

1 Network structure and transcriptomic vulnerability shape 2 atrophy in frontotemporal dementia

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1 **Abstract**

2 Connections among brain regions allow pathological perturbations to spread from a single source region
3 to multiple regions. Patterns of neurodegeneration in multiple diseases, including behavioral variant of
4 frontotemporal dementia (bvFTD), resemble the large-scale functional systems, but how bvFTD-related
5 atrophy patterns relate to structural network organization remains unknown. Here we investigate whether
6 neurodegeneration patterns in sporadic and genetic bvFTD are conditioned by connectome architecture.
7 Regional atrophy patterns were estimated in both genetic bvFTD (75 patients, 247 controls) and sporadic
8 bvFTD (70 patients, 123 controls). We first identify distributed atrophy patterns in bvFTD, mainly
9 targeting areas associated with the limbic intrinsic network and insular cytoarchitectonic class. Regional
10 atrophy was significantly correlated with atrophy of structurally- and functionally- connected neighbors,
11 demonstrating that network structure shapes atrophy patterns. The anterior insula was identified as the
12 predominant group epicenter of brain atrophy using data-driven and simulation-based methods, with some
13 secondary regions in frontal ventromedial and antero-medial temporal areas. Finally, we find that FTD-
14 related genes, namely C9orf72 and TARDBP, confer local transcriptomic vulnerability to the disease,
15 modulating the propagation of pathology through the connectome. Collectively, our results demonstrate
16 that atrophy patterns in sporadic and genetic bvFTD are jointly shaped by global connectome architecture
17 and local transcriptomic vulnerability, providing an explanation as to how heterogenous pathological
18 entities can lead to the same clinical syndrome.

19 **Keywords:** connectome; frontotemporal dementia; disease epicentre; gene expression; network spreading

20

1. Introduction

Frontotemporal dementia (FTD) is one of the most common forms of early-onset dementia^{1,2}. The behavioral variant of FTD (bvFTD), which presents with various combinations of behavioral (apathy, disinhibition, compulsions and stereotypies), personality (decreased empathy and sympathy, altered personal preferences) and cognitive (executive dysfunction and social cognitive deficits) changes, is the most common clinical variant of FTD^{2,3}. Despite its distinctive clinical presentation, bvFTD is pathologically heterogeneous, with the most common subtypes being related to the accumulation of hyperphosphorylated aggregates of either Tau or TAR DNA-binding protein 43 (TDP-43)⁴. This group of pathological proteinopathies causing FTD are classified under the frontotemporal lobar degeneration (FTLD) umbrella. Most cases are sporadic, however around 20% are caused by an autosomal-dominant genetic mutation including hexanucleotide repeat expansions near the chromosome 9 open reading frame gene-C9orf72, progranulin-GRN, and microtubule-associated tau protein-MAPT, as the most common causative genes⁴.

FTLD pathology cause clinical bvFTD symptoms through their predominant localization in frontal and anterior temporal brain regions⁴. Clinically this is reflected by progressive cortical atrophy, which is a crucial biomarker for the diagnosis^{5,6}. While there is major overlap in atrophy patterns between sporadic and genetic bvFTD, each genetic subtype has distinctive features including antero-medial atrophy in *MAPT*, posterior frontal and parietal involvement in *GRN* and thalamic/cerebellar volume loss in *C9orf72*⁷. In recent years, there has been an interest to understand how heterogeneous pathological changes could lead to similar clinical and atrophy profiles⁸.

In early work based on functional magnetic resonance imaging (fMRI), it was hypothesized that atrophy in neurodegenerative diseases progresses predominantly along functional neural networks⁹, with the salience network being predominantly affected in bvFTD^{10,11}. Within the salience network, the anterior insula was identified as the most likely disease epicenter^{9,11}, a finding that was further supported by pathologic accumulation of tau or TDP-43 aggregates in fork cells and Von Economo neurons, which are specific to this region¹². While the anterior insula clearly plays a significant role in the disease, other studies using data-driven methods on structural atrophy patterns revealed distinct morphological subtypes including two salience network-predominant subgroups (a frontal/temporal subtype and a frontal subtype), a semantic appraisal network-predominant group, and a subcortical-predominant group¹³. This opens the possibility that there is not a single unique epicenter at the origin of all bvFTD cases.

1 Emerging theories emphasize that connectome architecture shapes the course and expression of multiple
2 neurodegenerative diseases¹⁴⁻¹⁸. Misfolding of endogenous proteins and their subsequent trans-neuronal
3 spread has been documented in FTLD, Alzheimer's, Parkinson's, Huntington's and amyotrophic lateral
4 sclerosis (ALS)^{9,19-26}. Despite differences in origin and the proteins involved in each disease, the spread
5 of the pathology appears to reflect brain network organization at the macroscale level. Namely,
6 anatomical connectivity is thought to support the propagation of toxic protein aggregates, such that focal
7 pathology can spread between connected neuronal populations and infiltrate distributed networks in the
8 brain.

9 Two key questions remain unanswered about the spread of pathology in bvFTD. First, the spread of
10 pathology is likely to occur via physical white matter connections but the contribution of structural
11 connectivity to atrophy progression has been less explored in bvFTD. Evidence for transneuronal spread
12 of FTLD pathology is mostly based on extrapolation from functional imaging^{8,9}, with some support from
13 studies using animal models²⁷, autopsy data²⁸ and prediction of atrophy patterns²⁹. Although functional
14 connectivity reflects the underlying structural connectivity patterns and is sometimes used as a proxy for
15 structural connectivity if no such data is available, the two modalities capture fundamentally different
16 features of brain network organization and are only moderately correlated with each other³⁰. Second, the
17 role of local vulnerability is poorly understood. It is possible that regional differences in molecular and
18 cellular make-up render some nodes more or less vulnerable³¹⁻³³. In particular, recent reports in other
19 neurodegenerative diseases suggest that regional differences in gene expression may confer vulnerability,
20 effectively guiding the pathological process through the network³⁴⁻³⁶. Altogether, we hypothesize that
21 brain network architecture, in concert with local vulnerability conferred by expression of specific genes,
22 shapes the spatial distribution of atrophy patterns in brain disorders, including FTD^{11,37}.

23 In the present report we test a structural network-based atrophy propagation model in bvFTD across
24 sporadic and genetic variants. Specifically, we test the hypothesis that atrophy patterns in bvFTD reflect
25 the underlying network organization and local transcriptomic vulnerability. We first estimate cortical
26 atrophy patterns as regional changes in tissue deformation in bvFTD patients. We then use structural and
27 functional connectivity networks derived from an independent sample of healthy individuals, to
28 investigate whether regions that are connected with each other display similar atrophy patterns. Finally,
29 we identify potential disease epicenters using a data-driven approach as well as a simulation-based
30 approach that models the spread of atrophy across the brain network. We further explore the potential
31 contribution of FTD-related genes to the propagation of atrophy.

32

1 **2. Methods**

2 **2.1 Participants**

3 We retrieved data from subjects with bvFTD and cognitively normal controls (CNCs) from the
4 Frontotemporal Lobar Degeneration Neuroimaging Initiative (FTLDNI) database that had T1-weighted
5 (T1w) MRI scans matching with each clinical visit (<http://4rtmi-ftldni.ini.usc.edu/>). The inclusion criteria
6 for bvFTD patients were a diagnosis of possible or probable bvFTD according to the FTD consortium
7 criteria ³, resulting in 70 patients with bvFTD (mostly sporadic) and 123 CNCs available for analyses.
8 Several patients had more than one scan therefore there was a total of 156 scans in the bvFTD group and
9 the 326 in the CNC group. We also accessed data from the third data freeze (12/2017) of the Genetic
10 Frontotemporal Dementia Initiative 2 (GENFI2 - <http://genfi.org.uk/>), which includes 23 centers in the
11 UK, Europe and Canada ³⁸. GENFI2 participants include known symptomatic carriers of a pathogenic
12 mutation in *C9orf72*, *GRN* or *MAPT* and their first-degree relatives who are at risk of carrying a mutation,
13 but who did not show any symptoms (i.e., at-risk subjects). Healthy first-degree relatives who were found
14 to be non-carriers of a mutation are considered as CNCs. Since the aim of the present study was to study
15 network propagation of atrophy in the bvFTD clinical phenotype, presymptomatic carriers and
16 symptomatic carriers whose clinical diagnosis was other than bvFTD were excluded. This GENFI2 cohort
17 included 75 patients with bvFTD and 247 CNCs. Demographic and clinical characteristics of those two
18 cohorts are described in table 1. Two-sample *t*-tests were conducted to examine demographic and clinical
19 variables at baseline. Categorical variables were analyzed using chi-square analyses. Results are
20 expressed as mean \pm standard deviation and median [interquartile range] as appropriate.

21 **2.2 MRI acquisition and processing**

22 For the FTLDNI cohort, 3.0T MRIs were acquired at three sites (T1w MPRAGE, TR=2 ms, TE=3 ms,
23 IT=900 ms, flip angle 9°, matrix 256x240, slice thickness 1mm, voxel size 1mm³). For the GENFI2
24 sample, volumetric T1w MPRAGE MRI was obtained at multiple centers using the GENFI imaging
25 protocol on either Siemens Trio 3T, SiemensSkyra3T, Siemens1.5T, Phillips3T, General Electric (GE)
26 1.5T or GE 3T scanners. Scan protocols were designed at the outset of the study to ensure adequate
27 matching between the scanners and image quality control.

28 All T1w scans were pre-processed through our longitudinal pipeline that includes image denoising,
29 intensity non-uniformity correction and image intensity normalization into range (0–100) using histogram
30 matching ³⁹⁻⁴². The image processing tools used in this study were designed to process data from multi-

1 site studies to handle biases due to multi-site scanning and they have been successfully applied to a
 2 number of multi-site projects ^{37,43-45}. Each native T1w volume from each time point was linearly
 3 registered first to the subject-specific template which was then registered to the ICBM152 template. All
 4 images were then non-linearly registered to the ICBM152 template using ANTs diffeomorphic
 5 registration pipeline ⁴⁶. The images were visually assessed by two experienced raters (MD and ALM) to
 6 exclude cases with significant imaging artifacts (e.g., motion, incomplete field of view) or inaccurate
 7 linear/nonlinear registrations. This visual quality control was completed blind to the diagnosis. Out of
 8 1724 scans, only 43 (2.5%, 36 scans in GENFI2, and 7 in FTLDNI) were rejected. This resulted in a total
 9 of 515 subjects that were included to perform cross-sectional morphometric analyses.

10 **2.3 Deformation-based morphometry (DBM) analyses**

11 DBM ^{47,48} analysis was performed using Montreal Neurological Institute (MNI) MINC tools ⁴⁹. The local
 12 deformations, obtained from the non-linear transformations mapping the MNI-ICBM152-2009c template
 13 to the subject's MRI, encode the local tissue volume difference between the MNI average template and
 14 subject's brain. The determinant of the Jacobian of the deformation field is measured at each voxel.
 15 Determinant values larger than 1.0 indicate that the local volume in the subject is larger than the average
 16 template (e.g., ventricular or sulci enlargement in the case of FTD). Determinant values smaller than one
 17 indicate that the local volume in the subject is smaller than the template. The latter is often interpreted as
 18 tissue atrophy despite the use of only cross-sectional data. DBM was used to assess voxel-wise cross-
 19 sectional group related volumetric differences. To obtain a voxel-wise map reflecting the patterns of
 20 difference between bvFTD and CNCs, the following mixed effects model was applied on a voxel-by-
 21 voxel basis, separately for each dataset:

$$22 \quad DBM \sim 1 + Dx + AGE + SEX + (1/SITE)$$

23 The mixed effects model included *age* as a continuous fixed variable and *diagnosis* (*Dx*) and *sex* as fixed
 24 categorical variables. *Site* was included as a categorical random variable. The variable of interest was
 25 *diagnosis*, reflecting the brain regions that were significantly different between bvFTD and CNCs,
 26 controlling for age and sex. Statistical t-maps were extracted from the model and used for the rest of the
 27 analyses throughout the manuscript. Finally, the t-statistics were multiplied by (-1) such that higher
 28 positive values correspond to higher atrophy and negative values correspond to volume expansion in
 29 patients.

30

1 **2.4 Anatomical parcellation**

2 Statistical t-maps obtained through DBM analysis and mixed effects models were parcellated into 219 and
3 1000 approximately equally sized cortical regions or parcels using the Cammoun atlas,⁵⁰ a
4 multiresolution extension of the anatomical Desikan-Killiany atlas⁵¹. We refer to 219 and 1000
5 parcellation resolutions as low and high parcellation resolutions, respectively. The parcel-wise t-statistics
6 (i.e., atrophy) were estimated as the mean t-statistic of all the voxels that were assigned to that parcel
7 according to the atlas. We repeated all the analyses at both parcellation resolutions to ensure that results
8 are replicable across multiple spatial scales.

9 **2.5 Structural and functional network reconstruction**

10 Connection patterns from healthy individuals are used to represent the architecture of brain networks for
11 the distributed atrophy patterns that are observed in bvFTD patients. Structural and functional
12 connectivity data of 70 healthy individuals (mean age 28.8 ± 9.1 years) were obtained from a publicly
13 available dataset⁵². Details about data acquisition parameters and preprocessing analysis are available in
14 ⁵². Briefly, the participants were scanned in a 3T MRI scanner (Trio, Siemens Medical, Germany) using a
15 32-channel head-coil. The session protocol included: (1) a magnetization-prepared rapid acquisition
16 gradient echo (MPRAGE) sequence sensitive to white/gray matter contrast (1-mm in-plane resolution,
17 1.2-mm slice thickness); (2) a DSI (diffusion spectrum imaging) sequence (128 diffusion-weighted
18 volumes and a single b_0 volume, maximum b -value $8,000 \text{ s/mm}^2$, $2.2 \times 2.2 \times 3.0 \text{ mm}$ voxel size); and (3) a
19 gradient echo EPI sequence sensitive to BOLD (blood-oxygen-level-dependent) contrast (3.3-mm in-
20 plane resolution and slice thickness with a 0.3-mm gap, TR 1,920 ms, resulting in 280 images per
21 participant). Diffusion spectrum imaging data and deterministic streamline tractography were used to
22 construct structural connectivity networks for each healthy individual. Each pair-wise structural
23 connection was weighted by the log-transform of the fiber density. Individual structural connectivity
24 networks were parcellated into the low and high parcellation resolutions using the Cammoun atlas
25 described before. Resting-state functional MRI data collected in the same healthy individuals (with eyes
26 open) were used to construct functional connectivity networks. The preprocessed resting-state functional
27 MRI time series were also parcellated using both the low and high resolution versions of the Cammoun
28 atlas and were correlated to estimate functional connectivity between pairs of brain regions using Pearson
29 correlation coefficients. Finally, a consensus group-average structural connectivity preserving the edge
30 length distributions in individual networks⁵³⁻⁵⁵ was constructed and a group-average functional
31 connectivity was estimated as the mean pairwise connectivity across individuals.

1 2.6 Network atrophy

2 Group-average structural and functional connectivity networks were used to estimate average atrophy
 3 values of neighbors of each brain region⁵⁶. Briefly, neighbors of a given brain region were defined as
 4 regions that are connected to it with a structural connection for both structurally- and functionally-
 5 defined neighbors. The structurally-connected neighbor atrophy value of each brain region was then
 6 estimated as the average weighted atrophy values of all the neighbors of that region:

$$A_i = \frac{1}{N_i} \sum_{j=1}^{N_i} a_j \times SC_{ij} \quad , \quad j \neq i$$

7 where A_i is the average neighbor atrophy value of brain region or node i , a_j is atrophy of j -th neighbor of
 8 node i , SC_{ij} is the strength of structural connection between nodes i and j , and N_i is the total number of
 9 neighbors that are connected to node i with a structural connection (i.e., node degree). Normalization by
 10 term N_i ensures that the estimated neighbor atrophy value is independent from the node degree. The
 11 neighbor atrophy estimation excludes self-connections ($j \neq i$). The functionally-connected neighbor
 12 atrophy values were estimated using the same equation as above, with the exception that regional atrophy
 13 values were weighted by the strength of functional connections between nodes i and j (FC_{ij}):

$$A_i = \frac{1}{N_i} \sum_{j=1}^{N_i} a_j \times FC_{ij} \quad , \quad j \neq i$$

14 For both structurally- and functionally-defined neighbor atrophy estimates, neighbors were defined as
 15 nodes that were structurally connected to the node under consideration. Altogether, a single neighbor
 16 atrophy value was estimated for each region. We used Pearson correlation coefficients to assess the
 17 relationship between node atrophy and mean neighbor atrophy for structurally- and functionally-defined
 18 neighbors, separately (Fig. 2a).

19 2.7 Data-driven epicenter analysis

20 To identify potential disease epicenters, we hypothesized that an epicenter would be a node with high
 21 atrophy that is also connected to highly atrophied neighbors, compared to a high atrophy node with
 22 healthy neighbors, or a healthy node with atrophied neighbors. Using a data-driven approach^{56,57}, we
 23 first ranked the nodes based on their estimated regional atrophy values. We also ranked the nodes based
 24 on the average atrophy values of their neighbors in a separate list. We then calculated the average ranking

1 of each node in the two lists and identified nodes that were highly ranked in both lists (i.e., nodes with
2 both high local and neighborhood average rankings) as the potential epicenters (Fig. 2b).

3 **2.8 Agent-based spreading model**

4 **2.8.1 Simulation-based epicenter analysis**

5 To investigate the transneuronal spread hypothesis, we simulated the spread of pathology on the left
6 hemisphere of the low-resolution weighted consensus structural connectivity network (111 regions) using
7 a Susceptible-Infected-Removed (S.I.R) agent-based model ³⁴. Briefly, the model consists of simulating
8 the misfolding of normal proteins in the cortex and their trans-neuronal spreading through the structural
9 connections between brain regions. The accumulation of pathology, which act as pathogenic agents, then
10 leads to the atrophy of the afflicted regions. Importantly, this model incorporates synthesis and clearance
11 rates, which can heterogeneously vary across brain regions. More details about the model's main
12 equations can be found in the *Supplemental Information*. To explore the likelihood that a brain region acts
13 as an epicenter of this spreading process, we first used baseline clearance and synthesis rates for all
14 regions. We simulated the spread of pathology and the resulting atrophy using, one at a time, each
15 individual brain region as the seed of the process. For each seed region, and at each time point, we then
16 computed the Pearson correlation between the simulated and empirical patterns of atrophy.

17 **2.8.2 Gene expression**

18 To investigate the potential role of gene expression in shaping the modelled patterns of atrophy, we
19 accessed the Allen Human Brain Atlas (AHBA; <http://human.brain-map.org/>) ⁵⁸ which provides regional
20 microarray expression data from six post-mortem brains (1 female, ages 24-57, 42.5 +/- 13.38). We
21 generated vectors storing gene expression scores for each of the 111 regional parcels of the left
22 hemisphere. These vectors were then incorporated into the S.I.R. model to regulate the synthesis and
23 clearance rate of each region, such that a greater expression score entailed greater synthesis and clearance
24 rates. More specifically, our analyses focused on four vectors of gene expression associated with genes
25 that have been previously linked to bvFTD, namely MAPT, GRN, C9orf72 and TARDBP. Given that
26 subjects were selected based on their clinical phenotype (bvFTD) rather than on a specific pathological
27 subtype or genetic mutation, we explored the potential role of the expression of all four genes for both
28 synthesis and clearance. Our objective was to identify potentially new mechanistic processes underlying
29 the spreading of atrophy, particularly in sporadic bvFTD where we do not have adequate knowledge of
30 the contribution of genes related to the various proteinopathies. In complementary experiments, we also

1 used the first principal component of the full *genes x brain regions* matrix of gene expression. This
2 component captures the principal axis of transcriptional variation across the human cortex⁵⁹.

3 The AHBA data was pre-processed and mapped to the parcellated brain regions using the *abagen* toolbox
4 (<https://github.com/rmarkello/abagen>)⁶⁰. During pre-processing, we first updated the MNI coordinates of
5 tissue samples to those generated via non-linear alignment to the ICBM152 template anatomy
6 (<https://github.com/chrisgorgo/alleninf>). We also reannotated the microarray probe information for all
7 genes using data provided by [Arnatkevičiūtė](#) and colleagues⁶¹. We then filtered the probes by only
8 retaining those that have a proportion of signal to noise ratio greater than 0.5. When multiple probes
9 indexed the expression of the same gene, we selected the one with the most consistent pattern of regional
10 variation across donors. Samples were then assigned to individual regions in the Cammoun atlas. If a
11 sample was not found directly within a parcel, the nearest sample, up to a 2mm-distance, was selected. If
12 no samples were found within 2mm of the parcel, we used the sample closest to the centroid of the empty
13 parcel across all donors. To reduce the potential for misassignment, sample-to-region matching was
14 constrained by hemisphere and gross structural divisions (i.e., cortex, subcortex/brainstem, and
15 cerebellum, such that e.g., a sample in the left cortex could only be assigned to an atlas parcel in the left
16 cortex). All tissue samples not assigned to a brain region in the provided atlas were discarded. Tissue
17 sample expression scores were then normalized across genes using a scaled robust sigmoid function⁶²,
18 and were rescaled to a unit interval. Expression scores were also normalized across tissue samples using
19 the same procedure. We then aggregated the microarray samples belonging to the same regions by
20 computing the mean expression across samples for individual parcels, for each donor. Regional
21 expression profiles were finally averaged across donors.

22 **2.9 Null models**

23 To assess the statistical significance of the node-neighbor relationships and the epicenter analysis, we
24 used a spatial autocorrelation preserving null model (i.e., “spin tests”^{63,64}). We first used the Connectome
25 Mapper toolkit⁶⁵ (<https://github.com/LTS5/cmp>) to generate a surface-based representation of the
26 Cammoun atlas (both low and high resolution) on the Freesurfer fsaverage surface. We then defined the
27 spatial coordinates of each parcel by selecting the vertex on the spherical projection of the generated
28 fsaverage surface that was closest to the center of mass of the parcel^{56,57}. Finally, we used the resulting
29 parcel spatial coordinates to generate null models of brain maps (e.g., atrophy maps, epicenter rankings)
30 by randomly rotating the maps and reassigning node values with the values of closest parcels. The
31 rotations were first applied to one hemisphere and the mirrored rotations were used for the other

1 hemisphere. This procedure was repeated 10,000 times to generate a null distribution of brain maps with
2 preserved spatial autocorrelation.

3 To ensure the specificity of our transcriptomic results, we relied on a second spatial autocorrelation-
4 preserving null model. This model was proposed by Burt and colleagues⁶⁶ and can be implemented using
5 the brainSMASH python toolbox (<https://github.com/murraylab/brainsmash>). First, the empirical brain
6 map is randomly permuted. Then, this permuted brain map is spatially smoothed and re-scaled to re-
7 introduce the spatial autocorrelation (SA) of the empirical brain map. The smoothing process is achieved
8 via the following transformation:

$$y = |\beta|^{1/2}x + |\alpha|^{1/2}z$$

9 where y is the surrogate map, x is the permuted data and z is a vector of random gaussian noise. The α
10 and β parameters are estimated via a least-square optimization between variograms of the original and
11 permuted data. By maximizing the fit between the variograms of the original and permuted data, we
12 ensure that the SA of the surrogate map matches the SA of the empirical map.

13 To ensure that the observed correlation between the empirical and simulated atrophy map from the agent-
14 based model is explained by the topological organization of the structural connection between brain
15 regions and not solely by the spatial embedding of brain regions, we generated surrogate networks that
16 preserve the geometry of the structural connectome. The edges of the consensus network were first binned
17 according to inter-regional Euclidean distance. Within each length bin, pairs of edges were then selected
18 at random and swapped⁶⁷. This procedure was repeated 500 times, generating a population of rewired
19 structural networks that preserve the degree sequence of the original network and that approximately
20 preserve the edge length distribution (i.e., wiring cost) of the empirical network.

21 **2.10 Data availability**

22 Data used in this study are part of FTLDNI and GENFI databases and de-identified data can be accessed
23 upon request at <http://4rtni-ftldni.ini.usc.edu/> and <http://genfi.org.uk/>, respectively, after agreeing to their
24 corresponding data terms.

25

1 **3. Results**

2 **3.1 Demographics**

3 Table 1 compares demographic and clinical variables between bvFTD and CNCs across the two research
4 databases. Subjects with bvFTDs were on average older than CNCs in the GENFI2 cohort, but not in
5 FTLDNI. As expected, significantly lower MMSE and higher FTLD-CDR average scores were observed
6 in symptomatic subjects compared to healthy controls.

7 **3.2 Distribution of atrophy and resting state networks and** 8 **cytoarchitectonic classes**

9 We used a linear mixed effects model to obtain a group-level, bvFTD-related atrophy map, controlling for
10 age, sex and acquisition site. The voxel-level and parcellated atrophy maps are depicted in Fig. S1a,b. In
11 order to assess whether distributed atrophy patterns are more pronounced in specific brain systems, we
12 used two brain system definitions (Fig. 1): (1) intrinsic functional networks defined by Yeo and
13 colleagues⁶⁸; (2) a cytoarchitectonic classification of human cortex based on the classic von Economo
14 atlas⁶⁹⁻⁷². Nodes were first stratified according to their network assignments based on the Yeo networks
15 and von Economo classes. We then calculated the mean atrophy values for each intrinsic network (Fig. 1,
16 left) and cytoarchitectonic class (Fig. 1, right) for FTLDNI (Fig.1a) and GENFI (Fig. 1b) datasets,
17 separately. To assess the statistical significance of network atrophy values, we compared the empirical
18 values to a distribution of means calculated from a set of spatial autocorrelation-preserving null models
19 (i.e., “spin tests”^{63,64}; see *Methods* section for more details on null model). Specifically, network labels
20 were randomly rotated while preserving the spatial autocorrelation and the mean network atrophy values
21 were calculated for each rotation (10,000 repetitions; two-tailed test).

22 The observed mean network atrophy and the corresponding null distribution of means are depicted for
23 each intrinsic network and cytoarchitectonic class in Fig. 1. The anatomical distributions of intrinsic
24 networks and cytoarchitectonic classes are depicted in Fig. 1 (bottom row). Note the difference in the
25 definition of “limbic” system between the intrinsic networks and cytoarchitectonic classes. The intrinsic
26 limbic network mainly consists of the temporal poles and orbitofrontal cortex, whereas the
27 cytoarchitectonic limbic class mainly includes the cingulum. In terms of intrinsic networks, limbic and
28 default mode intrinsic networks were the most affected (i.e., higher than expected atrophy) with relative
29 preservation of somatomotor and visual intrinsic networks (i.e., lower than expected atrophy). In terms of

1 cytoarchitectonic classes, the insular and association cytoarchitectonic classes displayed greater atrophy
2 compared to nulls, with lower atrophy in primary sensory cytoarchitectonic classes. While there are
3 marginal variations in statistical significance of the findings, the overall trend of network atrophy patterns
4 is consistent across the two datasets.

5 **3.3 Relationship between atrophy maps and connectivity**

6 We next investigated whether atrophy patterns in bvFTD are conditioned by network organization, such
7 that connected regions display similar atrophy patterns. Specifically, we assessed whether the
8 connectivity profile of a node can predict the atrophy of its neighbors by investigating the relationship
9 between node and neighbor atrophy values (Fig. 2a). Structural and functional connectivity (SC and FC)
10 networks (Fig. S1c), derived from an independent sample of 70 healthy participants⁵², were used to
11 estimate mean neighbor atrophy value for each region. The relationship between node and neighbor
12 atrophy was then examined by correlating the mean neighbor atrophy with nodal atrophy (Fig. 2c,d).
13 Regional atrophy was significantly correlated with the mean atrophy of its connected neighbors in both
14 datasets. Fig. 2c (left panel) shows the results for FTLDNI dataset (high resolution parcellation: $r = 0.69$,
15 $p_{\text{spin}} = 0.0001$ and $r = 0.65$, $p_{\text{spin}} = 0.0001$, for SC- and FC- defined neighbors respectively) and Fig. 2d
16 (left panel) shows the results for GENFI dataset (high resolution parcellation: $r = 0.61$, $p_{\text{spin}} = 0.001$ and r
17 $= 0.54$, $p_{\text{spin}} = 0.0006$, for SC- and FC- defined neighbors respectively). These correlations are
18 significantly greater when considering connected versus not-connected neighbors, across datasets and
19 resolutions (Table S1).

20 To assess whether the relationship between node and neighbor atrophy is specifically driven by network
21 topology rather than spatial autocorrelation, we used a spatial autocorrelation-preserving null model to
22 construct a null distribution of node-neighbor correlations⁶³. Fig. 2c,d (middle panel) displays the
23 observed correlation between node and neighbor atrophy along with the corresponding null distribution of
24 correlations for both datasets. We also repeated all analyses at a lower parcellation resolution to ensure
25 that the findings are robust to how network nodes are defined. The relationship between node and
26 neighbor atrophy was consistent across resolutions and significantly greater in empirical networks
27 compared to null networks in both datasets (Fig. 2c,d; $p_{\text{spin}} < 0.05$, two-tailed tests). The results were
28 consistent when the binarized structural connectivity network was used to defined SC- defined neighbors
29 (Fig. S2).

30

3.4 Data-driven epicenters analysis

Given that the distribution of atrophy patterns reflects structural and functional network organization, we next investigated whether there are brain regions that may act as potential epicenters for bvFTD. We define an epicenter as a high atrophy node that is connected to high atrophy neighbors (Fig. 2b). Nodes were ranked based on their atrophy and their neighbors' mean atrophy values. Epicenter likelihood ranking was then estimated as the mean node ranking across the two lists. Fig. 2c,d (rightmost panel) shows the epicenter likelihood rankings on the cortex for FTL DNI (Fig. 2c) and GENFI (Fig. 2d) datasets, where the highly ranked regions are associated with insular cortex, ventromedial cortex and antero-medial temporal areas. Empirical epicenter likelihood rankings were then compared with rankings estimated from spatial autocorrelation-preserving null models (10,000 spin tests⁶³). Several regions were identified as potential epicenters including the anterior insular cortex bilaterally, but also areas in the anterior temporal poles, in addition to ventromedial and dorsomedial areas. The results were consistent when binarized structural connectivity network was used to defined SC- defined neighbors (Fig. S2).

3.5 Dynamic spreading model

We next used an S.I.R model to explore how the brain's structural connectivity shapes the progressive spread of FTL D changes. This model has been previously used to study Parkinson's disease-related atrophy³⁴ and works by simulating the misfolding of normal proteins in the cortex and their trans-neuronal spread through the structural connections between brain regions. The accumulation of pathology, acting as pathogenic agents, leads to the atrophy of the afflicted regions (Fig. 3a). Epicenters are defined as those regions in which misfolded proteins are introduced. We tested which is the most likely epicenter for the observed empirical patterns of atrophy by running the model and initiating the spread in each region. As the misfolded agents spread through the network, we measured the Pearson correlation between the simulated and empirical (FTL DNI) patterns of atrophy (Fig. 3b; left panel). We then define a region's r_{max} as the largest correlation value observed across all values of t when it is used as the epicenter of the spreading process. Regions that have large r_{max} scores are the most likely epicenters. The three nodes with the largest r_{max} are located in the insular, superior-frontal and lateral orbito-frontal cortex. For these three potential epicenters, the r_{max} is greater when considering directly-connected neighbors than when considering non-connected nodes (Fig. S3).

An important factor that can influence the probability that a brain region is identified as the epicenter of an atrophy pattern is its spatial location in the brain. To isolate the role of structural connectivity, we compared these r_{max} scores to those obtained by simulating the spread of pathology in rewired networks

1 that preserve the density, degree sequence and wiring cost of the empirical structural network (Fig. 3b;
2 right panel). We find that the fit obtained by initiating the spread in the insular region of the empirical
3 network is significantly larger than the fit obtained in the rewired networks ($r = 0.601$, $p < 0.002$). We
4 also find that it is larger than the fit obtained by replacing the structural connectivity matrix in our model
5 with matrices of either Euclidean or geometric distances between nodes (Fig. S4a). In other words, the fit
6 observed by seeding the insula is significantly larger than what would have been expected from its degree
7 and spatial position alone and can be attributed to its embedding in the global topology of the network.
8 This result suggests that the topology of the structural connectome plays a significant role in shaping
9 patterns of simulated atrophy that have a high correspondence with the empirical atrophy.

10 More generally, by looking at the topographic distribution of r_{max} scores, we find that the brain regions
11 that show the largest fits are located in the insular, medial prefrontal and anterior temporal cortices (Fig.
12 3c). These results are in accordance with our finding that these regions have large epicenter likelihood
13 rankings. Fig. 3d shows the empirical pattern of atrophy for the FTLDNI dataset. This pattern is
14 compared to the simulated pattern of atrophy producing the maximal fit. This largest fit was obtained by
15 seeding the insula and was measured at $t=4410$. We find a significant relationship between the two
16 distributions ($r = 0.60$, $p = 0.0013$). Results are presented for the FTLDNI dataset, but similar results are
17 found in the GENFI dataset (Fig. S5). Up to this point, we focused on group effects because deformation-
18 based morphometry is a technique mainly intended to detect population-level differences in brain
19 structure. To better understand patient heterogeneity, we considered genetic subtypes in GENFI. We
20 stratified the GENFI cohort into C9orf72, GRN and MAPT mutation carriers and repeated the main
21 analyses separately for each genetic group. Fig. S6,a,b,c shows the three main findings for each genetic
22 group separately. We find a significant network spreading effect in each group. In addition, both the data-
23 driven and simulation-based analysis identified frontal, temporal and insular epicenters in C9orf72 and
24 MAPT carriers, with more pronounced involvement of the antero-medial temporal poles in MAPT as well
25 as frontal and lateral parietal regions in GRN carriers, consistent with previous research⁷.

26 **3.6 Contribution of gene expression to network spreading**

27 Given the contribution of genetic variants to bvFTD⁷³, we next assessed whether the incorporation of
28 gene expression information into the S.I.R model can enhance the fits. We used regional microarray
29 expression data from the Allan Human Brain Atlas⁵⁸ to generate vectors of gene expression for four
30 genes that have been previously associated with bvFTD: MAPT, GRN, C9orf72 and TARDBP⁴. Fig. 4a
31 shows their topographic distributions. We used this genetic information to set regional heterogeneity for

1 the clearance and synthesis of proteins in the model. We used the insula as the seed region of the
2 spreading process as it is the region that showed the largest fit to the empirical data.

3 For both FTLDNI (Fig. 4b) and GENFI (Fig. 4c) datasets, we measured the r_{\max} scores obtained by
4 incorporating regional expression for each of the four genes. With MAPT, GRN, C9orf72 and TARDBP,
5 we obtain correlation scores of $r_{\max}=0.42$, $r_{\max}=0.44$, $r_{\max}=0.61$ and $r_{\max}=0.71$ for the FTLDNI dataset, and
6 $r_{\max}=0.28$, $r_{\max}=0.30$, $r_{\max}=0.58$ and $r_{\max}=0.68$ for the GENFI dataset. We find that adding regional
7 heterogeneity for synthesis and clearance using expression of C9orf72 and TARDBP increased model fit
8 while the incorporation of information regarding the regional expression of GRN and MAPT decreased
9 model fit. To investigate the significance of the findings, we spun the vectors of gene expression 10,000
10 times to generate spatially auto-correlated null distributions of r_{\max} scores that we compared to the
11 empirical results. We find that the scores obtained with C9orf72 and TARDBP are significantly larger
12 than those obtained with permuted gene expression vectors ($p=0.014$ and $p<0.0001$, respectively for the
13 FTLDNI dataset, and $p<0.0001$, for both genes, for the GENFI dataset). The scores obtained with
14 C9orf72 and TARDBP are also significantly larger than those obtained with spatially auto-correlated
15 distributions of gene expression generated using a variogram-based method (Fig. S7). These results
16 suggest that C9orf72 and TARDBP may play a significant role in driving the spatial patterning of the
17 empirical atrophy.

18 To investigate the relationship between gene expression and the brain's structural connectivity, we
19 compared the fits to those obtained using rewired networks preserving the wiring-cost of the empirical
20 network. For C9orf72, we find that the fits obtained using the empirical networks were significantly
21 larger than the fits obtained using rewired null networks, for both FTLDNI ($p < 0.002$) and GENFI ($p <$
22 0.002). The fits obtained with the empirical connectome were also greater than the fits obtained by
23 replacing the structural connectivity matrix in the S.I.R model with matrices of either Euclidean or
24 geometric distances between nodes (Fig. S4b). For TARDBP, we find that the fits obtained using the
25 empirical networks were significantly larger than the fits obtained using rewired nulls for FTLDNI
26 ($p=0.014$), but not for GENFI ($p=0.508$). Similarly, the fits obtained with the empirical connectome were
27 greater than the fits obtained by replacing it with matrices of Euclidean or geometric distances between
28 nodes for the FTLDNI dataset, but not the GENFI dataset (Fig. S4b). Altogether, these results
29 demonstrate that the topology of the structural connectome has a positive influence on the increase in
30 model fit observed when incorporating either TARDBP or C9orf72 into the S.I.R. model, more so than
31 would the spatial distances between nodes. For TARDBP, this influence is observed when trying to fit our
32 model to patterns of atrophy associated to both sporadic and genetic bvFTD while for C9orf72, this
33 influence is only observed when trying to fit our models to patterns of atrophy associated to sporadic

1 bvFTD. In other words, our investigations suggest that C9orf72 and TARDBP expression can influence
2 pathogenic spreading processes unfolding on the structural connectome. Interestingly, both TARDBP
3 ($r=0.83$) and C9orf72 ($r=0.61$) are strongly correlated to the principal axis of transcriptional variation
4 across the human cortex (gene PC1⁵⁹), which also enhances the fit of the S.I.R model when used to
5 incorporate regional heterogeneity (Fig. S8). However, contrary to TARDBP and C9orf72, this increased
6 fit is not significantly larger than the fits obtained using rewired networks. It therefore suggests that the fit
7 obtained with gene PC1 is largely due to its spatial distribution on the cortical surface and not necessarily
8 to its influence on pathogenic spreading processes unfolding on the structural connectome. For
9 completeness, we also repeated these analyses in the three genetic subgroups of GENFI. Fig. S6,d shows
10 that the results are consistent across subgroups, with TARDBP and C9orf72 being the two gene
11 distributions that give the largest model fits.

12 4. Discussion

13 The present report provides a comprehensive and statistically robust model supporting the theory of
14 network-based atrophy in bvFTD, both in sporadic and genetic forms. Our findings are consistent across
15 two datasets and the genetic/sporadic heterogeneity. Namely, for both sporadic and genetic variants, there
16 is a strong correlation between node deformation and the mean of neighbor deformation defined by both
17 structural and functional connectivity, supporting the theory that atrophy progresses through network-
18 based connections. Similar findings were observed at small (219) and large (1000) cortical parcellation
19 resolutions. Data-driven epicenter mapping identified the bilateral anterior insular cortex, as well as
20 ventromedial cortex and antero-temporal areas as potential epicenters. The involvement of the antero-
21 medial areas as epicenters ties into previous research showing that data-driven atrophy subtypes include a
22 “semantic appraisal network” predominant group^{13,74}. The genetic bvFTD cohort showed a very similar
23 profile of most likely epicenters, with the addition of some dorsal frontal areas. The role of these regions
24 as epicenters was further supported by the agent-based spreading model.

25 The localization of cortical atrophy was most significant in the limbic resting state network, and less
26 present in the visuospatial network (expectedly given its posterior localization). There was significant
27 atrophy in the default mode network (DMN) in genetic FTD, with a positive trend in sporadic FTD. Of
28 note, the salience network which has been previously identified as being predominantly involved in
29 bvFTD^{10,11} did not show statistically significant atrophy. However, when looking at von Economo
30 cytoarchitectonic classes, the insular cortex was the most affected, with relative sparing of the primary
31 sensory neurons. This suggests that the insular cortex plays a central role in the disease, but not
32 necessarily by spreading through the entire ventral attention network including its most posterior regions.

1 In addition, while there have been some reports of opposite connectivity pattern of changes in the salience
2 versus the DMN in bvFTD and AD¹⁰, our results rather suggest that there is significant involvement of
3 DMN regions in bvFTD.

4 Finally, although exploratory, using a simulation-based approach and gene expression profile data from
5 the Allen Human Brain Atlas, we identified that the *C9orf72* and *TARDPB* gene expression could play a
6 role in the propagation of atrophy in sporadic bvFTD. Indeed, factoring an impact on clearance and
7 synthesis of both genes related to TDP-43 improved the fit between the modeling spreading models and
8 the actual atrophy maps based on DBM. While we cannot exclude that some subjects in the FTLDMI had
9 an unidentified *C9orf72* mutation, the involvement of *TARDPB* is of interest given that mutations in this
10 gene constitute only a very small fraction of genetic FTD. Results suggest that the activity of this gene
11 could play a role in sporadic bvFTD, which could be of interest for future therapeutic avenues.
12 Interestingly, we find that the atrophy in each of the three genetic groups in GENFI (*C9orf72*, *GRN*,
13 *MAPT*) displays a significant network spreading effect and overall has a similar dependence on local gene
14 expression, but different network epicenters. Consistent with previous studies⁷, *C9orf72* and *MAPT* are
15 marked by prominent epicenters in frontal, temporal and insular cortices that resemble sporadic cases,
16 with more pronounced antero-medial temporal involvement in *MAPT*. *GRN*-related atrophy is marked by
17 greater epicenter likelihood in more dorsal frontal areas and lateral parietal cortex. How population-level
18 genetic variation shapes the molecular and network cascades that lead to atrophy remains an exciting
19 question for future research.

20 It is important to note that these findings are mainly correlational and do not prove causal influence of
21 network structure on atrophy. Specifically, it is not possible to determine whether connectivity drives the
22 progression of grey matter atrophy or that connectome architecture itself is compromised in patients as a
23 result of white-matter lesions reported in bvFTD, estimated by white-matter hyperintensities⁷⁵⁻⁷⁸. We
24 used structural and functional networks reconstructed from a sample of young healthy participants as the
25 underlying architecture that supports pathogen transmission. However, extensive changes in network
26 architecture may reroute or restrict the spread of pathology. It is also possible that white-matter changes
27 disrupt normal transneuronal transport of trophic factors, resulting in atrophy among connected regions
28 without involvement of any pathogens or misfolded proteins. These additional factors could be further
29 investigated in more complex models using simultaneous measures of regional atrophy and changes in
30 white-matter architecture and structural and functional networks in a longitudinal sample of FTD patients.
31 Specifically, a highly sampled, multimodal longitudinal dataset with simultaneous measurements of
32 regional pathology, white-matter lesions, gene expression, metabolism, cerebrospinal fluid biomarkers,

1 vascular and neuroimaging factors in bvFTD would allow precise multifactorial modeling of the disease,
2 improving individualized diagnosis, therapeutic interventions and prognosis in bvFTD patients^{79,80}.

3 How could these results apply to individual patients? Because deformation-based morphometry is a
4 technique intended to detect population-level differences in brain structure, we focused on group effects.
5 Our findings provide a neurobiological explanation as to why patients with such different genetic and
6 pathological variations can present with similar clinical syndromes in practice (i.e., because the disease
7 propagation is constrained by the network architecture). Given the multifactorial nature of the disease and
8 considerable inter-individual variability, it is necessary to tailor therapeutic interventions to individual
9 patient needs. The central clinical promise of these network models is that they may effectively
10 summarize the complex multimodal measurements available, yielding a small number of clinically
11 relevant features. These features may then allow identification of at-risk pre-symptomatic individuals,
12 candidates for enrollment in clinical trials, and targets or outcome measures for novel disease modifying
13 therapies.

14 Altogether, our results build on previous literature that patterns of neurodegeneration reflect network
15 architecture¹⁴⁻¹⁸. Consistent with reports in other neurodegenerative diseases, we demonstrate that atrophy
16 patterns in bvFTD are associated with global connectome architecture and local transcriptomic
17 vulnerability^{9,11,19-26,37}. The present findings were replicated in two separate samples of genetic and
18 sporadic bvFTD and were validated using a range of methodological choices. We also confirmed that the
19 findings are independent from potential confounding factors such as spatial distance and parcellation
20 resolution. However, there are several methodological considerations that need to be taken into account
21 when interpreting the findings.

22 First, there are currently no available molecular techniques to directly measure FTLD changes in vivo. To
23 overcome this limitation, we opted to use DBM to estimate atrophy in bvFTD patients since it is a robust
24 method to capture local changes in brain tissue volume. Given that in vivo positron emission tomography
25 (PET) tracers of TDP-43 and tau PET tracers are not currently reliable in FTLD, using post-mortem
26 assessments of pathology such as immunohistochemistry of phosphorylated 43-kDa TAR DNA-binding
27 protein (pTDP-43⁸¹) would provide a more direct measure of FTD-related pathology⁸²⁻⁸⁴.

28 Second, we identified potential disease epicenters using cross sectional data and undirected networks,
29 precluding reconstruction of the temporal sequence of pathology. In particular, the epicenter model
30 cannot assess the cascade of pathology, including molecular, metabolic, vascular, and functional changes,
31 that may begin before grey matter atrophy and start years before emergence of the clinical syndromes and
32 disease diagnosis⁸⁵. Modeling disease progression and spread of atrophy across brain networks over time

1 remains an exciting open question that could eventually be addressed by increased longitudinal sampling
2 in large FTD datasets (including GENFI and ALLFTD^{86,87}), that include multimodal data from
3 presymptomatic genetic carriers to symptomatic patients at later stages of diseases.

4 Third, diffusion spectrum imaging and streamline tractography were used to estimate structural
5 connectivity networks. Although recent technological and analytical developments provide powerful
6 methods to reconstruct white matter fibers in vivo, with biologically interpretable weights and good
7 correspondence with histology, they may still yield false positives and negatives⁸⁸⁻⁹⁶ . Fourth, the two
8 multi-site datasets included in this study have different demographics that could potentially influence the
9 results. Although the morphometric procedure controls for site, age and sex, and the results are consistent
10 across the two datasets, our findings should be interpreted in light of these potential confounding
11 variables^{97,98} .

12 **5. Conclusion**

13 Altogether, structural and functional connectivity networks and rigorous statistical analyses that account
14 for spatial autocorrelation and network embedding are used in the present study to demonstrate that
15 bvFTD-related neurodegeneration is conditioned by connectome architecture, accounting for 30-40% of
16 variance in atrophy, as well as local transcriptomic vulnerability. FTD-related atrophy appears to be
17 particularly targeting regions associated with the anterior insular cortex, but it is likely that there are
18 multiple potential epicenters leading to bvFTD clinical phenotypes. The similarity between genetic and
19 sporadic forms of bvFTD suggests that multiple pathological changes are constrained by the network
20 architecture in the spread of atrophy, explaining why many different pathological and genetic entities lead
21 to the same clinical syndrome. Although exploratory, our results suggest that *TARDPB* gene expression
22 could have a significant contribution to disease progression, particularly in sporadic bvFTD.

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28

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14 **8. Competing interests**

15 The authors report no competing interests.

16 **9. Supplementary material**

17 Supplementary material is available at *Brain* online.

18 **10. Appendix 1**

19 Further details of the FTLDNI investigators and GENFI consortium members are provided in the
20 Supplementary material.

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22

1 Figure legends

2 **Figure 1 Atrophy patterns in intrinsic networks and cytoarchitectonic classes.** Mean network atrophy
 3 (i.e., t -value) was calculated for Yeo intrinsic functional networks⁶⁸ (left column) and von Economo
 4 cytoarchitectonic classes⁶⁹⁻⁷² (right column). Higher t -values correspond to greater atrophy. The observed
 5 mean atrophy values are shown by filled circles for each intrinsic network and cytoarchitectonic class.
 6 Network labels are then randomly permuted using 10,000 rotations from spin tests, preserving the spatial
 7 autocorrelation in the data. The null distributions of means from spin tests are depicted using box plots for
 8 intrinsic networks and cytoarchitectonic classes for both (a) FTLDNI and (b) GENFI datasets (10,000
 9 repetitions; two-tailed test). The bottom row displays the location of intrinsic networks (left) and
 10 cytoarchitectonic classes (right) on the cortex. List of Yeo networks: visual (vis), somatomotor (sm),
 11 dorsal attention (da), ventral attention (va), limbic (lim), frontoparietal (fp), default mode (dmn). List of
 12 von Economo classes: primary sensory cortex (ps), primary motor cortex (pm), primary/secondary
 13 sensory cortex (pss), limbic (lb), insular cortex (ic), association cortex (ac, ac2).

14 **Figure 2 Network-dependent atrophy.** (a) Atrophy of a node, estimated by t -values, was correlated with
 15 the mean atrophy of its connected neighbors to examine whether the distributed atrophy patterns in
 16 bvFTD reflect the underlying network organization. (b) If atrophy of a node is related to the atrophy of its
 17 connected neighbors (panel a), a node with high atrophy whose neighbors are also highly atrophied would
 18 be more likely to be a potential disease epicenter, compared to a high atrophy node with healthy
 19 neighbors. To quantify the epicenter likelihood across the cortex, the nodes were first ranked based on
 20 their atrophy values and their neighbors' atrophy values. Epicenter likelihood ranking of each node was
 21 then defined as its mean ranking in the two lists. (c, d) Left panel: Node atrophy value was correlated with
 22 the mean atrophy value of its structurally- and functionally-weighted neighbors (SC and FC) for FTLDNI
 23 (panel c) and GENFI (panel d) datasets. Scatter plots show the correlation for high parcellation resolution.
 24 Middle panel: The observed correlation values (depicted by filled circles) were compared to a set of
 25 correlations obtained from 10,000 spin tests (depicted by box plots). Asterisks denote statistical
 26 significance ($p_{\text{spin}} < 0.05$, two-tailed). The association between node and neighbor atrophy was consistent
 27 across resolutions and significantly greater in empirical networks compared to null networks in both
 28 datasets. Right panel: Epicenter likelihood rankings are depicted across the cortex. The most likely
 29 epicenters with high significant rankings are regions that are mainly located at the bilateral anterior
 30 insular cortex and temporal lobes (10,000 spin tests).

31

1 **Figure 3 Agent-based modeling.** (a) The S.I.R model simulates the spread of pathology in the brain.
 2 Proteins propagate via the structural connections between brain regions and induce atrophy, both pre- and
 3 post-synaptically. (b) Left panel: the spreading process was initiated in every brain region and the
 4 correlation between the simulated and empirical patterns of atrophy was computed. The three largest
 5 correlations were obtained by seeding regions of the insula ($r_{\max} = 0.601$; red), the superior-frontal cortex
 6 ($r_{\max} = 0.473$; blue) and lateral orbito-frontal cortex ($r_{\max} = 0.471$; green). The correlations for other brain
 7 regions are shown in gray. Right panel: to control for the potential effect of a brain region's spatial
 8 embedding, r_{\max} values were compared to r_{\max} correlations obtained using rewired networks that preserve
 9 the wiring-cost of the empirical structural network. Asterisks denote statistical significance ($p < 0.05$,
 10 two-tailed). The r_{\max} computed by seeding the insula of the empirical network ($r_{\max} = 0.60$) was
 11 significantly larger than the r_{\max} computed by seeding the insula of the rewired networks ($p < 0.002$). (c)
 12 The largest fit (r_{\max}) obtained by seeding each brain region is shown on the surface of the brain. Larger
 13 values of r_{\max} were generally obtained by seeding insular and prefrontal regions. (d) Left panel: empirical
 14 pattern of atrophy (FTLDNI). Middle panel: simulated pattern of atrophy producing the maximal fit. This
 15 pattern of atrophy was obtained with the insula as the seed, and at $t=4410$ (see the arrow in panel b).
 16 Right panel: scatterplot of the relationship between standardized empirical and simulated patterns of
 17 atrophy ($r = 0.60$, $p = 0.0013$).

18 **Figure 4 Contribution of gene expression.** (a) Vectors of regional gene expression were generated for
 19 four genes that have been associated with bvFTD: TARDBP, C9orf72, GRN and MAPT. These vectors of
 20 gene expression were incorporated into the S.I.R model. The correlations between empirical atrophy and
 21 simulated atrophy, with the insula selected as the seed of the simulated spreading process, were then
 22 computed for the FTLDNI dataset (b) and for the GENFI dataset (c). The maximal correlation scores
 23 (r_{\max}) obtained for each gene were compared to the maximal correlation scores (r_{\max}) obtained with spun
 24 distributions of gene expression vectors (grey boxplots). Asterisks denote statistical significance ($p < 0.05$,
 25 two-tailed). For both datasets, we find that the r_{\max} scores obtained by incorporating information about the
 26 expression of C9orf72 and TARDBP are significantly larger than those obtained with permuted gene
 27 expression vectors. The maximal correlations are also compared to the maximal correlation scores
 28 obtained in distance-preserving rewired networks (white boxplots).

29

30

1 **Table I Demographic and clinical characteristics of the FTLDNI and GENFI2 samples**

	FTLDNI N=193			GENFI2 N=322		
	CNCs N=123	bvFTD N=70	p-value	CNCs N=247	bvFTD N=75	p-value
Total number of scans	326	156		409	119	
Age mean (SD), y	63±6	62±6	0.36	48±14	64±8	< 0.001
Male sex no. (%)	53(43%)	47(67%)	0.001	106(43%)	41(55%)	0.07
Education mean (SD), y	17.5±1.9	15.6±3.4	< 0.001	13.9±3.5	11.8±4.03	< 0.001
Estimated years of onset mean (SD), y	-	N/A	-	-	5.2±5.7	-
Disease duration mean [min-max], y					5.1[3.5-8.2]	
MMSE score mean (SD)	29.4±0.8	23.6±4.9	< 0.001	29.4±1.1	21.9±7.2	< 0.001
FTLD-CDR Score mean (SD)	0.04±0.2	6.3±3.3	< 0.001	0.21±0.7	9.7±1.4	< 0.001
Genetic Group no. (%)						
C9orf72	-	-		-	39(52%)	
MAPT	-	-		-	17(22.7%)	
GRN	-	-		-	19(25.3%)	

2
3 CNCs in GENFI2 cohort correspond to non-carrier first degree relative of a family member with a documented genetic mutation related to
4 FTD. Genetic groups listed for CNCs in the GENFI2 cohort refer to mutation present in the family of these non-carrier subjects. Values are
5 expressed as mean ± standard deviation, median [interquartile range]. Data available is specified for each clinical variable as N, whereas N/A
6 indicates data not available from the original databases. (FTLDNI: frontotemporal lobar degeneration neuroimaging initiative; GENFI: genetic
7 frontotemporal dementia initiative; bvFTD: behavioral-variant frontotemporal dementia; CNCs: cognitively normal controls; MMSE: Mini
8 Mental State Examination. FTLD-CDR: Frontotemporal lobar degeneration clinical dementia rating.)

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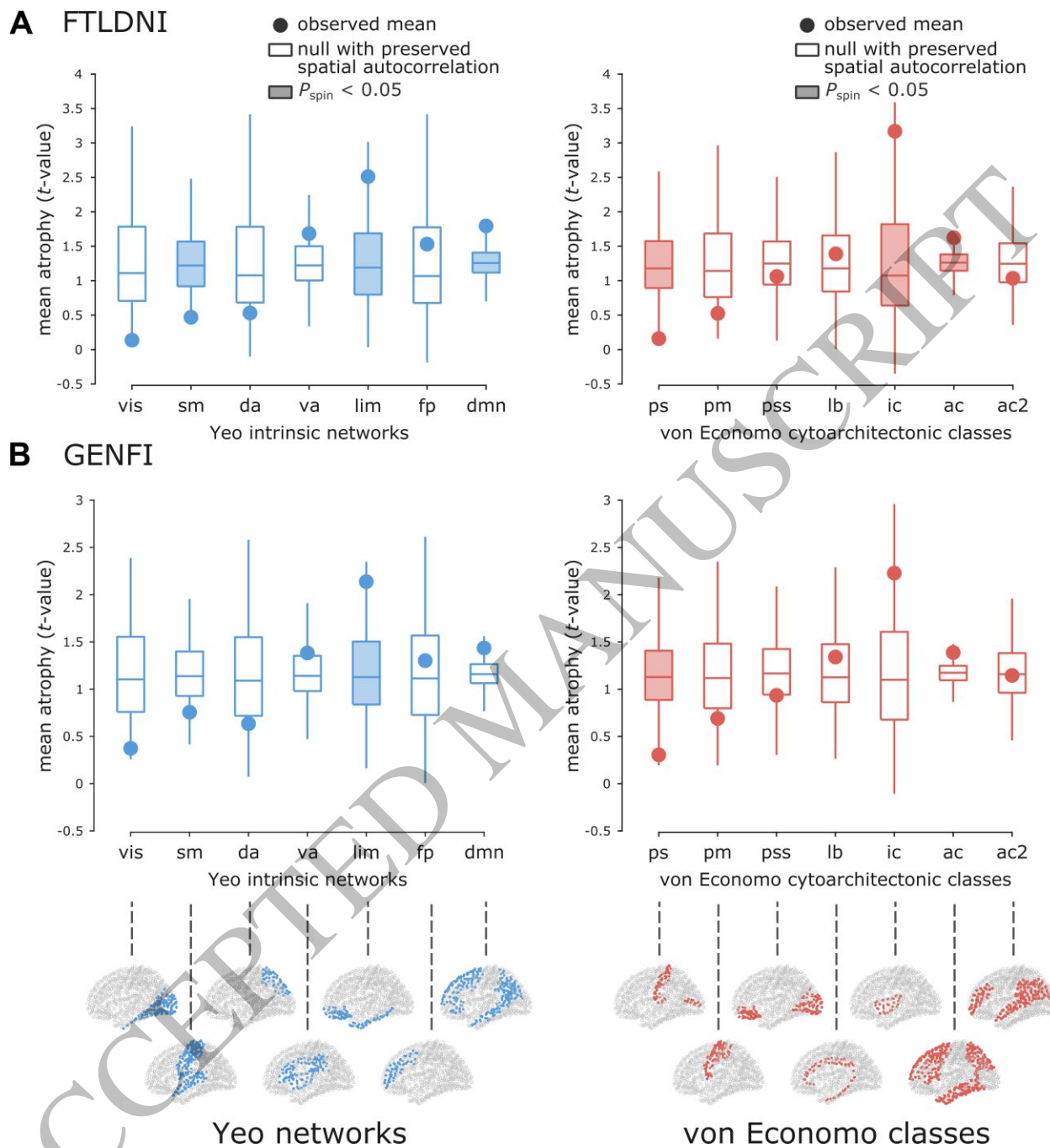
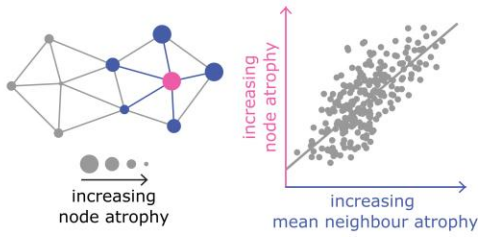


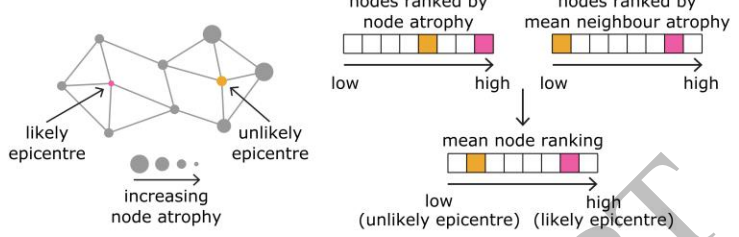
Figure 1
 165x178 mm (6.0 x DPI)

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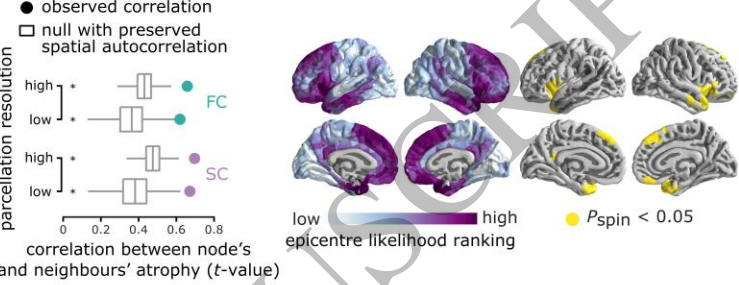
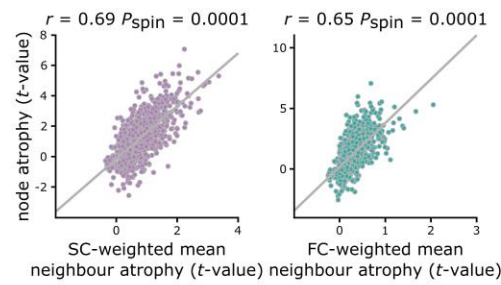
A node-neighbour relationship



B epicentre



C FTLDNI



D GENFI

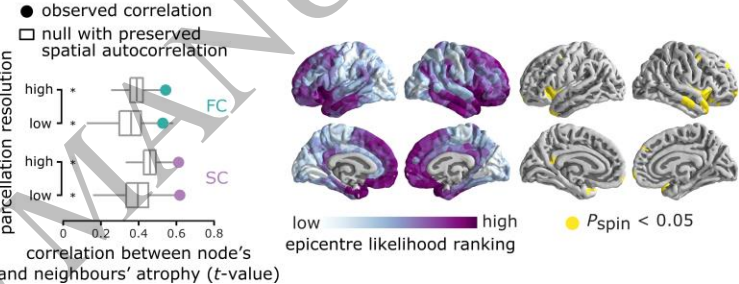
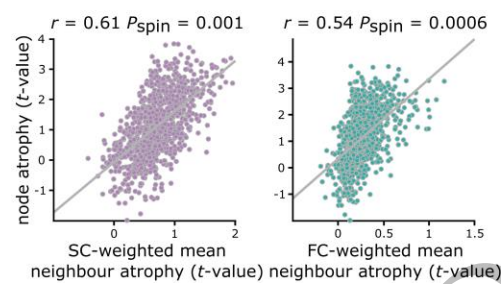
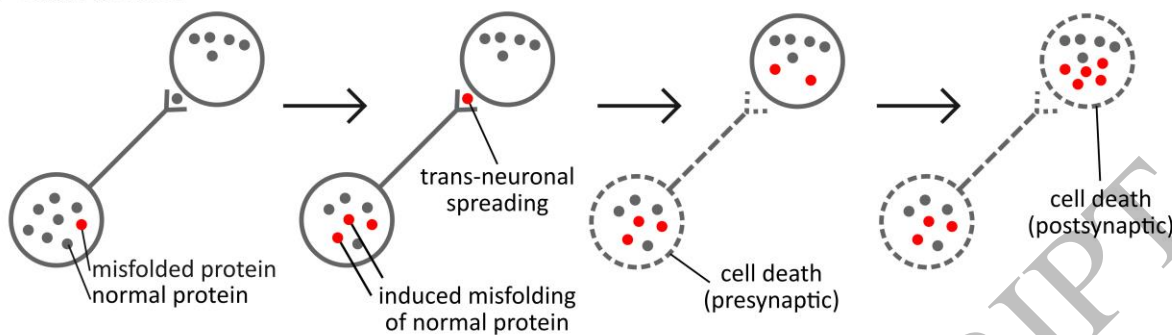


Figure 2
165x121 mm (6.0 x DPI)

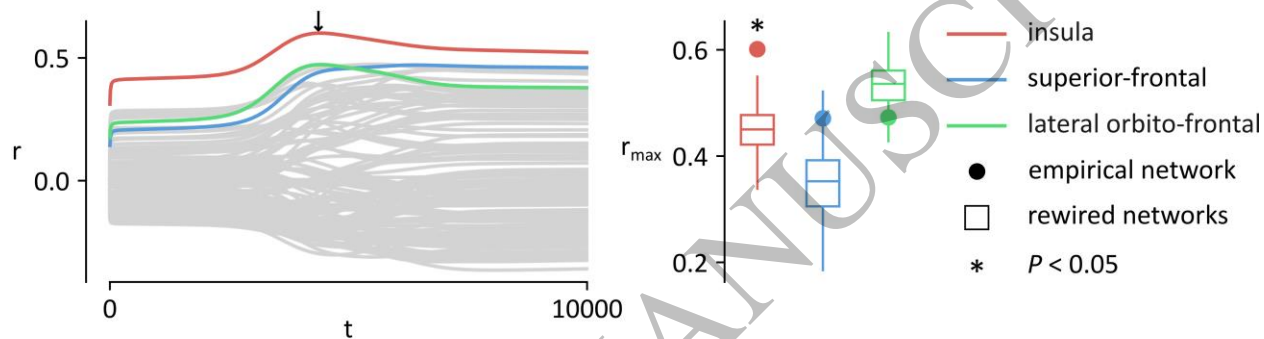
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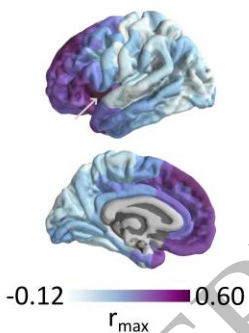
A S.I.R model



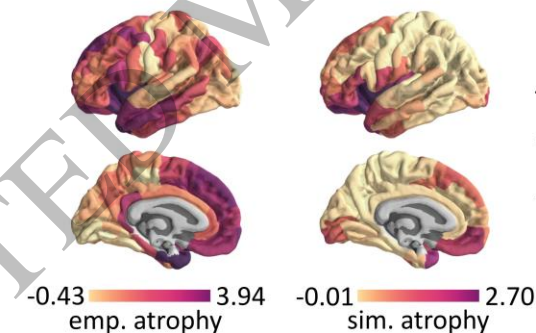
B model fit



C r_{max} distribution



D best seed region (insula)



$r = 0.60$ $P_{spin} = 0.0013$

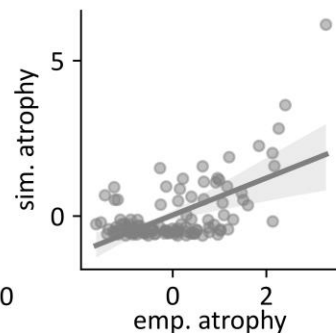
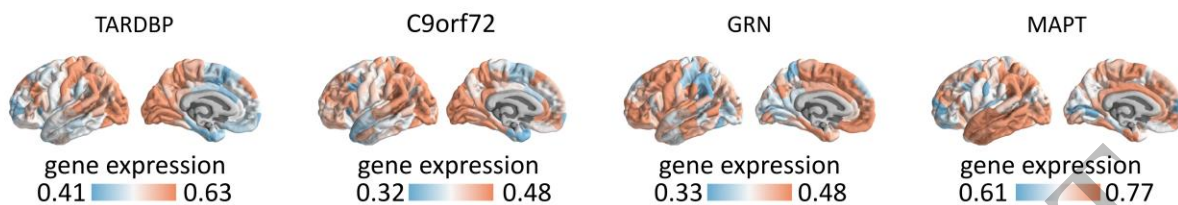


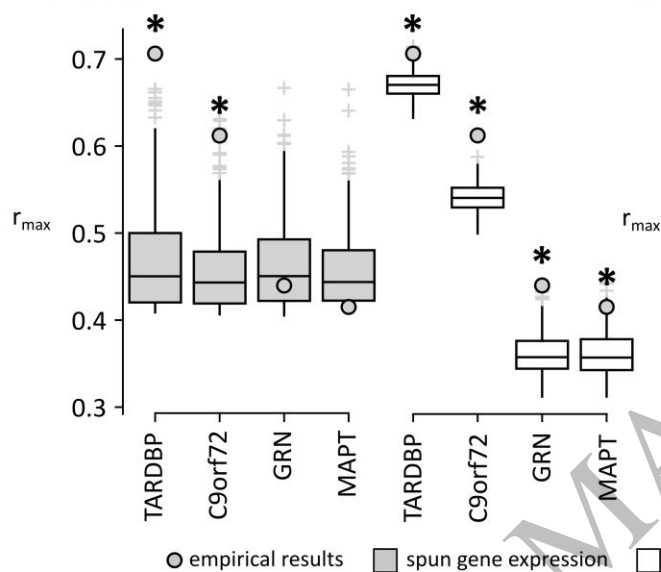
Figure 3
165x154 mm (6.0 x DPI)

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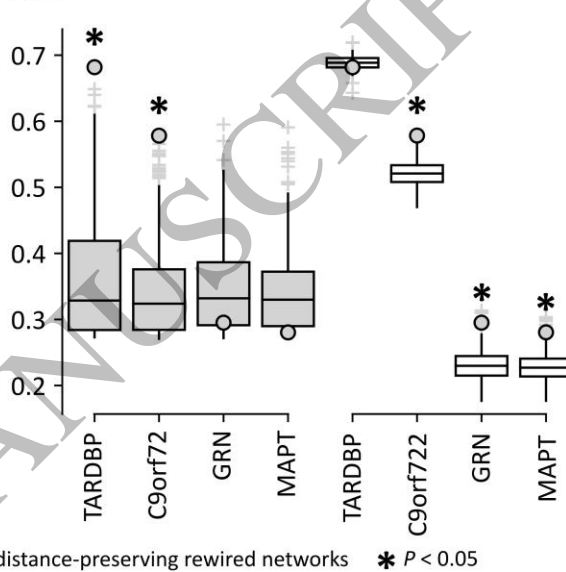
A gene expression



B FTLDNI



C GENFI

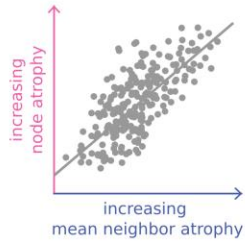
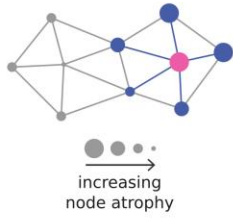


○ empirical results ■ spun gene expression □ distance-preserving rewired networks * $P < 0.05$

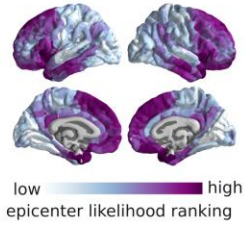
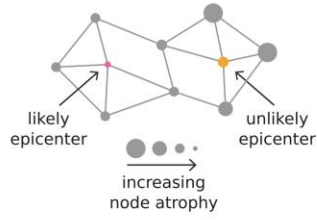
Figure 4
165x116 mm (6.0 x DPI)

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FTD network atrophy



epicenter mapping



network spreading with local genetic vulnerability

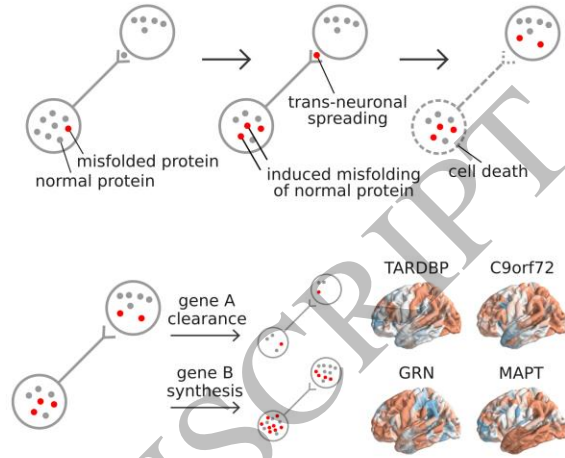


Figure 5
165x83 mm (6.0 x DPI)

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