

Haplotypes associated to gene expression in breast cancer: can they lead us to the susceptibility markers?

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Abstract

We have undertaken a systematic haplotype analysis of the positional type of biclusters analysing samples collected from 164 breast cancer patients and 86 women with no known history of breast cancer. We present here the haplotypes and LD patterns in more than 80 genes distributed across all chromosomes and how they differ between cases and controls. We aim by this to 1) identify genes with different haplotype distribution or LD patterns between breast cancer patients and controls and 2) to evaluate the intratumoral mRNA expression patterns in breast cancer associated particularly to the cancer susceptibility haplotypes. A significant difference in haplotype distribution between cases and controls was observed for a total of 35 genes including *ABCC1*, *AKT2*, *NFKB1*, *TGFBR2* and *XRCC4*. In addition we see a negative correlation between LD patterns in cases and controls for neighboring markers in 8 genes such as *CDKN1A*, *EPHX1* and *XRCC1*.

Introduction

The common disease common variant hypothesis is the foundation for large scale whole genome analyses of extensive population cohorts aiming at identifying low penetrant markers that in concert result in an increased risk of cancer. Nearly 1300 published GWAS studies have so far identified 6551 markers associated with various diseases and traits such as asthma, multiple sclerosis and various cancer types (1). For breast cancer specifically SNPs in 41 genes including *FGFR2*, *TOX3*, *TERT* and *ERBB4* have been associated to the disease (2-5). These studies view the risk of common genetic variation only and the number of markers is restricted to the number of SNPs on the studied arrays without focus on particular genes or functionality. Here we have taken an alternative route based on a candidate gene approach without restriction to frequency. Moreover, we did not study single disease associated SNPs but looked for differences in haplotype distribution and LD patterns between cases and controls. Linkage disequilibrium (LD) is the association between two markers (SNPs) resulting from common inheritance of two typically nearby loci. LD is eroded by mutations, gene conversions and recombination events, and is influenced by the age of the mutations as well as the history and size of the populations in which they are studied. Several measurements are used to estimate LD such as D' (6) and r^2 (7). D' shows larger variability within and between populations and is more influenced by sample size (8,9). D' takes into account the history of the markers and is more robust with regards to

frequency while r^2 is less affected by problems related to sampling (8). It is also possible to use statistical estimates of population recombination rates (ρ) instead of pairwise measures of LD (9). This measure correlates well across populations and relates the LD pattern directly to the underlying recombination process (7). Haplotypes are strings or combinations of co-inherited SNPs residing at regions of high LD and separated by areas with high recombination and low LD (8). They are inherited from parents as a single unit and tend to break at recombination hotspots (3). In population studies in contrast to linkage analysis in families, an absolute determination of haplotypes is not possible, but studies of phased estimations have proven these to be a very good approximation. The results from these studies indicate an error in assigning phase to genotypes of approximately 5 % in unrelated individuals (10). This uncertainty can be adjusted for as we have previously described (11).

The choice of LD block was motivated by our studies in eQTLs. Our findings indicate that the breast cancer risk variants found by the GWASs may exert their effect through the regulation of expression, and that the genes harboring these risk variants are significantly differentially expressed between the well established breast cancer subtypes (12). Given the significant role mRNA expression patterns play in the development of breast cancer, we hypothesize that SNPs associated to clusters of deregulated co-expressed mRNA transcripts may lead us to novel susceptibility markers. We have previously described that among 583 candidate SNPs in 203 genes of the reactive oxygen species metabolism/signaling, there are SNPs significantly

associated over the random to the expression of subsets of unselected transcripts in the tumor of breast cancer (13). Furthermore, these subsets of transcripts are enriched for given functional pathways also over the random. Multiple SNPs (biclustes) that together share significantly many common associations to a set of transcripts were identified. These biclusters were either located in different genes on different chromosomes, suggesting a multi-locus regulatory effect on a pathway (functional biclusters) or clustered in the same gene or chromosomal region (positional biclusters). With the present study we have undertaken a systematic haplotype analysis of these positional biclusters extending the analysis to samples collected from 164 breast cancer patients and 86 women with no known history of breast cancer. We aim by this study to 1) formally assess the degree of LD between the SNPs in the positional biclusters associated to expression 2) use these eQTL hits to identify cancer susceptibility haplotypes by comparing the distribution or LD patterns between 1592 breast cancer patients and 1892 controls.

Material and Methods

Genotyping

We have genotyped 164 breast cancer patients and 86 healthy women with no known history of cancer (two negative mammography screenings). The panel of SNPs genotyped are thoroughly described in (14) but in short, SNPs in candidate genes involved in the metabolism of reactive oxygen species and

xenobiotics, DNA repair, cell cycle and apoptosis were genotyped using a mini-sequencing (SNP-IT) method multiplexing up to twelve SNPs in one tube. The polymerase chain reaction, clean up with Exol and SAP and SNP-IT reaction are performed in one tube and the reaction mix hybridized to an array. Each of the twelve SNP-IT primers contain a tag that utilizes sorting of the multiplex reaction on the array. The mini-sequencing reaction is a two colour reaction and signal is detected after laser excitation of the fluorophores on the SNP-stream UHT system.

Validation analysis of selected SNPs

Validation of selected SNPs were done using the Sequenom MassARRAY platform and iPLEX genotyping assays (www.sequenom.com/home/) (15).

Microarray expression analysis.

For 50 of the breast cancer patients, expression data were also available. Tumour tissue (20-50mg) was dissected and powdered in liquid nitrogen and total RNA was prepared by standard procedures. Whole genome microarray expression analysis has been performed using cDNA microarrays as described in (16-18).

SNP-expression association analysis

Unselected subset of 3351 mRNA transcripts was obtained by filtering for signal quality (ratio of spot intensity over background exceeding 1.5 in at least 80% of the experiments in each dye channel). The analysis of the SNP-expression associations are published earlier in (13). For these patients

additional 28 SNPs were available for the haplotype analysis. In short, the correlation between genotypes and expression level of the different mRNA transcripts were assessed using three, different statistical approaches; ANOVA, QMIS and LOOCV. For each SNP locus and each transcript, the one-way ANOVA p-value was computed for the expression vector and grouping of the samples based on SNP locus genotypes (19) assuming the null hypothesis that the expression level distributions are the same, regardless of the genotype class. QMIS (Quantitative Mutual Information Score). For a SNP locus s and an expression vector q of transcript t , let G be a partition of samples induced by the genotype values at locus s . For an expression level threshold p , let C_p be a partition of samples defined by the $q < p$ and $q \geq p$. The mutual information score (MIS) is the difference between the entropy of the partition C_p and the conditional entropy of C_p given G : $MIS(C_p, G) = H(C_p) - H(C_p | G)$, where H is the entropy function. The quantitative mutual information score is defined to be the maximum possible MIS, i.e., $QMIS(C, G) = \max_{\min(q) \leq p \leq \max(q)} MIS(C_p, G)$. An exact p-value for the mutual information score can be computed exactly by an efficient exhaustive approach (20). In this case, the null hypothesis is that genotype values have the same distribution, regardless of expression levels. For QMIS, 769 SNP-transcript association pairs with p-values $\leq 1.0E-04$ were observed, representing an FDR of 0.2. LOOCV (Leave Out Cross Validation) for a given SNP in the data set, its genotypes were utilized to group samples. For each grouping, leave-one-out-cross-validation analysis was performed, trying to

predict from the expression data which genotype group each sample belongs to (similar to the methods described in (21)).

Gene Ontology analysis (GO)

The group of transcripts associated to the same SNP or group of SNPs was analysed with regards to enrichment of GO terms based on GO terms downloaded from Source (<http://source.stanford.edu/cgi-bin/source/sourceSearch>), for this analysis the p-value cut-off for the SNP-expression association was set at 0.05 and 0.01. The significant overrepresentation for a GO term was calculated taking into account the total number of; 1) genes on the expression array, 2) genes associated with the GO term, 3) genes associated to the SNP and 4) the number of genes associated with the SNP or group of SNPs, that belong to the GO term. The z score was calculated according (14) by subtracting the expected number of genes in a GO term from the observed and dividing this by the standard deviation of the observed.

$$z = \frac{(\textit{observed} - \textit{expected})}{\textit{std}(\textit{observed})}$$

Calculation of LD and Spearman's correlation coefficient

SNPs that had discovery rate lower than 75% were excluded. Initially, the panels of SNPs were screened for clusters containing a minimum of 3 SNPs with no more than 100 kb between neighboring SNPs. For the genes represented in

these clusters – all genotyped SNPs were included. LD estimations were done in two steps. First, we estimated the haplotypes for cases and controls separately from our population genotype data using the recombination model implemented in the program PHASE (Stephens, M. et al.) with 5 different seeds and 100. The significance of the difference in haplotype distribution between cases and controls was calculated in Phase. The second step was the evaluation of the LD for all included genes. For this purpose, we calculated pairwise D' for cases and controls separately for all possible SNP combinations within a gene and under consideration of the uncertainty in phase estimation (11). PHASE also provides the recombination rate as a measure of dependency between the SNPs for all adjacent SNPs within a gene. To evaluate the difference for each gene between the LD-patterns of cases and controls, we calculated Spearman's correlation coefficient ρ as done in (9). The correlation is given as a value between $-1 \leq \rho \leq 1$, where 0 indicates no correlation, whereas -1 and 1 indicates high negative and positive correlation respectively. We calculated this nonparametric correlation coefficient 1) using all markers for D' and 2) using only adjacent markers for ρ .

Analysing the relationship between haplotypes and expression levels of transcripts associated to multiple SNPs within a gene

The non-parametric Mann Whitney or Kruskal Wallis test was used to analyse the possible connection between the haplotypes estimated for a gene and the expression levels of transcripts associated to all or a subset of the SNPs within the given haplotypes. The analysis were performed using SPSS v15.0, the

p-values are exact (50 iterations), two-tailed and not corrected for multiple testing.

Estimating population subdivision – calculating the fixation index

Population subdivision was estimated using the Arlequin Software to calculate the Fixation index (F_{st}). This index measures the population differentiation between two groups and its values range from 0 to 1 (with 0 meaning that the populations are completely similar with regard to allele frequencies and 1 being that the populations are completely differentiated (22).

Results and discussion

The overall study design is given in **Supplementary Figure 1**. A total of 687 SNPs in 203 genes selected from pathways related to the ROS metabolism and signaling were genotyped in 169 breast cancer patients and 86 controls (14). Haplotypes were inferred and of the 687 SNPs, a subset of 457 SNPs were available at HapMap with associated frequency information. The full list of SNPs used in the analysis can be found in **Supplementary Table 1** together with information on gene affiliation, chromosomal position, allelic variation and strand genotyped.

Impact of multiple SNPs (biclusters) on the expression profile;

For 50 of the patients genotyped here expression data were available and we have previously reported the association of 538 SNPs to the intratumoral mRNA expression in these patients (13). Many of the studied genes, e.g. *ABCC1*, *ALOX12*, *DPYD*, *GSTM3*, *NOX3*, *IL10* and *IL8* were shown to harbor multiple SNPs significantly associated to the level of transcripts *in cis* and *trans* (for full list see **Supplementary Table 2**). We have formally assessed the degree of LD between the multiple SNPs regulating the same group of transcripts and observe that many of these are in strong linkage disequilibrium such as in the genes of *DPYD*, *TXNIP*, *GSTA4*, *PPP1R9A*, *NFKBIA*, *IGF1R*, *ABCC1* and as shown for *XDH* and *IL1R1* on chromosome 2 **Figure 1** (figures for all other chromosomes are given in **Supplementary Figure 2a-u**). Further analyzing the characteristics of these subsets of coexpressed transcripts by gene ontology analysis (p-value cut-off for the SNP-transcript association: 0.01), we find for SNPs in more than 25 genes a significant overrepresentation of GO terms in the list of regulated transcripts at p-value < 0.001 (**Table 1**). Compelling examples are: 1) 18 SNPs in *DPYD* (involved in pyrimidine base degradation) which together with a SNP in *GSTM4* all are associated to the expression of a group of 10 transcripts among which there is an overrepresentation of the GO term *regulation of cell growth* and 2) 6 SNPs in *GSTA4* associated to a group of 20 transcripts with an overrepresentation of the GO term *transcriptional activator activity*.

In addition, we also found transcripts such as *ANKS1*, *CREG*, *NFKB1*, *TYMS* and *USP1* that were associated each to multiple SNPs (**Supplementary Table 3**).

Analysis of the haplotype distribution and chromosome wise LD pattern in the case vs. the control population

Haplotypes were estimated for all genes harboring more than 3 SNPs with a maximum distance between neighboring SNPs of 100 kb (n=83). Haplotypes were inferred for the case and control groups separately and the significance of the difference in their distribution was evaluated. A significant difference ($p < 0.05$) in haplotype distribution between cases and controls was observed for 35 genes such as *ABCC1*, *AKT2*, *NFKB1*, *ALOX15B*, *GSR* and *PIK3CA* (**Table 2**).

The pairwise LD was estimated for: 1) all markers and 2) only between neighboring markers by the standard measurements D' and r^2 under consideration of the uncertainty in phase estimation as described in (11). In addition for the neighboring markers, ρ (estimating the population recombination rate across multiple populations) was calculated as described by Evans and Cardon (9). Looking at neighboring markers there is a negative correlation ($\rho < -0.700$) between the LD patterns in cases and controls in 8 genes such as *CDKN1A*, *EPHX1* and *XRCC1* (**Table 3, panel A**). When including all possible pairwise comparisons for the D' measure, the Spearman's correlation analysis revealed a negative correlation for *PQLC2*, *SOD2* and *PIK3CA* (**Table 3, panel B**). Comparing the pairwise correlation analysis between cancers and controls

with the haplotype distribution analysis we see that for the genes where we find a significant different haplotype distribution between cases and controls the correlation is either very low or positive. These results indicate that the difference between cases and controls may be identified by studying together the degree of correlation of LD patterns and the haplotype frequency distribution.

Additionally, we investigated neighboring clusters of genes for differences in LD structure and found a negative correlation between the LD values for cases and controls in neighboring regions for gene-pairs such as *IL1A+IL1B*, *RAF1+XPC* and *NFKBIA+FOS* (**Supplementary Table 4**). These results suggest that the impact of a SNP on susceptibility may be fortified by its organization into haplotype structure including more than one gene, which together may confer higher risk.

Impact of the identified putative susceptibility haplotypes on the expression profile;

The haplotypes that were found significantly differently distributed between cases and controls in the genes *ABCC1*, *BCL2*, *IGF1R*, *LIG4*, *PPP1R9A* and *TXNIP*. were then tested for association to intratumoral expression. The increased complexity with increasing number of estimated haplotypes made it difficult to detect any significant trends for *ABCC1*, *BCL2*, *IGF1R* and partly *PPP1R9A* but for both *LIG4* and *TXNIP* a significant association between the expression level of several transcripts and the estimated haplotypes was identified. For *TXNIP*, the second most frequent haplotype (AAAGGAG, **Table 1**) was found associated

to the expression level of *MADH4*, *NFE2L1* and *TRAP240* (exact p-value <0.001 and 0.001 respectively, **Figure 2 a** and **b**). For *LIG4*, three transcript probes linked to the overrepresented GO term “ubiquitin cycle” were available representing the expression levels of *FBXO11*, *TSG101* and *CDC34*. Combinations of the second most frequent haplotype (CACCT, **Table 1**) show a significantly different expression level for *FBXO11* (exact p-value 0.009, **Figure 2c**).

Frequency distribution of the htSNPs derived from the putative susceptibility haplotypes associated to expression in cases and controls.

A total of 42 htSNPs in 9 genes (*ABCC1*, *IL1R1*, *PPP3CA*, *NFKB1*, *BCL2*, *IGF1R*, *LIG4*, *PPP1R9A* and *TXNIP*) with both significant difference in haplotype distribution between cases and controls and an association between multiple SNPs in the gene an intratumoral expression, either *in cis* or *trans*, were selected for case control analysis. All in all we genotyped 3484 samples divided in 1592 samples from BC patients/survivors and 1892 controls. 16 of the 42 investigated SNPs were found associated or borderline associated with case-control status (**Table 4**). Three SNPs, rs 215094 in *ABCC1*, ($p < 2.25E-04$) rs878335 in *IGF1R* ($p < 5.58E-09$) and rs1805388 in *Lig4* ($p < 7.73E-6$) were significant after BonFerroni correction with the SNP in *IGF1R* reaching genome wide significance level.

Controls vs hapmap Caucasians

Population subdivision between our sample material and the HapMap samples was estimated by the Fixation index (F_{st}) which measures the population differentiation between two or more (22). The F_{st} was calculated separately for the nine genes with ≤ 7 loci available for analysis (*BCL2*, *IGF1R*, *IL10*, *NFKB1*, *NOX3*, *TANK*, *TGFBR2*, *TXNIP* and *XRCC4*, **Table 1**) and then averaged over all genes. The average F_{st} was 0.0065, indicating a negligible difference between the two populations.

Conclusion

Several studies have looked into the relationship between single SNPs and risk of sporadic breast cancer both at the single SNP level and the GWAS level. The success of the former in identifying low penetrance alleles have been limited while the latter has identified regions of 10q26 (*FGFR2*), 16q12.1 (*TNRC9*), 5q11.2 (*MAP3K1*), 8q24, 11p15.5, 5q12 and recently 1p11.2, 14q24.1 (*RAD51L1*), 3p24 and 17q23.2 to be linked to risk of sporadic breast cancer (3,23-27). In this study we have chosen to look at the association between haplotypes and LD patterns in more than 80 genes distributed across all chromosomes and how they differ between cases and controls and identify differences in both, interestingly not at the same time, in important cancer related genes such as *NFKB1*, *PIK3CA* and *CDKN1A*. We also link the results of our haplotype analysis to our previously published results revealing an association

between the germline variation and the expression level in the tumor itself (13). Our SNPs are not representative for the whole genome – they are selected from a candidate gene approach but they anyway make grounds for comparing haplotype patterns between cases and controls and to estimate to what extent these results can be extrapolated to other populations through the genetic similarity with data extracted for the Caucasian samples included in the HapMap project. If we manage to find SNPs in the classical and novel regulatory areas of the genes that correlate to the expression of genes in breast cancer, we will be able to predict the risk of developing certain molecular portraits of breast cancer before the cancer has at all occurred.

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Table legends

Table 1. GO analysis of the set of transcripts associated to groups of SNPs in single genes reveals an overrepresentation of GO terms among these transcripts (p-value<0.001, Supplementary Table 5: p-value<0.05). Genes with a significant difference in haplotype distribution between cases and controls are given in bold (Table 3).

Table 2. Genes with significantly different haplotype distribution between cases and controls. *P* value of 0.01 indicates 0.01 or less.

Table 3. Spearman's correlation between LD of cases and controls for neighbouring SNPs (panel A) and all SNPs (panel B) within a gene based on *r* and *D'* values respectively. Listed here are only genes with an absolute correlation between 0.7 and 1

Supplementary Table 1. SNPs included in analysis with information on gene affiliation, chromosomal position, allelic variants and strand genotyped.

Supplementary Table 2. Multiple SNPs located in the same gene were found associated to the expression level of a number of transcripts by both ANOVA and QMIS analysis in [1]. Listed here are the gene info, rs-numbers, probe id of associated transcripts, most significant p-value from association analysis as well as whether the association is *in cis* or *in trans*.

Supplementary Table 3 Transcripts associated to genetic variation of multiple SNPs located within the same gene by both ANOVA and QMIS analysis in [1]. Listed here are gene info for identified transcripts,rs-numbers and gene info of associated SNPs, most significant p-value from association analysis as well as whether the association is *in cis* or *in trans*.

Supplementary Table 2. Spearman's correlation based on *D'* values between LD of cases and controls calculated in the intergenic areas. Listed here are only intergenic regions with an absolute correlation between 0.4 and 1

Supplementary Table 4. List of transcripts regulated by several SNPs

Supplementary Table 5. GO analysis of the set of transcripts associated to groups of SNPs in single genes reveals an overrepresentation of GO terms among these transcripts (p-value < 0.05). "Top" indicates the number of the regulated transcripts associated with the given GO term.

Figure legends

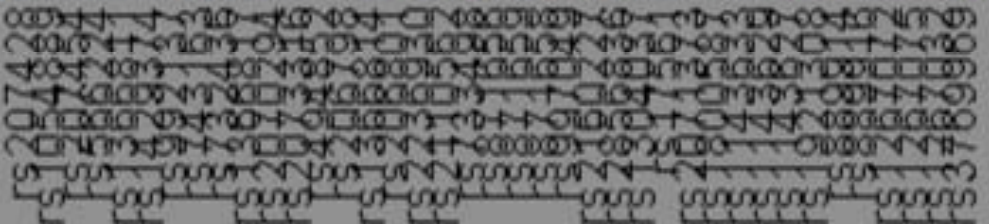
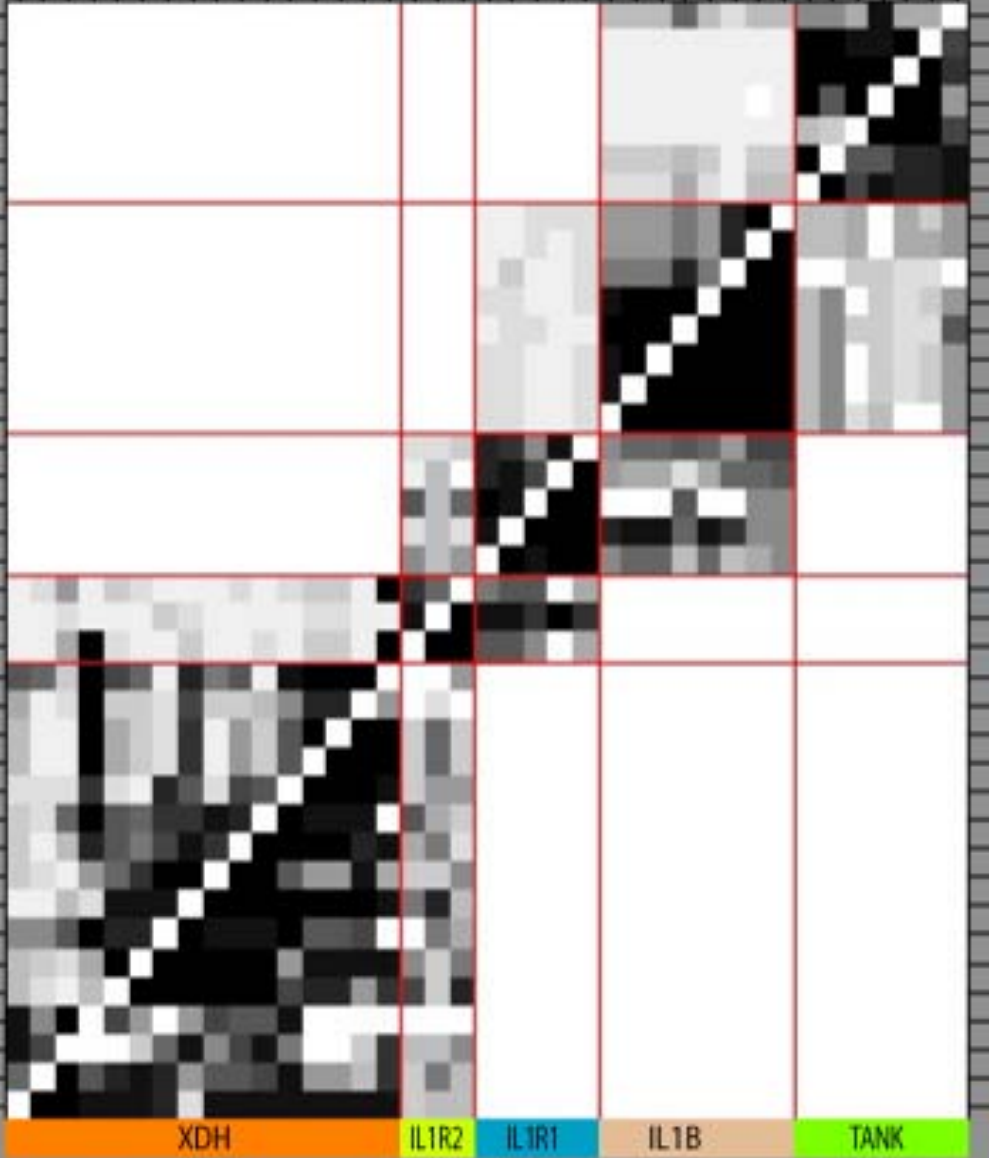
Figure 1 LD pattern in chromosome 2 for the cases together with information on overrepresented GO terms among associated transcripts. X-axis indicates the significance level of the LD while the $|D'|$ values are plotted on the Y-axis, values along the diagonal are intragenic, adjacent panels give information on intergenic regions.

Figure 2 Boxplots showing the spread in the expression levels of the transcripts probes for *MADH4* (A) and *NFE2L1* (B) for the different haplotype combinations of *TXNIP* as well as the spread in the expression levels of the transcripts *FBXO11* for the different haplotype combinations of *LIG4*

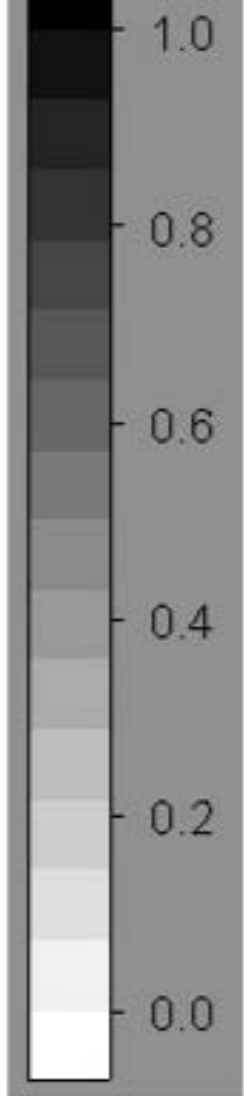
Supplementary Figure 1 Flow chart of the sample material and analysis

Supplementary Figure 2a-u. Chromosome wise LD for the cases together with information on overrepresented GO terms among associated transcripts. X-axis indicates the significance level of the LD while the $|D'|$ values are plotted on the Y-axis, values along the diagonal are intragenic, adjacent panels give information on intergenic regions.

D prime



1-p-value



GO term	Associated transcripts
blood coagulation	TFPI, WAS, THBD
transmembrane receptor activity	IL1R1, FCER1G, FCER2

GO term	Associated transcripts
rho small monomeric gtpase activity	ARHG, ARHE, RHOA, RHOB, RHOA2

Figure 2 Boxplots showing the spread in the expression levels of the transcripts probes associated to haplotypes of 1) *TXNIP*: *MADH4* (A) and *NFE2L1* (B) and 2) *LIG4*: *FBXO11* (C). The haplotypes presented in the figure is as follows (1=CAAGGAG, 3=CAAAGT, 4=CGGGGAG and 5=AAAGGAG) for *TXNIP* and (1=TACCT, 2=TATCT, 3=TATTT and 4= CACCT) for *LIG4*, (for full list of the haplotypes with a frequency of more than 1% in the studied sample set and identified frequency in the controls and cases separately see Supplementary Table 2).

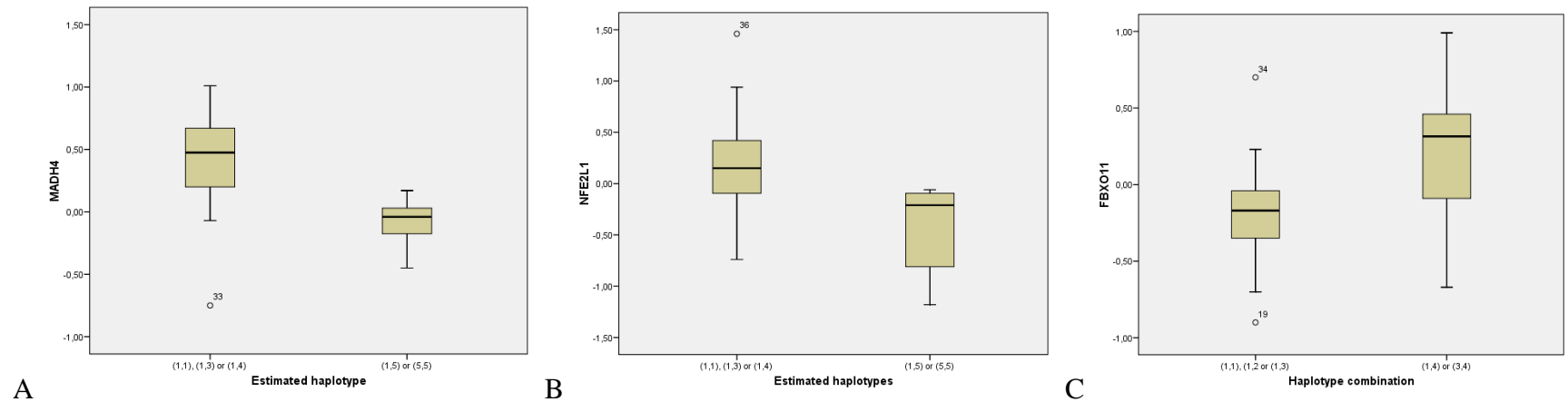


Table 1. GO analysis of the set of transcripts associated to groups of SNPs in single genes reveals an overrepresentation of GO terms among these transcripts (p-value<0.001). Genes with a significant difference in haplotype distribution between cases and controls are given in bold.

Gene	# of associated SNPs	SNP(s)	# of transcripts regulated	GO term overrepresented in group of transcripts	z-score	p-value	Top	Top transcript members of Go term
ABCC1	5	212083, 212088, 215067, 215094, 2062541	51	intracellular signaling cascade	4.017746	2.93787E-05	6	SHC1, RAB2L, SYK, PARG1, HSPC163, AKAP13
BCL2	8	1381548, 2551402, 899966, 1481031, 720321, 1016860, 1982673, 2062011	16	heparin binding	3.4840574	0.000246937	3	AAMP, SERPINC1, SERPINE2
DPYD	19	1889229, 2151563, 2065943, 1023245, 2786507, 1337521, 1337522, 1801265, 290855, 866129, 1413229, 2039448, 828054, 1879371, 1415681, 827500, 1333727, 2811187, (569998, GSTM4)	7	ossification	3.7774165	7.92318E-05	3	SPARC, OSTF1, MGP
			10	inner membrane	4.15958	1.59417E-05	4	COX6A1, SURF1, UQCR, COX6C
			10	regulation of cell growth	4.15958	1.59417E-05	4	COVA1, TSG101, IGFBP5, CTGF
			5	mitochondrial electron transport chain	4.7101364	1.23776E-06	3	SURF1, UQCR, CYC1
GSTA4	6	1032419, 316128, 316130, 316131, 316132, 367836	20	transcriptional activator activity	4.087544	2.17982E-05	3	MYB, TP53BP1, FOXC1
			11	protein kinase activity	5.894784	1.87586E-09	3	CCL2, CDK4, TRB2
HIF1AN	1	2295779	19	extracellular matrix structural constituent	14.076864	<1E-14	3	MFAP2, LUM, COL6A1
IER3	1	14350	28	structural constituent of ribosome	5.9378867	1.4436E-09	3	MRPS2, RPL31, RPS6
IGF1R	8	907799, 907807, 2137680, 1568502, 2229765, 871335, 1567811, 2715438	76	endoplasmic reticulum	4.275154	9.55026E-06	6	STS, SYNCRIP, ALG5, CYP1B1, VHL, GNAZ
			21	microsome	4.501634	3.37165E-06	3	STS, CYP1B1, STCH
			38	transcription coactivator activity	5.535717	1.54979E-08	5	ELF4, RNF4, NCOA2, DP1, TIF1
IL1R1	5	871656, 997049, 871658, 2160227, 871659	18	blood coagulation	4.4390535	4.51777E-06	3	TFPI, WAS, THBD
			17	transmembrane receptor activity	4.601597	2.09632E-06	3	IL1R1, FCER1G, THBD
IL8	3	4073, 2227547, 2227306	19	extracellular matrix structural constituent	6.5541277	2.79841E-11	5	FBN1, COL5A2, BGN, COL3A1, MFAP2
LIG3	4	3136027, 2074516, 2074522, 1003918	73	intracellular	4.359937	6.50499E-06	3	BAT4, RFP, ASB1
LIG4	4	868284, 1805388, 1805389, 1805386	28	ubiquitin cycle	4.4994664	3.40621E-06	3	FBXO11, TSG101, CDC34
NDUFA8	2	6822, 1411445	19	extracellular matrix structural constituent	8.083895	<1E-14	4	COL4A2, COL4A1, COL6A2, COL6A1
NFAT5	2	1437134, 920191	38	transcription coactivator activity	4.962491	3.47974E-07	3	TAF7, TIF1, HTATIP2
NFKB1	10	230498, 230505, 230525, 230526, 230531, 1609798, 1585214, 1598857, 1020760, 1020759	10	epidermal differentiation	5.8582754	2.33849E-09	3	KRT5, PLOD, FLOT2
			8	central nervous system development	6.6552978	1.41364E-11	3	DRPLA, RPS6KA3, ADORA2A
NFKBIA	3	696, 2233415, 1022714	24	response to stress	7.2226477	2.54907E-13	3	HIF1A, MAPK8, MKNK2
NQO1	3	1800566, 1541979, 744972	20	protein modification	4.7224402	1.16516E-06	3	AGPAT1, GPAA1, MMP15
PDGFC	2	1425492, 2113992	250	integral to membrane	3.3582497	0.000392189	3	STX17, FLOT1, SLC39A1
PPP1R15A	3	638050, 557806, 626140	38	transcription coactivator activity	4.9209385	4.30651E-07	4	TFDP1, ELF3, NFATC3, SF1
PPP1R9A	7	854549, 854518, 705377, 854537, 854524, 854523, 854539	29	inflammatory response	5.0928392	1.7637E-07	4	TLR5, NFATC3, RAC1, TNFRSF5
PPP3CA	3	1021965, 920559, 958379	11	antigen processing	6.4047303	7.53178E-11	3	HLA-DMA, HLA-DQB1, HLA-DPB1
			10	antigen presentation	6.7584443	6.97409E-12	3	HLA-DMA, HLA-DQB1, HLA-DPB1
			8	exogenous antigen	7.648024	1.02141E-14	3	HLA-DMA, HLA-DQB1, HLA-DPB1
			8	mhc class ii receptor activity	7.648024	1.02141E-14	3	HLA-DMA, HLA-DQB1, HLA-DPB1
			8	exogenous antigen via mhc class ii	7.648024	1.02141E-14	3	HLA-DMA, HLA-DQB1, HLA-DPB1
TGFBR3	17	284170, 284176, 284190, 284873, 284874, 901917, 1192529, 2253316, 913059, 2038931, 2799547, 1805113, 2279455, 1192524, 2007686, 2634021, 717923	10	core complex	3.818641	6.70944E-05	3	POLR2K, POLR2G, POLR2F
			10	dna-directed rna polymerase ii	3.818641	6.70944E-05	3	POLR2K, POLR2G, POLR2F
TNFAIP2	4	8126, 2234131, 2234143, 710100	45	extracellular space	5.1493545	1.30692E-07	5	HSPG2, YARS, APOD, TNFAIP2, SERPING1
TOP2B	3	1881708, 1881709, 1001647	28	structural constituent of ribosome	4.6068473	2.0441E-06	3	LAMR1, NHP2L1, MRPL15
TXNIP	4	4755, 7211, 7212, 9245	13	transcription cofactor activity	6.652163	1.44408E-11	3	MADH4, NFE2L1, TRAP240
UGT2A1	3	1432314, 1432324, 1432336	56	protein biosynthesis	6.098483	5.35399E-10	5	ETF1, MRPS21, KIAA0256, SCYE1, NACA
XDH	15	2073316, 206798, 206801, 1042039, 1366814, 1366817, 494852, 992137, 732436, 1366811, 1429374, 1054889, 743163, 2070294, 207428	6	rho small monomeric gtpase activity	5.165976	1.19594E-07	3	ARHG, ARHE, CDC42

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Table 2. Genes with significantly

Gene (s)	Nr. of SNPs	p-value*	Location	Tot. Nr of hap	No. Of hap > 1%"	Haplotype frequency (%)			
						Hap. freq.>1% "	Controls	Cases	
PTGS2	4	0.01	1q31.1	3	1	AAATA	0.871953	0.004498	
					2	AAGA	0.122233	0.995413	
						CAAGGAG	0.912659	0.865665	
						AAAGGAG	0.052922	0.078901	
TXNIP	7	0.02	1q21.1	13	3	CAAACCTG	0.004535	0.035556	
						ACGCGCCG	0.233689	0.168315	
						ATCCGCCG	0.177444	0.241212	
						ATCTAATG	0.170937	0.205880	
						GCGTGCCG	0.017846	0.003165	
						ACGCGCCA	0.029069	0.012455	
						ATGCGCCG	0.005971	0.017908	
						ATGTAATG	0.001858	0.016724	
						ATCCGATG	0.034942	0.031330	
						9	ATCCAATG	0.017556	0.012814
IL10	8	0.03	1q32.1	30	1	CTGCAAC	0.514038	0.494153	
						CTGTAAC	0.293175	0.251378	
						CTACGGC	0.139476	0.224557	
						4	CTGCGGC	0.032224	0.000295
TANK	7	0.02	2q24.2	17		ACCAC	0.221693	0.225895	
						TTCAC	0.173862	0.146918	
						ATCAC	0.078671	0.084747	
						ATGAA	0.091558	0.047522	
						ATGAC	0.013087	0.026784	
						ATCAA	0.016711	0.023701	
						ACCAA	0.028107	0.010536	
						9	ACCTC	0.027812	0.006547
							GAGCC	0.223666	0.201174
							CAGCC	0.174941	0.185088
IL1R1	5	0.03	2q11.2	18		CGGAT	0.131953	0.160631	
						CAGAC	0.130723	0.130002	
						GAGAT	0.052045	0.023673	
						GAGAC	0.033055	0.010527	
						8	GGGAT	0.009673	0.014249
							AIC	0.442989	0.503389
XPC, MGC3222	5	0.01	3p25.1	14		CTC	0.533736	0.456775	
						3	ATG	0.010836	0.038121
							GTGAGTGATCAGTG	0.055400	0.081952
PIK3CA	3	0.01	3q26.32	5		GTAGACGGCTGCC	0.066236	0.060786	
						GTGAACGGCTAGTG	0.033521	0.060892	
						GTAGATGGCTAGCC	0.042002	0.050078	
						GTAGATGGCTAGTG	0.042402	0.049279	
						GTAGATGGCCGCC	0.032147	0.034859	
						TTAGACGGCTGGTG	0.016937	0.033880	
						GTGAACGGCTGCC	0.011456	0.035070	
						GTAGATAATTAGTG	0.021577	0.024749	
						GTAGATGGCTGGCC	0.036540	0.016798	
						TTAGATAATCGGCC	0.018181	0.025054	
						GTGAATAATTAGTG	0.028556	0.016599	
						GTAGATGGCTGCTG	0.012651	0.023713	
						GTAGACGGCTGGCC	0.017967	0.020195	
						GTAGATGGCTGGTG	0.023750	0.016411	
						TTAGATAATCGGCC	0.007683	0.024318	
						TTAGACGGCTGCC	0.019633	0.017260	
						TTAGATGGCTGCC	0.012387	0.015041	
						GTGAACGGCTGGCC	0.000746	0.020181	
						TTGAACGGCTGCC	0.007766	0.014837	
						GTAGATGGCCAGCC	0.010506	0.012902	
TGFB2	14	0.01	3p24.1	215	24	GTAGATGGCCAGTG	0.006027	0.013500	
						AGCTCCTGCT	0.034303	0.235505	
						GATTTACGGC	0.138890	0.130323	
						AGCTCCTCCT	0.249885	0.014257	
						GGTCTACGGC	0.066730	0.098851	
						AGTTTCCGCC	0.075465	0.064106	
						GGTTTACGGC	0.042786	0.056117	
						AGCTCCTGCC	0.009937	0.056837	
						GGTCTACGGT	0.021990	0.025563	
						GGTTTCTGCC	0.013938	0.011156	
						11	AGTTTCTGCC	0.004538	0.015111
							GATGC	0.144510	0.177623
							GGTTC	0.284364	0.005556
							AGTGC	0.038653	0.074460
NFKB1	10	0.01	4q24	51		GATTC	0.068521	0.002134	
						GATGA	0.020773	0.017663	
						AATGC	0.008002	0.019636	
						8	AGTTC	0.031469	0.000032
							AAC	0.111075	0.068700
PDGFRA	5	0.01	4q12	19		AAG	0.046110	0.061877	
						GGC	0.052271	0.012229	
						5	GAG	0.091910	0.048143
PPP3CA	3	0.01	4q24	8		TCCGG	0.391092	0.412018	
						CTTTG	0.439001	0.407780	
						TCTGA	0.073988	0.094056	
						CCCGG	0.005581	0.018047	
CCNB1	5	0.01	5q13.2	16	5	TTCGG	0.029482	0.000644	

Nr. of p- Tot. Nr No. Of hap Haplotype frequency (%)

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Gene	Nr. of p-	Tot. Nr	No. Of hap	Haplotype frequency (%)
				CGGAACTAACGTG 0.121548 0.051329
				CGGAGTCAGTGTG 0.058801 0.081718
				TAAGACTCACACA 0.026756 0.037067
				CGGAACTCACACA 0.022659 0.038418
				TAAGACTAACGTG 0.032373 0.002874
				CGGAGTCAGTACA 0.011860 0.012605
				TAAGGTCACTACA 0.004883 0.014989
				TAAGGTCACTGTG 0.009525 0.012409
XRCC4	13	0.02 5q14.2	60	11 CGGAACTAACACA 0.020216 0.006561
				CACC 0.006744 0.023071
				CATC 0.834971 0.171974
				CATT 0.111069 0.003507
IER3, FLOT1	4	0.01 6p21.33	6	4 CTTC 0.037016 0.001007
				GGGGTCC 0.016381 0.332584
				GGGGCCA 0.434521 0.011417
				GGGGCCC 0.364135 0.009913
				GGAATCA 0.037590 0.079271
				GGAATCC 0.028165 0.069558
				GGGTAC 0.000116 0.021412
NOX3	7	0.01 6q25.3	44	8 GGGGCAC 0.034837 0.000207
				TTGGCT 0.261208 0.306296
				TTGACT 0.186323 0.131406
				ACAGCT 0.050812 0.071011
				TCAACT 0.075680 0.054396
				ACAAC 0.033680 0.052567
				TCAGCT 0.037238 0.028066
				TTGGTC 0.045283 0.014458
PPP1R9A	6	0.04 7q21.3	25	9 TCAGTC 0.015332 0.018127
				CAG 0.921753 0.960371
GSR	3	0.01 8p12	4	2 CAA 0.054588 0.036553
				ACGATC 0.151244 0.152154
				AGAATC 0.142394 0.140139
				GGAGTC 0.046576 0.091591
				GGAATC 0.027317 0.057604
				ACAATC 0.029419 0.037510
				AGGATC 0.052660 0.018406
				ACAGTC 0.015068 0.030906
				AGAGTC 0.055505 0.000532
PDGFRL	6	0.01 8p22	31	10 GGAGTG 0.033848 0.000709
				ACC 0.604080 0.638464
				GTT 0.354126 0.339410
GSTP1	3	0.04 11q13.2	7	3 ATT 0.017792 0.021478
				IAG 0.357149 0.463277
				TGC 0.406703 0.289934
CCND1, FLJ42258	3	0.05 11q13.3	6	3 TGG 0.221147 0.237858
				CAGGGC 0.832252 0.912600
				CAGGGG 0.079164 0.075237
				CATGGC 0.031895 0.003168
CDK2, SILV, RAB5B	6	0.01 12q13.2	12	4 CAGGAC 0.025254 0.002869
				ACCT 0.664213 0.679079
				CACCT 0.161037 0.131308
				TATCT 0.132246 0.132383
LIG4, C13orf6	5	0.04 13q33.3	10	4 TATTT 0.024655 0.056769
				GGAG 0.911390 0.946262
				GGGG 0.047386 0.046985
NOX5	4	0.02 15q23	4	3 TGAG 0.041224 0.003765
				GCATGGG 0.089676 0.095857
				GCATGGA 0.078899 0.094462
				GCATATA 0.071077 0.061278
				GCACAGA 0.065305 0.048441
				CTATGGA 0.024052 0.051052
				CTATAGA 0.025723 0.035314
				GCATGTA 0.034747 0.029203
				CTATGGG 0.022218 0.030210
				CTATATA 0.014430 0.029300
				CCATGGA 0.013170 0.024623
				CTACAGA 0.019649 0.019941
				CCATAGA 0.031387 0.012467
				GCATAGG 0.024496 0.015017
				GCGTGGG 0.021673 0.015105
				CTACGTA 0.004887 0.021284
				GCACGTA 0.008105 0.017565
				CTATGTA 0.009085 0.015981
				CCATGGG 0.016483 0.011514
				CGGTAGA 0.011778 0.013432
IGF1R	7	0.04 15q26.3	115	22 CTACGGG 0.010612 0.012677
				TACACG 0.060470 0.153020
				TATCTA 0.068313 0.086060
				TATACG 0.046879 0.078974
				TACCCG 0.104373 0.034471
				CGCCCG 0.044661 0.025139
				TACCTA 0.049865 0.021073
				TACATA 0.013110 0.043541
				CACCCG 0.046067 0.021520
				CACACG 0.020836 0.033933
				CGCAGC 0.022173 0.031074
ABCC1	6	0.01 16p13.11	51	12 TACCTG 0.021234 0.012495
				GCCT 0.796801 0.035392
				ATCT 0.010251 0.089543
				ACCC 0.044981 0.021830
				GCCC 0.013049 0.034648
ALOX15B	4	0.01 17p13.1	10	6 ACCT 0.056381 0.003313
				GGGC 0.978139 0.819479
MAPK7, MFAP4	4	0.01 17p11.2	5	2 GGGT 0.021688 0.176348

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	Nr. of	p-	Tot. Nr	No. Of hap	Haplotype frequency (%)	
PRKCA	5	0.01	17q24.2	26	12	CAAAG 0.186905 0.118722 CCCGA 0.098155 0.118051 CCCAA 0.070620 0.098702 TACAA 0.097847 0.076954 CACGA 0.087234 0.039990 TAAAG 0.054397 0.039115 CACAG 0.019759 0.019017 CCAAA 0.005873 0.022615 TCAAG 0.000995 0.018576 CCTGT 0.198348 0.172466 CCCAC 0.136531 0.114793 ACTGT 0.051837 0.055525 CTCGT 0.060769 0.049999 CCCGT 0.030241 0.063912 ATTGT 0.067519 0.034288 CTCAC 0.028492 0.033244
COX10	5	0.03	17p12	24	8	GTAGCTGG 0.274158 0.267773 GTAGCTGA 0.174956 0.156950 GTAATAGG 0.068641 0.086111 ATAGCTGG 0.058198 0.034983 GTAGCTAG 0.041844 0.037817 GGAGCTGG 0.028740 0.043804 GTAATAGA 0.033515 0.035419 GTAAGTGG 0.012179 0.042986 GTAATTGG 0.020741 0.033496 GGAGCTGA 0.028100 0.026647 GTAATAAG 0.034400 0.018203 GGAATAGG 0.01733 0.023541 GTAATTGA 0.019188 0.02208 GTAAGTGA 0.009672 0.017863 GTAGCAAG 0.011460 0.016258 ATAGCTGA 0.025580 0.008679 GTAGCTAA 0.009443 0.015063 GGAATAGA 0.011744 0.012961 TGGA 0.149831 0.248644 CGGA 0.159086 0.177101 TGAG 0.209520 0.123112 TGAA 0.081176 0.156805 TAGA 0.001043 0.055969 TAAA 0.000000 0.028195
BCL2	8	0.04	18q21.33	89	19	TGG 0.982558 0.999882 AGG 0.017442 0.000089 TGC 0.737205 0.825207 TAA 0.029907 0.163548
AKT2	4	0.01	19q13.2	11	7	CAA 0.225907 0.010979 GTC 0.652538 0.566495 GGG 0.318276 0.415658 GAC 0.020529 0.007874
POLD1	5	0.04	19q13.33			
COX4I2	3	0.03	20q11.21	2	1	
TXN2	3	0.01	22q12.3	5	3	
GSTT2	3	0.04	22q11.23	6	3	

* calculated based on the output from Phase which only gives two decimals. This means that the minimum p-value will be 0.01 for this calculations

*in cases and controls combined

Table 3. Spearman's correlation between LD of cases and controls for neighbouring SNPs (panel A) and all SNPs (panel B) within a gene based on ρ and D' values respectively. Listed here are only genes with an absolute correlation between 0.7 and 1. The tables are sorted by gene name.

A. Between all pairwise LD measurements of neighbouring SNPs			
Gene (s)	Nr. of SNPs	Localisation	ρ
ABCB1	7	7q21.12	0.943
ABCC1	6	16p13.11	0.800
AKR7A2,PQLC2	3	1p36.13	1.000
ALOX15B	4	17p13.1	1.000
BCL2	8	18q21.33	0.786
CAT	4	11p13	1.000
CCND1,FLJ42258	3	11q13.3	1.000
CDC42BPB	3	14q32.32	-1.000
CDK2, SILV,RAB5B	6	12q13.2	0.700
CDKN1A	3	6p21.31	-1.000
COX10	5	17p12	1.000
COX4I2	3	20q11.21	-1.000
CYP2C8	3	10q23.33	1.000
DPYD	17	1p21.3	0.894
EGF	6	4q25	0.900
EPHX1	6	1q42.12	-0.700
FGF2	4	4q27	1.000
FOS	3	14q24.3	1.000
GADD45A	3	1p31.2	1.000
GCLC	9	6p12.1	0.762
GSR	3	8p12	1.000
GSTA4	6	6p12.1	0.900
GSTM3	3	1p13.3	1.000
GSTP1	3	11q13.2	1.000
GSTT2	3	22q11.23	1.000
IGF1	5	12q23.2	0.800
IGF1R	7	15q26.3	0.943
IGF2R	6	6q25.3	0.900
IL10	8	1q32.1	0.750
IL10RA	3	11q23.3	1.000
IL1A	3	2q13	1.000
IL1B	4	2q13	-1.000
IL1R2	3	2q11.2	1.000
KCNMB1	3	5q35.1	1.000
LIG3	3	17q12	-1.000
LIG3,RFFL	3	17q12	-1.000
LIG4,C13orf6	5	13q33.3	0.800
MAPK9	3	5q35.3	1.000
MGMT	7	10q26.3	0.886
NDUFA8	3	9q33.2	1.000
NOX3	7	6q25.3	0.829
NQO2	3	6p25.2	1.000

PCNA, C20orf30,CDS2	3	20p12.3	1.000
PDGFRB	4	5q32	1.000
PIK3CA	3	3q26.32	1.000
PLCG2	3	16q23.2	-1.000
PPP1R15A, PLEKHA4, TULP2	3	19q13.33	-1.000
PPP1R1A, PDE1B	3	12.q13.2	1.000
PPP3CA	3	4q24	1.000
PRKCA	5	17q24.2	1.000
RAF1	3	3p25.2	1.000
SOD1, SFRS15	3	21q22.11	1.000
SOD2	3	6q25.3	1.000
TGFB2	4	1q41	1.000
TNFRSF6	3	17q25.1	1.000
TXN	3	9q31.3	1.000
TXN2	3	22q12.3	1.000
TXNRD2	4	22q11.21	1.000
XDH	16	2p23.1	0.800
XPC, MGC3222	5	3p25.1	0.800
XRCC1	3	19q13.31	-1.000
XRCC4	13	5q14.2	0.797

B. Between all pairwise LD measurements

Gene (s)	Nr. of SNPs		D'
AKR7A2,PQLC2	3	1p36.13	-1.000
SOD2	3	6q25.3	-1.000
PIK3CA	3	3q26.32	-0.866
AKT2	4	19q13.2	0.714
IGF1	5	12q23.2	0.758
IGF1R	7	15q26.3	0.765
NAT2	4	8p22	0.771
TNFAIP2	4	14q32.32	0.771
PDGFRL	6	8p22	0.836
GSTA4	6	6p12.1	0.846
GSR	3	8p12	0.866
GSTP1	3	11q13.2	0.866
TXN2	3	22q12.3	0.866
CAT	4	11p13	0.868
IL1B	4	2q13	0.886
COX10	5	17p12	0.891
ABCC1	6	16p13.11	0.925
PDGFRB	4	5q32	0.943
EPHX1	6	1q42.12	0.943
PPP1R3B	5	8p23.1	0.988
CDC42BPB	3	14q32.32	1.000
TXNRD2	4	22q11.21	1.000
FOS	3	14q24.3	1.000
IL1R2	3	2q11.2	1.000
MAPK9	3	5q35.3	1.000
NDUFA8	3	9q33.2	1.000
NQO2	3	6p25.2	1.000
PPP1R1A, PDE1B	3	12q13.2	1.000
TNFRSF6	3	17q25.1	1.000
TXN	3	9q31.3	1.000