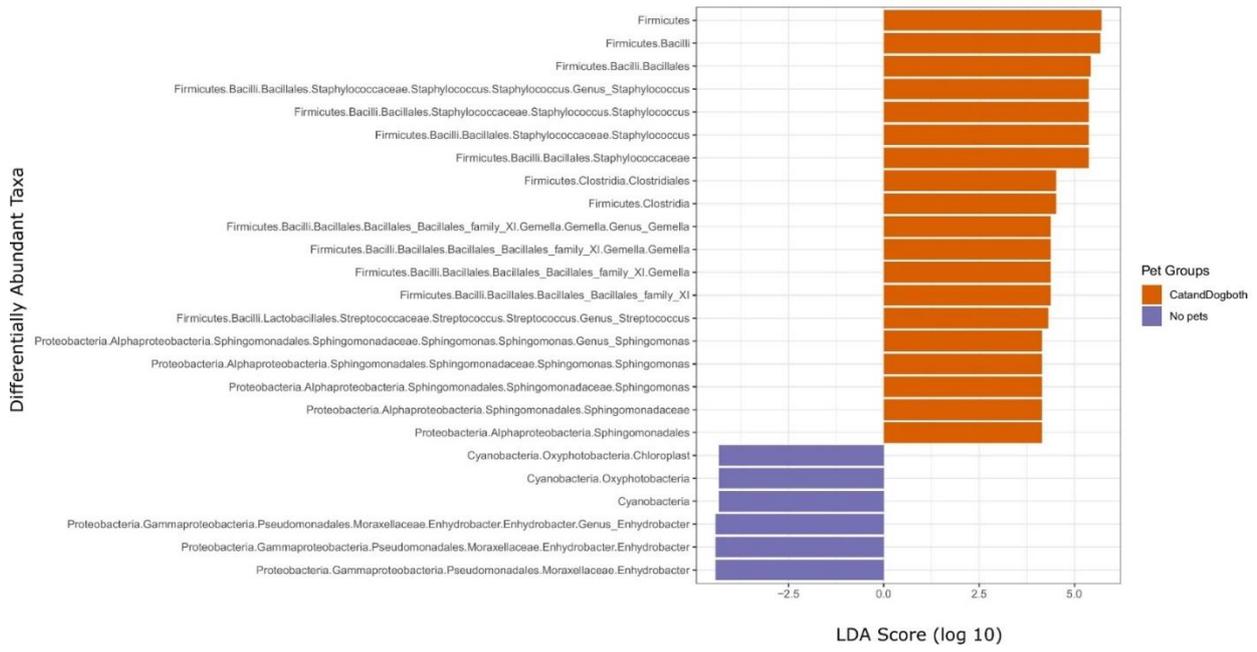
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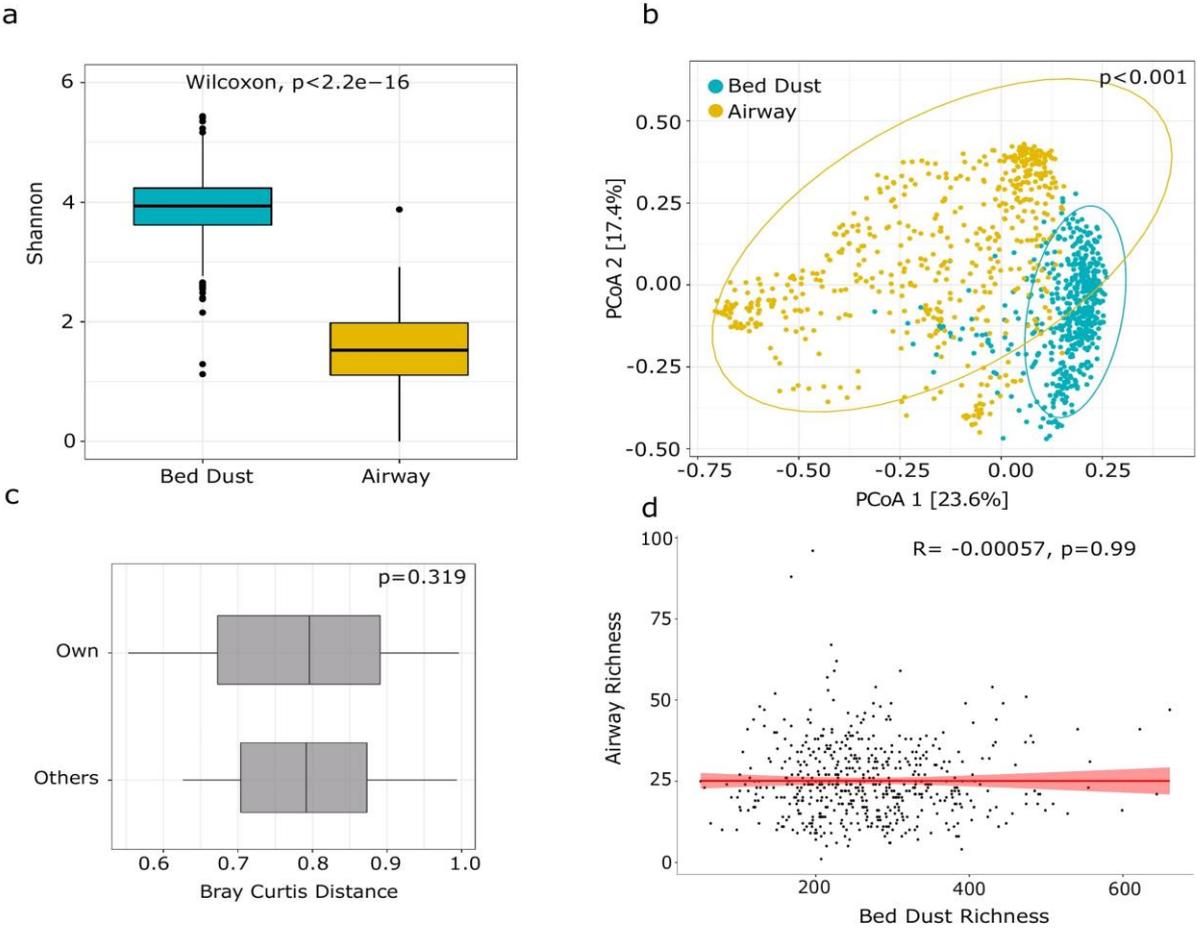
**Fig. 3.**



**Fig. 4.**



**Fig. 5.**





# Figures

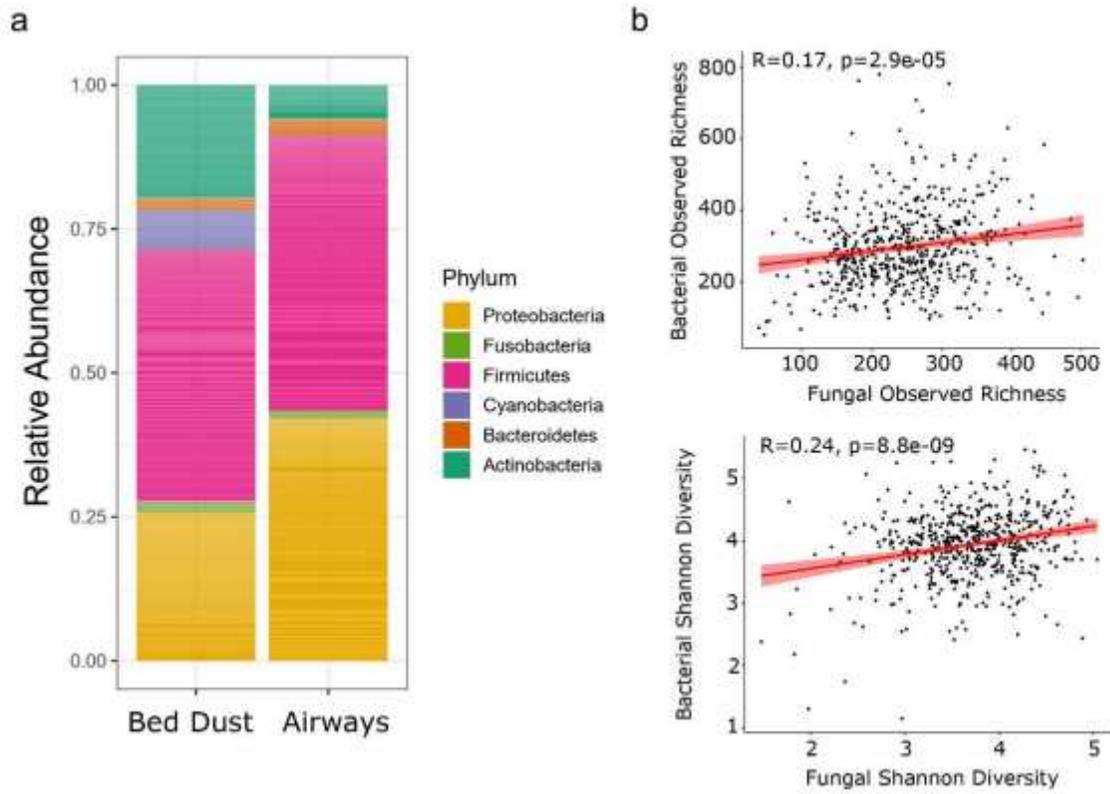
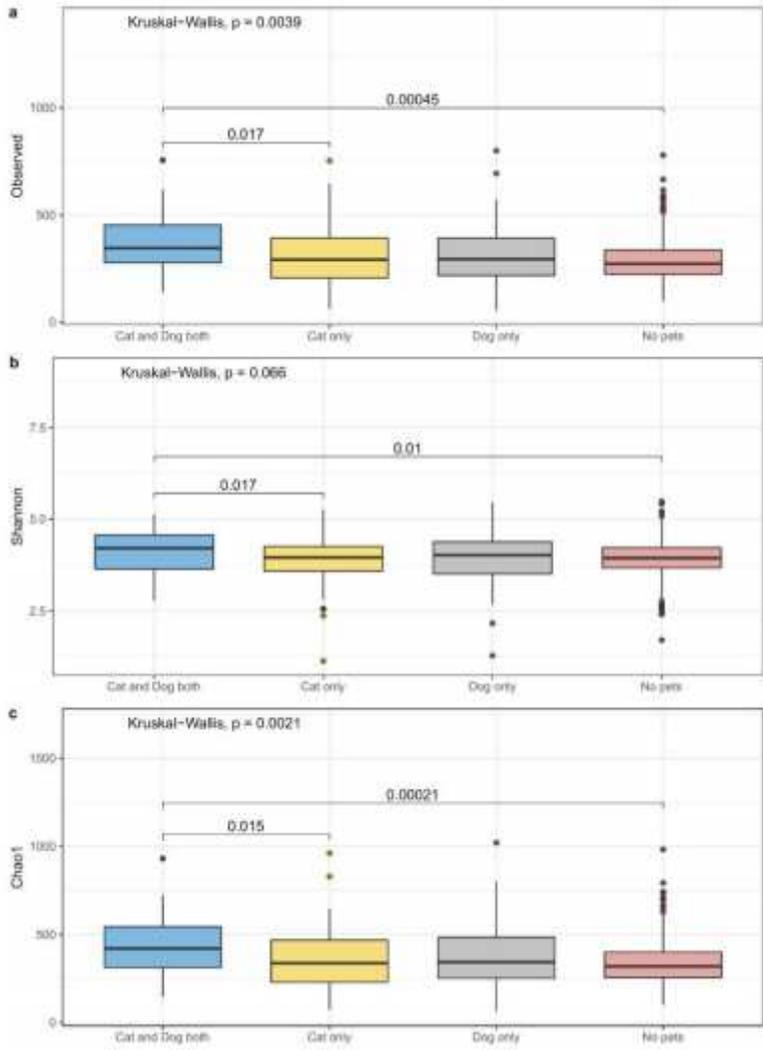


Figure 1

[Please see the manuscript file to view the figure caption.]





**Figure 3**

[Please see the manuscript file to view the figure caption.]

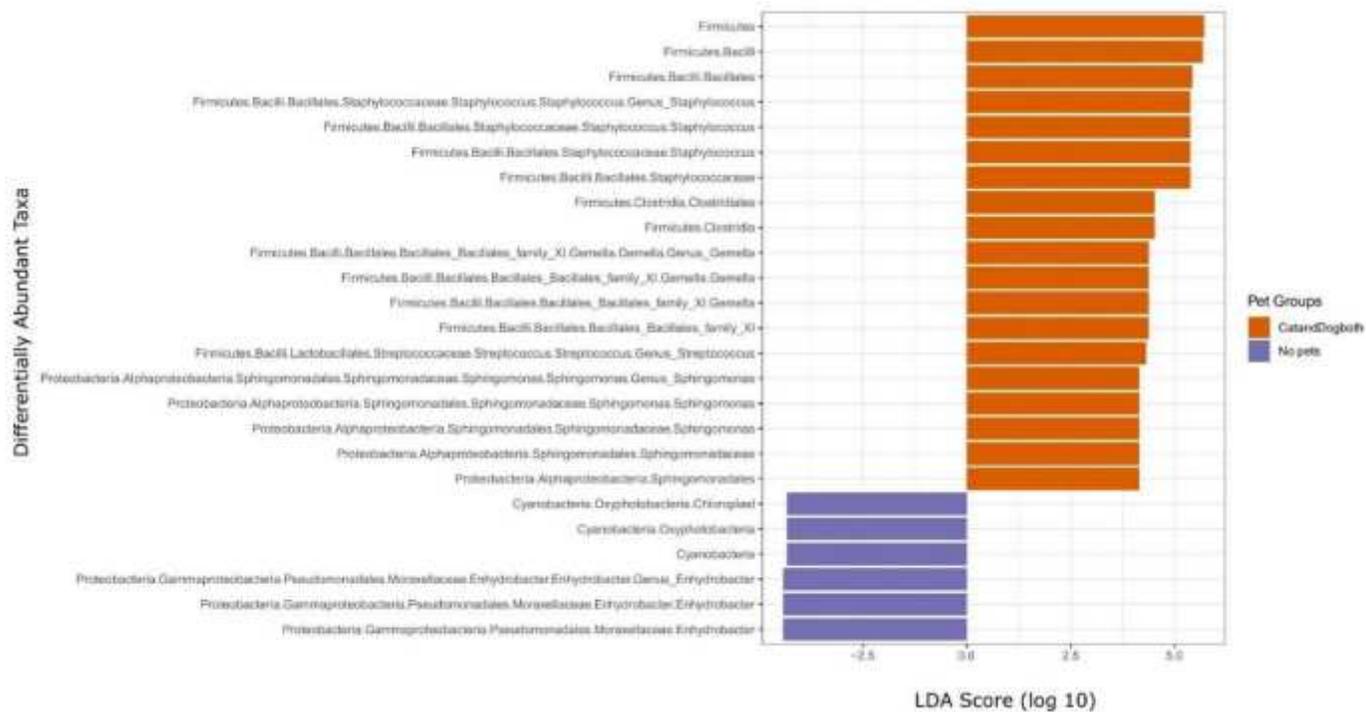


Figure 4

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