Single-Cell Analysis Identifies Thymic Maturation Delay in Growth-Restricted Neonatal Mice

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Abstract

Fetal growth restriction (FGR) causes a wide variety of defects in the neonate which can lead to increased risk of heart disease, diabetes, anxiety and other disorders later in life. However, the effect of FGR on the immune system, is poorly understood. We used a well-characterized mouse model of FGR in which placental Igf-2 production is lost due to deletion of the placental specific *Igf-2* P_0 promotor. The thymi in such animals were reduced in mass with a ~70% reduction in cellularity. We used single cell RNA sequencing (Drop-Seq) to analyze 7264 thymus cells collected at postnatal day 6.

We identified considerable heterogeneity among the Cd8/Cd4 double positive cells with one subcluster showing marked upregulation of transcripts encoding a sub-set of proteins that contribute to the surface of the ribosome. The cells from the FGR animals were underrepresented in this cluster. Furthermore, the distribution of cells from the FGR animals was skewed with a higher proportion of immature double negative cells and fewer mature T-cells. Cell cycle regulator transcripts also varied across clusters. The T-cell deficit in FGR mice persisted into adulthood, even when body and organ weights approached normal levels due to catch-up growth. This finding complements the altered immunity found in growth restricted human infants. This reduction in T-cellularity may have implications for adult immunity, adding to the list of adult conditions in which the *in utero* environment is a contributory factor.

Introduction

Fetal growth restriction (FGR) is a serious condition affecting between 3 and 7% of infants in developed nations (1) but can be higher than 40% in low-income nations (2). The growth restricted infants suffer from an increased risk of a wide variety of acute complications, including necrotizing enterocolitis, perinatal asphyxia, hypothermia, hypoglycemia, immunodeficiency and death (3). FGR is commonly attributed to insufficient fetal nutrients. This may be because either the mother is malnourished, as in the prototypical case of the Dutch Hunger Winter (4), or because the placenta is dysfunctional, leading to poor nutrient transport to the fetus (5). Severely growth restricted infants exhibit asymmetric growth wherein resources are reallocated to the fetal brain at the cost of the rest of the body (6), so called 'brain sparing'. The infants undergo 'catch-up growth' for years, although some may remain small for life (7). Unfortunately, this rapid growth often fails to overcome the complications of intrauterine restriction, as a wide variety of morbidities including diabetes (8), polycystic ovary

syndrome (9) or perturbed mental health (10) have been linked to FGR or catch-up growth (11). Together, these support the 'Developmental Origins of Adult Disease' paradigm, wherein adverse factors during critical periods of fetal growth irreversibly impact development (11, 12). To overcome these effects, a clear understanding of the mechanism for each of these sequelae is necessary (13).

Several animal models have been developed for the study of adult diseases originating in the uterus. Most of these involve restricting certain nutritional components, such as protein (14) or oxygen (15) in pregnant dams. However, this does not distinguish between maternal placental effects. The *Igf-2*^{P0} model overcomes this through knock-out of placenta-specific insulin-like growth factor 2. There are four *Igf-2* isoforms which result from the use of different promoters although they ultimately generate the same protein. The P_0 promoter is specific to the placenta. This gene is paternally imprinted, allowing for generation of both wildtype and affected offspring within the same litter. Importantly, all offspring develop in a wildtype dam, preventing maternal variables from affecting development. This targeted knock-out reduces placental growth and therefore the nutrient transport to the fetus, resulting in a brain-sparing phenotype reminiscent of human FGR (16). These mice have been shown to develop anxiety later in life (17), which recapitulates known FGR long-term effects on mental health (18).

While long-term effects are a subject of much interest, most acute FGR complications are simply attributed to a lack of tissue mass and developmental delay: for example, a smaller and less mature kidney (19), pancreas (20) or bowel (21) will simply not function as well. Adaptive immunity is mediated by T-cells which develop in the thymus. However, while the thymus is a short-lived organ which involutes shortly after birth it continues to function well into adult life (22). Deleterious effects on this transient organ could, therefore, have a significant and irreversible impact on immunity in adult life. Initially, infants with FGR have acutely smaller thymi and altered CD4/CD8 ratios of peripheral T cells (23). Later in life, FGR is associated with abnormal responses to vaccines and higher rates of death due to infection (24). For example, indirect evidence comes from a study showing that young adults born in the annual 'hungry season' in rural Gambia – and therefore likely to be born with FGR – have a 10-fold higher risk of premature death, largely due to infection (25).

At a cellular level, broad definitions classify cells based on discrete cell-surface markers. In T-cell development, lymphoid progenitors travel from the bone marrow through the bloodstream to arrive at the thymus where NOTCH signaling directs them towards the T-cell lineage (26). These cells divide and differentiate through four stages of DN (double negative, referring to lack of either CD4 or CD8 T-cell surface markers) whilst undergoing Tcr_{β} rearrangements in the thymic cortex. With the correct set of signals, a minority of the cells become γδ T cells. The rest gain CD8 and then CD4 surface makers (DP, double-positive) at which point Tcr_{α} rearrangements take place. The rearrangements provide the diverse T-cell

receptor repertoire necessary for antigen recognition. The cell is then activated by either MHC Class I or Class II molecules presenting self-antigens. Strong affinity for either MHC Class I or Class II leads to apoptosis to prevent auto-immune disease. Weak affinity to Class I or II leads to differentiation into either CD8+ cytotoxic T cells or CD4+ T helper cells, respectively. Intermediate affinity to Class II molecules leads to differentiation into a T-regulatory cell. Errors anywhere along this pathway of T-cell differentiation, from insufficient *Tcr* rearrangements to underrepresentation of any of the T cell lineages, can lead to impaired immune function (27), (28).

Single-cell RNA sequencing, for example Drop-Seq (29), In-Drop, or the commercial 10X Genomics and Dolomite platforms allow the analysis of the transcriptomes of thousands of single-cells (30). These analyses have been invaluable for identifying immune-cell subtypes within populations traditionally classified by discrete cell surface markers (31) and revealed new regulatory pathways (32).

Here, we used a previously established murine model of FGR in order to assess the effect of an adverse *in utero* environment on neonatal and adult immunity. The *Igf-2*^{P0} (P_0) transcript is imprinted and paternally expressed leading to specific loss of placental *Igf2* and growth restriction in the fetuses carrying a P_0 transcript deletion (16). We then used Drop-Seq to profile the transcriptomes of 7264 cells from neonatal thymi in order to characterize possible immune perturbations at a cellular level.

Results

Placental Insufficiency leads to brain sparing at expense of Thymus

When crossing wildtype (WT) C57BL/6 females with heterozygous mutant *Igf2* P_0 males, both WT and P_0 offspring develop in the WT mother. The P_0 neonates exhibit poor placental and fetal growth. Animals were assessed five days after birth for body and immune organ weights (Fig. 1*A*). Consistent with previous data(16), the overall body weight was reduced while brain weight was only marginally affected. Spleens of FGR P_0 neonates were smaller than WT but this change was proportionate to body weight. However, overall cell number was reduced (Fig. 1*B*). Further investigation using flow cytometry revealed a number of perturbed lineages, where neutrophils and macrophages were the most affected by FGR (Fig. 1*C*). The thymus suffered markedly more growth restriction than the spleen with disproportionately reduced size and a nearly 70% reduction in cells compared to littermate controls. Given the overall severity

in thymocyte reduction, we used Drop-Seq to investigate the effects of FGR at the single-T-cell level. Within the *Igf-2* locus, neither WT nor P_0 thymocytes cells contained reads aligned to the P_0-specific upstream exon U2 (Fig. S1), confirming that placental-specific P_0 was not expressed in T cells. This suggests, therefore, that the observed phenotype was a not result of a direct effect of loss of local *Igf-2* but rather, insufficient placental supply of nutrients. The Igf2 locus contains a number of transcript variants from the placental P_0 through to P_4 (33). We also examined reads mapping to the other isoforms and did not notice any distinct patterns except that in the P_0 mutant there were a number of reads mapping to an untranscribed region upstream of P_1.

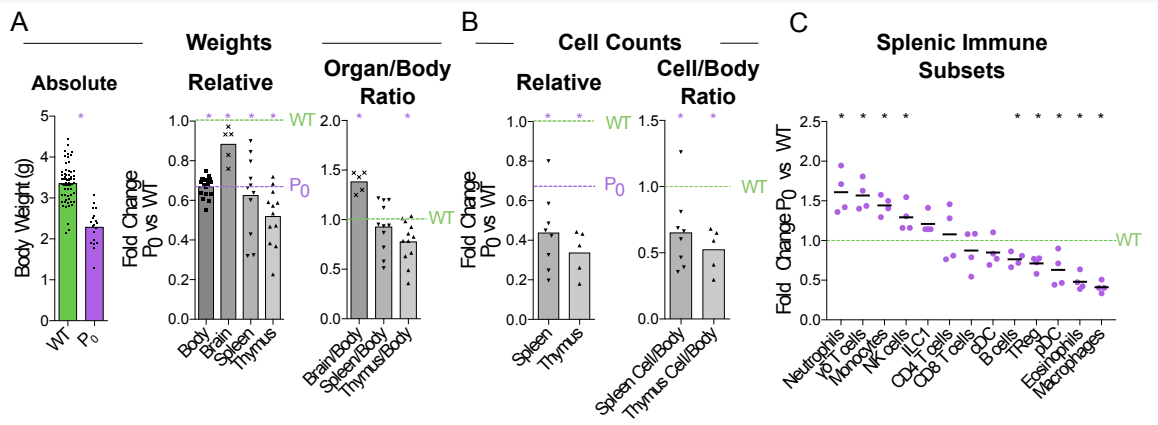

Figure 1: FGR leads to Brain-Sparing at the Expense of Thymus. WT dams were mated with P_0 males to produce P_0 and WT offspring. The number of WT and P_0 animals or organs analyzed for each measurement is given in parentheses. (*A*) Neonates were analyzed five days after birth for absolute body weight (n = 61, 19). Relative body and organ weights from P_0 neonates were compared with littermate controls. Purple dashed line was defined by the average P_0 body weight, to allow relative comparison of organ weights to both P_0 and WT. (Relative Body Weight n = 41, 18; Brain n = 7, 5; Spleen n = 32, 11; Thymus n = 28, 12). Organ/Body ratios were compared between P_0 and WT littermates. (*B*) Absolute cell counts within the spleen and thymus were compared with littermate controls (Spleen Cells n = 16, 8; Thymus Cells n = 7, 5). Cell counts as a ratio to mouse weights were compared with littermate controls. (*C*) Spleen cells were analyzed using flow cytometry and the proportions of the indicated immune cell populations were compared with littermate controls (Spleen Flow Cytometry n = 10, 5, with 1 outlier removed using the ROUT method). Datasets were tested for normality using the Shapiro-Wilk normality test. Normally distributed data were compared using unpaired two-tailed t-tests while nonparametric data were compared using Mann-Whitney Rank comparison tests. For all tests, * indicates $P < 0.05$.

Drop-Seq Identifies Developing Thymocytes

To investigate the effect of FGR on T-cell development, we performed Drop-Seq analysis of 4,679 WT and 2,585 P_0 thymic cells (n = 4 and 3 animals respectively) with an average read

depth of 32,399 reads/cell resulting in an average of 994 transcripts per cell (sequencing statistics are in Table S1). The transcript signatures of each WT cell were used to identify clusters and the genes driving that clustering. We regressed out cell cycle regulator genes from analysis as otherwise they drove some of the clustering (Fig. S2). Using the resultant list of cluster determinants, we mapped both WT and P_0 cells into 8 clusters of 7,264 single cells (Fig. *2A*). Initially, we used known differentiation markers to define these clusters (Fig. 2*B* & *C*). We identified the known T-cell maturation pathway, beginning with cells containing high levels of *Il2ra* (Double Negative, DN) through to *Cd4/8* containing cells (Double Positive, DP) and ending with high levels of *Ccr7* and *Itm2a* (T_{Mature}). In this map dominated by DP cells, we were unfortunately not able to distinguish CD4 and CD8 single positive mature T cells. Bias in identifying clusters was checked using various degrees of resolution, from 0 (identifying only 1 cluster) to 1 (identifying 11) (Fig. 2*D* and Fig. S3). This shows distinct DN1 separation even at the lowest resolution but heterogeneous DP subclustering. Regardless of resolution, cells clustered into distinct T-cell populations based upon differentiation status (Fig. 2*E*). Of note, we found that the DP cells were highly heterogeneous and could be divided into multiple clusters, suggesting that the traditional definition using two markers is insufficient to fully characterize these cells. Cells in Cluster 7 were identified as contaminating red blood cells due to high hemoglobin mRNA levels, while Cluster 8 contained macrophages, identified by abundant *Aif1*, *Lyz2*, Complement and H2 complex transcripts. As both of these clusters contained fewer than 100 cells, we focused our attention on the larger T-cell clusters.

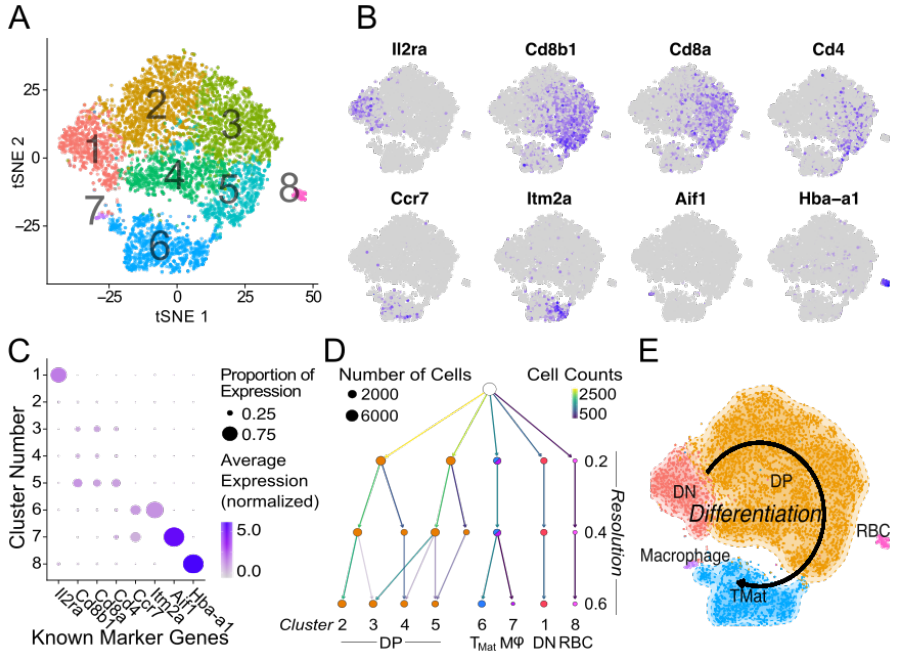

Figure 2: Single Thymic Cell Transcriptomics reveal T-Cell Differentiation Pathway. (*A*) Drop-Seq of 7,264 single-cells from WT and P_0 thymi were mapped using non-linear dimensional reduction (t-Distributed Stochastic Neighbor Embedding (tSNE)) using WT signatures derived from linear dimensionality reduction (Principal Component Analysis, PCA), excluding known cell cycle genes. Cells separated into eight clusters, denoted by color and number. Known marker genes were used to identify each cluster. (*B*) Marker transcript levels across cells. Purple indicates detected transcripts. (*C*) Marker transcript levels within each cluster. Average Expression Normalized refers to the amount of transcripts discovered while Percentage Expression denotes the proportion of cells within a given cluster containing the transcript. (*D*) Consistency of sub clustering was assessed at three levels of resolution. (*E*) Overall, these markers yielded a differentiation map from DN in Cluster 1 through to mature T cells in Cluster 6. RBC: Red blood cell.

Drop-Seq identifies Transcript Signatures in T-Cell Maturation

To further characterize these cell clusters, we identified the top marker genes in each cluster by performing a differential analysis of each cluster compared to all remaining cells in an unsupervised manner (average fold change ≥5, adjusted P value <0.01; TableS1). These genes included both known T cell specific markers such as Cd8 and Ccr9 and cytoskeletal components (Fig.3A). Despite preventing cell cycle genes from driving the clustering, a number of cell cycle regulators were found to differ between mapped clusters, demonstrating a clear connection between cellular phenotype and its cycling activity. Cluster 1, containing the DN cells, was characterized by early T-cell markers *Il2ra* and *Hes1*. *Tcrγ-C1* and *C2* were also found within these cells, likely because only DN cells contain precursor Tγδ cells. Cluster

2, the early DP cluster, contained T-cell genes G*ranzyme A* and *Ctage5*, as well as *Ranbp1*, *Nolc1*, and *Hspd1*, which are associated with nuclear pore transport, rRNA processing and protein folding, respectively. *Plac8* was also found, which was previously implicated in T-cell development (34) but here specifically found within DN cells. Clusters 3 to 5, which we have identified as increasingly mature DP cells, contained high levels of *Tarpp* (also known as *Arpp21*), *Rag1* and *Rag2*, whose proteins are present during TCR rearrangements. During T-cell positive selection, *Tarpp* levels are reduced(35), which is shown here as the T_{Mat} cluster contains few Tarpp transcripts. These cells also showed increasing levels of *Ccr9*, the CCL25 receptor expressed on late DN and DP T cells. These known T-cell markers were found alongside *Btg2*, a cell cycle inhibitor, and *Rmnd5a*, which is necessary for mitotic division. Clusters 2 & 3 both contained *Rrm2*, *Tyms*, and *Esco2*, which synthesize nucleotides and bind sister chromatids, respectively, and are required for S phase of the cell cycle. The variations of Clusters 2 through 5 then are likely in part due to progressive rounds of proliferation as the T cells mature.

The mature lymphocyte markers *Itm2a* and *Cd52* are specific to Cluster 6, alongside a number of cytoskeletal (*Cd2*, *Tmsb4x*, and *Tmsb10*). Negative growth regulators *Slfn2*, *Gimap4*, *Ms4a4b*, and *Shisa5* are also present in high levels in the T_{Mat} cluster, likely involved with positive and/or negative selection. Interestingly, the DN Cluster 1, DP Cluster 4, and T_{Mat} Cluster 6 contained heterogeneous mixtures of cells with high and low levels of transcripts coding for ribosomal proteins.

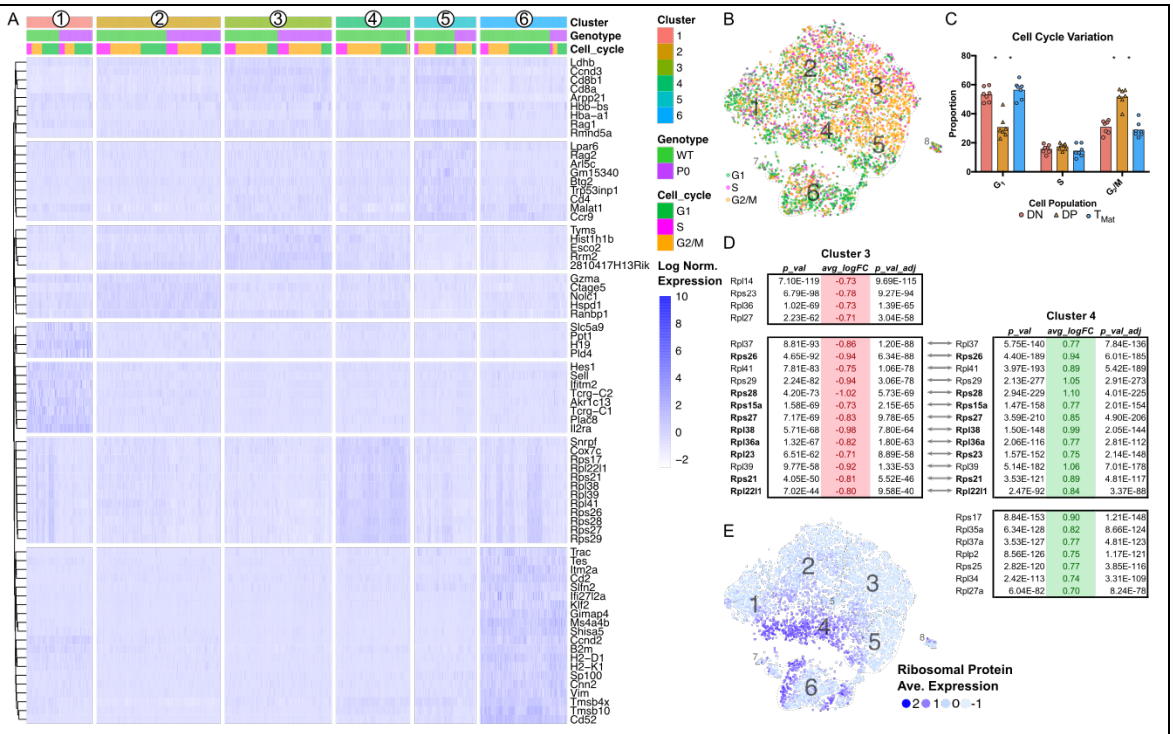

Figure 3: Unsupervised Clustering Driven by T-Cell, Cell Cycling, and Ribosomal Genes. (*A*) Transcript levels of each cluster were compared with the remaining overall cell population. The top 20 genes with an absolute fold change above 5 and an adjusted p value < 0.01 for each cluster were visualized in a heat map and ordered by genotype (WT vs P_0) followed by cell cycle score (G1, G2/M, or S). The top 20 genes for each of the six clusters results 120 genes, reduced to 72 unique entries. Each column represents one cell. Signal intensities are shown on a $\log_2$ scale. The complete gene lists are provided in Data Table S1. (*B*) Individual cells were scored for their cell cycle genes (G_1, S and G_2/M, as described in Methods). (*C*) The proportions of these cells within each cell population were compared using student t-tests (DN, Cluster 1; DP, Clusters 2-5; T_{Mat}, Cluster 6). (* indicates $P < 0.05$; n = 7). (*D*) Significant changes ($p < 0.01$; $\log_{10}$ Fold Change > 0.7) in ribosomal protein transcripts within Cluster 3 and Cluster 4 were compared. Ribosomal genes in **bold** code for proteins found on the surface of the ribosome. (*E*) Ribosomal protein transcript levels are displayed across cells using average expression values for the 13 genes identified by comparing Clusters 3 and 4.

Cell Cycling and Ribosomal Protein Structures Drive Thymocyte Maturation

We further investigated the trends in cell cycle and ribosomal protein genes. Despite preventing known cell cycle genes from determining the cluster map, cell cycle genes were still found significantly different across the clusters (See *SI Appendix* Fig. S2 for cluster mapping with and without cell cycle regression). We scored each cell for its G_1, S, or G_2/M

phase transcript signature (Fig. 3*B*) and compared cycling between cell types (Fig. 3*C*). DN and T_{Mat} stages had lower levels of proliferation than the DP stage.

A differential transcript analysis for each cluster against all others revealed that within the DP stage, ribosomal protein transcripts were varied, most notably between Clusters 3 and 4. We made the same observation of a differential ribosomal protein transcript population in the unsupervised clustering in Figure 3. The ribosomal protein mRNAs that significantly changed in Cluster 3 were compared against those found in Cluster 4 (Fig. 3*D*). In each case, cells in Cluster 3 were notable for low ribosomal protein transcript abundance while in Cluster 4 such transcripts were increased. The majority of the transcripts (9 out of 13, 69%) found by this comparison between clusters coded for proteins that contributed to the ribosome surface, which would make them more likely to play a functional or regulatory role. The protein subunits of a ribosome are known to play a key role in directing translation of specific mRNA pools (36). Looking at the overall cluster mapping, we found that the ribosomal transcripts appeared in waves dominating Cluster 4 and dividing Cluster 6 (Fig. 3*E*).

FGR prevents Thymocyte Maturation

Having identified each cluster and compared the top gene signatures, we then compared the WT and P_0 thymocytes within each cluster (Fig. *4A*). Even after accounting for the higher number of WT cells present, we still found a higher proportion of DN cells in the P_0 thymus than WT (Fig. 4*B* & *C*). The opposite held true with the late stage T_{Mat} cluster, as there were proportionally more T_{Mat} cells in the WT thymus than the P_0. Overall, there was a general skew of P_0 cells towards earlier, more immature clusters in the DP pathway, while the WT thymus favored the later stage clusters. Using flow cytometry for surface markers, we detected discrete increases in DN cells at the expense of mature CD4+ cells in the P_0 (Fig. *4D*). Within the smaller DN cell population, there were proportionally more DN3 cells in the P_0 over the WT, which is noteworthy given that rearrangement of V and D chains as well as β selection occur at this stage in T-cell differentiation.

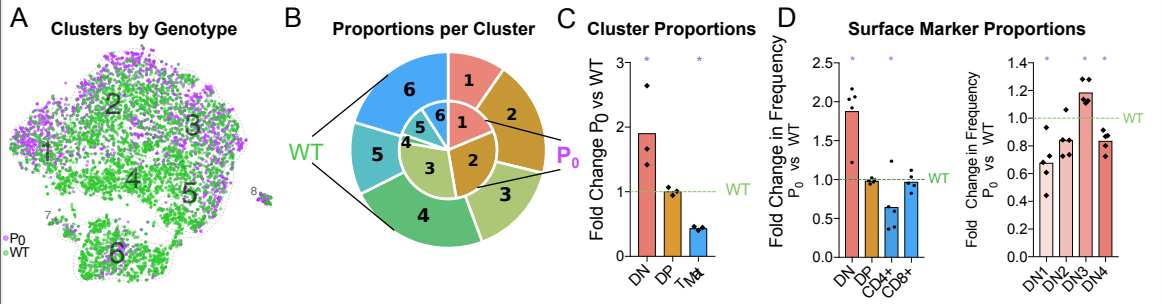

Figure 4: FGR Leads to T-Cell Differentiation Delay. (*A*) Single-cell map colored by genotype with previous cluster numbering. Red: P_0, 2,585 cells, n = 3. Teal: WT, 4,679 cells, (n = 4). (*B*) Visual representation of the proportions of cells in each genotype per cluster, averaged from each trial and labelled for each cluster. Clusters are labelled by number, from the DN T-cell stage in Cluster 1 to T_{Mat} in Cluster 7. P_0 is in the inner circle, while WT is in the outer circle. (*C*) Proportions of cells within each cell population as determined by Drop-Seq were compared to WT levels. (*D*) Cells were classified by their surface markers using flow cytometry as DN, DP, CD4+ or CD8+ cells and proportions were compared with littermate controls (n = 9, 5). (*E*) Within the DN population, cells were classified from DN1 to DN4 based on their CD25 and CD44 status. These proportions were then compared with littermate controls. Comparisons were calculated using Student's t test with the exception of the Cluster 5 (*C*), DN and DN3 (*D*) subsets, which failed to pass the Shapiro-Wilk test for normality and were instead analyzed using Mann-Whitney Rank comparison tests (* indicates $P < 0.05$).

Immune Defect Lasts into Adulthood

Thymus size is correlated with thymus function (37). Humans with DiGeorge syndrome have little or no thymus, resulting in a significant immunodeficiency (38, 39). We wondered whether the maturation delay in the thymus of the 6-day old neonate would affect the immune cell population in the adult. Infants with FGR exhibit increased growth and 'catch up' relative to their unrestricted counterparts (40). Adult male mice displayed signs of catch-up growth, although they were still found to be significantly lighter than their littermate controls (Fig. 5*A*). However, the spleen and thymus weights were not different from littermate controls. Despite this, the cellularity of the thymus was still significantly reduced (58% $\pm$ 19%, P = 0.019, Figure 5*B*). However, as both DN and CD4+ lineages recovered to WT proportions the long-term effects of poor placentation on cell distributions in the adult thymus are less clear (Fig. 5*C*). While we did not evaluate the repertoire diversity or clonality, we did observe that DN subtypes were statistically distinct from WT (Fig. 5*D*).

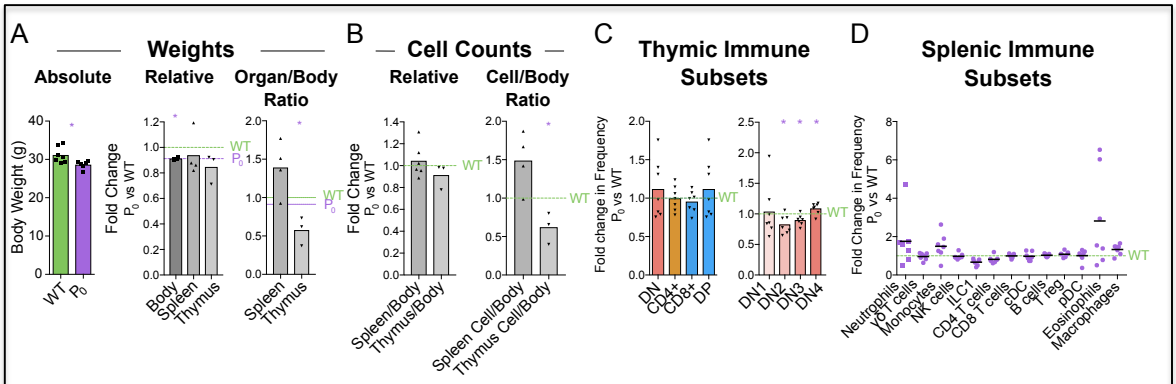

Figure 5: Immune defect persists into adulthood. (*A*) Absolute weights of 8 week male P_0 and WT were compared (n = 7, 6). Body (n = 7, 4), spleen (n = 7, 4), and thymus (n = 5, 3) weights were compared with littermate controls. Spleen/body and thymus/body weight ratios were also compared relative to littermate controls to account for lower overall body weight in the P_0 mice. (*B*) Total cells within the spleen (*n* = 4, 4) and thymus (n = 5, 3) were compared directly with littermate controls as well as relative to overall mouse weight. (*C*) Surface markers were used to classify T cells within the thymus and the proportions were compared to littermate controls (n = 8, 7). (*D*) Splenic immune subset proportions were determined from flow cytometry and compared with littermate controls (n = 5, 7). Datasets were tested for normality using the Shapiro-Wilk normality test. Normal data were compared using unpaired two-tailed t-tests while nonparametric data were compared using Mann-Whitney Rank comparison tests. For all tests, * indicates $P < 0.05$.

Discussion

We present the first single-cell analysis of the neonatal thymus, in the context of a disease model for FGR. Recently, interest in fetal immunity has led to the generation of a cell atlas for the developing thymus (41). Here, we add to this atlas with an insight into thymic development after birth. We found a number of genes in common with these early developmental snapshots, such as *H19* and *Plac8,* but were further able to resolve multiple developing T-cell populations due to the seemingly increased thymic activity after birth.

The “fetal programming of adult disease” theory has largely been associated with noncommunicable diseases such as obesity or heart disease. Within this wider context, we present the first genetic model suggesting that an adverse *in utero* environment perturbs immune cell development. This may lead to poor immune function later in life and consequently a higher risk of communicable diseases.

Our study has identified a novel sequela of FGR in the mouse: a deficit in T cells, resulting from a maturation delay found in the growth restricted neonate. At the cellular level, there were more DN cells and a skew towards early DP cells. The high heterogeneity of DP cells found here suggests that current definitions of DP are not specific enough given the large proportion of the thymic T cells in this category. Of particular note is the high number of

ribosomal protein transcripts driving clustering within this group. Ribosome biogenesis has recently been shown to play a key role in stem cell differentiation (42) and translation of specific pools of mRNAs depends on the ribosomal protein composition (36). This is particularly noticeable with defects in specific ribosomal protein genes, which can lead to discrete effects such as an erythropoiesis block in hematopoietic stem cells (43) or a loss of body hair (44), as opposed to an expected generalized protein deficit. Clusters 1, 4 & 6 - comprised of DN, late DP and maturing T cells - seem to subcluster based on ribosomal protein transcript levels. The ribosomal proteins encoded by these transcripts, located largely on the outside of the ribosome, are missing in the P_0 mice. It is interesting to speculate that within this T-cell differentiation pathway, ribosome biogenesis, and hence function, plays a role in directing maturation.

The clusters were defined by transcript signatures after excluding cell cycle regulators. Nevertheless, distinct cell cycle signatures were present within the clusters, confirming that proliferation and T-cell maturation are inexorably linked, which is consistent with a similar finding in specifically CD4+ T-cell differentiation (45).

How this early phenotype leads to low thymic cellularity in the adult remains unclear. Infants with FGR typically undergo 'catch-up growth' to reach normal or near normal weight. T-cell maturation, however, is linked at a molecular level to cell cycling because RAG2 is degraded during G2, S, and M phases (46). Perhaps thymic 'catch-up growth' and T cell diversification and maturation are incompatible because proliferation inhibits T-cell maturation. It is also possible that catch-up growth cannot occur because the thymus is programmed to involute after birth, rather than expand. In either case, growth restriction early in life would be irreversible: the number of T-cell clones generated in the neonatal thymus restricts the number of T-cell clones present in the adult.

In both mice and humans, thymus output declines with age, with the memory T cells dominating the peripheral pool in old age (47). The diversity and clonality of naive T cell also change with age (48). Immune function declines with age and there is an increased risk of infection and malignancy late in life (37). Genetically manipulated mice with enlarged thymi have increased thymic activity and enhanced recovery from γ irradiation (49). In contrast, patients with DiGeorge syndromes where the thymus is small display immune vulnerability early in life (38, 39). Thus, a thymic deficit early in life could have dramatic effects on adult immunity which would only become exacerbated by normal thymic involution.

Overall, we have identified key immune phenotypes caused by placental insufficiency. Future studies will ultimately determine the role of FGR in both neonatal and adult immunity. Nevertheless, we have shown a distinct and negative impact of FGR on immune cells in the mouse.

Methods

Detailed methods can be found in the *Supplemental Information,* which describes mouse lines, flow cytometry, statistical analysis, Drop-Seq, sequencing output, and bioinformatic analysis. Raw sequencing data have been deposited in the ArrayExpress database at EMBL-EBI under accession number E-MTAB-6945. https://www.ebi.ac.uk/arrayexpress/experiments/E-MTAB-6945. Code and data tables can be found here: https://github.com/CTR-BFX/2018_Bacon_Charnock-Jones.

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Footnotes

Author contributions: F.C., J.K., D.S.C-J. and W.B. designed the experiments. W.A.B., J.K., D.H. and A.M.K. performed the research. R.S.H. and W.A.B. analyzed the data. R.S.H. contributed novel bioinformatic tools. Z.Y. and C.A. contributed microfluidic equipment and expertise. W.A.B., R.S.H. and D.S.C-J. wrote the paper.

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Supplementary Information for

Single-Cell Analysis Identifies Thymic Maturation Delay in Growth-Restricted Neonatal Mice

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Supplementary Information Text

Methods

Mouse Tissue Preparation. Mice were maintained at Central Biomedical Services in accordance with the UK Home Office, Animals (Scientific Procedures) Act 1986 which mandates ethical review. C57BL/6 dams were mated with Igf-2^{P0} heterozygous males. Mice were genotyped as previously described (1). For neonatal analysis, mice were weighed five days after birth prior to organ collection. For adult mice, body and organ weights were assessed at 8 weeks of age. Spleens were digested with collagenase D (11088866001, Sigma, Gillingham, UK) at 1mg/mL in HBSS (24020091, ThermoFisher, Paisley, UK) for 30 minutes at 37°C and washed with PBS (D8537, Sigma). Single cell thymic suspensions were prepared by maceration of the thymi through a 40 µm strainer. Red blood cell lysis was performed with PharmLyse (555899, BD Biosciences, Wokingham, UK) for 3 minutes at RT for both spleens and thymi. Resultant suspensions were passed through a 40 µm strainer and live cells counted using trypan blue (T8154-20ML, Sigma).

Flow Cytometry. Isolated cells were incubated with antibodies listed in Table S2 on ice for 30 min in PBS prior to washing. Cell types were identified as in Table S3. Samples were processed on a BD LSR Fortessa and the data was analyzed using FlowJo 10.

Statistical Analysis. For fold change calculations, Igf-2^{P0} mice were compared to litter mate controls with each metric being divided by the mean value obtained from WT litter mates. Outliers were identified within each data-set using the ROUT method in GraphPad Prism where Q = 1. This identified only one outlier (Splenic immune subsets, Figure 1, P_0) which was subsequently removed. Datasets were tested for normality using the Shapiro-Wilk normality test. Normally distributed data were compared using unpaired two-tailed Student's t-test while nonparametric data were compared using the Mann-Whitney Rank comparison test. Cell cycle data was analyzed using a two-way ANOVA with Tukey's multiple comparisons test.

Drop-Seq. Thymi were dissected from postnatal day (PND) 6 neonates and homogenized in PBS before passing through a 40 µm filter. Cells were counted and diluted to 200,000 cells / mL in PBS/0.1% BSA (A7906-100G, Sigma) for processing according to Drop-Seq protocol (2). Single cells were encapsulated in droplets with primer barcoded beads (MACOSKO-2011-10, ChemGenes, Wilmington USA). After RNA binding to the oligo-dT portion of the primer, the droplets were broken to pool beads for reverse transcription (EP0743, ThermoFisher). Exonuclease (EN0581, ThermoFisher) treatment removed unused primers from the beads prior to PCR amplification at up to 8,000 beads / tube (~400 cells/tube). Samples were pooled with up to 4,000 cells / sample and the DNA purified before determining concentration. DNA was fragmented and tagged with Illumina adapter and index sequences using Nextera Sequencing kit (FC-131-109, Illumina, Little Chesterford UK) and 600 pg DNA/sample. Samples were diluted 1:1 in ddH_20 water before double-sided purification with Agencourt Ampure beads (A63881, Beckman Coulter, High Wycombe, UK), using 0.6x beads to remove large fragments and 1x beads twice to remove contaminating primers. Samples were analyzed for size distribution using an Agilent HS DNA kit (5067-4626, Agilent, Stockport UK) and concentration and sequenced on an Illumina HiSeq4000 with an Index read of 8bp, Read 1 of 25 bp and Read 2 of 100 bp.

Bioinformatic Analysis. All custom code is freely available https://github.com/darogan/2018_Bacon_Charnock-Jones. Raw Fastq files are

demultiplexed (dropseq_demultiplex.sh) using the Nextera indices and then converted to uBAM using PicardTools:FastqToSam (v2.9.0). Quality control, alignment (STAR v020201) gene quantification and final matrix generation were performed using DropSeqTools (v1.12, http://mccarrolllab.com/dropseq). Alignments were performed against the mouse reference genome (mm10 available from http://mccarrolllab.com/dropseq/). Initial thresholds of a minimum 200 genes per cell and genes must be present in at least 3 cells were applied. The resulting digital expression matrix (DEM) was imported into Seurat (3) (v2.3.0) for downstream analysis and is split into two scripts. The first, dropseq_seurat_splitDEMs.R, performs the more computationally intensive tasks intended to be run on high performance computers, the Seurat object is saved in Robj format to be imported in to second script, dropseq_seurat_splitDEMs_Plots.R, for differential transcript analysis and figure creation.

Two separate DEMs were calculated for the WT and WT+P0 samples. The WT only samples were used to calculate variable genes (FindVariableGenes), which were then used as input to generate the PCA (RunPCA), find clusters (FindClusters) and produce a tSNE (t-distributed stochastic neighbor embedding) visualization (RunTSNE) from the combined WT and P0 sample DEM. FindClusters is run across multiple resolutions (0.2, 0.4, 0.6 0.8 and 1.0), each stored on the Seurat Object. Normalization (NormalizeData), UMI and MT regression (FilterCells) were performed using Seurat including a more stringent threshold of a minimum 300 genes per cell and genes must be present in at least 3 cells was applied. Cell cycle assignments were performed using SCRAN (4) (v1.6.9) on the combined WT+P0 DEM, using an intermediate SingleCellExperiment (v1.0.0) data structure, and then added back to the Seurat Object. Cell cycle genes were regressed out using a subtraction of G2M from S cell cycle scores per cell. The resulting Seurat data object is saved as an RObj for input into the plotting and differential analysis part of the pipeline.

The RObj generated from first dropseq_seurat_splitDEMs.R script are imported into dropseq_seurat_splitDEMs_Plots.R to extract (e.g. with GetCellEmbeddings) the required data for each of the plots in the figures. Custom tSNE plots were generated using ggplot2. Transcript abundance dotplots were generated from AverageExpression extracted from the Seurat object and ggplot2. Cluster trees were generated using clustree (5). Differential transcript analysis was performed by comparing each cluster in turn to all others (FindAllMarkers) and using a log fold change threshold of > 0.7 and adjusted p value < 0.01. The heatmap (pHeatmap), used the same thresholds, and the top 20 genes for each cluster selected.

A custom tool was created to classify whether ribosomal proteins are localized on the surface or are internal to the ribosome structure (https://github.com/darogan/Ribosomal-Protein)

Supplementary Figure S1

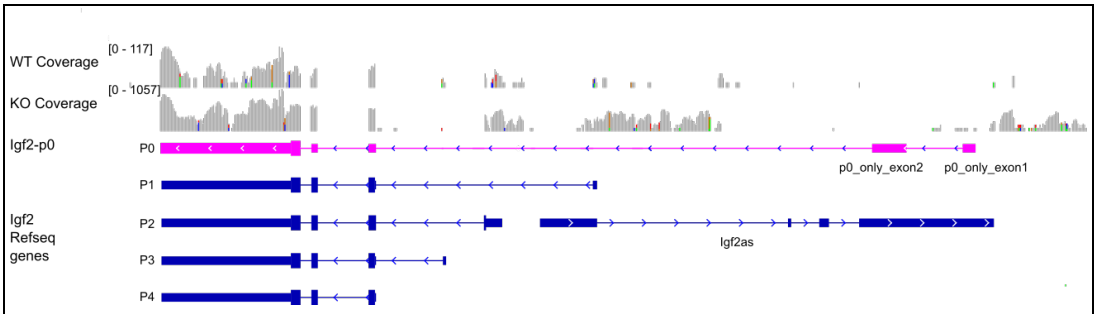

Fig. S1. P_0 *Igf-2* transcript not found in thymus. Total reads from both WT and P0 single-cell transcript sequencing were visualized within the *Igf-2* locus. Transcript isoforms from P0 to P4 are shown. All isoforms yield the same translated product.

Supplementary Figure S2

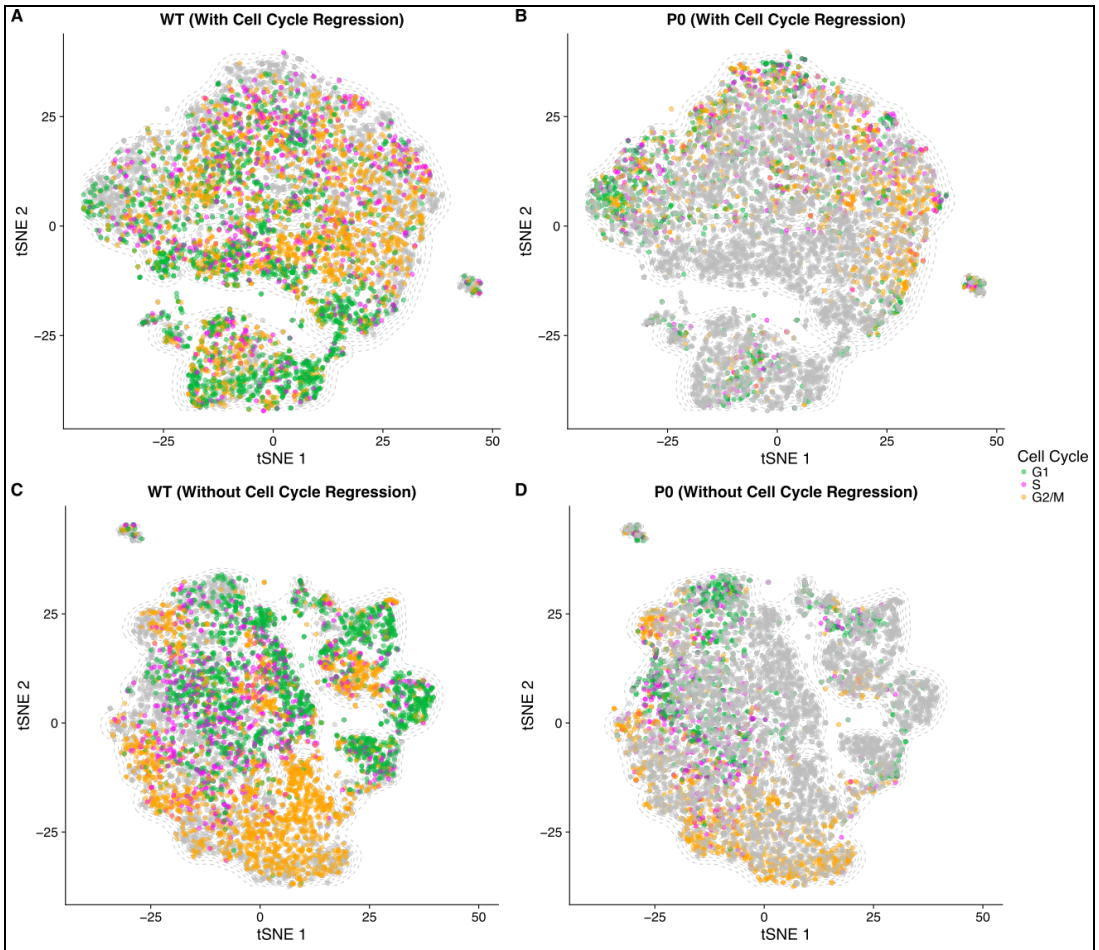

Fig. S2. Effect of Cell Cycle Regression on Cluster Mapping. Cells were clustered before and after regressing cell cycle determinants. (*A*) WT and (*B*) P0 cells with cell cycle regression, as compared with (*C*) WT and (*D*) P0 cells mapped without cell cycle regression. Cells are colored by genotype (grey if the opposing genotype) and cell cycle phase (G1: Green, S: Pink; G2/M: Orange).

Supplementary Figure S3

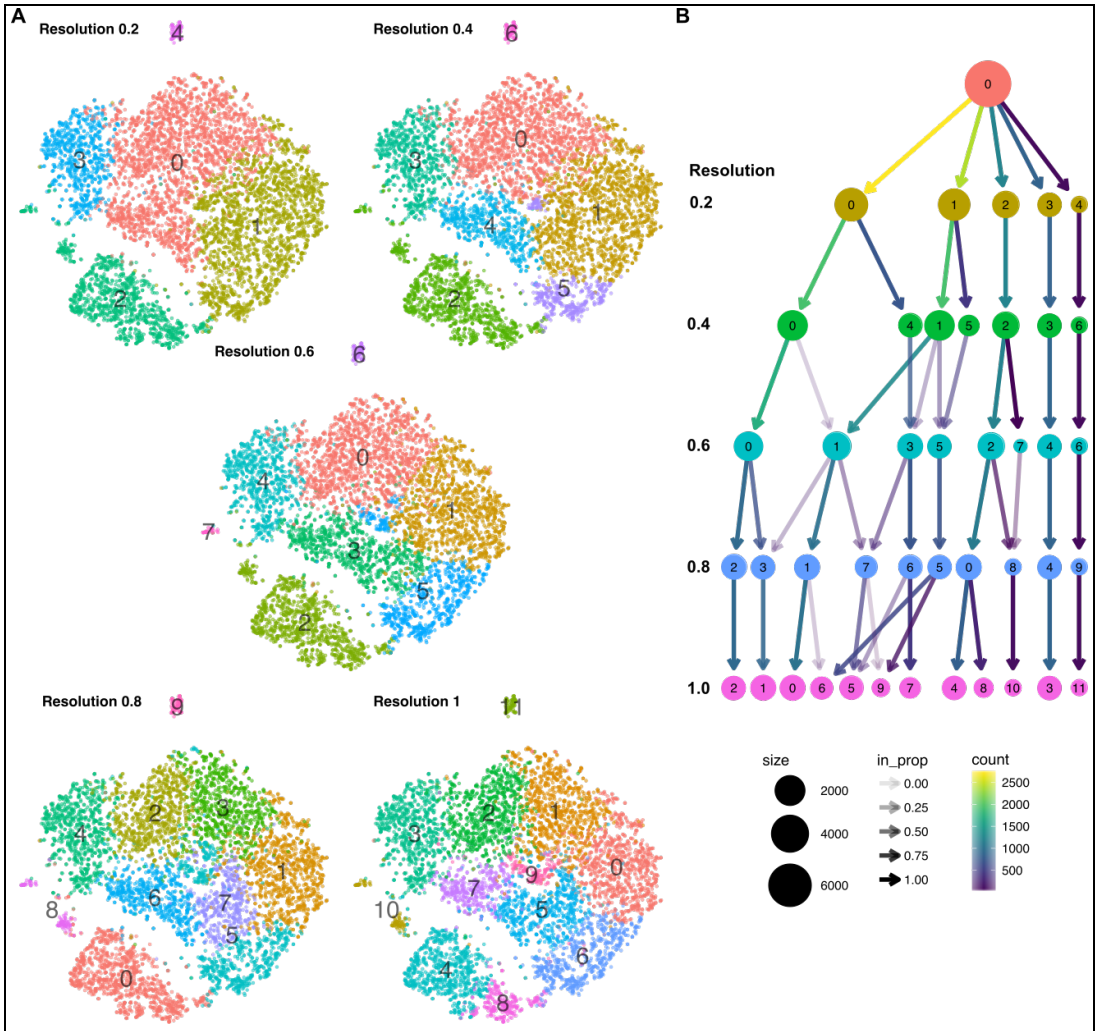

Fig. S3. Resolution Effects on Cluster Calling. (*A*) In relation to Figure 2, an increase in resolution of cluster calling leads to increased numbers of clusters. (*B)* The cluster tree diagram shows how consistently clusters are called, for instance the clusters at the right (first row, numbers 3 & 4) are unique clusters no matter what resolution is used. At higher resolutions clusters divide and cells from one or more of the lower resolution clusters contribute.

Table S1. Sequencing and processing statistics for single-cell sequencing.

Pre-processing and alignment using DropSeqTools and ctr-dropseq-tools (200 genes per cell, 3 cells per gene min)

Alignment Rates

IDX	Geno -type	Total Reads	Unique (#)	Unique (%)	Multi (#)	Multi (%)	Many (#)	Many (%)	Un-mapped (#)	Un-mapped (%)
N701	WT	32468733	26055586	80.2	3351483	10.3	346732	1.1	2714932	8.4
N702	P0	20962102	16847146	80.4	1817857	8.7	214847	1	2082252	9.9
N703	P0	11749198	9081883	77.3	1357304	11.6	121328	1	1188683	10.1
N704	WT	32297193	25720288	79.6	3029288	9.4	274716	0.9	3272901	10.1
N705	WT	77791423	56701446	72.9	11964824	15.4	672228	0.9	8452925	10.9
N706	WT	26006979	18412761	70.8	4057400	15.6	399552	1.5	3137266	12.1
N707	P0	26807105	18534932	69.1	5136585	19.2	235983	0.9	2899605	10.8

UMI Stats

IDX	Genotype	Ave UMI / Cell	Ave # Genes	Ave UMI	Ave UMI (uniq)	Ave Dup Rate
N701	WT	952.04	659.55	3699.07	952.04	3.89
N702	P0	881.86	636.59	2451.86	881.86	2.78
N703	P0	561.98	439.75	1561.27	561.98	2.78
N704	WT	595.79	450.01	2561.21	595.79	4.3
N705	WT	1826.7	1038.41	9550.17	1826.7	5.23
N706	WT	710.91	474.05	2674.37	710.91	3.76
N707	P0	597.74	459.67	2015.11	597.74	3.37

Seurat Processing (300 genes per cell, UMI/MT/CC regression)

Genes & UMI

	Mean Num Genes Per Cell	Mean Num UMIs Per Cell
WT	706.4	1,089.0
P0	600.2	820.1
All	668.6	993.5

Number of Reads Per Cell

	Mean Number of Reads Per Cell
WT	4,693.6
P0	2,384.2
All	3,871.8

	WT				P0		
	N701	N704	N705	N706	N702	N703	N707
WT	3708.6	3496.3	9241.9	4011.2	-	-	-
P0	-	-	-	-	2512.0	2068.6	2460.8

Number of Cells

	Number of Cells
WT	4,679
P0	2,585
All	7,264

	WT				P0		
	N701	N704	N705	N706	N702	N703	N707
WT	1220	1341	813	1305	-	-	-
P0	-	-	-	-	1300	675	610

Cluster Cell Numbers

Cluster	WT	P0
0	964	745
1	730	743
2	961	231
3	974	48
4	448	456
5	554	293
6	28	57
7	20	12

Cluster	WT				P0		
	N701	N704	N705	N706	N702	N703	N707
0	382	526	25	31	414	200	131
1	276	320	100	34	353	204	186
2	292	215	130	324	121	55	55
3	8	29	373	564	1	1	46
4	106	148	72	122	205	169	82
5	142	100	94	218	194	36	63
6	6	1	15	6	5	8	44
7	8	2	4	6	7	2	3

Table S2. Antibodies Used in Flow Cytometry.

Marker	Clone	Company
CD11b	M1/70	BD Biosciences
CD11c	N418	BioLegend
CD19	1D3	BD Biosciences
CD25	PC61	BioLegend
CD3	17A2,	BioLegend
CD4	RM4-5	eBioscience
CD44	IM7,	BioLegend
CD8a	53-6.7	eBioscience
Eomes	Dan11mag	eBioscience
F4/80	BM8	eBioscience
FOX3Pm	NRRF-30	eBioscience
Gr1	RB6-8C5	BioLegend
LyC6	AL-21	BD Pharmingen
Ly6g	1A8	BioLegend
MHC-II	M5/114.15.2	BioLegend
mPDCA	eBio129c	eBioscience
NK1.1	PK-136	BioLegend
NKp46	29A1.4	BioLegend
SiglecF	E50-2440	BD Bioscience
TCR_{β}	H57-597	eBioscience
TCR_{δ}	GL3	BioLegend
TER-119	TER-119	eBioscience

Table S3. Cell marker combinations used to identify splenic and thymic subsets as shown in Figures 1, 4, and 5.

Cell Type	Identification
B cells	CD3$^-$ TER119$^-$ CD19$^+$
ILC1	CD3$^-$ TER119$^-$ CD19$^-$ NK1.1$^+$ NKp46$^+$ EOMES$^-$
NK Cells	CD3$^-$ TER119$^-$ CD19$^-$ NK1.1$^+$ NKp46$^+$ EOMES$^+$
Conventional Dendritic Cell	CD3$^-$ TER119$^-$ CD19$^-$ NK1.1$^-$ MHC$^-$II high CD11c high
Eosinophils	CD3$^-$ TER119$^-$ CD19$^-$ NK1.1$^-$SiglecF$^+$ SSC high
Monocytes	CD3$^-$ TER119$^-$ CD19$^-$ NK1.1$^-$ Ly6G$^-$ CD11b$^+$ Ly6c$^+$
Neutrophils	CD3$^-$ TER119$^-$ CD19$^-$ NK1.1$^-$ Ly6G$^+$
Plasmacytoid Dendritic Cell	CD3$^-$ TER119$^-$ CD19$^-$ NK1.1$^-$ mPDCA$^+$ Ly6c$^+$
Macrophages	F4/80$^+$
T$^-$Cell Subtypes	
Regulatory	CD19$^-$ TER119$^-$ CD3$^+$ TCRd$^-$ TCRβ$^+$ CD4$^+$ FoxP3$^+$
δγ	CD19$^-$ TER119$^-$ CD3$^+$ TCRδ $^+$
αβ	CD19$^-$ TER119$^-$ CD3$^+$ TCRδ$^-$ TCRβ$^+$
SP CD4$^+$	CD11b$^-$ NK1.1$^-$ CD19$^-$ TER119$^-$ CD11c$^-$ Gr1$^-$ TCRδ $^-$ CD4$^+$ CD8$^-$
SP CD8$^+$	CD11b$^-$ NK1.1$^-$ CD19$^-$ TER119$^-$ CD11c$^-$ Gr1$^-$ TCRδ$^-$ CD4$^-$ CD8$^+$
DN	CD11b$^-$ NK1.1$^-$ CD19$^-$ TER119$^-$ CD11c$^-$ Gr1$^-$ TCRδ$^-$ CD3low/negative CD4$^-$ CD8$^-$
DP	CD11b$^-$ NK1.1$^-$ CD19$^-$ TER119$^-$ CD11c$^-$ Gr1$^-$ TCRδ$^-$ CD4$^+$ CD8$^+$
DN1	CD11b$^-$ NK1.1$^-$ CD19$^-$ TER119$^-$ CD11c$^-$ Gr1$^-$ TCRδ$^-$ CD3low/negative CD4$^-$ CD8$^-$CD25low CD44high
DN2	CD11b$^-$ NK1.1$^-$ CD19$^-$ TER119$^-$ CD11c$^-$ Gr1$^-$ TCRδ$^-$ CD3low/negative CD4$^-$ CD8$^-$CD25high CD44high
DN3	CD11b$^-$ NK1.1$^-$ CD19$^-$ TER119$^-$ CD11c$^-$ Gr1$^-$ TCRδ$^-$ CD3low/negative CD4$^-$ CD8$^-$CD25high CD44low
DN4	CD11b$^-$ NK1.1$^-$ CD19$^-$ TER119$^-$ CD11c$^-$ Gr1$^-$ TCRδ$^-$ CD3low/negative CD4$^-$ CD8$^-$ CD25low CD44low

Additional data table S1 (separate file)

Top 20 transcripts distinguishing each cluster. Each cluster transcript signature was compared against all other cells. The top 20 transcripts with an absolute fold change above 5 and an adjusted p value < 0.01 are shown here.

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