Excessive fetal growth affects HSC quiescence maintenance through epigenetic programming of EGR1 transcriptional network

Running title: Early epigenetic influence on HSC quiescence maintenance

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Summary

Fetal development is a critical period to shape stem cell identity and functions. Detrimental environments during this period are associated with epigenetics alteration of hematopoietic stem and progenitor cells (HSPC) with unknown functional impacts. We implemented a single-cell resolution integrative analysis combining epigenomics, transcriptomics, and functional data to elucidate the epigenetic influence associated with excessive fetal growth on HSPCs. We showed that hematopoietic stem cells (HSC) from large for gestational age neonates present a coordinated DNA hypermethylation and decrease expression for genes of the EGR1 transcriptional network including *SOCS3, KLF2*, and *JUNB* known to sustain stem cell quiescence and pluripotency. Furthermore, these changes were associated with a decreased ability for HSCs to stay undifferentiated and a decreased ability to expand in response to stimulation. Taken together, these results show that fetal overgrowth affects hematopoietic stem cells quiescence maintenance program through an epigenetic programming of the EGR1 related transcriptional network.

Introduction

The hematopoietic stem cells (HSC) are involved in essential processes such as angiogenesis, cardiovascular repair, and immunity throughout the entire life.[1, 2] Thus, alterations in HSC ability to self-renew and to adequately produce differentiated progeny have been suggested to contribute to the onset and progression of age-related diseases such as cancer and cardiovascular diseases.[3, 4] Systemic alterations or action of various stressors like aging[5, 6] can result in alteration of HSC destiny, and ultimately HSC's functions. Although HSCs have been extensively studied, the early mechanisms that control their long-term functions are not well understood, in part due to the extensive heterogeneity in phenotypes and behaviors present in HSCs.[7]

The perinatal period, a time of rapid growth and cell differentiation, represents a critical window for tissue development. Detrimental environmental exposures during this period can lead to long-term consequences as exemplified by the concept of fetal programming of adult chronic diseases.[8, 9] Extremes of fetal growth, such as large for gestation age (LGA), have been associated with increased susceptibility to obesity, hypertension, and hypertriglyceridemia later in life.[10-14] Even if the number of infants born LGA has increased in the recent years, from less than 1% to 14.9% in developing countries[15], the long-term impact of being born LGA is not completely understood.

Fetal growth impacts the number of circulating CD34+ HSCs[16, 17] in human. In mice, it has been shown that maternal high-fat diet limits fetal hematopoietic stem and progenitor cells (HSPC) expansion and repopulation ability while inducing myeloid-biased differentiation.[18] Only few molecular studies have addressed the impact of early deleterious environment on the HSPCs development and function in human. In a previous study, we found a global increase of DNA methylation in cord blood derived

CD34+ HSPCs from LGA infants[19], suggesting that epigenetic modifications may play

a role in the association between early-life exposures and induce life-long changes

within the hematopoietic system. Still, the molecular and functional impacts of these

early epigenetic alterations on human HSPCs remained to be elucidated.

To identify signalling pathways under epigenetic influences and characterize the

impact of early environment on HSPCs functions, we conducted a combined

epigenomic, transcriptomic, and functional analysis on human cord blood derived

CD34+ HSPCs from either appropriately grown (CTRL) or LGA neonates in both

steady state and in response to extrinsic stimuli (stimulated state). We significantly

increased our initial DNA methylation dataset[19] and developed novel analytical

approach to improve integration of the epigenomic and transcriptomic data. CD34+

HSPCs are a relatively heterogeneous cell population[20] and the interaction between

DNA methylation and gene expression depends on cell specific genomic context.[21, 22]

Therefore, we performed single-cell RNA sequencing analysis. Finally, we challenged

HSPCs *in vitro* to measure the impact of early epigenetic programming on stem cell

capacities to differentiate and proliferate. We found that the epigenetic programming

associated with extreme foetal growth affects gene expression across EGR1

associated transcriptional networks impairing HSC maintenance and expansion

capacity.

Results

Extreme fetal growth is associated with hypermethylation of key genes

regulating HSPCs proliferation and differentiation

In this study, we added 32 new cord-blood derived human CD34+ HSPC samples to

the DNA methylation analysis, in addition to our initial DNA methylation dataset

(*n*=40).[19] First, we independently retrieved in this new set of data the global DNA

hypermethylation initially found in LGA compared to controls (**Supplemental Figure**

1). Thus, we pooled both data and detected a total of 4815 differentially methylated

CpGs (DMC) with 4787 CpGs hypermethylated and 28 CpGs hypomethylated in LGA

compared to CTRL (*p*-value<0.001 and |methylation change|>25; **Figure 2A,**

Supplemental Table 1).

To determine which pathways could be affected by these epigenetic changes, we used

gene set enrichment analysis (GSEA). However, a major issue in performing DNA

methylation gene set testing is how to assign DMCs to specific genes. Thus, we

developed a novel methylation gene-score that better reflects the influence of DNA

methylation changes on gene expression than considering only CpG methylation

change or significance of this change (see Supplemental Method section,

Supplemental Figure 2). For this methylation gene-score, we defined gene-CpG

association based on both distance and cell-type specific regulatory information for

CD34+ HSPCs and summarized this information at gene level. We obtained for each

gene (*n*=24857, **Supplemental Table 2**) a unique methylation gene-score

recapitulating any change in DNA methylation associated with LGA condition.

This methylation gene-score was used to rank genes and perform GSEA. Using the

gene ontology (GO) reference database, we found a significant enrichment for

signaling regulating fetal development as well as for key stem cell pathways such as

Wnt signaling, cell fate specification, and cell fate commitment pathways (adjusted *p*-

value<0.01, **Figure 2B**). Furthermore, considering as a reference the putative

susceptibility gene for each clinical traits included in the GWAS catalog[23], we found

significant enrichment of the differentially methylated genes (adjusted *p*-value<0.01,

Figure 2C) for blood related traits (*e.g.* Red blood cell count, Lymphocyte counts,

Monocyte count) and for several metabolic parameters (*e.g.* Triglyceride levels, Birth

weight, Obesity-related traits) indicating that DNA methylation changes target genes

influencing hematopoiesis and metabolism.

Finally, to identify regulatory factors likely impacted by these DNA methylation

changes, we performed transcription factor (TF) motif analysis using HOMER.

Considering proximal regions surrounding each DMCs (±20bp), we found significant

enrichment for 23 TF motifs (adjusted *p*-value<0.05, **Figure 2D**). Among them, we

found several members of the Kruppel-like factors and specificity protein (KLF/SP)

family: KLF14, KLF5, KLF1, KLF6, SP1, SP2, and SP5 that are known to bind to GC-

rich regions as well as known to be involved in the regulation of hematopoietic stem

cells pluripotency and self-renewal.[24-27] We also found a significant enrichment for

EGR1 motif, another key TF controlling proliferation and activation of HSCs[28]

suggesting that EGR1 regulatory network may be impacted by early epigenetic

programming in LGA neonates.

Epigenetic programming impacts quiescence associated genes in

hematopoietic stem cell subpopulation

To get further biological insight into the epigenetic reprogramming observed in LGA

HSPCs, we performed single-cell transcriptomic analysis in two conditions steady

state and stimulated state to challenge quiescence and proliferation. We first created

a hematopoietic reference map (*i.e.* hematomap) by integrating CD34+ cells

(*n*=18520) from 7 control neonates (**Figure 3A**). Based on cluster specific gene

expression, we identified 18 distinct clusters representative of major lineages (Long-

Term HSC, HSC, Multi-Potent progenitor, Lymphoid, Myeloid, and Erythroid) of the

hematopoietic compartment (**Figure 3B**, **Supplemental Figure 3**). This hematomap

was then used as reference to annotate cells though our different conditions to enable

lineage specific transcriptomic analysis.

We first analyzed differentially expressed genes (DEGs) at steady state. We

integrated single-cell transcriptomic data from 6 LGA (*n*=16791 cells) to the 7 CTRL

samples describe above. We only detected few DEGs among the lineages (only one

DEGs for Erythroid and Myeloid lineages, but none for the other lineages, adjusted *p*-

value<0.05 and |log$_2$Fold Change (FC)|>0.5) indicating no major gene expression

changes between CTRL and LGA at steady state (**Supplemental Figure 4**).

We then compared gene expression between steady state cells and stimulated state

cells to identify transcriptomic differences between CTRL and LGA upon stimulation

of the CD34+ HSPCs. First, we validated the cell stimulation considering steady state

cells and stimulated state cells from the same CTRL samples (*n*=3 samples

representing a total of 6776 steady state cells and 1749 stimulated state cells,

Supplemental Figure 5A, Supplemental Figure 5B). We identified a consistent

response to stimulation with 1518 differentially expressed genes associated to the

stimulated state (stimulation signature gene set, adjusted *p*-value<0.05 and

|log$_2$FC|>0.5; **Supplemental Table 3**). Using GO Biological Process reference, we

demonstrated that the upregulated genes from this signature (*n*=1075) were enriched

in key pathways regulating HSPCs differentiation as well as response to stress and

extrinsic stimulation (adjusted *p*-value<0.05; **Supplemental Figure 5C,**

Supplemental Table 4). Similarly, using KEGG reference, we identified MAPK, FoxO,

TNF, and NF-kappa B signaling pathways known to be involved in the immediate-early

response process, further validating our stimulation protocol (adjusted *p*-value<0.05;

Supplemental Figure 5C, Supplemental Table 4). Stimulation was further validated

looking at cell cycle with increase in cell proportion in S and G2M phases

(**Supplemental Figure 5D**). We then performed differential expression analysis

across lineages comparing steady state and stimulated state HSPCs and we found a

significant enrichment in DEGs in the HSC population compared to the other lineages

(*p*-value<2.2×10^{-16}, Chi-Squared Test; **Supplemental Figure 5E**). These findings are

consistent with a response to stimulation associated to a transition from quiescence

to proliferation in HSCs.

Then, we extended our analysis by integrating single-cell transcriptomic data from 6

LGA and 8 CTRL stimulated HSPC samples representing 6861 and 5823 cells,

respectively, and conducted a lineage specific analysis. Focusing on the 1518 DEGs

previously identified in response to stimulation, we observed a global similar pattern

of change in expression in both LGA and CTRL comparing steady state and stimulated

state within each group especially in HSCs (rho=0.7 and *p*-value<2.2×10^{-16},

Spearman's rank correlation; **Figure 4A; Supplemental Figure 6**). However, when

comparing stimulated LGA HSC to stimulated CTRL HSC, we observed in stimulated

LGA a shift toward downregulated genes (*n*=285 downregulated genes over 373

DEGs, adjusted *p*-value<0.05 and $\log_2$FC<(-0.5), **Figure 4A; Supplemental Table 5**),

especially for key genes of the immediate early response promoting quiescence and

self-renewal such as *SOCS3*, *EGR1*, *KLF2*, *DUSP2, JUNB*, *ID1*, *PLK3,* and *ZFP36*

(**Figure 4B).** This shift toward downregulation of expression was also observed at

pathway level with MAPK signaling pathway and TNF signaling pathway being now

enriched in downregulated genes (adjusted *p*-value<0.05; **Supplemental Figure 7**).

Taken together, these observations suggest that the LGA condition is associated with

an alteration of the stem cell response to stimulation at molecular level especially in

HSC lineage.

We then analyzed the correlation between DNA methylation and gene expression

changes using the methylation gene-score to compare DNA methylation and

expression at similar gene-level resolution. For expression data, we considered gene

expression fold change in stimulated state (stimulated LGA vs stimulated CTRL) as

no differences were found in steady state. DEGs also found in the stimulation

signature have a higher methylation gene-score (*p*-value<0.001) compared to other

DEGs or non-DEG genes (**Figure 4C**). More specifically, the downregulated genes

involved in the regulation of proliferation and differentiation of HSPCs such as *SOCS3*,

PLK3, *EGR1*, *KLF2, ZFP36*, *DUSP2,* and *JUNB* were hypermethylated according to

their methylation gene-score (**Figure 4D**) indicating that early epigenetic programming

observed in LGA was able to modulate expression of target genes regulating stem cell

activation, proliferation, and differentiation processes.

Epigenetic programming affects key regulons essential to HSCs quiescence

and differentiation

A challenge when modeling epigenetic influences on gene expression is the

identification of upstream regulators. Transcription factors (TF) have been often

suggested as such, with key role in modulating gene expression as well as

demonstrated susceptibility to DNA methylation.[29] TFs are also essential in regulating

HSCs function and differentiation with well-established lineage specific TFs.[30] We

therefore performed coregulatory network analysis to identify co-regulated genes, *i.e.*

regulons, and performed analysis of cis-regulatory motif to assign TF to each regulon

(SCENIC). We observed a lineage specific pattern of regulons associated with key

hematopoietic TFs such as SPI1, GATA1, GATA2, GATA3, MEIS1, TAL1, TCF3,

EGR1, CEBPB, HOXB4, and STAT1/3 (**Supplemental Figure 8, Supplemental**

Table 6).

To identify master regulators associated with the changes in gene expression

observed in stimulated LGA HSCs, we used the AUCell algorithm proposed by

SCENIC to score the activity of the entire regulon in each cell. We observed six

regulons with a significant decrease in activity in the stimulated LGA HSC population

(adjusted *p*-value<0.001 and |activity score difference|>0.04, **Supplemental Table 7**).

These regulons were associated to ARID5A, EGR1, KLF2, KLF4, FOSB, and JUN

consistent with the hypothesis that regulatory mechanisms underlying proliferation and

differentiation of HSCs were affected (**Figure 5A**).

We then assessed if the correlation observed between DNA methylation and

expression was preserved at the regulon level. Thus, we performed GSEA using our

list of regulons as reference, to first identify regulons enriched for differentially

methylated genes. We ranked genes by their methylation gene-score comparing LGA

vs CTRL samples. Among the enriched regulons (adjusted *p*-value<0.01 and

normalized enrichment score >1.6, *n*=33), we found the regulons associated with

ARID5A, EGR1, FOSB, JUN, KLF2, and KLF4. We also found enrichment for key

HSPC specific regulons such as ATF3 and ATF4 regulating HSC stress response;[31,]

[32] CEBPA and SPI1 promoting myeloid differentiation;[33] and HOX family (HOXA9,

HOXA10, HOXB4) promoting HSC expansion.[34-36] Interestingly, we identified master

functional modules (*i.e.*, network of co-regulated regulons) considering the top

enriched regulons for hypermethylated genes (*n*=33; **Figure 5B**). The principal module

included ARID5A, EGR1, FOSB, JUN, JUNB, KLF2, KLF4, and KLF10 highlighting

how these key regulons are co-regulated and altered in LGA. We then identified

another module based on HOXA9, HOXA10, and HOXB4. The last module including

FOXJ3, FOXO1, FOXP1, IRF8 and XBP1 is more involved in proliferation and lineage

specific differentiation process.

Furthermore, considering only the regulons enriched for differentially methylated

genes (*n*=33), we looked for enrichment on DEGs. We observed that our top affected

regulons ARID5A, JUN, FOSB, KLF4, KLF2 and EGR1 were enriched in DMCs and

in downregulated genes (adjusted *p*-value<0.01, **Figure 5C**). Looking at a gene

regulatory network constructed based on the top affected regulons (**Figure 5D**), we

confirmed that *SOCS3*, *ID1*, *DUSP2* and *ZFP36,* genes previously identified as

downregulated in stimulated LGA (**Figure 4B**), were targets of these affected

regulons. Interestingly, SPI1 and XPB1 regulons associated with HSPC expansion

were enriched in DMCs and in upregulated genes (adjusted *p*-value<0.01, **Figure 5C**).

Together, these results confirm at regulon level, the correlation between change in

expression and change in DNA methylation observed at gene level. They also

demonstrate an alteration of signaling pathways involved in the balance between stem

cell quiescence and differentiation, notably through programming of the early

immediate response regulatory network, in LGA.

Epigenetic programming is associated with a HSC shift toward more

differentiated cells

HSPCs represent a population of cells from progenitors to progressively restricted

cells of the erythroid, myeloid, or lymphoid lineages. To follow cell distribution through

these levels of differentiation and assess the influence of the LGA environment we

used Monocle.[37] Monocle generates a pseudotime, *i.e.* a measure that reflects how

far an individual cell is in the differentiation process. Collecting these pseudotimes

across our different cell populations, we observed a positive correlation between

pseudotime and lineage differentiation as expected (*r*=0.99, Pearson correlation,

Figure 6A, **Supplemental Figure 9A**). We then compared the distribution of the

pseudotime between LGA and CTRL using long-term HSCs as roots. At steady state,

no major differences were observed (**Supplemental Figure 9B)**. However, upon

stimulation, we observed at population level an increase in pseudotime in stimulated

LGA (*p*-value<0.001), suggesting that in response to stimulation LGA cells fail to

maintain their pool of progenitor cells. Indeed, we observed a decrease in number of

cells presenting pseudotime associated with the HSC state in stimulated LGA (*p*-

value<0.05) and a shift toward cells presenting elevated pseudotime suggesting that

stimulated LGA HSCs leave quiescence but failed to properly self-renew compared to

stimulated CTRL HSCs (**Figure 6B**).

Epigenetic programming is associated with alteration of the hematopoietic

compartment function and subpopulation distribution

To further assess the influence of LGA exposure on stem compartment homeostasis,

we monitored cell populations distribution across conditions at molecular resolution

using our single-cell expression dataset. At steady state, no significant changes in

lineage distribution were observed (**Supplemental Figure 10**). After stimulation, we

observed a decrease in HSC cells (*p*-value=0.015) and a trend toward increased MPP

cells (*p*-value=0.13, **Figure 6C**). Such a shift in cell populations is likely to reflect the

altered balance between quiescence and differentiation in LGA HSCs.

Finally, we tested *in vitro* differentiation and proliferation capacities of HSPCs using

colony forming unit (CFU) assays on 4 CTRL and 4 LGA samples. After 14 days of

expansion, colonies were classified in 3 categories: common myeloid progenitors

(CFU_GEMM), erythroid progenitors (BFU-E), and granulocyte-macrophage

progenitors (CFU_GM) based on the morphology of each colony. We observed a

significant decrease in the number of common myeloid progenitors in LGA samples

(*p*-value<0.05; **Figure 6D**) as well as striking differences in shape and size of more

differentiated colonies (**Figure 6E**) validating that HSPCs from LGA were less able to

expand and confirming the functional impact of the early epigenetic programming.

Discussion

Hematopoietic stem cells differentiation and self-renew rely on a synergic interplay

between genetically encoded signaling as well as cell-intrinsic and cell-extrinsic

factors. The integration of these inputs toward a coherent lineage specific

differentiation program is thought to rely on epigenetic modifiers.[38] In our previous

study[19], we considered bulk DNA methylation and we suggested an alteration of this

program in response to extreme fetal growth. Here, our integrative analysis combining

single-cell expression, DNA methylation, and *in vitro* data allowed us to build, at cell

subpopulation resolution, a model around EGR1 associated networks in which early

epigenetic modifications are linked to defective HSC self-renewal and differentiation

capacities in neonates exposed to excessive fetal growth (**Figure 7**). This model,

based on human samples, demonstrated how early epigenetic programming

influences HSC response to further extrinsic stimulation with consequences toward

quiescence maintenance. It presents a possible mechanism to explain the association

found between LGA and increased susceptibility to adult chronic diseases. Indeed,

fine-tuning of HSC quiescence mechanisms is of crucial relevance for correct

hematopoiesis. While, not responsive dormant HSCs would lead to hematopoietic

failure due to a lack of differentiated blood cells. Highly responsive HSCs, as identified

in LGA, would get to exhaustion of the population and lack of long-term maintenance

of the hematopoietic system.[39]

We demonstrated correlated increase of DNA methylation and decrease of gene

expression associated with extreme fetal growth, targeting interconnected regulons

under the influence of key transcription factors known to regulate HSC self-renew and

differentiation ARID5A, EGR1, FOSB, JUN, JUNB, KLF2, and KLF4. ARID5A, a

quiescence associated transcription factor[40] interacts with STAT3 and IL6[41, 42], two

key regulators of HSC self-renewal and proliferation, respectively.[43, 44] EGR1, FOSB,

and JUN are member of the immediate-early response transcription factor family with

essential roles in stress response and in differentiation[45]. EGR1 promotes quiescence

in HSCs.[28] JUNB regulates myelopoiesis[46], HSC proliferation and differentiation.[47] A

recent study in human has demonstrated that downregulation of *JUN* promotes HSC

expansion.[48] FOS members are thought to be gatekeepers to HSC mitotic entry[49] with

FOSB being downregulated in highly proliferative HSCs.[50] Finally, KLF family is

implicated in key stem cell functions. KLF4 is the most well-known factor of this family

due to its role in reprogramming somatic cells into induced pluripotent stem cells

suggesting a function in preservation of stemness.[51] Thus, our approach supports a

model in which the influence of early exposure to deleterious environment (LGA) on

HSPCs is mediated through an epigenetically programmed down regulation of key

signaling pathways involved in HSC quiescence maintenance.

Interestingly, ARID5A, EGR1, and KLFs are known to interact with epigenetic

regulators. ARID5A is a subunit of the SWI/SNF family of chromatin-remodeling

complexes implicated in the control of cell differentiation and lineage specification.

EGR1 forms a complex with the DNA methyltransferase 3 responsible for targeted *de*

novo methylation.[52] While it was reported that TET2 binds to KLF4 through protein-to-

protein interaction to drive locus-specific demethylation during reprogramming of B

cells into iPSCs.[53] These observations further support the interaction between

epigenetic modifications and regulatory activities of the transcription factors founds in

our study.

We then challenged differentiation and proliferation of HSPCs *in vitro* and

demonstrated that the LGA associated epigenetic programming was linked to an

alteration of HSC preservation and expansion. Even if we did not directly measure

HSC quiescence, the study of the cell populations at molecular level reveals a

decrease in HSC population associated with an increase of multipotent progenitor

population suggesting that upon stimulation, HSCs are prone to leave quiescence

toward differentiation failing to properly maintain the initial pool of HSCs. Alterations

at progenitor level were further confirm using lineage specific cytokine exposure (CFU

assays). The decreased in common myeloid progenitors (CMPs) colonies observed in

LGA may be associated with a decrease in the initial HSC cells proportion or with an

alteration of their capacity to respond to stimulation leading to decreased proliferation

as CMPs originate from HSCs. These findings corroborate previous studies on

developmental programming of the hematopoietic system.[16, 17] A reduction in self-

renewal of HSPCs and increase differentiation in both lymphoid and myeloid lineages

have been observed in a mouse model of maternal obesity.[18] These effects may drive

long-term consequences in human health as illustrated by the study performed by

Kotowski et *al.* in which the integrity of the hematopoietic system in neonates was

associated with susceptibility to onset of hematopoietic pathologies, that can be further

associated to age-related diseases.[54]

Interestingly, the LGA associated epigenetic influence at the transcriptomic and

functional levels was exacerbated upon stimulation of the HSC compartment. Indeed,

in the absence of environmental stimuli (steady state), no major difference was

detected at transcriptomic level as HSCs linger in a quiescent state. However, under

extrinsic stimulation (stimulated state), HSCs adaptative response was altered leading

to a decrease in early progenitors' pool likely to impact long-term system function. This

observation fits with the concept of developmental programming which relies not only

on early impairment of organ development but most importantly on a decreased

adaptability to further environmental challenges that will enhance disease

susceptibility and highlights that an interaction between epigenetic programming and

further environmental factors is needed to trigger disease.

In summary, we provided a comprehensive model recapitulating the epigenetic early

programming of the hematopoietic system and its influence on the hematopoietic stem

cell fitness in response to stimulation. This study by identifying epigenetic

modifications associated with gene expression and functional alterations contribute to

elucidate how early exposure can affect long-term tissue maintenance and possibly

increase risk to chronic diseases.

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396   Author contributions

397   AP, AC, YMZ, ED, LBF, and FD were responsible for conducting research and

398   analyzing data. MD and MC provided feedback on the data analysis. AP, AC, FD, AB,

399   and PF contributed to writing the manuscript. FD, FH, and JG were responsible for

400   designing the study.

401   Competing Interest

The authors declare no competing financial interests in relation to the work

described.

Figure Legend

Figure 1: Overview of the experimental design.

Figure 2: LGA is associated with DNA hypermethylation targeting key stem cell

signaling pathways. (A) Volcano plot of DNA methylation score differences for LGA

compared to CTRL based on 754931 loci throughout the genome. Differentially

methylated loci with p-value <0.001 and |methylation difference| > 25 are shown in

red. (B) Network representation of GO pathways. Significantly enriched pathways

were identify using GSEA based on the methylation gene-score. Edges represent

interactions between pathways. (C) Gene-set enrichment analysis for susceptibility

genes associated to pathophysiological traits based on GWAS catalog. Dot plot

representing enrichment for selected relevant traits. Gene ratio corresponds to the

ratio between the total number of genes associated to the trait (using GWAS catalog)

and the number of differentially methylated genes. (D) Dot plot representing

enrichment for TF binding motifs using HOMER considering a ±20bp region around

DMCs. Dots are color coded based on significance of the enrichment and y-axis

represent the number of regions with binding motif among DMCs.

Figure 3: HSPCs lineage annotation using single-cell RNAseq. (A) Hematomap,

UMAP representation of distinct HSPC lineages. (B) Dot plot representing key markers

used to annotate cell populations. LT-HSC, long-term hematopoietic stem cell; HSC,

hematopoietic stem cell; MPP, multipotent progenitor; LMPP, lymphoid-primed

multipotent progenitors; Erythro-Mas, erythroid and mast precursor; Mk/Er,

megakaryocyte and erythrocyte; DC, dendritic cell.

Figure 4: Response to stimulation is altered in LGA. (A) Heatmap representing

change in expression for stimulation associated DEG (n=1518) in HSC population. (B)

Volcano plot representing DEG comparing LGA vs CTRL in stimulated state.

Differentially expressed genes with adjusted p-value <0.05 and |log$_2$FC| >0.5 are

shown in red if also part of the stimulation associated DEGs, otherwise in pink. (C)

Boxplots representing methylation gene-score distribution associated to non DEG,

DEG and stimulation associated DEG (p-value< 0.001, Wilcoxon test). (D) Scatter plot

representing the correlation between change in expression and change in methylation.

x-axis represents the log$_2$FC of expression in stimulated HSCs and y-axis represents

the percentile of methylation gene-score comparing LGA vs CTRL. Differentially

expressed gene with adjusted p-value <0.05 and |log$_2$FC| >0.5 are shown in red if also

part of the stimulation associated DEGs, otherwise in pink.

Figure 5: Epigenetic programming of HSC specific regulons altered in LGA

neonates. Regulons and TF target information were obtained through the SCENIC

workflow. (A) Boxplots representing regulon activity score in stimulated CTRL and

stimulated LGA HSC lineage. Barplot representing the change in regulon activity and

significance comparing stimulated LGA vs stimulated CTRL. Only significantly affected

regulons are represented (adjusted p-value <0.001 and |activity score difference|

>0.04). (B) Network analysis representing regulons interactions considering regulons

significantly enriched for differentially methylated genes (adjusted *p*-value<0.01,

GSEA). Edges represent overlap between regulons (a minimum of 20% overlap is

required to connect regulons). (C) Dot plot representing enrichment for DEGs in

regulons enriched for differentially methylated genes. (D) Network representing

interactions between target genes and transcription factors considering our top

affected regulons ARID5A, EGR1, KLF2, KLF4, FOSB and JUN. Each dot represents

a gene within the network, triangle represents transcription factor, arrow represents

interaction between transcription factor and target genes, shapes are color coded to

reflect the change in methylation gene-score, and DEGs are labeled in red. Size of the

shape represents the number of interactions. Only genes with 2 or more interactions

are represented.

Figure 6: LGA is associated with a HSC shift toward more differentiated cells

and decrease expansion capacity. (A) UMAPs representing pseudotimes across

lineages. (B) Box plots representing the cumulative percentage of cells per

pseudotime in stimulated CTRL and stimulated LGA. Boxplots in the vignette

represent overall pseudotime distribution in stimulated CTRL and stimulated LGA.

Density plots correspond to cell populations distribution across pseudotimes. (C) Dot

plot representing change in cell distribution comparing stimulated LGA vs stimulated

CTRL. Dot sizes represent for each lineage the percent distribution of total distribution.

Boxplots representing the cell distribution across hematopoietic main lineages in

stimulated CTRL and stimulated LGA. (D) Bar plot representing colonies distribution

after CFU assays. (E) Representative capture of colonies morphological differences

found in CTRL and LGA. LT-HSC, long-term hematopoietic stem cell; HSC,

hematopoietic stem cell; MPP, multipotent progenitor; LMPP, lymphoid-primed

multipotent progenitors; Erythro-Mas, erythroid and mast precursor; Mk/Er,

megakaryocyte and erythrocyte; DC, dendritic cell; CFU-GEMM, common myeloid

progenitors; BFU-E, erythroid progenitors; CFU-GM, granulocyte-macrophage

progenitors.

Figure 7: Model recapitulating the epigenomic, transcriptomic, and functional

influence of extreme fetal growth on HSCs. HSC, hematopoietic stem cell; MPP,

multipotent progenitor.

Methods

See the Supplemental Methods for additional information. Overview of the study

design is presented in Figure 1.

Ethics approval. This study was approved by the Institutional Review Board of the

Montefiore Medical Center and the Committee on Clinical Investigation at the Albert

Einstein College of Medicine and is in accordance with Health Insurance Portability

and Accountability Act regulations. Written informed consent was obtained from all

subjects before participation.

Clinical sample collection. Cord blood samples were obtained from CTRL and LGA

neonates. LGA were defined by birth weight and ponderal index values greater than

the 90th percentile adjusted for gestational age and sex. Control infants had normal

parameters (between 10th and 90th percentiles) for both birth weight and ponderal

index. Maternal and infant characteristics are shown in Supplemental Table 8.

Isolation of CD34+ HSPCs. Mononuclear cells were separated using PrepaCyte-WBC following which CD34+ cells were obtained by positive immunomagnetic bead selection, using the AutoMACS Separator (Miltenyi Biotech). Cells were cryopreserved in 10% dimethyl sulfoxide using controlled rate freezing upon analysis.

Genome-Wide DNA methylation assay. DNA methylation levels for >1.7M CpGs were obtained using the HELP-tagging assay as previously described.[55]

Single-cell RNA sequencing libraries preparation. After cell count and viability check, cell suspension was loaded into the Chromium 10x Genomics controller and library was generated using the chromium single-cell v3 chemistry following manufacturer recommendations. Gene expression library was sequenced using 100bp paired-end reads on the Illumina NovaSeq 6000 system.

HSPCs extrinsic stimulation. After cell counting and viability check and prior to cell suspension loading on the Chromium 10x Genomics controller, cell hashtag (HTO) staining was used following the cell-hashing protocol.[56] This protocol resulting in extended cell manipulation was used to mimic response to extrinsic stimulation. Response to stimulation was validated at transcriptomic level.

Colony Forming Unit Assay. To assess clonogenic progenitor frequencies, 3×10^4 CD34+ HSPC cells were plated in methylcellulose containing SCF, GM-CSF, IL-3, and EPO (H4434; STEMCELL Technologies). Colonies were scored 14 days later.

Data processing and statistical analysis. For DNA methylation analysis, low quality CpGs were filtered out based on detection rate and confidence score. 754931 out of 1709224 CpGs were conserved for further analysis. Linear regression and statistical modeling using LIMMA R package[57] were used to identify differentially methylated

CpGs (DMC). To link gene to CpGs and performed gene set enrichment analysis

(GSEA), we generated a methylation gene-score; first by scoring association between

individual CpG and unique gene, based on evidence for association between gene

and CpG (distance, eQTL) and on belonging in regulatory regions; and then, by

concatenating CpG scores across each gene. We assessed enrichment for biological

pathways performing GSEA using the ClusterProfiler package.[58] We performed

transcription factor (TF) motif enrichment analysis using HOMER tool[59] considering a

20bp region around the DMCs.

For single-cell RNAseq (sc-RNAseq) analysis, data were preprocessed using the

CellRanger count pipeline. Data filtering, normalization and integration as well as

cluster identifications were performed using Seurat (v4) pipeline. Pseudo-bulk

differential expression analysis between LGA and CTRL cells within each

hematopoietic lineage was performed using DESeq2 R package.[60] Over

representation test was performed on differentially expressed genes (DEGs) using

enrichGO and enrichKEGG of the ClusterProfiler Package. The SCENIC workflow[61]

was used to identify co-regulated modules associated to a TF (regulons) and to

generate cell-specific activity score for each regulon. Differentiation trajectory analysis

and pseudotime attribution were conducted with Monocle.[37] The code to perform the

analyses   in   this   manuscript   is   available   at

https://github.com/umr1283/LGA_HSPC_PAPER.git.

Data sharing statement. The DNA methylation and gene expression data will be

made available upon request to A.P., P.F., or F.D.

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CTRL neonate

LGA neonate

CD34+ cells isolation from cord blood samples

Genome wide DNA methylation analysis

Steady state

Stimulated state

HTO staining

10X Genomics scRNA-seq

in vitro analysis

14 days

Scoring

Colony Forming Unit Assay

Integrative analysis

Differential methylation analysis

Clustering

Differential expression analysis

Subpopulations distribution

Network analysis