Genome-wide association study, replication, and mega-analysis using a dense marker panel in a multi-generational mouse advanced intercross line

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Author contributions

XZ imputed genotypes, performed SNP and individual QC, and conducted GWAS in F_{34} and $F_{39\text{-}43}$ AILs under supervision of AAP. AAP also provided computational resources for the analyses in this paper. CS prepared GBS libraries for sequencing, as well as organizing portions of the $F_{39\text{-}43}$ phenotypes. NMG de-multiplexed GBS sequencing results and performed alignment and variant calling. RC helped with kinship relatedness matrix calculated from AIL pedigree. AC provided technical support for running programs and scripts. GS collected $F_{39\text{-}43}$ phenotypes, respectively. XZ co-wrote the manuscript with AAP, who designed the study and oversaw data collection.

Data Availability

All relevant data are within the paper and its Supporting Information files. Genotypes and phenotypes of F_{34} ("AIL LGSM F34 (Array)": GN655; "AIL LGSM F34 (GBS)": GN656), $F_{39\text{-}43}$ ("AIL LGSM F39-43 (GBS)": GN657), and mega-analysis cohort ("AIL LGSM F34 and F39-43 (GBS)": GN654) of AIL are uploaded to GeneNetwork2 (http://gn2.genenetwork.org/).

Abstract

Replication is critical for genome-wide association studies (**GWAS**) in humans. In contrast, replication is not routinely performed in model organism GWAS. Advanced intercross lines (**AILs**) are produced by crossing two inbred strains and then breeding unrelated offspring for additional generations. We re-genotype a previously reported cohort of sparsely genotyped LG/J x SM/J AIL mice (F_{34}; n=428) using genotyping-by-sequencing (**GBS**). In addition, we genotyped a second novel cohort of LG/J x SM/J AIL mice (F_{39-43}; n=600) also using GBS. The denser set of GBS markers in the F_{34} allowed us to identify 110 significant loci, 36 of which had not been identified in our previously published studies, for 79 behavioral and physiological traits. The genotypes in the F_{39-43} were then used to perform a GWAS which identified 27 significant loci for 21 behavioral and physiological traits. We then attempted to replicate loci identified in either F_{34} or F_{39-43} in the other cohort, focusing on the subset of traits that were measured in both cohorts (locomotor activity, body weight, and coat color). While coat color loci were robustly replicated, we observed only partial replication of associations for locomotor activity and body weight. Finally, to achieve better mapping power, we performed a mega-analysis of locomotor activity and body weight by combining F_{34} and F_{39-43} cohorts (n=1,028), which identified four novel loci. The present study provides empirical insights into replication, the utility of denser genotyping, and identifies new candidate loci for numerous behavioral and physiological traits.

Introduction

The use of multi-parental crosses and commercially available outbred populations for genome-wide association studies (**GWAS**) in model organisms such as mice (1–17), rats (18), chickens (19,20), zebrafish (21,22), fruit flies (23–27), *C. elegans* (28) and various plant species (29–31) has become increasingly common over the last decade. These mapping populations can further be categorized as multi-parental crosses, which are created by interbreeding two or more inbred strains, and commercially available outbred populations, in which the founders are of unknown provenance. An F_2 cross between two inbred strains is the prototypical mapping population; however, F_2s provide poor mapping resolution (32). To improve mapping resolution, Darvasi and Soller (33) proposed the creation of advanced intercross lines (**AILs**), which are produced by intercrossing F_2 mice for additional generations. AILs accumulate additional crossovers with every successive generation, leading to a population with shorter linkage disequilibrium (**LD**) blocks, which improves mapping precision, albeit at the expense of power (32,34).

The longest running mouse AIL was generated by crossing LG/J and SM/J inbred strains, which were selectively bred for large and small body size. We obtained this AIL in 2006 at generation 33 from Dr. James Cheverud (Jmc: LG,SM-G_{33}). Since then, we have collected genotype and phenotype information from multiple generations, including F_{34} (16,35–38), F_{39}-F_{43} and $F_{50\text{-}56}$ (39). Our previous publications using the F_{34} generation employed a custom Illumina Infinium genotyping microarray to obtain genotypes for 4,593 SNPs (35,36), we refer to this set of SNPs as the 'sparse markers'. Those genotypes were used to identify significant associations for numerous traits, including methamphetamine sensitivity (35), pre-pulse inhibition (16), musculoskeletal measurements (17), muscle weight (37), body weight (40), open field (36), conditioned fear (36), red blood cell parameters (41), and murine soleus muscle (38). Although not previously published, we also collected phenotype information from the F_{39}-F_{43} generations,

including body weight, fear conditioning, locomotor activity in response to methamphetamine,

and the light dark test for anxiety.

While the prior GWAS using the F_{34} generation detected many significant loci, the

sparsity of the markers likely precluded the discovery of some true loci, and also made it difficult

to clearly define the boundaries of the loci that we did identify. For example, Parker et al

conducted an integrated analysis of F_2 and F_{34} AILs (40). One of their body weight loci spanned

from 87.93–102.70 Mb on chromosome 14. Denser markers might have more clearly defined

implicated region. In the present study, we used genotyping-by-sequencing (**GBS**), which is a

reduced-representation sequencing method (42–44), to obtain a much denser set of SNPs in

the F_{34} and to genotype mice from the F_{39}-F_{43} generations for the first time. With this denser set

of SNPs, we attempted to identify novel loci in the F_{34}s that were not detected using the sparse

SNPs.

We also performed a GWAS using the mice from the F_{39}-F_{43} AILs. Because F_{39}-F_{43} AILs

are direct descendants of the F_{34}, they are uniquely suited to be a replication population for

GWAS in the F_{34} generation. Replication of GWAS results is indented to identify false positives

and can also be used to more accurately estimate effect sizes (45–47), which are typically over-

estimated in the discovery sample due to the "winner's curse" (48). Despite its importance in human

GWAS, replication has been infrequently used in model organism GWAS. Flint and Eskin

pointed out that GWAS using inbred strains, in which the individuals are genetically identical,

could be fully replicated using another cohort of individuals from the same strain (49). Using

multiple cohorts of the same mouse intercross strain, we attempted to examine which loci are

replicable between the F_{34} and F_{39-43} LG/J x SM/J AILs. In addition to their use as a replication

sample, the F_{39}-F_{43} can also provide improved resolution and allow for the discovery of novel

loci not detected in the F_{34} generation.

100   Finally, we performed a mega-analysis of F_{34} mice and F_{39}-F_{43} mice to identify loci that

101   were not identified in either individual dataset. For all significant loci detected, we used credible

102   set analysis for fine-mapping, which calculated a Bayes-factor estimate per SNP per association

103   and provided complementary evidence for the size of the association block (50). Finally, we

104   explored whether imputation from the array SNPs could have provided the additional coverage

105   we obtained using the denser GBS genotypes.

Results

We used 214 males and 214 females from generation F_{34} (Aap:LG,SM-G34) and 305

males and 295 females from generations F_{39-43}. We performed association studies on 79 traits in

the F_{34} AIL and 49 traits in the F_{39-43} AIL (S1 Table). F_{34} mice had been previously genotyped on

a custom SNP array (35,36). The average minor allele frequency (**MAF**) of those 4,593 array

SNPs was 0.388 (Fig 1). To obtain a denser set of SNP markers, we used genotyping-by-

sequencing in F_{34} and F_{39-43} AIL mice. Since data about the F_{39-43} AIL mice had been collected

over the span of approximately two years, we carefully considered the possibility of sample

contamination and sample mislabeling (51). We removed samples based on four major features:

heterozygosity distribution, number of reads aligned to sex chromosomes, discrepancies

between pedigree and genetic kinship relatedness, and coat color genotype to phenotype

mismatch (see Methods; S1 and S2 Figs). The final SNP sets included 60,392 GBS-derived

SNPs in 428 F_{34} AIL mice, 59,790 GBS-derived SNPs in 600 F_{39-43} AIL mice, and 58,461 GBS-

derived SNPs that existed in both F_{34} and F_{39-43} AIL mice (S2 Table). The MAF for the GBS

SNPs was 0.382 in F_{34}, 0.358 in F_{39-43}, and 0.370 in F_{34} and F_{39-43} (Fig 1). There were 66 SNPs

called from our GBS data that were also present on the genotyping array. The genotype

concordance rate, which reflects the sum of errors from both sets of genotypes, was 95.4% (S3

Fig). We found that LD decay rates using F_{34} array, F_{34} GBS, F_{39-43} GBS, and F_{34} and F_{39-43} GBS

genotypes were generally similar to one another, though levels of LD using the GBS genotypes

appear to be slightly reduced in the later generations of AILs (S4 Fig).

GBS genotypes produced more significant associations than array genotypes in

F_{34}

We used a linear mixed model (**LMM**) as implemented in GEMMA (52) to perform

GWAS. We used the leave-one-chromosome-out (**LOCO**) approach to address the problem of

proximal contamination, as previously described (39,53–55). We performed GWAS using both

the sparse array SNPs and the dense GBS SNPs to determine whether additional SNPs would

produce additional genome-wide significant associations. Autosomal and X chromosome SNPs

were included in all GWAS. We obtained adjusted significance threshold for each SNP set using

MultiTrans and SLIDES (56,57).To select independently associated loci ("lead loci"), we used a

LD-based clumping method implemented in PLINK to group SNPs that passed the adjusted

genome-wide significance thresholds over a large genomic region flanking the index SNP (58).

Applying the most stringent clumping parameters ($r^2 = 0.1$ and sliding window size = 12,150kb,

S3 Table), we identified 110 significant lead loci in 49 out of 79 F_{34} phenotypes using the GBS

SNPs. In contrast, we identified 83 significant lead loci in 45 out of 79 F_{34} phenotypes using the

sparse array SNPs (Table 1, S4 Table). Among the loci identified in the F_{34}, 36 were uniquely

identified using the GBS genotypes, whereas 11 were uniquely identified using the array

genotypes. GBS SNPs consistently yielded more significant lead loci compared to array SNPs

regardless of the clumping parameter values (S3 Table), indicating that a dense marker panel

was able to detect more association signals compared to a sparse marker panel. Significant

lead loci in F_{34} GBS and array are summarized in Table S4.

Table 1. Select lead SNPs with association regions containing less than 5 coding genes. Credible set analysis was performed to define the boundaries of the locus (r^2 threshold = 0.8, posterior probability threshold = 0.99). Genes contained in and/or immediately downstream of the credible set interval were included as associated genes.

Generation	Genotypes	Phenotype	chr	lead snp	pos	P-value	af	beta	se	Associated genes
F34	array	Quadriceps femoris muscle weight (mg)	1	chr1:22249888	22249888	$5.69{\times}10^{-06}$	0.596	$1.93{\times}10^{-01}$	$4.21{\times}10^{-02}$	Kcnq5, Rims1
F34	array	Quadriceps femoris muscle weight (mg)	4	chr4:54609724	54609724	$1.29{\times}10^{-05}$	0.707	$1.99{\times}10^{-01}$	$4.54{\times}10^{-02}$	Zfp462, Rad23b
F34	array	Extensor digitorum longus muscle weight (mg)	4	chr4:54609724	54609724	$1.54{\times}10^{-06}$	0.553	$2.23{\times}10^{-01}$	$4.59{\times}10^{-02}$	Zfp462, Rad23b
F34	array	Gastrocnemius muscle weight (mg)	6	chr6:80659015	80659015	$1.69{\times}10^{-05}$	0.484	$1.78{\times}10^{-01}$	$4.11{\times}10^{-02}$	Lrrtm4, Gcfc2
F34	array	Quadriceps femoris muscle weight (mg)	6	chr6:81465256	81465256	$1.41{\times}10^{-05}$	0.553	$1.90{\times}10^{-01}$	$4.33{\times}10^{-02}$	Lrrtm4, Gcfc2
F34	array	Coat color, albino	7	chr7:87689885	87689885	$3.76{\times}10^{-109}$	0.568	$5.84{\times}10^{-01}$	$1.90{\times}10^{-02}$	Tyr
F34	array	Locomotor test day 2, total distance travelled in 30min (cm)	8	chr8:17159295	17159295	$7.15{\times}10^{-06}$	0.827	$-7.72{\times}10^{-02}$	$1.70{\times}10^{-02}$	Csmd1
F34	array	Quadriceps femoris muscle weight (mg)	8	chr8:128443469	128443469	$1.05{\times}10^{-07}$	0.496	$2.23{\times}10^{-02}$	$4.14{\times}10^{-02}$	Nrp1, Itgb1, Ccdc7b
F34	array	Retic parameters concentration of hemoglobin in reticulocytes (pg)	8	chr8:128607127	128607127	$1.83{\times}10^{-05}$	0.414	$2.70{\times}10^{-01}$	$6.26{\times}10^{-02}$	Nrp1, Itgb1, Ccdc7b
F34	array	Retic parameters concentration of hemoglobin in reticulocytes, repeat (pg)	8	chr8:128607127	128607127	$3.50{\times}10^{-06}$	0.349	$-3.45{\times}10^{-01}$	$7.38{\times}10^{-02}$	Nrp1, Itgb1, Ccdc7b
F34	array	Routine CBC cell hemoglobin concentration mean (g/dL)	15	chr15:29893263	29893263	$3.86{\times}10^{-06}$	0.483	$2.93{\times}10^{-01}$	$6.30{\times}10^{-02}$	Ctnnd2
F34	array	Routine CBC hemoglobin distribution width (g/dL)	16	chr16:70166221	70166221	$2.01{\times}10^{-05}$	0.511	$2.85{\times}10^{-01}$	$6.63{\times}10^{-02}$	Gbe1, Speer2, Robo1
F34	GBS	Routine CBC hematocrit (%)	1	chr1:41580321	41580321	$1.37{\times}10^{-05}$	0.724	$-3.08{\times}10^{-01}$	$6.99{\times}10^{-02}$	Mfsd9, Pou3f3, 930448I06Rik
F34	GBS	Tibia length (cm)	1	chr1:77255381	77255381	$1.39{\times}10^{-05}$	0.433	$-3.70{\times}10^{-01}$	$8.40{\times}10^{-02}$	Epha4, Sgpp2, Pax3
F34	GBS	Routine CBC red blood cell count (x10^6 cells/uL blood)	1	chr1:148977286	148977286	$1.30{\times}10^{-06}$	0.526	$-3.05{\times}10^{-01}$	$6.25{\times}10^{-02}$	Brinp3, Pla2g4a
F34	GBS	Routine CBC hemoglobin (g/dL)	1	chr1:148977286	148977286	$1.88{\times}10^{-06}$	0.522	$-3.46{\times}10^{-01}$	$7.16{\times}10^{-02}$	Brinp3, Pla2g4a
F34	GBS	Iron content in spleen (ug/kg)	2	chr2:95390277	95390277	$4.96{\times}10^{-06}$	0.528	$2.49{\times}10^{-01}$	$5.38{\times}10^{-02}$	Lrrc4c, Api5, Alkbh3, Hsd17b12
F34	GBS	Routine CBC cell hemoglobin concentration mean (g/dL)	2	chr2:128412068	128412068	$7.07{\times}10^{-06}$	0.449	$3.03{\times}10^{-01}$	$6.63{\times}10^{-02}$	Bcl2l11, Spdye4c, Anapc1, Mertk
F34	GBS	Iron content in spleen (ug/kg)	3	chr3:52749950	52749950	$9.06{\times}10^{-06}$	0.508	$2.55{\times}10^{-01}$	$5.70{\times}10^{-02}$	Cog6, Lhfp
F34	GBS	Iron content in spleen z score	3	chr3:52749950	52749950	$1.31{\times}10^{-05}$	0.508	$2.68{\times}10^{-01}$	$6.10{\times}10^{-02}$	Cog6, Lhfp
F34	GBS	Gastrocnemius muscle weight (mg)	6	chr6:80767933	80767933	$2.68{\times}10^{-06}$	0.483	$1.92{\times}10^{-01}$	$4.06{\times}10^{-02}$	Lrrtm4
F34	GBS	Quadriceps femoris muscle weight (mg)	6	chr6:81267890	81267890	$6.35{\times}10^{-07}$	0.597	$2.14{\times}10^{-01}$	$4.24{\times}10^{-02}$	Lrrtm4, Gcfc2
F34	GBS	Body weight, day 1	6	chr6:81405109	81405109	$5.89{\times}10^{-06}$	0.497	$2.06{\times}10^{-01}$	$4.51{\times}10^{-02}$	Lrrtm4, Gcfc2
F34	GBS	Quadriceps femoris muscle weight (mg)	6	chr6:93488270	93488270	$3.28{\times}10^{-08}$	0.497	$2.30{\times}10^{-01}$	$4.11{\times}10^{-02}$	Prickle2, Adamts9, Magi1
F34	GBS	Coat color, albino	7	chr7:87642045	8764204	$5.00{\times}10^{-106}$	0.432	$-5.81{\times}10^{-01}$	$1.91{\times}10^{-02}$	Tyr
F34	GBS	Routine CBC red blood cell distribution width (%)	7	chr7:115540157	115540157	$1.04{\times}10^{-06}$	0.379	$-3.35{\times}10^{-01}$	$6.79{\times}10^{-02}$	Sox6, Plekha7
F34	GBS	Locomotor test day2, total distance travelled in 30min (cm)	8	chr8:17410225	17410225	$4.96{\times}10^{-06}$	0.171	$7.91{\times}10^{-02}$	$1.71{\times}10^{-02}$	Csmd1
F34	GBS	Retic parameters concentration of hemoglobin in reticulocytes (pg)	8	chr8:128524048	128524048	$3.01{\times}10^{-06}$	0.255	$-3.54{\times}10^{-01}$	$7.50{\times}10^{-02}$	Nrp1, Itgb1, Ccdc7b
F34	GBS	Retic parameters concentration of hemoglobin in reticulocytes, repeat (pg)	8	chr8:128524048	128524048	$1.04{\times}10^{-05}$	0.471	$-3.00{\times}10^{-01}$	$6.75{\times}10^{-02}$	Nrp1, Itgb1, Ccdc7b
F34	GBS	Quadriceps femoris muscle weight (mg)	8	chr8:128571869	128571869	$1.32{\times}10^{-06}$	0.531	$-1.97{\times}10^{-01}$	$4.03{\times}10^{-02}$	Nrp1, Itgb1, Ccdc7b
F34	GBS	Routine CBC red blood cell distribution width (%)	10	chr10:66602511	66602511	$3.42{\times}10^{-08}$	0.671	$-4.10{\times}10^{-01}$	$7.32{\times}10^{-02}$	Reep3, Jmjd1c, Nrbf2
F34	GBS	Retic parameters cell hemoglobin distribution width (pg)	10	chr10:99307553	99307553	$3.30{\times}10^{-06}$	0.499	$-2.84{\times}10^{-01}$	$6.00{\times}10^{-02}$	Dusp6
F34	GBS	Retic parameters hemoglobin distribution width (g/dL)	13	chr13:45281420	45281420	$1.86{\times}10^{-06}$	0.45	$2.61{\times}10^{-01}$	$5.43{\times}10^{-02}$	Dtnbp1, Mylip, Gmpr
F34	GBS	Routine CBC hemoglobin distribution width (g/dL)	16	chr16:70311614	70311614	$5.81{\times}10^{-06}$	0.674	$3.15{\times}10^{-01}$	$6.90{\times}10^{-02}$	Speer2, Gbe1
F39-43	GBS	Coat color, albino	7	chr7:87255156	87255156	$5.91{\times}10^{-167}$	0.389	$-6.24{\times}10^{-01}$	$1.57{\times}10^{-02}$	Tyr
F34, F39-43	GBS	Locomotor test day 2, total distance travelled in 30min (cm)	1	chr1:40907532	40907532	$3.53{\times}10^{-08}$	0.289	$-2.53{\times}10^{-01}$	$4.56{\times}10^{-02}$	Mfsd9, Tmem182
F34, F39-43	GBS	Locomotor test day 1, total distance travelled in 30min (cm)	1	chr1:122479820	122479820	$1.94{\times}10^{-07}$	0.373	$2.16{\times}10^{-01}$	$4.13{\times}10^{-02}$	Htr5b, Ddx18, Dpp10
F34, F39-43	GBS	Body weight	4	chr4:66866758	66866758	$1.64{\times}10^{-09}$	0.403	$-1.84{\times}10^{-01}$	$3.01{\times}10^{-02}$	Pappa, Trim32, Astn2, Tlr4
F34, F39-43	GBS	Body weight	6	chr6:81267890	81267890	$8.61{\times}10^{-07}$	0.507	$1.40{\times}10^{-01}$	$2.83{\times}10^{-02}$	Lrrtm4, Gcfc2
F34, F39-43	GBS	Coat color, albino	7	chr7:87665727	87665727	$6.71{\times}10^{-275}$	0.592	$5.97{\times}10^{-01}$	$1.18{\times}10^{-02}$	Tyr

To determine the boundaries of each locus, we performed a Bayesian-framework

credible set analysis, which estimated a posterior probability for association at each SNP (r^2

threshold = 0.8, posterior probability threshold = 0.99; (50)). The physical positions of the SNPs

in the credible set were used to determine the boundaries of each locus. As expected, the

greater density of the GBS genotypes allowed us to better define each interval. For instance,

the lead locus at chr17:27130383 was associated with distance travelled in periphery in the

open filed test in F_{34} AILs (Fig 2). However, no SNPs were genotyped between 26.7 and 28.7

Mb in the array SNPs, which makes the size of this LD block ambiguous. In contrast, the

LocusZoom plot portraying GBS SNPs in the same region shows that SNPs in high LD with

chr17:27130383 are between 27 Mb and 28.3 Mb. The more accurate definition of the

implicated intervals allowed us to better refine the list of the coding genes and non-coding

variants associated with the phenotype (Table 1).

In our prior studies using the sparse marker set, we did not attempt to increase the

number of available markers by using imputation. Therefore, we examined whether the disparity

between the numbers of loci identified by the two SNP sets could be resolved by imputation,

which should increase the number of markers available for GWAS. We used LG/J and SM/J

whole genome sequencing data as reference panels (59) and performed imputation on array

and GBS SNPs using Beagle v4.1 (60). After QC filtering, we obtained 4.3M SNPs imputed from

the array SNPs and 4.1M SNPs imputed from the GBS SNPs. More imputed GBS SNPs were

filtered out because GBS SNPs were called from genotype probabilities, thus introducing

uncertainty in imputed SNPs. We found that imputed array genotypes and imputed GBS

genotypes did not meaningfully increase the number of new loci discovered (Fig S5).

Under a polygenic model where a large number of additive common variants contribute

to a complex trait, heritability estimates could be higher when more SNPs are considered (61).

Given that there were more GBS SNPs than array SNPs, we used autosomal SNPs to examine

whether GBS SNPs would generate higher SNP heritability estimates compared to the sparse

array SNPs. Heritability estimates were similar for the two SNP sets, with the exception of

agouti coat color, which showed marginally greater heritability for the GBS SNPs (S6 Fig; S5

Table). Our results show that while the denser GBS SNP set was able to identify more genome-

wide significant loci, greater SNP density did not improve the polygenic signal.

Partial replication of loci indented in F_{34} or F_{39-43} and mega-analysis

We identified 27 genome-wide significant loci for 21 phenotypes in the F_{39-43} cohort. A

subset of those traits, including coat color, body weight, and locomotor activity, were also

phenotyped in the F_{34} AILs (Table 2; S8 Table). To assess replication, we determined whether

loci that were significant in one cohort (either F_{34} or F_{39-43}) would also be significant in the other.

We termed the cohort in which a locus was initially discovered as its "discovery set" and the

cohort we attempted replication in as the "replication set" (Table 2). Coat color phenotypes (both

albino and agouti) are Mendelian traits and thus served as positive control. As expected, all

body weight loci were replicated; specifically, the three body weight loci identified in the F_{34} were

replicated at nominal levels of significance ($p<0.05$) in F_{39-43}; similarly, the only body weight

locus identified in F_{39-43} was replicated in F_{34}. However, none of the five locomotor activity

associated loci were replicated in the reciprocal (replication) cohorts. We also used the "sign

test" to determine whether the directions of the effect (beta) of the loci were in the same

direction between the discovery and replication cohorts. We found that 11 of 13 loci passed this

much less stringent test of replication. The two loci that did not pass the sign test were the two

locomotor loci "discovered" in F_{39-43} (Table 2).

Table 2. Replication of significant SNPs between F_{34} and F_{39-43} AIL association analyses. "Discovery set" indicates the AIL generation that significant SNPs were identified. "Replication set" shows the association p-value, β estimates, etc. of the "discovery set" significant SNPs in the replication AIL generation. SNPs that replicated (p<0.05, same sign for the beta) between F_{34} and F_{39-43} are highlighted in bold italics. Genetic correlations for phenotypes measured in both F_{34} and F_{39-43} are listed (see also Supplementary Table 6).

Phenotype	rG(*s.e.*)(*p<0.05)	SNP	Discovery set				Replication set			
			P F34 GBS	af	beta	se	P F3943 GBS replicate	af	beta	se
Body weight		*chr4.66414508*	$8.06×10^{-08}$	0.419	$-2.50×10^{-01}$	$4.56×10^{-02}$	$1.56×10^{-02}$	0.406	$-1.05×10^{-01}$	$4.33×10^{-02}$
	0.711(0.25)*	*chr6.81405109*	$5.89×10^{-06}$	0.497	$2.06×10^{-01}$	$4.51×10^{-02}$	$2.36×10^{-02}$	0.518	$9.48×10^{-02}$	$4.18×10^{-02}$
		chr14.79312393	$7.53×10^{-06}$	0.514	$-2.01×10^{-01}$	$4.45×10^{-02}$	$1.44×10^{-02}$	0.566	$-1.04×10^{-01}$	$4.26×10^{-02}$
Coat color, albino	0.967(0.04)*	*chr7.87642045*	$5.00×10^{-106}$	0.432	$-5.81×10^{-01}$	$1.91×10^{-02}$	$2.85×10^{-163}$	0.387	$-6.07×10^{-01}$	$1.55×10^{-02}$
Coat color, agouti	0.971(0.04)*	*chr2.154464466*	$9.43×10^{-191}$	0.129	$9.39×10^{-01}$	$1.25×10^{-02}$	$5.70×10^{-93}$	0.207	$7.20×10^{-01}$	$2.57×10^{-02}$
Locomotor test day 1, total distance travelled in 30min	0.968(0.24)*	chr19.21812298	$9.28×10^{-07}$	0.461	$-6.90×10^{+02}$	$1.39×10^{+02}$	$7.72×10^{-01}$	0.52	$-1.94×10^{-02}$	$6.74×10^{-02}$
Locomotor test day2, total distance travelled in 30min	0.988(0.19)*	chr7.45084416	$1.12×10^{-05}$	0.246	$6.77×10^{+02}$	$1.53×10^{+02}$	$3.40×10^{-01}$	0.217	$7.38×10^{-02}$	$7.77×10^{-02}$
		chr8.17410225	$4.96×10^{-06}$	0.171	$7.91×10^{+02}$	$1.71×10^{+02}$	$4.03×10^{-01}$	0.192	$7.04×10^{-02}$	$8.43×10^{-02}$
			F3943 GBS				F34 GBS replicate			
Body weight	0.711(0.25)*	*chr14.82586326*	$2.63×10^{-06}$	0.658	$-2.09×10^{-01}$	$4.43×10^{-02}$	$2.87×10^{-05}$	0.575	$-1.89×10^{-01}$	$4.50×10^{-02}$
Coat color, albino	0.967(0.04)*	*chr7.87255156*	$5.91×10^{-167}$	0.389	$-6.24×10^{-01}$	$1.57×10^{-02}$	$7.80×10^{-97}$	0.444	$-5.75×10^{-01}$	$2.07×10^{-02}$
Coat color, agouti	0.971(0.04)*	*chr2.155091628*	$1.78×10^{-115}$	0.218	$7.42×10^{-01}$	$2.17×10^{-02}$	$1.51×10^{-185}$	0.135	$8.98×10^{-01}$	$1.33×10^{-02}$
Locomotor test day 2, total distance travelled in 30min	0.988(0.19)*	chr15.67235072	$3.21×10^{-06}$	0.47	$3.14×10^{-01}$	$6.63×10^{-02}$	$1.69×10^{-01}$	0.522	$-1.72×10^{+02}$	$1.25×10^{+02}$
Locomotor test day 3, total distance travelled in 30min	0.577(0.22)*	chr7.113250866	$5.88×10^{-06}$	0.389	$3.29×10^{-01}$	$7.20×10^{-02}$	$8.27×10^{-01}$	0.483	$-1.21×10^{+02}$	$5.45×10^{+02}$

In addition to evaluating the replication of specific loci, we also evaluated whether or not

the traits showed genetic correlations across the two cohorts (F_{34} and F_{39-43}). We used

autosomal SNPs to calculate genetic correlations between the F_{34} and F_{39-43} generations for

body weight, coat color, and locomotor activity phenotypes (S6 Table), using GCTA-GREML

(62). Locomotor activity on days 1 and 2, albino and agouti coat color, and body weight were

highly genetically correlated (r_{G}s >0.7). In contrast, locomotor activity on day 3 showed a

significant but weaker genetic correlation (r_{G}=0.577), perhaps reflecting variability in the quality

of the methamphetamine injection, which was unique to day 3. Overall, these results suggest

that genetic influences on these traits were broadly similar in the two cohorts. We also

calculated the SNP heritabilities for all traits using GCTA. SNP heritability was consistently

lower in the F_{39-43} compared to the F_{34}, possibly a result of increased experimental variance

introduced by our extended phenotype collection period (Fig 3; S7 Table).

Due to the high genetic correlations (S6 Table), we suspected that a mega-analysis

using the combined sample set would allow for the identification of additional loci; indeed,

mega-analysis identified four novel genom×10-wide significant associations (Fig 4; S9 Table).

The significance of the associations identified by the mega-analysis was often greater than in

either individual cohort. For instance, the p-values obtained by mega-analysis for

chr4:66866758 (p = $1.64×10^{-9}$) and chr14:82672838 (p = $2.06×10^{-10}$) for body weight were

lower than the corresponding p-values for the same loci for F_{34} (chr4:65246120, p = $9.06×10^{-8}$;

chr14:78926547, p = $6.24×10^{-6}$) and F_{39-43} (chr4:66414508, p = $8.06×10^{-8}$; chr14:79312393, p =

$7.53×10^{-6}$; S7 Fig).

Discussion

We used F_{34} and F_{39-43} generations of a LG/J x SM/J AIL to perform GWAS, SNP

heritability estimates, genetic correlations, replication and mega-analysis. We had previously

performed several GWAS using a sparse marker set in the F_{34} cohort. In this study we used a

denser set of SNPs, obtained using GBS, to reanalyze the F_{34} cohort. We found 110 significant

loci, 36 of which had not been identified in our prior studies using the sparse marker set. We

used a new, previously unpublished F_{39-43} cohort to show that some by not all loci replicated

across cohorts. We also found that genetic correlations were high from most traits measured in

both cohorts. Imputation to reference panels increased the number of SNPs available for

analysis but did not meaningfully enhance the number of loci we discovered because it did not

improve our ability to capture recombination events. Taken together, we have identified refined

regions of associations for numerous physiological and behavioral traits in multiple generations

of AILs, providing resources for future functional validation studies as well as GWAS replication

studies.

Previous publications from our lab used a sparse set of array genotypes for GWAS of

various behavioral and physiological traits in 688 F_{34} AILs (16,17,35–38,40,41). In this study we

obtained a much denser marker set for 428 of the initial 688 AIL mice using GBS. The denser

genotypes allowed us to identify most of the loci obtained using the sparse set, as well as many

additional loci. For instance, using the sparse markers we identified significant locus on

chromosome 8 for locomotor day 2 activity that contained only one gene: *Csmd1* (CUB and

sushi multiple domains 1). Gonzales et al. (39) replicated this finding in F_{50-56} AIL and identified

a *cis*-eQTL mapped to the same region. *Csmd1* mutant mice showed increased locomotor

activity compared to wild-type and heterozygous mice, indicating that *Csmd1* is likely a causal

gene for locomotor and related traits (39). We replicated this locus in the r×10-analysis of the

F_{34} cohort that used the denser marker set (S7 Fig). We also replicated a locus on chromosome

17 for distance traveled in the periphery in the open field test (Fig 4; (36,39)), three loci on

chromosomes 4, 6, and 14 for body weight (Supplementary Fig 7; (40)), one locus on

chromosome 7 for mean corpuscular hemoglobin concentrations (MCHC, complete blood count;

S7 Fig; (41)), and numerous loci on chromosome 4, 6, 7, 8, and 11 for muscle weights

(Supplementary Fig 7; (37)). We noticed that even using original spares markers, some

previously published loci were not replicated in the current GWAS. The most likely explanation

is that we had only 428 of the 688 mice used in the previous publications. Methodological

differences between prior studies and the current study, such as the use of QTLRel rather than

GEMMA and the choice of pedigree rather than genotypes for estimating relatedness, may also

lead to lack of complete replication [56].

F_{39-43} AILs replicated some, but not all, significant loci identified in F_{34}, despite generally

high genetic correlations between the two cohorts. Significant loci for coat color, which are

monogenic and served as positive controls, were consistent between the two cohorts. Loci for

body weight were fully replicated ($p<0.05$) between F_{34} and F_{39-43}, while loci for locomotor

activity were not. Nevertheless, the beta estimates for all but two loci shared the same sign,

which provides modest evidence for replication. Several possibilities may cause the lack of

replication for locomotor activity. Firstly, unlike the F_{34} dataset, the F_{39-43} used multiple

technicians to conduct the behavioral tests and occurred over a prolonged period of time in

which numerous environmental factors may have changed. The circumstances under which the

F_{39-43} data were collected may have introduced greater environmental differences, possibly

contributing to their lower heritability and the limited replication. Secondly, the loci for locomotor

activity identified in F_{34} could be false positives. However, given that our F_{34} results replicated

the same locus on chromosome 8 as in F_{50-56} (39), we believe that these loci are true

discoveries. Future studies in other AIL cohorts should attempt to replicate the loci for locomotor

activity again.

266  We performed a mega-analysis using F_{34} and F_{39-43} AIL mice. The combined dataset

267 increased our power and allowed us to identify four novel genome-wide significant associations

268 that were not detected in either the F_{34} or the F_{39-43} cohorts. For example, the mega-analysis

269 identified a locus for body weight on chromosome 2 (Fig S7). Parker et al. (40) identified the

270 same locus using an integrated analysis of LG/J x SM/J F_2 and F_{34} AILs.

271  LD in the LG/J x SM/J AIL mice is more extensive than in the Diversity Outbred mice and

272 Carworth Farms White mice (1). Some of the loci that we identified are relatively large, making it

273 difficult to infer which genes are responsible for the association. We focused on loci that

274 contained 5 or fewer genes (Table 1). We highlight a few genes that are supported by the

275 existing literature for their role in the corresponding traits. The lead SNP at chr1:77255381 is

276 associated with tibia length in F_{34} AILs (Table 1; S7 Fig). One gene at this locus, *EphA4*, codes

277 for a receptor for membrane-bound ephrins. EphA4 plays an important role in the activation of

278 the tyrosine kinase Jak2 and the signal transducer and transcriptional activator Stat5B in muscle,

279 promoting the synthesis of insulin-like growth factor 1 (IGF-1) (64–66). Mice with mutated

280 EphA4 shows significant defect in body growth (66). Curiously, another gene at this locus, *Pax3*,

281 has been shown as a transcription factor expressed in resident muscle progenitor cells and is

282 essential for the formation of skeletal muscle in mice (67). It is possible that both *EphA4* and

283 *Pax3* are associated with the trait tibia length because they are both involved in organismal

284 growth. Another region of interest is the locus at chr4:66866758, which is associated with body

285 weight in all AIL cohorts (Table 1; S4 Table; S8 Table; S9 Table). The lead SNP is immediately

286 upstream of *Tlr4*, Toll-like receptor 4, which recognizes Gram-negative bacteria by its cell wall

287 component, lipopolysaccharide (68,69). TLR4 responds to the high circulating level of fatty acids

288 and induces inflammatory signaling, which leads to insulin resistance (70). Kim et al showed

289 TLR4-deficient mice were protected from the increase in proinflammatory cytokine level and

gained less weight than wild-type mice when fed on high fat diet (71). The association between

Tlr4 and body weight in the AILs corroborates these findings.

Many GWAS use a 1.0~2.0 LOD support interval to approximate the size of the

association region (see (72,73)). The LOD support interval, proposed by Conneally et al. (74)

and Lander & Botstein (75), is a simple confidence interval method involving converting the p-

value of the peak locus into a LOD score, subtracting "drop size" from the peak locus LOD score,

and finding the two physical positions to the left and to the right of the peak locus location that

correspond to the subtracted LOD score. Although Mangin et al. (76) showed via simulation that

the boundaries of LOD support intervals depend on effect size, others observed that a 1.0 ~ 2.0

LOD support interval accurately captures ~95% coverage of the true location of the loci when

using a dense set of markers (75,77,78). In the present study, we considered using LOD

support intervals but found that the sparse array SNPs produced misleadingly large support

intervals. Various methods have been proposed for calculating confidence intervals in

analogous situations (e.g. (12,79)). Rather than adopting a formal method, we performed

credible set analysis and compared LocusZoom plots of the same locus region between array

SNPs and the GBS SNPs (S7 Fig; (80)). For example, the benefit of the denser SNP coverage

is easily observed in the locus on chromosome 7 (array lead SNP chr7:44560350; GBS lead

SNP chr7:44630890) for the complete blood count trait "retic parameters cell hemoglobin

concentration mean, repeat" (Fig S7). Thus, there are advantages of dense SNP sets that go

beyond the ability to discover additional loci.

Our study has notable limitations. First, not all F_{34} and F_{39-43} animals that were

phenotyped were later genotyped by GBS due to missing DNA samples, which in turn lowered

our sample size and reduced the power of association analyses. Second, F_{39-43} traits have been

collected by different technicians over the span of several years, which introduced noise and

diminished trait heritability (Fig 2).

The present study explored the role of marker density and imputation in GWAS.

Furthermore, the combination of denser marker coverage and the addition of 600 F_{39-43} AIL mice

allowed us to identify novel loci for locomotor activity, open field test, fear conditioning, light dark

test for anxiety, complete blood count, iron content in liver and spleen, and muscle weight. Our

findings add to the large body of phenotypic/genotypic data available for the LG/SM AIL, which

can be found on GeneNetwork [http://www.genenetwork.org].

Materials and Methods

Animals

All mice used in this study were members of the advanced intercross line (**AIL**) between

LG/J and SM/J that was originally created by Dr. James Cheverud (Loyola University Chicago,

Chicago, IL). The AIL line has been maintained in the Palmer laboratory since generation F_{33}.

Age and exact number of animals tested in each phenotype are described in S1 Table. Several

previous publications (16,35–38,40,41) have reported on association analyses of the F_{34} mice

(n=428). No prior publications have described the F_{39-43} generations (n=600). The sample size

of F_{34} mice reported in this study (n=428) is smaller than that in previous publications of F_{34}

(n=688) because we only sequenced a subset of F_{34} animals using GBS. With the exception of

coat color and locomotor activities, we quantile normalized all phenotypes. Coat color traits

were coded in binary numbers (albino: 1 = white, 0 = non-white; agouti: 1 = tan, 0 = black,

NA=white). Locomotor activity traits were not quantile transformed in order to follow the

guideline described in Cheng et al. (35) for direct comparison.

F_{34}, F_{39-43} Phenotypes

We have previously described the phenotyping of F_{34} animals for locomotor activity (35),

fear conditioning (36), open field (36), coat color, body weight (40), complete blood counts (41),

heart and tibia measurements (37), muscle weight (37). Iron content in liver and spleen, which

have not been previously reported in these mice, was measured by atomic absorption

spectrophotometry, as described in Gardenghi et al. (81) and Graziano, Grady and Cerami (82).

Although the phenotyping of $F_{39\text{-}43}$ animals has not been previously reported, we used method

that were identical to those previously reported for locomotor activity (35), open field (36), coat

color, body weight (40), and light/dark test for anxiety (15).

F_{34} AIL Array Genotypes

F_{34} animals had been genotyped on a custom SNP array on the Illumina Infinium

platform (35,36), which yielded a set of 4,593 SNPs on autosomes and X chromosome that we

refer to as 'array SNPs'.

F_{34} and $F_{39\text{-}43}$ GBS Genotypes

F_{34} and $F_{39\text{-}43}$ animals were genotyped using genotyping-by-sequencing (**GBS**), which is

a reduced-representation genome sequencing method (1,39). We used the same protocol for

GBS library preparation that was described in Gonzales et al (39). We called GBS genotype

probabilities using ANGSD (83). GBS identified 1,667,920 autosomal and 43,015 X-

chromosome SNPs. To fill in missing genotypes at SNPs where some but not all mice had calls,

we ran within-sample imputation using Beagle v4.1, which generated hard call genotypes as

well as genotype probabilities (60). After imputation, only SNPs that had dosage $r^2 > 0.9$ were

retained. We removed SNPs with minor allele frequency < 0.1 and SNPs with $p < 1.0\times10^{-6}$ in the

Chi-square test of Hardy–Weinberg Equilibrium (**HWE**) (S2 Table). All phenotype and GBS

genotype data are deposited in GeneNetwork (http://www.genenetwork.org).

QC of individuals

We have found that large genetic studies are often hampered by cross-contamination

between samples and sample mix-ups. We used four features of the data to identify problematic

samples: heterozygosity distribution, proportion of reads aligned to sex chromosomes,

pedigree/kinship, and coat color. We first examined heterozygosity across autosomes and

removed animals where the proportion of heterozygosity that was more than 3 standard

deviations from the mean (S1 Fig). Next, we sought to identify animals in which the recorded

sex did not agree with the sequencing data. We compared the ratio of reads mapped to the X

and Y chromosomes. The 95% CI for this ratio was 196.84 to 214.3 in females and 2.13 to 2.18

in males. Twenty-two F_{34} and F_{39-43} animals were removed because their sex (as determined by

reads ratio) did not agree with their recorded sex; we assumed this discrepancy was due to

sample mix-ups. To further identify mislabeled samples, we calculated kinship coefficients

based on the full AIL pedigree using QTLRel. We then calculated a genetic relatedness matrix

(**GRM**) using IBDLD, which estimates identity by descent using genotype data. The comparison

between pedigree kinship relatedness and genetic kinship relatedness identified 7 pairs of

animals that showed obvious disagreement between kinship coefficients and the GRM. Lastly,

we excluded 14 F_{39-43} animals that showed discordance between their recorded coat color and

their genotypes at markers flanking *Tyr*, which causes albinism in mice. The numbers of animals

filtered at each step are listed in S2 Table. Some animals were detected by more than one QC

step, substantiating our belief that these samples were erroneous.

At the end of SNP and sample filtering, we had 59,561 autosomal and 831 X

chromosome SNPs in F_{34}, 58,966 autosomal and 824 X chromosome SNPs in F_{39-43}, and

57,635 autosomal and 826 X chromosome SNPs in the combined F_{34} and F_{39-43} set (S2 Table).

GBS genotype quality was estimated by examining concordance between the 66 SNPs that

were present in both the array and GBS genotyping results.

LD decay

Average LD (r^2) was calculated using allele frequency matched SNPs (MAF difference <

0.05) within 100,000bp distance, as described in Parker et al. (1).

Imputation to LG/J and SM/J reference panels

F_{34} array genotypes (n=428) and F_{34} GBS genotypes (n=428) were imputed to LG/J and

SM/J whole genome sequence data (59) using BEAGLE. For F_{34} array imputation, we used a

large window size (100,000 SNPs and 45,000 SNPs overlap). Imputation to reference panels

yielded 4.3 million SNPs for F_{34} array and F_{34} GBS imputed sets. Imputed SNPs with DR^2 > 0.9,

MAF > 0.1, HWE p value > 1.0×10^{-6} were retained, resulting in 4.1M imputed F_{34} GBS SNPs

and 4.3M imputed F_{34} array SNPs.

Genome-wide association analysis (GWAS)

We used the linear mixed model, as implemented in GEMMA (52), to perform a GWAS

that accounted for the complex familial relationships among the AIL mice (35,39). We used the

leave-one-chromosome-out (**LOCO**) approach to calculate genetic relatedness matrix, which

effectively circumvented the problem of proximal contamination (54). Separate GWAS were

performed using F_{34} array genotypes, F_{34} GBS genotypes, and F_{39-43} GBS genotypes. Apart

from coat color (binary trait) and locomotor activity, raw phenotypes were quantile normalized

prior to analysis. Locomotor activity was not quantile normalized because the trait was

reasonably normally distributed already and because we wanted our analysis to match those

performed in Cheng et al (35). Because F_{34} AIL had already been studied using array genotypes

(35) and mapped using QTLRel (63), we used the same covariates as described in Cheng et al.

(35) in order to examine whether our array and GBS GWAS would replicate their findings. We

included sex and body weight as covariates for locomotor activity traits (see covariates used in

(35))and sex, age, and coat color as covariates for fear conditioning and open field test in F_{34}

AILs (see covariates used in (36)). We used sex and age as covariates for all other phenotypes.

Covariates for each analysis are shown in S1 Table. Finally, we performed mega-analysis of F_{34}

and F_{39-43} animals (n=1,028) for body weight, coat color, and locomotor activity, since these

traits were measured in the same way in both cohorts. For the mega-analyses, locomotor

activity was quantile normalized after the combination of the two datasets to ensure that data

were normally distributed across generations.

Identifying suspicious SNPs

Some significant SNPs in F_{34} GWAS and in the mega-analysis of F_{34} and F_{39-43} were

suspicious because nearby SNPs, which would have been expected to be in high LD (a very

strong assumption in an AIL), did not have high -log10 values. We only examined SNPs that

obtained significant p-values; these examinations reveled that these SNPs had suspicious ratios

of heterozygotes to homozygotes calls and had corresponding HWE p-values that were close to

our 1.0×10^{-6} threshold (S10 and S11 Tables). To avoid counting these as novel loci, we

removed those SNPs prior to summarizing our results as they likely reflected genotyping errors.

Selecting independent significant SNPs

To identify independent "lead loci" among significant GWAS SNPs that surpass the

significance threshold, we used the LD-based clumping method in PLINK v1.9. We empirically

chose clumping parameters (r^2 = 0.1 and sliding window size = 12,150kb) that gave us a

conservative set of independent SNPs (S3 Table). For the coat color phenotypes, we found that

multiple SNPs remained significant even after LD-based clumping, presumably due to the

extremely significant associations at these Mendelian loci. In these cases, we used a stepwise

model selection procedure in GCTA (62) and performed association analyses conditioning on

the most significant SNPs.

Significance thresholds

We used MultiTrans and SLIDE to set significance thresholds for the GWAS (56,57).

MultiTrans and SLIDE are methods that assume multivariate normal distribution of the

phenotypes, which in LMM models, contain a covariance structure due to various degrees of

relatedness among individuals. We were curious to see whether MultiTrans/SLIDE produces

significance thresholds drastically different from the threshold we obtained from a standard

permutation test ('naïve permutation' as per Cheng et al. (54)). We performed 1,000

permutations using the F_{34} GBS genotypes and the phenotypic data from locomotor activity

(days 1, 2, and 3). We found that the 95th percentile values for these permutations were 4.65,

4.79, and 4.85, respectively, which were very similar to 4.85, the threshold obtained from

MultiTrans using the same data. Thus, the thresholds presented here were obtained from

MultiTrans but are similar (if anything slightly more conservative) than thresholds we would have

obtained had we used permutation. Because the effective number of tests depends on the

number of SNPs and the specific animals used in GWAS, we obtained a unique adjusted

significance threshold for each SNP set in each animal cohort (S12 Table).

Credible set analysis

We followed the method described in (50). The R script could be found on

GitHub: https://github.com/hailianghuang/FM-summary/blob/master/getCredible.r

Genetic correlation and heritability estimates between F_{34} and F_{39-43} phenotypes

Locomotor activity, body weight, and coat color had been measured in both F_{34} and F_{39-}

$_{43}$ populations. We calculated both SNP heritability and genetic correlations between F_{34} and

F_{39-43} animals using GCTA bivariate GREML analysis (62). Because F_{39-43} day 1 locomotor

activity data were not normally distributed, we quantile normalized locomotor activity data when

estimating SNP heritabilities and genetic correlations.

LocusZoom Plots

LocusZoom plots were generated using the standalone implementation of LocusZoom (80),

using LD scores calculated from PLINK v.1.9 --ld option and mm10 gene annotation file

downloaded from USCS genome browser.

Ethics Statement

475 All procedures were approved by the Institutional Animal Care and Use Committee (IACUC

476 protocol: S15226) Euthanasia was accomplished using CO_2 asphyxiation followed by cervical

477 dislocation.

Acknowledgements

480 We would like to recognize Jackie Lim and Kaitlin Samocha for collecting F_{34} AIL phenotype

481 data and Ryan Walters for collecting F_{39-43} AIL phenotype data. We wish to acknowledge Alex

482 Gileta for input on a draft of this manuscript.

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Main figure legends

Fig 1. Minor allele frequency distributions for F_{34} array, F_{34} GBS, F_{39}-F_{43} GBS, and F_{34} and F_{39}-F_{43} GBS SNP sets. MAF distributions are highly comparable between AIL generations.

Fig 2. Significant loci on chromosome 17 for open field, distance traveled in periphery in F_{34} AIL. As exemplified in this pair of LocusZoom plots, GBS SNPs defined the boundaries of the loci much more precisely than array SNPs. GBS SNPs that are in high LD ($r_2 > 0.8$, red dots) with lead SNP chr17:27130383 resides between 27 ~ 28.3 Mb. In contrast, too few SNPs are present in the array plot to draw any definitive conclusion about the boundaries or LD pattern in this region. Purple track shows the credible set interval. LocusZoom plots for all loci identified in this paper are in Fig S7.

Fig 3. Chip-heritability estimates in F_{34} and F_{39-43} AILs. All heritability estimates are highly significant (p < 1.0×10-05; see S7 Table).

Fig 4. Manhattan plots comparing F_{34} GBS, F_{39-43} GBS, and mega-analysis on locomotor day 1 test using 57,170 shared SNPs in all AIL generations. Mega-analysis identified a locus on chromosome 10 (chr10.104988207) that was not detected in the F_{34} or F_{39}-F_{43} alone, suggesting that mega-analysis enhanced power to detect some loci.

Supporting information

S1 Fig. Autosomal heterozygosity distribution in F_{34}, F_{39-43} AILs. Animals with excessive or insufficient heterozygosity (3 *s.d.* away from mean) were removed from further analysis. As controls, we have sequenced two F_2s of LG and SM, four LG mice and four SM mice (see annotated data points with 1 and 0 heterozygosity).

S2 Fig. Kinship coefficients in F_{34} and F_{39-43} AILs calculated from pedigree against genetic relatedness matrix calculated using IBDLD [49]. Each circle represents a pair of animals, which their genetic kinship relatedness on the x-axis and pedigree kinship relatedness on the y-axis. Color signifies relatedness based on AIIL pedigree. Blue circles represent identical twins, red full siblings, yellow parent-offspring pairs, grey other relationships. Seven animal pairs that deviate from the pedigree relationship clusters were excluded (see black arrows).

S3 Fig. Heatmap showing F_{34} array and F_{34} GBS genotype concordance in percentages, using 66 shared SNPs. "A" codes for the LG/J allele, and "B" codes for the SM/J allele. "AA" genotype concordance between array and GBS is 24.54%, "AB" 43.23%, "BB" 27.60%.

S4 Fig. LD decay in F_{34} array, F_{34} GBS, F_{39-43} GBS, and F_{34} and F_{39-43} GBS SNP sets.

S5 Fig. Manhattan plots comparing 4,593 F_{34} array, 60.3K F_{34} GBS, 4.3M imputed F_{34} array, and 4.1M imputed F_{34} GBS (N=428) SNPs on day 2 locomotor activity. Adjusted significance

724 thresholds for imputed array and GBS SNPs were estimated using LD pruned SNPs (r2=0.1,
725 window size=20kb; PLINK v1.9). Notice that even though the imputed sets have more SNPs
726 (the two right panels), they are frequently blocks of many SNPs with almost identical position
727 and LD=1, therefore making it hard to visualize the additional SNPs.
728
729 **S6 Fig. SNP heritability using F_{34} GBS and F_{34} array SNPs (slope=1).**
730
731 **S7 Fig. LocusZoom for F_{34} array, F_{34} GBS, F_{39-43} GBS, and mega-analysis QTLs.** Purple
732 track shows the credible set interval (r^2 threshold = 0.8, posterior probability threshold = 0.99).
733
734 **S1 Table. List of phenotypes used in GWAS.**
735
736 **S2 Table. SNP and individual QC filter table.** Numbers of animals and SNPs remained after
737 each step of filtering are shown per GBS SNP set.
738
739 **S3 Table. Effect of PLINK v1.9 clump-based pruning parameters on number of**
740 **independent SNPs remained.** At all r_2 values examined, a sliding window size of 12150kb was
741 the first smallest window that yield the most stringent number of clumped SNPs in both array
742 and GBS GWAS.
743
744 **S4 Table. Lead QTL in F_{34} GBS and F_{34} array GWAS studies across phenotypes.**
745 Significant SNPs are clumped using parameters r_2=0.1, 12150kb.
746
747 **S5 Table. F_{34} GBS and array SNP heritability estimates.**
748
749 **S6 Table. F_{34} and F_{39-43} genetic correlations in locomotor activity, coat color, and body**
750 **weight.**
751
752 **S7 Table. SNP-heritability comparison between F_{34} and F_{39-43} GBS.**
753
754 **S8 Table. Lead QTL in F_{39-43} N=600 GBS GWAS studies across phenotypes.** Significant
755 SNPs are clumped using parameters r_2=0.1, 12150kb.
756
757 **S9 Table. Lead QTL in F_{34} and F_{39-43} (N=1028) mega-analysis across phenotypes.**
758 Significant SNPs are clumped using parameters r_2=0.1, 12150kb.
759
760 **S10 Table. SNPs in F_{34} GBS set with HWE p-values close to 1.0×10-6 cutoff threshold.**
761 These SNPs are removed from QTL summary tables.
762
763 **S11 Table. SNPs in F_{34} and F_{39-43} mega-analysis GBS set with HWE p values close to**
764 **1.0×10-6 cutoff threshold.** These SNPs are removed from QTL summary tables.
765
766 **S12 Table. Adjusted significance threshold for each SNP set and GWAS cohort.**
767

F34 Array, open field, distance travelled in periphery (cm)

F34 GBS, open field, distance travelled in periphery (cm)

Phenotype