Single-cell analyses reveal that monocyte gene expression profiles influence HIV-1 reservoir size in
 acutely treated cohorts

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40 ABSTRACT

41 Elimination of latent HIV-1 is a major goal of AIDS research but the host factors determining the size of 42 these reservoirs are poorly understood. Here, we investigated whether differences in host gene 43 expression modulate the size of the HIV-1 reservoir during suppressive ART. Peripheral blood 44 mononuclear cells (PBMC) from fourteen individuals initiating ART during acute infection who 45 demonstrated effective viral suppression but varying magnitude of total HIV-1 DNA were characterized 46 by single-cell RNA sequencing (scRNA-seq). Differentially expressed genes and enriched pathways 47 demonstrated increased monocyte activity in participants with undetectable HIV-1 reservoirs. IL1B 48 expression in CD14+ monocytes showed the greatest fold difference. The inverse association of IL1B 49 with reservoir size was validated in an independent cohort comprised of 38 participants with different 50 genetic backgrounds and HIV-1 subtype infections, and further confirmed with intact proviral DNA assav (IPDA®) measurements of intact HIV-1 proviruses in a subset of the samples. Modeling 51 52 interactions with cell population frequencies showed that monocyte IL1B expression associated 53 inversely with reservoir size in the context of higher frequencies of central memory CD4+ T cells, 54 implicating an indirect effect of *IL1B* via the cell type well established to be a reservoir for persistent 55 HIV-1. Signatures consisting of co-expressed genes including IL1B were highly enriched in the "TNF α 56 signaling via NF- κ B" geneset. Functional analyses in cell culture revealed that IL1B activates NF- κ B, 57 thereby promoting productive HIV-1 infection while simultaneously suppressing viral spread, 58 suggesting a natural latency reversing activity to deplete the reservoir in ART treated individuals. 59 Altogether, unbiased high throughput scRNA-seq analyses revealed that monocyte IL1B variation could 60 decrease HIV-1 proviral reservoirs in individuals initiating ART during acute infection.

61 INTRODUCTION

62 HIV-1 infection is effectively treated with antiretroviral therapy (ART). However, the persistence of 63 stably integrated and replication-competent proviruses in the latent cell reservoir prevents a cure¹. ART 64 suppresses plasma viremia below the limit of detection but viral replication rebounds within weeks of 65 analytic treatment interruption (ATI) in the majority of individuals². This is attributed to a small pool of 66 latently infected cells harboring HIV proviruses, which can be reactivated to produce infectious viruses 67 that cause viral rebound in the absence of ART³. Several studies have implicated resting memory CD4+ 68 T cells and distinct memory CD4+ T cell compartments as the primary latent reservoirs in people living 69 with HIV (PLWH) on ART ⁴⁻⁷. In long-term non-progressors (LTNP) and elite controllers (EC), viremia 70 is controlled in the absence of treatment due to the presence of protective HLA alleles including B*57; 71 however, there exists a third considerably smaller group of post-treatment controllers (PTC) without 72 these protective alleles, suggesting a distinct mechanism of viral control^{8,9}. Although a recent clinical trial identified one controller who had HLA-B*57¹⁰ in the placebo study arm after ATI, perhaps the 73 74 most consistent correlate of post-treatment control is the presence of lower cell-associated HIV proviral 75 DNA levels as a surrogate of CD4+ T cell reservoir size ⁹.

76 Viral rebound is observed after treatment interruption in almost all people, whether ART is initiated at the early acute or later chronic stage of HIV infection ^{11,12}. However, there is increasing 77 78 evidence that the pool of latently infected cells, which persist despite treatment, varies in size between 79 individuals. Variation in reservoir size as determined by HIV DNA quantification in CD4+ T cells has 80 also been observed in virally suppressed patients who initiated ART during acute HIV infection ^{13,14}. 81 This inter-host variation in CD4+ T cell associated reservoir size is observed at various stages of acute infection and even after 24 weeks of ART ^{13,15}. Identifying host cellular factors that mark and influence 82 83 the HIV reservoir size could help in understanding the mechanisms associated with HIV persistence and

84 may reveal targets for achieving a functional cure. The majority of previous findings linking the host 85 transcriptome to latency have been limited to cell lines or models of infection, and ex vivo experiments with primary cells ¹⁶⁻¹⁸. Recent studies in humans have focused on assessing CD4+ T cells and HIV 86 87 persistence in the context of characterizing antigenicity, clonal expansion, and the whole transcriptomes 88 of single cells harboring virus ¹⁹⁻²². Here, we determined cellular immune profiles of the host that 89 associates with cell-associated HIV DNA levels, an established marker of viral persistence using 90 extreme phenotypes of reservoir size ²³. These in vivo quantitative phenotypes of multiple donors enable 91 unbiased approaches to interrogate all cell populations without ex vivo stimulation. A unique cohort of 92 PLWH that initiated ART treatment during Fiebig stage III of acute infection was selected in order to 93 minimize the effect of time-to-treatment as a confounder of reservoir size ²⁴. This was combined with 94 the use of analytical approaches that are unbiased and high throughput to avoid specifically targeting the 95 known latently infected T cell reservoir, and to enable broad screening for host variation most 96 prominently associated with reservoir size.

97 Given the sustained size variation in cellular reservoirs during acute HIV infection (AHI) and 98 post-ART initiation, we hypothesized that specific host genes might contribute to these differences 99 between individuals. We have previously shown that a bulk RNA-seq approach applied to multiple 100 specific sorted lymphocyte populations allowed us to identify protective gene signatures in response to 101 HIV vaccination ²⁵. Here, we used a more sensitive next-generation sequencing (NGS) approach to 102 identify differences in host transcriptomes from PLWH shown to harbor varying HIV DNA levels ²⁴. 103 Additionally, we recently showed that transcriptomics studies conducted with AHI samples can be 104 confounded by the presence of viremia ^{15,26}. Here, we achieved broader scope and resolution using an 105 unbiased droplet based single-cell RNA-seq (scRNA-seq) platform with peripheral blood mononuclear 106 cell (PBMC) samples from virally suppressed PLWH. This enabled the examination of gene expression

107	in all cell types in peripheral blood, to test expression of every gene in the transcriptome from individual
108	cells for associations with the size of the total cell-associated HIV reservoir in donors on ART. Our
109	unbiased single-cell analyses identified monocyte gene expression profiles as having the strongest
110	association with HIV reservoir size in two independent AHI cohorts, with significant expression of
111	higher <i>IL1B</i> with a smaller reservoir in both studies. Moreover we were able to confirm these findings
112	with IPDA® measurements of intact HIV-1 proviruses. Functional in vitro data support an effect via
113	IL1B-mediated activation of the transcription factor family NF-κB, which both stimulates HIV
114	transcription and induces antiviral gene expression ²⁷ .
115	
116	RESULTS
117	Participant selection and study design
118	We screened 163 Thai participants enrolled in the RV254 AHI cohort with varying cell-associated HIV-
119	1 DNA reservoir sizes to map the immune-microenvironment of PLWH. We further focused on
120	performing integrated transcriptome-wide scRNA-seq, high parameter multidimensional flow
121	cytometry, T-cell receptor (TCR) and B-cell receptor (BCR) sequence data from PBMCs of 14 selected
122	participants, who had been on ART for 48 weeks. All individuals had initiated ART following HIV
123	diagnosis during Fiebig stage III of AHI and were virally suppressed (<50 copies/ml) (Extended table 1).
124	We categorized the 14 participants with the most extreme reservoir size differences into "undetectable"
125	(n=8) versus "detectable" (n=6) reservoir groups from a total of 28 participants at Fiebig stage III (Fig.
126	1A-B). These phenotypes were based on both total cell associated and integrated HIV DNA levels in
127	PBMC as measured by quantitative PCR ^{14,28} . Further, HIV DNA decay from week 0 at AHI showed
128	that the phenotype categorizations were distinct (Fig. 1C). All 14 participants shared similar
129	demographics and were Thai males infected with viral subtype CRF01_AE, as described previously ²² .

130 Other than reservoir size there were no significant differences between the two groups (Figs. 1B, D).

The workflow including scRNA-seq, repertoire sequencing, and flow cytometry performed on samples from all 14 donors is illustrated in Fig. 1E. Furthermore, PBMC from an additional 38 male participants with viral subtype B infections and African and European ancestry from the USA (ACTG A5354) were assessed 48 weeks after ART initiation for validation of cell subset-specific differential gene expression patterns with reservoir size (Fig. 1E, Extended table 1).

136

137 CD14+ monocytes have the most differentially expressed genes associated with reservoir size

138 PBMC from the 14 Thai male participants collected 48 weeks after ART initiation were assessed by 139 scRNA-seq on the 10x Genomics platform using 5' gene expression profiling. A total of 62,925 single 140 cells passed quality filter and 19,581 genes were detected across all cell types from all donors. Cell 141 clustering based on gene expression of lineage markers revealed 24 discrete populations (Figs. 2A, S1). 142 All major canonical immune cell populations in PBMC could be detected through gene expression, 143 including cells from the innate, humoral and cellular arms of the immune system (Supplementary table 144 S1). There were no significant differences in uniform manifold approximation and projection (UMAP) 145 distributions or cell subset frequencies when comparing detectable versus undetectable reservoir groups 146 (Figs. S2A-B). Furthermore, no apparent differences in T cell receptor (TCR) or B cell receptor (BCR) 147 clonal diversity or in BCR isotype distribution were observed between detectable and undetectable 148 reservoir groups across all conventional T and B cell subsets captured in this analysis (Fig. S3A-C). We 149 performed differential expression analyses to identify genes whose expression showed quantitative 150 differences between people with undetectable or detectable amounts of HIV DNA 48 weeks after ART 151 initiation in all 14 participants. These analyses identified significant differences in gene expression 152 between the two groups in 20 cell subsets. There were 224 unique significantly differentially expressed

153	genes (DEG) which were independent of the size of the immune cell subsets. The cell types with the
154	highest number of DEGs were CD14+ monocytes (n=78), CD8+ T _{CM} cells (n=51), CD8+ T _{EM} cells
155	(n=46) and CD16+ monocytes (n=38) (Fig. 2B, Supplementary table S2). Analyses of the 224 DEG
156	identified the top 20 significant pathways and processes collectively enriched across the different cell
157	subsets (Supplementary table S3). The top 3 significant gene ontology terms were lymphocyte
158	activation, regulation of cytokine production, and cytokine-mediated signaling, with most of the
159	pathway enrichments resulting from the DEG in monocytes. The only pathways that were significantly
160	enriched in the detectable reservoir group were lymphocyte activation and immune response-activating
161	signal transduction in CD4+ naïve T cells (Supplementary table S4). DEG with the greatest significance
162	in different cell subsets are highlighted in Fig. 2C. The DEGs that were most significant, with an
163	average log fold change of >1, were thrombospondin-1 (<i>THBS1</i>) and interleukin-1 beta (<i>IL1B</i>) in
164	CD14+ monocytes (Fig. 2C). The median expression of these two genes in CD14+ monocytes was
165	significantly higher in the undetectable compared to the detectable reservoir group when assessed using
166	a single-cell approach (Padjusted <5e-324 and Padjusted =8.4e-197 for THBS1 and IL1B, respectively) or by
167	participant-specific average gene expression analyses (P=0.02 and P=0.001 for THBS1 and IL1B,
168	respectively) (Fig. 2D-E). These genes were consistently expressed at higher levels for individuals with
169	undetectable reservoirs, whether measurements were determined by total HIV DNA in PBMC or only in
170	CD4+ T cells (Figs. S4A-B). The associations remained significant even when the outcome was HIV
171	reservoir decay from week 0 (AHI) to week 48 (on ART) (Coefficient = $4.99e-04 P_{adjusted} < 5e-324$ and
172	Coefficient = 1.47e-04, P _{adjusted} =3.97e-104 for <i>THBS1</i> and <i>IL1B</i> , respectively (Fig. S4C-F). Thus, from
173	an unbiased screen of all peripheral blood cell populations, we observed the strongest correlations with
174	reservoir size not for CD4+ T cell subsets, but for monocytes, which showed enrichment for activation
175	pathways, and particularly increased expression of THBS1 and IL1B, in the undetectable reservoir group.

176

Monocyte-expressed genes in conjunction with central memory CD4+ T cell frequencies were associated with decreased reservoir size

179 To understand the association of monocyte gene expression with reservoir size, we used variation in cell 180 frequency data obtained by multi-parameter flow cytometry to determine if specific populations varied 181 between individuals. A total of 117 cell populations were identified and annotated by cell surface marker 182 expression from PBMC isolated at the same time as those used in scRNA-seq analyses. We first used a 183 univariate linear regression analysis of the cell population frequencies and identified CD4+ T cells 184 expressing CD39 on the cell surface as the only marker associated with significantly increased HIV 185 DNA after adjusting for multiple testing (beta=16.9, SE=3.6, P<0.001, q=0.08). In an exploratory 186 analysis, we next evaluated the two-way interaction of each of the 117 phenotypic population 187 frequencies with the top two genes (THBS1 and IL1B in CD14+ monocytes) that associated with 188 decreased HIV persistence. There were several population-specific phenotypic markers whose 189 frequencies increased in the presence of either THBS1 or IL1B and associated with lower reservoir size 190 that were nominally significant (Supplementary table S5). Of the 18 cell populations whose abundances 191 correlated with either the expression of *THBS1* or *IL1B* and associated with decreasing reservoir size, 192 two correlated with both of these genes (Supplementary table S5). The two populations were subsets of 193 central memory CD4+ T cells (CD4+ T_{CM} cells; CD4+CCR7+CD45RO+) that were negative for PD-1 194 or HLA-DR surface markers (Fig. S5A). Further grouping into other memory CD4+ phenotypes was not 195 possible because of the absence of CD27 surface antibodies in the T cell flow cytometry panel. However, we observed no differences in frequencies of these CD4+ T_{CM} cell subsets between 196 197 participants with detectable or undetectable reservoir size (Fig. S5B-D). Given the low frequencies of 198 $CD4+T_{CM}$ cells that are PD-1+ or HLA-DR+, we combined them with the frequencies of their

199	respective negative populations and obtained their combined parent CD4+ T _{CM} phenotype frequencies.
200	A multiple regression model with two-way interaction also demonstrated a significant inverse
201	relationship of CD4+ T_{CM} frequency and monocyte <i>THBS1/IL1B</i> expression with reservoir size (P =
202	0.02 and $P = 0.01$ for <i>THBS1</i> and <i>IL1B</i> , respectively, Fig. 2F-G). In this interaction model the
203	significance of <i>IL1B</i> over <i>THBS1</i> is further strengthened as shown by better accuracy (adjusted
204	coefficient of determination (adj. R ²)) and deviation (test root mean square error (test RMSE)) metrics
205	(Fig. 2G). Thus, increased expression of THBS1 or IL1B in monocytes in the presence of higher
206	frequencies of CD4+ T _{CM} associated with decreased reservoir size. This suggests that changes in
207	monocyte THBS1 and IL1B expression affect the size of the reservoir via an indirect effect on CD4+
208	T_{CM} , which was the only cell type to show this interaction in PBMC populations measured by flow
209	cytometry.
210	
211	Association of <i>IL1B</i> expression in monocytes with smaller HIV reservoir size in an independent
212	cohort using different measurements of HIV DNA
213	To verify the significance of our findings, we used an independent cohort of acutely treated PLWH from
214	the USA (ACTG A5354). This cohort was comprised of 38 male participants of European and African
215	ancestry, with treatment initiated during Fiebig stages III-V. Total HIV DNA reservoir was measured at
216	week 48 after ART initiation. Variation in HIV DNA levels was observed within both the European and
217	African population groups, and scRNA-seq was performed on samples from the week 48 timepoint (Fig.

- 218 3A-B). A total of 22 cell subsets were identified (Fig. 3C, Supplementary table S1), the majority of
- 219 which were consistent with the RV254 cohort from Thailand. In this cohort we expanded scRNA-seq
- analyses to all available participants with not only detectable or undetectable reservoir, but also the
- 221 middle group by using HIV DNA measurements as a continuous variable in the MAST statistical

222	framework ²⁹ . CD14+ monocytes had the greatest number of DEG associating with differences in
223	reservoir size (Fig. 3D). IL1B in this single-cell MAST analysis was significant in CD14+ monocytes
224	and validated the directionality seen in the RV254 cohort (coefficient = -0.13 , P = $5.1e-34$). A
225	categorical analysis of all 38 participants showed an independent significant association of <i>IL1B</i>
226	between the extremes as a continuum (p=0.006), but not THBS1, with reservoir size (Fig. 3E). Thus,
227	regardless of viral subtype (B or CRF01_AE) or host background (Black, White, Thai), <i>IL1B</i> expression
228	in monocytes had a significant inverse association with HIV reservoir size in both the discovery and
229	replication cohorts. Further, IPDA® measurements of the persistent proviruses that comprise the
230	reservoir were available in a subset of the ACTG A5354 study (n=21), where intact or defective
231	proviruses could be analyzed separately. Significantly higher frequencies of persistent intact proviruses
232	compared to defective proviruses after 48 weeks of ART initiation were observed in this cohort of
233	PLWH treated during AHI (Fig. 3F). Participant-specific analyses of <i>IL1B</i> expression showed an inverse
234	correlation with different forms of proviruses (Fig. 3G). Notably, when we harnessed the power of
235	single-cells using the MAST framework for continuous analyses, the inverse IL1B association was
236	significant across most forms of the persistent provirus as measured by IPDA®, showing that findings
237	were valid across total, intact and defective proviruses (Fig. 3G).

238

239 Transcriptional programs implicated NF-KB with the differences in HIV-1 reservoir size

240 Given these significant effects of individual monocyte genes on reservoir size, we explored the broader

241 consequences of transcriptional changes in monocytes using unbiased weighted gene co-expression

- 242 network analyses (WGCNA) and identified nine modules of co-expressed genes within CD14+
- 243 monocytes from RV254 (Fig. 4A). The second largest module, M3, was significantly more highly
- expressed in the original Thai cohort from participants with an undetectable reservoir and contained 452

245 genes, including *IL1B* (P_{adjusted}<5e-324, Fig. 4B). Comparing expression between the detectable and 246 undetectable groups in the independent A5354 cohort using the M3 module genes identified in the Thai 247 cohort, we confirmed that this module was similarly enriched in the cells from the undetectable group 248 (P_{adjusted}= 1.3e-55, Fig. 4C). There were no other modules that were significantly associated with the 249 reservoir size in both studies. Expression of the top 25 hub genes in this M3 module was generally 250 higher in the undetectable than in the detectable reservoir group in both cohorts (Fig. 4D). The strength 251 of this signature was further reinforced by the predicted interaction of the genes at the protein level (Fig. 252 4E). Gene ontology analyses showed that genes in the M3 module were enriched in several pathways, 253 including regulation of apoptosis and NF-kappa B (NF-κB)(Fig. 4F). TNFα signaling via NF-κB had the 254 largest membership of genes from the M3 module. Complementing the findings in CD14+ monocytes, 255 once again the same signaling pathway was also enriched in a module that was highly expressed in the 256 undetectable reservoir group in the memory CD4+ T cell subset, suggesting an effect on NF-κB 257 signaling in the cell population which harbors the latent reservoir (Fig. S6). These pathways are 258 consistent with the *IL1B* findings, suggest a broader change in the inflammatory homeostatic state, and 259 may define a coordinated transcriptional change that accompanies *IL1B* expression differences which 260 associate with reservoir size.

261

262 IL1B activates NF-κB, enhancing productive HIV infection while inhibiting viral spread in vitro

263 Binding of IL1B to its IL1 receptor induces a signaling cascade ultimately leading to the activation of

264 NF-κB³⁰. This transcription factor plays a key role in LTR-mediated transcription of proviral DNA, and

its stimulation is well known to reactivate latent HIV-1 ^{31,32}. Thus, we explored whether activation of

266 NF-κB in CD4+ T cells could explain why increased monocyte *IL1B* expression could reduce the size of

267 the latent HIV reservoir. To assess whether IL1B activates NF-κB, we treated A549 NF-κB reporter

268	cells, which express the secreted embryonic alkaline phosphatase (SEAP) reporter gene under the
269	control of the IFN- β minimal promoter fused to five NF- κ B binding sites, with IL1B, TNF α , LPS or
270	medium only. We observed that IL1B increased NF-κB activity ~4-fold regardless of HIV-1 infection
271	status (Fig. 5A). Next, we examined the ability of IL1B to activate NF-κB in primary human T cells.
272	Degradation of inhibitory IkB proteins is a critical step in the activation of NF-kB, and their
273	phosphorylation one of the earliest and most specific events in this process. Treatment with IL1B
274	increased IkB phosphorylation and strongly reduced the overall levels of inhibitory IkB indicating
275	activation of NF-KB (Fig. 5B).
276	To more directly determine the impact of IL1B on latent and productive HIV-1 infection, we
277	used the HIV molecular clone pMorpheus-V5, which lacks a functional env gene but encodes all
278	accessory proteins ³³ . Cells productively infected with pMorpheus-V5 express V5-NGFR (Nerve
279	Growth Factor Receptor) driven by the PGK (phosphoglycerate kinase) promoter, as well as HSA and
280	mCherry driven by HIV-LTR, while latently infected cells express only V5-NGFR. Activated PBMC
281	from three healthy donors were treated with IL1B prior to, simultaneously, or after transduction with
282	pMorpheus-V5 pseudo-typed with the Env proteins of WT X4-tropic NL4-3, an R5-tropic derivative
283	thereof ³⁴ , and the dual R5X4-tropic CH078 transmitter-founder strain ³⁵ . The frequencies of latently
284	infected cells were generally lower compared to productive infection and in most cases not significantly
285	altered by IL1B treatment. In contrast, the number of productively infected cells increased significantly
286	(P < 0.05) for all 3 viruses when exposed to IL1B treatment during or 2 days prior to infection (Fig. 5C).
287	NF-kB plays a complex role in HIV infection because it not only activates LTR transcription but
288	also plays a key role in innate immunity and induces expression of numerous antiviral factors ^{36,37} .
289	Indeed, pretreatment of stimulated PBMC with IL1B for two days resulted in a dose-dependent decrease
290	in infection with the R5-tropic YU-2 virus as determined by the frequencies of sorted p24+ CD4+ T

291 cells (Fig. 5D, S7A). To further explore the effect of IL1B on spreading HIV-1 infection, stimulated 292 PBMC from five donors were treated with IL1B prior to, at the same time, or after infection with HIV-1 293 NL4-3 or the transmitted founder CH058 molecular clone. Infectious virus production at 2, 4, 6 and 9 294 days post-infection was determined by p24 ELISA and infection of TZM-bl indicator cells. Infectious 295 virus yields peaked at day 4 in most of the infected PBMC cultures (Fig. S8). Two-day pretreatment 296 with IL1B generally reduced viral replication compared to the untreated controls. Both infectious virus 297 and p24 antigen production by NL4-3 and (more strongly) the primary CH058 strain were significantly 298 (P < 0.05-0.001) reduced at 4 days post-infection (Figs. 5E, 5F, S8). In comparison, only modest effects 299 were observed when IL1B was added during or after infection, presumably because the induction of an 300 antiviral state requires de novo synthesis of antiviral factors. Notably, the levels of cell death were low 301 and did not differ significantly from the uninfected control (Fig. S9).

302 IL1B is also known to affect the differentiation of CD4+ T cells into various subsets ³⁸ that may 303 differ in their susceptibility to HIV-1 infection. Notably, in the YU-2 infected cultures over 95% of p24+ 304 cells expressed the CD45RO memory T cell marker, consistent with previous reports ^{39,40}, and p24+ 305 populations exhibited higher frequencies of both CD4+ T effector memory and transitional memory 306 subsets (CD4+ T_{EM} and CD4+ T_{TM}, respectively) compared to the p24- populations (Fig. S7B-C). These 307 findings underscore the importance of subset phenotypes for HIV infection and suggest that IL1B could 308 alter the frequencies or phenotypes of HIV-susceptible CD4+ T cell subsets to modulate HIV reservoir 309 size. We observed an IL1B dose-dependent increase in the frequency of CD4+ T_{CM} , accompanied by 310 decreases in the frequencies of both CD4+ T_{TM} and CD4+ T_{EM}, when PBMC from healthy participants 311 were cultured in vitro (Figs. S10A-B). Altogether, our in vitro data suggest that IL1B could decrease the 312 HIV reservoir size in vivo through multiple mechanisms, including by promoting NF- κ B mediated

activation of latent HIV, inducing innate antiviral factors and changing the composition of T cellpopulations (Fig S11).

315

316 **DISCUSSION**

317 In this study, we used an unbiased high throughput single-cell approach to identify differences in host 318 transcriptional profiles that associate with the size of the viral reservoir in acutely treated PLWH by 319 screening extreme phenotypes of reservoir size. Recent single-cell transcriptomic studies have focused 320 on the effects of differentially expressed host genes specifically in CD4+ T cells from PLWH on treatment ^{20,41}, but it is important to also examine other cell populations that might influence the viral 321 322 reservoir. We observed significant differences in the gene expression profiles of multiple immune cell 323 subsets even after almost one year of complete viral suppression on ART, distinguishing participants 324 with variably-sized viral reservoirs, which were conserved across two cohorts comprising a total of 52 325 individuals and encompassing multiple host and viral genotypes. Significant differences were discovered 326 in part due to accounting for potential confounders by selecting participants matched for Fiebig stage at 327 the time of ART initiation, viral subtype, and sex prior to examining gene expression in single cells from 328 participants in the Thai discovery cohort. These differences were generalizable to a subtype B cohort 329 comprised of participants with greater variability and having IPDA® reservoir measurements. 330 Frequencies of defective viruses in the ACTG study were lower than intact proviruses when measured 331 by IPDA® which is not surprising considering the timing of sampling after ART initiation ⁴²⁻⁴⁶. 332 Regardless, the single-cell association of *IL1B* with reservoir size remained significant with different 333 reservoir measures. These findings were also enabled by the use of scRNA-seq with its advantage 334 compared to bulk transcriptomics that gene expression differences can be traced to specific cells rather 335 than to "averaged" signals from heterogeneous populations.

336

337	We found that monocytes, specifically the CD14+ subset, showed the highest number of enriched
338	pathways and DEGs, with IL1B being associated with differing reservoir sizes in two independent
339	cohorts using various measurements of total, defective, and intact proviruses. IL1B is a potent
340	proinflammatory cytokine ⁴⁷ , expressed in cells such as monocytes, neutrophils, B cells, and DCs, that is
341	involved in a variety of cellular activities. Though <i>IL1B</i> was the most significant DEG, we also detected
342	a network of coexpressed genes that support a coordinated change in the monocyte transcriptional
343	profile. Together, these findings are consistent with our previous observations that monocytes can play
344	an important role both after vaccination and after treatment initiation when virus is suppressed ⁴⁸ . In
345	addition to assessing differences in host gene expression, frequencies of all major cell populations
346	comprising PBMC were assessed by surface protein-based flow cytometry. These frequencies were
347	evaluated in the context of scRNA-seq gene expression for potential combined effects on peripheral
348	blood reservoir size. Of the 117 immune population frequencies assessed by flow cytometry, only CD4+
349	T _{CM} and its subsets were associated with a smaller reservoir size when <i>IL1B</i> expression levels in CD14+
350	monocytes were high. Interestingly, this is supported orthogonally by a recent report that CD4+ T_{CM}
351	host the smallest quantity of intact proviruses compared to naïve and other memory subsets ^{7,49} . Our
352	findings suggest a link between DEG in monocytes from different extreme reservoir size phenotypes and
353	a specific CD4+ T cell subset previously implicated as harboring the latent HIV reservoir.
354	How exactly IL1B expression levels in monocytes influence the reservoir in vivo remains to be
355	determined. However, IL1B-mediated activation of NF-κB is well established ^{30,50} and may explain the
356	link between increased IL1B expression in CD14+ monocytes and a reduced latent HIV reservoir size
357	(Fig. S11). Besides IL1B, TNF α is one of the strongest endogenous inducers of NF- κ B and the pathway

358 "TNF α signaling via NF- κ B" had the largest number of enriched genes in the M3 and M4 modules in

359 CD14+ monocytes and memory CD4+ T cells, respectively. The key role of NF-κB in proviral HIV-1 360 gene expression has been known for decades. However, NF-kB also plays key roles in immunity and 361 inflammation, inducing numerous antiviral factors ^{36,37}. Notably, NF-κB activates LTR transcription 362 directly, while inhibitory effects require de novo synthesis of antiviral factors. Thus, HIV-1 and 363 lentiviruses tightly regulate NF- κ B activity to enable viral transcription while minimizing antiviral gene expression 51-53. The induction of innate antiviral immunity by NF- κ B may reduce viral reservoir 364 365 seeding during acute infection. However, induction of proviral transcription by NF-kB is likely the more 366 important mechanism in ART treated individuals, where viral replication is effectively suppressed and 367 induction of productive infection renders the latent reservoir susceptible to elimination. IL1B, TNF α and 368 NF- κ B all play complex roles in the survival, activation, and differentiation of T cells and other immune 369 cells ³⁸. Thus, they may also impact the frequency of reservoirs harboring cells by more indirect 370 mechanisms, such as shifts in the T cell subtype composition or cell survival. IL1B is best known for its 371 role as a secreted cytokine. In some cases, however, it may also act in a cell-associated manner and the 372 potential of IL1B-expressing CD14+ monocytes warrants further investigation. Notably, latency 373 reversing agents that stimulate NF-kB have been extensively studied in shock-and-kill approaches and 374 shown to reactivate HIV-1 from latency in both CD4+ T cell latency models and HIV-1-infected patientderived cells ⁵⁴⁻⁵⁶. Thus, it is tempting to speculate that, similar to TNFα, IL1B acts as a natural NF-κB 375 376 inducing latency-reversing agent.

In addition to the strongest effect observed of higher *IL1B* levels, we also detected that *THBS1* in CD14+ monocytes associated with a smaller reservoir of infected cells. The association of *THBS1*, encoding for thrombospondin, with reservoir size was only observed in the RV254 Thai cohort, and not validated in A5354 participants from the USA, most likely attributable to differences in genetic ancestry and so our mechanistic analyses focused on *IL1B*. However, population specific associations are

17

382 important and further studies are warranted to understand the effect of *THBS1* on reservoir size given 383 that anti-HIV properties have been attributed previously ⁵⁷. Similarly these studies were limited to AHI 384 cohorts and exploration in the context of untreated chronic infection is also necessary. Another 385 limitation to this unbiased single-cell approach is that it lacks equal power to detect effects across all 386 cellular subsets and could miss effects in populations less frequent than monocytes. Additionally, how 387 other monocyte genes or additional factors interact in vivo to influence the decreased reservoir size 388 observed in participants with increased monocyte *IL1B* remains to be investigated further. Though intact 389 proviral DNA measurements are still being adapted for use beyond subtype B⁴² and therefore were not 390 available for participants in the RV254 cohort, we were able to bridge our findings by leveraging 391 IPDA® measurements of persistent intact and defective proviruses in the ACTG A5354 cohort. 392 Although the strength of the associations differed, *IL1B* remained inversely associated with smaller 393 reservoir size regardless of proviral intactness. It is plausible that different host factors exert effects 394 depending on the form of the provirus and raises the need for additional in-depth investigations. 395 Overall, our findings support that immune cells other than T cells can modulate the HIV 396 reservoir in a clinical cohort, and that this effect may be influenced by specific genes and pathways. 397 These findings were based on unbiased single-cell approaches and give rise to new hypothesis-driven 398 questions that should be tested in other cohorts, where further confirmation of host cellular gene 399 products and pathways involved in reservoir formation or maintenance may provide targets for 400 therapeutic intervention and remission strategies. In particular, our implementation of single-cell 401 approaches that are unbiased and allow broad screening for effects that impact reservoir size in ART 402 treated individuals in vivo suggests that IL1B-induced NF- κ B dependent mechanisms for induction of 403 proviral transcription may represent latency reversing strategies which could be effective in vivo.

404

18

405 MATERIALS AND METHODS

406 Study design

- 407 Demographic and clinical data (viral load, CD4+ T cell counts, HIV DNA, HIV subtype, Fiebig stage)
- 408 were available from 163 acutely-treated PLWH from the men who have sex with men (MSM)
- 409 RV254/SEARCH010 cohort (NCT00796146) in Thailand ^{13,24,58}. For discovery analyses, scRNA-seq,
- 410 immune receptor sequencing (TCR and BCR), and flow cytometry were performed on initially
- 411 cryopreserved PBMC from 14 selected participants in this cohort and validated in an additional 38 male
- 412 participants from the ACTG A5354 study (NCT02859558), a single-arm, open-label study to evaluate
- 413 the impact of ART initiation during AHI conducted at 30 sites in the Americas, Africa, and Asia.
- 414 Samples from all participants were collected at 48 weeks post-ART initiation. In a subset of participants
- 415 samples were also available from week 0 at AHI. Blood from healthy participants without HIV for in
- 416 vitro experiments was obtained from the WRAIR 2567.05 protocol. All participants provided informed
- 417 consent, and use of samples for research was approved by institutional review boards in Thailand and
- 418 the USA.
- 419

420 HIV Reservoir measurements

Total HIV DNA and integrated DNA were measured by quantitative PCR (qPCR) as described
previously ^{14,28}. Briefly, pellets of PBMC or CD4+ T populations were suspended in 15ul of Proteinase
K lysis buffer per approximately 100,000 cells, and digested for 18h at 55°C. Total HIV DNA was
quantified using primers and a probe situated in the 5'-LTR, while primers and probe used for integrated
DNA were situated in Alu and the 5'- LTR. ACH-2 cells, which carry a single copy of the integrated
HIV genome, were used to generate a standard curve for both assays. The cell input for each of the three
replicates was approximately 100,000 per replicate (~300,000 total) and the lower limit of detection of

428	this assay was 3.3 copies/10 ⁶ cells. Participants were grouped into detectable or undetectable reservoir
429	based on the presence of total HIV and integrated viral DNA measured independently in both PBMC
430	and CD4+ T cell populations, depending on sample availability for the latter. Presence of integrated HIV
431	DNA was used as a criterion for defining the categorical groupings. The reservoir phenotype was
432	defined as undetectable when both total and integrated HIV DNA were below the LOD. In contrast, the
433	reservoir was defined as detectable when total HIV DNA > LOD.
434	
435	IPDA
436	Accelevir Diagnostics performed HIV-1 intact proviral DNA assays (IPDA®) to discriminate between,
437	and separately quantify, the frequencies of intact and defective persistent proviruses. The design and
438	performance of this assay have been described previously ^{42,59} . Briefly, cryopreserved PBMC were
439	thawed and CD4+ T cells were isolated and assessed for cell count, viability, and purity by flow
440	cytometry. RNA-free genomic DNA was then isolated from the recovered CD4+ T cells, with
441	concentration and quality determined by fluorometry and ultraviolet-visible (UV/VIS)
442	spectrophotometry, respectively. The IPDA® was performed, and data reported as proviral frequencies
443	per million input CD4+ T cells. These procedures were performed by blinded operators using standard
444	operating procedures.

445

446 Single-cell RNA library generation and sequencing

447 PBMC from the 14 RV254 participants on ART for 48 weeks were washed, resuspended in PBS plus

448 0.5% FBS, and simultaneously processed for scRNA-seq and flow cytometry. A total of 50,000 cells (at

449 1,000 cells/ul) from each donor were set aside for scRNA-seq library construction and the remaining

450 cells were used for flow staining as described later. The diluted PBMC suspensions were prepared for

451 scRNA-seq using the Chromium Next GEM 5' Single Cell V(D)J Reagent Kit and the Chromium 452 Controller (both 10x Genomics) per manufacturer's instructions. Briefly, targeting a recovery of 8,000 453 cells/donor, samples were loaded into separate wells of Chromium chips. Amplified cDNA was used to 454 make gene expression (GEX), TCR, and BCR libraries. The GEX library construction used a 14 or 16 455 cycle Sample Index PCR program, based on amplified cDNA concentrations. PBMC from the 38 A5354 456 participants were individually stained with TotalSeq-C anti-human hashtag antibodies (BioLegend), 457 batched, and processed for gene expression (GEX) and hashtag oligo (HTO) libraries as previously described to improve cost-effectiveness ²⁶. Cells from each batch were loaded into 4 different wells of 458 459 Chromium chips for targeted recoveries of 16,000 cells/well. 460 Libraries from both studies were then assessed for quality and concentrations using the DNA High 461 Sensitivity D5000 ScreenTape Assay with the TapeStation (both Agilent, CA), and subsequently pooled 462 and quantitated with a MiSeq Nano Reagent Kit v2 (300 cycles) (Illumina, CA) sequencing run. Final 463 libraries were sequenced using the NovaSeq 6000 S4 Reagent Kit (300 cycles) on a NovaSeq 6000 464 instrument (both Illumina). 465 466 **Multiparameter flow cytometry**

467 PBMC from 14 participants were stained with Aqua Live/Dead stain (Molecular Probes), washed, and 468 blocked using normal mouse IgG (Caltag). The cells from each donor were then split into four to run 469 four different polychromatic flow panels using conjugated fluorescently labeled monoclonal antibodies 470 against several surface markers to define B, T, Myeloid, and NK cell subsets (Extended table 2). For the 471 T cells panel, cells were pre-stained with an MR-1 tetramer ⁶⁰ prior to staining for additional surface 472 markers. Following surface marker staining, cells were washed, permeabilized and fixed with FoxP3 473 Fixation/Permeabilization Set (eBiosciences). Cells were then washed, stained intracellularly, washed 474 again, and analyzed using a BD FACS Symphony A5. Data were analyzed with FlowJo v.9.9.6 or higher
475 (Becton Dickinson).

476

477 Virus production

478 HEK293T cells were transfected with NL4-3, CH058 and pMorpheus-proviral constructs using the

479 TransIT-LT1 (Mirus) transfection reagent per manufacturer's protocol. Infectious molecular clones of

480 HIV CH058 and CH077 were kindly provided by Beatrice H. Hahn ^{52,61}. Media were changed 24h post

481 transfection and virus stocks were collected 24h later. PBMC were infected with freshly produced virus.

482 The HIV YU-2 infectious molecular clone stock was obtained from the HIV Reagent Program.

483

484 In vitro functional characterization

<u>Effects of IL1B on cell population frequencies and HIV infection</u>: PBMC were isolated from the blood
of healthy donors by density centrifugation on a Ficoll-Paque gradient (GE Healthcare) and stimulated
by anti-CD3/CD28 Dynabeads at a 1:1 ratio with the estimated CD4+ T cell population in PBMC (25%)

488 in total PBMC) in Complete Cell Culture Medium (RPMI Medium, GlutaMAX supplemented HEPES

489 with 10% fetal bovine serum, penicillin/streptomycin) (all Gibco) supplemented with 40 U/ml IL2 and

490 with or without recombinant IL1B at four different concentrations (0.01-10 ng/ml, at 10-fold intervals)

491 (both R&D Systems) for 4 days. Treated PBMC were either immediately analyzed by flow cytometry to

492 assess frequencies of T cell subpopulations, or infected with an R5 tropic molecular clone, YU-2, at a

493 concentration of 1 µg of p24 per million cells and cultured for a further two days before assessing the

494 relative frequencies of infected cells by flow cytometry.

495

496 <u>Effects of IL1B on HIV infectivity</u>: PBMC isolated from healthy donors were treated with 10 ng/ml
497 IL1B concentrations at different times relative to HIV infection initiation: pre-treated 2 days prior to

498 infection, added simultaneously, or added 2 days post-infection. Briefly, PBMC were isolated by Ficoll 499 gradient centrifugation and cells were stimulated by PHA in Complete Cell Culture Medium with 100 500 U/ml IL2 for 3 days. On day 1 post-isolation the required cells were set aside for IL1B treatment for 2 501 days prior to infections. On day 3 post-isolation, PBMC were infected by spinoculation (1200 xg, 2 h, 502 26°C) with 150 ng of freshly produced NL4-3, or 500 ng of CH058 virus strains, per million cells. After 503 spinoculation cells were washed 5 times with 1x PBS and resuspended in fresh medium containing IL2 504 and IL1B per the schedule. Cells were cultured for an additional 9 days during which 400 µl of 505 supernatant was removed every second day for determination of infectious virus yields. To determine 506 infectious virus yield, 10,000 TZM-bl reporter cells per well were seeded in 96-well plate. The next day 507 cells were infected in triplicate for 9 days with the collected supernatants. Three days post infection the 508 TZM-bl cells were lysed and *b-galactosidase* reporter gene expression was assessed with the GalScreen 509 Kit (Applied Bioscience) per manufacturer's protocol using an Orion microplate luminometer 510 (Berthold).

511

512 Flow cytometry staining of pMorpheus infection

513 PBMC infected with pMorpheus were collected on day 5 post-infection and stained for membrane 514 marker V5 and viability. Cells were harvested, washed 3x with PBS and resuspended in surface staining 515 of V5 and viability dyes (V5 Alexa Fluor 647; eBioscience fixable viability dye efluor 780; both 516 Thermo Fisher Scientific). After 30 min incubation, cells were washed 3x with PBS, fixed with 4% PFA 517 for 30 min and analyzed by flow cytometry.

518

519 Western blotting

520	PBMC were isolated as described and cultured for 3 days with IL2 and PHA. On day 3 cells were
521	treated with IL1B (10 and 50 ng/ml) and TNF α (10 ng/ml) for 1, 1.5, and 2 hr. Cell lysates were
522	prepared and western blotting was performed as described previously ⁶² . Proteins were stained with the
523	following primary antibodies: phospho-IkBa (Cell Signaling), IkBa (Santa Cruz), GAPDH
524	(BioLegend).
525	
526	NF-KB reporter assay
527	A549-Dual TM Cells (InvivoGen) were seeded at a density of 20,000 cells per well on 96-well plates.
528	Cells were treated on the following day with IL1B (10 ng/ml), TNFa (10 ng/ml), LPS (1000 U/ml) and
529	infected or not with VSV-G pseudotyped HIV-1 NL4-3 or CH058 for 24h when the Quanti Blue assay
530	was performed as described by the manufacturer (Invitrogen).
531	
532	Viability assay
533	Cells were harvested, washed once with PBS and stained for 15 min at RT in the dark with eBioscience
534	fixable viability dye 780 (Thermo Fisher Scientific). Cells were then washed twice with PBS, fixed in
535	2% PFA for 30 min at 4 °C and analyzed by FACs.
536	
537	Bioinformatics analyses
538	Sequence data processing: Single-cell gene expression data from PBMC were generated using the 10x
539	Genomics Cell Ranger pipeline (v3.0.0 - 3.1.0) (10x Genomics) per manufacturer's recommendations
540	and the 10x Genomics human reference library (GRCh38 and Ensembl GTF v93). For the RV254
541	sequencing run without hashing, the average number of genes per cell was 1,236 and the average

542 number of unique molecular identifiers (UMI) was 3,288. The mean read depth per cell was

543	approximately 103,000-236,000 reads. The minimum fraction of reads mapped to the genome was
544	92.95% and sequencing saturation was on average greater than 94%. For the hashed A5354 sequencing
545	runs, the average number of genes per cell was 1,432 and the average number of UMIs for RNA
546	transcripts was 4,192. The mean read depth per cell was approximately 69,000-88,000 reads for the gene
547	expression library and 9,000-14,000 reads for the antibody library. The minimum fraction of gene
548	expression reads mapped to the genome was 88.5% and RNA sequencing saturation was on average
549	greater than 89%. Downstream analysis of Cell Ranger outputs including quality filtering,
550	normalization, multi-sample integration, visualization, and DEG were performed using the R package
551	Seurat (v3.1.1 - 4.3.0).
552	RV254 gene expression processing: Cells with mitochondrial percentages greater than 10% and cells
553	that had <200 or >6,000 expressed genes were removed from analyses. 62,925 cells remained after the
554	quality control (QC) process. After log-normalization with a scale factor of 10,000, the top 2000
555	variable features within each sample were selected. We found integration anchors using dimensions 1:30
556	and integrated cells from all 14 participants. Shared Nearest Neighbor-based (SNN) clustering was
557	performed using the top 30 principal components (PC) with a resolution of 0.5, and cells in the clusters
558	were visualized by UMAP projection. Cluster marker genes were determined using Seurat
559	FindAllMarkers and cluster identities were manually annotated using differentially expressed genes
560	between the clusters and known lineage cell markers.
561	A5354 demultiplexing and gene expression processing: HTO expression matrices were normalized,
562	demultiplexed, and assigned to specific participants using the methods described ²⁶ . Negative cells and
563	cells with greater than 10% mitochondrial gene expression were removed. Gene expression matrices
564	(containing a total of 21,870 genes) for all 38 participants and for doublet cells were normalized. We
565	performed reference-based integration using two participants from each ADT batch as the references.

566 Cells that were identified as doublets via hash demultiplexing and cells in clusters from an initial round 567 of QC that were enriched for doublets or had high expression of HBB were removed and SNN clustering 568 at resolution 0.3 was performed on the remaining 140,172 cells. Clusters were visualized and annotated 569 using lineage markers and differentially expressed genes similar to the process for RV254. No γδ T cell 570 or monocyte-platelet aggregation clusters were identified, and CD4+ memory T cells were comprised of 571 one large cluster and one smaller cluster with upregulation of interferon-induced genes, instead of 572 subsets of CD4+ T cells as observed in RV254. 573 Differential gene expression: Categorical differential gene expression analyses within each cell type 574 subset between the two reservoir groups was performed within Seurat using a Mann-Whitney U test 575 with Bonferroni correction (n=19,581). Genes that were not expressed in at least 10% of cells in either 576 group or that did not have a log fold change of >|0.25| were excluded from consideration, as were 577 mitochondrial and ribosomal protein genes. The MAST framework was implemented to examine 578 correlation of gene expression of different cell subsets with the continuous total HIV DNA 579 measurements as the outcome 29 . Genes with expression frequencies <10% were removed before 580 analyses. Results from each cell subset were corrected for multiple testing using the Bonferroni 581 correction. Genes without a beta coefficient > |0.1| and additional manually curated genes were excluded 582 from consideration. Continuous MAST analyses for a subset of 21 participants with IPDA® data was 583 performed to see if *IL1B* remained significant using different reservoir measurement parameters. 584 Participant-specific expression values were generated for certain genes using Seurat's 585 AverageExpression in CD14+ monocytes within participants on the log-normalized expression data. 586 TCR/BCR sequence analyses: TCR/BCR clonotype identification, alignment, and annotation were

587 performed using the 10x Genomics Cell Ranger pipeline (v6.1.2; 10x Genomics) per manufacturer's

588 recommendations. Clonotype alignment was performed against the Cell Ranger human V(D)J reference

589 library 7.1.0 (GRCh38 and Ensembl GTF v94). The Cell Ranger clonotype assignments were used for 590 both BCR and TCR Clonotype visualization and diversity assessments, and analyses were performed 591 using R for IG chains within annotated B cell types (memory B cells, naïve B cells) or TRA/TRB chains 592 within annotated T cell types (CD4+ or CD8+ T_{CM}, T_{EM}, and naïve T cells). 593 Pathway analyses: Further DEG lists characterizing the detectable and undetectable reservoir groups 594 within cell subsets from RV254 were used to perform a multiple gene list analyses in Metascape to 595 acquire the top 20 representative terms of the most significant enriched pathways ⁶³. The genes 596 comprising each of these 20 pathways were used as input lists to perform Gene Set Enrichment Analysis (GSEA)⁶⁴ when comparing the detectable and undetectable groups, along with an average expression 597 598 matrix of all genes within each cell subset for each participant that was generated from the single-cell 599 data. The GSEA results were filtered by normalized enrichment score (NES) $\geq |1.4|$, P < 0.001. For 600 WGCNA-based pathway analyses, the CD14+ monocyte cell subset of the RV254 cohort Seurat object 601 was used as input for coexpression analyses implemented in the single-cell R package, hdWGCNA ^{65,66}. 602 Metacells and a signed network were constructed within participants using non-default parameters 603 (k=25, max shared=10 and soft power=9). The top 25 hub genes for each of the resulting modules were 604 used as a feature set for Seurat's AddModuleScore to generate a score for each module within each cell. 605 The Mann-Whitney U test was used to compare expression of the module scores between cells in the 606 detectable and undetectable reservoir categories. This module scoring and testing method for the same 607 sets of genes from RV254 was applied to the CD14+ monocyte cell subset in the independent A5354 608 cohort. Average scaled expression of the 25 hub genes from the M3 module containing IL1B within both 609 cohorts was used as input for the ComplexHeatmap tool ⁶⁷. Similarly, gene modules were identified in total CD4+ memory T cells and gene ontology analyses were performed using Enrichr⁶⁸. The 25 hub 610 611 genes for the M3 CD14+ monocyte module were used as input in a protein STRING DB pathway

- analysis ⁶⁹. The disconnected nodes were removed and the resulting network was investigated for degree
 of connectedness and visualized in Cytoscape ⁷⁰.
- 614

615 Statistical analyses

616 The associations between 117 phenotypic flow cytometry population frequencies and reservoir size were 617 assessed by univariate linear regression models and corrected for multiple testing using false discovery 618 rate (FDR). Exploratory analyses including multiple regressions without adjusting for significance were 619 also performed to evaluate the relationship between the reservoir size as the response variable and two 620 explanatory variables: THBS1/IL1B and each flow cytometry cell population. Finally, multiple 621 regression models were fitted with two-way interaction terms between *THBS1/IL1B* and each 622 phenotypic population marker, to test whether the effect of THBS1/IL1B on decreased reservoir size 623 differed depending on the frequencies of individual cell subsets. Interaction plots for THBS1/IL1B were 624 made to illustrate how the relationship between THBS1/IL1B expression and reservoir size changes with 625 different frequencies of combined CD4+ T_{CM}. The overall fitness of the simple regression models of the 626 combined CD4+ T_{CM} population was evaluated using the coefficient of determination, R-squared value (R^2) , and Root Mean Squared Error (RMSE). For multiple linear regression of the CD4+ T_{CM} cells, the 627 goodness-of-fit was measured using both R² and Adjusted-R² along with RMSE. The prediction error of 628 629 the combined CD4+ T_{CM} cell models was estimated using Leave One Out Cross Validation (LOOCV) 630 and the test RMSE value was reported. Assessment of model diagnostics (Q-Q plot for normality, 631 residuals vs. fitted values for homoscedasticity, leverage plots for influential observations, variance 632 inflation factors for multicollinearity; not shown) showed that the assumptions of the linear models were 633 reasonable after removing one outlier. All explanatory variables for all regression analyses were mean 634 centered.

635	All paired comparisons were performed by paired T test, when the assumptions were met, or the
636	Wilcoxon signed-rank test, while unpaired comparisons were performed by the Mann-Whitney U test.
637	Correlations were performed by Spearman's rank correlation coefficient. A two-sided P value of <0.05
638	was considered statistically significant for all statistical analyses. Bonferroni or FDR corrections were
639	applied for multiple testing when appropriate. All descriptive and inferential statistical analyses were
640	performed using R 3.4.1 GUI 1.70 build (7375) v3.0 and higher, and GraphPad Prism 8.0 statistical
641	software packages (GraphPad Software, La Jolla CA).
617	

642

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- 673 Data availability: All scRNA-seq gene expression data has been submitted to the GEO repository with
- 674 accession number (GSE220790, GSE256089). Code is available in the Figshare database.
- 675 List of Supplementary Materials
- 676 Figures S1 to S11
- Tables S1 to S5
- 678 Data files 1-2
- 679 **REFERENCES**

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856	855		interaction networks. <i>Genome Res</i> 13, 2498-2504 (2003). <u>https://doi.org/10.1101/gr.1239303</u>
	856		

857

858 FIGURE LEGENDS

859 860

861	Figure 1. Characteristics of study participants and experimental design. A) Distribution of total
862	HIV DNA in Fiebig stage III participants in RV254 at week 48 after ART initiation and their
863	categorization into three groups based on reservoir size. B) Selected participants from Fiebig stage III
864	with extreme reservoir size phenotypes (undetectable = below LOD and detectable = high) of cell-
865	associated total HIV DNA in the RV254 Thai discovery cohort (n=14). Significance was determined by
866	the Mann-Whitney U test. C) Total HIV DNA decay between weeks 0 (AHI) and 48 (after ART
867	initiation). D) Phenotypes of participants comprising the detectable versus undetectable reservoir size
868	categories. Mean values are shown for each group, NS: not significant. E) Single-cell RNA-seq and
869	multiparameter flow cytometry were performed on all 14 participants. Additional validation by scRNA-
870	seq was performed in an independent AHI cohort from the USA (A5354) (n=38).

871

872 Figure 2. Differentially expressed genes in monocytes associate with HIV reservoir size during

873 ART. A) scRNA-seq identified 24 unique clusters of immune cell subsets. B) CD14+ classical 874 monocytes have the highest number of DEG between the detectable and undetectable reservoir groups. 875 Circle color represents cell subset while circle size indicates corresponding cell number. C) Volcano plot 876 shows DEG in all cell types with p values that are significant after correction, as indicated above the 877 horizontal dotted line. Labeled genes have a p<10e-6 and absolute average log_e fold change \geq 1 (vertical 878 dotted lines) or p<10e-100 and absolute average log_e fold change ≥ 0.5 . D) The most significant DEG in 879 CD14+ monocytes comparing reservoir groups. Black dots represent the median normalized gene 880 expression values (log_e), and lines represent the interquartile ranges. Teal: undetectable reservoir, red: 881 detectable reservoir. Significance was determined by the Mann-Whitney U test with Bonferroni

correction (n=14). E) Participant-specific categorical analyses of the most significant DEGs. Normalized
gene expression within CD14+ monocytes was averaged per participant and correlation was determined
by the Spearman test (n=14). F-G) Interaction plots of multiple regression between *THBS1 or IL1B*expression in monocytes and reservoir size with varying frequency of the CD4+ T_{CM} population.
Nominal p values are indicated for the interaction analyses.

887

888 Figure 3. Validation of *IL1B* association with smaller reservoir size from an independent cohort 889 with a different infecting viral subtype across various Fiebig stages. A) HIV DNA levels vary within 890 the A5354 subtype B cohort from the USA (n=38). The participant samples used in this study are 891 highlighted based on reservoir size: red=detectable; teal=undetectable and yellow=middle. Black and 892 White indicate differences in ancestry of the participants. B) Characteristics of participants comprising 893 the detectable, middle, and undetectable reservoir size categories (mean values are shown) and p values 894 comparing the extreme phenotype groups. HIV-1 subtype information was only available for a subset of 895 the participants. NS: not significant C) Dimensionality reduction plot of the different immune clusters in 896 this cohort. D) CD14+ monocytes have the highest number of normalized DEG associated with reservoir 897 size using a continuous analysis including all 38 participants. E) IL1B participant-specific average gene 898 expression in CD14+ monocytes categorized by total HIV DNA (n=38). Spearman correlation p value 899 and rho are shown. F) IPDA® measurements from a subset of the participants in this cohort (n=21). G) 900 *IL1B* association with different reservoir type measurements (rows) from the participants with IPDA 901 measurements (n=21).

902

Figure 4. Pathway analyses identifies a distinct signature associating with reservoir size. A) Gene
co-expression modules in CD14+ monocytes from the RV254 Thai study. B) *IL1B* is in the M3

905	WGCNA module which was enriched in cells from RV254 participants with undetectable reservoir
906	based on the top 25 hub genes in the module (detectable=6, undetectable=8). C) Using the same module
907	hub genes found in RV254, the M3 module was also enriched in cells from the undetectable reservoir
908	participants in the A5354 cohort when HIV DNA levels were grouped categorically (detectable=12,
909	undetectable=11). D) Average expression of the 25 top hub genes from the M3 module had generally
910	higher expression in participants with undetectable reservoir in both cohorts. E) Predicted protein
911	interaction network of top 25 hub genes using the STRING protein database. Larger nodes have higher
912	degree of connectivity; node color indicates significance in the categorical DEG comparison between
913	the detectable and undetectable groups in RV254 CD14+ monocytes. F) Gene ontology analyses of
914	genes enriched in module M3 in CD14+ monocytes.
915	
916	Figure 5. <i>In vitro</i> IL1B activates NF-кB, increases HIV proviral transcription, and inhibits
917	spreading infection. A) Effects of IL1B on NF-κB activity were assessed using A549 NF-κB reporter
918	cells. Cultures were treated with IL1B, LPS, and TNFa and infected with VSV-pseudotyped NL4-3,
919	CH058, or Mock control. After 24h the Alkaline Phosphatase Blue Microwell assay was performed with
920	OD650 values relative to no treatment control (NT) reflecting NF-κB expression which is shown on the
921	Y-axis. B) PBMC from 3 donors were treated with IL1B or TNF α and examined for I κ B α
922	phosphorylation as described in the methods section. Graphs present the protein expression from these
923	donors; unpaired t test, *p<0.05, ****p<0.0001. C) Effects of IL1B in vitro when HIV was quantified
924	after a single round of infection. Plots show the relative proportions of pMorpheus-V5 latently (blue) or
925	productively (orange) infected PBMC in cultures treated with IL1B prior to, simultaneously, or after
926	transduction with Env viral particles carrying the indicated Env protein. The data represent the average

- 928 significance was established using unpaired t tests; *p<0.05, **p<0.002. D) Effects of IL1B on
- 929 spreading HIV-1 infection in cell culture. Using HIV-1 YU-2, bar plots display the relative p24-positive
- 930 cell fractions after pre-treatment with increasing concentrations of IL1B (from 0.01-10.0 ng/mL, 10-fold
- 931 increments) across four different donors. E, F) Bar plots display the average infectious virus yields (E)
- 932 and p24 antigen levels (F) at 4 days post-infection relative to the no IL1B treatment controls normalized
- 933 to 100%; unpaired t test, *p<0.05, **p<0.002, ***p<0.0002. Corresponding replication curves are
- shown in Fig. S8.
- 935

936 SUPPLEMENTARY DATA (LEGENDS)

937

Figure S1. Expression of select lineage markers in specific cell subsets. Expression of known lineage
 marker genes is localized to certain regions on the scRNA-seq UMAP and enables cell type assignment
 of clusters.

Figure S2. Clustering and frequency comparisons of scRNA-seq immune cell subsets. scRNA-seq
shows similar A) spatial patterns of cell populations and B) frequencies of cells between detectable (red)

943 and undetectable (teal) reservoir groups. Significance was determined by the Mann-Whitney U test. *

944 nominal p < 0.05

945 Figure S3. T cell receptor and B cell receptor clonal diversity and isotype distribution. Clonal

946 diversity of A) indicated T cell populations and B) memory and naive B cell populations. Significance

was determined by the Mann-Whitney U test. C) BCR isotype distribution of each donor within naïveand memory B cells.

949 Figure S4. Gene expression in CD14+ monocytes across participants in RV254. Gene expression in

950 CD14+ monocytes of *IL1B* and *THBS1* genes across participants based on categorization of total HIV

DNA measured from A) total PBMC and B) CD4+ T cells. Black circles represent the median values,

952 and vertical lines indicate the interquartile range. Teal: undetectable reservoir; red: detectable reservoir.

953 Three datapoints were missing due to technical differences and insufficient sample to perform the HIV

954 DNA assay in sorted CD4+ T cells. C, D) Total HIV DNA associations when examining change in

955 reservoir decay from week 0 (AHI) to 48 weeks after ART initiation with C) number of significant DEG

and D) top genes associating with reservoir decay. E, F) Correlation of total HIV DNA with E) *THBS1*

and F) *IL1B* gene expression in CD14+ monocytes.

958 Figure S5. No differences in frequencies of CD4+ T_{CM} cell subsets between reservoir groups. A)

959 Gating strategy for the identification of CD4+ T_{CM} cell subsets from the RV254 participants. B) DR-

39

960 CD4+ T_{CM}, C) PD-1- CD4+ T_{CM} and D) CD4+ T_{CM}. Significance was determined by the Mann-Whitney
961 U test. Teal: undetectable reservoir; red: detectable reservoir.

962 Figure S6. Pathway analyses identify distinct signatures associated with reservoir size. A) WGCNA

- 963 dendrogram shows modules of coexpressed genes in memory CD4+ T cells from the RV254 Thai study.
- B) The M4 and M9 WGCNA modules were enriched in cells from participants with undetectable
- 965 reservoir (N=8) compared to detectable reservoir (N=6) based on the top 25 hub genes in the module. C)
- 966 Using the same module hub genes found in RV254, these modules were enriched in cells from the
- 967 undetectable reservoir participants in the A5354 cohort when HIV DNA levels were grouped
- 968 categorically (detectable=12, undetectable=11). Enrichment analysis of D) M4 and E) M9 hub genes
- shows pathways significantly enriched (FDR < 0.05) in the two modules and the genes contributing to
- 970 enrichment in their respective modules.
- 971 Figure S7. Effects of HIV infection on in vitro CD4+ T cell memory phenotypes. A) Gating strategy.
- B) Bar plot depicts the mean percentages of CD45RO- CCR7- Naive (Naive), CD45RO- CCR7+
- 973 Effector (Eff), and CD45RO+ memory (Mem) CD4+ T cell populations in total CD4+ T cells infected
- 974 or not with HIV, as determined by intracellular p24 staining. C) Pie chart illustrates the mean
- 975 percentages of memory subsets T_{CM}, T_{TM}, and T_{EM} within total CD45RO+ memory CD4+ T cells. *
- 976 p<0.05.
- 977 Figure S8. Effects of recombinant IL1B on HIV replication in PBMC cultures. Time course plots of 978 the infectious virus and p24 antigen yields of NL4-3 or CH058 in 5 individual donors. PBMC were 979 isolated from buffy coats and incubated for 3 days, with PHA and IL-2, when they were infected with 980 NL4-3 or CH058. IL1B (10 ng/ml) was added 2 days prior to infection (2d-), at the same time (0d), or 2 981 days post-infection (2d+). Supernatants were collected at designated time points and assessed for
- 982 infectious virus and p24 antigen.

- 983 Figure S9: Effect of IL1B on cell viability. Isolated PBMCs were treated and infected as in Figures 5D
- 984 (A) and S8 (B), respectively. On day 3 post-infection cells were harvested, stained with fixable viability
- 985 dye and FACs analyzed for cell viability. Each dot represents a single donor.

986 Figure S10. Effects of recombinant IL1B on in vitro CD4+ T cell memory phenotypes. A) Gating

- 987 strategy. B) Mean percentages of T_{CM}, T_{TM}, and T_{EM} subsets within total memory CD4+ T cells were
- 988 determined following dose-dependent IL1B treatment. Statistical significance was assessed using the
- 989 Mann-Whitney U test, based on comparing each treated or infected sample to its respective untreated or
- 990 uninfected control. ** p<0.01.

991 Figure S11. Working model of potential mechanisms for IL1B effects on reservoir size. We

- hypothesize that IL1B may affect the latent HIV reservoir by 1) acting as a natural LRA, 2) contributing
- by to reduced seeding of the reservoir, and 3) changing the composition of CD4+ T cell subsets.
- 994
- 995 Supplementary table S1. Different cell populations as detected in scRNA-seq analyses
- 996 Supplementary table S2. Differentially expressed genes in each cell subset (log fold change >|0.25|,
- 997 Bonferroni p<0.05).
- 998 **Supplementary table S3.** Top 20 enriched pathways and processes.
- 999 Supplementary table S4. Enriched pathways for each reservoir phenotype stratified by cell subset

1000 (NES \geq |1.4|, p<0.001)

- 1001 Supplementary table S5. Associations of increased *THBS1/IL1B* expression with cell subset population
- 1002 frequencies obtained by flow cytometry, and their effects on reservoir size
- 1003 **Extended table 1**. Demographics and clinical data of participants from the study
- 1004 **Extended table 2**. List of antibodies.
- 1005



Total HIV DNA copies/10⁶ PBMCs





Α

Demographics & clinical data*	Undetectable reservoir (n=8) 26.5	Detectable reservoir (n=6) 29.8	p value
Age (years)			
Viral load copies/ml (week 0)	1857227	6784716	NS
Total CD4 cells/mm ³ (week 0)	415	326	NS
Viral load copies/ml (week 48)	<25	<25	
Total CD4 cells/mm ³ (week 48)	778	666	NS
Viral decay post-ART initiation in weeks (to <50 copies/ml)	10	19	NS
Total HIV DNA copies/10 ⁶ PBMCs (week 48)	Below LOD	255	0.0008
Integrated HIV DNA copies/10 ⁶ PBMCs (week 48)	Below LOD	83.2	0.003

Thai males, HIV Fiebig staging III, Subtype CRF01_AE



Figure 1. Characteristics of study participants and experimental design. A) Distribution of total HIV DNA in Fiebig stage III participants in RV254 at week 48 after ART initiation and their categorization into three groups based on reservoir size. B) Selected participants from Fiebig stage III with extreme reservoir size phenotypes (undetectable = below LOD and detectable = high) of cell-associated total HIV DNA in the RV254 Thai discovery cohort (n=14). Significance was determined by the Mann-Whitney U test. C) Total HIV DNA decay between weeks 0 (AHI) and 48 (after ART initiation). D) Phenotypes of participants comprising the detectable versus undetectable reservoir size categories. Mean values are shown for each group, NS: not significant. E) Single-cell RNA-seq and multiparameter flow cytometry were performed on all 14 participants. Additional validation by scRNA-seq was performed in an independent AHI cohort from the USA (A5354) (n=38).



Figure 2. Differentially expressed genes in monocytes associate with HIV reservoir size during ART. A) scRNA-seq identified 24 unique clusters of immune cell subsets. B) CD14+ classical monocytes have the highest number of DEG between the detectable and undetectable reservoir groups. Circle color represents cell subset while circle size indicates corresponding cell number. C) Volcano plot shows DEG in all cell types with p values that are significant after correction, as indicated above the horizontal dotted line. Labeled genes have a p<10e-6 and absolute average log_e fold change ≥ 1 (vertical dotted lines) or p<10e-100 and absolute average log_e fold change ≥ 0.5 . D) The most significant DEG in CD14+ monocytes comparing reservoir groups. Black dots represent the median normalized gene expression values (log_e), and lines represent the interquartile ranges. Teal: undetectable reservoir, red: detectable reservoir. Significance was determined by the Mann-Whitney U test with Bonferroni correction (n=14). E) Participant-specific categorical analyses of the most significant DEGs. Normalized gene expression within CD14+ monocytes was averaged per participant and correlation was determined by the Spearman test (n=14). F-G) Interaction plots of multiple regression between *THBS1 or IL1B* expression in monocytes and reservoir size with varying frequency of the CD4+ T_{CM} population. Nominal p values are indicated for the interaction analyses.



Figure 3. Validation of IL1B association with smaller reservoir size from an independent cohort with a different infecting viral subtype across various Fiebig stages. A) HIV DNA levels vary within the A5354 subtype B cohort from the USA (n=38). The participant samples used in this study are highlighted based on reservoir size: red=detectable; teal=undetectable and yellow=middle. Black and White indicate differences in ancestry of the participants. B) Characteristics of participants comprising the detectable, middle, and undetectable reservoir size categories (mean values are shown) and p values comparing the extreme phenotype groups. HIV-1 subtype information was only available for a subset of the participants. NS: not significant C) Dimensionality reduction plot of the different immune clusters in this cohort. D) CD14+ monocytes have the highest number of normalized DEG associated with reservoir size using a continuous analysis including all 38 participants. E) IL1B participant-specific average gene expression in CD14+ monocytes categorized by total HIV DNA (n=38). Spearman correlation p value and rho are shown. F) IPDA® measurements from a subset of the participants in this cohort (n=21). G) IL1B association with different reservoir type measurements (rows) from the participants with IPDA measurements (n=21).

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Figure 4. Pathway analyses identifies a distinct signature associating with reservoir size. A) Gene coexpression modules in CD14+ monocytes from the RV254 Thai study. B) *IL1B* is in the M3 WGCNA module which was enriched in cells from RV254 participants with undetectable reservoir based on the top 25 hub genes in the module (detectable=6, undetectable=8). C) Using the same module hub genes found in RV254, the M3 module was also enriched in cells from the undetectable reservoir participants in the A5354 cohort when HIV DNA levels were grouped categorically (detectable=12, undetectable=11). D) Average expression of the 25 top hub genes from the M3 module had generally higher expression in participants with undetectable reservoir in both cohorts. E) Predicted protein interaction network of top 25 hub genes using the STRING protein database. Larger nodes have higher degree of connectivity; node color indicates significance in the categorical DEG comparison between the detectable and undetectable groups in RV254 CD14+ monocytes. F) Gene ontology analyses of genes enriched in module M3 in CD14+ monocytes.



Figure 5. In vitro IL1B activates NF-KB, increases HIV proviral transcription, and inhibits spreading infection. A) Effects of IL1B on NF-κB activity were assessed using A549 NF-κB reporter cells. Cultures were treated with IL1B, LPS, and TNFα and infected with VSV-pseudotyped NL4-3, CH058, or Mock control. After 24h the Alkaline Phosphatase Blue Microwell assay was performed with OD650 values relative to no treatment control (NT) reflecting NF-KB expression which is shown on the Y-axis. B) PBMC from 3 donors were treated with IL1B or TNF α and examined for I κ B α phosphorylation as described in the methods section. Graphs present the protein expression from these donors; unpaired t test, *p<0.05, ****p<0.0001. C) Effects of IL1B in vitro when HIV was quantified after a single round of infection. Plots show the relative proportions of pMorpheus-V5 latently (blue) or productively (orange) infected PBMC in cultures treated with IL1B prior to, simultaneously, or after transduction with Env viral particles carrying the indicated Env protein. The data represent the average of 3 individual healthy donors, with error bars representing the average \pm SEM, and statistical significance was established using unpaired t tests; *p<0.05, **p<0.002. D) Effects of IL1B on spreading HIV-1 infection in cell culture. Using HIV-1 YU-2, bar plots display the relative p24-positive cell fractions after pre-treatment with increasing concentrations of IL1B (from 0.01-10.0 ng/mL, 10-fold increments) across four different donors. E, F) Bar plots display the average infectious virus yields (E) and p24 antigen levels (F) at 4 days post-infection relative to the no IL1B treatment controls normalized to 100%; unpaired t test, *p<0.05, **p<0.002, ***p<0.0002. Corresponding replication curves are shown in Fig. S8.