

GWAS and Candidate Studies of MRI and Amyloid PET Phenotypes for Alzheimer's Disease

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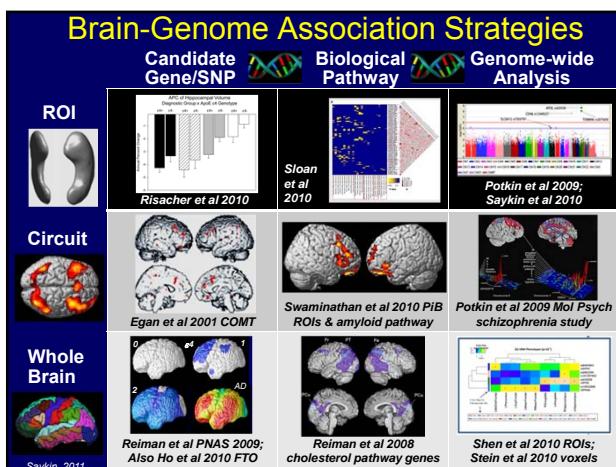
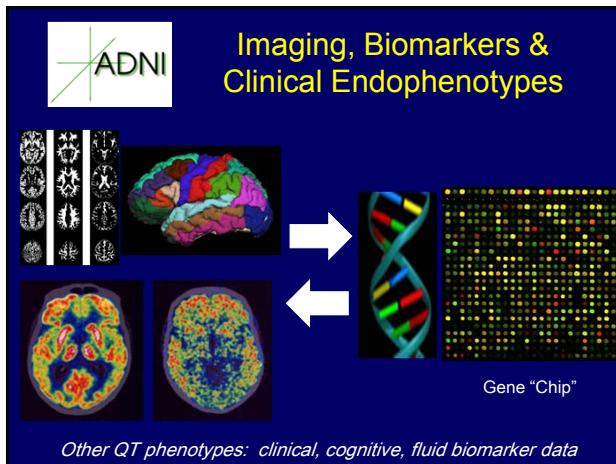
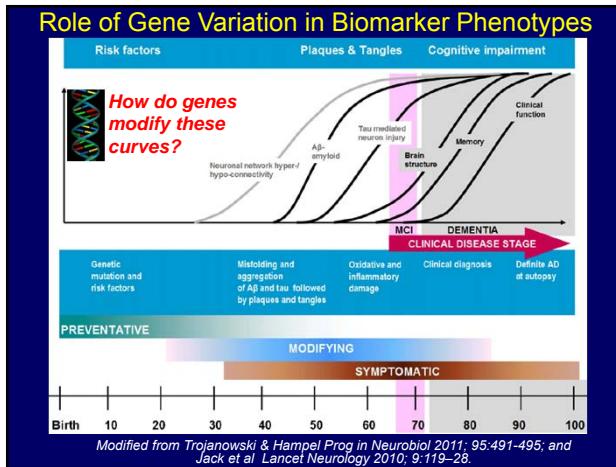


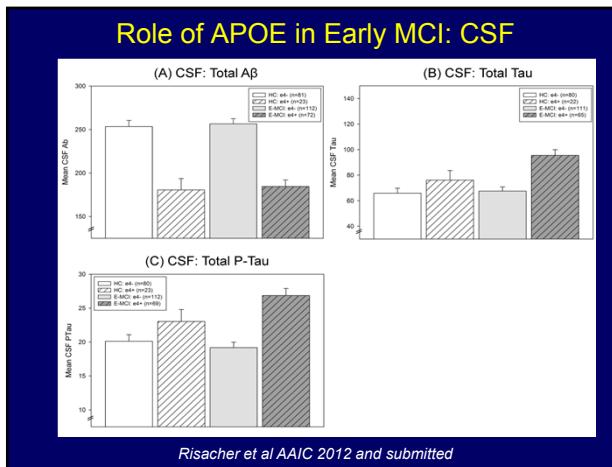
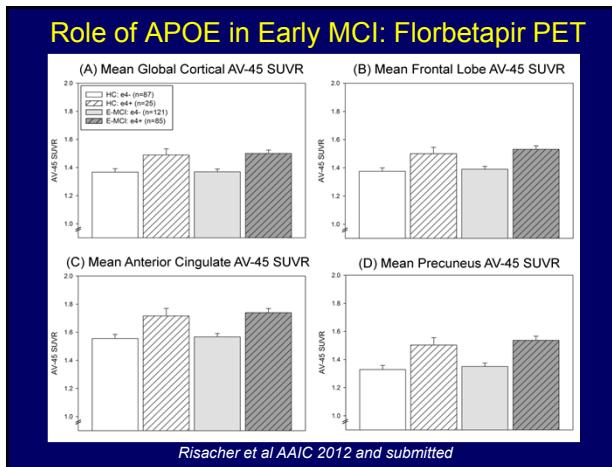
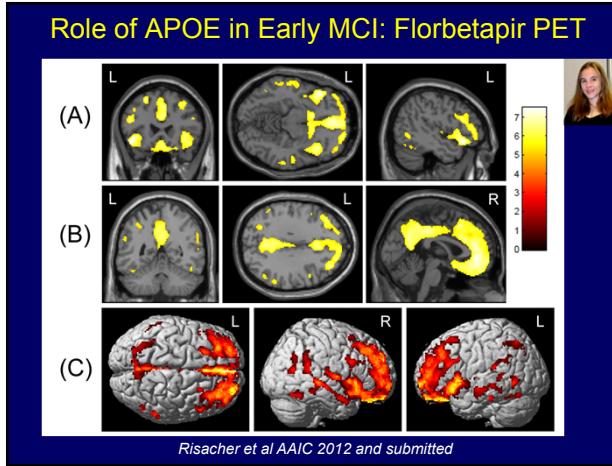
Acknowledgements & Disclosures

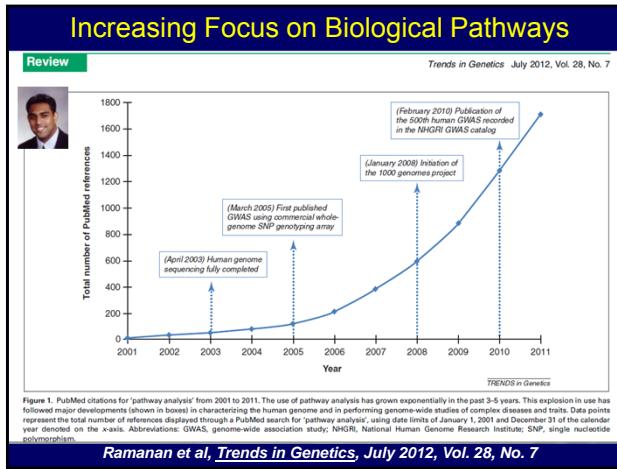
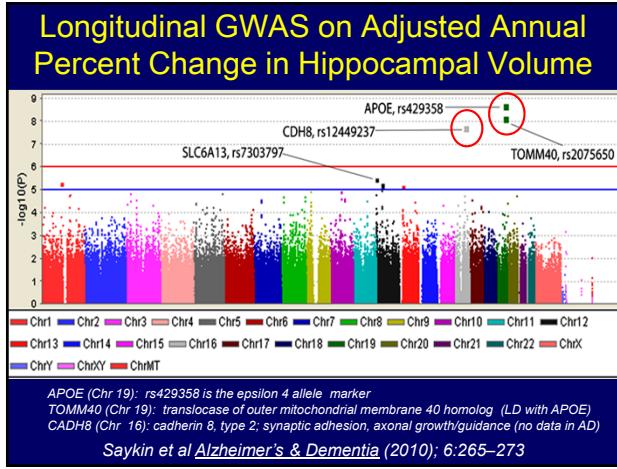
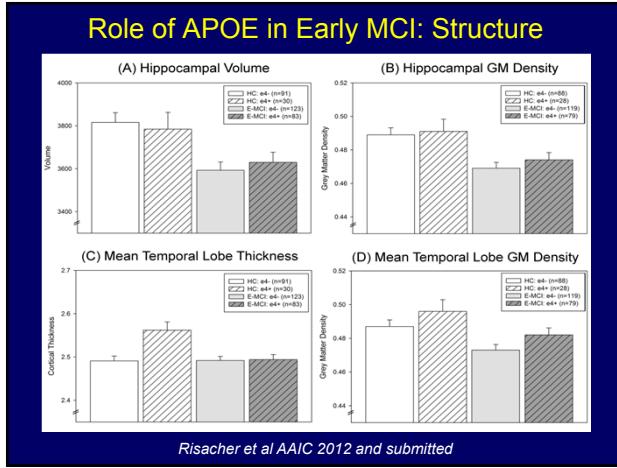
- National Institute on Aging
 - ADNI U01 AG024904 & RC2 AG036535
 - R01 AG19771 & P30 AG10133
 - U01 AG032984, U24 AG21886, P30 AG010129, K01 AG030514
- Natl. Inst. of Biomedical Imaging and Bioengineering
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 - Anonymous Foundation (Challenge Grant)
 - Gene Network Sciences, Merck, Pfizer (DNA ext.)
- Alzheimer's Association & Brin Wojcicki Foundation
 - Sequencing of ADNI-GO/2
- Saykin disclosures for related work:
 - Siemens Healthcare, Welch-Allyn, Eli Lilly

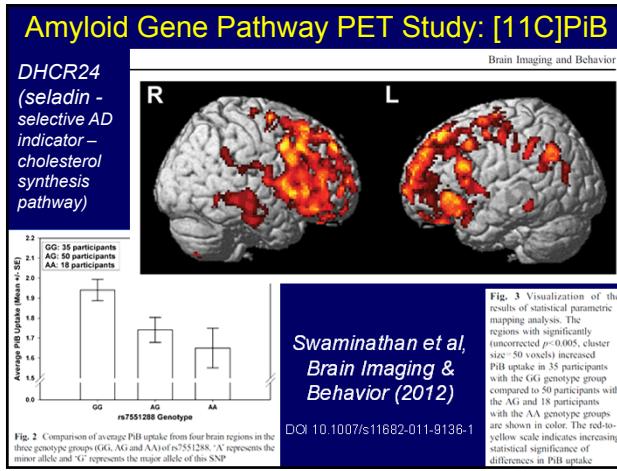
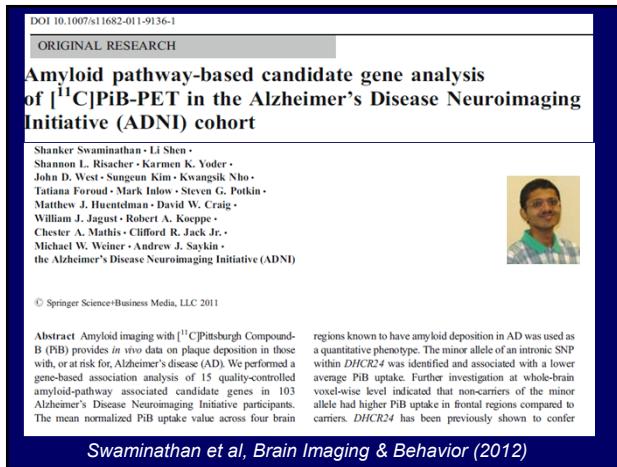
Overview

- Neuroimaging as an endophenotype
 - Enhanced statistical power and proximity to biology
- Methodological issues in mapping between quantitative biomarker phenotypes and genetic data
- Emerging findings, challenges & future directions:
 - Genome-wide whole brain analysis – MRI phenotypes
 - Candidate gene and pathway-based analyses
 - Example: PiB PET
 - New Flortetapir PET GWAS
 - Ongoing work and new directions
 - Exome and Whole Genome Sequencing





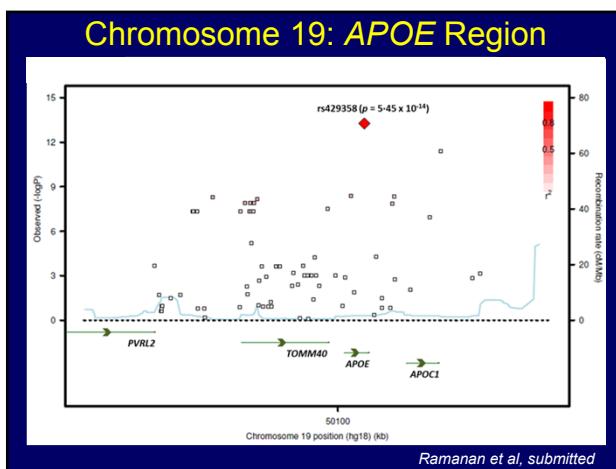
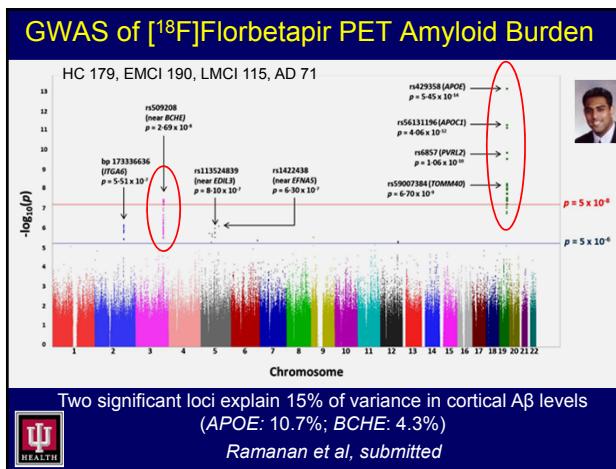
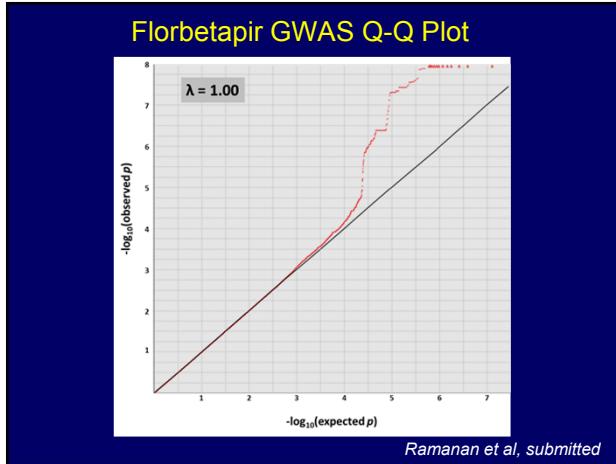


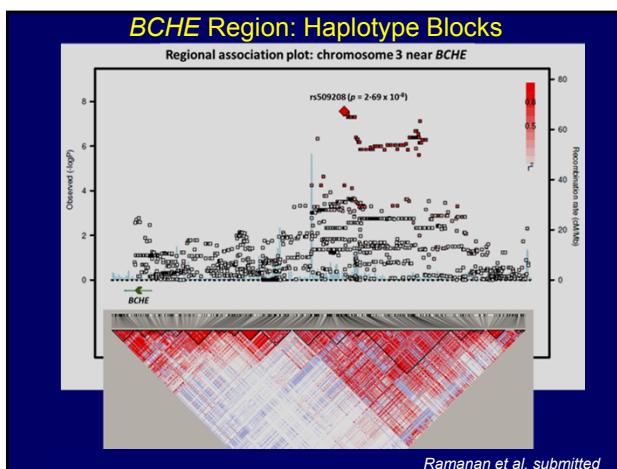
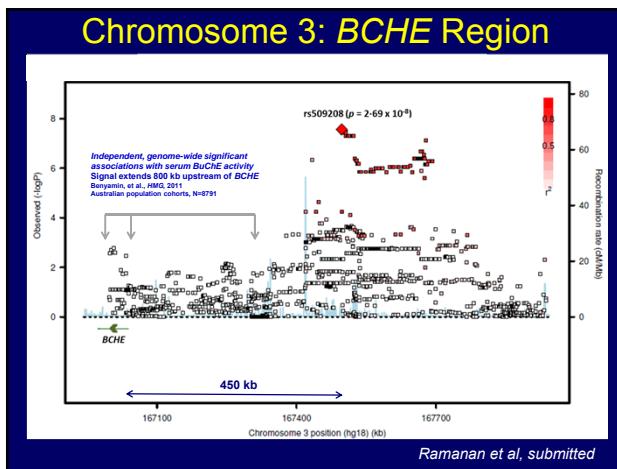
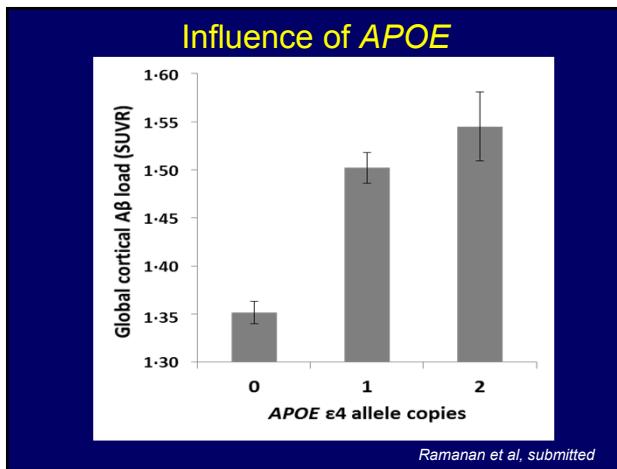


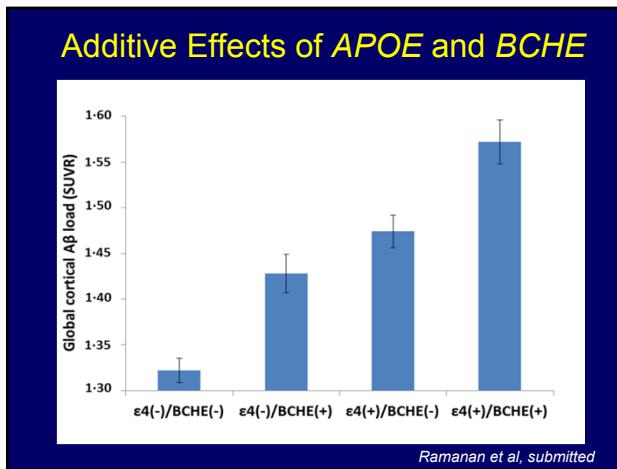
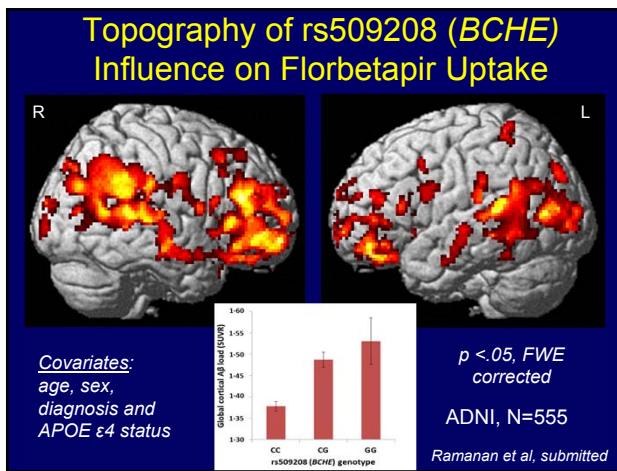
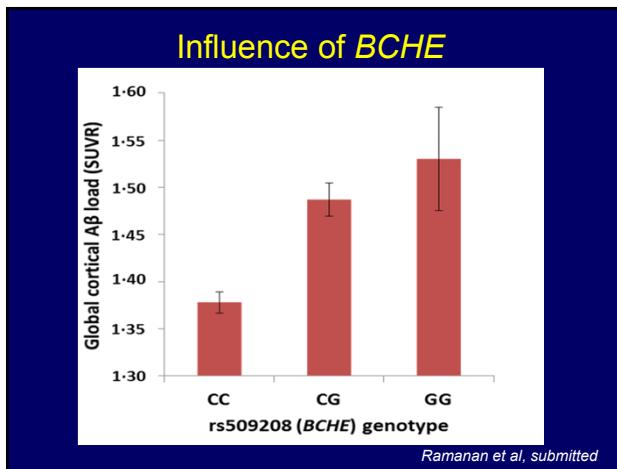
[¹⁸F]Florbetapir GWAS Sample (ADNI-GO/2, N=555)

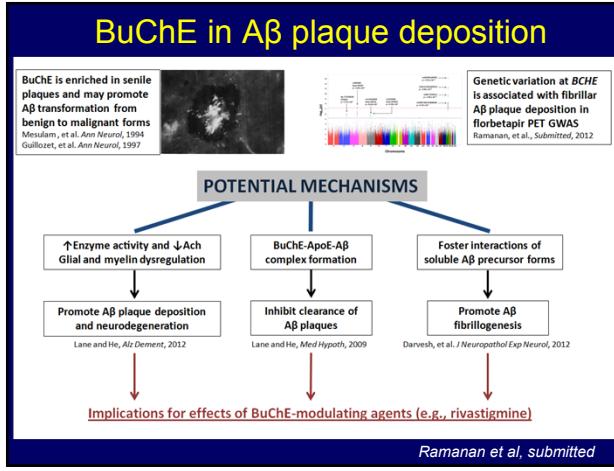
	HC (n=179)	EMCI (n=190)	LMCI (n=115)	AD (n=71)
Age (years)	76.68 (6.25)	71.04 (7.41)	75.61 (8.14)	75.87 (8.15)
Gender (women, %)	87 (49%)	83 (44%)	41 (36%)	27 (38%)
Education (years)	16.27 (2.72)	15.89 (2.65)	16.11 (2.90)	16.04 (2.87)
APOE ε4 allele (present, %)	41 (23%)	77 (41%)	49 (43%)	45 (64%)
CDR-SOB	0.07 (0.29)	1.22 (0.73)	1.73 (1.18)	5.63 (2.70)
Mini Mental Status Examination	29.07 (1.25)	28.39 (1.52)	27.74 (1.84)	21.68 (4.24)
Logical Memory Immediate Recall (WMS-R)	14.94 (3.36)	10.93 (2.81)	8.74 (4.35)	4.20 (3.10)
Logical Memory Delayed Recall (WMS-R)	14.08 (3.64)	8.87 (1.73)	6.13 (4.38)	1.67 (2.50)

Data are number (%) or mean (SD). CDR-SOB = Clinical Dementia Rating-Sum of Boxes. WMS-R = Wechsler Memory Scale-Revised. PET = positron emission tomography.
Ramanan et al., submitted









Combining Imaging and Proteomic Biomarkers to Enhance Detection

Identifying Neuroimaging and Proteomic Biomarkers for MCI and AD via the Elastic Net

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Abstract. Multi-modal neuroimaging and biomarker data were preexisting, but not integrated, in our studies. This study focuses on integrative analysis of structural MRI and proteomic data from an RHM panel to examine their relative power and identify relevant biomarkers. A learning machine was used to predict the presence of Alzheimer's disease based on proteomic measures. The proteomic measures of 88 regions estimated by FreeSolvR. RHM data included 146 proteomic analyses extracted from plasma and serum. A sparse learning model, elastic net logistic regression, was proposed to predict AD, MCI, and healthy control status. A support vector machine and a support vector machine coupled with feature selection were employed for comparison. Combining RHM and MRI data resulted in better performance: HD vs AD (0.975 vs 0.86), HD vs MCI (0.905 vs 0.805) and MCI vs AD (0.86 vs 0.75). This study demonstrated that the learning machine identified a small set of relevant neuroimaging and proteomic biomarkers. The elastic net has great power to optimize the sensitivity of feature selection while maintaining high predictive power. Its application to multi-modal imaging and proteomic data has the potential to identifying biomarkers and enhancing mechanistic understanding of AD and MCI.

Integrating structural MRI and RBM plasma proteomic panel data significantly decreased classification errors

Shen, Kim, Qi et al
Lect Notes Comput Sci
2011;7012:27-34

Whole exome sequencing: rate of hippocampal change in extreme phenotype design

