Host-pathogen genetic interactions underlie tuberculosis susceptibility

Short title: Collaborative Cross and Tuberculosis

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Abstract:

The outcome of an encounter with *Mycobacterium tuberculosis* depends on the

pathogen's ability to adapt to the variable immune pressures exerted by the host.

Understanding this interplay has proven difficult, largely because experimentally

tractable animal models do not recapitulate the heterogeneity of tuberculosis disease.

We leveraged the genetically diverse Collaborative Cross (CC) mouse panel in

conjunction with a library of *Mtb* mutants to associate bacterial genetic requirements

with host genetics and immunity. We report that CC strains vary dramatically in their

susceptibility to infection and produce qualitatively distinct immune states. Global

analysis of *Mtb* mutant fitness across the CC panel revealed that many virulence

pathways are only in specific host microenvironments, identifying the large fraction of

the pathogen's genome that has been maintained to ensure fitness in a diverse

population. Both immunological and bacterial traits were associated with genetic

variants distributed across the mouse genome, identifying the specific host-pathogen

genetic interactions that influence pathogenesis.

Keywords: Host-pathogen interactions, tuberculosis, *Mycobacterium*, systems genetics,

genomics, genetic diversity, natural variation, bacterial genetics, TnSeq, mouse models,

Collaborative Cross, QTL mapping, complex traits.

Introduction

Infection with *Mycobacterium tuberculosis* (*Mtb*) produces heterogeneous outcomes

that are influenced by genetic and phenotypic variation in both the host and the

pathogen. Classic human genetic studies show that host variation influences immunity

to tuberculosis (TB) (Abel et al., 2018; Comstock, 1978). Likewise, the co-evolution of

Mtb with different populations across the globe has produced genetically distinct

lineages that demonstrate variable virulence traits (Gagneux et al., 2006). The role of

genetic variation on each side of this interaction is established, yet the intimate

evolutionary history of both genomes suggests that interactions between host and

pathogen variants may represent an additional determinant of outcome (McHenry et al.,

2020). Evidence for genetic interactions between host and pathogen genomes have

been identified in several infections (Ansari et al., 2017; Berthenet et al., 2018),

including TB (Caws et al., 2008; Holt et al., 2018; Thuong et al., 2016). However, the

combinatorial complexity involved in identifying these relationships in natural

populations have left the mechanisms largely unclear.

Mouse models have proven to be a powerful tool to understand mechanisms of

susceptibility to TB. Host requirements for protective immunity were discovered by

engineering mutations in the genome of standard laboratory strains of mice, such as

C57BL/6 (B6), revealing a critical role of Th1 immunity. Mice lacking factors necessary

for the production of Th1 cells or the protective cytokine interferon gamma (IFNγ) are

profoundly susceptible to *Mtb* infection (Caruso et al., 1999; Cooper et al., 1993; Cooper

et al., 1997; Flynn et al., 1993; Saunders et al., 2002). Defects in this same immune

axis cause the human syndrome Mendelian Susceptibility to Mycobacterial Disease

(MSMD) (Altare et al., 1998; Bogunovic et al., 2012; Bustamante et al., 2014; Filipe-

Santos et al., 2006), demonstrating the value of knockout (KO) mice to characterize

genetic variants of large effect. Similarly, the standard mouse model has been used to

define *Mtb* genes that are specifically required for optimal bacterial fitness during

infection (Bellerose et al., 2020; Sassetti and Rubin, 2003; Zhang et al., 2013).

Despite the utility of standard mouse models, it has become increasingly clear that the

immune response to *Mtb* in genetically diverse populations is more heterogeneous than

any single small animal model (Smith and Sassetti, 2018). For example, while IFNγ-

producing T cells are critical for protective immunity in standard inbred lines of mice, a

significant fraction of humans exposed to *Mtb* control the infection without producing a

durable IFNγ response (Lu et al., 2019). Similarly, IL-17 producing T cells have been

implicated in both protective responses and inflammatory tissue damage in TB, but IL-

17 has little effect on disease progression in B6 mice, except in the context of

vaccination or infection with particularly virulent *Mtb* (Gopal et al., 2012; Khader et al.,

2007). The immunological homogeneity of standard mouse models may also explain

why only a small minority of the >4000 genes that have been retained in the genome of

Mtb during its natural history promote fitness in the mouse (Bellerose et al., 2020).

Thus, homogenous mouse models of TB fail to capture the distinct disease states,

mechanisms of protective immunity, and selective pressures on the bacterium that are

observed in natural populations.

The Collaborative Cross (CC) and Diversity Outbred (DO) mouse populations are new

mammalian resources that more accurately represent the genetic and phenotypic

heterogeneity observed in outbred populations (Churchill et al., 2004; Churchill et al.,

2012). These mouse panels are both derived from the same eight diverse founder

strains but have distinct population structures (Saul et al., 2019). DO mice are

maintained as an outbred population and each animal represents a unique and largely

heterozygous genome (Keller et al., 2018; Svenson et al., 2012). In contrast, each

inbred CC strain's genome is almost entirely homozygous, producing a genetically

stable and reproducible population in which the phenotypic effect of recessive mutations

is maximized (Shorter et al., 2019; Srivastava et al., 2017). Together, these resources

have been leveraged to identify host loci underlying the immune response to infectious

diseases (Noll et al., 2019). In the context of TB, DO mice have been used as individual,

unique hosts to identify correlates of disease, which resemble those observed in non-

human primates and humans (Ahmed et al., 2020; Gopal et al., 2013; Niazi et al.,

2015). Small panels of the reproducible CC strains have been leveraged to identify host

background as a determinant of the protective efficacy of BCG vaccination (Smith et al.,

2016) and a specific variant underlying protective immunity to tuberculosis (Smith et al.,

2019). While these studies demonstrate the tractability of the DO and CC populations to

model the influence of host diversity on infection, dissecting host-pathogen interactions

requires the integration of pathogen genetic diversity.

We combined the natural but reproducible host variation of the CC panel with a

comprehensive library of *Mtb* mutants to characterize the interactions between host and

pathogen. Using over 60 diverse mouse strains, we report that the CC panel

encompasses a broad spectrum of TB susceptibility and immune phenotypes, including

outlier lines that model non-canonical immune states. Through "Transposon

Sequencing" (TnSeq), we quantified the relative fitness of *Mtb* mutants across the CC

panel and specific immunological knockout strains. We report that approximately three

times more bacterial genes contribute to fitness in the diverse panel than in any single

mouse strain, defining a large fraction of the bacterial genome that is dedicated to

adapting to distinct immune states. Association of these immunological and bacterial

fitness traits with Quantitative Trait Loci (QTL) demonstrated the presence of discrete

Host-Interacting-with Pathogen QTL (*Hip*QTL) that represent inter-species genetic

interactions that influence the pathogenesis of this infection.

Results:

The spectrum of TB disease traits in the CC exceeds that observed in standard inbred mice

To characterize the diversity of disease states that are possible in a genetically diverse mouse population, we infected a panel of 52 CC lines and the 8 founder strains with *Mtb*. To enable TnSeq studies, the animals were infected via the intravenous route with a saturated library of *Mtb* transposon mutants, which in sum produce an infection that is similar to the wild-type parental strain (Bellerose et al., 2020; Sassetti and Rubin, 2003). Groups of 2-6 (average of n=3) male mice per genotype were infected, and the bacterial burden after four weeks of infection was assessed by plating (colony forming units, CFU) and quantifying the number of bacterial chromosomes in the tissue (chromosome equivalents, CEQ). These two metrics were highly correlated (r=0.88) and revealed a wide variation in bacterial burden across the panel (**Figure 1A** and **S1**). The susceptibility of the inbred founder strains was largely consistent with previous studies employing an aerosol infection (Smith et al., 2016). As expected, B6 mice were relatively resistant to infection, along with 129S1/SvlmJ (129) and NOD/ShiLtJ (NOD) strains. In contrast to the standard inbred lines, lung bacterial burden varied by more than 1000-fold across the more diverse CC panel, ranging from animals that are significantly more resistant than B6, to mice that harbored more than 10^9 bacteria in their lungs (**Figure 1A**). Bacterial burden in the spleen also varied several thousand-fold across the panel and was moderately correlated with lung burden (r=0.43) (**Table S1** and **Figure S1**). Thus, the CC panel encompasses a much greater quantitative range of susceptibility than standard inbred lines.

Comparing various measures of infection progression showed many expected

correlations but also an unexpected decoupling of some phenotypes. As an initial

assessment of the disease processes in these animals, we correlated bacterial burden

and lung cytokine abundance with measures of systemic disease such as weight loss

and sufficient morbidity to require euthanasia ("earliness of death"). In general,

correlations between these metrics indicated that systemic disease was associated with

bacterial replication and inflammation (**Figure 1B** and **Figure S1**). Lung CFU was

correlated with weight loss, mediators that enhance neutrophil differentiation or

migration (CXCL2 (MIP-2; r=0.79), CCL3 (MIP-1a; r=0.77), G-CSF (r=0.78) and CXCL1

(KC; r=0.76)), and more general proinflammatory cytokines (IL-6 (r=0.80) and IL-1α

(r=0.76)) (**Figure S1**). These findings are consistent with previous work in the DO panel,

that found both proinflammatory chemokines and neutrophil accumulation to be

predictors of disease (Ahmed et al., 2020; Gopal et al., 2013; Niazi et al., 2015).

The reproducibility of CC genotypes allowed us to quantitatively assess the heritability

(h^2) of these immunological and disease traits. The percent of the variation attributed to

genotype ranged from 56-87% (mean=73.4%; **Table S2**). The dominant role of genetic

background in determining the observed phenotypic range allowed a rigorous

assessment of outlier phenotypes that is not possible in the DO population. For

example, despite the correlation between lung CFU and weight loss (r=0.57), several

strains failed to conform to this relationship (**Figure 1C**). In particular, CC030/GeniUnc

(p=0.003), CC040/TauUnc (p=0.027) and A/J (p=0.03) lost significantly more weight

than their bacterial burdens would predict (**Figure 1C**; outlier genotypes determined by

studentized residuals; noted by #). Similarly, CXCL1 abundance was significantly higher

in CC030/GeniUnc (p=0.001) and lower in CC056/GeniUnc (p=0.040), than the level

predicted by their respective bacterial burden (**Figure 1C**; outlier genotypes noted by †).

Thus, these related disease traits can be dissociated based on the genetic composition

of the host.

The cluster of cytokines that was most notably unrelated to bacterial burden included

IFNγ and the interferon-inducible chemokines CXCL10 (IP10), CXCL9 (MIG), and CCL5

(RANTES) (Red cluster in **Figure 1B**; **Figure S1**) (r<0.3). Despite the clear protective

role for IFNγ (Cooper et al., 1993; Flynn et al., 1993), high levels have been observed in

susceptible mice, likely as a result of high antigen load (Barber et al., 2011; Lázár-

Molnár et al., 2010). While high IFNγ levels in susceptible animals was therefore

expected, it was more surprising to find a number of genotypes that were able to control

bacterial replication yet had very low levels of this critically important cytokine (**Figure

1D**). This observation is likely due the inclusion of two founder lines, CAST/EiJ (CAST)

and PWK/PhJ (PWK) that display this unusual phenotype (Smith et al., 2016). To further

investigate, a separate cohort of B6 and CAST animals was infected by the aerosol

route, and the number of IFNγ-producing T cells in lung and spleen was compared by

ELISPOT assays. At 4 weeks post-infection, B6 and CAST harbored comparable

burdens of *Mtb* in lung and spleen (**Figure 1E** and **1F**), and the infection elicited similar

numbers of *Mtb*-specific IFNγ-producing cells in the spleen (**Figure 1H**). In contrast,

while IFNγ producing cells were found in the lungs of B6 mice, none were detectable in

CAST (**Figure 1G**). Thus, while CAST animals are capable of producing IFNγ-secreting

cells in response to *Mtb* infection, these cells do not appear to be involved in bacterial

control in the lung. As CC strains that share this immune profile also produced low

levels of IL-17 (**Figure 1D**), the mechanism(s) conferring protection in these animals

remain unclear. In sum, this survey of TB-related traits in the CC demonstrated a broad

range of susceptibility and the presence of qualitatively distinct and genetically

determined disease states.

***Tip*QTL define genetic variants that control TB immunophenotypes**

Tuberculosis ImmunoPhenotype Quantitative Trait Loci (*Tip*QTL), which were

associated with TB disease or cytokine traits, were identified and numbered in

accordance with previously reported *Tip*QTL (Smith et al., 2019). Of the 32 TB-disease

traits, we identified 9 individual metrics that were associated with reasonable statistical

confidence to a chromosomal locus. Of these, three were associated with high

confidence (p≤0.053), and six other QTL met a suggestive threshold (p<0.2; **Table 1**).

Several individual trait QTL occupied the same chromosomal locations. For example,

spleen CFU and spleen CEQ, which are both measures of bacterial burden and highly

correlated, were associated with the same interval on distal chromosome 2 (**Table 1**,

Tip5; **Figure 2A** and **2C**). IL-10 abundance was associated with two distinct QTL (**Table

1**). While IL-10 was relatively uncorrelated with spleen CFU (r=0.48), one of its QTL fell

within the *Tip5* bacterial burden interval on chromosome 2 (**Figure 2A** and **2C**). At this

QTL, the NOD haplotype was associated with high values for all three traits (**Figure

2E**). Similarly, the correlated traits, CXCL1 abundance and lung CFU, were individually

associated to the same region on chromosome 7 (**Table 1**, *Tip8*; **Figure 2B** and **2D**). In

this interval, the CAST haplotype was associated with both low bacterial burden and

CXCL1 (**Figure 2F**). At both *Tip5* and *Tip8*, we found no statistical evidence that the

positions of the associated QTL were different (*Tip5* p=0.55; *Tip8* p=0.27; 400 bootstrap

samples)(Boehm et al., 2019). These observations support the role of a single causal

variant at each locus that is responsible for a pleiotropic trait. Coincident mapping can

provide both additional statistical support for QTL (p values by Fisher's combined

probability test: Chr 7, p=0.067; Chr 2, p=0.041) and suggests potential mechanisms of

disease progression.

A number of factors can limit the statistical significance of QTL identified in the CC

population, including small effect sizes, limited genotype availability, and the genetic

complexity of the trait. To determine if the statistically suggestive QTL were likely to

reflect genuine biological effects, we took an intercross approach to validate the lung

CFU QTL on chromosomes 7 and 15 (*Tip8* and *Tip10*, **Table 1**). Given that the

associations at both QTL were driven by the CAST haplotype (**Figure 2F**), we

generated an F_2 population based on two CC strains, CC029/Unc and CC030/GeniUnc,

that contained CAST sequence at *Tip8* and *Tip10*, respectively (**Figure 3A**). 46 F_2 mice

that were homozygous at either locus were infected with *Mtb*, and lung CFU were

enumerated as per the larger CC screen (**Table S3**). Compared to F_2 mice that were not

CAST at either locus, mice that contained CAST at *Tip8*, *Tip10* or both loci had reduced

CFU burden; however, the strongest predictor of significantly lower bacterial burden

was CAST at *Tip8* (p=0.005, 2-factor regression; **Figure 3B**). This study provides strong

independent support for a CAST-driven QTL on chromosome 7 that controls lung CFU

and verifies the validity of the genetic mapping in this dataset.

Table 1. Disease-related Tuberculosis ImmunoPhenotype QTL (*Tip*QTL). Multiple

QTL within the same interval and clear allele effects are designated with the same

*Tip*QTL number. Column headings: QTL, quantitative trait loci; Chr, chromosome; LOD,

logarithm of the odds; CEQ, chromosomal equivalents.

QTL	Trait	Chr	LOD	P value	Interval start (Mb)	Peak (Mb)	Interval end (Mb)
Tip5	Spleen CEQ	2	9.14	2.38E-02	174.29	178.25	178.25
Tip5	Spleen CFU	2	7.04	2.19E-01	73.98	174.29	180.10
Tip6	IL-9	2	8.61	4.52E-02	33.43	41.4	41.48
Tip6	IL-9	2	7.85	1.26E-01	22.77	24.62	25.65
Tip7	IL-17	15	7.84	5.27E-02	67.98	74.14	82.11
Tip8	CXCL1	7	7.57	1.06E-01	30.43	45.22	46.72
Tip8	Lung CFU	7	7.47	1.17E-01	31.06	37.78	45.22
Tip9	IL-10	17	7.16	1.85E-01	80.98	82.47	83.55
Tip10	Lung CFU	15	7.13	1.86E-01	77.00	78.16	78.70

***Mtb* adapts to diverse hosts by utilizing distinct gene repertoires**

This survey of disease-associated traits indicated that the CC panel encompasses a

number of qualitatively distinct immune phenotypes. To determine if different bacterial

functions were necessary to adapt to these conditions, we used TnSeq to estimate the

relative abundance of individual *Mtb* mutants after selection in each CC host genotype.

To serve as benchmarks of known immunological lesions, we also performed TnSeq in

B6 mice that were lacking the mediators of Th1 immunity, lymphocytes (*Rag2*[-/-]) and

IFNγ (*Ifnγ*[-/-]), or were lacking the immunoregulatory mediators that control disease by

inhibiting inflammation, nitric oxide synthase (*Nos2*[-/-]) (Mishra et al., 2013) or the

NADPH phagocyte oxidase (*Cybb*[-/-]) (Olive et al., 2018). The relative representation of

each *Mtb* mutant in the input pool versus the pools recovered from mouse spleens was

quantified (**Table S4**). Consistent with our previous work (Bellerose et al., 2020;

Sassetti and Rubin, 2003), we identified 234 *Mtb* genes that are required for growth or

survival in *Mtb* in B6 mice, based on significant underrepresentation of the

corresponding mutant after four weeks of *in vivo* selection. All but one of these genes

were found to be required in the larger panel, increasing confidence in this *Mtb* gene set

(**Figure 4A** and **4B**). While the number of genes found to be necessary in each

genotype across the panel was largely similar, the composition of these gene sets

varied considerably. As more CC strains, and presumably more distinct immune states,

were included in the analysis, the cumulative number of genes necessary for growth in

these animals also increased. This cumulative gene set plateaued at ~750, after the

inclusion of approximately 20-25 genotypes (**Figure 4A**). This number of genes far

outnumbered those identified in the panel of immunodeficient KO strains (**Figure 4B**

and **Table S4**).

To verify that our TnSeq study accurately predicted the effect of the corresponding loss-

of-function alleles, we assessed the phenotypes of selected bacterial deletion mutants

in a small set of mouse genotypes that were predicted to result in differential selection.

Individual *Mtb* mutants lacking genes necessary for ESX-1 type VII secretion (*eccB1*),

siderophore-mediated iron acquisition (*mbtA*), phosphate transport (*pstC2*), glycerol

catabolism (*glpK*), and RNA processing (*rnaseJ*) were generated and tagged with a

unique molecular barcode. These mutants were combined with a barcoded wild-type

parental strain, the resulting 'mini-pool' was subjected to *in vivo* selection in the same

manner as the TnSeq study, and the relative abundance of each mutant was

determined by sequencing the amplified barcodes. In each case, the difference in

relative abundance predicted by TnSeq was reproduced with deletion mutants (**Figure**

4C). In this simplified system, we were able to accurately quantify the expansion of the

bacterial population and calculate the "fitness" of each mutant relative to the wild-type

strain. Fitness reflects the inferred doubling time of the mutant, where a fitness of 1 is

defined as wild-type, and 0 represents a complete lack of growth. Even by this metric,

the deletion mutants displayed the differences in fitness between mouse strains that

was predicted by TnSeq (**Figure 4C**). The statistical significance of these differences in

abundance or fitness were similar for each mutant (between $p=0.009$ and $p=0.06$),

except for *mbtA* where the variation was higher, and confidence was modestly lower

($p=0.07$ and $p=0.12$). This study also allowed us to estimate the sensitivity of the TnSeq

method, which could detect even the 30% fitness defect of the $\Delta glpK$ strain between the

B6 and CC018 animals (**Figure 4C**), a defect that was not observed in previous studies

in BALB/c mice (Bellerose et al., 2019; Pethe et al., 2010).

To also validate TnSeq predictions in a single-strain aerosol infection model, we used a

biotin biosynthetic mutant. *bioA* is necessary for biotin production and is essential for

growth in B6 mice (Woong Park et al., 2011). Our TnSeq study (**Table S4**) predicted

this mutant was less attenuated in the CAST background (ratio of input/selected = 12.1)

than in the B6 strain (ratio of input/selected = 42.2). Two weeks after aerosol infection,

we found that the Δ*bioA* mutant was cleared from the lungs and spleen of B6 mice but

displayed similar growth to wild-type in the lungs of CAST mice (**Figure 4D**). By 6

weeks post infection the Δ*bioA* mutant had also been largely cleared from the lungs of

CAST (**Figure 4D**). Thus, while TnSeq was unable elucidate the complex kinetics of this

phenotype, it accurately predicted the relative levels of growth attenuation in these host

backgrounds.

The immunological diversity of CC mice is reflected in the pathogen's genetic

requirements

The distribution of *Mtb*'s requirements across the mouse panel suggested the presence

of two broad categories of genes. A set of 136 "core" virulence functions were required

in the majority of mouse genotypes, and a second larger set of 607 "adaptive" virulence

genes were required in only a subset of lines (**Table S4**). The core functions included a

number of genes previously found to be important in B6 mice, including those

necessary for the synthesis of essential cofactors, such as pyridoxine (*Pdx1*) (Dick et

al., 2010); for the acquisition of nutrients, such as siderophore-bound iron (*irtAB*)

(Ryndak et al., 2010), cholesterol (*mce4*) (Pandey and Sassetti, 2008), glutamine (*glnQ*

and *rv2563*) (Bellerose et al., 2020); and for type VII secretion (ESX1 genes) (Stanley et

al., 2003). Despite the importance of these core functions, a large range in the relative

abundance of these mutants was observed across the panel, and in some cases

specific immunological requirements could be discerned. Mutants lacking the major

structural components of the ESX1 system were attenuated for growth in B6 mice, as

expected. This requirement was consistently enhanced in mice lacking *Rag2, Ifnγ*, or

Nos2 (**Figure 4E**), consistent with the preferential role of ESX1 during the initial stage of

infection before the initiation of adaptive immunity (Stanley et al., 2003). In contrast, the

attenuation of mutants lacking the *glnQ* encoded glutamine uptake system was relieved

in all four immunodeficient mouse lines (**Figure 4E**). In both cases, the differential

mutant abundance observed in these KO mice was reproduced, or exceeded, in the CC

panel.

The adaptive virulence functions included a number of genes previously thought to be

dispensable in the mouse model and were only necessary in CC strains. For example,

the alkyl hydroperoxide reductase, AhpC has been proposed to function with the

adjacently encoded peroxiredoxin, AhpD and is critical for detoxifying reactive nitrogen

intermediates *in vitro* (Chen et al., 1998; Hillas et al., 2000). However, deletion of *ahpC*

has no effect on *Mtb* replication in B6 or BALB/c mice (Springer et al., 2001), and we

confirmed that *ahpC* and *ahpD* mutations had no effect in any of the B6-derived lines. In

contrast, *ahpC*, but not *ahpD* mutants were highly attenuated in a small number of CC

strains (**Figure 4E**). Similarly, the four phospholipase C enzymes of *Mtb* (*plcA-D*) are

implicated in both fatty acid uptake and modifying host cell membranes but are

dispensable for replication in B6 mice (Le Chevalier et al., 2015). Again, while we found

that none of these genes were required in B6-derived KO lines, the *plcD* mutants were

specifically underrepresented in a number of CC mice (**Figure 4E**). These individual

bacterial functions are controlled by regulatory proteins, such as the extracytoplasmic

sigma factors. Despite the importance of these transcription factors in the response to

stress, only *sigF* has been consistently been shown to contribute to bacterial replication

in standard inbred lines of mice (Geiman et al., 2004; Rodrigue et al., 2006). Our study

assesses the importance of each sigma factor in parallel across diverse host genotypes

and identified a clear role for several of these regulators. *sigC, sigI, sigF, sigL,* and *sigM*

mutants were each significantly underrepresented in multiple lines of mice, and several

of these phenotypes were only apparent in the diverse CC animals (**Figure 4E**). In

sum, the 607 adaptive functions that are differentially required across the host panel

represents nearly 20% of the non-essential gene set of Mtb, suggesting that a

significant fraction of the pathogen's genome is dedicated to maintaining optimal fitness

in diverse host environments.

Differential genetic requirements define virulence pathways in *Mtb*

To more formally investigate the distinct stresses imposed on the bacterial population

across this host panel, we characterized the differentially required bacterial pathways.

Upon performing each possible pairwise comparison between the *in vivo* selected

mutant pools, we found 679 mutants whose representation varied significantly (FDR <

5%) in at least two independent comparisons (**Table S4**). We then applied weighted

gene correlation network analysis (WGCNA) (Langfelder and Horvath, 2008) to divide

the mutants into 20 internally-correlated modules. Further enrichment of these modules

for the most representative genes (intramodular connectivity > 0.6) revealed that nearly

all modules contained genes that are encoded adjacently in the genome and many of

these modules consisted of genes dedicated to a single virulence-associated function

(**Figure 5A**). Module 3 contains two distally encoded loci both known to be necessary

for ESX1-mediated protein secretion, the primary ESX1 locus (*rv3868-rv3883*) and the

espACD operon (*rv3616c-rv3614c*). Similarly, other modules consisted of genes

responsible for ESX5 secretion (Module 7), mycobactin synthesis (Module 4), the Mce1

and Mce4 lipid importers (Modules 5 and 16), phthiocerol dimycocerosate synthesis

(PDIM, Module 8), PDIM transport (Module 16), and phosphate uptake (Module 14).

The 20 genes assigned to Module 6 included two components of an important oxidative

stress resistance complex (*sseA* and *rv3005c*) and were highly enriched for mutants

predicted to be involved in this same process via genetic interaction mapping (11/20

genes were identified in (Nambi et al., 2015), a statistically significant overlap (p< 2.8e-

10 by hypergeometric test)). Thus, each module represented a distinct biological

function.

Many pathway-specific modules contained genes that represented novel functional

associations. For example, the gene encoding the sigma factor, *sigC*, was found in

Module 1 along with a non-ribosomal peptide synthetic operon. Previous genome-wide

ChIP-seq and overexpression screens support a role for SigC in regulating this operon

(Minch et al., 2015; Turkarslan et al., 2015). Similarly, *rv3220c* and *rv1626* have been

proposed to comprise an unusual two component system that is encoded in different

regions of the genome (Morth et al., 2005). Both of these genes are found in Module 2,

along with the PPE50 and PPE51 genes that encode at least one outer membrane

channel (Wang et al., 2020)(**Figure 5A**). In both cases, these associations support both

regulatory and obligate functional relationships between these genes. Six of the 20

modules were not obviously enriched for genes of a known pathway, demonstrating that

novel virulence pathways are important for adapting to changing host environments.

To explore the complexity of immune environments in the CC, we used the TnSeq

profiles of the 679 differentially fit *Mtb* mutants to cluster the mouse panel into 6 major

groups of host genotypes (**Figure 5B**). One mouse cluster was significantly associated

with high CFU (Cluster F, **Figure 5B**), which contained susceptible *Nos2*$^{-/-}$, *Cybb*$^{-/-}$, *Ifnγ* $^{-}$

$^{/-}$, and *Rag2*$^{-/-}$ animals. This high CFU cluster was associated with alterations in a

diverse set of bacterial modules and corresponded to an increased requirement for lipid

uptake (Modules 5 and 16) and ESX1, consistent with previous TnSeq studies in

susceptible *Nos2*$^{-/-}$ and C3HeB/FeJ mice (Mishra et al., 2017). In addition, we identified

a significant reduction in the requirement for the oxidative stress resistance (Module 6)

in the highest CFU cluster. Despite these associations between bacterial genetic

requirements and susceptibility, the clustering of mouse genotypes was largely

independent of overall susceptibility. Similarly, while Module 1 was significantly

associated with high IFNγ levels, other bacterial fitness traits were not highly correlated

with cytokine abundance (**Figure S3**). Instead, each major mouse cluster was

associated with a distinct profile of *Mtb* genetic requirements. This observation

supported the presence of qualitatively distinct disease states and complex genetic

control of immunity.

Identification of host-pathogen genetic interactions

To investigate the host genetic determinants of the bacterial microenvironment, we

associated *Mtb* mutant fitness profiles with variants in the mouse genome. When the

relative abundance of each *Mtb* mutant was considered individually, the corresponding

"Host Interacting with Pathogen QTL" (*Hip*QTL) were distributed across the mouse

genome (**Figure 6A**). 41 of these traits reached an unadjusted p-value threshold of 0.05

and can be considered as robust for single hypothesis testing (*Hip1-41*, **Table S2** and

S5). These included *Hip*QTL associated with both *ahpC* and *eccD1*, that explain at

least a portion of the observed variable abundance of these mutants (**Figure 4E**). In

order to reduce complexity and increase the power of this analysis, we performed QTL

mapping based on the first principal component of each of the previously defined

modules of *Mtb* virulence pathways (**Figure 5A**). Three of these "eigentraits" were

associated with QTL at a similar position on chromosome 10 (**Figure 6B**),

corresponding to Module 3 (TypeVII secretion, ESX1), Module 4 (mycobactin synthesis,

mbt), or Module 16 (cholesterol uptake, *mce4*). In all three cases, a single mutant from

the module was independently associated with a QTL at the same position as the

module eigentrait (**Table S5**, *Hip21, Hip22, Hip24*), and all genes in the corresponding

network cluster (**Figure 5A**) mapped to the same location (**Figure 6C**-**E**). While not all

individual traits mapped with high confidence, the coincidence of these multiple QTL

was statistically significant (**Figure 6B**).

Both the relative positions of the module-associated QTL and the associated founder

haplotypes indicated that a single genetic variant controlled the abundance of ESX1 and

mbt mutants (*Hip42*). Specifically, we found no statistical support for differentiating

these QTL based on position (p=0.93)(Boehm et al., 2019) and the same founder

haplotypes were associated with extreme trait values at both loci, though they had

opposite effects on the abundance of ESX1 mutants and *mbt* mutants (**Figure 6F**). We

conclude that a single haplotype has a pleiotropic effect on *Mtb*'s environment and has

opposing effects of the requirement for mycobactin synthesis and ESX1 secretion. The

relationship between this variant and the *mce4*-associated QTL (*Hip43*) was less clear,

as the statistical support for independent QTL was weak (ESX1 and *mce4* QTL p=0.17;

mbt and *mce4* QTL p=0.08) and the effects of founder haplotypes were similar but not

identical (**Figure 6F**). Some of this ambiguity may be related to the relatively small

range in trait values for *mce4*, compared to either ESX1 or *mbt* (**Figure 6G**). Based on

this data, we report two distinct *Hip*QTL in this region (*Hip42* and *43*, **Table S5**).

Two *Tip*QTL overlapped with *Hip*QTL (**Figure S2**), suggesting specific interactions

between bacterial fitness and immunity. However, most *Tip-* and *Hip*QTL were distinct,

indicating that the fitness of sensitized bacterial mutants can be used to detect genetic

variants that subtly influence the bacterial environment but not overtly alter disease. We

chose to further investigate whether *Hip*QTL might alter overall bacterial disease using

the most significant *Hip*QTL on chromosome 10 (*Hip42*). We found that the founder

haplotypes associated with extreme trait values at this QTL could differentiate CC

strains with significantly altered total bacterial burden, and the NOD and WSB

haplotypes were associated with higher bacterial numbers (p=0.0085 for spleen CEQ;

p=0.027 for spleen CFU; **Figure 6H**). Thus, not only could the *Hip*QTL strategy identify

specific interactions between host and bacterial genetic variants, but it also appears to

be a sensitive approach for identifying host loci that influence the trajectory of disease.

Identifying candidate genes underlying QTL

A pipeline was designed to prioritize genetic variants based on genomic and

tuberculosis disease criteria. We concentrated on three QTL: two that were highly

significant and with clear allele effects (*Tip5, Hip42*), and the *Tip8* locus which we

validated by intercross. For each QTL region, we identified genes that belonged to a

differentially expressed transcriptional module in mouse lungs following *Mtb* infection

(Moreira-Teixeira et al., 2020). Next, we identified genetic variants segregating between

the causal CC haplotypes in the gene bodies corresponding to these transcripts, and

prioritized missense or nonsense variants.

For the *Tip5* QTL underlying CEQ, CFU, and IL-10 levels, we identified nine candidate

genes with regulatory or splicing variants and two genes with missense variants specific

to the NOD haplotype. Of these candidates, cathepsin Z (*Ctsz)* encodes a lysosomal

cysteine proteinase and has previously been associated with TB disease risk in humans

(Adams et al., 2011; Cooke et al., 2008). The QTL underlying lung CFU and CXCL1

abundance (*Tip8*), which was driven solely by the genetically divergent CAST founder

haplotype, contained over 50 genes (**Table S6**) and will need further refinement. The

QTL associated with the abundance of ESX1 and *mbt* mutants (*Hip42*) had a complex

causal haplotype pattern (AJ/B6/NZO vs. 129/CAST/PWK vs. NOD/WSB) suggesting

multiple variants might be impacting common genes. Within this interval, we identified

13 genes expressed in response to *Mtb* infection, three of which had SNPs fully or

partially consistent with at least one of the identified causal haplotype groups (**Table**

S6). *Ank3* contains several SNPs in the 3' UTR and other non-coding exons that

differentiated NOD/WSB from the other haplotypes. Similarly, *Fam13c* had two

missense mutations following the same haplotype pattern. For the AJ/B6 haplotype

state, we identified a missense mutation and several variants in the 3' UTR of *Rhobtb1*,

which belongs to the Rho family of the Ras superfamily of small GTPases (Goitre et al.,

2014). Overall, the evidence supports a role for *Rhobtb1* in a monogenic effect at the

chromosome 10 locus. This evidence includes both protein coding differences dividing

AJ/B6 from the other haplotypes, a potential expression/transcript regulatory difference

that segregates the NOD/WSB state from the remaining parental haplotypes, and a

plausible role for this gene in controlling intracellular trafficking (Long et al., 2020) and

the opposing requirements for ESX1 and mycobactin.

Discussion

Our immunological analysis of the CC panel identified correlates of TB disease

progression that were consistent with previous studies in both mice and human patients

(Ahmed et al., 2020; Niazi et al., 2015; Zak et al., 2016). More importantly, we identified

outlier strains that produce distinct immunological states, highlighting how our previous

reliance on genetically homogenous lab strains of mice has oversimplified our

understanding of TB pathogenesis. For example, despite the generally strong

correlation between lung bacterial burden and disease, CC030/GeniUnc and

CC040/TauUnc mice suffered from more inflammation and wasting than would be

predicted from the number of bacteria in their lungs or spleens. This phenotype reflects

a failure of disease "tolerance", which is proposed to be a critical determinant of

protective immunity (Ayres and Schneider, 2012; Olive et al., 2018). Similarly, we

identified a number of CC genotypes that produce very low, or undetectable, levels of

the protective cytokine IFNγ, but still control lung bacterial replication. While a growing

body of literature suggests that immune responses distinct from the canonical Th1

response can control infection (Lu et al., 2019; Sakai et al., 2016), these CC strains are

the first example of an animal model in which IFNγ appears to be dispensable. The

reproducibility of the CC strains facilitated the identification of these phenotypes and

provides tractable models for their characterization.

The ability to separate aspects of the immune response from disease progression

implied that these features are under distinct multigenic control. This conclusion is

supported by genetic mapping, which identified a number of variants that control distinct

aspects of the immune response to *Mtb*. The QTL identified in this study are generally

distinct from CC loci that control immunity to viruses (Ferris et al., 2013; Gralinski et al.,

2017; Noll et al., 2020) or another intracellular bacterial pathogen, *Salmonella* (Zhang et

al., 2019). However, *Tip8* and *Tip10* overlap with QTL previously defined via *Mtb*

infection of CC001xCC042 F_2 intercross population (Smith et al., 2019) suggesting that

common variants may have been identified in both studies. While the specific genetic

variants responsible for these QTL remain unknown, both coincident trait mapping and

bioinformatic analysis suggest mechanistic explanations for some QTL-phenotype

associations. For example, a single interval on chromosome 2 controls CFU levels and

IL-10, and contains a variant in the *Ctsz* gene encoding Cathepsin Z. *Ctsz* is a strong

candidate considering its known roles in autophagy (Amaral et al., 2018), dendritic cell

differentiation and function (Obermajer et al., 2008), its upregulation in non-human

primates (Ahmed et al., 2020) and human patients with *Mtb* (Zak et al., 2016), and the

association of *CTSZ* variants with disease risk in human TB studies (Adams et al.,

2011; Cooke et al., 2008).

Using TnSeq as a multidimensional phenotyping method across this population

provided insight into how the diversity of host-derived microenvironments have shaped

the pathogen's genome. While *Mtb* is an obligate pathogen with no significant

environmental niche, only a minority of the genes in its genome have been found to

contribute to bacterial fitness in either laboratory media or individual inbred mouse

models, leaving the pressures that maintain the remaining genomic content unclear. We

find that approximately three times more genes contribute to bacterial growth or survival

in the CC population than in the standard B6 model. While some bacterial genetic

requirements could be associated with known immune pathways, most of the differential

pressures on bacterial mutants could not be attributed to these simple deficiencies in

known mechanisms of immune control. Instead, it appears that the CC population

produces a spectrum of novel environments, and that a relatively large fraction of the

pathogen's genome is needed to adapt to changing immune pressures. Differential

pressures on these adaptive virulence functions are similarly apparent in genomic

analyses of *Mtb* clinical isolates. Signatures of selection have been detected in ESX1-

related genes (Holt et al., 2018; Sousa et al., 2020), *phoPR* (Gonzalo-Asensio et al.,

2014), and the oxidative stress resistance gene *sseA* (de Keijzer et al., 2014),

suggesting that *Mtb* is exposed to similarly variable host pressures in genetically diverse

human and mouse populations. While the combinatorial complexity of associating host

and pathogen genetic variants in natural populations is daunting, the identification of

*Hip*QTL in the CC panel indicates that these inter-species genetic interactions can be

important determinants of pathogenesis and can be dissected using tractable models of

diversity.

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Materials and Methods:

Ethics statement:

Mouse studies were performed in strict accordance using the recommendations

from the Guide for the Care and Use of Laboratory Animals of the National

Institute of Health and the Office of Laboratory Animal Welfare. Mouse studies at

the University of Massachusetts Medical School (UMASS) were performed using

protocols approved by the UMASS Institutional Animal Care and Use Committee

(IACUC) (Animal Welfare Assurance Number A3306-01) in a manner designed to

minimize pain and suffering in *Mtb*-infected animals. Any animal that exhibited

severe disease signs was immediately euthanized in accordance with IACUC

approved endpoints. All mouse studies at UNC (Animal Welfare Assurance

#A3410-01) were performed using protocols approved by the UNC Institutional

Animal Care and Use Committee (IACUC).

Mice:

Male and female Collaborative Cross parental strains (A/J #0646; C57BL/6J #0664;

129S1/SvlmJ #02448; NOD/ShiLtJ #01976; NZO/HiLtJ #02105; CAST/EiJ #0928,

PWK/PhJ #3715 and WSB/EiJ #01145) and single gene immunological knockout mice

were purchased from The Jackson Laboratory ($Nos2^{-/-}$ #2609, $Cybb^{-/-}$ #2365, $Ifn\gamma^{-/-}$

#2287) or Taconic (*Rag*N12) and bred at UMASS. Male mice from 52 CC strains were

purchased from the UNC Systems Genetics Core Facility (SGCF) between July 2013

and August 2014. The 52 CC strains used in this study include: CC001/Unc,

CC002/Unc, CC003/Unc, CC004/TauUnc, CC005/TauUnc, CC006/TauUnc,

CC007/Unc, CC008/GeniUnc, CC009/Unc, CC010/GeniUnc, CC011/Unc,

CC012/GeniUnc, CC013/GeniUnc, CC015/Unc, CC016/GeniUnc, CC017/Unc,

CC018/Unc, CC019/TauUnc, CC021/Unc, CC022/GeniUnc, CC023/GeniUnc,

CC024/GeniUnc, CC025/GeniUnc, CC027/GeniUnc, CC028/GeniUnc, CC029/Unc,

CC030/GeniUnc, CC031/GeniUnc, CC032/GeniUnc, CC033/GeniUnc, CC034/Unc,

CC035/Unc, CC037/TauUnc, CC038/GeniUnc, CC039/Unc, CC040/TauUnc,

CC041/TauUnc, CC042/GeniUnc, CC043/GeniUnc, CC044/Unc, CC045/GeniUnc,

CC046/Unc, CC047/Unc, CC051/TauUnc, CC055/TauUnc, CC056/GeniUnc,

CC057/Unc, CC059/TauUnc, CC060/Unc, CC061/GeniUnc, CC065/Unc,

CC068/TauUnc. More information regarding the CC strains can be found at

http://csbio.unc.edu/CCstatus/index.py?run=AvailableLines.information.

CC030 x CC029 F_2 mice were generated at UNC by crossing CC030 and CC029

mice (purchased from the SGCF in 2016) to generate F_1s (both CC030 dam by

CC029 sires as well as CC029 dam by CC030 sires). The resulting F_1s were

subsequently intercrossed to generate F_2 mice with all possible grandparental

combinations. Male and female F_2 mice were shipped to UMASS for *Mtb*

infections.

All mice were housed in a specific pathogen-free facility under standard

conditions (12hr light/dark, food and water ad libitum). Mice were infected with

Mtb between 8-12 weeks of age. Male and female mice were used, unless

otherwise noted.

M.tuberculosis strains:

All *M. tuberculosis* strains were grown in Middlebrook 7H9 medium containing

oleic acid-albumin-dextrose-catalase (OADC), 0.2% glycerol, and 0.05% Tween

80 to log-phase with shaking (200 rpm) at 37°C. Hygromycin (50 ug/ml) or

kanamycin (20 ug/ml) was added when necessary. The Δ*bioA* strain was made

by homologous recombination as previously described (Woong Park et al.,

2011). For pooled mutant infections, deletion strains were constructed using

ORBIT (Murphy et al., 2018), which included gene replacement by the vector

pKM464 carrying unique q-Tag sequences to identify each mutant for deep

sequencing. The *rnaseJ* mutant was also made by ORBIT and was kindly

provided by Dr. Nathan Hicks and Dr Sarah Fortune. Prior to all *in vivo* infections,

cultures were washed, resuspended in phosphate-buffered saline (PBS)

containing 0.05% Tween 80, and sonicated before diluting to desired

concentration (see below).

Mouse Infections:

For TnSeq experiments, 1×10^6 CFU of saturated *Himar1* transposon mutants

(Sassetti et al., 2003) was delivered via intravenous tail vein injection. Mice were

infected over 3 infection batches, as denoted in **Table S1**). At indicated time

points mice were euthanized, and organs were harvested then homogenized in a

FastPrep-24 (MP Biomedicals). CFU was determined by dilution plating on 7H10

agar with 20 ug/mL kanamycin. For library recovery, approximately 1×10^6 CFU

per mouse was plated on 7H10 agar with 20ug/mL kanamycin. After three weeks

of growth, colonies were harvested by scraping and genomic DNA was extracted.

The relative abundance of each transposon mutant was estimated as described

(Long et al., 2015).

Single strain aerosol infections were performed in a Glas-Col machine to deliver

50-150 CFU/mouse. At indicated time points, mice were euthanized, and organs

were harvested then homogenized in a FastPrep-24 (MP Biomedicals). CFU was

determined by dilution plating on 7H10 agar with 20 ug/mL kanamycin or

50ug/mL hygromycin as required.

Chromosomal equivalent (CEQ) was enumerated according to previously

published protocol (Lin et al., 2014; Muñoz-Elías et al., 2005). Cytokines and

chemokines were assayed from organ homogenates using the pro-inflammatory

focused 32-plex (Eve Technologies, Calgary, CA) or IFNγ DuoSet ELISA (R&D

Systems) according to manufacturer protocol. IFNγ release was assayed by

ELISPOT (BD Biosciences #551083) according to manufacturer protocol. Single

cell suspensions of lung or spleen tissue were stimulated for 18-24 hours with

4ug/ml purified protein derivative (PPD) and after development, spots were

quantified using a CTL Immunospot S5 Analyzer.

For pooled mutant infections, mice were infected with a pool of deletion mutants at

equal ratios via the intravenous route (1×10^6 CFU/mouse). At indicated time points,

approximately 10,000 CFU from the spleen homogenate of each mouse was plated on

7H10 agar. Genomic DNA was extracted for sequencing as described previously (Long

et al., 2015). Sequencing libraries spanning the variable region of each q-Tag were

generated using PCR primers binding to regions common among all q-Tags, similar to

previously described protocols (Bellerose et al., 2020; Martin et al., 2017). In each PCR,

a unique molecular counter was incorporated into the sequence to allow for the

accurate counting of input templates and account for PCR jackpotting. The libraries

were sequenced to 1,000-fold coverage on an Illumina NextSeq platform using a 150-

cycle Mid-Output kit with single-end reads. Total abundance of each mutant in the

library was determined by counting the number of reads for each q-Tag with a unique

molecular counter. Relative abundance of each mutant in the pool was then calculated

by dividing the total abundance of a mutant by the total abundance of reads for wild-

type H37Rv. The relative abundance was normalized to relative abundance at initial

infection (Day 0) and $\log_2$ transformed. Fitness was calculated as previously described

(Palace et al., 2014).

QUANTIFICATION AND STATISTICAL ANALYSIS

TnSeq analysis:

TnSeq libraries were prepared and counts of each transposon mutant were estimated

as described (Long et al., 2015). NCBI Reference Sequence NC_018143.1 was used

for H37Rv genome and annotations. In the majority of cases, two replicate mouse

libraries were used per genotype. Only a single TnSeq library was obtained for CC010,

CC031, CC037, CC059, CC016, and PWK/PhJ. Insertion mutant counts across all

libraries were normalized by beta-geometric correction (DeJesus et al., 2015), binned

by gene, and replicate values for each mouse genotype averaged. Mean values for

each gene were divided by the grand mean then $\log_2$ transformed and quantile

normalized. The resulting phenotype values were used for both WGCNA and QTL

mapping.

To eliminate genes having no meaningful variation across the mouse panel, statistical

tests of $\log_2$ fold change (LFC) in counts between all possible pairs of mouse genotypes

were performed by resampling (DeJesus et al., 2015). 679 "significantly varying genes"

were identified whose representation varied significantly (FDR < 5%) in at least two

independent comparisons. For relative mutant abundance estimates, LFC in counts

between *in vitro*-grown H37Rv (6 replicate libraries) vs libraries from each mouse

genotype were determined by resampling as above.

WGCNA analysis:

Weighted gene correlation network analysis (WGCNA) was applied to categorize the

679 significantly varying genes into 20 internally-correlated modules (Langfelder and

Horvath, 2008). Modules were filtered (intramodular connectivity > 0.6) to obtain the

most representative genes. First principal component scores of module eigengenes

were used as phenotype values for QTL mapping after first winsorizing (q=0.05) using

the R package *broman* (https://cran.r-project.org/web/packages/broman/index.html).

In order to perform association analysis between modules of genes and clusters of mice

(**Figure 5B**), the mice were clustered based on the matrix of TnSeq LFCs for

significantly varying genes using *hclust* in R (with the "Ward.D2" distance metric). Then,

for each module of genes, the LFCs in each cluster of mice were pooled and compared

to all the other mice using a T-test, identifying modules with a mean LFC in a specific

mouse cluster that is significantly higher or lower than the average across all the other

mice. The resulting p-values over all combinations of gene modules and mouse

clusters were adjusted using Benjamini-Hochberg for an overall FDR < 0.05.

Disease-related trait analysis and Heritability estimation:

For the trait heatmap, trait values were clustered (*hclust* in R package *heatmaply;* traits

scaled as per default function) and dendrogram nodes colored by 3 k-means.

Correlation between disease-related TB traits was determined by Pearson's correlation

and visualized using *corrplot* (ordered by *hclust*). Heritability (h^2) of the immunological

and TB disease-related traits was calculated by estimating the percent of variation

attributed to a genotype as previously described (Noll et al., 2020).

Genotyping and QTL mapping:

A subset of the inbred CC mice used in the analysis were genotyped on the GigaMUGA

array (Morgan et al., 2015) available from Neogen Inc. The inbred parents, F_1s and F_2

mice from the CC030xCC029 cross were genotyped on the MiniMUGA array (Sigmon et

al., 2020) at Neogen Inc.

For CC030 x CC029 F_2 analysis, markers were filtered, restricting only to those

diagnostic between these strains (See **Table S3**). To assess the relative impact of the

Chr7 and 15 loci, a linear regression on CFU was run with CAST haplotypes on Chr7,

Chr15, and their interaction as factors.

For QTL mapping in the CC panel, the Most Recent Common Ancestor (Srivastava et

al., 2017) 36-state haplotypes were downloaded from the UNC Systems Genetics Core

Facility and simplified to 8-state haplotype probabilities (for the 8 CC founder strains),

which is appropriate for additive genetic mapping. We generated 36-state haplotype

probabilities from the individual CC mice genotyped on GigaMUGA and combined these

data with the MRCA data to obtain a common genome cache.

For CC QTL analysis, genotype and phenotype data were imported into R (version

3.6.1) and reformatted for R/qtl2 (version 0.20) (Broman et al., 2019). Individual TnSeq

and clinical trait phenotype values were winsorized (q = 0.006) as above. GigaMUGA

annotations were downloaded from the Jackson Laboratory, and markers were thinned

to a spacing of 0.1 cM using the reduce_markers function of R/qtl2. The final genetic

map contained 10,067 markers. QTL mapping was carried out using a linear mixed

model with LOCO (leave one chromosome out) kinship. For clinical trait scans, batch

(denoted by "block" in Table S1) was included as an additive covariate. Significance

thresholds for QTL were estimated using 10,000 permutations (scan1_perm function).

For each trait, the maximum LOD scores from the permutation scans were used to fit

generalized extreme value distributions, from which genome-wide permutation p-values

were calculated. LOD profiles and effect plots were generated using the plotting

functions of the R/qtl2 package. Multiple QTL at similar genetic locations were assessed

for independence using qtl2pleio with 400 bootstrap samples (Boehm et al., 2019). The

quantile-based permutation thresholding method of Neto et al. (Neto et al., 2012) was

used to assess the statistical significance of co-mapping traits. The NL-method, which

determines the LOD thresholds controlling genome wide error rate for a given p-value

and "hotspot" size, was employed.

Candidate gene prioritization:

To identify potential candidate genes, we focused on three QTL that were either

statistically significant (*Tip5*, *Hip42*) or were validated by intercross (*Tip8*). For each

QTL interval (determined by Bayesian interval in qtl2), we identified mouse genes that

were in differentially expressed modules between infected lungs of resistant and

susceptible mouse strains (Moreira-Teixeira et al., 2020). Of these genes, we next used

the Sanger sequence data (Keane et al., 2011) to filter on genetic variants segregating

between CC haplotypes. Where there were clear causal haplotypes, we further filtered

to genes with missense or nonsense variants.

Data availability:

All relevant data to support the findings of this study are located within the paper and

supplemental files or are in the process of being made publicly available at the time of

this submission; all mouse phenotype data are being deposited in Mouse Phenome

Database (https://phenome.jax.org), and sequence data is being deposited in the NCBI

Gene Expression Omnibus (GEO).

Supplemental information titles and legends:

Table S1 - CC TB phenotypes. TB disease-related phenotypes measured in the CC

and parental strains. Recorded values are the average of measurements from 2-6 mice

per genotype (average n=3). Mice were infected over 3 batches (denoted by "block").

"Blaze" denotes genotypes with white head-spotting coat color trait (WSB haplotype for

Kitl; used as a positive control/proof-of-concept for QTL mapping as per (Aylor et al.,

2011; Smith et al., 2019).

Table S2 - Heritability (h^2) estimates for each measured TB-disease associated

phenotype (Tuberculosis ImmunoPhenotypes). h^2 was calculated from the

percentage of variation attributed to strain differences in each trait across the CC

strains, as previously described (Noll et al., 2020). Weight change is the percentage of

weight (grams), CFU/CEQ is $\log_{10}$ transformed, cytokines are measured in pg/mL lung

homogenate and $\log_{10}$ transformed**.**

Table S3 - F_2 Intercross phenotype data. Lung CFU measured in 46 F_2 mice derived

from CC030xCC029 intercross strategy. F_2 mice were CAST at chromosome 7, CAST

at Chromosome 15, CAST at both or CAST at neither locus. The infected F_2 cohort

included both male and female mice, as indicated.

Table S4 - TnSeq Summary Table. LFC values represent the $\log_2$ fold-change (LFC)

between input and mouse-selected pools. "NA" indicates genes with fewer than 3

occupied TA transposon insertion sites for the indicated comparison. Qvals represent

adjusted p-values comparing mutant abundance in input and selected pools. "NA"

indicates genes with fewer than 3 occupied TA transposon insertion sites for the

indicated comparison. Required *in vivo*: "TRUE" indicates the mutant is significantly

underrepresented (Qval<0.05) after in mouse-selection in at least two mouse strains.

Required in B6: "TRUE" indicates the mutant is significantly underrepresented (Qval

<0.05) after in selection in B6 mice. Required in KO mice: "TRUE" indicates the mutant

is significantly underrepresented (Qval<0.05) after in selection in $Rag^{-/-}$, $Nos2^{-/-}$, $Cybb^{-/-}$,

or $Ifng^{-/-}$ mice. Core gene set: TRUE indicates the mutant is significantly

underrepresented (Qval<0.05) in 30 mouse strains. "Module" corresponds to WGCNA

module number as illustrated in **Figure 5A**. Mouse strains are listed in the same order

as **Figure 5B**, with the corresponding cluster designation.

Table S5 - *Hip*QTL for single *Mtb* mutant QTL and eigentrait/module QTL. *Hip1-41*

each represent host loci associated with the relative abundance of a single mutant

(p<0.05). *Hip42-46* correspond to *Mtb* eigentraits identified in network analysis in **Figure**

5 (including significant p<0.05 and suggestive p<0.25). Figure column headings: QTL,

quantitative trait loci; *Mtb*, *Mycobacterium tuberculosis*; Module #, number determined

from WGCNA modules; ORF, open reading frame; ID, identification number; LOD,

logarithmic of the odds; Chr, chromosome.

Table S6 - Candidate genes within QTL regions. Prioritized candidates shown for

selected QTL. Candidates were prioritized by filtering on 1) differential expression

during *Mtb* infection, and 2) variants within TB-expressed genes that segregated

between informative CC haplotypes. Genes listed below contain non-synonymous

variants (ie. amino acid changes, regulatory mutations or splicing mutations) consistent

with the identified singly causal haplotype (NOD for *Tip5;* CAST for *Tip8*). *Hip42*

displayed a more complex haplotype pattern (WSB/NOD vs AJ/B6/NZO), and candidate

selection is discussed in the main text. Genes with missense or nonsense variants

(denoted by *).

Figure S1 - Phenotypic relationships between TB disease-related traits. Correlation

between 32-measured TB traits was determined by Pearson's correlation and visualized

using corrplot version 0.84 (ordered by hclust method "complete") in R version 4.0.3.

Violet indicates a positive correlation, and yellow indicates negative correlations. The

correlation coefficient for each trait comparison (r value) is noted on each square. EoD

(earliness of Death); CEQ (Chromosomal equivalents).

Figure S2 - Visual representation of QTL mapped in the CC TnSeq infection

screen. Tuberculosis ImmunoPhenotypes (*Tip*) QTL (QTL mapped by disease-

associated traits in CC mice), are shown in green. *Tip*QTL mapped by separate traits

that share similar founder effects were considered to be the same QTL and were named

accordingly. Host Interacting with Pathogen (*Hip*) QTL, (QTL mapped by individual

TnSeq mutant relative abundance profiles), are shown in purple. After WGCNA mutant

clustering and mapping with representative eigengenes from each module, QTL

mapped by module eigengenes are shown in magenta.

Figure S3 - Module-trait associations. Rows correspond to modules, columns to

clinical traits. Numbers in each cell give the Pearson correlation between the module

eigengene and the trait values across the 60-mouse panel (p-values in parentheses).

Cells are colored by correlation as shown in the color legend (right).

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Figure 1. The spectrum of M. tuberculosis disease-related traits across the Collaborative Cross.
(A) Average lung CFU (log10) across the CC panel at 4 weeks post-infection. Bars show mean +/- SD for CFU per CC or parental strain; groups of 2-6 (average of n=3) mice per genotype. Bars noted with * indicate strains that were statistically different from B6 (P<0.05; 1-factor ANOVA with Dunnett's post-test). (B) Heatmap of the 32 disease-related traits (log10 transformed) measured including: lung and spleen colony forming units (CFU); lung and spleen chromosomal equivalents (CEQ); weight loss (% change); cytokines from lung, "earliness of death" (EoD) reflecting the number of days prior to the end of experiment that moribund strains were euthanized. Mouse genotypes are ordered by lung CFU. Scaled trait values were clustered (hclust in R package heatmaply) and dendrogram nodes colored by 3 k-means. Blue node reflects correlation coefficient r>0.7; green r=0.3-0.6 and red r<0.2. (C) Correlation of lung CFU and weight (% change) shaded by CXCL1 levels. Genotypes identified as statistical outliers for weight are noted by #; CXCL1 by †. (D) Correlation of lung CFU and IFNγ levels shaded by IL-17. Strains identified as outliers for IFNγ noted by #. Each point in (C) and (D) is the average value per genotype. Outlier genotypes were identified after linear regression using studentized residuals. (E-H) B6 and CAST traits measured at 4 weeks post aerosol infection (E) lung CFU; (F) spleen CFU; (G) number of IFNγ producing lung T cells; (H) number of IFNγ producing spleen T cells. Bar plots show the mean +/- SD. Significance between groups was determined by Welch's t test. Groups consist of 4-10 mice per genotype from 2 independent experiments. All mice in the initial CC screen were male; validation studies in panels E-H included both sexes, where no statistical difference at the 4-week timepoint between sexes was observed.

Figure 2. Host loci underlying TB disease-related traits.
(A-B) Whole genome QTL scans of (A) spleen CEQ, spleen CFU and IL-10 (B) lung CFU and CXCL1. (C) Zoom of chromosome 2 loci. (D) Zoom of chromosome 7 loci. Thresholds were determined by permutation analysis; solid line, middle dashed line, and lowest dotted lines represent P = 0.05, P = 0.1, and P = 0.2. (E-F) Scaled phenotype value per haplotype at the QTL peak marker. Each dot represents the mean value for a genotype.

Figure 3. An F2 intercross approach to validate QTL underlying lung CFU. (A) Cross schema between CC030 and CC029 CC strains that contain CAST informative haplotypes at Chr 7 or 15. CC030 contains CAST at 30-45Mb on Chr 7 and CC029 contains CAST at 77-79Mb on Chr 15. The F2 population based on these founders were genotyped and informative segregants were infected with Mtb. (B) Lung CFU at 1-month post-infection. F2 mice are grouped by the four possible genotypes: CAST at both 7 and 15, CAST at 7, CAST at 15, or non-CAST at both loci. To determine the effect of CAST haplotype on lung CFU, data was analyzed by 2-factor ANOVA to determine statistical significance.

Figure 4. Mtb genetic requirements vary across diverse hosts. (A) The number of Mtb genes required for growth or survival in each diverse mouse strain across the panel (Qval ≤ 0.05). Orange indicates the mutants required for each strain; turquoise shows the cumulative requirement as each new host strain is added. (B) Venn diagram showing the composition of Mtb gene sets required in each category of host (white, largest circle), only required in the CC panel (grey), required in specific immunological KO mice (blue) and genes required in B6 mice (red). In order to be called "essential" in each mouse strain, Mtb genes had to be significantly over or unrepresented in at least 2 genotypes. (C) Each box shows Log2 fold change (LFC) of individual mutants from the TnSeq screen relative to the input pool in indicated mouse strains (top); Log2 fold change of the indicated deletion mutants relative to WT from a pooled mutant validation infection (middle panel); Relative fitness calculated from (middle panel) to account for generation differences in each host due to differential growth rate. Bars are the average of 3-6 mice per mutant/genotype +/- SD. Statistical differences between mini-pool validation groups was assessed by Welch's t test. (D) Lung CFU and spleen CFU from single strain low-dose aerosol infections of ΔbioA mutant or WT H37Rv strain in B6 and CAST mice at 2- or 5-weeks post-infection. Dashed line indicates the limit of detection. Each point indicates the average CFU +/- SD of 4-5 mice per group. (E) Log2 fold change of selected mutants from the TnSeq screen across the CC panel and immunological KO mice. Each dot represents the average LFC per mouse genotype. All mice in the complete mouse panel TnSeq screen were male; mice in the ΔbioA aerosol validation were female; mice in the mini-pool validation studies were male and female with no significant differences detected.

Figure 5. Mtb virulence pathways associate with distinct host immune pressures. (A) Weighted gene correlation network analysis (WGCNA) of the 679 Mtb genes that significantly vary across the diverse mouse panel. The most representative genes of each module (intramodular connectivity > 0.6) are shown. (B) Mouse genotypes were clustered based on the relative abundance (log fold change relative to *in vitro*) of the 679 variable *Mtb* mutants. The six major clusters (Cluster A-F) were associated with both CFU and the relative abundance of mutants in each bacterial module (1-20; right hand-side with known functions). Cluster F is associated with high CFU (p<0.05, as described in methods). * indicate modules significantly associated with specific mouse clusters (P<0.05).

Figure 6. Identification of 'Host Interacting with Pathogen' QTL mapping (HipQTL). (A) Manhattan plot of single Mtb mutant QTL mapping across the mouse genome. Each dot represents an individual Mtb mutant plotted at the chromosomal location of its maximum LOD score. Red dashed line indicates P<0.01; Blue P<0.05. (B) Chromosome 10 QTL corresponding to Mtb eigentraits identified in network analysis in Figure 5. Module 3 (type VII secretion, ESX1 operon; orange), Module 4 (Mycobactin synthesis, mbt; green) and Module 16 (Cholesterol uptake, mce4; purple) are shown. Solid and dotted lines indicated P = 0.05 and P = 0.1, respectively. (C-E) QTL mapping of single Mtb mutants corresponding to the (C) ESX1 module, (D) mbt module and (E) mce4 modules. Coincidence of multiple QTL was assessed by the NL-method of Neto et al (Neto et al., 2012). Thresholds shown are for N=9, N=8, and N=6 for panels C, D, and E, respectively. (F) Parental founder effects underlying Module 3, 4 and 16 QTL. Allele effects were calculated at the peak LOD score marker on chromosome 10. (G) Distribution of log fold change (LFC) of representative single mutants from each module; eccCa1 (ESX1 module), mbtE (mbt module) and mce4F (mce4 module) relative to in vitro. Each dot is the LFC of the specified mutant in each CC mouse strain. Box and whiskers plots (Tukey) of each trait indicate the median and interquartile range. (H) Spleen CEQ and Spleen CFU for CC strains (box plots as in G). Mouse values are grouped by the parental haplotype allele series underlying the chromosome 10 Hip42 locus (NOD/WSB vs AJ/B6/NZO). Each dot represents the average CFU/CEQ of each CC genotype. Statistical differences in disease-associated traits and distinct haplotypes groups was assessed by t-test. LOD, logarithm of the odds; LFC, log fold change; CEQ, Chromosomal equivalents; CFU, colony forming units.