Parity modulates impact of BMI and Gestational Weight Gain on gut microbiota in human pregnancy

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Summary

Shifts in the gut microbiome have been implicated in mediating maternal metabolic adaptations to pregnancy. We investigated the impact of pre-pregnancy BMI (pBMI) and gestational weight gain (GWG) on pregnancy-associated remodeling of the maternal gut microbiome and infant colonization, and whether previous pregnancies modulated observed associations. We found that the gut microbiota of participants with higher pBMI changed less over the course of pregnancy in primiparous, but not multiparous participants This suggests that previous pregnancies may have persistent impacts on maternal microbiotal adaptations to pregnancy. This ecological memory appears to be passed to the next generation, as parity impacted infant microbial composition of first-pass meconium and modulated the impact of maternal GWG on the infant gut microbiome. This work supports a role for the gut microbiome in maternal adaptations to pregnancy and highlights parity as a key consideration for studies of the microbiome in pregnancy and infants.

Background

Pregnancy requires physiological, metabolic, and immune adaptations to support fetal growth and development (Tan and Tan, 2013). Pregnancy-induced metabolic adaptations mirror those seen in non-pregnant metabolic syndrome; including hyperglycemia and hyperinsulinemia and increased adiposity. Although some data suggest that these adaptations may influence (Nuriel-Ohayon *et al.*, 2019) and/or be influenced by (Koren *et al.*, 2012) shifts in the gut microbiota over the course of pregnancy, most studies have investigated only one (sometimes two) timepoints during gestation (Aatsinki et al., 2018; Crusell et al., 2018; Koren et al., 2012; Zacarías et al., 2018). An evaluation of whether gut microbiota change temporally across pregnancy, birth and the postnatal period are required to robustly assess whether host-microbe interactions could govern pregnancy adaptations. Of note, we currently lack even a foundational understanding of whether the maternal microbiome does indeed change over the course of pregnancy.

The impact of pregnancy on the gut microbiome in humans is challenging to assess due to the large effect of interpersonal variation (Turnbaugh *et al.*, 2007). One of the first studies of the gut microbiome during pregnancy reported an increase in differences in overall community composition between samples (beta diversity) and a decrease in community richness within samples (alpha diversity) in otherwise normal pregnant individuals during the third trimester of pregnancy compared to the first (Koren *et al.*, 2012). In contrast, others have found the maternal gut microbiota to be stable over the course of pregnancy

(DiGiulio *et al.*, 2015; Faucher *et al.*, 2020; Kumbhare *et al.*, 2020). Even fewer studies have investigated

pregnancy-associated maternal microbial shifts in the context of pregnancy complications like excessive

pre-pregnancy body mass index (pBMI) or gestational weight gain (GWG) (Collado *et al.*, 2008;

Santacruz *et al.*, 2010; Stanislawski *et al.*, 2017). If microbial shifts do occur, no studies to date have

investigated whether these shifts are influenced by previous pregnancies in humans.

Both high maternal pBMI and excess GWG are significantly associated with pregnancy complications

(Triunfo and Lanzone, 2014) and impaired offspring metabolism (Ludwig et al., 2013; Retnakaran et al.,

2012). Reports suggest that some of these maternal and infant associations may be mediated by obesity-

associated "dysbiosis" of the maternal gut microbiome during pregnancy (Santacruz *et al.*, 2010; Zacarías

et al., 2018). As humans are sterile before birth (Kennedy *et al.*, 2021) the maternal microbiome may

influence offspring development both via changes to the in utero environment (e.g. altered maternal

metabolic adaptations to pregnancy) and via altered seeding of the infant microbiome during and after

birth. Indeed, shortly after birth, maternal vaginal, skin, and gut microbes can be detected in the infant gut

microbiota (Dominguez-Bello *et al.*, 2010), but only specific gut-adapted microbes such as

Bifidobacterium and *Bacteroides* persist at least up to 1 year (Korpela *et al.*, 2018). As temporary shifts in

the microbiota during critical developmental windows can have long-term effects on offspring (Cox *et al.*,

2014) and priority effects influence gut microbiota community composition (Martínez *et al.*, 2018), the

initial seeding of the neonate gut by maternal microbes can have long-term effects even in the absence of

persistent colonization. Thus, we set out to determine whether temporal changes in maternal gut microbial

composition occur with pregnancy and whether maternal BMI and/or excess GWG and parity impact

maternal microbiotal adaptations to pregnancy in a prospective study. We also investigated how these

contexts influence infant microbiome at 6 months of age.

Results

Study cohort

A total of 89 participants were recruited in Berlin, Germany. After excluding participants who reported

nicotine or antibiotic use during pregnancy, maternal samples from 65 participants were analyzed

(primiparous n=40; multiparous n=25). Pre-pregnancy BMI (pBMI) was used as a continuous variable or

by BMI category as defined by the World Health Organization(1995): optimal (18.5-24.9, n=39),

overweight (25-29.9, n=12), or obese (>30, n=14). GWG was categorized into below (n=9), within

(n=18), or above (n=38) the recommended range by pBMI category according to Institute of Medicine

guidelines(2010). The majority of participants with pre-pregnancy overweight (10 of 12; 83%) or obesity

(12 of 14; 86%) had GWG above the recommended range, compared to less than half of participants with

an optimal pBMI (12 of 39; 33%; Table S1). Participants predominantly delivered vaginally overall

(51/65; 78%) and within each pBMI category: optimal (30/39; 81%), overweight (10/12; 83%), obese

(10/14; 71%). Multiparous participants (n=25) were older than primiparous participants (n=40; 32.8±3.1

years of age vs 29.6±4.4, p=0.002), but there was no significant effect of parity on pBMI, GWG, post-

partum weight retention, length of gestation, or delivery mode.

Parity modulates the impact of pBMI and GWG on pregnant gut microbiota

Maternal stool samples were collected in the first (10-17 weeks gestation), second (26-28 weeks

gestation), and third trimesters (>36 weeks gestation) of pregnancy, at delivery, and at 6 months

postpartum. We assessed the maternal gut microbiota using 16S ribosomal RNA gene sequencing of the

combined V3-V4 region. We identified a total of 7577 ASVs after removal of host-associated reads

(Kingdom Eukaryota, Order Chloroplast, Family Mitochondria, or no assigned Phylum). The median

sample read count was 62,853 (minimum 14,872; maximum 136,000).

To assess differences in diversity within samples, the Shannon Index alpha diversity metric was used as a

measure of richness and evenness (Whittaker, 1972). Consistent with previous studies (DiGiulio *et al.*,

2015; Faucher *et al.*, 2020; Kumbhare *et al.*, 2020), alpha diversity was similar throughout pregnancy

(p=0.60) and across all sample time points including 6 months post-partum (p=0.057; Fig. S1). Alpha

diversity was decreased by GWG outside the recommended range in multiparous (p=0.013), but not

primiparous participants (p=0.78; Fig. 1a) and was positively correlated with pBMI ($R^2 = 0.11$, p=0.010),

particularly in participants with GWG above the recommended range ($R^2 = 0.12$, p=0.0069; Fig. 1b). This

correlation was significant within each pregnancy time point ($R^2 = 0.14$-0.21, p=0.012-0.046) but not at 6

months post-partum (R^2=0.014, p=0.57; Fig. S1). This suggests that GWG may have a greater influence

on microbial diversity within individuals experiencing their second (or third) pregnancies compared to

those in their first pregnancy (multiparous vs primiparous) and that the effects of pBMI on alpha diversity

do not persist post-partum.

Differences in overall microbiota community composition between samples were assessed by the Bray-

Curtis dissimilarity beta-diversity metric and visualized by principal coordinate analysis (PCoA; Fig 1c,

d). Interindividual variability explained the majority of variation between samples (PERMANOVA;

R^2=62.1%, p=0.0001), with comparatively small effects of GWG category (R^2 = 2.5%, p=0.0001; Fig.

1c), pBMI category (R^2 = 2.8%, p=0.0001; Fig. 1d), parity (R^2 = 1.4%, p=0.0001; Fig. S2a), and sample

time point (R^2 = 1.0%, p=0.0001; Fig. S2b). Within sample time points, the effect of pBMI was

significant in the first trimester (R^2=2.6%, p=0.0052) and third trimester (R^2=2.5%, p=0.030; Fig. S2c)

and the effect of GWG category was significant at 6 months post-partum (R^2=6.0%, p=0.026; Fig. S2d).

This indicates that the impact of pBMI is greatest during pregnancy and does not persist post-partum,

when the impact of GWG is greatest. The contributions of pBMI and GWG to overall beta-diversity were

modest relative to the large effect of inter-individual variation. High inter-individual variation prior to

pregnancy may lead to inter-individual variation in microbiotal adaptations to pregnancy, and in the

impacts of pBMI and GWG on those adaptations.

To investigate whether pBMI impacts beta-diversity within individual participants, we calculated the

mean distance to the centroid within each participant (beta dispersion) using the Bray-Curtis dissimilarity

metric. We found that pBMI is negatively correlated with mean beta dispersion in primiparous (R^2 = 0.26,

p=0.016) but not multiparous participants (R^2 = 0.0013, p=0.90; Fig. S3). We further assessed the effect

of pBMI on sample beta-diversity within each participant by mixed linear model with pBMI and sample

time point as interacting fixed effects and participant ID as a random effect. Overall, beta-diversity within

participants is negatively correlated with pBMI across all sample time points in primiparous (R^2 = 0.083,

p=0.0017) but not multiparous participants (R^2 = 0.0026, p=0.70; Fig. 1e). These data suggest that over

the course of primiparous pregnancy overall gut microbiota community composition changes less in

participants with a higher pBMI and may reflect a reduced requirement for microbiotal adaptations to

pregnancy. Together these data highlight the impact of pre-gravid BMI on microbiota diversity and

suggest that this impact exists not only during pregnancy but also up to 6 months postpartum. These data

also highlight a novel observation: gut microbial diversity during pregnancy is influenced by previous

pregnancies. Parity therefore is a key confounder that must be considered in all future studies

investigating the maternal microbiome.

Parity modulates impact of pBMI and GWG on fecal SCFA levels

Because of their importance in metabolic signalling pathways (Koh *et al.*, 2016), we assessed SCFA level

associations with pBMI and GWG. We analyzed relative SCFA concentrations in a subset of maternal

fecal samples (primiparous, n=16; multiparous, n=16) across all timepoints by gas-chromatography mass

spectroscopy (GC-MS). To account for variability in recovery between samples, the relative concentration

of each SCFA was assessed as a percentage of total SCFAs (Fig. 2). Fecal acetate was decreased by GWG

above the recommended range (p=0.0011), particularly in primiparous participants (p=0.00055). This

decrease was accompanied by corresponding increases in propionate (p=0.019) and butyrate (p=0.015)

with GWG above the recommended range in primiparous participants. Lactate was also decreased in

participants with GWG above the recommended range (p=0.0074), particularly in multiparous

participants (p=0.028). In participants with GWG above the recommended range, the relative abundance

of the branched SCFAs isobutyrate and isovalerate were decreased by pBMI>25 (p=0.020, p=0.051

respectively), particularly in multiparous participants (p=0.014, p=0.020). These data suggest that parity

not only modulates the impact of pBMI and GWG on the gut microbiota community composition but may

also modulate the relative abundance of key microbial metabolites.

Maternal taxonomic associations with pBMI, GWG, and parity

Taxa that were differentially abundant during pregnancy between GWG and pBMI categories and by

parity were identified using DESeq2 (RRID: SCR_015687). The relative abundances of 9 genera (mean

abundance >150) differed by parity across all participants (Table S2). Primiparous participants had

increased abundances of several butyrate-producing genera within the family Lachnospiraceae, including

Roseburia and *NK4A136 group*, compared to multiparous participants (Fig. 3a-b, Table S2). Conversely,

compared to primiparous participants, multiparous participants have an increased relative abundance of

Bifidobacterium and *Romboutsia* (Table S1), both of which have been linked to improved glucose control

in obesity (Schellekens *et al.*, 2021; Therdtatha *et al.*, 2021).

All but 4 of the 26 participants with a pBMI > 25 experienced excess GWG (Table S1). As pBMI and

GWG did not vary independently, and we were not able to assess interacting effects of pBMI and GWG

and therefore these 4 participants were excluded from analysis. The impact of pBMI category was

assessed within participants who experienced excess GWG (pBMI <25, n=12; pBMI 25-30, n=10; pBMI

> 30, n=12; Fig. 2a-c) and the impact of excess GWG was assessed within participants with a pBMI < 25

(below, n=7; within, n=17; above, n=12; Fig 3a-c). The relative abundances of 6 and 11 genera (mean

abundance >150) were significantly impacted by a pBMI of 25-30 and >30 respectively, compared to

pBMI <25 overall (Fig. 2c). An additional 7 genera differed significantly by pBMI only in multiparous

participants (Fig. 2c; Table S2). *Bacteroides* and *Anaerostipes* were decreased in participants with pBMI

>30 (Fig. 2a-c). *Blautia* was also decreased in participants with a pBMI 25-30 and > 30 (Fig. 2a-c) and

increased with excess GWG (vs. GWG within the recommended range; Fig. 3a-c), particularly in

primiparous participants (Table S2). In contrast, *Prevotella 9* was markedly increased in participants with

pBMI > 25 or > 30 but decreased by excess GWG. Excess GWG was also associated with decreased

relative abundances of 6 genera of the SCFA-producing family Ruminococcaceae (Fig. 3c), including

uncultured genus (UCG) 005 which has previously been reported to decrease with gestational diabetes

mellitus (Ma *et al.*, 2020) .

Maternal taxonomic associations with diet during pregnancy

As diet plays a role not only gut microbial composition but also the production of bacterial metabolites,

we assessed maternal diet during pregnancy. Dietary data was collected in the first, second, and third

trimester using a semiquantitative 25-item food frequency questionnaire (FFQ) adapted from the validated

PrimeScreen FFQ (Rifas-Shiman *et al.*, 2001). There was no significant effect of pBMI, GWG, or parity

on overall diet quality score or average weekly intake of any one FFQ item in any trimester after

correction for multiple comparisons (FDR correction). FFQ data were further analyzed by principal

component analysis (PCA) to identify dietary patterns. The first three principal components (PCs)

cumulatively describe 31.4% of the FFQ data set variance (13.1%, 9.9%, and 8.4%). Each PC was

divided into tertiles and genera that were differentially abundant between the high and low tertiles were

identified by DESeq2. The first principal component (PC1) was characterized by high factor loadings for

fried foods, processed meat, and refined grains and negative loadings for vegetables, nuts, and legumes

(Fig. 5a). Participants with low PC1 scores had increases in *Roseburia* and *Prevotella* (Fig. 5b), consistent

with their ability to degrade plant-derived polysaccharides (Fehlner-Peach *et al.*, 2019; La Rosa *et al.*,

2019). The second principal component (PC2) was characterized by high factor loadings for meats, fruits,

and vegetables and had few associations with differentially abundant taxa. The third principal component

(PC3) was characterized by high loadings for meats and dairy, and negative loadings for vegetables,

grains, and legumes. As with PC1, participants with low PC3 scores had increases in *Roseburia* and

Prevotella, while participants with high PC3 scores had increases in *Bifidobacterium* and

Catenibacterium, both of which have previously been associated with fermented dairy-product

consumption (Volokh *et al.*, 2019). These data indicate that diet likely contributes to interindividual

variability in gut microbiome community composition, but does not differ by pBMI, GWG or parity.

Impact of delivery mode, parity, and sex on first-pass meconium

Of 70 total first-pass meconium samples, only 44 (62.9%) produced any sequencing reads. This

proportion varied by delivery mode: primary C-section neonates had the lowest proportion of samples

with any reads (17%; 1 of 6 samples), while other delivery modes had similar proportions of samples with

any reads: secondary C-section, 62.5% (5 of 8 samples); normal spontaneous vaginal delivery, 68.9% (31

of 45 samples); vacuum extraction, 63.6% (7 of 11 samples). Of samples with any reads, the number of

reads also varied by delivery mode: the single remaining primary C-section neonate had the fewest reads

per sample (172 reads, n=1), followed by vacuum extraction (median, 397; mean, 14,681; n=7), normal

spontaneous vaginal delivery neonates (median, 11353; mean, 31848.23.18; n=28), and secondary C-

section (median, 21,906; mean, 27,744; n=5). To the extent that read counts reflect microbial load, these

data are consistent with colonization during delivery as neonates born without labour (primary C-section)

are not exposed to the densely populated maternal vaginal and gut microbiomes. These data support our

previous finding(Kennedy *et al.*, 2021) that microbial colonization begins during birth.

Meconium samples with fewer than 100 reads were removed from further analyses, leaving 30 samples

(primary C-section, n=1; secondary C-section; n=4, normal spontaneous vaginal delivery, n=21; vacuum

extraction, n=4). Consistent with out previous study(Kennedy *et al.*, 2021), the microbiota of first-pass

meconium samples was highly variable. A large proportion of samples (14 of 30 total) were dominated by

one or two genera, including *Escherichia/Shigella*, *Enterococcus*, *Lactobacillus*, and *Streptococcus*. The

most prevalent genus was *Bacteroides*, which was detected in 21 of 30 samples (70%), followed by

Faecalibacterium (20 of 30, 67%), *Blautia* (19 of 30, 63%) and *Escherichia*/*Shigella* (19 of 30, 63%). Of

244 genera detected, only 20 were present in more than half of first-pass meconium samples. Among

infants who were not exposed to perinatal antibiotics (n=22 total; vaginal, n=21; C-section, n=1), no

samples were dominated by *Enterococcus*, and *Bacteroides* (18 of 22; 82%) and *Streptococcus* (16 of 21;

73%) were the most prevalent genera.

To eliminate potential confounding effects of delivery mode and antibiotics further analysis was

performed using only first-pass meconium from spontaneous vaginal deliveries without antibiotic

exposure during delivery (n=17). Due to limited sample size, we performed descriptive analysis and

found that, consistent with a previous report (Cong *et al.*, 2016), most females were dominated by

Clostridiales (7 of 10 with abundance greater than 65%), while males were more commonly dominated by

Enterobacteriales (4 of 7 with abundance greater than 41%), which was rare among females (detected in 3

of 10 females with a maximum abundance of 2.1%; Fig. S4). The mean abundance of *Bifidobacterium*

was greater in neonates of multiparous participants (9.2%) than those of primiparous participants (0.30%;

Fig. S5). This was also true for *Bacteroides* (multiparous, 20.9%; primiparous, 6.1%), particularly in

females (multiparous, 33.7%; primiparous, 7.8%), who also had a greater mean abundance compared to

males (female, 20.8%; male 4.3%). There was also an effect of neonate sex on *Escherichia/Shigella*,

which was detected in only 3 of 10 females (mean abundance, 0.34%; maximum abundance, 2.1%) but

was detected in 5 of 7 males (mean abundance, 40.6%), and in 4 of males was the dominant genus

(minimum abundance, 41.3%; maximum abundance, 98.4%). These data suggest that parity and infant

sex may impact the initial colonization of the infant gut microbiota, although this should be confirmed in

a larger sample size.

Impact of perinatal antibiotic exposure on the infant gut microbiota

Of the 63 total mother-infant dyads who provided an infant fecal sample at 6 months of age, we excluded

3 for nicotine exposure during pregnancy, 1 for pre-term birth, and 1 for low sequencing read count,

which left 58 infants for full analysis. As perinatal antibiotic exposure has previously been shown to

perturb the infant gut microbiota (Mueller *et al.*, 2015), we assessed the impact of perinatal antibiotics

(between 33 weeks gestation and birth) on the infant gut microbiota in this cohort. The majority of infants

delivered by C-section were exposed to perinatal antibiotics (12/14; 86%;) while relatively few vaginally

delivered infants were exposed (9/44; 20%). While there was no significant impact of antibiotics on alpha

diversity (Observed p=0.70, Shannon p=0.39; Fig. S5a), infant gut microbiota beta diversity differed by

antibiotic exposure in primiparous participants (PERMANOVA, R^2=0.068, p=0.019), but not in

multiparous participants (R^2=0.043, p=0.56; Fig. S5b). Differentially abundant taxa were identified by

DESeq2 (RRID: SCR_015687) and showed that antibiotic exposure was associated with a decreased

abundance of 8 genera, including *Bifidobacterium*, *Streptococcus*, *Blautia*, and *Parabacteroides* (Fig. S6).

Three additional genera (*Lachnoclostridium*, *Flavonifractor*, *Intestinibacter*) were significantly decreased

by antibiotic exposure only in primiparous participants. *Akkermansia* and an unidentified genus of the

family Lachnospiraceae were the only genera that increased with antibiotic exposure, although again only

in primiparous participants, and both were decreased by antibiotic exposure in multiparous participants.

These data show that perinatal antibiotic exposure significantly perturbs the infant gut microbiota, and

that parity may influence these effects.

Infant participant characteristics

We excluded 21 infants due to perinatal antibiotic use, leaving 37 infants included in our analyses

(female, n=19; male, n=18). Compared to our study cohort overall, a greater proportion of participants

with infant samples delivered vaginally overall (35/37; 95%) and within each pBMI category—optimal

(21/22; 95%), overweight (7/8; 88%), obese (7/7; 100%)—likely due to the exclusion of infants exposed

to antibiotics during delivery. Infant characteristics at birth did not differ by maternal pBMI category

overall or within primiparous and multiparous participants. Although infant birth weight did not differ by

GWG overall, excess GWG was associated with higher birth weight in multiparous participants (p=0.028;

Table S6), although this was not significant after adjusting for multiple testing. Among infants with

available feeding data, at 6 months of age the majority were both breastfed (27/30; 90%) and eating solid

foods (23/28; 82%). At 6 months of age, infant weight did not differ significantly by maternal pBMI or

GWG.

Maternal GWG and the infant gut microbiota at 6 months of age

We evaluated the impacts of maternal pBMI and GWG on the gut microbiota of infants at 6 months of

age. We identified a total of 1063 ASVs after removal of host-associated reads (Kingdom Eukaryota,

Order Chloroplast, Family Mitochondria, or no assigned Phylum). The median sample read count was

59,561 (minimum 6,045; maximum 124,303). There were only 3 participants (1 male, 2 female) with

maternal pre-pregnancy overweight/obesity who did not experience excess GWG. Therefore, pBMI and

GWG did not vary independently, and we were not able to assess interacting effects of pBMI and GWG.

The impact of pre-pregnancy BMI was assessed within participants who experienced excess GWG (pBMI

<25, n=8; >25, n=12) and the impact of excess GWG was assessed within participants with an optimal

pre-pregnancy BMI (GWG below, n=4; within, n=12; above, n=8).

Infant microbiota alpha diversity (number of observed ASVs) was increased by GWG above the

recommended range (p=0.0342; main effect of GWG category, p=0.0336; Fig. 5a) but did not differ by

maternal pBMI (p=0.255), mode of delivery (0.30), or infant sex (p=0.78). There was a significant effect

of maternal GWG on beta diversity in infants of multiparous (R^2=0.378, p=0.0011), but not primiparous,

mothers (R^2=0.0950, p=0.377; Fig. 5b). Infant beta diversity did not differ by maternal pBMI category

(R^2=0.0511, p=0.565) or infant sex (R^2 = 0.0126, p=0.914). Differentially abundant taxa were identified

by DESeq2 (RRID: SCR_015687). Excess maternal GWG was associated with an increase in

Bifidobacterium in the infant gut microbiota (Fig. 6a-c), echoing increased levels of this genus in the

maternal gut microbiota during pregnancy (Fig. 3c). Excess GWG was also associated with a decreased

relative abundance of *Bacteroides* in infants of multiparous, but not, primiparous mothers (Fig. 6c).

Maternal pBMI >25 was associated with a decreased relative abundance of Clostridiales genera *Blautia*

and *Intestinibacter* in the infant gut microbiota, which were also decreased by pBMI >25 in the maternal

gut microbiota. Members of the order Clostridiales typically increase in abundance with the introduction

of solid food in association with increased levels of propionate and butyrate (Tsukuda *et al.*, 2021), and

have previously been found to protect against colonization by enteric pathogens (Kim *et al.*, 2017).

Depleted *Blautia* in obese children has been linked to intestinal inflammation (Benítez-Páez *et al.*, 2020)

which is consistent with an observed association between maternal excess adiposity with childhood
obesity and inflammation (Singer and Lumeng, 2017). The overlap in differentially abundant taxa
between the maternal and infant gut microbiota is consistent with vertical transmission of the maternal gut
microbiota(Ferretti *et al.*, 2018). In addition to previous reports linking maternal GWG and BMI to shifts
in the infant gut microbiota (Baumann-Dudenhoeffer et al., 2018; Collado et al., 2010; Galley et al., 2014;
Mueller et al., 2016; Robinson et al., 2017; Stanislawski et al., 2017; Tun et al., 2018), we now show that
that parity modulates the impact of maternal GWG on the infant gut microbiota, and that this observation
is likely driven by the effect of parity on the maternal gut microbiota.

Discussion

Maternal metabolic adaptations to pregnancy mirror changes seen in non-pregnant obesity and the gut
microbiota have been implicated in mediating these adaptations (Koren *et al.*, 2012), but few studies have
investigated the gut microbiota longitudinally over the course of pregnancy (DiGiulio *et al.*, 2015; Ruebel
et al., 2021). In this study, we investigated the independent and combined impacts of maternal pBMI and
GWG on the maternal gut microbiota over the course of pregnancy and during lactation, and the infant
gut microbiota at 6 months of age. Overall, our study suggests that parity modulates the impact of pBMI
on pregnancy-associated remodeling of the maternal gut microbiota, colonization of the neonatal gut, and
the impact of GWG and antibiotic exposure on the infant gut microbiota.

We found that the gut microbiota of participants with higher pBMI changed less over the course of
pregnancy in primiparous, but not multiparous, participants. Due to the large effect of intraindividual
variation on beta diversity across all samples, the effects of sample time point and pBMI were relatively
small. Previous studies of the gut microbiota have found little-to-no overall effect of pBMI on overall
beta diversity in the first trimester (Gomez-Arango *et al.*, 2016) and across pregnancy (Faucher *et al.*,
2020; Ruebel *et al.*, 2021) but have not investigated beta diversity within individuals over the course of
pregnancy. Shifts in the gut microbiome due to diet or antibiotic perturbation are highly individual-
specific (Fassarella *et al.*, 2021) and our data suggest pregnancy-associated remodeling of the gut
microbiota is also individual-specific. Our observed decrease in intra-individual beta diversity with
increasing pBMI in primiparous participants is consistent with a decreased magnitude of metabolic
adaptation to pregnancy with increasing pBMI (Forbes *et al.*, 2015; Mouzon and Lassance, 2015; Tinius
et al., 2020), and highlights the necessity of longitudinal sampling for investigations of pregnancy-
associated microbiota remodeling.

As this remodeling was not associated with pBMI in multiparous participants, microbiotal adaptations to

pregnancy appear to be modulated by previous pregnancies. First-pregnancies are associated with greater

maternal constraint (Gluckman and Hanson, 2004; Juntunen, 1997), which may include reduced or

delayed metabolic adaptations to pregnancy (Abu-Heija et al., 2017). The impact of parity on the gut

microbiome and its contribution to metabolic adaptations to pregnancy has not previously been

investigated in human pregnancy. Recently, Berry et al. (2021) found that maternal microbiotal

adaptations to pregnancy occurred more rapidly with increasing parity in pigs. This may reflect increased

maternal metabolic flexibility resulting from persistent effects of adaptations to first pregnancy

(Deslypere et al., 1990). Whether the same is true in humans is still unclear, but our data support the

notion that parity influences microbial community composition and must be taken into account when

investigating human pregnancy-related microbial (and intestinal) adaptations.

Maternal adaptations to pregnancy include increased intestinal surface area and increased transit time,

allowing increased nutrient uptake to provide the energy required by fetal development and lactation

(Astbury et al., 2015). SCFAs may support these intestinal adaptations: butyrate promotes proliferation of

the intestinal epithelium and propionate promotes migration of intestinal epithelial cells (IECs) up the

crypt-villus axis (Bilotta et al., 2021). Both butyrate (Wang et al., 2012) and propionate (Tong et al.,

2016) contribute intestinal barrier maintenance. Although human data on intestinal adaptations to

pregnancy are limited, animal models have found excess adiposity during pregnancy is associated with

decreased intestinal length and increased intestinal permeability (Ribeiro et al., 2022). We found that

parity modulated the impact of pBMI and GWG on the relative abundance of maternal fecal SCFAs. In

primiparous participants, GWG above the recommended range was associated with increased butyrate

and propionate. This is consistent with a study that found increased fecal propionate in pregnant

individuals with a pBMI>25 compared to pBMI<25, although parity and GWG were not reported

(Szczuko et al., 2020). As SCFAs are a fuel source for IECs (Morrison and Preston, 2016), increased fecal

SCFAs could be due to decreased uptake by IECs resulting from reduced intestinal adaptations to

pregnancy, but we did not test this hypothesis.

Alternatively, differences in fecal SCFA levels may result from shifts in microbial production due to

altered microbiota community composition. *Prevotella*-dominant microbiota produce more propionate—

and more SCFAs overall—than *Bacteroides*-dominant microbiota (Chen et al., 2017). This is consistent

with our finding that both *Prevotella* and propionate were increased in participants with a pBMI>25,

while *Bacteroides* was decreased, particularly in primiparous participants. A previous study also found

decreased *Bacteroides* in the first and third trimester with pre-pregnancy overweight (Santacruz et al.,

2010), although others have reported increased levels in the third trimester with pre-pregnancy

overweight but not obesity (Collado et al., 2008; Sugino et al., 2019). Crusell et al. (2018) found

Prevotella abundance was positively correlated with oral glucose-stimulated plasma glucose in the third

trimester of pregnancy, but did not differ by pBMI, potentially due to the low prevalence of this taxon (23

of 184 participants). In independent studies, *Prevotella* has been associated with improved glucose

tolerance (Kovatcheva-Datchary et al., 2015), impaired glucose tolerance and insulin resistance (Pedersen

et al., 2016), and increases susceptibility to colitis (Scher et al., 2013). This functional diversity mirrors

that of *Bacteroides* and suggests the impacts of both genera depend on host physiology including

pregnancy history.

Shifts in the maternal gut microbiota can impact the infant gut microbiome by (1) altering fetal intestinal

development through the *in-utero* environment and (2) direct transmission of maternal microbes to the

infant during and after birth. Our finding that the proportion of meconium samples with any sequencing

reads varied by delivery mode is consistent with our previous report that fetal meconium does not have a

microbiome (Kennedy et al., 2021). The greatest proportion of meconium samples without any reads (i.e.

low microbial presence)—and the lowest number of reads per sample—came from neonates delivered by

primary C-section and therefore not exposed to the maternal vaginal or fecal microbiota during labour or

delivery. Delivery mode has been shown to impact the mother-to-infant transmission of key bacterial

taxa, including the genus *Bifidobacterium* (Makino et al., 2013). We found that *Bifidobacterium* was

increased not only in all multiparous participants, but also in the meconium of their infants born via

spontaneous vaginal delivery, compared to primiparous participants. Disruption of this vertical

transmission may have persistent effects on the infant gut microbiota, as we found perinatal antibiotic

exposure was associated with a decrease in *Bifidobacterium* in the infant gut microbiota at 6 months of

age. Unexpectedly, we found that infant sex also impacted the bacterial taxa present in meconium of

vaginally delivered infants; females were dominated by Clostridiales and males by Enterobacteriales.

These data are consistent with one previous report (Cong et al., 2016). Although the mechanism behind

this sex-effect is unclear, it is possible this is related to sex-specific differences in intestinal development.

Other corroborative data include higher rates of necrotizing enterocolitis in preterm males (Boghossian et

al., 2018). These data suggest that the impacts of parity on the maternal microbiome may be transmitted

to the next generation and could be sex-specific. Future studies should continue to combine parity with

infant sex in determining impacts on offspring microbial communities.

Parity modulated the impact of maternal GWG on infant characteristics at birth and the infant gut

microbiota at 6 months of age. GWG above the recommended range is often associated with a reduced

risk of small for gestational age (SGA) birth weight and an increased risk of large for gestational age

(LGA) birth weight (Goldstein et al., 2017), although some data suggest that maternal obesity can also be

associated with intrauterine growth restriction (IUGR) (Radulescu et al., 2013). Little to no data exist on the modulating effect of parity. We found excess GWG was associated with higher birth weight in multiparous participants, and a trend towards lower birthweight in primiparous participants. Others have shown that excess GWG is associated with increased intrapartum weight retention (Nehring et al., 2011) – which may then predispose multiparous pregnant individuals to excess adiposity. These impacts of excess GWG were also associated with a shift in microbiota beta diversity at 6 months of age in infants of multiparous—but not primiparous—participants, who also had a decrease in *Bacteroides* and increase in *Bifidobacterium* reflecting similar shifts in the maternal gut microbiota. Therefore, health behaviours both during pregnancy and the postpartum/intrapartum interval should be supported not only for maternal health but also infant microbiotal health.

Our study has both strengths and limitations. Our longitudinal sampling of a prospective pregnancy cohort allowed us to explore beta-diversity within participants to overcome the overwhelming effect of inter-individual variation. However, as we recruited participants in the first trimester of pregnancy, we are not able to address pregnancy-associated shifts in the gut microbiota that may occur early in gestation. We also show functional outcomes of observed microbial shifts in our analysis of fecal SCFA levels, but did not quantify circulating SCFA levels, which more directly modulate host metabolism (Müller et al., 2019). Finally, although our study is unique among studies of the pregnancy microbiome in its design and sample size, we were unable to examine any interacting effects of pBMI and GWG as the vast majority of participants with high pBMI had GWG above the recommended range.

In conclusion we show that parity modulates impact of pBMI on pregnancy-associated remodeling of the maternal gut microbiota, colonization of the neonatal gut, and the impact of GWG on the infant gut microbiota. We also show that high pBMI is associated with diminished remodeling of the gut microbiome during pregnancy, which may reflect a reduced requirement for metabolic adaptations to pregnancy. Overall, these data support a role for the gut microbiota in modulating maternal metabolic adaptations to pregnancy and suggest the gut microbiome may retain an "ecological memory"(Letourneau et al., 2022) of prior pregnancies (Berry et al., 2021).

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438   Author Contributions

439   Conceptualization, K.M.K., S.A., T.B., A.P., and D.M.S.; Investigation, K.M.K, J.S., M.H., and T.B.;

440   Data Curation, K.M.K; Formal Analysis, K.M.K.; Visualization, K.M.K; Writing – Original Draft,

441   K.M.K; Writing – Review & Editing, K.M.K, M.G.S., T.B., and D.M.S; Supervision, J.F.R.B., T.B., A.P.,

442   W.H., and D.M.S.; Project Administration, T.B., A.P., W.H., and D.M.S.; Resources, T.B., A.P., W.H.,

443   M.G.S., and D.M.S.; Funding Acquisition, T.B. and D.M.S.

444   Competing Interests statement

445   The authors declare that they have no competing interests.

Figure Legends

Figure 1. Parity modulates impact of pBMI and GWG on pregnant gut microbiota. a, Boxplots of
Shannon alpha diversity by gestational weight gain (GWG) category in primiparous participants (circles;
n=23) and multiparous participants (stars; n=13) with a pBMI <25. Alpha diversity differed by GWG in
multiparous participants (p=-0.013) but not primiparous participants (p=0.76). Significance assessed by a
linear mixed model (Kenward–Roger d.f.), with GWG category as a fixed effect and participant ID as a
random effect. The box plot centre line represents the median; the box limits represent the upper and
lower quartiles; the whiskers represent the 1.5× interquartile range; the points represent the outliers. **b**,
Shannon alpha diversity is positively correlated with pBMI across all participants with excess GWG
(R^2=0.12, p=0.0074), particularly in multiparous participants (n=14, R^2=0.21, p=0.036) but not
primiparous participants (n=20, R^2=0.073, p=0.11). Significance assessed by linear mixed model
(Kenward–Roger d.f.), with pBMI as a fixed effect and participant ID as a random effect. **c-d**, PCoA of
Bray-Curtis distances in primiparous (n=39) and multiparous (n=23) participants shows modest clustering
by **c**, GWG category (primiparous, R^2=0.039, p<0.0001; multiparous R^2=0.068, p<0.0001) and **d**, pBMI
category (primiparous, R^2=0.041, p<0.0001; multiparous R^2=0.071, p<0.0001). Significance was assessed
by PERMANOVA. **e**, Bray-Curtis dissimilarity at each timepoint to all other timepoints within individual
participants are negatively associated with pBMI in primiparous participants, but not in multiparous
participants.

Figure 2. Relative SCFA concentrations differ with pBMI >25 and excess GWG. Dot plots of relative
SCFA concentrations as a percentage of total SCFAs show decreased acetate (p=0.014) and lactate
(p=0.034) with GWG above the recommended range and decreased isobutyrate with pBMI >25
(p=0.044). Individual points are shown (transparent dots) as well as the mean (solid black dot) and
standard deviation (whiskers). Significance was assessed by mixed linear model with pBMI category,
GWG category, and timepoint as fixed effects and participant ID as a random effect.

Figure 3. Taxonomic shifts with pBMI in pregnant gut microbiota. a-b, The relative abundances of
the 20 most abundant genera in the maternal gut microbiota by pBMI <25 (blue), 25-30 (red), and >30
(yellow) are shown as **a**, mean relative abundance in taxa bar plots and **b**, mean ± standard error of the
mean for primiparous (pBMI <25, n=7; 25-30, n=6; >30, n=7) and multiparous (pBMI <25, n=5; 25-30,
n=4; >30, n=5) participant with excess GWG. **c**, Dot plots showing DESeq2 results of differentially
abundant genera by pBMI category overall (filled dots) and in primiparous (no fill dots) and multiparous

(stars) participants (dot size based on mean abundance, colours correspond to genus colour in a where a

differentially abundant genus is among the 20 most abundant genera).

Figure 4. Taxonomic shifts with GWG in pregnant gut microbiota. a-b, The relative abundances of

the 20 most abundant genera in the maternal gut microbiota by GWG below (orange), within (purple), and

above (dark blue) the recommended range are shown as **a**, mean relative abundance in taxa bar plots and

b, mean ± standard error of the mean for primiparous (below, n=5; within, n=11; above, n=7) and

multiparous (below, n=2; within, n=6; above, n=5) participant with pBMI <25. **c**, Dot plots showing

DESeq2 results of differentially abundant genera by GWG category overall (filled dots) and in

primiparous (no fill dots) and multiparous (stars) participants (dot size based on mean abundance, colours

correspond to genus colour in a where a differentially abundant genus is among the 20 most abundant

genera).

Figure 5. Taxonomic shifts associated with maternal diet. a, Principal Component Analysis (PCA)

dimensionality reduction of the Food Frequency Questionnaire (FFQ) factors was performed and the

relative contributions (loadings) of these factors to Principle Component 1 (PC1), PC2, and PC3 are

shown. **b,** Dot plots showing DESeq2 results of differentially abundant genera between individuals who

score in the top tertile for each PC versus individuals who scored in the bottom tertile (dot size based on

mean abundance, colours correspond to genus colour in a where a differentially abundant genus is among

the 20 most abundant genera).

Figure 6. Parity modulates impact of GWG on infant gut microbiota. a, Box plots of alpha diversity

by gestational weight gain (GWG) category in primiparous participants (n=26) and multiparous

participants (n=14). Alpha diversity (observed ASVs) was significantly increased by GWG above the

recommended range (p=0.034) in infants of participants with pBMI <25. Significance assessed by a linear

model (Kenward–Roger d.f.), with GWG category as a fixed effect. The box plot centre line represents

the median; the box limits represent the upper and lower quartiles; the whiskers represent the 1.5×

interquartile range; the points represent the outliers. **b**, PCoA of Bray-Curtis distances shows modest

clustering by GWG category (primiparous, R^2=0.039, p<0.0001; multiparous R^2=0.068, p<0.0001).

Significance was assessed by PERMANOVA.

Figure 7. Taxonomic shifts with maternal GWG in infant gut microbiota. a-b, The relative

abundances of the 20 most abundant genera in the infant gut microbiota by GWG below (orange), within

(purple), and above (dark blue) the recommended range are shown as **a**, mean relative abundance in taxa

bar plots and **b**, mean ± standard error of the mean for primiparous (below, n=4; within, n=7; above,

n=12) and multiparous (within, n=5; above, n=8) participant with pBMI <25. **c,** Dot plots showing

DESeq2 results of differentially abundant genera by GWG category overall (filled dots) and in

primiparous (no fill dots) and multiparous (stars) participants (dot size based on mean abundance, colours

correspond to genus colour in a where a differentially abundant genus is among the 20 most abundant

genera).

Star Methods
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Resource availability
513

Lead contact
514

515   Further information and requests should be directed to the lead contact, Deborah Sloboda

516   (sloboda@mcmaster.ca)

Materials availability
517

518   This study did not generate new unique reagents.

Data and code availability
519

•   Sequencing data have been deposited at [repository] and are publicly available as of the data of

publication. Accession numbers are listed in the key resources table.

•   All original code has be deposited at [repository] and is publicly available as of the date of

publication.

•   Any additional information required to reanalyze the data reported in this paper is available from

the lead contact upon request

Experimental model and subject details

Study design

The study protocol was reviewed and approved by the Charité ethics committee (EA 4/059/16). All participants provided written informed consent. Study participants were part of an ongoing research program at the Charité University Berlin. Healthy females >18 years of age with singleton pregnancies were prospectively recruited between 9-17 weeks of gestation. We excluded participants who (1) had severe chronic gastrointestinal diseases or conditions, (2) had any significant heart, kidney, liver, or pancreatic diseases, (3) had pre-existing diabetes, (4) had depression, or (5) delivered infants with severe malformations noted at birth. A total of 89 participants were included in the study. We additionally excluded maternal and infant samples from participants who smoked during pregnancy and excluded maternal samples from participants who took antibiotics during pregnancy. After these exclusions, this study included first-pass meconium samples from 70 participants, infant samples from 58 participants, and maternal samples from 65 participants.

Sample collection

Participants were evaluated at the end of the first trimester (9-17 weeks gestation), second trimester (26-28 weeks), and third trimester (>33 weeks) of pregnancy, at delivery, and at 6 months postpartum. Pre-pregnancy body mass index (pBMI) was obtained from measured height recruitment and recalled pre-pregnancy weight. BMI was categorized into normal weight (18.5-24.9kg/m2), overweight (25-29.9 kg/m2), and obese (>30<40 kg/m2). At each study visit, participant weight was measured and participants completed a 25-item food frequency questionnaire (FFQ) (Atkinson *et al.*, 2022) adapted from the validated PrimeScreen FFQ (Rifas-Shiman *et al.*, 2001). Participant collected fecal samples at home prior to each study visit following a standardized sterile stool collection protocol. Additionally, offspring fecal samples were obtained after delivery (meconium) and at six months of age. Stool was frozen at -20°C immediately after collection in provided sample collection bags and stored at -80°C upon arrival until further use. None had taken prebiotics, laxatives, or diarrhea inhibitors in the days before the sampling.

Method details

DNA extraction and amplification

Genomic DNA (gDNA) was extracted from fecal samples as described previously (Whelan *et al.*, 2014) with the addition of a mechanical lysis step using 0.2 g of 2.8 mm ceramic beads to improve extraction efficiency and without mutanolysin. PCR amplification of the variable 3 and 4 (V3-V4) regions of the 16S rRNA gene was performed on the extracted DNA from each sample using methods previously described(Bartram *et al.*, 2011). Each reaction contained 5 pmol of primer (341F – CCTACGGGNGGCWGCAG, 806R – GGACTACNVGGGTWTC-TAAT), 200 mM of dNTPs, 1.5μl 50 mM MgCl2, 2 μl of 10 mg/ml bovine serum albumin (irradiated with a transilluminator to eliminate contaminating DNA) and 0.25μl Taq polymerase (Life Technologies, Canada) for a total reaction volume of 50 μl. 341F and 806R rRNA gene primers were modified to include adapter sequences specific to the Illumina technology and 6-base pair barcodes were used to allow multiplexing of samples.

16S rRNA gene sequencing

16S DNA products of the PCR amplification were sequenced using the Illumina MiSeq platform (2x300bp) at the Farncombe Genomics Facility (McMaster University, Hamilton ON, Canada). Primers were trimmed from FASTQ files using Cutadapt (Martin, 2011) (RRID: SCR_011841) and DADA2(Callahan *et al.*, 2016) was used to derive amplicon sequence variants (ASVs). Taxonomy was assigned using the Silva 132 reference database (Quast *et al.*, 2013). Non-bacterial ASVs were culled (kingdom Eukaryota, family Mitochondria, order Chloroplast, or no assigned phylum), as was any ASV to which only 1 sequence was assigned.

Quantification of short-chain fatty acids

SCFA levels were measured in a subset of fecal samples by the McMaster Regional Centre of Mass Spectrometry. A weight equivalent amount of 3.7% HCl, 10 μL of internal standard, and 500 μL of diethyl ether was added to each fecal sample and vortexed for 15 min. After vortexing, 400 μL of diethyl ether fecal extract was transferred to a clean 1.5 mL Eppendorf tube. In a chromatographic vial containing an insert, 20 μL of N-tert-butyldimethylsilyl-N-methyltrifluoroacetamide was added, after which 60 μL of diethyl ether fecal extract was added. The mixture was incubated at room temperature for 1 hour and analyzed using gas chromatography-mass spectrometry (6890N GC, coupled to 5873N Mass Selective

579   Detector; Agilent Technologies, Santa Clara, CA, USA). Statistical significance was assessed by mixed

580   linear model with pBMI, GWG category, and parity as fixed effects and participant ID as a random effect,

581   and multiple comparisons by pBMI and GWG category were performed within primiparous and

582   multiparous participants (Kenward-Rogers degrees of freedom with Tukey adjustment for multiple

583   comparisons).

Quantification and statistical analysis

Participant characteristics

586   Participant characteristic variables shown in Tables S1 and S6 were analyzed in R using the gtsummary

587   package (RRID: SCR_021319). Normality was determined by Shapiro-Wilk test (rstatix; RRID:

588   SCR_021240) and significance was assessed by Kruskal-Wallis test and false discovery rate correction

589   for multiple testing.

16S analysis

We performed alpha and beta-diversity analyses in R using phyloseq (McMurdie and Holmes, 2013)

(RRID: SCR_013080) and tested for whole community differences across groups using vegan's(Oksanen

et al., 2013) (RRID: SCR_011950) implementation of permutational multivariate analysis of variance

(PERMANOVA) in the adonis command. These results were visualized via Principal Coordinate

Analysis (PCoA) ordination using R's ggplot2 package (RRID: SCR_014601) (Wickham, 2016).

Significance of alpha diversity was analyzed by linear mixed model with pBMI and GWG categories as

fixed effects and participant ID as a random effect. Significance of Bray-Curtis dissimilarity was analyzed

within primiparous and multiparous participants by mixed linear model with pBMI, GWG category, and

sample time point as fixed effects and participant ID as a random effect. Differential abundance analysis

was performed using DESeq2 (RRID: SCR_015687) across all pregnancy time points. Due to the

interdependence of pBMI and GWG, taxa differing by pBMI category were analyzed within participants

with excess GWG and taxa differing by GWG category were assessed within participants with a pBMI

<25.

SCFA analysis

605   Statistical significance was assessed by mixed linear model with pBMI, GWG category, and parity as

606   fixed effects and participant ID as a random effect, and multiple comparisons by pBMI and GWG

607   category were performed within primiparous and multiparous participants (Kenward-Rogers degrees of

608   freedom with Tukey adjustment for multiple comparisons). All statistical details, including statistical tests

609   used, sample sizes, and definition of center and dispersion can be found in the figure legends.

References

Aatsinki, A.-K., Uusitupa, H.-M., Munukka, E., Pesonen, H., Rintala, A., Pietilä, S., Lahti, L., Eerola, E., Karlsson, L., and Karlsson, H. (2018). Gut Microbiota Composition in Mid-Pregnancy Is Associated with Gestational Weight Gain but Not Prepregnancy Body Mass Index. J. Womens. Health *27*, 1293–1301. https://doi.org/10.1089/jwh.2017.6488.

Abu-Heija, A.T., Al-Bash, M.R., and Al-Kalbani, M.A. (2017). Effects of maternal age, parity and pre-pregnancy body mass index on the glucose challenge test and gestational diabetes mellitus. J. Taibah Univ. Med. Sci. *12*, 338–342. https://doi.org/10.1016/j.jtumed.2017.01.005.

Astbury, S., Mostyn, A., Symonds, M.E., and Bell, R.C. (2015). Nutrient availability, the microbiome, and intestinal transport during pregnancy. Appl. Physiol. Nutr. Metab. *40*, 1100–1106. https://doi.org/10.1139/apnm-2015-0117.

Atkinson, S.A., Maran, A., Dempsey, K., Perreault, M., Vanniyasingam, T., Phillips, S.M., Hutton, E.K., Mottola, M.F., Wahoush, O., Xie, F., et al. (2022). Be Healthy in Pregnancy (BHIP): A Randomized Controlled Trial of Nutrition and Exercise Intervention from Early Pregnancy to Achieve Recommended Gestational Weight Gain. Nutrients *14*, 810. https://doi.org/10.3390/nu14040810.

Bartram, A.K., Lynch, M.D.J., Stearns, J.C., Moreno-Hagelsieb, G., and Neufeld, J.D. (2011). Generation of multimillion-sequence 16S rRNA gene libraries from complex microbial communities by assembling paired-end illumina reads. Appl. Environ. Microbiol. *77*, 3846–3852. https://doi.org/10.1128/AEM.02772-10.

Baumann-Dudenhoeffer, A.M., D'Souza, A.W., Tarr, P.I., Warner, B.B., and Dantas, G. (2018). Infant diet and maternal gestational weight gain predict early metabolic maturation of gut microbiomes. Nat. Med. *24*, 1822–1829. https://doi.org/10.1038/s41591-018-0216-2.

Benítez-Páez, A., Gómez Del Pugar, E.M., López-Almela, I., Moya-Pérez, Á., Codoñer-Franch, P., and Sanz, Y. (2020). Depletion of Blautia species in the Microbiota of obese children relates to intestinal inflammation and metabolic phenotype worsening. MSystems *5*. https://doi.org/10.1128/mSystems.00857-19.

Berry, A.S.F., Pierdon, M.K., Misic, A.M., Sullivan, M.C., O'Brien, K., Chen, Y., Murray, S.J., Ramharack, L.A., Baldassano, R.N., Parsons, T.D., et al. (2021). Remodeling of the maternal gut microbiome during pregnancy is shaped by parity. Microbiome *9*, 146. https://doi.org/10.1186/s40168-021-01089-8.

Bilotta, A.J., Ma, C., Yang, W., Yu, Y., Yu, Y., Zhao, X., Zhou, Z., Yao, S., Dann, S.M., and Cong, Y. (2021). Propionate Enhances Cell Speed and Persistence to Promote Intestinal Epithelial Turnover and Repair. Cell Mol Gastroenterol Hepatol *11*, 1023–1044. https://doi.org/10.1016/j.jcmgh.2020.11.011.

Boghossian, N.S., Geraci, M., Edwards, E.M., and Horbar, J.D. (2018). Sex Differences in Mortality and Morbidity of Infants Born at Less Than 30 Weeks' Gestation. Pediatrics *142*. https://doi.org/10.1542/peds.2018-2352.

Callahan, B.J., McMurdie, P.J., Rosen, M.J., Han, A.W., Johnson, A.J.A., and Holmes, S.P. (2016).

DADA2: High-resolution sample inference from Illumina amplicon data. Nat. Methods *13*, 581–583.
https://doi.org/10.1038/nmeth.3869.

Chen, T., Long, W., Zhang, C., Liu, S., Zhao, L., and Hamaker, B.R. (2017). Fiber-utilizing capacity
varies in Prevotella- versus Bacteroides-dominated gut microbiota. Sci. Rep. *7*, 2594.
https://doi.org/10.1038/s41598-017-02995-4.

Collado, M.C., Isolauri, E., Laitinen, K., and Salminen, S. (2008). Distinct composition of gut microbiota
during pregnancy in overweight and normal-weight women. Am. J. Clin. Nutr. *88*, 894–899. .

Collado, M.C., Isolauri, E., Laitinen, K., and Salminen, S. (2010). Effect of mother's weight on infant's
microbiota acquisition, composition, and activity during early infancy: a prospective follow-up study
initiated in early pregnancy. Am. J. Clin. Nutr. *92*, 1023–1030. https://doi.org/10.3945/ajcn.2010.29877.

Cong, X., Xu, W., Janton, S., Henderson, W.A., Matson, A., McGrath, J.M., Maas, K., and Graf, J.
(2016). Gut Microbiome Developmental Patterns in Early Life of Preterm Infants: Impacts of Feeding and
Gender. PLoS One *11*, e0152751. https://doi.org/10.1371/journal.pone.0152751.

Cox, L.M., Yamanishi, S., Sohn, J., Alekseyenko, A.V., Leung, J.M., Cho, I., Kim, S.G., Li, H., Gao, Z.,
Mahana, D., et al. (2014). Altering the intestinal microbiota during a critical developmental window has
lasting metabolic consequences. Cell *158*, 705–721. https://doi.org/10.1016/j.cell.2014.05.052.

Crusell, M.K.W., Hansen, T.H., Nielsen, T., Allin, K.H., Rühlemann, M.C., Damm, P., Vestergaard, H.,
Rørbye, C., Jørgensen, N.R., Christiansen, O.B., et al. (2018). Gestational diabetes is associated with
change in the gut microbiota composition in third trimester of pregnancy and postpartum. Microbiome *6*,
89. https://doi.org/10.1186/s40168-018-0472-x.

Deslypere, J.P., Van Trappen, Y., and Thiery, M. (1990). Influence of parity on plasma lipid levels. Eur.
J. Obstet. Gynecol. Reprod. Biol. *35*, 1–6. https://doi.org/10.1016/0028-2243(90)90135-n.

DiGiulio, D.B., Callahan, B.J., McMurdie, P.J., Costello, E.K., Lyell, D.J., Robaczewska, A., Sun, C.L.,
Goltsman, D.S.A., Wong, R.J., Shaw, G., et al. (2015). Temporal and spatial variation of the human
microbiota during pregnancy. Proc. Natl. Acad. Sci. U. S. A. *112*, 11060–11065.
https://doi.org/10.1073/pnas.1502875112.

Dominguez-Bello, M.G., Costello, E.K., Contreras, M., Magris, M., Hidalgo, G., Fierer, N., and Knight,
R. (2010). Delivery mode shapes the acquisition and structure of the initial microbiota across multiple
body habitats in newborns. Proc. Natl. Acad. Sci. U. S. A. *107*, 11971–11975.
https://doi.org/10.1073/pnas.1002601107.

Fassarella, M., Blaak, E.E., Penders, J., Nauta, A., Smidt, H., and Zoetendal, E.G. (2021). Gut
microbiome stability and resilience: elucidating the response to perturbations in order to modulate gut
health. Gut *70*, 595–605. https://doi.org/10.1136/gutjnl-2020-321747.

Faucher, M.A., Greathouse, K.L., Hastings-Tolsma, M., Padgett, R.N., Sakovich, K., Choudhury, A.,
Sheikh, A., Ajami, N.J., and Petrosino, J.F. (2020). Exploration of the Vaginal and Gut Microbiome in
African American Women by Body Mass Index, Class of Obesity, and Gestational Weight Gain: A Pilot
Study. Am. J. Perinatol. *37*, 1160–1172. https://doi.org/10.1055/s-0039-1692715.

Fehlner-Peach, H., Magnabosco, C., Raghavan, V., Scher, J.U., Tett, A., Cox, L.M., Gottsegen, C.,
Watters, A., Wiltshire-Gordon, J.D., Segata, N., et al. (2019). Distinct polysaccharide utilization profiles
of human intestinal Prevotella copri isolates. Cell Host Microbe *26*, 680-690.e5.

https://doi.org/10.1016/j.chom.2019.10.013.

Ferretti, P., Pasolli, E., Tett, A., Asnicar, F., Gorfer, V., Fedi, S., Armanini, F., Truong, D.T., Manara, S.,
Zolfo, M., et al. (2018). Mother-to-Infant Microbial Transmission from Different Body Sites Shapes the
Developing Infant Gut Microbiome. Cell Host Microbe *24*, 133-145.e5.
https://doi.org/10.1016/j.chom.2018.06.005.

Forbes, S., Barr, S.M., Reynolds, R.M., Semple, S., Gray, C., Andrew, R., Denison, F.C., Walker, B.R.,
and Norman, J.E. (2015). Convergence in insulin resistance between very severely obese and lean women
at the end of pregnancy. Diabetologia *58*, 2615–2626. https://doi.org/10.1007/s00125-015-3708-3.

Galley, J.D., Bailey, M., Kamp Dush, C., Schoppe-Sullivan, S., and Christian, L.M. (2014). Maternal
obesity is associated with alterations in the gut microbiome in toddlers. PLoS One *9*, e113026.
https://doi.org/10.1371/journal.pone.0113026.

Gluckman, P.D., and Hanson, M.A. (2004). Maternal constraint of fetal growth and its consequences.
Semin. Fetal Neonatal Med. *9*, 419–425. https://doi.org/10.1016/j.siny.2004.03.001.

Goldstein, R.F., Abell, S.K., Ranasinha, S., Misso, M., Boyle, J.A., Black, M.H., Li, N., Hu, G., Corrado,
F., Rode, L., et al. (2017). Association of gestational weight gain with maternal and infant outcomes: A
systematic review and meta-analysis. JAMA *317*, 2207–2225. https://doi.org/10.1001/jama.2017.3635.

Gomez-Arango, L.F., Barrett, H.L., McIntyre, H.D., Callaway, L.K., Morrison, M., Dekker Nitert, M.,
and SPRING Trial Group (2016). Connections Between the Gut Microbiome and Metabolic Hormones in
Early Pregnancy in Overweight and Obese Women. Diabetes *65*, 2214–2223.
https://doi.org/10.2337/db16-0278.

Juntunen, K. (1997). Grand grand multiparity and birth weight. Obstet. Gynecol. *90*, 495–499.
https://doi.org/10.1016/s0029-7844(97)00269-x.

Kennedy, K.M., Gerlach, M.J., Adam, T., Heimesaat, M.M., Rossi, L., Surette, M.G., Sloboda, D.M., and
Braun, T. (2021). Fetal meconium does not have a detectable microbiota before birth. Nature
Microbiology *6*, 865–873. https://doi.org/10.1038/s41564-021-00904-0.

Kim, Y.-G., Sakamoto, K., Seo, S.-U., Pickard, J.M., Gillilland, M.G., 3rd, Pudlo, N.A., Hoostal, M., Li,
X., Wang, T.D., Feehley, T., et al. (2017). Neonatal acquisition of Clostridia species protects against
colonization by bacterial pathogens. Science *356*, 315–319. https://doi.org/10.1126/science.aag2029.

Koh, A., De Vadder, F., Kovatcheva-Datchary, P., and Bäckhed, F. (2016). From dietary fiber to host
physiology: Short-chain fatty acids as key bacterial metabolites. Cell *165*, 1332–1345.
https://doi.org/10.1016/j.cell.2016.05.041.

Koren, O., Goodrich, J.K., Cullender, T.C., Spor, A., Laitinen, K., Bäckhed, H.K., Gonzalez, A., Werner,
J.J., Angenent, L.T., Knight, R., et al. (2012). Host remodeling of the gut microbiome and metabolic
changes during pregnancy. Cell *150*, 470–480. https://doi.org/10.1016/j.cell.2012.07.008.

Korpela, K., Costea, P., Coelho, L.P., Kandels-Lewis, S., Willemsen, G., Boomsma, D.I., Segata, N., and
Bork, P. (2018). Selective maternal seeding and environment shape the human gut microbiome. Genome
Res. *28*, 561–568. https://doi.org/10.1101/gr.233940.117.

Kovatcheva-Datchary, P., Nilsson, A., Akrami, R., Lee, Y.S., De Vadder, F., Arora, T., Hallen, A.,
Martens, E., Björck, I., and Bäckhed, F. (2015). Dietary Fiber-Induced Improvement in Glucose

Metabolism Is Associated with Increased Abundance of Prevotella. Cell Metab. *22*, 971–982.
https://doi.org/10.1016/j.cmet.2015.10.001.

Kumbhare, S.V., Patangia, D.V., Mongad, D.S., Bora, A., Bavdekar, A.R., and Shouche, Y.S. (2020). Gut
microbial diversity during pregnancy and early infancy: an exploratory study in the Indian population.
FEMS Microbiol. Lett. *367*. https://doi.org/10.1093/femsle/fnaa022.

La Rosa, S.L., Leth, M.L., Michalak, L., Hansen, M.E., Pudlo, N.A., Glowacki, R., Pereira, G.,
Workman, C.T., Arntzen, M.Ø., Pope, P.B., et al. (2019). The human gut Firmicute Roseburia intestinalis
is a primary degrader of dietary β-mannans. Nat. Commun. *10*, 905. https://doi.org/10.1038/s41467-019-
08812-y.

Letourneau, J., Holmes, Z.C., Dallow, E.P., Durand, H.K., Jiang, S., Carrion, V.M., Gupta, S.K., Mincey,
A.C., Muehlbauer, M.J., Bain, J.R., et al. (2022). Ecological memory of prior nutrient exposure in the
human gut microbiome. ISME J. https://doi.org/10.1038/s41396-022-01292-x.

Ludwig, D.S., Rouse, H.L., and Currie, J. (2013). Pregnancy weight gain and childhood body weight: a
within-family comparison. PLoS Med. *10*, e1001521. https://doi.org/10.1371/journal.pmed.1001521.

Ma, S., You, Y., Huang, L., Long, S., Zhang, J., Guo, C., Zhang, N., Wu, X., Xiao, Y., and Tan, H.
(2020). Alterations in Gut Microbiota of Gestational Diabetes Patients During the First Trimester of
Pregnancy. Front. Cell. Infect. Microbiol. *10*, 58. https://doi.org/10.3389/fcimb.2020.00058.

Makino, H., Kushiro, A., Ishikawa, E., Kubota, H., Gawad, A., Sakai, T., Oishi, K., Martin, R., Ben-
Amor, K., Knol, J., et al. (2013). Mother-to-infant transmission of intestinal bifidobacterial strains has an
impact on the early development of vaginally delivered infant's microbiota. PLoS One *8*, e78331.
https://doi.org/10.1371/journal.pone.0078331.

Martin, M. (2011). Cutadapt removes adapter sequences from high-throughput sequencing reads.
EMBnet.Journal *17*, 10–12. https://doi.org/10.14806/ej.17.1.200.

Martínez, I., Maldonado-Gomez, M.X., Gomes-Neto, J.C., Kittana, H., Ding, H., Schmaltz, R., Joglekar,
P., Cardona, R.J., Marsteller, N.L., Kembel, S.W., et al. (2018). Experimental evaluation of the
importance of colonization history in early-life gut microbiota assembly. Elife *7*.
https://doi.org/10.7554/eLife.36521.

McMurdie, P.J., and Holmes, S. (2013). phyloseq: an R package for reproducible interactive analysis and
graphics of microbiome census data. PLoS One *8*, e61217. https://doi.org/10.1371/journal.pone.0061217.

Morrison, D.J., and Preston, T. (2016). Formation of short chain fatty acids by the gut microbiota and
their impact on human metabolism. Gut Microbes *7*, 189–200.
https://doi.org/10.1080/19490976.2015.1134082.

Mouzon, S.H., and Lassance, L. (2015). Endocrine and metabolic adaptations to pregnancy; impact of
obesity. Horm. Mol. Biol. Clin. Investig. *24*, 65–72. https://doi.org/10.1515/hmbci-2015-0042.

Mueller, N.T., Bakacs, E., Combellick, J., Grigoryan, Z., and Dominguez-Bello, M.G. (2015). The infant
microbiome development: mom matters. Trends Mol. Med. *21*, 109–117.
https://doi.org/10.1016/j.molmed.2014.12.002.

Mueller, N.T., Shin, H., Pizoni, A., Werlang, I.C., Matte, U., Goldani, M.Z., Goldani, H.A.S., and
Dominguez-Bello, M.G. (2016). Birth mode-dependent association between pre-pregnancy maternal

weight status and the neonatal intestinal microbiome. Sci. Rep. *6*, 23133.
https://doi.org/10.1038/srep23133.

Müller, M., Hernández, M.A.G., Goossens, G.H., Reijnders, D., Holst, J.J., Jocken, J.W.E., van Eijk, H.,
Canfora, E.E., and Blaak, E.E. (2019). Circulating but not faecal short-chain fatty acids are related to
insulin sensitivity, lipolysis and GLP-1 concentrations in humans. Sci. Rep. *9*, 12515.
https://doi.org/10.1038/s41598-019-48775-0.

Nehring, I., Schmoll, S., Beyerlein, A., Hauner, H., and von Kries, R. (2011). Gestational weight gain and
long-term postpartum weight retention: a meta-analysis. Am. J. Clin. Nutr. *94*, 1225–1231.
https://doi.org/10.3945/ajcn.111.015289.

Nuriel-Ohayon, M., Neuman, H., Ziv, O., Belogolovski, A., Barsheshet, Y., Bloch, N., Uzan, A., Lahav,
R., Peretz, A., Frishman, S., et al. (2019). Progesterone Increases Bifidobacterium Relative Abundance
during Late Pregnancy. Cell Rep. *27*, 730-736.e3. https://doi.org/10.1016/j.celrep.2019.03.075.

Oksanen, J., Blanchet, F.G., Kindt, R., Legendre, P., Minchin, P.R., O'Hara, R.B., Simpson, G.L.,
Solymos, P., Henry, M., Stevens, H., et al. (2013). Vegan: Community Ecology Package. 2013. R-
package version 2.0-10.

Pedersen, H.K., Gudmundsdottir, V., Nielsen, H.B., Hyotylainen, T., Nielsen, T., Jensen, B.A.H.,
Forslund, K., Hildebrand, F., Prifti, E., Falony, G., et al. (2016). Human gut microbes impact host serum
metabolome and insulin sensitivity. Nature *535*, 376–381. https://doi.org/10.1038/nature18646.

Quast, C., Pruesse, E., Yilmaz, P., Gerken, J., Schweer, T., Yarza, P., Peplies, J., and Glöckner, F.O.
(2013). The SILVA ribosomal RNA gene database project: improved data processing and web-based
tools. Nucleic Acids Res. *41*, D590-6. https://doi.org/10.1093/nar/gks1219.

Radulescu, L., Munteanu, O., Popa, F., and Cirstoiu, M. (2013). The implications and consequences of
maternal obesity on fetal intrauterine growth restriction. J. Med. Life *6*, 292–298. .

Retnakaran, R., Ye, C., Hanley, A.J.G., Connelly, P.W., Sermer, M., Zinman, B., and Hamilton, J.K.
(2012). Effect of maternal weight, adipokines, glucose intolerance and lipids on infant birth weight
among women without gestational diabetes mellitus. CMAJ *184*, 1353–1360.
https://doi.org/10.1503/cmaj.111154.

Ribeiro, T.A., Breznik, J.A., Kennedy, K.M., Yeo, E., Kennelly, B.K.E., Jazwiec, P.A., Patterson, V.S.,
Bellissimo, C.J., Anhe, F.F., Schertzer, J.D., et al. (2022). Intestinal permeability and peripheral immune
cell composition are altered by pregnancy and adiposity at mid- and late-gestation in the mouse.

Rifas-Shiman, S.L., Willett, W.C., Lobb, R., Kotch, J., Dart, C., and Gillman, M.W. (2001). PrimeScreen,
a brief dietary screening tool: reproducibility and comparability with both a longer food frequency
questionnaire and biomarkers. Public Health Nutr. *4*, 249–254. https://doi.org/10.1079/phn200061.

Robinson, A., Fiechtner, L., Roche, B., Ajami, N.J., Petrosino, J.F., Camargo, C.A., Jr, Taveras, E.M.,
and Hasegawa, K. (2017). Association of Maternal Gestational Weight Gain With the Infant Fecal
Microbiota. J. Pediatr. Gastroenterol. Nutr. *65*, 509–515.
https://doi.org/10.1097/MPG.0000000000001566.

Ruebel, M.L., Gilley, S.P., Sims, C.R., Zhong, Y., Turner, D., Chintapalli, S.V., Piccolo, B.D., Andres,
A., and Shankar, K. (2021). Associations between Maternal Diet, Body Composition and Gut Microbial
Ecology in Pregnancy. Nutrients *13*. https://doi.org/10.3390/nu13093295.

Santacruz, A., Collado, M.C., García-Valdés, L., Segura, M.T., Martín-Lagos, J.A., Anjos, T., Martí-
Romero, M., Lopez, R.M., Florido, J., Campoy, C., et al. (2010). Gut microbiota composition is
associated with body weight, weight gain and biochemical parameters in pregnant women. Br. J. Nutr.
104, 83–92. https://doi.org/10.1017/S0007114510000176.

Schellekens, H., Torres-Fuentes, C., van de Wouw, M., Long-Smith, C.M., Mitchell, A., Strain, C.,
Berding, K., Bastiaanssen, T.F.S., Rea, K., Golubeva, A.V., et al. (2021). Bifidobacterium longum
counters the effects of obesity: Partial successful translation from rodent to human. EBioMedicine *63*,
103176. https://doi.org/10.1016/j.ebiom.2020.103176.

Scher, J.U., Sczesnak, A., Longman, R.S., Segata, N., Ubeda, C., Bielski, C., Rostron, T., Cerundolo, V.,
Pamer, E.G., Abramson, S.B., et al. (2013). Expansion of intestinal Prevotella copri correlates with
enhanced susceptibility to arthritis. Elife *2*, e01202. https://doi.org/10.7554/eLife.01202.

Singer, K., and Lumeng, C.N. (2017). The initiation of metabolic inflammation in childhood obesity. J.
Clin. Invest. *127*, 65–73. https://doi.org/10.1172/JCI88882.

Stanislawski, M.A., Dabelea, D., Wagner, B.D., Sontag, M.K., Lozupone, C.A., and Eggesbø, M. (2017).
Pre-pregnancy weight, gestational weight gain, and the gut microbiota of mothers and their infants.
Microbiome *5*, 113. https://doi.org/10.1186/s40168-017-0332-0.

Sugino, K.Y., Paneth, N., and Comstock, S.S. (2019). Michigan cohorts to determine associations of
maternal pre-pregnancy body mass index with pregnancy and infant gastrointestinal microbial
communities: Late pregnancy and early infancy. PLoS One *14*, e0213733.
https://doi.org/10.1371/journal.pone.0213733.

Szczuko, M., Kikut, J., Maciejewska, D., Kulpa, D., Celewicz, Z., and Ziętek, M. (2020). The
Associations of SCFA with Anthropometric Parameters and Carbohydrate Metabolism in Pregnant
Women. Int. J. Mol. Sci. *21*. https://doi.org/10.3390/ijms21239212.

Tan, E.K., and Tan, E.L. (2013). Alterations in physiology and anatomy during pregnancy. Best Pract.
Res. Clin. Obstet. Gynaecol. *27*, 791–802. https://doi.org/10.1016/j.bpobgyn.2013.08.001.

Therdtatha, P., Song, Y., Tanaka, M., Mariyatun, M., Almunifah, M., Manurung, N.E.P., Indriarsih, S.,
Lu, Y., Nagata, K., Fukami, K., et al. (2021). Gut Microbiome of Indonesian Adults Associated with
Obesity and Type 2 Diabetes: A Cross-Sectional Study in an Asian City, Yogyakarta. Microorganisms *9*.
https://doi.org/10.3390/microorganisms9050897.

Tinius, R.A., Blankenship, M.M., Furgal, K.E., Cade, W.T., Pearson, K.J., Rowland, N.S., Pearson, R.C.,
Hoover, D.L., and Maples, J.M. (2020). Metabolic flexibility is impaired in women who are pregnant and
overweight/obese and related to insulin resistance and inflammation. Metabolism *104*, 154142.
https://doi.org/10.1016/j.metabol.2020.154142.

Tong, L.-C., Wang, Y., Wang, Z.-B., Liu, W.-Y., Sun, S., Li, L., Su, D.-F., and Zhang, L.-C. (2016).
Propionate Ameliorates Dextran Sodium Sulfate-Induced Colitis by Improving Intestinal Barrier Function
and Reducing Inflammation and Oxidative Stress. Front. Pharmacol. *7*, 253.
https://doi.org/10.3389/fphar.2016.00253.

Triunfo, S., and Lanzone, A. (2014). Impact of overweight and obesity on obstetric outcomes. J.
Endocrinol. Invest. *37*, 323–329. https://doi.org/10.1007/s40618-014-0058-9.

Tsukuda, N., Yahagi, K., Hara, T., Watanabe, Y., Matsumoto, H., Mori, H., Higashi, K., Tsuji, H.,

Matsumoto, S., Kurokawa, K., et al. (2021). Key bacterial taxa and metabolic pathways affecting gut
short-chain fatty acid profiles in early life. ISME J. *15*, 2574–2590. https://doi.org/10.1038/s41396-021-
00937-7.

Tun, H.M., Bridgman, S.L., Chari, R., Field, C.J., Guttman, D.S., Becker, A.B., Mandhane, P.J., Turvey,
S.E., Subbarao, P., Sears, M.R., et al. (2018). Roles of Birth Mode and Infant Gut Microbiota in
Intergenerational Transmission of Overweight and Obesity From Mother to Offspring. JAMA Pediatr.
172, 368–377. https://doi.org/10.1001/jamapediatrics.2017.5535.

Turnbaugh, P.J., Ley, R.E., Hamady, M., Fraser-Liggett, C.M., Knight, R., and Gordon, J.I. (2007). The
human microbiome project. Nature *449*, 804–810. https://doi.org/10.1038/nature06244.

Volokh, O., Klimenko, N., Berezhnaya, Y., Tyakht, A., Nesterova, P., Popenko, A., and Alexeev, D.
(2019). Human Gut Microbiome Response Induced by Fermented Dairy Product Intake in Healthy
Volunteers. Nutrients *11*. https://doi.org/10.3390/nu11030547.

Wang, H.-B., Wang, P.-Y., Wang, X., Wan, Y.-L., and Liu, Y.-C. (2012). Butyrate enhances intestinal
epithelial barrier function via up-regulation of tight junction protein Claudin-1 transcription. Dig. Dis.
Sci. *57*, 3126–3135. https://doi.org/10.1007/s10620-012-2259-4.

Whelan, F.J., Verschoor, C.P., Stearns, J.C., Rossi, L., Luinstra, K., Loeb, M., Smieja, M., Johnstone, J.,
Surette, M.G., and Bowdish, D.M.E. (2014). The loss of topography in the microbial communities of the
upper respiratory tract in the elderly. Ann. Am. Thorac. Soc. *11*, 513–521.
https://doi.org/10.1513/AnnalsATS.201310-351OC.

Whittaker, R.H. (1972). Evolution and measurement of species diversity. Taxon *21*, 213–251.
https://doi.org/10.2307/1218190.

Wickham, H. (2016). ggplot2: Elegant Graphics for Data Analysis (Springer).

Zacarías, M.F., Collado, M.C., Gómez-Gallego, C., Flinck, H., Aittoniemi, J., Isolauri, E., and Salminen,
S. (2018). Pregestational overweight and obesity are associated with differences in gut microbiota
composition and systemic inflammation in the third trimester. PLoS One *13*, e0200305.
https://doi.org/10.1371/journal.pone.0200305.

(1995). The World Health Report 1995--bridging the gaps. World Health Forum *16*, 377–385. .

(2010). Weight Gain During Pregnancy: Reexamining the Guidelines (Washington (DC): National
Academies Press (US)).

Supplementary Figure 1. Alpha diversity correlated with pBMI during pregnancy. Boxplots of Shannon alpha diversity overlayed with dot plots show a positive correlation with pBMI at each pregnancy timepoint (p=0.012-0.044) but not at 6 months postpartum (p=0.58) in participants with excess GWG and no overall difference in alpha diversity between timepoints across all participants. Significance assessed by linear model (Kenward–Roger d.f.), with pBMI as a fixed effect. The box plot centre line represents the median; the box limits represent the upper and lower quartiles; the whiskers represent the 1.5× interquartile range; the points represent the outliers.

Supplementary Figure 2. Impacts of pBMI, GWG, parity, and sample timepoint on maternal gut microbiome beta diversity. PCoA of Bray-Curtis distances shows modest clustering by **a**, parity (R^2=0.014, p<0.0001) and **b**, timepoint (R^2=0.010, p<0.0001). **c**, Clustering by pBMI category within timepoints is significant in the first trimester (R^2=0.026, p=0.0052) and the third trimester (R^2=0.025, p=0.033). **d**, Clustering by GWG category was significant at 6 months post-partum (R^2=0.060, p=0.026). First trimester, n=62; second trimester, n=58; third trimester, n=56; delivery, n=41; 6 months post-partum, n=43. Significance was assessed by PERMANOVA.

Supplementary Figure 3. Beta dispersion is negatively correlated with pBMI in primiparous participants. Mean beta-dispersion (Bray-Curtis dissimilarity) within individual participants is negatively associated with pBMI in primiparous participants (R2=0.26, p=0.016), but not in multiparous participants (R2=0.0013, p=0.9).

Supplementary Figure 4. Relative abundance of bacterial orders in first-pass meconium of vaginally-delivered neonates differ by parity and sex. The relative abundances of the 20 most abundant orders in first-pass meconium by infant sex and parity show female neonates tend to be dominated by the order Clostridiales, while males are more commonly dominated by Enterobacteriales. Neonates with peripartum antibiotic exposure are indicated by red text.

Supplementary Figure 5. Relative abundance of bacterial genera in first-pass meconium of vaginally-delivered neonates differ by parity and sex. The relative abundances of the 20 most abundant genera in first-pass meconium by infant sex and parity. Neonates with peripartum antibiotic exposure are indicated by red text.

Supplementary Figure 6. Parity modulates impact of peripartum antibiotics on infant gut microbiota. a, Box plots of alpha diversity at 6 months of age shows no effect of peripartum antibiotic exposure. Significance assessed by a linear model (Kenward–Roger d.f.), with antibiotic exposure as a fixed effect. The box plot centre line represents the median; the box limits represent the upper and lower quartiles; the whiskers represent the 1.5× interquartile range; the points represent the outliers. **b,** PCoA of Bray-Curtis distances in primiparous (n=38) and multiparous (n=20) participants shows modest clustering by GWG category (primiparous, R2=0.039, p<0.0001; multiparous R2=0.068, p<0.0001). Significance was assessed by PERMANOVA.

Supplementary Figure 7. Taxonomic shifts with peripartum antibiotics in infant gut microbiota. a-

b, The relative abundances of the 20 most abundant genera in the infant gut microbiota by peripartum

antibiotic exposure are shown as **a**, mean relative abundance in taxa bar plots and **b**, mean ± standard

error of the mean for primiparous (n=38) and multiparous (n=20) participant with pBMI <25. **c**, Dot plots

showing DESeq2 results of differentially abundant genera by perinatal antibiotic exposure (dot size based

on mean abundance, colours correspond to genus colour in a where a differentially abundant genus is

among the 20 most abundant genera).

Table S1. Participant characteristics

Characteristic	Parity				Overall pBMI					Primiparous pBMI					Multiparous pBMI				
	primiparous[1]	multiparous[1]	p[2]	q[3]	<25[1]	25-30[1]	>30[1]	p[2]	q[3]	<25[1]	25-30[1]	>30[1]	p[2]	q[3]	<25[1]	25-30[1]	>30[1]	p[2]	q[3]
n	40	25			39	12	14			24	7	9			15	5	5		
Age	29.6 (4.4)	32.8 (3.1)	0.002	**0.009**	30.9 (4.3)	31.3 (4.6)	30.3 (3.9)	0.8	0.8	29.9 (4.6)	29.6 (5.3)	29.1 (3.5)	>0.9	>0.9	32.60 (3.20)	33.80 (2.17)	32.40 (4.04)	0.8	>0.9
Primigravida	27 (68%)	0 (0%)	<0.001	**<0.001**	17 (44%)	3 (25%)	7 (50%)	0.4	0.8	17 (71%)	3 (43%)	7 (78%)	0.3	0.6	0 (0%)	0 (0%)	0 (0%)		
pBMI	23.8 (21.0, 29.0)	23.5 (21.2, 26.6)	>0.9	>0.9	21.3 (19.6, 23.2)	26.4 (25.8, 28.4)	33.2 (31.3, 34.9)	<0.001	**<0.001**	21.2 (19.4, 22.0)	28.0 (25.7, 28.8)	33.4 (32.7, 33.6)	<0.001	**<0.001**	21.3 (20.2, 23.4)	26.1 (25.9, 26.6)	31.0 (30.9, 35.3)	<0.001	**<0.001**
GWG (kg)	15.0 (12.0, 19.0)	15.0 (13.0, 20.0)	0.8	>0.9	15.0 (13.0, 18.3)	16.5 (14.6, 21.1)	13.5 (10.0, 19.4)	0.6	0.8	14.9 (13.0, 17.3)	19.0 (15.5, 21.8)	12.0 (10.0, 18.0)	0.4	0.6	15.0 (13.0, 20.0)	15.0 (14.8, 16.0)	16.0 (10.0, 19.9)	>0.9	>0.9
GWG category			0.5	0.8				0.001	**0.004**				0.014	0.056				0.069	0.2
below	6 (15%)	3 (13%)			7 (19%)	2 (17%)	0 (0%)			5 (22%)	1 (14%)	0 (0%)			2 (15%)	1 (20%)	0 (0%)		
within	13 (33%)	6 (26%)			17 (47%)	0 (0%)	2 (14%)			11 (48%)	0 (0%)	2 (22%)			6 (46%)	0 (0%)	0 (0%)		
above	20 (51%)	14 (61%)			12 (33%)	10 (83%)	12 (86%)			7 (30%)	6 (86%)	7 (78%)			5 (38%)	4 (80%)	5 (100%)		
pp Weight Retained	3.1 (-0.2, 7.6)	3.2 (2.0, 8.8)	0.3	0.6	1.8 (0.3, 5.0)	4.7 (1.4, 8.1)	7.6 (3.1, 11.9)	0.053	0.14	1.6 (-1.3, 3.8)	4.4 (1.0, 6.5)	7.8 (3.1, 12.4)	0.083	0.2	2.5 (1.3, 7.4)	8.0 (2.7, 8.7)	6.0 (3.2, 9.8)	0.5	>0.9
Length of gestation (days)	282 (274, 284)	277 (273, 282)	0.3	0.6	280 (273, 284)	276 (272, 284)	279 (275, 288)	0.7	0.8	282 (276, 284)	273 (270, 283)	282 (277, 289)	0.5	0.6	277 (270, 282)	276 (275, 284)	278 (274, 279)	0.9	>0.9
Delivery mode = vaginal	32 (80%)	18 (78%)	0.9	>0.9	30 (81%)	10 (83%)	10 (71%)	0.7	0.8	20 (83%)	5 (71%)	7 (78%)	0.8	0.9	10 (77%)	5 (100%)	3 (60%)	0.3	0.7

[1] n; Mean (SD); n (%); Median (IQR)
[2] Kruskal-Wallis rank sum test
[3] False discovery rate correction for multiple testing

Table S3. Infant characteristics

Characteristic	Parity				Overall GWG				Primiparous GWG				Multiparous GWG			
	primiparous[1]	multiparous[1]	p[2]	q[3]	within[1]	above[1]	p[2]	q-value[3]	within[1]	above[1]	p[2]	q-value[3]	within[1]	above[1]	p[2]	q-value[3]
n	24	13			12	20			7	12			5	8		
Age	30.4 (4.3)	32.7 (3.5)	0.073	0.3	32.0 (3.6)	31.1 (4.0)	0.5	>0.9	30.6 (3.7)	30.7 (4.2)	0.9	>0.9	34.0 (2.4)	31.9 (3.9)	0.3	0.5
pBMI	24.2 (20.7, 29.1)	23.5 (21.5, 25.9)	0.6	0.7	21.4 (18.6, 23.6)	25.8 (24.2, 30.5)	0.002	**0.011**	18.7 (18.6, 25.4)	25.8 (24.2, 31.1)	0.031	0.2	21.5 (21.3, 23.3)	25.0 (23.9, 27.7)	0.019	0.076
GWG (kg)	15.0 (11.5, 19.0)	16.0 (14.0, 20.0)	0.4	0.7	13.5 (13.0, 15.0)	19.0 (17.0, 20.2)	<0.001	**0.002**	13.0 (12.0, 15.0)	19.0 (17.8, 20.2)	0.003	**0.036**	14.0 (13.0, 15.0)	18.8 (16.8, 21.2)	0.027	0.076
Length of gestation (days)	281 (276, 284)	280 (277, 284)	0.8	0.8	282 (275, 282)	281 (278, 288)	0.4	>0.9	282 (282, 283)	280 (276, 287)	0.7	0.9	277.0 (270.0, 280.0)	283.0 (279.0, 289.0)	0.078	0.14
Delivery mode = vaginal	22 (92%)	13 (100%)	0.3	0.6	11 (92%)	19 (95%)	0.7	>0.9	6 (86%)	11 (92%)	0.7	0.9	5 (100%)	8 (100%)		
Infant sex = female	14 (58%)	5 (38%)	0.3	0.6	5 (42%)	12 (60%)	0.3	>0.9	4 (57%)	8 (67%)	0.7	0.9	1 (20%)	4 (50%)	0.3	0.5
Birth weight (g)	3,431 (447)	3,655 (353)	0.11	0.3	3,540 (306)	3,526 (490)	>0.9	>0.9	3,665 (246)	3,320 (510)	0.069	0.3	3,366 (318)	3,835 (245)	0.028	0.076
Birth length (cm)	51.83 (2.62)	51.38 (2.26)	0.5	0.7	52.17 (2.48)	51.60 (2.58)	0.6	>0.9	53.29 (2.75)	51.42 (2.54)	0.2	0.3	50.60 (0.55)	51.88 (2.80)	0.4	0.5
Birth weight:length	65 (61, 70)	72 (70, 74)	0.024	0.3	68 (64, 71)	71 (61, 74)	0.8	>0.9	69.0 (65.5, 71.6)	61.7 (59.9, 66.7)	0.10	0.3	66.6 (64.7, 69.6)	72.9 (72.2, 74.9)	0.023	0.076
Birth weight percentile	50 (20, 60)	61 (50, 80)	0.073	0.3	57 (51, 62)	54 (20, 80)	0.8	>0.9	59 (52, 62)	26 (12, 60)	0.11	0.3	46 (28, 58)	72 (57, 82)	0.062	0.14
Birth length percentile	46 (18, 74)	34 (23, 46)	0.4	0.7	41 (30, 78)	46 (18, 62)	0.5	>0.9	72 (42, 89)	49 (18, 68)	0.3	0.5	31 (24, 38)	38 (20, 52)	0.6	0.6
Infant weight at 6 months (g)	7,730 (6,960, 8,250)	7,738 (7,632, 8,154)	0.5	0.7	7,800 (7,305, 8,280)	7,815 (7,611, 8,200)	>0.9	>0.9	7,730 (6,960, 8,450)	7,940 (7,634, 8,200)	>0.9	>0.9	7,959 (7,752, 8,154)	7,662 (7,598, 8,342)	0.6	0.6

[1] n; Mean (SD); Median (IQR); n (%)
[2] Kruskal-Wallis rank sum test
[3] False discovery rate correction for multiple testing