

SUPPLEMENTARY INFORMATION

NetDecoder: A Network Biology Platform that Decodes Context-Specific Biological Networks and Gene Activities

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SUPPORTING INFORMATION FILES

The following additional data are available with the online version of this paper. Supporting Information has all the supplementary figures Figure S1 to Figure S18 included in the analysis, and a supporting note to provide further discussion on context-specific functionalities of common biological processes mediated by key genes in respect to breast cancers, dyslipidemia, and Alzheimer's disease (AD).

SUPPLEMENTARY FIGURE LEGENDS

Figure S1. The information flow profiles of ER-negative breast cancer edge-specific subnetwork. The subnetwork was derived from identified edges as shown in Figure 2B. Edge thickness represents the amount of edge flow. Additionally, edges are colored according to the directionality of Pearson correlation coefficient (PCC) (red for positive correlation and blue for negative correlation). Source genes are indicated as diamonds, intermediary proteins as circles, and target genes (sinks) as squares and are colored according to node flow difference (see gradient bar on the right). The size of gene nodes is proportional to the total node flow.

Figure S2. ER-positive breast cancer-specific edge-centered subnetwork. **(A)** Heatmap of differentially expressed genes (DEGs) across control and ER-positive breast cancer. **(B)** Total edge flow profiles in control and ER-positive breast cancer for edges with higher flows in disease than in control subnetworks. **(C)** Jaccard index to evaluate the similarity between edge-centered control and disease subnetworks and Venn diagrams showing the overlap across genes, edges, and paths. Pathway enrichment analysis for: i) gene signatures (DEGs), ii) key edge-centered subnetworks in control, and iii) disease. Pathway enrichment analysis for genes that compose disease-specific edge-centered subnetworks captures signaling pathways that are relevant to disease etiology. No significant enrichment was detected for the gene signature. **(D)** Heatmap showing node flow differences across control and ER-positive breast cancer for top 20 network

routers and key target genes showing high node flow difference (red) and low node flow difference (blue).

Figure S3. Dyslipidemia heterozygote-specific edge-centered subnetwork. **(A)** Heatmap of differentially expressed genes (DEGs) across control and dyslipidemia heterozygote. **(B)** Total edge flow profiles in control and dyslipidemia heterozygote for edges with higher flows in disease than in control subnetworks. **(C)** Jaccard index to evaluate the similarity between edge-centered control and disease subnetworks and Venn diagrams showing the overlap across genes, edges, and paths. Pathway enrichment analysis for: i) gene signatures (DEGs) (red), ii) key edge-centered subnetworks in control (blue) and iii) disease (green). Pathway enrichment analysis for genes that compose disease-specific, edge-centered subnetworks captures signaling pathways that are relevant to disease etiology. No significant enrichment was detected for the gene signature. **(D)** Heatmap showing node flow differences across control and dyslipidemia heterozygote for top 20 network routers and key target genes showing high node flow difference (red) and low node flow difference (blue).

Figure S4. Dyslipidemia homozygote-specific edge-centered subnetwork. **(A)** Heatmap of differentially expressed genes (DEGs) across control and dyslipidemia homozygote. **(B)** Total edge flow profiles in control and dyslipidemia homozygote for edges with higher flows in disease than in control subnetworks. **(C)** Jaccard index to evaluate the similarity between edge-centered control and disease subnetworks and Venn diagrams showing the overlap across genes, edges, and paths. Pathway enrichment analysis for: i) gene signatures (DEGs) (red), ii) key edge-centered subnetworks in control (blue) and iii) disease (green). Pathway enrichment analysis for genes that compose disease-specific, edge-centered subnetworks captures signaling pathways that are relevant to disease etiology. No significant enrichment was detected for the gene

signature. **(D)** Heatmap showing node flow differences across control and dyslipidemia homozygote for top 20 network routers and key target genes showing high node flow difference (red) and low node flow difference (blue).

Figure S5. AD incipient-specific edge-centered subnetwork. **(A)** Heatmap of differentially expressed genes (DEGs) across control and AD incipient stage. **(B)** Total edge flow profiles in control and dyslipidemia homozygote for edges with higher flows in disease than in control subnetworks. **(C)** Jaccard index to evaluate the similarity between edge-centered control and disease subnetworks and Venn diagrams showing the overlap across genes, edges, and paths. Pathway enrichment analysis for: i) gene signatures (DEGs) (red), ii) key edge-centered subnetworks in control (blue) and iii) disease (green). Pathway enrichment analysis for genes that compose disease-specific, edge-centered subnetworks captures signaling pathways that are relevant to disease etiology. No significant enrichment was detected for the gene signature. **(D)** Heatmap showing node flow differences across control and AD incipient for top 20 network routers and key target genes showing high node flow difference (red) and low node flow difference (blue).

Figure S6. AD moderate-specific edge-centered subnetwork. **(A)** Heatmap of differentially expressed genes (DEGs) across control and AD moderate stage. **(B)** Total edge flow profiles in control and dyslipidemia homozygote for edges with higher flows in disease than in control subnetworks. **(C)** Jaccard index to evaluate the similarity between edge-centered control and disease subnetworks and Venn diagrams showing the overlap across genes, edges, and paths. Pathway enrichment analysis for: i) gene signatures (DEGs) (red), ii) key edge-centered subnetworks in control (blue) and iii) disease (green). Pathway enrichment analysis for genes that compose disease-specific, edge-centered subnetworks captures signaling pathways that are

relevant to disease etiology. No significant enrichment was detected for the gene signature. **(D)** Heatmap showing node flow differences across control and AD moderate for top 20 network routers and key target genes showing high node flow difference (red) and low node flow difference (blue).

Figure S7. AD severe-specific edge-specific subnetwork. **(A)** Heatmap of differentially expressed genes (DEGs) across control and AD severe stage. **(B)** Total edge flow profiles in control and dyslipidemia homozygote for edges with higher flows in disease than in control subnetworks. **(C)** Jaccard index to evaluate the similarity between edge-centered control and disease subnetworks and Venn diagrams showing the overlap across genes, edges, and paths. Pathway enrichment analysis for: i) gene signatures (DEGs) (red), ii) key edge-centered subnetworks in control (blue) and iii) disease (green). Pathway enrichment analysis for genes that compose disease-specific, edge-centered subnetworks captures signaling pathways that are relevant to disease etiology. No significant enrichment was detected for the gene signature. **(D)** Heatmap showing node flow differences across control and AD severe for top 20 network routers and key target genes showing high node flow difference (red) and low node flow difference (blue).

Figure S8. The MAPK1 motif. **(A)** MAPK1 as high impact gene in ER-negative breast cancer; **(B)** high impact gene in dyslipidemia homozygote; and **(C)** key target in AD severe.

Figure S9. The CSNK2A1 motif. **(A)** CSNK2A1 as high impact gene in ER-negative breast cancer; **(B)** key target in dyslipidemia homozygote; and **(C)** key target in AD incipient.

Figure S10. The RARA motif. **(A)** RARA as high impact gene in ER-negative breast cancer; **(B)** high impact gene in dyslipidemia homozygote; and **(C)** key target in dyslipidemia heterozygote.

Figure S11. The HDAC1 motif. (A) HDAC1 as high impact gene in ER-negative breast cancer; (B) key target in dyslipidemia heterozygote; and (C) high impact gene in AD severe.

Figure S12. The TERF2IP motif. (A) TERF2IP in AD incipient control. (B) TERF2IP as key target in AD moderate; (C) as key target in AD severe.

Figure S13. The CALR motif. (A) CALR as key target in dyslipidemia homozygote; (B) key target in AD moderate; and (C) key target in AD severe.

Figure S14. The EEF1A1 motif. (A) EEF1A1 as high impact gene in ER-negative breast cancer; (B) high impact gene in dyslipidemia homozygote; and (C) high impact gene in AD severe.

Figure S15. The CTNNB1 motif. (A) CTNNB1 as key target in AD incipient; (B) key target in AD moderate; and (C) high impact gene in AD severe.

Figure S16. Analyses of NetDecoder Robustness. Venn diagrams showing overlap of paths (A) and impact genes (B) identified by NetDecoder using size of the functional neighborhood, SFN=0.91, 0.93, 0.97 and 0.99 when compared to results obtained with SFN=0.95 (default). The number of predicted paths detected under a certain SFN is shown in the table at the bottom. (C-D) Heatmaps showing node flow differences across control and ER-negative breast cancer for top 20 key target genes (C) and network routers (D) for SFN=0.91, 0.93, 0.95 (default) 0.97 and 0.99. High node flow difference indicates in red and low node flow difference in blue. (E) Total edge flow profiles in control and ER-negative breast cancer for edges with higher flows in disease than in control-specific subnetworks using SFN=0.91, 0.93, 0.95 (default) 0.97 and 0.99 in control and ER-negative breast cancer.

Figure S17. Assigning flow paths based on shared biological processes. To decide which paths leads to maximum flow at the lowest cost, the process-guided flow algorithm takes into account the overlap between the functional neighborhoods of protein 1 and protein 2, and such overlap

becomes part of the protein 1 functional neighborhood (GO1, GO2 and GO7). Note that the functional neighborhood of a given protein also includes GO terms of the protein itself. If the functional neighborhood of protein 1 shares any biological process with the functional neighborhood of protein 2 (GO1, GO3, GO4 and GO7), protein 2 is included in the selected flow path. On the contrary, when protein 4 is considered as a candidate protein in a new path, there is no biological process being shared with the functional neighborhood of protein 1. Consequently, the flow is not directed through protein 4.

Figure S18. Context-dependence of key genes associated with FOXM1. **(A)** FOXM1 as a key gene (high impact gene and key target) in the ER-negative breast cancer context. **(B)** FOXM1 is not a key gene in the ER-positive breast cancer context. The identities of key genes cannot be directly located in a PPI network, but properties dictated by the way information flows are conveyed along the context-specific PPI network can be.

Supplementary Discussion

This Supplementary Discussion provides further discussion on context-specific functionalities of common biological processes mediated by key genes in respect to breast cancer, dyslipidemia, and Alzheimer's disease (AD). Many of these common biological processes are frequently enriched in transcriptome analyses but their context-dependent functionalities are seldom discussed. Understanding context-dependent activities of common biological processes can illuminate how the same enriched biological processes can show marked different properties in different biological contexts and what are the key genes that modulate information flows in resulting context-dependent behaviors.

Disease-specific canonical cellular processes

MAPK cascade is one of the major canonical signaling components that cross-talks with many other signaling pathways and its altered activities have been implicated in a number of human diseases. MAPK1, which is the key executor of the MAPK cascade, is a high impact gene in both ER-negative breast cancer and dyslipidemia homozygote (Figure 3) but a key target in AD severe (Figure S6D). Both EGFR and receptor tyrosine kinase (RYK) show uncoordinated function (negative co-expression coefficient) with MAPK1 (Figure S8A) probably due to reduced levels of internalized receptors that attenuate receptor kinase signaling in cancer cells. This is consistent with activation of the MAPK cascade in cancers with general functional coordination of BRAF and RAF1 with MAPK1 in ER-negative breast cancer (Figure S8A). In contrast, BRAF, GRB1 and SOS1 show coordinated function (positive co-expression coefficient) in the control case and RAF1 shows uncoordinated function with MAPK1 in dyslipidemia homozygote (Figure S8B), which suggests deregulated MAPK1 cascade activity in dyslipidemia homozygote. AD severe also shows altered MAPK cascade activity distinct from that observed in cancer and dyslipidemia. For instance, Polo-like kinase 3 (PLK3), which regulates cell cycle, shows uncoordinated function with MAPK1 in AD severe case (Figure S8C) where their pathological roles in AD remain to be elucidated.

Regulation of cell cycle

Cell cycle is a key process in cell growth, differentiation, and tissue repair in response to stress. Deregulated cell cycle processes can lead to uncontrolled cell proliferation in cancers or cell death via apoptosis. Casein kinase 2 (CSNK2A1), which regulates cell proliferation, is a high impact genes in ER negative breast cancer (Figure 3A), and a key target in dyslipidemia (Figure 3B) and incipient AD (Figure 3C). This gene shows positive correlation with positive regulators

of cell cycle such as Aurora kinase A (AURKA), CDC25B, CDK1, G2 checkpoint kinase WEE2, chromatin remodeler chromobox homolog 4 (CBX4) and topoisomerase 2A (TOP2A) in ER-negative breast cancer (Figure S9A). This in general suggests enhanced cell proliferative activity. However, in the control case the function of CSNK2A1 is coordinated with centrosomal protein CEP57 that is not captured in ER-negative breast cancer (Figure S9A), implicating deregulation of the chromosomal segregation process in cancer. In dyslipidemia homozygote, CSNK2A1 in general shows positive functional correlations with elongation factors in protein synthesis such as EIF2S2, EIF3J, EIF5B and heat shock protein HSP90B1 (Figure S9B). In incipient AD, CSNK2A1 shows functional coordination with heat shock protein HSP90AB1 and complement component C1R (Figure S9C). Our results suggest CSNK2A1 acts as cell cycle regulator in breast cancer, but its function is redirected to the modulation of protein fidelity in dyslipidemia and AD. However, the pathological roles of the functional coordination in the pathogenesis of dyslipidemia homozygote and AD remain unclear.

Regulation of transcriptional activities

Regulation of gene expression via transcriptional processes in response to environmental cues and cellular stress constantly takes place in all cell types. Altered interactions in transcription factors, co-activators, repressors, mediators, and RNA polymerase subunits are key events that lead to differential gene expression in cells of different biological contexts. Among transcription regulators, nuclear receptors are capable of regulating myriad cellular processes such as sensing cellular cues (in the form of steroid hormones), modulating homeostasis, and controlling metabolism. Retinoic acid receptor alpha (RARA) is a nuclear receptor that is a high impact gene in ER-negative breast cancer and dyslipidemia homozygote (Figure 3) and is a key target in

dyslipidemia heterozygote (Figure S3D). As shown in Figure S10 (bar charts), we found an increase in the overall edge flow of RARA in ER-negative breast cancer but reduced overall edge flows in both types of dyslipidemia. It is interesting to note that the transcription factor RUNX1, whose gene expression had been reported to correlate with poor prognosis in triple-negative breast cancer (1), shows functional coordination with RARA (Figure S10A). Methyl-CpG-binding protein 1 (MBD1) and Methyl-CpG-binding protein 3 (MBD3) also show positive correlation with RARA. How these protein interactions affect the reading of methyl code on CpG islands in cancer cells remains to be elucidated. In dyslipidemia homozygote, it seems there is increased functional coordination of transcriptional mediator MED25 with RARA due to low flow difference value of MED25 but positive correlative flow with RARA (Figure S10B). Interestingly, the autophagy receptor sequestosome 1 (SQSTM1), which regulates activity of the NFkB pathway shows marked coordinated function with RARA (Figure S10B), implying there is altered NFkB pathway activity in dyslipidemia homozygote patients. It is also interesting to note that there is a negative correlation between RXRA and RARA in dyslipidemia homozygote (Figure S10C). This suggests there is a reduced level of the RXRA-RARA heterodimer that associates with a multiprotein complex containing transcription corepressors that induce histone acetylation, chromatin condensation and transcriptional suppression. Decreased RXRA-RARA heterodimers in dyslipidemia homozygote patients might be involved in promoting expression of genes that promote dyslipidemia progression. In the dyslipidemia heterozygote case, the transcriptional mediator MED25 shows marked functional coordination with RARA than that of the homozygote case (Figure S10C). Unlike the homozygote case, in dyslipidemia heterozygote the methyl-CpG-binding protein 3 (MBD3) shows positive correlation with RARA that its role in disease etiology remained to be studied.

Chromatin remodeling, epigenetic and genome integrity

Epigenetic regulation can be mediated via methylating chromosomal DNA on the CpG islands or acetylating and methylating histones that wrap the chromatin. Epigenetic modifications can alter the structure of chromatin organization and change epigenetic states by remodeling chromatin structures leading to altered gene expression regulation. Key players in epigenetic regulation are DNA methyltransferases (DNMTs), histone acetyltransferases (HATs), and histone deacetylases (HDACs). Also, instability of a genome is the hallmark of many human common diseases. For instance, DNA damage and repair have been reported in atherosclerosis and metabolic syndromes (2, 3).

HDAC1 is a high impact gene in ER-negative breast cancer (Figure 3A). DNMT3A and DNMT3B, which are responsible for unmethylated CpG island methylation, and SMARCA4 and SMARCA1, which regulate chromatin remodeling, show negative correlations with HDAC1 in ER-negative breast cancer (Figure S11A). Given recent reports that inhibiting HDAC can sensitize cancer cells to radiotherapy (4), the fact that DNA topoisomerase II alpha (TOP2A) shows uncoordinated function with HDAC1 in ER-negative breast cancer (Figure S11A), might shed light on the mechanism behind this recent finding. For dyslipidemia heterozygote, RAP1A, a Ras oncogene family protein that regulates blood vessel formation, is found to show preferential functional coordination with HDAC1 (Figure S11B).

Histone acetylation catalyzed by histone acetyltransferases (HATs) on chromatin in the hippocampus corresponds with contextual learning (5) and reduced acetylation levels correspond with impaired memory (6). HDACs reverse the process of histone acetylation on chromatin and inhibiting their activities increases histone acetylation and enhances hippocampal-dependent

memory formation (7). Our finding that HDAC1 is a high impact gene in AD severe (Figure 3C) is consistent with the above observations. KDM5A, an enzyme that specifically demethylates lysine-4 of histone H3, shows positive correlation with HDAC1 in AD severe (Figure S11C). In contrast, BRCA1, a regulator of genome integrity, negatively correlates with HDAC1, which may lead to reduced DNA repair in AD severe patients. Interestingly, IKZF1, which regulates hematopoietic cell differentiation, shows uncoordinated function with HDAC1 (Figure S11C) that we suspect might cause deregulated blood supply in the brain of AD severe patients (8).

Telomeric repeat binding factor 2 (TERF2IP), which is involved in telomere length regulation, is a key target for AD moderate and severe states (Figure S6D, S7D). This highlights the importance of telomere maintenance in the pathogenesis of AD. On the other hand, our result suggests TERF2IP does not play a significant role in the development of incipient AD (Figure S12A) but begins to show its contribution as key targets in the moderate and severe stages of AD. General reduced overall edge flow and negative correlations of DNA damage response genes RAD50 and PML with TERF2IP in AD moderate and severe, respectively, (Figure S12B, S12C) suggest enhanced telomere damage in AD patients.

Unfolded protein responses

Correctly folded protein is essential for cellular function and accumulation of misfolded proteins inside a cell can cause cellular toxicity. In response to protein misfolding, a cell evokes unfolded protein responses (UPRs) to refold or degrade misfolded proteins. Molecular chaperones such as heat shock proteins and components of ubiquitin-proteasome system are keys to regulating the fidelity of the protein homeostasis inside a cell.

Calreticulin (CALR), a calcium-binding chaperone that promotes folding, is a key target for dyslipidemia homozygote (Figure S4D), AD moderate (Figure S6D), and AD severe (Figure S7D). This protein shows negative functional correlation with CUL7, a key protein that is required to regulate microtubule dynamics and genome integrity in dyslipidemia homozygote (Figure S13A), suggesting “disconnected” repairing processes mediated by CALR on microtubule and damaged DNA in the pathogenesis of dyslipidemia. HSP90B1 and GANAB, which regulate glycogen storage, show positive correlations with CALR in the dyslipidemia homozygote control case (Figure S13A) indicating folding and proper functioning of these proteins is important to rescue dyslipidemia. In the AD moderate and severe control cases, there are positive functional correlations between HSPB1 and ANP32B, which is an anti-apoptotic protein with CALR (Figure S13B, C), suggesting the involvement of apoptosis in AD pathogenesis. Interestingly, tumor necrosis factor receptor-associated factor-6 (TRAF6), which is an E3 ubiquitin ligase, is the top high impact gene for AD severe (Figure 3). TRAF6 had been shown to be essential for polyubiquitination of TrkA (a NGF receptor) when the complex TRAF6-p75 (NTR) is bound with TrkA-p62 complex upon NGF stimulation, leading to cell survival and neuronal differentiation. However, in AD the ubiquitination of TrkA is attenuated leading to apoptosis (9). In our study, we found uncoordinated function between TRAF6 with CALR in AD severe case (Figure S13C) suggesting increased misfolded states of TRAF6 in AD patients.

Regulation of protein synthesis

The rate of protein synthesis varies greatly among different tissues (10). Differences in the rate of protein synthesis are in fact intricate homeostatic regulations corresponding to diverse

functional states of a cell (11). Modulation of the assembly of ribosomal subunits contributes to differences in protein synthesis (12). Tightly regulated protein synthesis promotes tissue homeostasis by preventing uncontrolled cell proliferation. This is evidenced by the fact that cancer cells synthesize proteins more rapidly than normal cells (13) and suppressed protein synthesis could halt tumorigenesis (14).

The protein synthesis elongation factor EEF1A1 is a high impact gene in ER-negative breast cancer, dyslipidemia homozygote, and AD severe (Figure 3). There is preferential functional coordination between heat shock proteins (HSP90AA1) and ribosomal subunits in EEF1A1 in the control case of ER-negative breast cancer (Figure S14A), and this is also the general cases for dyslipidemia homozygote controls (Figure S14B) and AD severe control (Figure S14C) cases implying a more regulated protein synthesis, folding, and degradation in normal cases than in disease states. GAPDH (glyceraldehyde-3-phosphate dehydrogenase) and ENO3 (enolase 3), which are key metabolic regulators show positive and negative functional correlation with EEF1A1, respectively in dyslipidemia homozygote (Figure S14B). How these key metabolic regulators affect protein synthesis in driving pathogenesis of dyslipidemia remain to be studied. On the other hand, IMMT, which is an inner mitochondria membrane protein shows high values of flow difference in AD severe, suggesting malfunction of mitochondrial-mediated processes in AD pathogenesis. Interestingly, high values of node flow difference but negative functional correlation between IMMT and EEF1A1 shows their dissociated function in the AD severe case (Figure S14C). This observation might provide clues on how mitochondrial-driven bioenergetics processes can affect the progression of AD.

Cell-cell adhesion, integrity of cytoskeletal organization, and intracellular trafficking

Cell-cell adhesion provides the necessary avenue to support the cellular microenvironment. Deregulation of cytoskeletal organization is known to play a key role in many human diseases such as AD with the brain of patients marked by extensive extracellular β -amyloid ($A\beta$) plaques and intracellular neurofibrillary tangles (15, 16). We found amyloid- β precursor protein (APP) and heat shock proteins (HSP90AB1, HSP1A1, HSPA8) generally show functional coordination with catenin (CTNNB1) in AD control cases (Figure S15A). This suggests these functions are deregulated in AD. Interestingly, transcriptional regulator TCF4 plays an important role in nervous system development and also shows functional coordination with CTNNB1 in AD control cases (Figure S15C), indicating that there is a loss of neuronal function in AD patients' brains.

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Figure S1

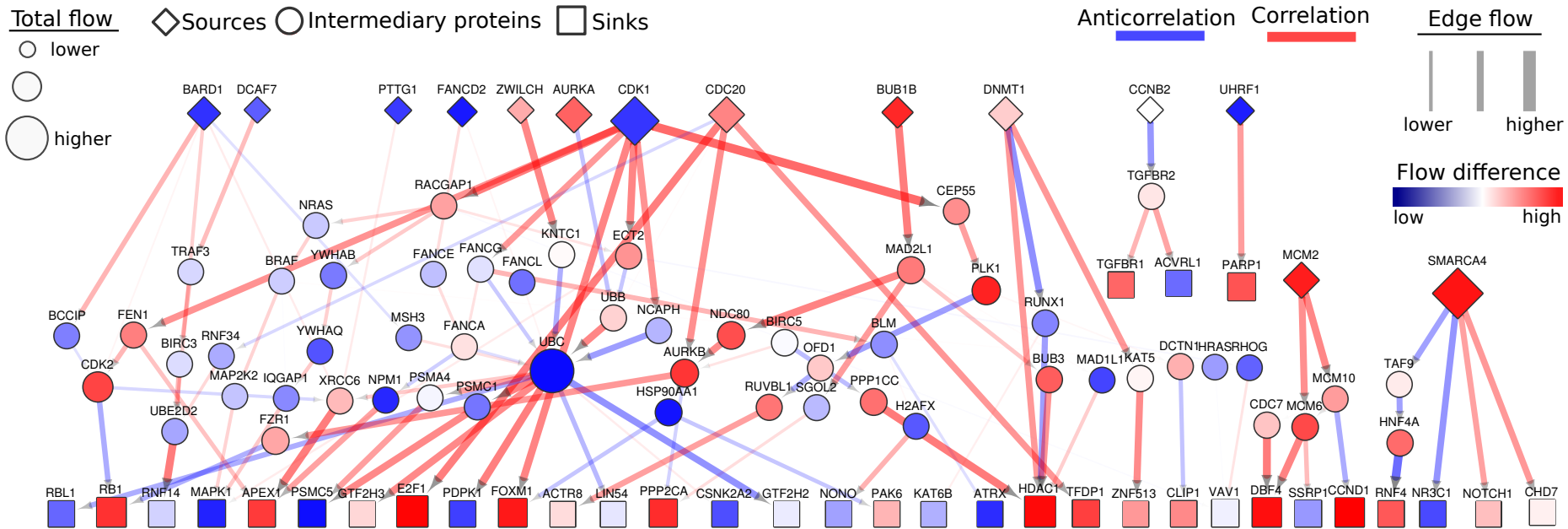


Figure S2

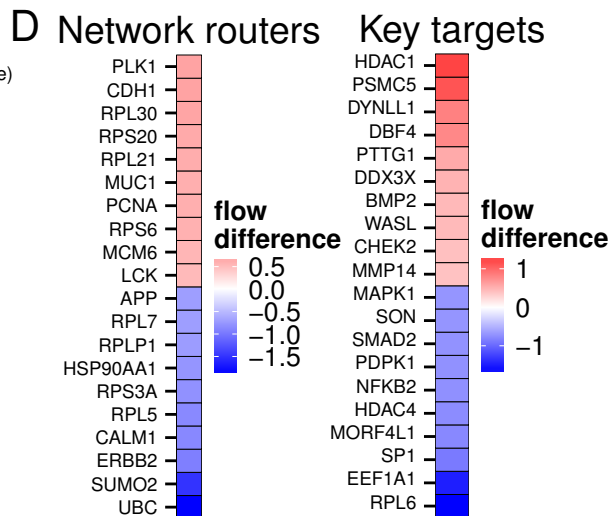
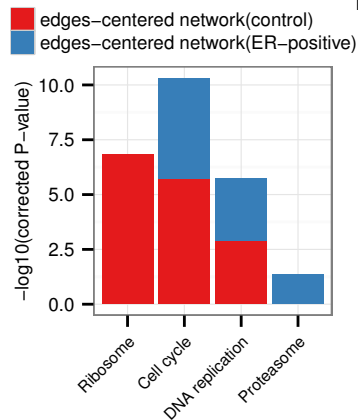
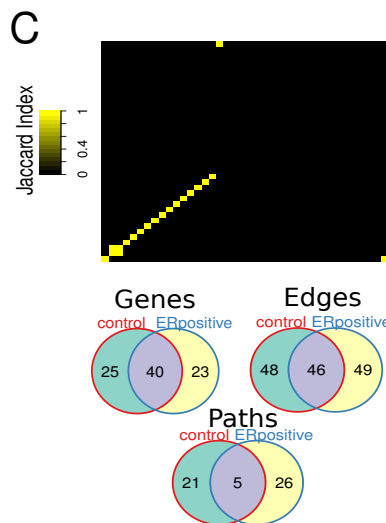
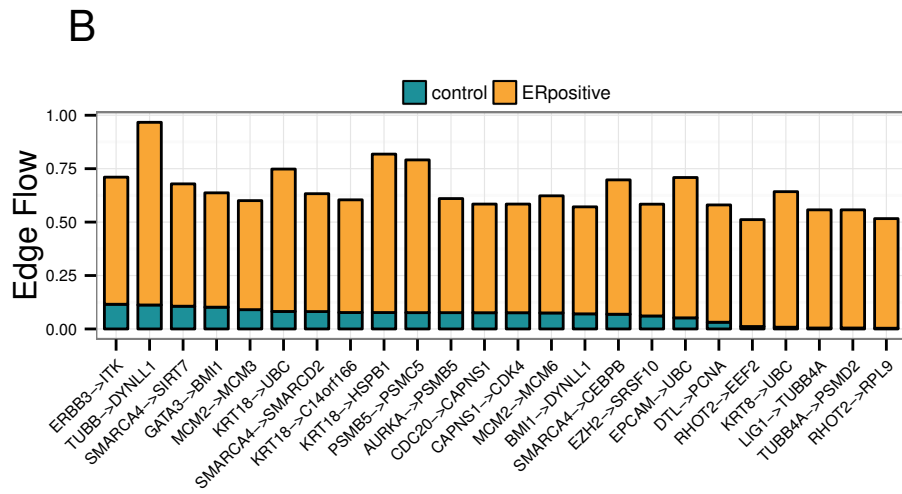
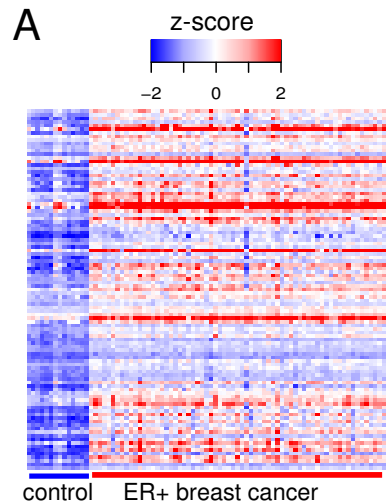
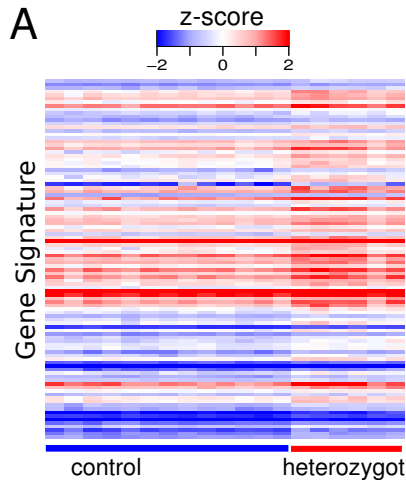
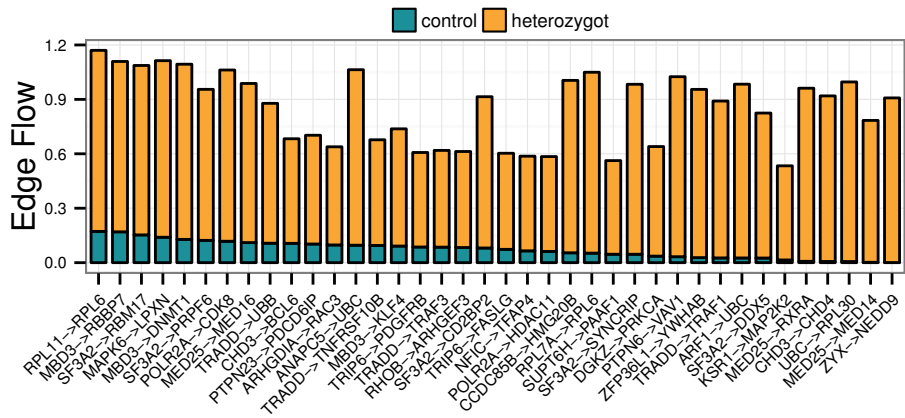


Figure S3

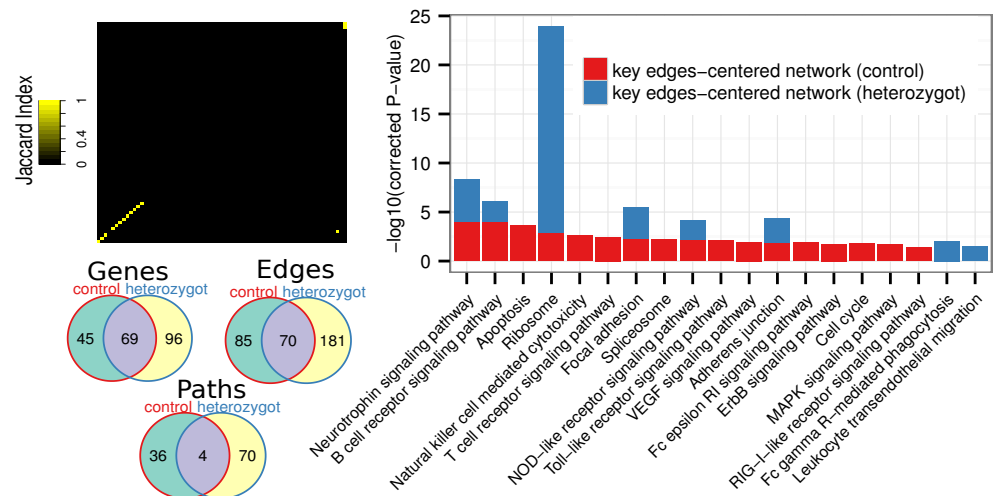
A



B



C



D

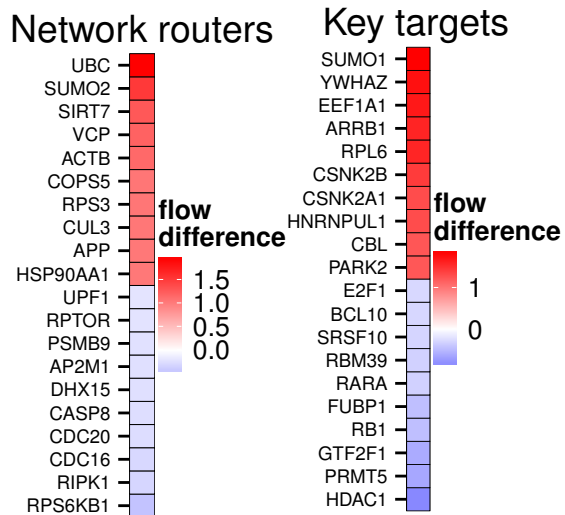
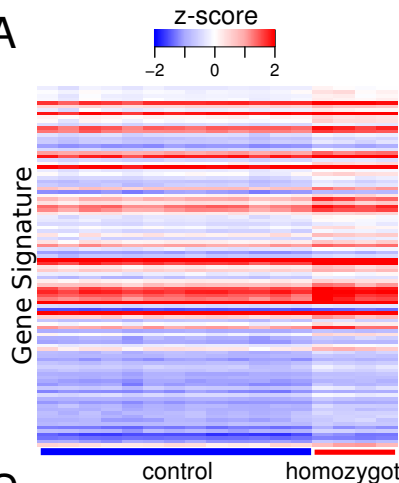
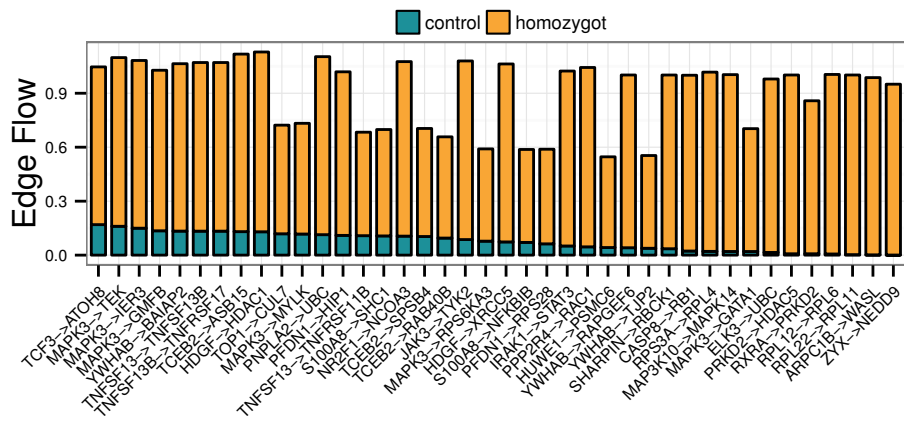


Figure S4

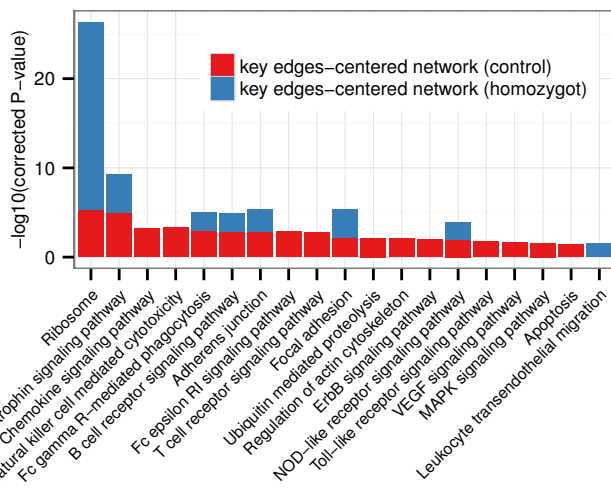
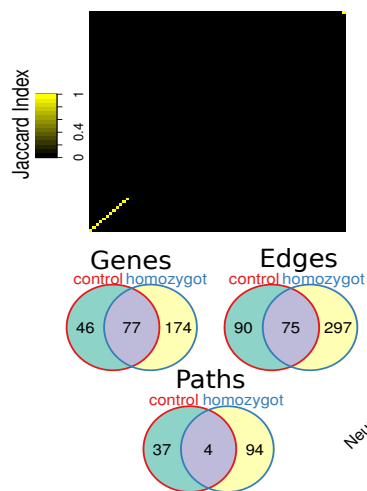
A



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C



D

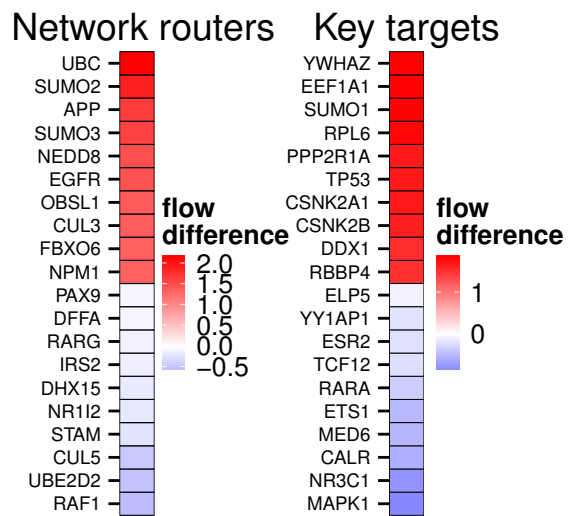
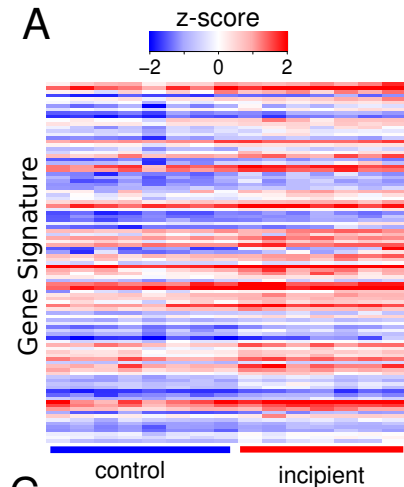
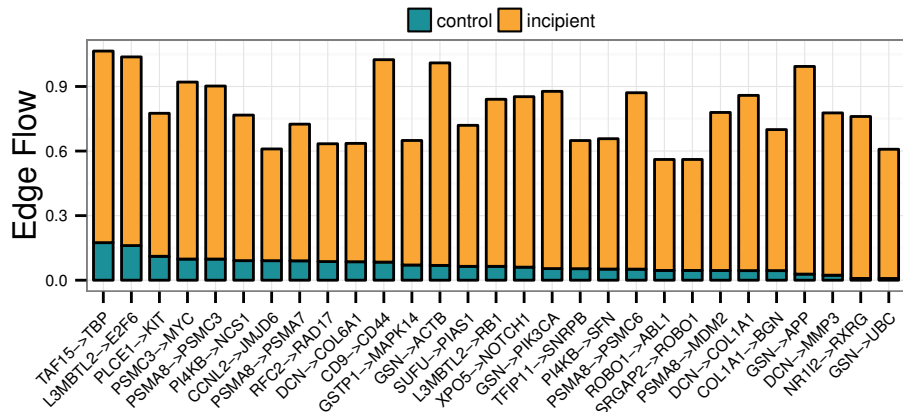


Figure S5

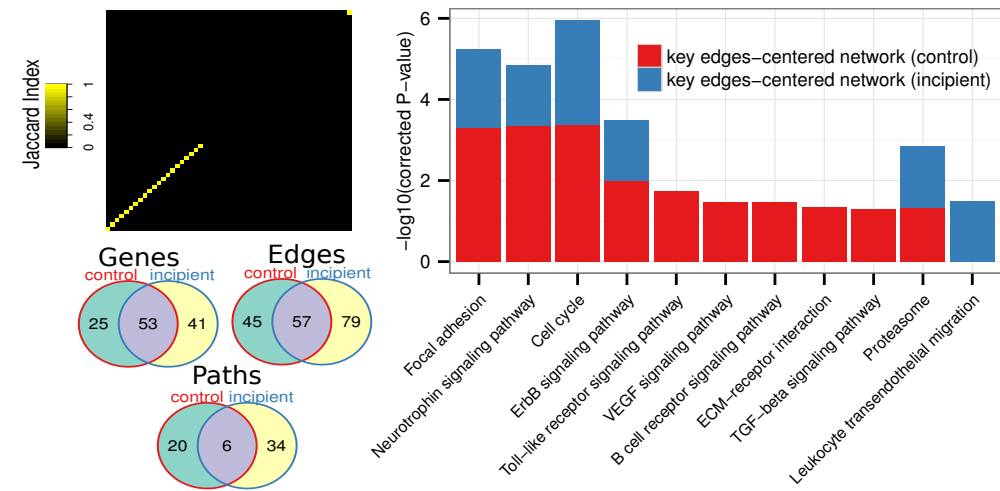
A



B



C



D

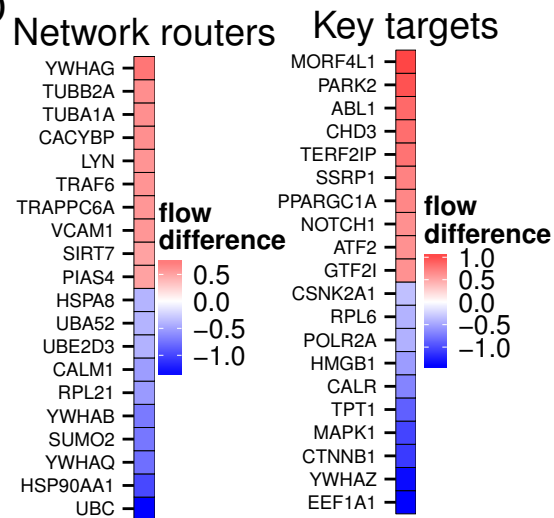


Figure S6

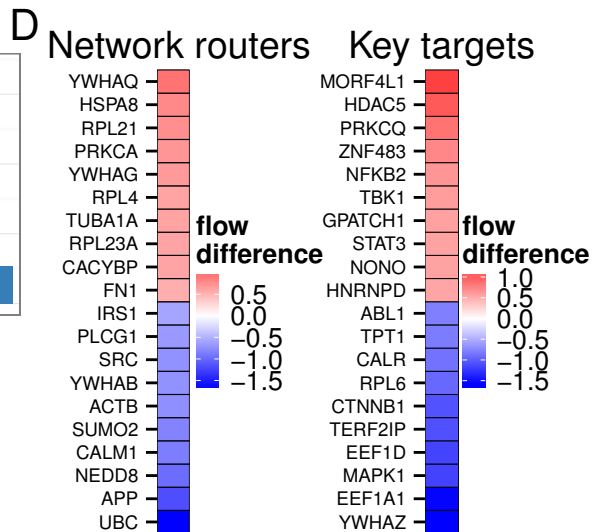
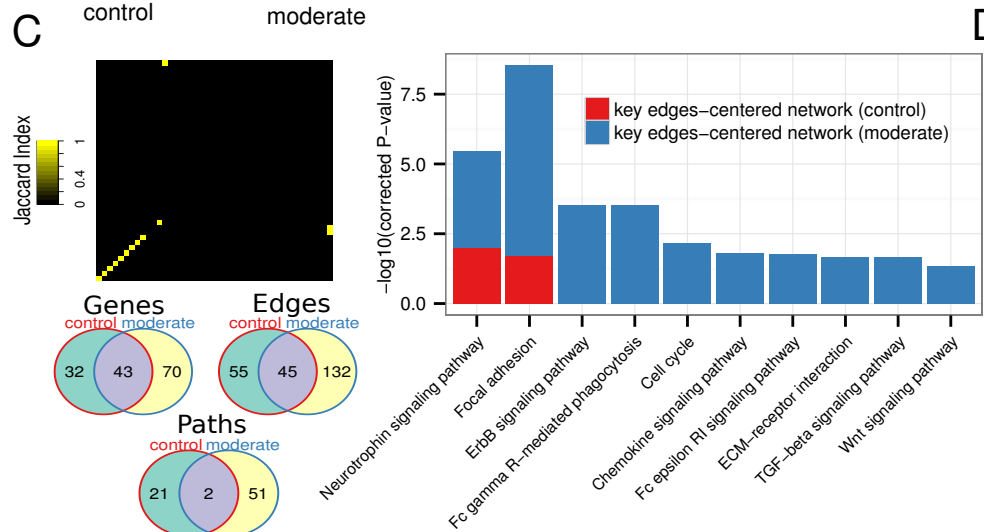
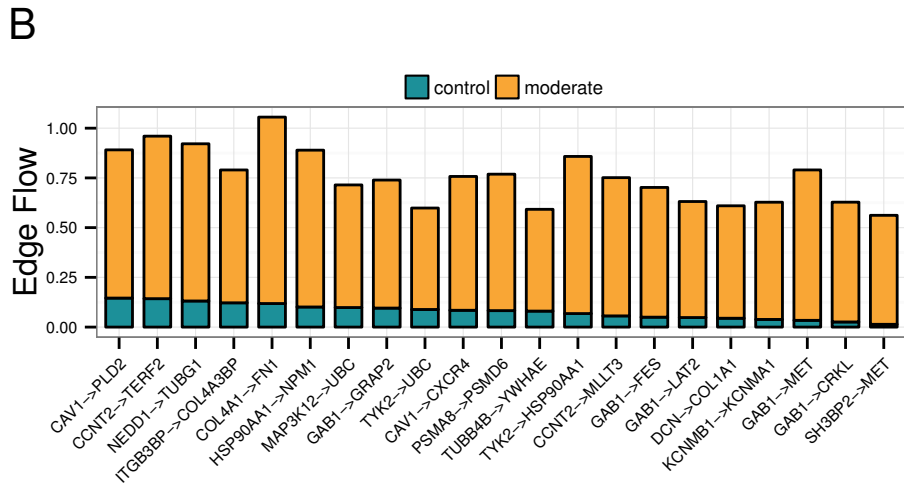
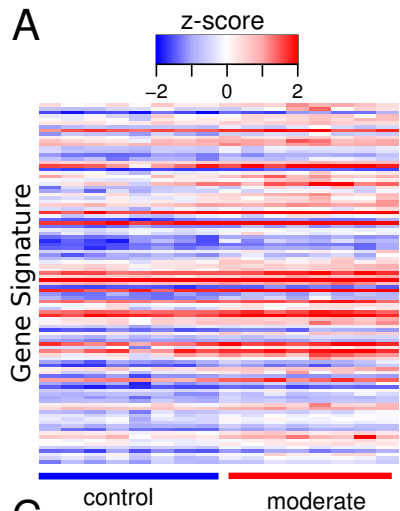
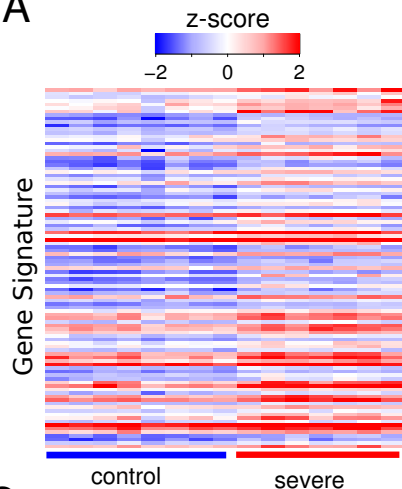
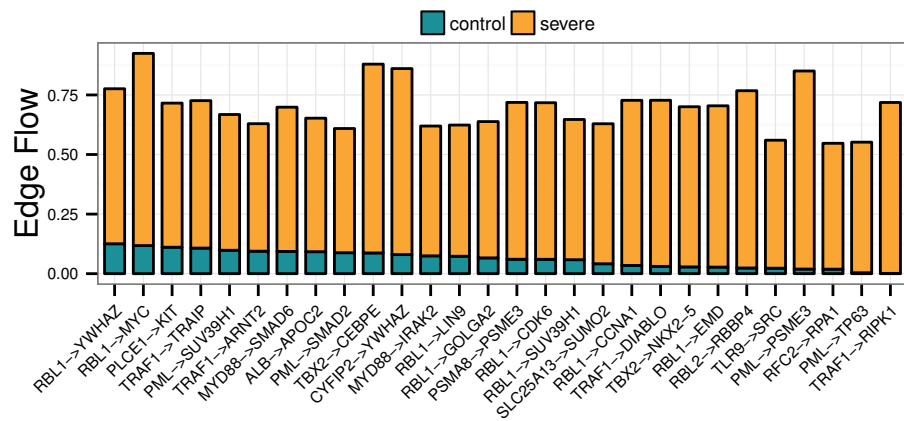


Figure S7

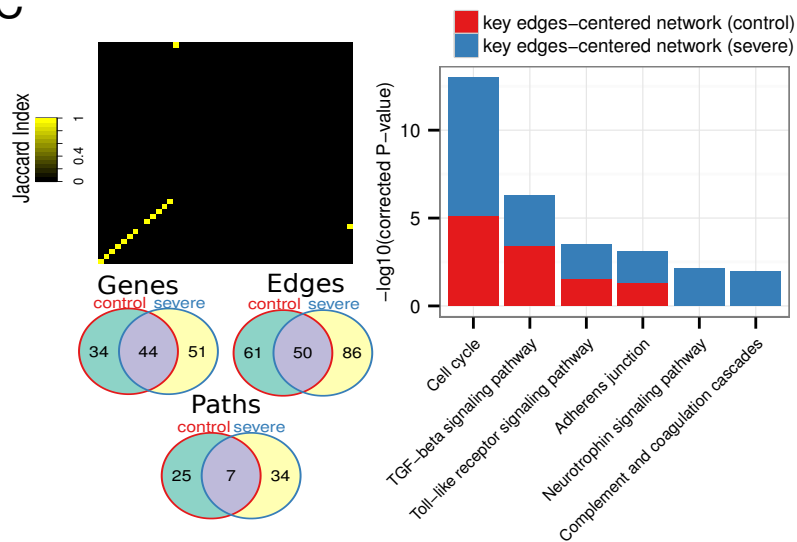
A



B



C



D

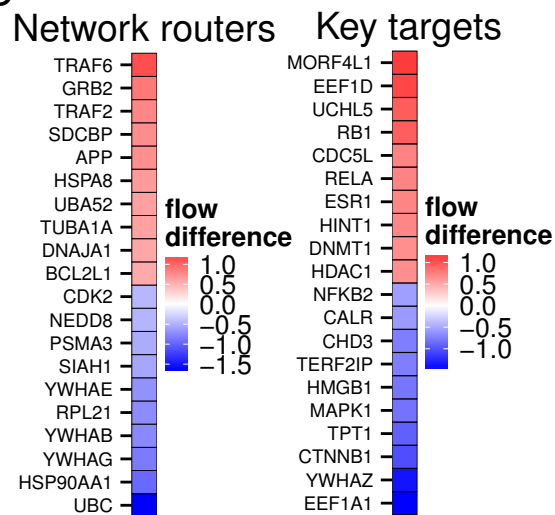
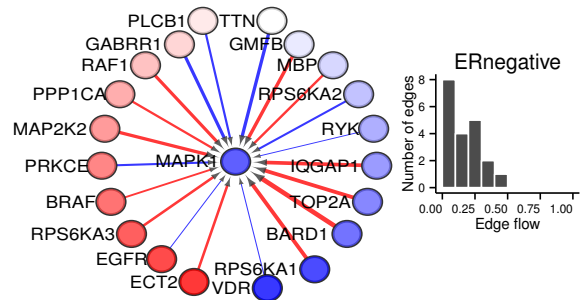
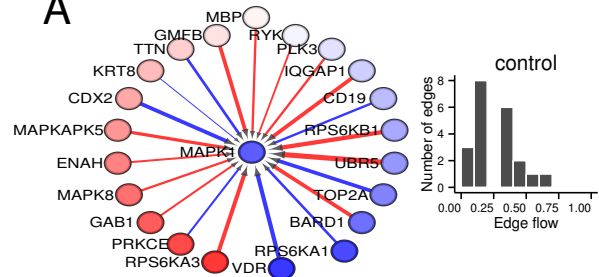
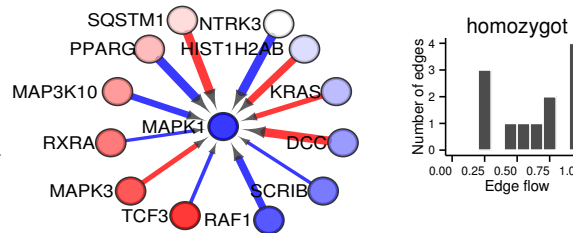
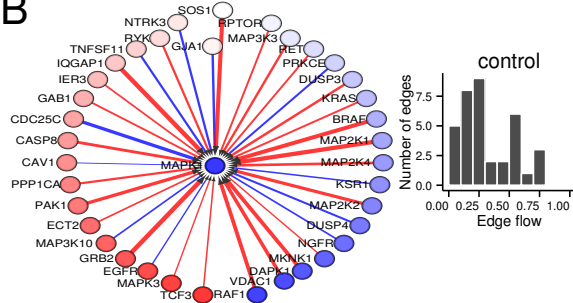


Figure S8

A



B



C

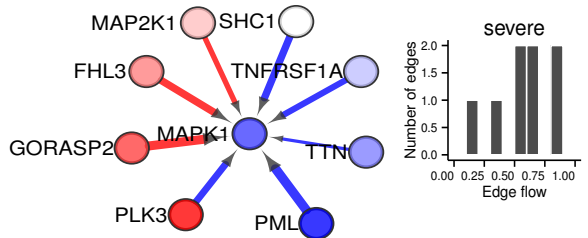
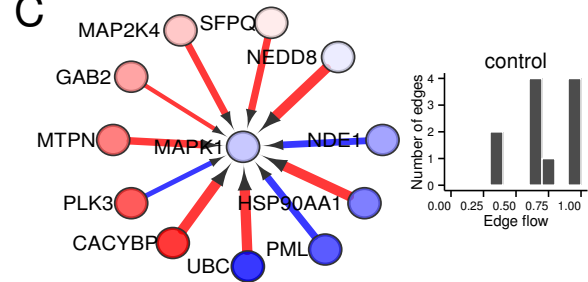
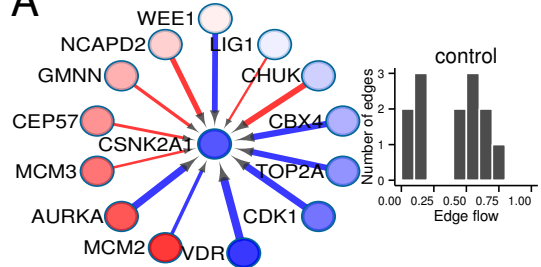
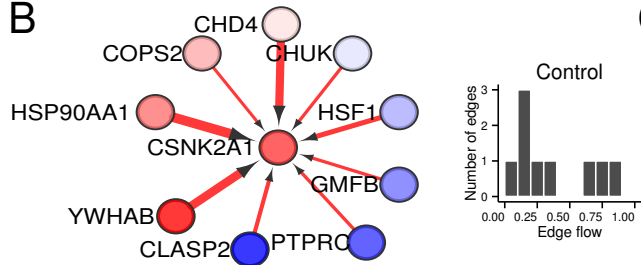


Figure S9

A



B



C

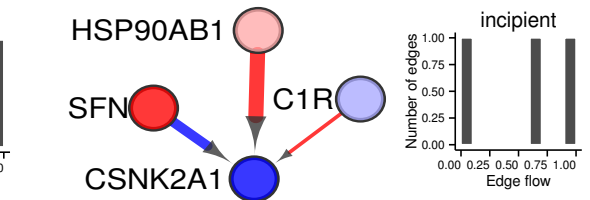
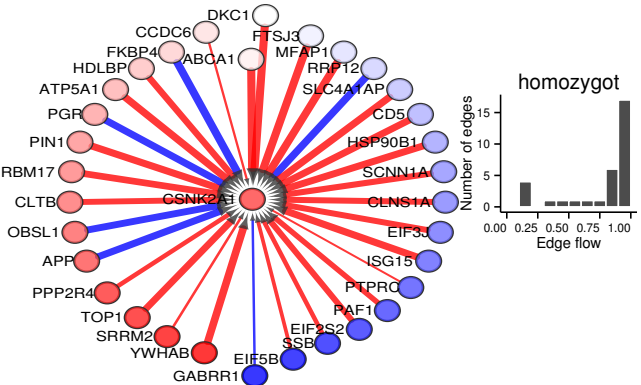
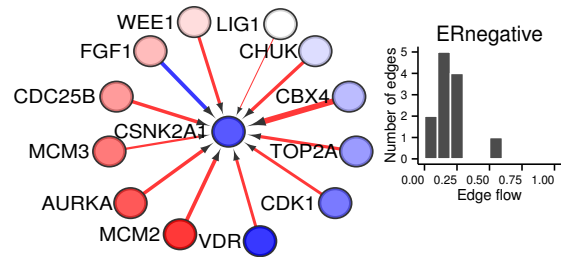
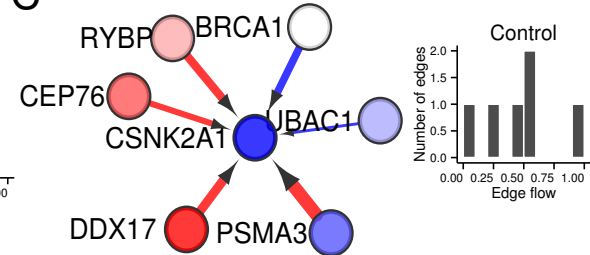
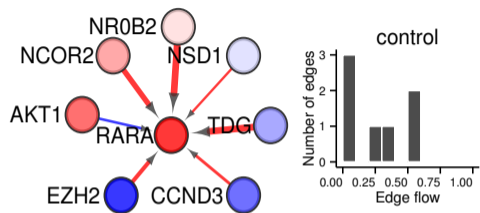
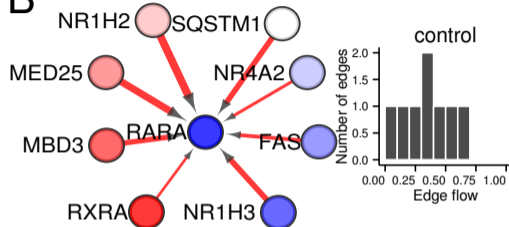


Figure S10

A



B



C

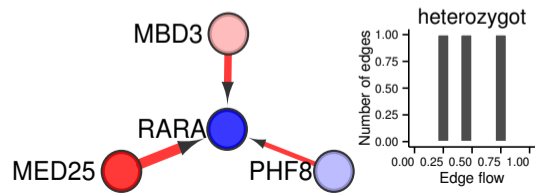
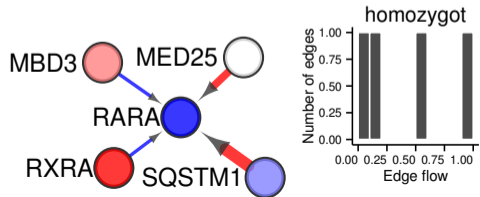
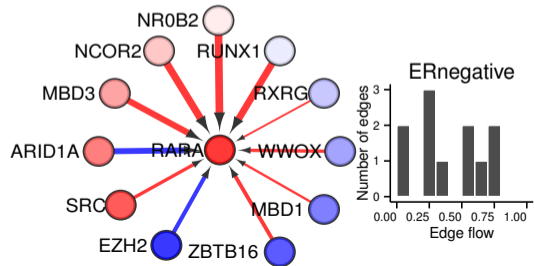
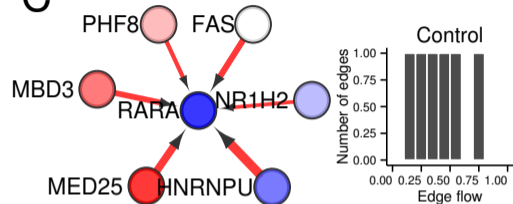
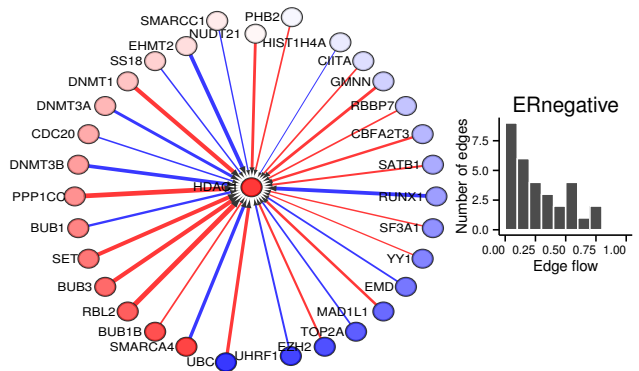
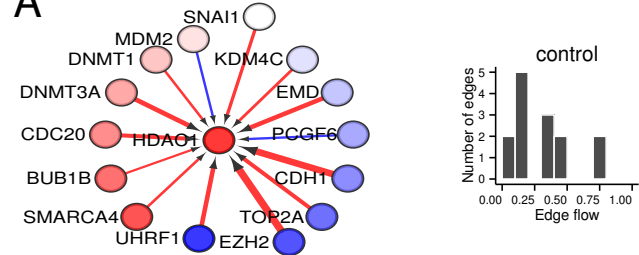
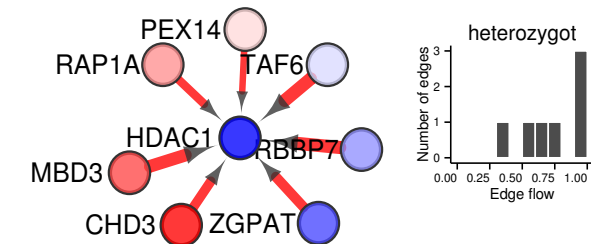
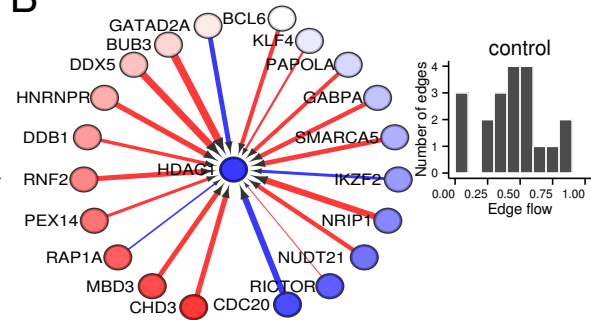


Figure S11

A



B



C

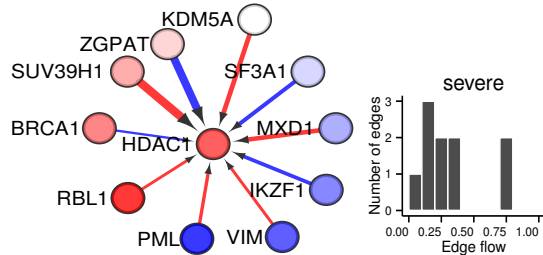
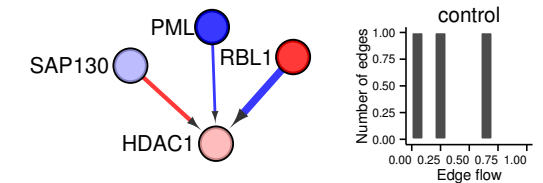
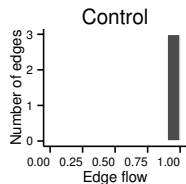
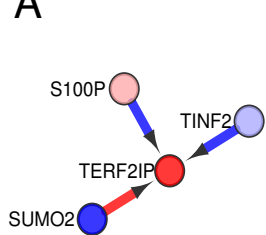
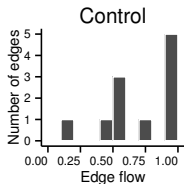
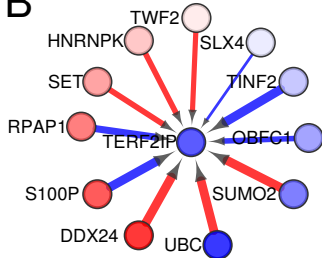


Figure S12

A



B



C

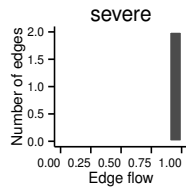
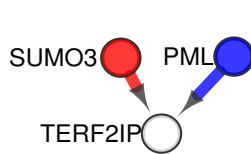
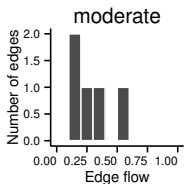
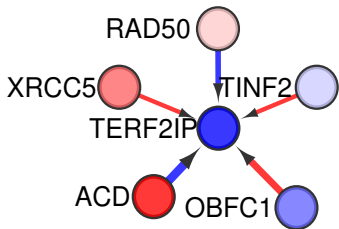
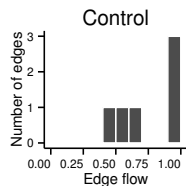
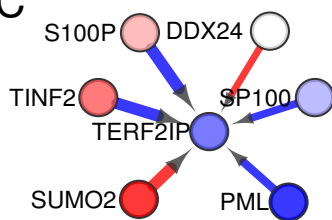
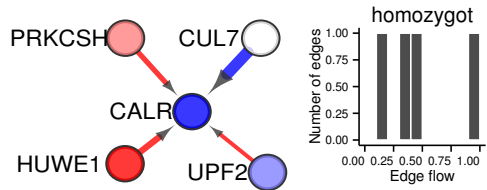
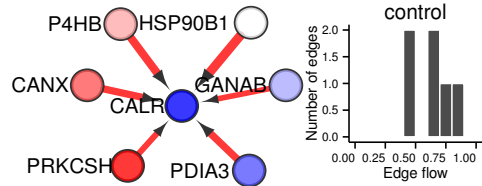
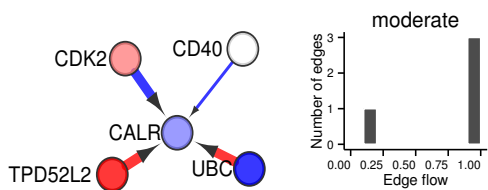
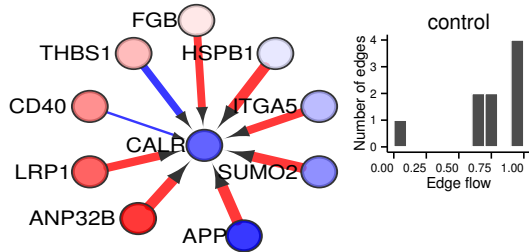


Figure S13

A



B



C

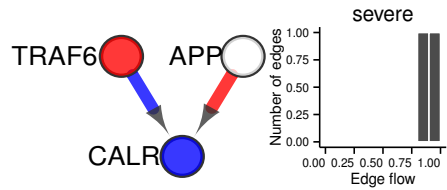
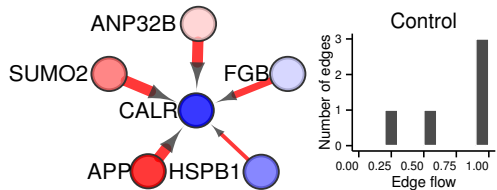
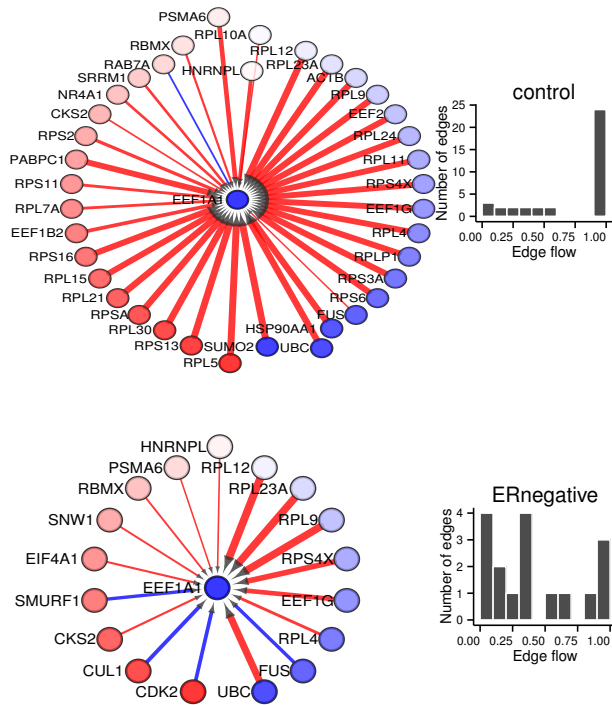
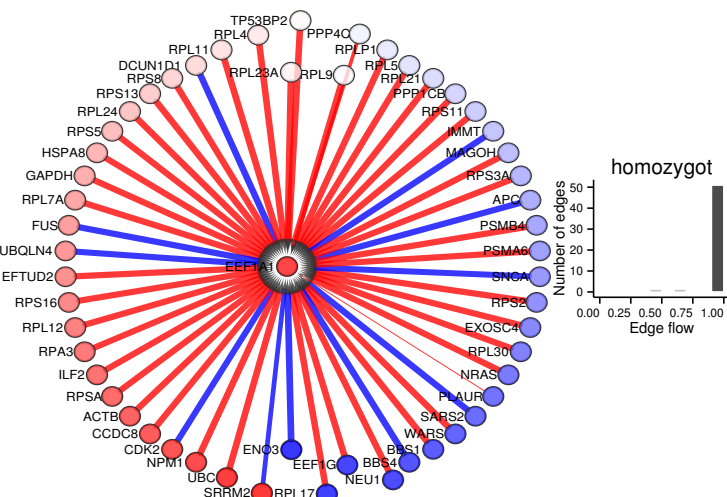
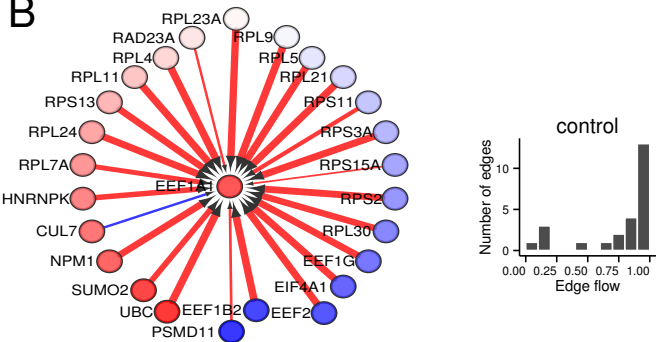


Figure S14

A



B



C

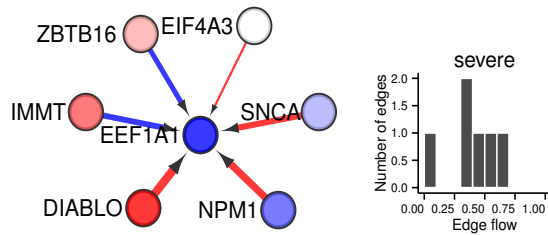
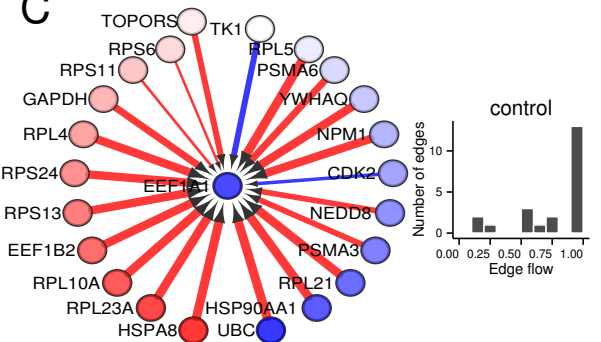
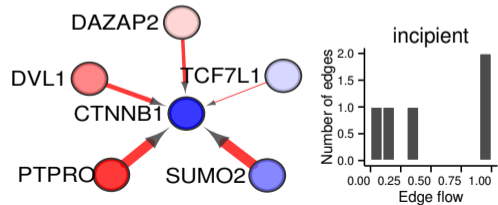
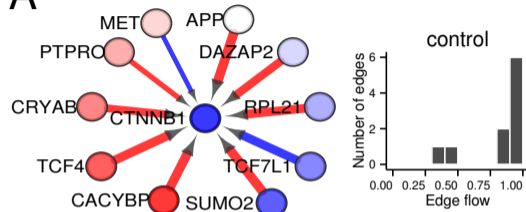
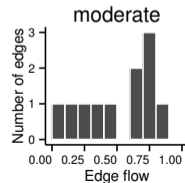
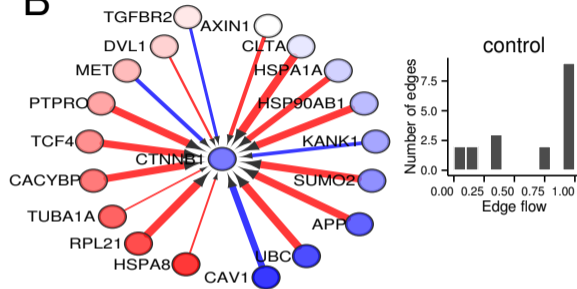


Figure S15

A



B



C

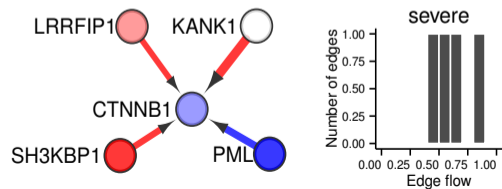
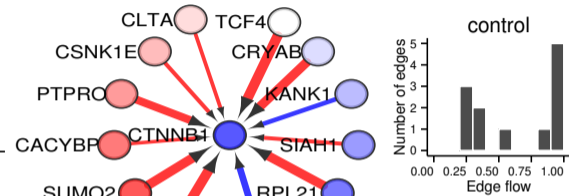
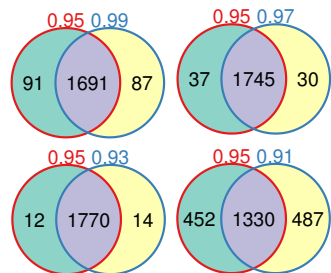


Figure S16

A

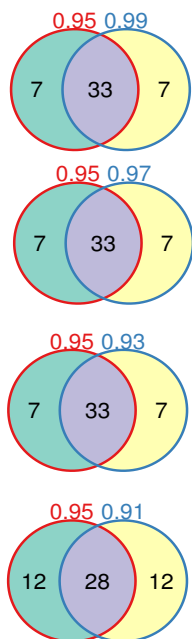
Paths



Size of functional neighborhood	Number of paths
0.91	1818
0.93	1785
0.95	1783
0.97	1776
0.99	1779

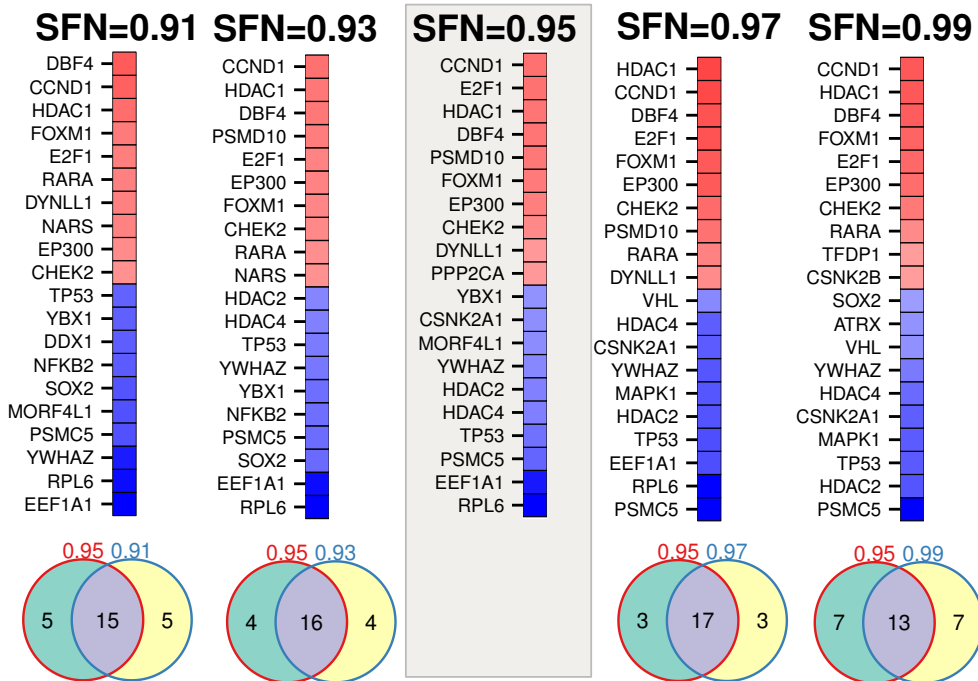
B

Impact genes



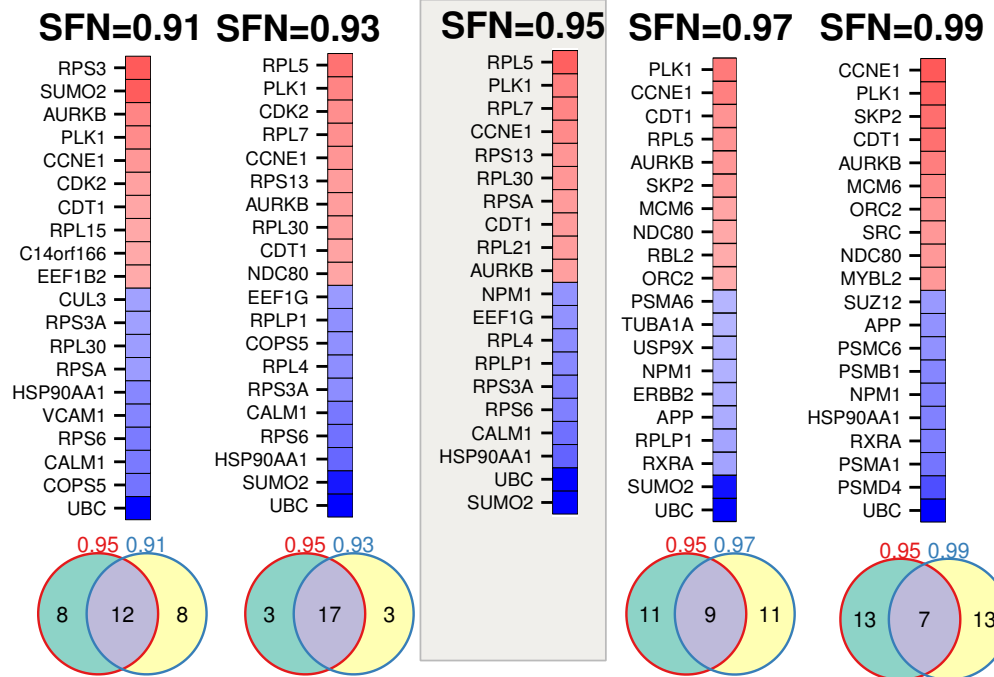
C

Key targets



D

Network routers



E

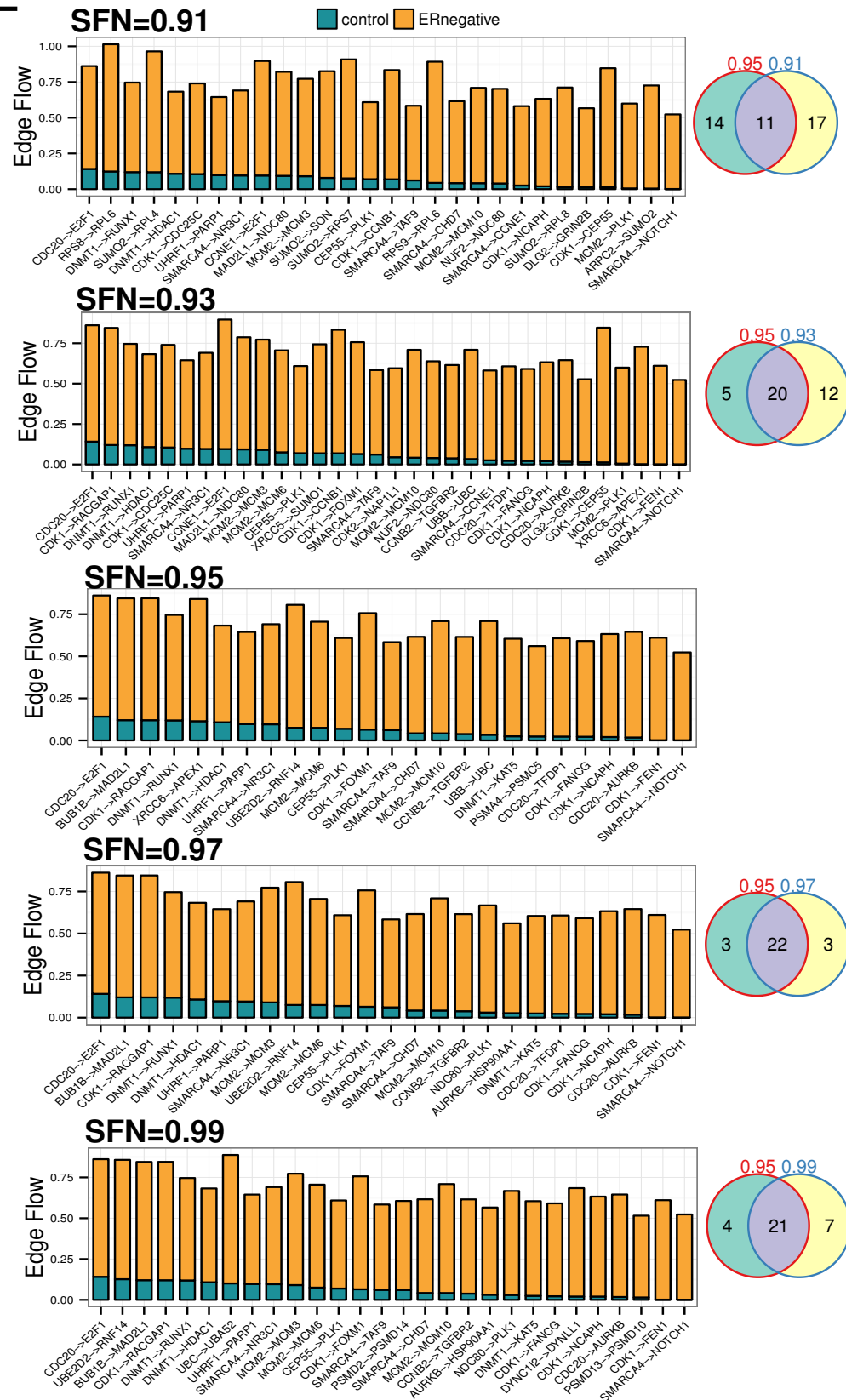


Figure S17

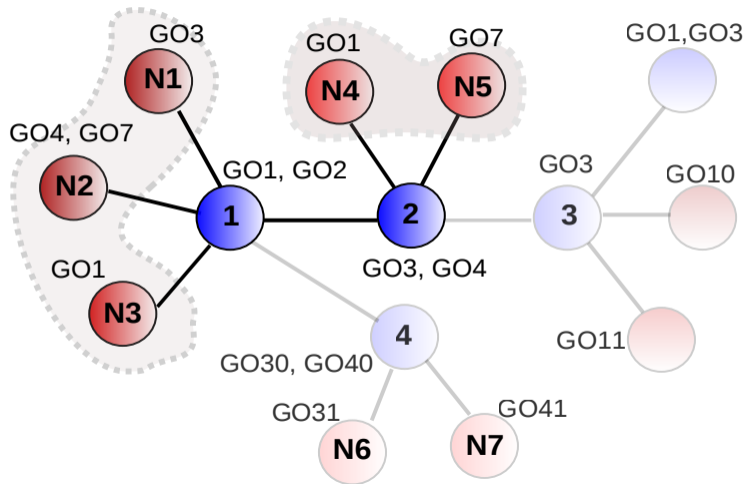
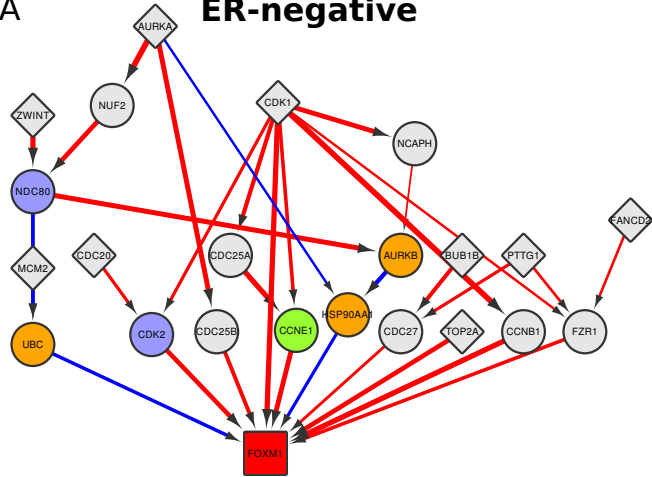


Figure S18

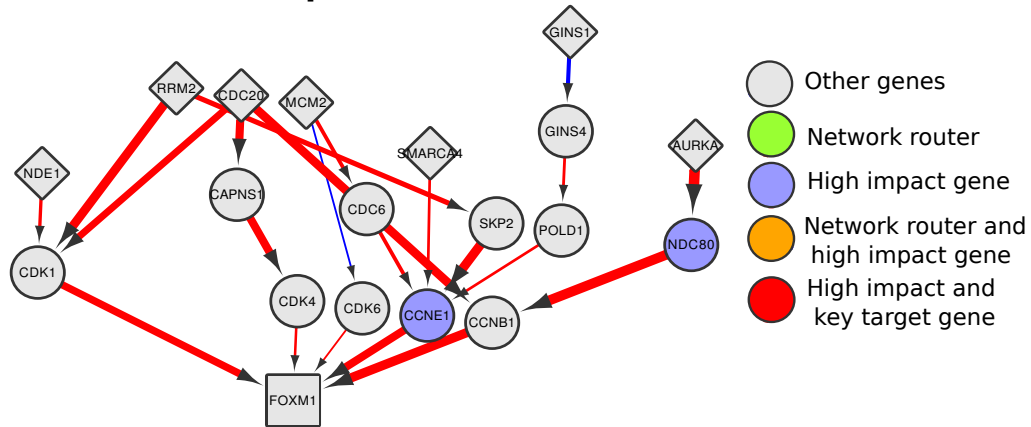
A

ER-negative



B

ER-positive



- Other genes
- Network router
- High impact gene
- Network router and high impact gene
- High impact and key target gene