Supplementary

Cellular deconvolution

In this study, we used AutoGeneS[1] that automatically extracts informative genes and outperforms other methods for analyzing bulk RNA samples with closely correlated cell types and noisy single-cell reference profiles. The number of informative genes was manually set to 300 and 400 genes and we selected the one (n=400) with the most stable results across cohorts. Similarly, the proportions of major cell types--goblet, secretory, and ciliated cells- were consistent using different cell type resolutions.

scRNA-Seq data was used from bronchial biopsies[2]. Due to highly similar gene expression profiles, the scRNA-Seq signatures from the club and the 2 goblet cell clusters were combined to generate a uniform scRNA-Seq signature of secretory cells. The merged scRNA-seq count data was normalized to count per million (CPM) and highly variable (HV) genes (n=5,000) were selected. We used the method implemented in single-cell analysis in Python (SCANPY)[3] for selecting HV genesin which genes are binned by their mean expression and those with the highest variance-to-mean ratio are selected as HV genes in each bin. We then performed AutoGeneS[1] to filter 400 informative genes from the highly variable ones that differentiated the cell types. The informative genes minimized correlation and maximized distance between the clusters in the single-cell reference data. For visualisation, single-cell neighbourhood graph (kNN-graph) was computed on the first 50 principal components using 30 neighbours and low-dimensional uniform manifold approximation and projection

(UMAP) embedding was used. Bulk deconvolution was then conducted on all bulk samples using support vector regression (SVR) method[4] for samples measured by both RNA-Seq and microarray.

Interaction analysis

The interaction analysis was conducted on TAC signatures and Mast cell signatures using a linear mix effect (LME) model investigating the interaction between time and treatment with patient ID as the random factor.

Figure S1. TSNE plots made from epithelial only cell/subtypes

TSNE plots for ICS sensitive TAC1 genes (IL1RL1, TPSB2 and CPA3), obtained from of single cell seq data obtained from asthmatic (n=4) and healthy controls (n=4) (A-D).

Figure S2 Individual expression of genes from the mast cells signature. Heatmap of the genes in the mast cell signature.

Figure S3. Relationship between corticosteroid sensitive signature and the influence of inhaled corticosteroid (ICS) treatment Mean ± SEM is presented in the figure. The interaction analysis was conducted on TAC signature using a LME model investigating the interaction between time and treatment with patient ID as the random factor. For two-way anovas a Benjamin Hochberg adjusted pvalue<0.05 was considered significant.

Figure S4. Percentage of sputum cell correlations with TAC1. Correlation with TAC1 and baseline A) sputum neutrophils and B) sputum eosinophils and C) delta between 30 months ICS+/-LABA compared to baseline. Spearman correlations were conducted.

Table S2. GLUCOLD patient characteristics

Table S3. Clinical characteristics separated by TAC grouping

*=p<0.05 compared to TAC3. t-test conducted

Table S4. Interaction analysis of Time and treatment for TAC signatures and Mast cell signatures

Abbreviation FC= Fold Change, FDR=False Discovery Rate

References

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