Immune Checkpoint Blockade induces peripheral cytotoxicity and persistence of large effector CD8+ T cell clones

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ONE SENTENCE SUMMARY

Using single-cell and bulk transcriptomics we show that checkpoint immunotherapy has divergent
effects on CD8+ T cells, with the impact on cell division and gene expression determined by the baseline
clone size and phenotype of the cell; these findings have ramifications for our understanding of inter-
individual variation in response to treatment.

ABSTRACT

Immune checkpoint blockers (ICB) exert their anti-cancer effects via CD8+ T cells, although how
responses vary over sub-populations and across clones is incompletely understood. We performed
single-cell RNA-sequencing of CD8+ T cells and their receptors pre and post ICB across eight patients,
integrating results with bulk-sequencing data (n=169). We identify seven phenotypic subsets with
divergent sensitivity to ICB, finding the effector subset demonstrates the most pronounced changes.
ICB response was related to clone size, with small and large clones markedly differing in the magnitude
and immunological relevance of regulated genes. ICB upregulates mitotic pathways and promotes
expansion and survival of larger, more cytotoxic clones. Notably, baseline cytotoxicity, but not
correlates of mitosis, associated with progression-free survival; highlighting the importance of the pre-
treatment CD8+ immune landscape in long-term response. This work further advances understanding
of the molecular determinants of ICB response and assists in the search for peripheral prognostic
biomarkers.

INTRODUCTION

Antibodies binding the checkpoint proteins CTLA4 (cytotoxic T-lymphocyte-associated protein 4) and PD-1 (programmed cell death protein 1) – Immune Checkpoint Blockers (ICBs) – have revolutionised the treatment of metastatic melanoma (MM) and numerous other cancers[1, 2]. There is, however, marked heterogeneity in ICB-induced clinical benefit[2] and insights into determinants of ICB activity and variation in clinical response remain limited. Although tumour mutational burden has been linked to clinical outcome across multiple cancers[3, 4], its absolute importance is unclear[5]. Similarly, the prognostically favourable association of tumour infiltrating lymphocytes (TILs) is long-established, but factors controlling T cell infiltration remain unresolved[6, 7]. Crucially, it is increasingly apparent that general aspects of immune function may play a critical, yet comparatively under-investigated role in determining tumour recognition and control[8].

CD8[+] T cells are cardinal to the immune response against MM[9] and much work has focussed on the response seen in pre-existing TILs[10, 11]. However, recent studies in non-melanoma skin cancer have shown that the T cell response to ICB derives from a distinct repertoire of T cell clones, denoted by shared carriage of specific T cell receptors (TCR), that may have recently migrated to the tumour[12]. Shared T cell clones can be observed within both cancers and blood of MM patients[11, 13–15], whilst the number of peripheral expanded clones (occupying >0.5% of the repertoire) post-ICB is associated with long-term response to treatment[16]. Taken together, it is evident the clonal T cell response to ICB detected in peripheral blood can provide relevant insights into immune-control of cancer and may allow for on-treatment prognostication. Nonetheless, there are several unresolved questions regarding the effect of ICB at the level of T cell clones. Centrally, the determinants of ICB response across subsets and on a clone-by-clone basis are unresolved. The T cell ICB response has multiple, potentially orthogonal, components, including mitotic cell division[17] and increased cytotoxicity as exemplified by interferon gamma (IFNγ) induction[18]. Whether these responses vary according to T cell subset[19], their heterogeneity across clones and if they are derived from novel or pre-existing clones is unknown.

To explore the peripheral CD8$^+$ T cell response to ICB we have used single cell RNA-sequencing

(scRNA-seq) to track the transcriptomic response of individual T cell clones to ICB treatment,

identifying baseline markers of clonal sensitivity to ICB, and charting how response varies according

to phenotypic subset and clonal size. We indeed find that T cell responses to ICB vary substantially

according to clonal size and phenotypic subset. Effector T cells show notably increased responsivity to

ICB but remain proportionally stable with treatment – instead, ICB drives an increase in a subset of

highly cycling, but phenotypically exhausted mitotic cells which, by and large, fail to clonally expand.

Further dissection of ICB response according to clonal size reveals that basal gene expression and

changes imparted by treatment vary markedly, with larger T cell clones developing enhanced TCR

signalling compared to all other clones. Finally, by tracking TCRs over longer periods of treatment we

identify markers of clonal persistence following ICB, demonstrating that ICB promotes expansion and

survival of pre-existing large, cytotoxic T cell clones; indicating that the effectiveness of ICB is dictated

by the baseline immune state.

RESULTS

Single-cell profiling of peripheral CD8$^+$ T cells from patients with metastatic melanoma

We generated paired baseline (day 0 – 'C1') and on-treatment (day 21 – 'C2') 5' scRNA-seq and V(D)J

profiles across peripheral CD8$^+$ T cells from eight patients with MM undergoing treatment with cICB

(ipilimumab plus nivolumab, n=4) or sICB (pembrolizumab, n=4) (**fig. 1a; table S1; Methods**). In

total, 22,445 *CD3*/*CD8* expressing cells passed quality control, of which 17,909 cells had TCR

sequences, with similar distribution across C1 and C2 samples (**fig S1a**). To identify distinct CD8$^+$ T

cell populations, we performed unsupervised clustering and subsequently cross-referenced each cluster

to reference identities from published CD8$^+$ T cell single-cell datasets (**Methods**, **fig. S1b-e**). Seven

distinct groups of CD8$^+$ T cells were identified (**fig. 1b-c**); Naïve, central memory (CM), effector

memory (EM) and effector cells (ECs) which collectively represent the majority of T cells, as well as

highly cycling cells (Mitotic), γδ T cells (gd), and *KLRB1*-expressing mucosal-associated invariant T

cells (MAIT), which formed a separate cluster from the rest of the cells. Mitotic cells had higher nUMI

detected per cell and a bias towards S and G2M cell cycle phases (**fig. S1f-g**), with a similar expression

profile to previous single-cell descriptions of mitotic T cells*(13, 20)*. Expression of *TRDC* was used to

identify the gd subset *(21)*, which was enriched for *KLRC3*, *KIR3DL2* and *KIR3DL3* (**fig. 1c**). To

distinguish the biological features of each subset, we performed Gene Ontology Biological Pathways

(GOBP) enrichment analysis (**fig. 1d**) which highlighted key immune pathways such as *IFNG* signalling

and T cell activation selectively enriched in EM and ECs, whilst Naïve/CM and Mitotic subsets were

marked by upregulated translational and mitochondrial machinery respectively. Lastly, we examined

the expression of T cell activation and exhaustion markers across the cell subsets either as distinct

markers (**fig. 1e**) or using co-correlated expression scores (**Methods**, **fig. 1c**). Increased expression of

genes associated with T cell exhaustion (*TOX*, *TOX2*, *HAVCR2, LAG3*) resulted in distinct grouping of

Mitotic, ECs, EM and gd cells from the remaining subsets. Across the 'conventional' T cell subsets,

activation, cytotoxicity and exhaustion all increased towards more differentiated cells, peaking in the

ECs. Altogether, we identified highly distinct sub-populations with divergent activation and functional

profiles.

Figure 1: Identification of peripheral CD8⁺ T cell subsets in metastatic melanoma before and during ICB. (a) *Workflow for sample collection and processing for single-cell RNAseq.* **(b)** *UMAP clustering of 22,445 peripheral CD8⁺ T cells from 8 individuals sampled at pre-treatment and following 21 days of ICB, across seven distinct subsets as represented by each colour.* **(c)** *Expression heatmap showing distinct gene expression profiles and functional scores for the identified subsets. Genes were selected as the top 5 distinguishing genes for each subset at both pre-treatment and at 21d post-ICB. Activation, cytotoxicity and exhaustion scores were calculated for each subset as displayed.* **(d)** *Dotplot heatmap showing Gene Ontology Biological Process (GOBP) terms significantly enriched across each subset (adjusted p-value<0.05).* **(e)** *Expression heatmap of selected T cell activation and exhaustion markers.*

Effector CD8⁺ T cells show increased sensitivity to immune checkpoint blockade

To characterise responses to ICB at a sub-population level we focused on the four 'conventional' T cell subsets of Naïve, CM, EM and ECs. We controlled for increased power to detect differentially expressed (DE) genes in larger subsets by subsampling varying numbers of cells across each subset (analysis bootstrapped 100 times). Across the four subsets, when accounting for increasing numbers of cells sampled, ECs had higher DE gene counts with treatment (**fig. 2a**, **S2a**). The most significantly upregulated genes included markers of maturation (*CD52*), and interferon response (*CD74*, *IFITM3*) (**fig. 2b**). Most of the DE genes in ECs were exclusively modulated in this subset (**fig. S2b**), suggesting a unique effect of ICB on these cells. Subset-wise GOBP analysis of the induced genes demonstrated both conserved biological pathways upregulated across all subsets (**fig. 2c, S2c**), and an additional set of pathways specific to ECs. Pathways commonly induced were ubiquitously expressed across subsets at baseline (**fig. S2d**), unlike those uniquely regulated in EM and ECs, and were enriched in expression in Naïve and CM cells (**fig. S2e**). Pathways restricted to ECs instead encompassed metabolic and immune pathways including NFκB and TNF signalling (**fig. 2d**), further supporting the enhanced stimulatory effect of ICB on this subset.

To assess broad changes in T cell function following checkpoint blockade, we examined changes in activation and exhaustion scores across each of the subsets. All subsets showed significant or borderline significant (EM) increases in activation score at C2, whereas cytotoxicity appeared unchanged and exhaustion score increased in the CM and EC subsets (**fig. 2e, S2f**). When we scored cells for both stimulatory and inhibitory pathways induced by ICB*(22)*, we found that *IFNA*-signalling was upregulated post-treatment across all T cell subsets, suggesting extrinsic exposure; whilst IFNγ, PD-1 and TCR signalling were more restricted to EM and ECs (**fig. 2f, S2g**). Dissimilar to their relationship with *IFNA* pathways; TCR, PD-1 and IFNγ signalling showed modest/high correlation, reflecting overlapping regulation (**fig. S2h**). These three signalling pathways were most notably induced in EM and EC subsets, with IFNγ signalling being confined to these two sub-populations (**fig. 2f**). Thus, ECs are uniquely responsive to ICB, displaying activation and pro-inflammatory gene expression consistent

with increased TCR ligation, denoted by increases in exhaustion markers, PD-1 signalling and TCR

signalling*(22)*.

Figure 2: Subset-specific gene expression changes upon ICB. (a) Number of differentially expressed

(DE) genes (adjusted p-value<0.05) upon ICB for each conventional T cell subset with >300 cells at

both timepoints. To control for the distinct numbers of cells in each subset, we subsampled to differing

numbers of cells, bootstrapped to 100 iterations. A linear mixed effect model determined differences in

the gradients of the slope across all subsets as indicated, with adjusted p-value<8x10⁻¹⁴ comparing

effector cells and each other subset. (b) Volcano plot of DE genes in ECs upon ICB (adjusted p-

value<0.05). (c) Using the maximal number of cells present in all subsets (n=1180), pathway analysis

using GOBP was performed on genes upregulated by ICB in each subset; the overlap across each of

the pathways visualised using an Upset plot. (d) GOBP pathways uniquely upregulated in effector cells

*ordered by fold change. (e) Changes in activation score for each subset upon treatment (**Methods**); the*

150 *median score per individual is plotted. (**f**) Change in AUC scores for selected Reactome pathways*

151 *following ICB across CD8$^+$ T cell subsets (two-sided Wilcoxon-ranked sign test).*

ICB leads to a subset specific mitotic response

In parallel to exploring effects on gene expression, we assessed whether ICB treatment changed the

relative proportions of these subsets. Across individuals we found ICB significantly reduced CM

proportion (**fig. 3a**), whilst other subsets remained relatively unchanged. To explore the generalisability

of these findings we developed composite expression signatures for each single-cell subset (**table S2**)

and characterised the geometric mean expression of these signatures in bulk RNA-sequencing data

isolated in a similar fashion from CD8$^+$ T cells[16] (n=220 paired C1/C2 samples from 110 individuals).

For almost all single-cell samples, bulk data had been generated, and comparing score-inferred versus

known proportions in these two datasets showed that, except for EM, bulk expression scores

significantly correlated with single-cell proportions (**fig. S3a**), supporting the validity of this approach.

Furthermore, as expected, Naïve and CM scores were anti-correlated with age, whilst EM and EC scores

increased with participant age[23] (**fig. S3b**). Interestingly, whilst ICB significantly reduced Naïve and

CM expression scores, in tandem increasing EM and mitotic scores (**fig. 3b**), no significant change in

the EC score was observed, inferring that proportions of ECs remained stable. Correcting for age,

mitotic scores demonstrated a weighted increase in cICB compared to sICB treated individuals (**fig.

S3c-d**), reflecting the stronger effect of cICB on CD8$^+$ T cell responses[16]. Finally, the decrease in

Naïve and CM score was inversely correlated with mitotic score increase (**fig. S3e**), suggesting ICB

elicits shuttling from these subsets into the highly-cycling mitotic pool.

To explore differentiation patterns across subsets we employed trajectory analysis[24, 25]. Visualisation

of the pseudotime map showed a starting state populated with Naïve cells with gradual progression

towards CM and EM phenotypes (Branch A), which subsequently bifurcates into effector and mitotic-

dominated endpoints (Branch B & C respectively) (**figure 3c, S4a**), implying two alternate fate

branches for peripheral CD8$^+$ T cells. As expected, progression along pseudotime was significantly

correlated with increasing cell maturity and cytotoxicity (**fig. S4b**). We examined whether changes in

pseudotime could be detected upon treatment. Visual examination of pseudotime-ordered cells at C1 vs

C2 showed an under-representation of cells in Branch C pre-treatment (**fig. S4c**). Pseudotime

significantly increased following ICB, the largest increase occurring when we considered cells in

Branch A and C only (**fig. S4d**). Additionally, when we separated cells from each individual amongst

the three branches and compared cell proportions between C1 and C2, we found significant increases

in the proportion of cells in Branch C, with a concordant decrease in cells located in Branch A (**fig.**

S4e). This supports the remodelling of the peripheral CD8$^+$ T cell compartment from Naïve/CM cells

by ICB, towards a mitotic population within 21 days, with a more marked effect of cICB.

Mitotic cells fail to attain cytotoxic markers

Given their marked expansion following ICB, we further characterised the phenotype of the mitotic cell

subset. Since they typify the pseudotime end-point state of trajectory Branch C, we examined the key

distinctions between the Branch B and Branch C. We clustered genes that significantly associated with

pseudotime (adjusted p-value<1x10^{-4}) and showed divergent patterns of expression across branches

(**fig. S4f**). Consistent with increased proportion of EM and ECs, cytotoxic and early activation genes

were enriched in Branch B, whilst markers of proliferation and cell-cycle regulation were associated

with Branch C. We assessed pseudotime effect at the subset level by comparing expression for the

same subset across branches. EM and ECs from Branch B were comparatively enriched for MHC-I and

cytotoxic markers, whilst Branch C EM/ECs showed upregulation of naïve and exhaustion markers

including *CD27* and *GZMK(26)*, and translation and metabolic pathways (**fig. S4g-h**). The lack of

functional cytotoxicity accrued by mitotic cells was illustrated by projection of various T cell markers

onto the pseudotime trajectory (**fig. 3d**), with expression of *IFNG* and the activation-induced

transcription factor *EOMES* localised to Branch B. The TCR-signalling associated molecule *CD247*

was expressed on most cells except for mitotic cells at the very endpoint of Branch C. Interestingly,

MKI67 expression was limited to terminal cells at both ends of Branch B and C whilst *PDCD1*

expression, upregulated post-activation, was enriched across cells in Branch B and to a lesser extent,

Branch C. Accordingly, *MKI67* expression on mitotic cells was far in excess of other subsets (**fig. S4i**),

reflecting their likely involvement in the ICB-induced proliferative burst*(27, 28)*. Additionally, mitotic

cells expressed minimal *CCR7* and had an enrichment of *TIGIT* expression, again concordant with a

more terminally exhausted state*(26)*.

Using the VDJ sequences we determined clonal relationships between mitotic cells and other sub-

populations. Whilst most mitotic compartment cells represented clones restricted to this subset (68% at

C1 and 76% at C2), cells from clones common to other subsets were predominantly shared with ECs

pre (OR 11.6, $P<1\times10^{-10}$, Fisher's test), and post-treatment (OR 1.5, $p < 1.3 \times10^{-6}$, Fisher's test, **fig. 3e**).

Mitotic clones represented in other cell subsets were typically larger than those that were not (C1;

$P<2.9\times10^{-9}$, C2; $P<2\times10^{-16}$, Kolmogorov-Smirnov test), with a number of clones in the former

comprising >0.5% of the repertoire (**fig. 3f**), suggesting a proportion of the mitotic cell compartment is

composed of clonally expanded cells. Conversely, when considering *all* clones within the mitotic

subset, we found they were on average smaller than their effector counterparts (**fig. 3g**). We further

explored this clonal relationship using bulk RNA-sequencing samples, correlating mitotic score with

number of expanding clones. Interestingly, baseline mitotic score and subsequent clonal expansion were

not associated, whereas C2 mitotic score was highly correlated with expanding clone count (**fig. 3h**),

suggesting ICB allows mitotic cells to undergo clonal expansion and switch compartments. In keeping

with this, the mitotic score in bulk data significantly anti-correlated with the proportion of clones

occupying >0.5% of repertoire at C2 (**fig. S5a**). Thus, whilst the mitotic subset contributes to persistence

of established clones, the majority of mitotic cells observed in MM fail to form persistent clones. Thus

C1 mitotic cell clones were comparatively less frequently detected at C2 than C1 EC clones, and C2

mitotic clones were correspondingly less detected at day 63 or onwards of treatment (C4+) (**fig. 3i**).

The disconnect between the mitotic subset and sustained T cell responses is also evidenced by the lack

of association between mitotic score, at either pre or post-treatment, with patient outcome, as measured

by progression-free survival (PFS) (**fig. 3j**), whilst higher EC score at C2 was associated with

significantly longer PFS (**fig. S5b**). Despite this, mitotic score at C4+ remained significantly increased

compared to at C1 (**fig. 3k**), indicative of ongoing T cell stimulation across multiple cycles of ICB.

Collectively, these findings suggest that Ki67^{+} cells at day 21 post-ICB predominantly represent short-

lived cells that do not progress to outcome-associated expanded clones.

*Figure 3: **Dynamic changes in the peripheral CD8^{+} T cell compartment during early ICB. (a-b) (a-***

***b)** Changes in the proportion of each cell subset between pre-treatment (C1) and 21d post-ICB (C2) as*

*determined by single-cell RNAseq (n=8, two-sided Wilcoxon-signed rank test) **(a)** or inferred from bulk*

*RNAseq data (n=110, two-sided Wilcoxon-signed rank test) **(b)**. For the bulk RNAseq inference, subset*

scores were calculated for each bulk RNAseq sample based on a list of markers that distinguished each

subset at both pre-treatment and 21d post-ICB in the single-cell RNAseq data (Methods, Extended Data

Fig. 2a-b). (c) Visualisation of inferred pseudotime trajectories for CD8$^+$ T cells excluding γδ and MAIT

cells, coloured by subset and arrows indicating increasing pseudotime along three branches (Branches

A-C). (d) Expression of selected genes along the pseudotime map. (e) Fisher's exact test results showing

enrichment for overlapping TCR CDR3 sequences between the indicated subsets at C1 (left) and C2

(right), determined using single-cell RNA/VDJ-seq. Filled boxes represent comparisons between

subsets that shared significant overlap (adjusted p-value < 0.05). (f) Comparison of clonal sizes of

mitotic clonotypes that are found across other subsets (n=23 and 77 clones) or solely as mitotic cells

(n=49 and 244 cells) at C1 and C2 respectively based on single-cell RNA/VDJ-seq (two-sided

Kolmogorov-Smirnov test). (g) Comparison of clonal sizes of effector cells (n=2537 and 3507 cells)

and mitotic cells (n=72 and 321 cells) at C1 and C2 respectively based on single-cell RNA/VDJ-seq

(two-sided Mann Whitney U-test). (h) Pearson's correlation between calculated mitotic score in bulk

RNAseq samples and the number of expanding TCR clones detected in those samples via MiXCR with

an adjusted p-value < 0.001, at C1 (left, n=111) and C2 (right, n=111). (i) Proportion of effector and

mitotic cells that have CDR3 sequences at C1 (left) and C2 (right) that are also detected at C2 and C4

respectively across each individual (n=7, two-sided Wilcoxon-signed rank test). (j) Kaplan Meier

curves of progression-free survival according to mitotic score at C1 (left, n=131) or C2 (right, n=109).

(k) Changes in mitotic scores at C1 (d0), C2 (d21) or C4 (d63) of treatment (n=49 individuals, two-

sided Wilcoxon-signed rank test).

259 CD8$^+$ T cell clones have canonical gene expression associations with clonal size

We have previously shown that patients with more peripheral large clones post-treatment have

improved oncological outcome*(16)*. To explore this further we grouped CD8$^+$ T cell clones into five

categories based on clonal size as a proportion of the total repertoire (**Table 1**). As expected, most Naïve

cells were found in the smallest size categories (**fig. 4a**). Interestingly, EC proportion increased with

clone size at C1, whereas the proportion of CM cells decreased (**fig. 4a**). Of note, at C2 there was a

higher proportion of EM cells and the greatest proportion of ECs was found in the large and very large

size category (>0.5% of the repertoire). As expected, Shannon diversity decreased as clonal size

category increased (**fig. 4b**) and when plotted on a UMAP, clones clustered according to size, in

accordance with differences in underlying phenotypes (**fig. 4c**). Larger clones predominantly group

within pseudotime Branch B, with higher pseudotime scores, suggesting greater differentiation of CD8$^+$

T cells as clonal size increased (**fig. 4d**).

Category	Clonal size (proportion of repertoire)
Very small	< 0.1%
Small	≥ 0.1 < 0.25%
Medium	≥ 0.25 < 0.5%
Large	≥ 0.5 ≤ 2.5%
Very large	≥ 2.5%

Table 1: Clonal size category bins.

To further define expression correlates of clone size we performed differential gene expression across

bulk RNA-sequencing from 169 individuals (**Methods, fig. 4e**). As per the single-cell data, smaller

clones associated with genes of naivety (e.g. *CD27, LEF1*) whilst larger clones expressed markers of

cytotoxic maturity such as *FCRL6(29)*. Hierarchical cluster analysis demonstrated smaller clones to be

the most dissimilar from others, with further degrees of separation between the medium-sized subsets

and the large, notably associated with *PDCD1* expression, and very large clones (**fig. 4e**).

ICB differentially affects peripheral CD8$^+$ T cell clones as a function of their size

We next assessed the relationship between clonal size and ICB effect, agnostic to subset type, by

performing category-wise differential expression analysis across treatment, using sampling to control

for variation in cell number across sub-population and timepoint, with analysis bootstrapped 100 times

(**fig. 4f**). This produced a U-shaped response pattern of DE genes according to clone size, with very

small clones having a comparatively more DE genes than intermediate-sized clones but fewer than very

large clones. We went on to qualitatively analyse the differences in gene expression profile and noted

that medium, large and very large clones (0.25-0.5%, 0.5-2.5% and >2.5% of total repertoire) upregulate

a number of pro-inflammatory and pro-migratory genes when compared to smaller clones, along with

TCR encoding genes, previously shown to associate with clinical outcome*(16)* **(fig. S6)**.

To further understand these qualitative differences, we analysed GOBP pathways corresponding to the

DE genesets (**fig. 4g**). We again noted that large and very large clones had a strikingly divergent gene

expression profile following ICB compared to smaller clones, with upregulation of pathways including

leukocyte migration, inflammatory response, cell adhesion and adaptive immune response, which were

downregulated in very small and small clones. Thus clonal size influences both the magnitude of

response to ICB as well as the types of genes regulated, with larger clones displaying marked

enhancement of immune function post-treatment.

Figure 4: T cell clones have canonical markers, and differentially respond to ICB, as a function of clonal size. (a) *Clonal size bins are coloured according to phenotypic cluster at baseline (C1, left) and*

21 days post-treatment (C2, right). (b) Shannon diversity decreases across increasing clonal size categories both pre- and post-treatment with ICB. (c) CD8$^+$ T cell clones are binned based on clonal size and displayed on a UMAP plot, coloured by clonal size category. (d) Pseudotime scores per clonal size category (left) and pseudotime plot coloured per clonal size category (right) demonstrating increasing pseudotime as clonal size increases. (e) Heatmap demonstrating canonical gene markers that associate with clonal size (n=169 individuals). (f) Number of differentially expressed genes (DEGs) pre- and post-ICB for clones of different size categories. Random samples of even size were taken and the analysis bootstrapped 100x. There is a statistically significant difference (p<0.001) between all groups. (g) Gene Ontology: Biological Pathways analysis for DEGs following ICB treatment in different size clone categories.

Cytotoxic clones demonstrate propensity to persist post-ICB treatment

To understand the temporal relationship across the peripheral CD8$^+$ T cell compartment and establish whether cytotoxic T cells are present at baseline, or 'emerge' post-ICB, we divided T cell clones into four categories, namely; (1) clones represented in data from C1 but undetected at C2, (2) those present in the C1 data and resampled at C2, (3) from the perspective of the C2 data, those present at C1, and (4) those uniquely sampled at C2 – 'emergent'. Cytotoxicity scores were calculated for each identified clone. Whilst clones resampled across timepoints were predominantly large or very large **(fig. 5a)**, we found persistent clones consistently displayed higher cytotoxicity scores pre and post-ICB, irrespective of clonal size **(fig. 5b)**. Small emergent C2 clones conversely had lower cytotoxicity than similar-sized persistent clones, whereas large and very large emergent clones had equivalent or higher cytotoxicity scores **(fig. 5a)**. Thus clones with higher cytotoxicity pre-treatment have an increased propensity to persist post-ICB. Whilst we did not find ICB increased EC cytotoxicity in the subset based analysis **(fig. S2f)**, in keeping with persistence of baseline-cytotoxic clones post-treatment we find that, unlike smaller clones, large clones show increased cytotoxicity with treatment **(fig. S7c)**, illustrating clone size induces heterogeneity in the EC response.

To investigate the validity of these findings over longer timescales, we examined bulk RNA-sequencing

of peripheral CD8$^+$ T cells from the same individuals at 63-106 days post-treatment (C4+, n=6). Within

these samples, we were able to identify 992 unique TCRβs associated with 4,245 cells that were present

in C2 single-cell samples. Cells from these more durable clones were mainly effector in phenotype, and

from large or very large clones (**fig. 5c**). This was similarly the case for the C1 samples, where 880

predominant effector phenotype cells were found across 297 clones persisting to C4+ (**fig. S7a**). Thus,

persistence was strongly associated with T cell size, with almost 100% of large and very large clones

persisting (**fig. 5d, S7b**). Furthermore, clonal size remained closely correlated between C2 and C4+,

with very large clones at C2 also being detected as very large clones at C4+ (rho=0.88, p<2.2x10^{-16}, **fig.**

5e), indicating persistence of very large clones is not simply due to resampling probability, but that

large clones are maintained for prolonged periods post-ICB.

Genes associated with persistence were found to consist of cytotoxic markers (e.g. *CCL4, CCL5, PRF1*)

and markers of large clonal size (**fig. S7c**). To delineate between markers of clonal size and persistence,

we constrained analysis to non-naïve clones (those >0.1% of the repertoire), and noted that persistent

clones were enriched for pro-inflammatory and migratory GOBP pathways, such as TNF/IFNγ

signalling, T cell activation, antigen presentation and cellular/subcellular movement (**fig. 5f,g;**

supplementary data 1). Finally, we examined the baseline phenotype of C4+ persistent clones based

on their cytotoxicity score at C1. As per clones persisting to C2, cells from clones that persisting for

this longer duration similarly display elevated baseline cytotoxicity across small and medium clone

categories (**fig. S7d**). Thus cells from clones persisting post-ICB show increased cytotoxicity before

treatment, indicating ICB preferentially enhances pre-existing anti-tumour immunity as opposed to

generating a *de novo* response. Using cytotoxicity scores for each individual generated from bulk

sequencing data (C1 n=131, C2 n=109) we find a cytotoxicity score above the cohort median construes

significantly increased PFS (**fig. 5h**). This was true at both C1 and C2, supporting the finding that

baseline immune responses, as well as the enhancement conferred by ICB, is critical in determining

clinical outcome.

Figure 5: ICB promotes persistence of activated and cytotoxic CD8$^+$ T cells. (a) *CD8$^+$ T cells were*

classified as to whether they were resampled at both C1 and C2, or whether they were only found at

one timepoint. Groups are coloured by binned clonal size as a proportion of total repertoire. **(b)**

Cytotoxicity score of CD8$^+$ T cell clones at baseline (C1, left) or d21 (C2, right). Clones are categorised

as to whether they are only sampled at C1 versus if they are resampled at C1 and C2 or if they are

found at both timepoints versus if they are novel at C2. Median score per clone is displayed with each

point representing a T cell clone. *p<0.05, **p<0.01, ****p<0.0001 **(c)** *Clones present in single-cell*

data at d21 (C2) that can be detected at d63+ (C4+) in bulk RNA-sequencing data, by phenotypic

cluster and coloured by clonal size category. **(d)** *Proportion of clones in each size category at C2 that*

*can be detected in C4+ in bulk RNA-sequencing data. **(e)** Size of CD8^{+} T cell clones at C2 compared*

*to the size of the same clone at C4+, coloured by clonal size category. **(f)** Volcano plot showing*

upregulated (red) or downregulated (blue) genes in cells from very small, small, medium, large or very

large clones that persist in the peripheral blood to C4+ when compared to those cells from the same

*clonal size categories that do not persist. **(g)** Pathways (GOBP) that are up- or down-regulated in the*

*same cells as in (f). **(h)** Kaplan-Meier curve showing progression free survival in those patients with*

above median, versus below median, cytotoxicity score at baseline (left) and C2 (right).

ICB drives expansion of large cytotoxic CD8^{+} T cell clones

Finally, in order to explore CD8^{+} T cell dynamics with ICB, we focused on cells from clones

significantly changing in size following treatment. We identified 44 clones that expand and 56 that

contract (**fig. 6a**), with the very large clone category displaying the greatest proportion of expanding

and contracting clones (**fig. 6b**). These clones were over-represented amongst those at C2 that persisted

to C4+, indicating clones undergoing dynamic change may have greater longevity (**fig 6c**). Whilst we

found ICB increased the cytotoxicity score in both expanding and non-expanding clones, expanding

clones had higher cytotoxicity at both timepoints (**fig. 6d**), suggesting ICB preferentially drives

expansion of more cytotoxic clones.

To further corroborate this observation we sought baseline markers of clones that expand following

ICB. We identified an enrichment of pro-inflammatory genes, as well as markers associated with tissue

trafficking and residency. Interestingly, such clones at baseline over-expressed the transcription factor

T-bet (*TBX21)*, and, as per clones that persist, displayed elevated expression of cytotoxic markers

including *GNLY, GZMH,* and *CCL5* (**fig. 6e**).

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Figure 6: ICB drives expansion of large, cytotoxic CD8+ T cell clones. (a) *CD8+ T cell clonal size as*

a proportion of total repertoire at baseline (C1) compared to 21 days post ICB treatment (C2). **(b)**

Proportion of each clonal size category coloured by whether a clone has significantly expanded or

contracted between C1 and C2 of ICB treatment. **(c)** *Proportion of cells that have either expanded,*

contracted or not changed in size between C1 and C2. Light grey columns represent all cells present at

*C2, dark grey columns represent those present at C2 that persist to C4+. ***p < 0.001, ****p<0.0001.*

(d) *Median cytotoxicity score for clones at C1 (light green) and C2 (dark green) depending on whether*

*the clone significantly expands or not. ***p < 0.001, ****p<0.0001.* **(e)** *Volcano plot showing genes*

at baseline that are upregulated (red) or downregulated (blue) in clones that subsequently expand

following ICB treatment. Top 30 genes by log₂FC are labelled.

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DISCUSSION

Identifying T cell subsets most responsive to ICB is vital in understanding the mechanisms of ICB response and resistance. In this study we have sought to characterise the peripheral CD8$^+$ T cell response to ICB at a single-cell level, characterising responses by sub-populations as well as by clones. We identify seven phenotypic subsets that, as well as sharing a conserved response to ICB, display subset-specific changes, the greatest and most divergent being within the effector cells (ECs). The T effector memory (EM) subset has been described as a crucial mediator in light of its expansion intratumorally and peripherally[15, 30, 31], and we observe increases in the peripheral EM score, inferring commensurate expansion of this subset. We show though that, whilst ICB does not change EC proportion, ECs exhibit the greatest magnitude and most relevant changes post-ICB. Further, the EC compartment preferentially persists following ICB. As such, we posit that in peripheral blood, the effector T cell compartment is most sensitive to ICB treatment. In keeping with this, recent work shows that clones common to blood and tumour are enriched for effector markers and are not exhausted in patients who respond to ICB[14].

We find cells undergoing mitosis form a mixed-population of cells, with a proportionally higher clonal overlap with ECs counter-balanced by the majority of mitotic cells not belonging to established clones. In addition to having higher nUMI and increased cell cycle activity, mitotic cells had high exhaustion scores and only moderate levels of cytotoxicity. The use of bulk sequencing data from CD8+ T cells from up to 169 MM patients provided appropriate power to test observations from the scRNA-seq data. Crucially, this demonstrated post-treatment mitotic cell counts were inversely correlated with large clone proportion, indicating that increased peripheral mitotic cells denotes failure to establish large cytotoxic clones, and that it is the cytotoxic as opposed to mitotic response to ICB that dictates outcomes. Of interest, cells from this mitotic sub-population clustered at the end of branch C of the pseudotime trajectory, suggesting inability to establish differentiated progeny is common to most cells within this branch and, instead of progressing to cytotoxic states, these cells remain exhausted and fail to persist. It is important to note that our analysis was at day 21 post commencing treatment and mitotic

events will likely fluctuate across cycles of treatment although, given the half-life of ICB is >21 days,

cells will be exposed throughout.

That ICB is found to preferentially affect large clones reveals mechanistic underpinnings to our previous

observations linking number of large peripheral T cells with clinical outcomes*(16)*. Smaller clones

downregulate expression of immunological pathways and increase expression of ribosomal genes and

translational activity post-ICB; whereas, consistent with the observation that translational suppression

occurs in terminal effector T cells, larger clones have an opposite response*(32)*.

The observation that ICB promotes survival and expansion of clones that display markers of

cytotoxicity *prior* to treatment was supported by the inclusion of late bulk-sequencing data which

highlighted that cytotoxic clones persist across multiple cycles of ICB and that baseline cytotoxicity

was associated with clinical outcome. That these persistent CD8$^+$ T cells have already attained

cytotoxicity pre-treatment indicates ICB leads to promotion of clone survival. The increased response

in clones showing baseline cytotoxicity supports the major bottlenecks in response to ICB to be centred

on the lack of tumour immunogenicity and antigen presentation, with consequential insufficient effector

T cell activation*(33)*. This implies therapeutics targeted at overcoming further immune checkpoints may

lead to diminishing clinical returns, whereas future approaches focussed on effective antigen

presentation and priming may be more fruitful.

In summary, our work combines in-depth analysis of responses to ICB at the single-cell level with

observations corroborated in a large dataset to provide a unique insight into peripheral effects of ICB

on CD8$^+$ T cells. The use of V(D)J sequencing allows us to track clones over time, determining that

most mitotic cells fail to expand into differentiated large effector clones. Instead, clone size plays a key

role in determining the magnitude and nature of response to ICB, and we find the effector subset is most

sensitive to treatment. Finally, we reveal that cytotoxic clones have successfully expanded to form

persistent subsets – and that much of the effect of ICB appears to rely upon this pre-existent response,

highlighting failure of immune recognition as being the major limiter of response to ICB.

MATERIALS AND METHODS

Sample collection

Patients provided written informed consent to donate samples to the Oxford Radcliffe Biobank (Oxford Centre for Histopathology Research ethical approval nos. 16/A019, 18/A064, 19/A114); 30 – 50 ml blood was collected into EDTA tubes (BD vacutainer system) taken immediately pre-treatment at d0 and d21 following one cycle of treatment. Peripheral blood mononuclear cells were obtained by density centrifugation (Ficoll Paque). CD8$^+$ cell isolation was carried out by positive selection (Miltenyi) according to the manufacturer's instructions, with all steps performed either at 4 °C or on ice. Unless otherwise stated, patients receiving cICB (ipilimumab plus nivolumab, n=4) or sICB (pembrolizumab, n=4) were pooled for the purposes of analysis, based on previous work showing qualitatively similar genetic changes induced in peripheral CD8$^+$ T cells by both cICB and sICB[16].

Single-cell sample preparation and sequencing

Magnetically separated CD8$^+$ cells were immediately oil-partitioned into single-cell droplets, followed by cell lysis and a reverse transcription reaction using the 10x Genomics Chromium system. 6000 CD8$^+$ T cells were loaded onto each partitioning cassette. Single-cell 5' RNA transcriptome and V(D)J Libraries were constructed from the cDNA, according to the manufacturer's instructions (https://www.10xgenomics.com/). Sequencing was performed on an Illumina HiSeq4000; 75bp PE reads for the 5' RNA libraries, 150 bp PE reads for the V(D)J libraries to a depth of approximately 50000 reads per cell.

Data processing, quality control and clustering

Single-cell reads were aligned, counted and filtered for initial quality control (QC) as previously described[12]. In short, FASTQ files were generated from Illumina BCL outputs, used to produce gene expression and barcoding libraries, and then combined using the Cellranger *mkfastq*, *count* and *aggr* functions respectively. For V(D)J data, Cellranger *vdj* was applied. For QC, the R package *scater*[34] was used to identify single-cell outliers as low-quality libraries and *scran* utilised to detect doublets which were removed from analysis. Following alignment and data pre-processing, CD8$^+$ T cells were

filtered on detectable *CD3D* and either *CD8A* or *CD8B* UMIs whilst lacking *CD14* expression. The R

package *Seurat(35)* was used for further QC, data normalisation and identification of variable features;

low quality cells were excluded if they had less than 500 total UMIs, less than 300 detected features

and mitochondrial gene percentage above 20%. Genes expressed in <5 cells were also removed. The

percentage of mitochondrial genes, total nUMIs and cell cycle scores were regressed out upon scaling

of the normalised data. Principal component analysis (PCA) was performed on the scaled data and the

top 16 principal components selected for dimensionality reduction and UMAP clustering as the most

variable and biologically informative components. To determine an ideal resolution value, cell clusters

generated using values between 0.1 and 2.5 were compared using the R package *clustree(36)* with

values between 1.5 and 2.0 showing high cluster stability.

Identification of cell subsets

To assign each cell cluster generated in Seurat to a functional T cell subset, we curated transcripts per

million (TPM) normalised counts for CD8[+] T cells from previous T cell cancer scRNAseq datasets*(12,*

13, 37–39). Using the R package *SingleR(40)*, each individual cell was matched to one of the CD8[+] T

cell subsets present in the reference datasets based on global gene expression similarity, from which

subset identity for each cluster was determined.

Clonal definitions, size change and diversity

T cell chains were filtered based on called productivity, and chain identity (TRA or TRB). Cells were

selected as those that either contained a single TCRβ chain, a combination of one TCRα with one TCRβ

chain or a group of three chains – two TCRα and TCRβ. A clone ID was defined by a concatenation of

amino acid CDR3 chains present, with cells sharing identical clone IDs classed as members of the same

clonotype. Clonal proportions were calculated by dividing the number of cells in each clone per sample

by the total of number of cells per sample. Clones were designated to be expanding/contracting if the

counts of that clone were greater/less than expected by chance post treatment (P<0.05, Fisher's exact

test). Shannon diversity was calculated from count data of clones per sample using the R package

entropy(41).

Downstream expression analysis

Differential gene expression analysis with subsampling. Differential gene expression was performed in *Seurat* for all detected genes using the FindMarkers function. Where specified, to control for differences in statistical power in detecting DE genes across groups with varying cell counts, the number of cells used for analysis was standardised to the number present in the smallest group and bootstrapped 100 times to account for sampling bias. For comparison of ICB effect according to clone size 245 cells were used as this was the minimum number of cells across categories/timepoints.

Pathway analysis. Pathway enrichment analysis was performed using the R package *XGR(42)* with the GOBP database. Significantly induced or suppressed genes were assessed separately against a background of all detected genes using a hypergeometric test with a minimum overlap set to 8 (figures 4, 5) or 10 (figure 2), ontology algorithm specified as 'elimination' and an elimination p value of 0.01.

Generation of cell phenotype and pathway scores. Scores for cell activation, cytotoxicity, exhaustion and maturation were calculated for each individual cell using the AddModuleScore function in Seurat. The top 50 genes that significantly correlated with *CD38, IFNG*, *HAVCR2* and *CD52* expression respectively and were identified as variable features in Seurat were grouped to form gene sets for each score. Each gene set was then used as an input to generate phenotype scores. Cell scores for GOBP and Reactome pathways were generated using the R package *AUCell(43)*, based on the genes in each pathway that were also detected by single-cell RNAseq.

Pseudotime analysis. Pseudotime trajectories were constructed using the R package *monocle(44),* excluding cells assigned gamma-delta or MAIT identity due to their distinct developmental pathways. Cells were downsampled to only those that contained both an alpha and beta CDR3 sequence in the corresponding VDJ-seq due to memory constraints. To identify genes significantly associated with changes in pseudotime, the BEAM test in monocle was performed and genes with qval scores less than $1x10^{-4}$ considered significant.

Bulk RNA-sequencing

Analysis of bulk RNA-sequencing was performed on CD8[+] T cells from 169 individuals receiving ICB

for MM. For paired analysis of subset scores we used samples with both day 0 and day 21 expression

(n=110). For full methods please see*(16)*. Data can be downloaded from the European Bioinformatics

Institute and the Centre for Genomic Regulation under accession no. EGAS00001004081.

Generation of subset and cytotoxicity scores from bulk RNA-sequencing samples. Genes with

expression significantly enriched in a given subset above all others were identified using the

FindAllMarkers function in Seurat across all cells from C1 and C2 samples separately. To minimise

timepoint-specific gene expression associations, the top 20 genes at each timepoint were compared and

the overlapping genes retained to identify robust subset-specific genes. Subset scores were then

generated for each bulk RNAseq sample by first normalising expression data using the *DESeq2* R

package*(45)* and then calculating the geometric mean of expression across each list of subset genes. A

similar approach was used for cytotoxic score but instead based on the top 50 genes used for single-cell

cytotoxic scoring (Data file S2). Out of 136 C1 and 113 C2 samples, 110 individuals had paired C1/C2

data with a further 49 having C4 samples. Clinical follow-up was available for 131 C1 and 109 C2

samples.

Identification of clonal category-associated genes. To identify genes significantly associated with each

clonal category, samples with greater than 1,000 detected TCR-beta chains by MiXCR*(46)* (allowing

for detection of clones representing <0.1% of the TCR repertoire) were counted for the number of clones

belonging in the five clonal bins based on β-chain CDR3 sequence. In total, 169 individuals were used

for analysis across 63 healthy individuals and 106 MM patients. Genes were tested for significance in

DESeq2 using a binomial Wald test with 750 iterations after correcting for size factors and dispersion.

For clonal persistence at later timepoints (C4+) we used samples from four individuals taken at day 63,

one at day 84 and one at day 106. Clones were defined within these samples using MiXCR according

to the beta chain, and then compared with earlier scRNA-seq data with matching beta chain usage.

Correlating mitotic score with clonal expansion. Clones identified using MiXCR from bulk RNA-

sequencing data were tracked between C1 and C2. Clones were designated to be expanding if the counts

of that clone were greater than expected by chance post treatment (P<0.001, Fisher's exact test). This

created a number of expanding clones per sample which was correlated with mitotic score, with

overlapping metrics available for 111 individuals.

General statistical analysis

Statistical comparisons were performed as indicated in each figure and conducted in R. Where indicated

(by n=7), cells and statistics from donor 6 were excluded due to low numbers of cells at C1. For analysis

of clonal persistence, n=6 as only six out of the eight individuals profiled had samples at C4+. All

statistical tests were performed in R or *rstatix,* and *lme4/lmerTest* for linear effect models. Gene

correlation analysis for phenotype scores was performed using *DGCA(47)*. Survival analysis was

performed using *survival/survminer*. For all data, *p<0.05, **p<0.01, ***p< 0.001, ****p<0.0001.

Adjusted p-values have been reported using Bonferroni correction for multiple comparisons.

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0349-1.

ACKNOWLEDGEMENTS

We are very grateful to all patients who generously contributed samples and participated in the study. We thank all the staff of the Day Treatment Unit, Oxford Cancer Centre, and The Brodey Centre at the Horton General Hospital. We also thank M. Payne, N. Coupe and R. Matin for assistance in collecting patient samples. We thank M. H. Al-Mossawi for discussion and advice.

FUNDING

This study was funded by a Wellcome Intermediate Clinical Fellowship to BPF (no. 201488/Z/16/Z), additionally supporting AV, EAM and IN. RAW was a National Institute for Health Research (NIHR) Academic Clinical Fellow at the time of this project, and was supported by a Cancer Research UK (CRUK) predoctoral Fellowship (no. ANR00740); currently funded by a Wellcome Trust Doctoral Training Fellowship (no. BST00070). OT is supported by The Clarendon Fund, St Edmund Hall, and an Oxford Australia Scholarship. RC is supported by a CRUK Clinical Research Training Fellowship. CAT is funded by the Engineering & Physical Sciences Research Council and the Balliol Jowett Society (no. D4T00070). MRM and BPF are supported by the NIHR Oxford Biomedical Research Centre. The views expressed are those of the authors and not necessarily those of the NHS, the NIHR or the Department of Health.

AUTHOR CONTRIBUTIONS

RAW & BPF conceived the study; RAW, OT, IN & BPF performed the analysis, figures were generated by OT & RAW, manuscript was drafted by RAW, OT & BPF; RAW & RC performed single-cell experiments; RAW, EAM, RC, CAT, AV & OT collected and prepared samples, MRM contributed to discussions throughout the work; BPF oversaw the project. All authors read, edited and approved the final manuscript.

COMPETING INTERESTS

RAW, OT, RC, CAT, AV, EAM, IN – no competing interests

MRM – reports grants from Roche, grants from Astrazeneca, grants and personal fees from GSK,

personal fees and other from Novartis, other from Millenium, personal fees and other from

Immunocore, personal fees and other from BMS, personal fees and other from Eisai, other from Pfizer,

personal fees, non-financial support and other from Merck/MSD, personal fees and other from Rigontec

(acquired by MSD), other from Regeneron, personal fees and other from BiolineRx, personal fees and

other from Array Biopharma (now Pfizer), non-financial support and other from Replimune, personal

fees from Kineta, personal fees from Silicon Therapeutics, outside the submitted work.

BPF – received conference support from BMS.

DATA AND MATERIALS AVAILABILITY

784   Raw expression matrices and associated cell metadata for all cells that passed upstream QC will be

785   deposited on EGA. All scripts used in data analysis and the generation of figures will be made available

786   on the Fairfax group bitbucket account.

Figure S1: **Workflow for CD8⁺ T cell subset assignments.** *(a) UMAP distribution of cells from pre-*

treatment (C1) and day 21 on-treatment (C2) samples. (b) UMAP visualisation of 25 Seurat clusters

generated at a FindClusters resolution of 1.5. (c) Heatmap of assigned subset identities for each Seurat

cluster using external cancer patient single-cell RNAseq datasets as a reference (refs). For each cell,

SingleR was used to cross-match its expression profile to that of one of the subsets in each reference

set. The proportion of cells in each cluster that were assigned a particular identity from each reference

set is represented by the intensity of shading (between 0 and 1). (d) Summary table of subset identities

for each reference set and assigned identities for each cluster based on the best match from the SingleR

analysis. (e) Phylogenetic tree for each Seurat cluster coloured by assigned subset showing similarity

between clusters within the same subset. (f) Violin plot showing the nUMI per cell across each of the

seven CD8⁺ T cell subsets. (g) Bar plot of the proportion of cells in each stage of the cell cycle, assigned

using the CellCycleScoring function in Seurat, across each subset.

Figure S2: ***Differential gene expression upon ICB in CD8[+] T cell subsets.*** *(a) Summary of the number*

of differentially expressed genes modulated by ICB for each subset at n=1180 cells. (b) Upset plot for

overlapping significantly induced (left) and suppressed (right) genes across each subset. (c) GOBP

pathways upregulated by ICB in effector cells coloured based on whether they were uniquely induced

*in effector cells or also upregulated across other CD8$^+$ T cell subsets (adjusted p-value < 0.05). **(d)***

Pathway AUC scores at pre-treatment (C1) for all induced pathways across all T cell subsets, separated

*based on the patterns of overlap. **(e)** AUC scores for pathways commonly induced in all T cell subsets*

*across all T cell populations. **(f)** Changes in cytotoxicity and exhaustion score for each subset upon*

treatment. Scores were calculated using the AddModuleScore function in Seurat using a list of the top

50 genes with expression correlated with that of IFNG and HAVCR2 respectively, and the median score

*per individual plotted (n=8, two-sided Wilcoxon-ranked sign test). **(g)** Overlay of AUC scores on cell*

*UMAP at d21 post-treatment (C2) for selected Reactome pathways. **(h)** Pearson's correlation values*

for AUC scores of Reactome pathways across all C2 cells.

Figure S3: *Inference of subset proportions in bulk RNAseq data using single-cell expression*

profiles. **(a)** *Concordance plot between subset proportions for each single-cell sample and scores*

calculated for each subset using bulk RNAseq data of CD8⁺ T cells. For 15/16 of the samples used for

single-cell RNAseq, bulk RNAseq on the purified CD8⁺ T cells was also performed. A list of the top 20

discriminating markers for each subset was generated using FindAllMarkers in the single-cell data for

all pre-treatment cells, and separately for all cells at d21 post-ICB. The overlapping genes were

retained as markers of each cell subset irrespective of treatment, and the geometric mean expression

for each set of genes was calculated using normalised bulk RNAseq data, thus generating subset scores

for each bulk RNAseq sample. Pearson's correlation was used to determine the accuracy of this scoring

approach for each subset, showing good concordance for all subsets except effector memory (EM). **(b)**

As a further validation of the bulk RNAseq scores, subset scores across n=399 samples were correlated

against participant age using Pearson's correlation. (c) Linear mixed effect model for mitotic score

showing a significant increase in score following ICB upon controlling for age and fitting sequencing

run as a random effect (n=110 individuals). (d) Linear mixed effect model for change in mitotic score

following ICB showing a significantly higher change in patients treated with combination ICB

compared to single-agent ICB, controlling for age and fitting sequencing run as a random effect (n=110

individuals). (e) Pearson's correlation between changes in mitotic score upon ICB, and corresponding

changes in Naïve score (left) and CM score (right) per individual (n=110).

Figure S4: ***Pseudotime analysis of CD8+ T cells. (a)*** *Pseudotime and trajectory component values*

generated using Monocle across each conventional CD8+ T cell subset. ***(b)*** *Pearson's correlation*

between pseudotime values per cell, and maturation and cytotoxicity scores calculated using the

AddModuleScore function in Seurat using a list of the top 50 genes with expression correlated with that

of CD52 and IFNG respectively. (c) Distribution of cells from pre-treatment samples (C1) or d21 on-

treatment samples (C2) along the pseudotime map. (d) Changes in pseudotime upon ICB were assessed

using a linear mixed effect models with individual being fitted as a fixed intercept. Different branch

combinations of the pseudotime map were included to pinpoint the changes occurring. Filled points

and line ranges represent the estimated fold change in pseudotime upon treatment and standard error

respectively. (e) Changes in proportion of cells present in each pseudotime branch upon ICB across

each individual (n=7, two-sided Wilcoxon-ranked sign test). (f) Relative expression heatmap of genes

significantly associated with increasing pseudotime (adjusted p-value < $1x10^{-4}$) from Branch A along

Branch B or Branch C (left and right respectively). (g) Volcano plot of differentially expressed genes

between effector cells (left) and EM cells (right) in Branch C vs Branch B of the trajectory map

(adjusted p-value < 0.05). (h) GOBP pathway analysis of significantly enriched pathways in the

differentially expressed genes between Branch C and B from (e) (adjusted p-value<0.05). (i) Violin

plots for expression of indicated genes across each $CD8^{+}$ T cell subset.

*Figure S5: **Subset score associations with clonal and clinical characteristics.** (a) Pearson's*

correlation between calculated mitotic score in bulk RNAseq samples and the proportion of clones that

*occupy >0.5% of the TCR repertoire in those samples at C1 (left, n=111) and C2 (right, n=111). **(b)***

Kaplan Meier curves of progression-free survival according to effector score at C1 (left, n=131) or C2

(right, n=109).

862 ***Figure S6: Differentially expressed genes across clonal categories. (a-e)*** *Volcano plots showing*

863 *DEGs for each clonal size category post ICB.*

Figure S7: Clones present in peripheral blood at day 63+ are more cytotoxic and activated at baseline

and day 21. *(a) Phenotypic cluster at baseline of clones that can be detected in peripheral blood at day*

63+ (C4+), coloured by clonal size category. (b) Proportion of clones that persist to C4+ compared to

those that do not persist, faceted by phenotypic subset and categorised by clonal size as proportion of

repertoire.(c) Comparison of cytotoxicity scores for the ECs between C1 and C2, with analysis

performed within clone size category (Two-sided Wilcoxon signed-rank test). (d) Volcano plot of

differentially expressed genes between all cells at C2 that persist to C4+ versus those cells that do not

persist. (e) Cytotoxicity score of cells at baseline, categorized as to whether they are only sampled at

*C1 versus if they are resampled at C2 or if they are found at C4+. ****adjusted p<0.0001. There is no*

 significant difference in cytotoxicity score between those persisting to C2 and those persisting to C4+,

875 *except for cytotoxicity score in small clones (0.1-0.25% of repertoire, p<0.05).*

Donor	Age	Sex	Treatment	Cycle	Cells
1	82	M	sICB	C1	1731
				C2	2273
2	72	F	sICB	C1	439
				C2	1262
3	57	M	cICB	C1	1993
				C2	2004
4	45	F	cICB	C1	1028
				C2	643
5	43	F	sICB	C1	1391
				C2	1349
6	56	M	cICB	C1	28
				C2	2405
7	68	M	cICB	C1	1160
				C2	1224
8	69	M	sICB	C1	1925
				C2	1590

877 **Table S1: Donor characteristics and cell count per sample.**

Naïve	CM	EM	Effector	Mitotic
CCR7	LTB	GZMK	FGFBP2	TYMS
LEF1	GPR183	DUSP2	GZMH	RRM2
TCF7	CRIP2	CMC1	GZMB	MKI67
NOSIP	ARHGAP15	CD74	NKG7	CENPF
SELL	FXYD5	CCL5	KLRD1	UBE2C
AIF1	RCAN3	GZMA	ADGRG1	CENPM
ACTN1	NELL2	XCL2	PRF1	CDKN3
EEF1B2	FXYD2	RGS1	PRSS23	TK1
RPS5		TIGIT	SPON2	CLSPN
RPS13		FCRL3	ZEB2	GINS2
NPM1		COTL1	CX3CR1	
RPL32			ZNF683	
LRRN3			EFHD2	
RPS3A			FCRL6	
RPL22				

Table S2: Genes for bulk scores. List of genes used to generate scores (geometric mean) in CD8[+] T

cell bulk RNAseq samples for each subset indicated.

Data file S1 – included as separate file

CSV file containing differentially expressed genes between large CD8+ T cell clones that persist

following ICB and those that do not persist

Data file S2 – included as separate file

CSV file containing lists of genes use to generate activation, exhaustion and cytotoxicity scores