

Supporting Information

Fejer et al. 10.1073/pnas.1302877110

SI Materials and Methods

Detection of Secreted Cytokines, Surface Antigens, and Intracellular Proteins. The following cytokines were detected with ELISA using commercially available antibody pairs or kits: mouse IL-6 (BD Bioscience), IL-1 α (eBioscience), IL-1 β (eBioscience), IL-10 (eBioscience), human IL-6 (R&D Systems), IL-1 α (BioLegend), and IL-10 (BD Bioscience). IFN- $\alpha\beta$ and TNF- α activities were measured bioassays as described (1). Surface markers were detected with FACS using the following antibodies: major histocompatibility class II I-Ab (AF6-120.1), granulocyte differentiation antigen-1 (RB6-8C5), and cluster of differentiation molecule (CD)11b (M1/70) from BD Pharmingen; mouse homolog of EGF-like module-containing mucin-like hormone receptor-like (F4/80, BM8) and CD11c (N418) from eBioscience; CD32/16 (93) and CD14 (Sa14-2) from BioLegend; and macrophage receptor with collagenous structure (ED31) from AbD Serotec. Intracellular proteins were detected on immunoblots with antibodies from Pharmingen BD (IL-1 α and IL-1 β) and Cell Signaling (phosphorylated isophorm of p38 MAPK).

Microarray and Cluster Analysis. All microarrays were preprocessed and quantile-normalized with the RMA package (2). For the unsupervised cluster analysis, we calculated the Spearman correlation coefficient, C , for all pairs of probesets and defined a corresponding distance measures as $(1 - C)/2$. Based on those distances we performed a hierarchical clustering using the function `hclust` in R, which give rise to the dendrograms of Fig. 2. To highlight functional differences between the different cell types, the global cluster analysis for all genes was complemented by an identical analysis for targeted subsets of 285 genes associated with cell-cycle processes

[Gene Ontology (GO) 0007049] and 456 immune response genes (GO 0006955).

Linear Modeling. To account for the systematic variability in the data, we applied a linear model for each gene and determined a number of statistics, such as fold changes, t -statistics, and P values for the contrasts between specified conditions (different treatments/cell types). An empirical Bayes method was applied to moderate the t -statistics using the information from all genes. For all of the above steps, we used the functionalities provided by the `limma`-package in R (3). A false discovery rate (FDR) threshold of 5% was chosen to define subsets of differentially expressed genes. To define differential genes upon LPS treatment in different cell types, we require that a probeset is significantly up-regulated in one but not the other cell type [generated from BM precursors with M-CSF (BMM), Max Planck Institute (MPI)] and that the cell effect is also significant at a 5% FDR.

Enrichment Analysis. To identify functional differences more systematically, we used the gene set enrichment analysis (GSEA) on preranked gene lists. The ranking for different contrasts was based on the moderated t -statistics from `limma`, and we investigated possible enrichment in gene ontologies and canonical pathways from the MSigDB database (4). Importantly, this method does not impose any cutoff on the rank list of genes, but instead uses a model of random rank lists to assess the significance of observed deviations for any given functional category. Because many categories were being tested, multiple testing corrections were applied to rank the categories by their FDR.

1. Fejer G, et al. (2008) Key role of splenic myeloid DCs in the IFN- α response to adenoviruses in vivo. *PLoS Pathog* 4(11):e1000208.
2. Irizarry RA, et al. (2003) Summaries of Affymetrix GeneChip probe level data. *Nucleic Acids Res* 31(4):e15.
3. Smyth GK (2004) Linear models and empirical bayes methods for assessing differential expression in microarray experiments. *Stat Appl Genet Mol Biol* 3:Article3.

4. Subramanian A, et al. (2005) Gene set enrichment analysis: A knowledge-based approach for interpreting genome-wide expression profiles. *Proc Natl Acad Sci USA* 102(43):15545-15550.

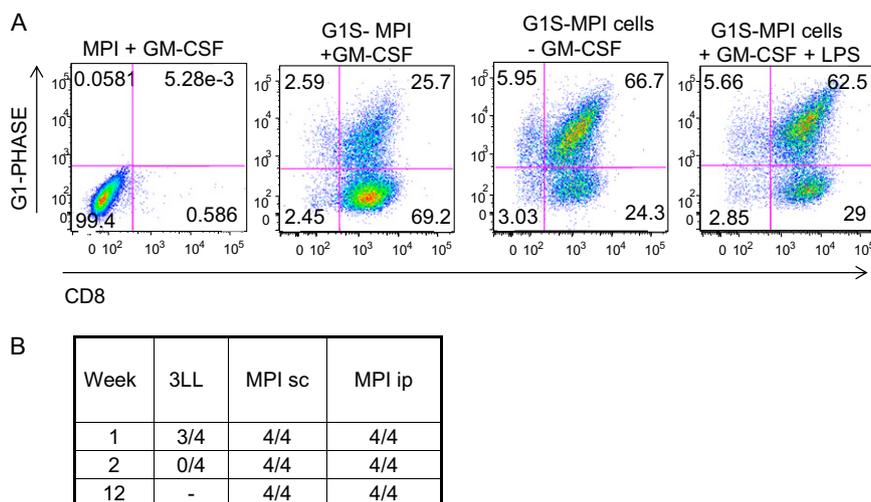


Fig. S1. MPI cells are growth factor-dependent nontransformed cells. LPS treatment and GM-CSF deprivation arrests replicating MPI cells in the G1 phase of cell cycle. MPI cells transduced with a retrovirus coding for CD8 and a reporter protein (G1S-MPI) emitting at 578 nm in G1 phase only were analyzed when grown with GM-CSF, with GM-CSF in addition to 0.1 μ g/mL LPS for 16 h, or for 2 d in the absence of GM-CSF. Control nontransduced, GM-CSF cultured MPI cells are shown in A, Lower Left. MPI cells are not tumorigenic. Recombination-activating gene-2 $^{-/-}$ mice (four per group) were injected with 2×10^5 Lewis lung carcinoma cells (3LL) i.p. or with MPI cells s.c. or i.p. The number of living, tumor-free animals at the indicated time points after injection is shown (B).

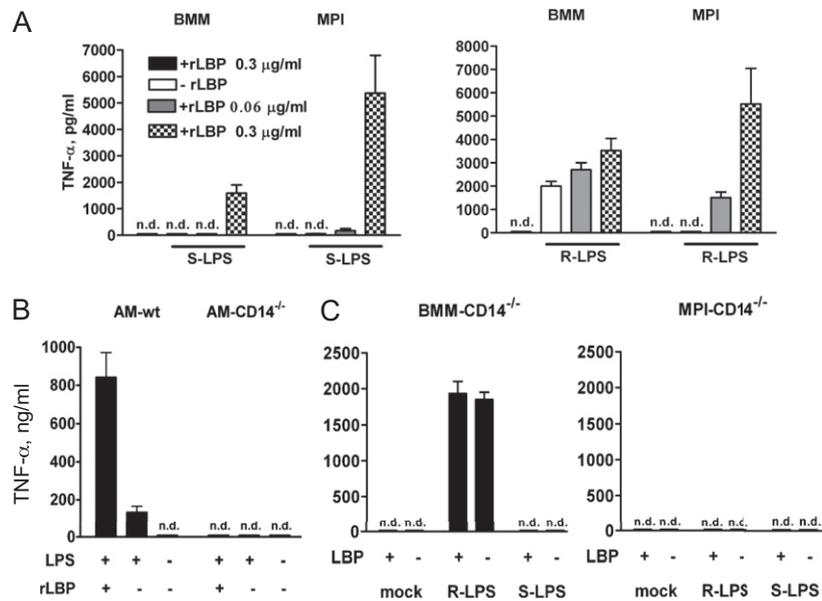


Fig. 54. MPI cells and AMs require CD14 to sense rough LPS. TNF- α response of BMMs and MPI cells to smooth form LPS (S-LPS) or rough form LPS (R-LPS) (0.1 μ g/ml) in serum-free medium with or without recombinant LBP (A). TNF- α response of AMs from WT and CD14^{-/-} mice to 0.01 μ g/mL R-LPS with or without recombinant LPS binding protein (rLBP) (B). TNF- α response of CD14^{-/-} BMMs and MPI cells to 0.1 μ g/mL R-LPS or S-LPS with 5% of serum of WT or LBP^{-/-} mice (C).

Dataset S1. Results from a functional enrichment analysis when comparing MPI cells with BMM cells using microarray data of triplicate samples of total cellular RNA

[Dataset S1](#)

The first column contains the name of the enriched pathway as used by MsigDB and the second column denotes the FDR of the observed enrichment as obtained from the GSEA algorithm (1). Only enrichments with an FDR smaller than 5% are shown.

1. Subramanian A, et al. (2005) Gene set enrichment analysis: A knowledge-based approach for interpreting genome-wide expression profiles. *Proc Natl Acad Sci USA* 102(43): 15545–15550.

Dataset S2. Results from a functional enrichment analysis when comparing BMM cells with MPI cells using microarray data of triplicate samples of total cellular RNA

[Dataset S2](#)

The first column contains the name of the enriched pathway as used by MsigDB and the second column denotes the FDR of the observed enrichment as obtained from the GSEA algorithm (1). Only enrichments with an FDR smaller than 5% are shown.

1. Subramanian A, et al. (2005) Gene set enrichment analysis: A knowledge-based approach for interpreting genome-wide expression profiles. *Proc Natl Acad Sci USA* 102(43): 15545–15550.

Dataset S3. Results from a functional enrichment analysis when comparing SP37A3 dendritic cells with MPI cells using microarray data of triplicate samples of total cellular RNA

[Dataset S3](#)

The first column contains the name of the enriched pathway as used by MsigDB and the second column denotes the FDR of the observed enrichment as obtained from the GSEA algorithm (1). Only enrichments with an FDR smaller than 5% are shown.

1. Subramanian A, et al. (2005) Gene set enrichment analysis: A knowledge-based approach for interpreting genome-wide expression profiles. *Proc Natl Acad Sci USA* 102(43): 15545–15550.

