# **A. Bellacosa et al. Altered Gene Expression in Morphologically Normal Epithelial Cells from Heterozygous Carriers of BRCA1 or BRCA2 Mutations**

#### **SUPPLEMENTARY INFORMATION**

#### **Correlation between Affymetrix Data and Low-Density Arrays**

In order to determine the correlation between fold changes from the original Affymetrix microarray data and the LDA real-time RT-PCR data, we measured Spearman's  $\rho$  for select candidate biomarkers, divided with respect to the genotypes and epithelial cultures in which the biomarkers were originally identified. The results, shown in Table S1, indicate that the highest correlations were found for breast and ovarian candidate biomarkers originally associated with the *BRCA1* genotype.

## **Exploratory Data Mining**

For initial exploratory analyses, we considered the pre-processed data for breast and ovarian samples for each of the three genotypes (*BRCA1, BRCA2 and WT*). With 6 biological replicates in each condition, this dataset consisted of 36 samples and corresponding expression profiles for 54675 probe sets. In order to reduce the dimensionality, we applied several variation filters to this dataset. Specifically, we first removed probe sets whose maximum expression intensity was less than 200 across the 36 samples. We then removed probe sets whose coefficient of variation (computed as a percentage ratio of standard deviation to mean) was less than 75, i.e., we retained only the top 25% of the most variable probe sets. This resulted in 4635 most variable probe sets being retained in our dataset.

We applied the bi-clustering procedure based on non-negative matrix factorization (NMF) (Pascual-Montano et al., BMC Bioinformatics, 2006) to this reduced dataset consisting of breast and ovarian samples. This method potentially identifies sub-groups of genes that are strongly correlated with sub-groups of samples. The best model based on 200 random runs of the NMF algorithm was chosen. This model identified six clusters of probe sets, with clusters 1 and 5 preferentially correlating with ovarian epithelial cultures, and clusters 2, 3, 4 and 6 preferentially correlating with breast epithelial cultures. However, no difference related to the genotype was identified in this approach.

We then considered the breast and ovarian datasets separately and further filtered the datasets as above. These resulted in 1832 and 2553 probe sets, respectively, for breast and ovarian samples. We applied standard NMF in conjunction with consensus clustering  $(1, 2)$  based on 200 runs of the algorithm to the dataset for each target organ. In addition, we applied hierarchical clustering using average linkage with correlation as the metric. Neither approach was able to identify a clear separation of the genotypes (BRCA1, BRCA2 and WT) within each target organ (Figure S1).

### **Pathway and ontology analyses – Methods and discussion**

An association analysis was conducted to identify the association between BRCA1 and BRCA2 profiles. We identified 4 datasets *viz.* i,ii,iii and iv described in main methods section. The datasets except Hedenfalk *et al.* study (iv), data were normalized using RMA and lists of differentially expressed genes were obtained by applying Linear Models for Microarray Data (LIMMA) (3) using a p-value cutoff of 0.001. These analyses involved a much larger number of microarrays relative to our study for the various comparisons of interest. LIMMA is suitable for analyzing microarray data involving factorial designs (multiple conditions) and enables to extract relevant contrasts (treatment combinations) of interest for further analysis. For the Hedenfalk *et al.* study (4), pre-normalized data were obtained from supplemental information (http://www.nejm.org/general/content/supplemental/hedenfalk/index.html) and LIMMA was applied to obtain lists of differentially expressed genes between BRCA1 vs. MCF10-A, BRCA2 vs. MCF10-A, sporadic vs. MCF10-A, BRCA1 vs. BRCA2, BRCA2 vs. sporadic and BRCA1 vs. sporadic. We also generated a manually curated list of over 180 genes involved in DNA repair by parsing functional information from GeneRIF in Entrez Gene database.

In addition to pathway and association analyses, gene ontology analysis was performed to identify overrepresented biological processes on upregulated and downregulated genes, separately for all four comparisons. This approach allowed the identification of overrepresented categories for up- and down-regulated genes (see Table S2). This analysis revealed that a significant number of down-regulated genes in breast *BRCA1* heterozygous cells are involved in major cellular processes such as differentiation, development, proliferation, adhesion and apoptosis. On the other hand, significant numbers of up-regulated genes are involved in biosynthetic metabolic processes, including transcription, splicing, DNA replication and repair (Fig. 2, Table S2). Likewise, for down-regulated genes in breast *BRCA2* heterozygous cells, processes such as small GTPase-mediated signal transduction and cell cycle progression are enriched. For up-regulated genes in breast *BRCA2* heterozygous cells, biological processes such as immunologic and inflammatory processes, adhesion, oocyte differentiation and ovulation are over-represented (Fig. 2, Table S2).

In the case of ovary, in *BRCA1* heterozygous cells, up-regulated genes show significant enrichment for processes involved in development, differentiation and cell morphogenesis, and down-regulated genes are associated with DNA repair, replication and cell cycle (Fig. 2, Table S2). *BRCA2* heterozygous cells show an enrichment of genes involved in catabolic processes, antigen processing, DNA fragmentation and G2/M transition (Fig. 2, Table S2).

**Table S1 – Correlation between fold changes from microarray and low density array (LDA) data for candidate biomarkers in breast and ovarian cultures for different genotypes (Spearman's ρ are shown)** 





**Table S2. Over-represented gene ontology categories for clusters of up- and down-regulated genes in breast and ovary BRCA1 and BRCA21 mutant cells vs. WT**









#### **Cluster**



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**Table S3. Msig Db gene sets enriched in breast and ovarian BRCA1 and BRCA2 mutant cells**



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**Figure S1**. Hierarchical clustering for comparisons between *BRCA1* and *WT*, and *BRCA2* and *WT*, for breast and ovarian epithelial cultures.



## **References**

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