# Principal axis of laminar thickness covariance in the human cortex

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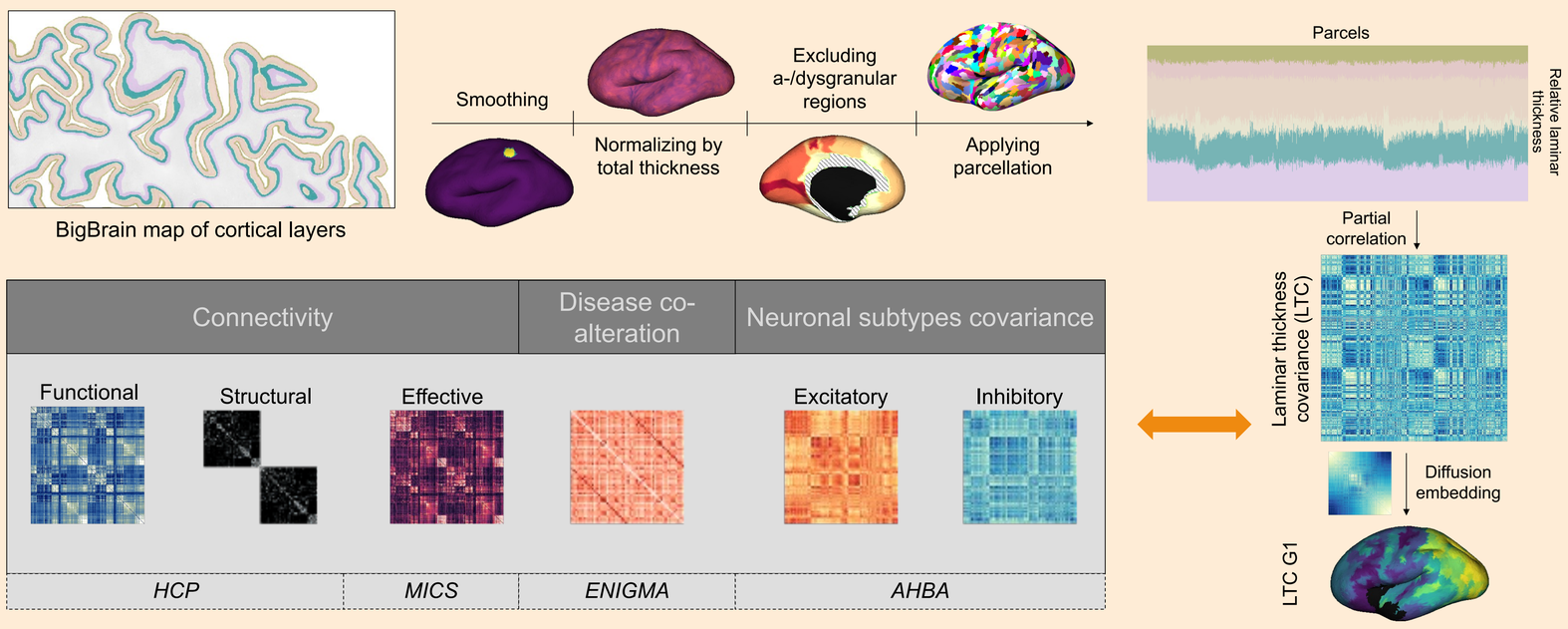
## Introduction

**We quantitatively characterized the main axis of laminar thickness covariance, and studied its relation to connectivity, disease vulnerability and microcircuitry, using a deep-learning based approximation of six cortical layers in the BigBrain[1].**

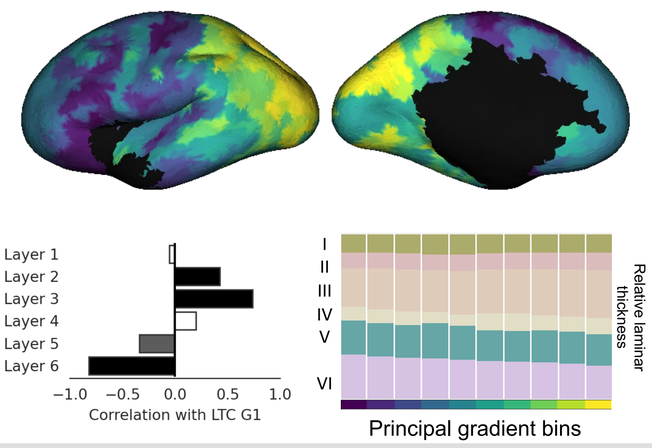
- Laminar thickness varies along the cortical mantle[2]
- Laminar cytoarchitecture (dis)similarity of two regions is related to their connectivity (The Structural Model)[3]
  - Similarity ➔ Strength
  - Dissimilarity ➔ Direction (feedback/-forward)
- Laminar cytoarchitecture also relates to the degree of plasticity and disease vulnerability[3]
- Excitatory and inhibitory neuronal subtypes have specific laminar and regional distribution[4]

## Methods

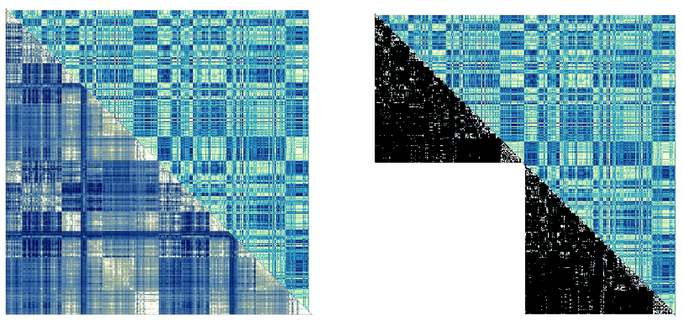



## Results

### Laminar thickness covariance gradient differentiates dominance of deep versus superficial layers



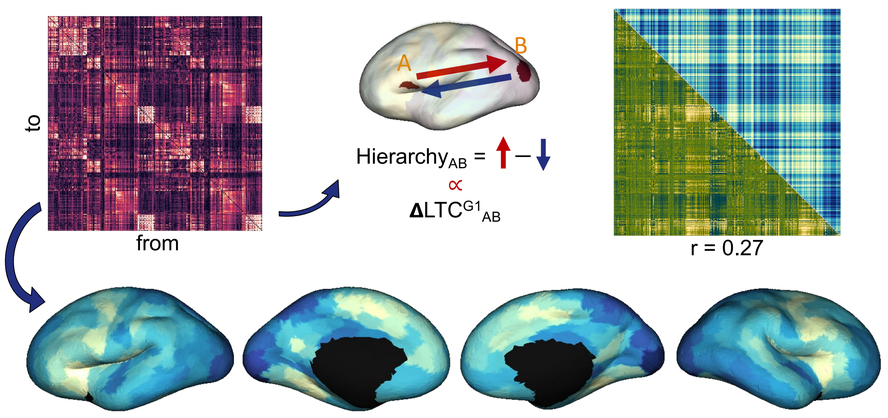

### Regions with similar laminar structure connect together



Functional connectivity (r = 0.16)

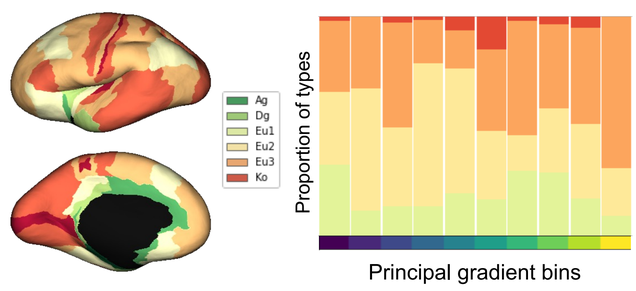
Structural connectivity (r = 0.25)

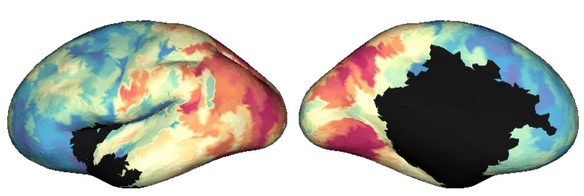
### Difference of laminar structure relates to cortical hierarchy




Hierarchical strength = Out-degree – In-degree
(r = 0.39, p < 0.001)

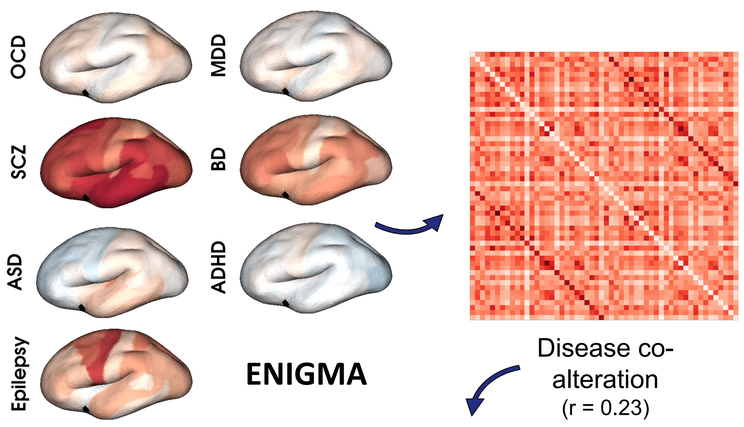
### Laminar thickness covariance is aligned with cortical types and microstructural profile covariance

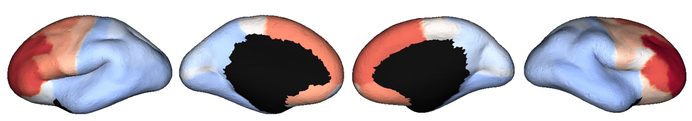


Principal gradient of BigBrain microstructural profile covariance
(r = 0.63, p < 0.001)

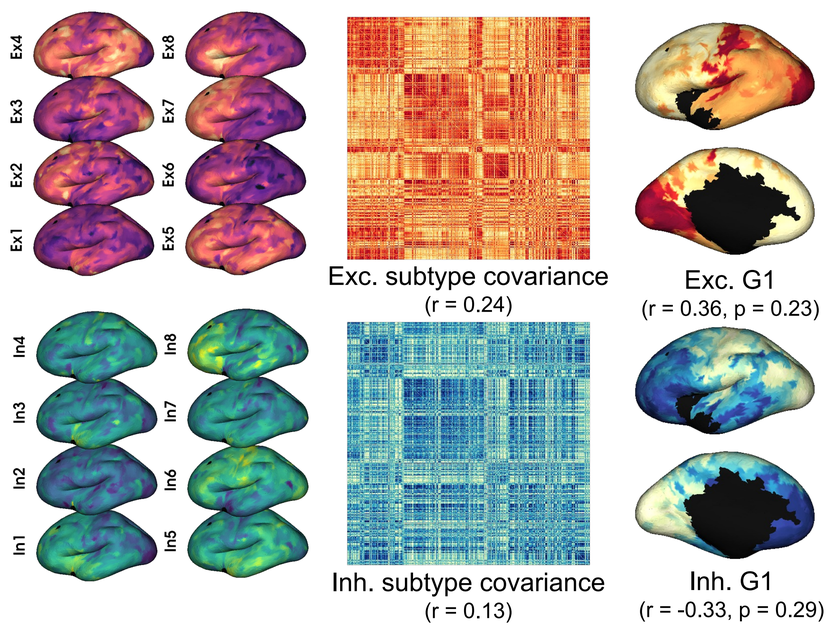
### Regions with similar laminar structure are similarly impacted in disorders



Principal gradient of disease co-alteration
(r = -0.49, p < 0.001)

### Main axes of neuronal subtypes covariance and laminar thickness covariance do not correlate




## Discussion

**Principal axis of laminar thickness covariance**

- The main axis of cortical laminar thickness covariance differentiates the dominance of infragranular and supragranular layers, spanning frontal ➔ temporal ➔ occipital and parietal regions.
- This axis is highly correlated to the main axis of microstructural profile covariance in the BigBrain[5] and shows some correspondence to the map of cortical types[6], transitioning from eulaminate I and II towards eulaminate III regions.

**Association of laminar thickness covariance with connectivity and hierarchy**

- Regions with similar laminar structure tend to connect together (structural > functional).
- Regions with more prominent infragranular layers have higher hierarchy, i.e., influence the activity in other regions. This may relate to the laminar pattern of feedback/-forward connections.

**Association of laminar thickness covariance with disease vulnerability**

- The main axis of laminar thickness covariance is aligned with the main axis of disease co-alteration[7], which supports the hypothesis that disease vulnerability of regions relate to their laminar structure[3].

**Laminar thickness covariance in relation to regional covariability of neuronal subtypes**

- Main axes of covariance in excitatory and inhibitory neuronal subtypes showed a sensory-transmodal pattern, but were not significantly correlated to the main axis of laminar thickness covariance.

**Limitations**

- This study was based on the laminar thickness data from a single individual and needs to be validated in more subjects.

## References

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