

Defining DNA Methylation Signatures Associated with Metabolic Dysfunction in a Mexican American Cohort



Melanie Carless

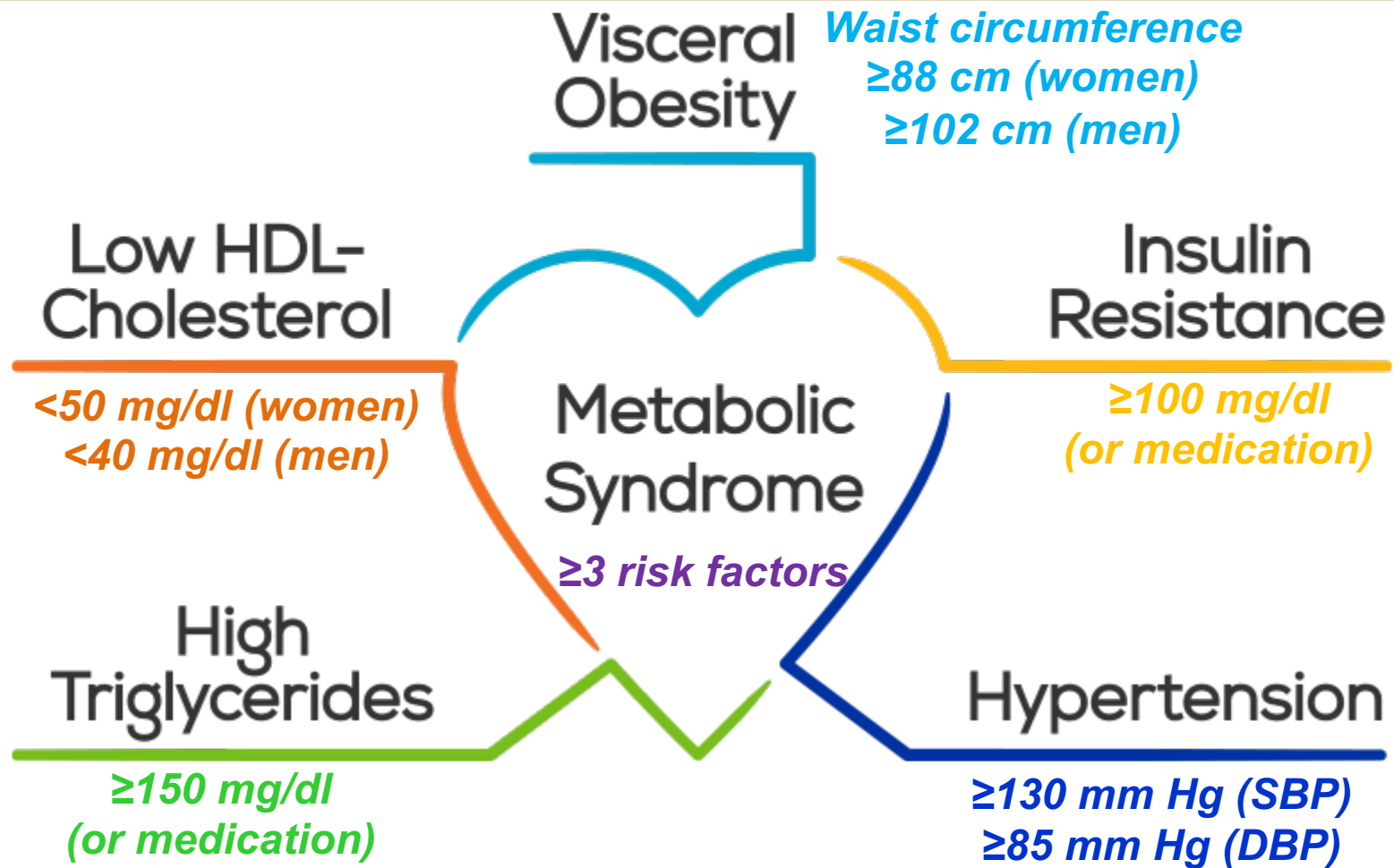
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Population Health Program

**TEXAS BIOMEDICAL
RESEARCH INSTITUTE**

Metabolic Syndrome (MetS)

Risk Factors



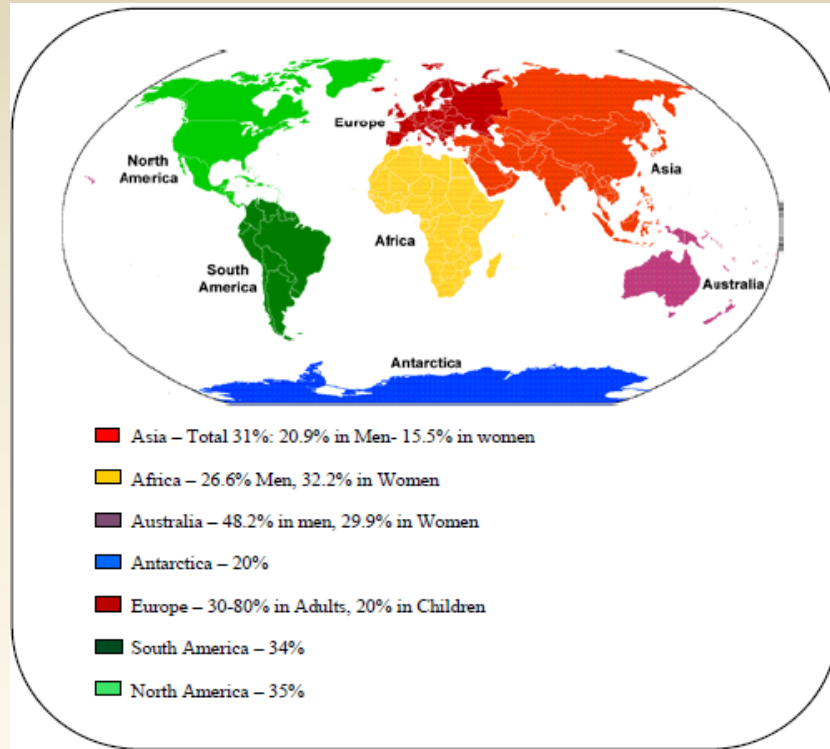
Metabolic Syndrome

Consequences

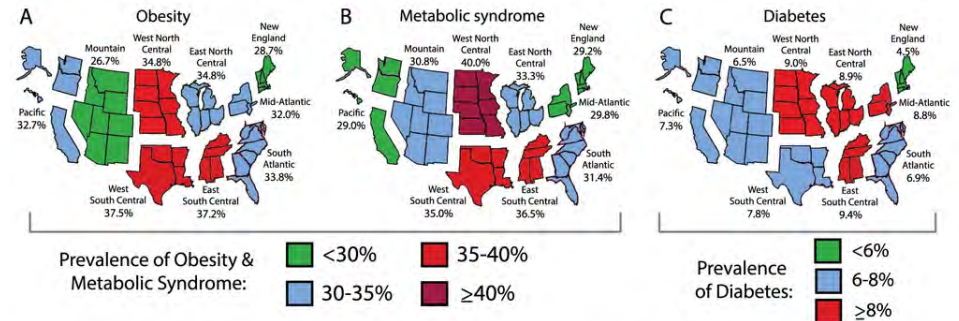


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Metabolic Syndrome Prevalence



From: Geographical variation in the prevalence of obesity, metabolic syndrome, and diabetes among US adults



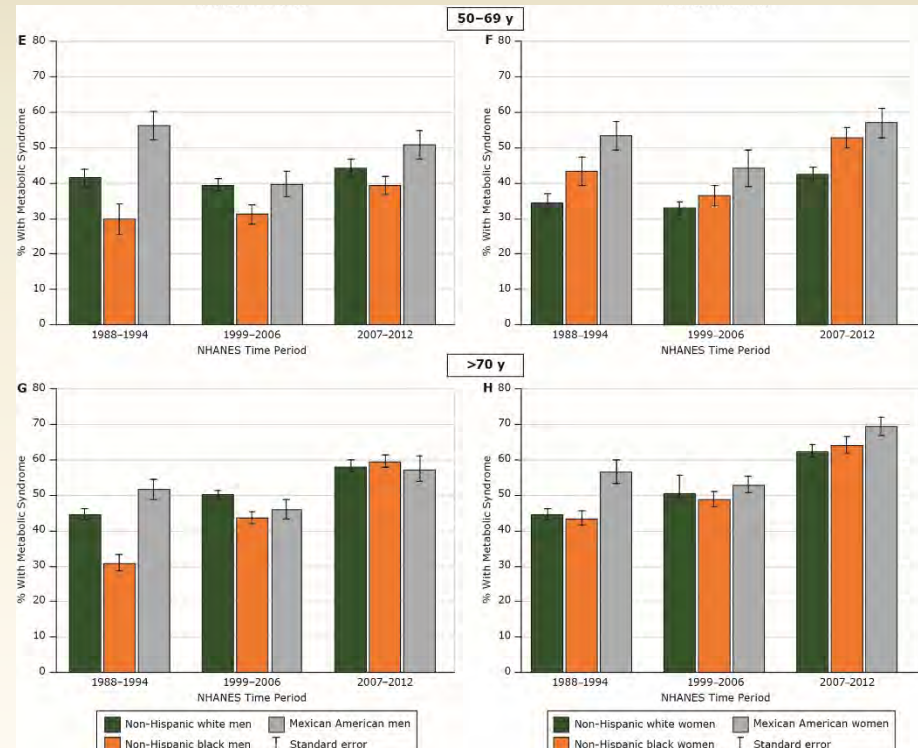
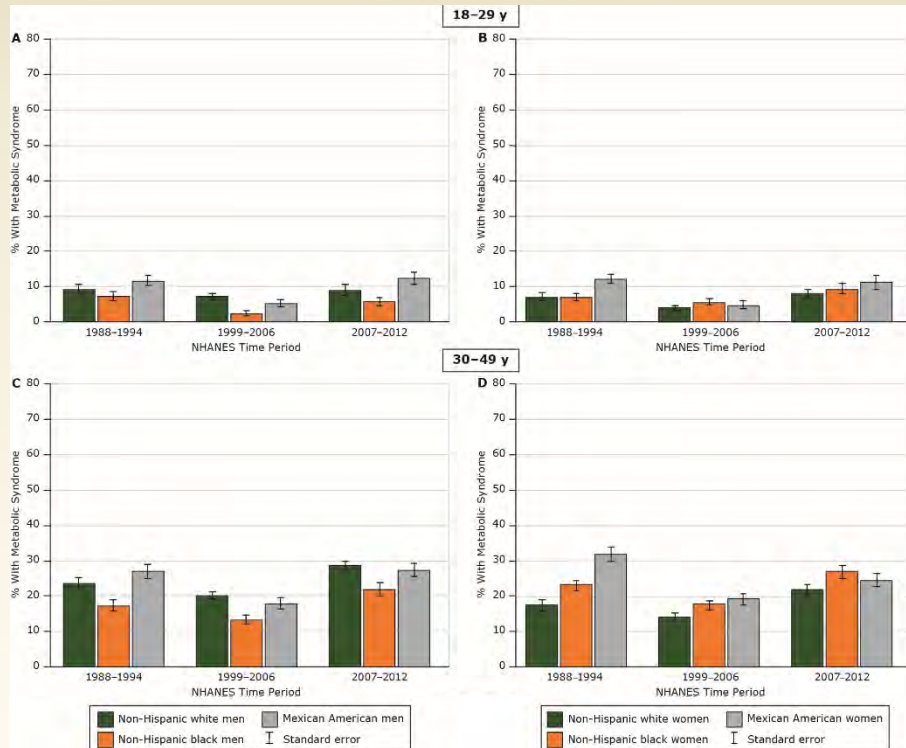
Data shown for prevalence of **a** obesity, **b** metabolic syndrome, and **c** diabetes are among US adults aged 20–65 years, from the National Health and Nutrition Examination Survey, 1999–2014

Gurka *et al* (2018) *Nutrition and Diabetes* 8:14.

Pudata and Konduru (2011) *Journal of Diabetes and Metabolism*

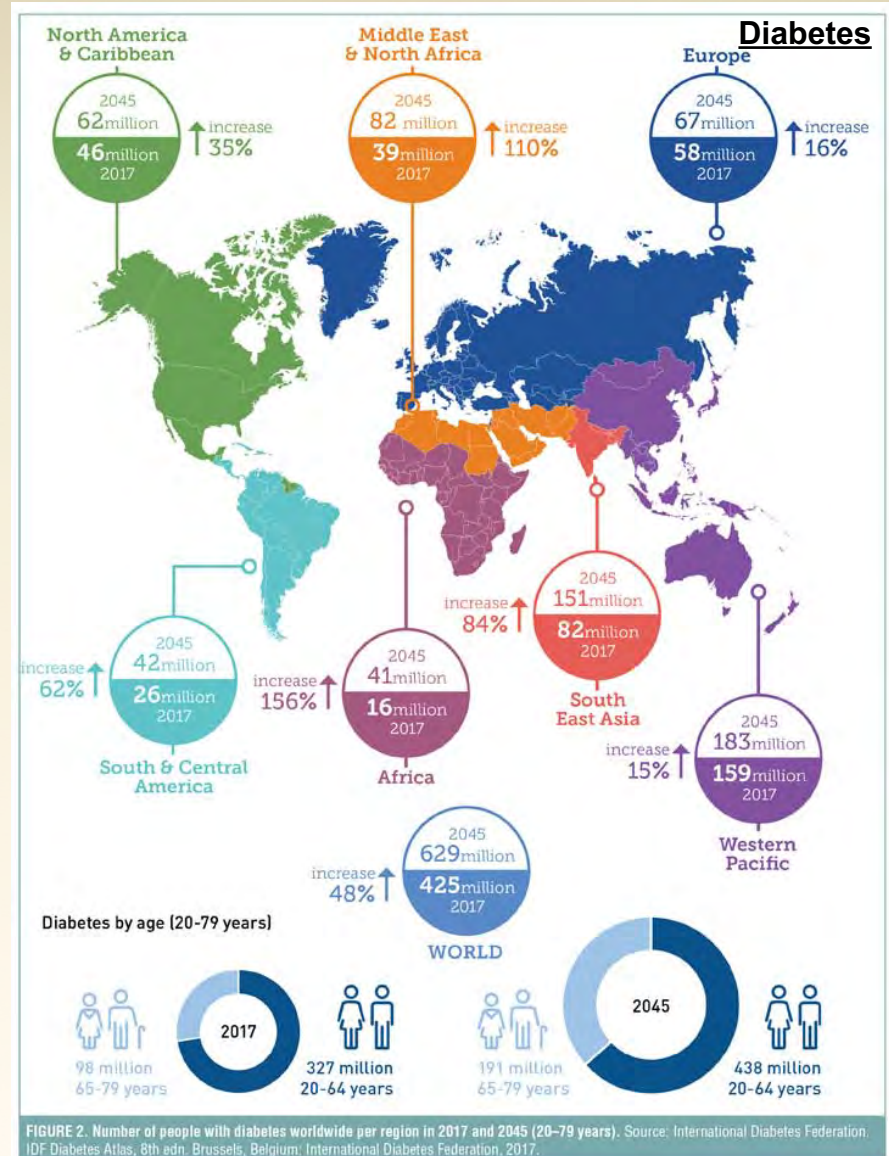
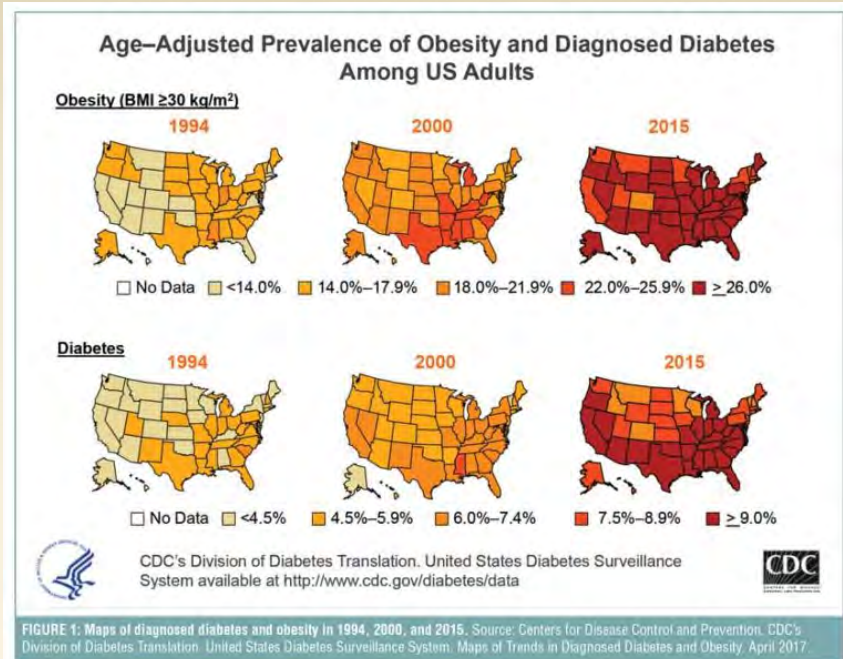
Metabolic Syndrome

At risk populations



How did we get here?

Where are we going?



San Antonio Family Heart Study

- 👉 Ongoing study of Mexican Americans to understand the genetics of complex diseases
 - 👉 Initiated in 1991 (to present); 5 collections
 - 👉 Large pedigrees (family-based study)
 - 👉 Extensive phenotypic data related to MetS

Trait	Visit 1	Visit 2	Visit 3	Visit 4
# Examined	1,431	859	950	1,378
Mean age at exam	39.3	42.9	47.5	44.8
Hypertension (%)	17.8	28.8	34.8	32.3
Obesity (%)	38.8	50.4	54.7	55.5
Type 2 diabetes (%)	15.1	19.7	21.3	20.1
Lipid lowering medication (%)	1.8	5.2	14.2	16.6
Metabolic Syndrome (%)		42.9	42.2	

Why Epigenetics?

... genetic variants explain little of phenotypic variance

Trait	Heritability* (p-value)	GWAS-Explained Phenotypic Variance	Reference
Type 2 diabetes	0.61 (2.0×10^{-7})	17.5% (AA)	Ng <i>et al</i> , 2014. PLoS Genet, 10:e1004517.
Fasting glucose	0.42 (4.5×10^{-23})	4.8% (C)	Scott <i>et al</i> , 2012. Nat Genet, 44:991-1005.
Fasting insulin	0.42 (4.5×10^{-21})	1.2% (C)	
2hr glucose	0.37 (2.1×10^{-17})	1.7% (C)	
Total cholesterol	0.45 (4.6×10^{-28})	12.4% (C)	Teslovich <i>et al</i> , 2010. Nature, 466:707-13.
Triglycerides	0.49 (7.2×10^{-31})	9.6% (C)	
HDLC	0.54 (1.4×10^{-38})	12.1% (C)	
LDLC	0.36 (3.0×10^{-17})	12.2% (C)	
BMI	0.54 (5.9×10^{-37})	1.4% (C) (adj.) 16.5% (M) (all autosomal SNPs)	Shungin <i>et al</i> , 2015. Nature, 518:187-96. Yang <i>et al</i> , 2011. Nat Genet, 43:519-25.

* Heritability determined for the San Antonio Family Study cohort (Mexican Americans)

A: African American cohort

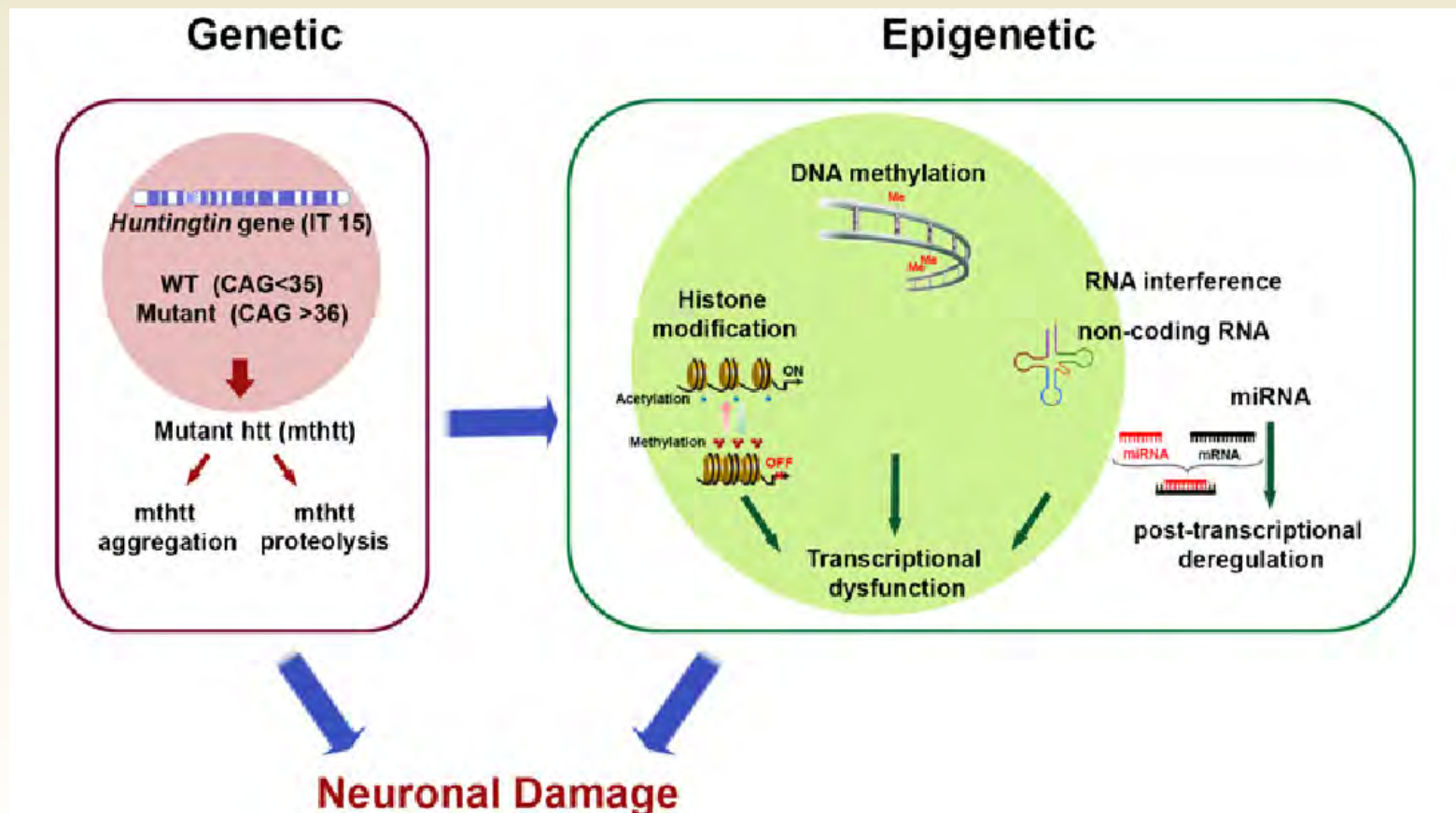
C: Caucasian cohort

M: Mixed race

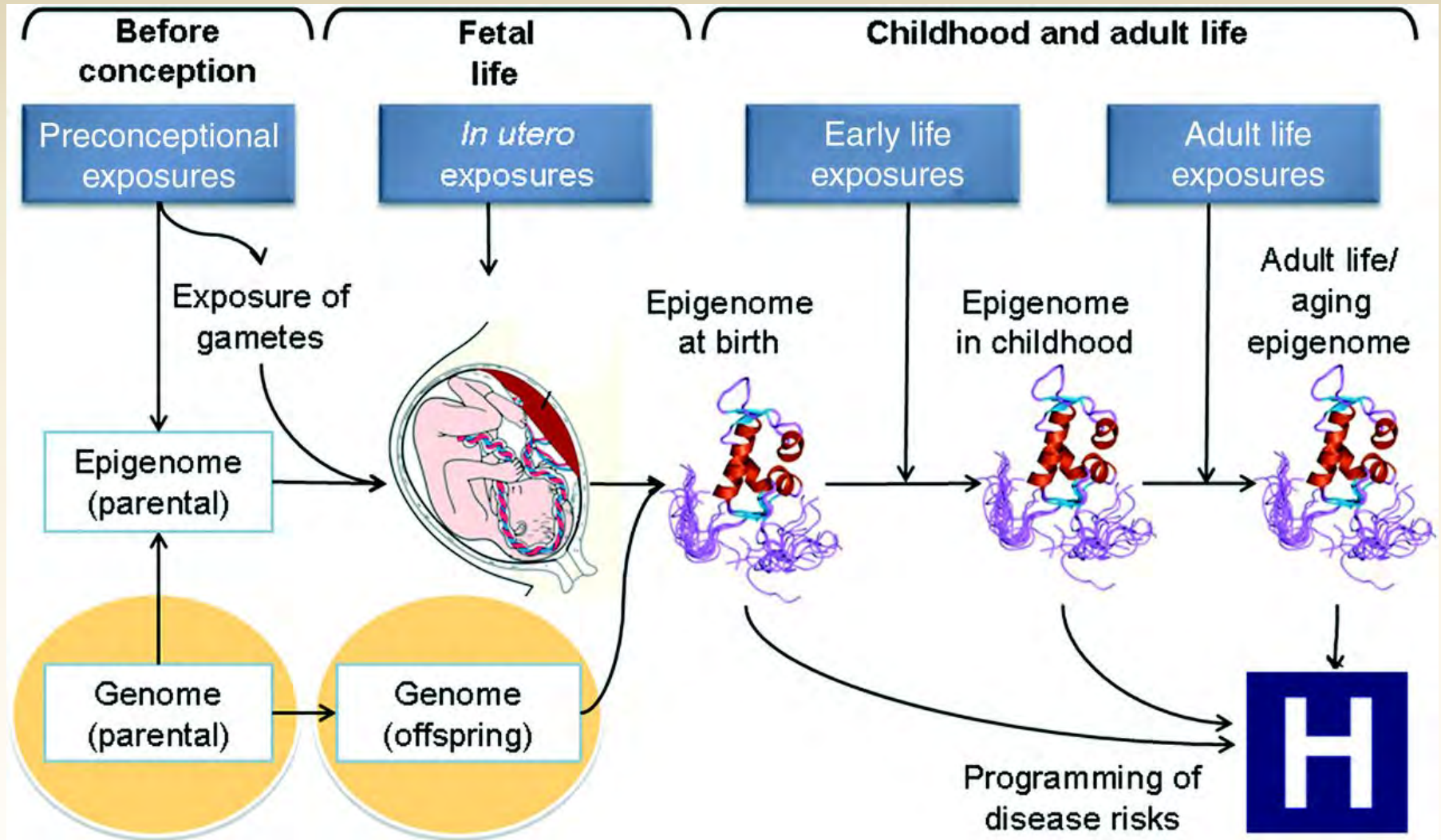
adj.: Adjusted for waist hip ratio

Epigenetics

Heritable phenotype changes that do not involve alterations in the DNA sequence
~ typically affects gene activity and expression



Why/When Does Epigenetics Matter?



DNA Methylation

- Covalent addition of methyl group at C5 position of cytosines in cytosine-guanine (CpG) dinucleotides
- Typically silences gene expression, but may increase expression, terminate transcription, or alter splicing
- May predispose to additional mutational events

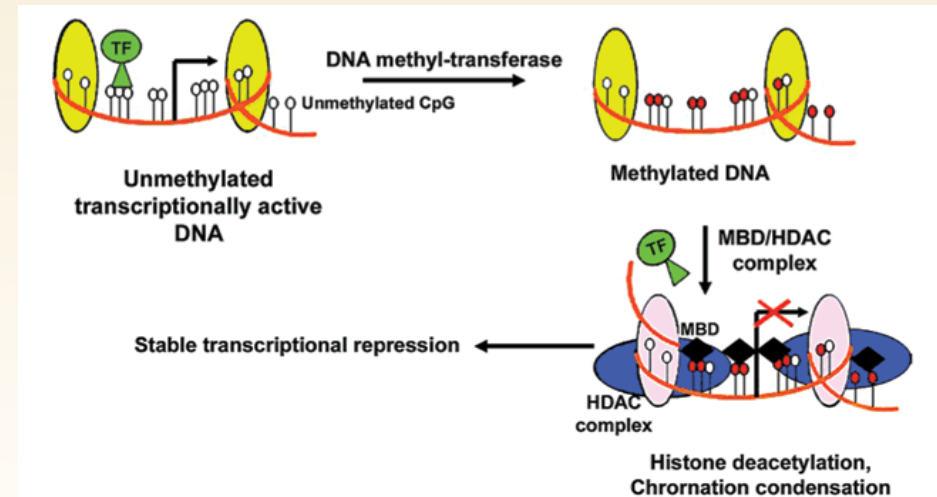
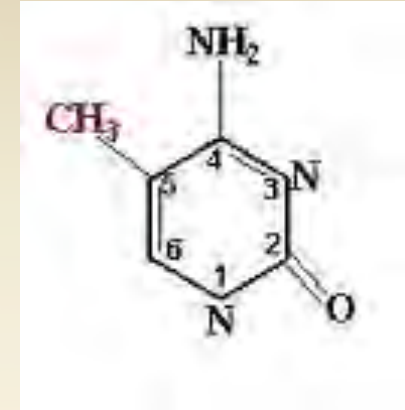
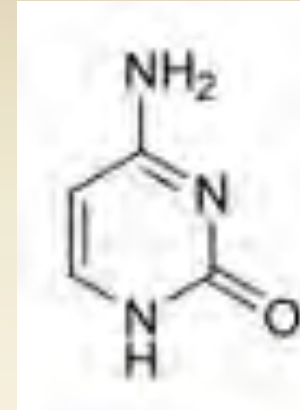
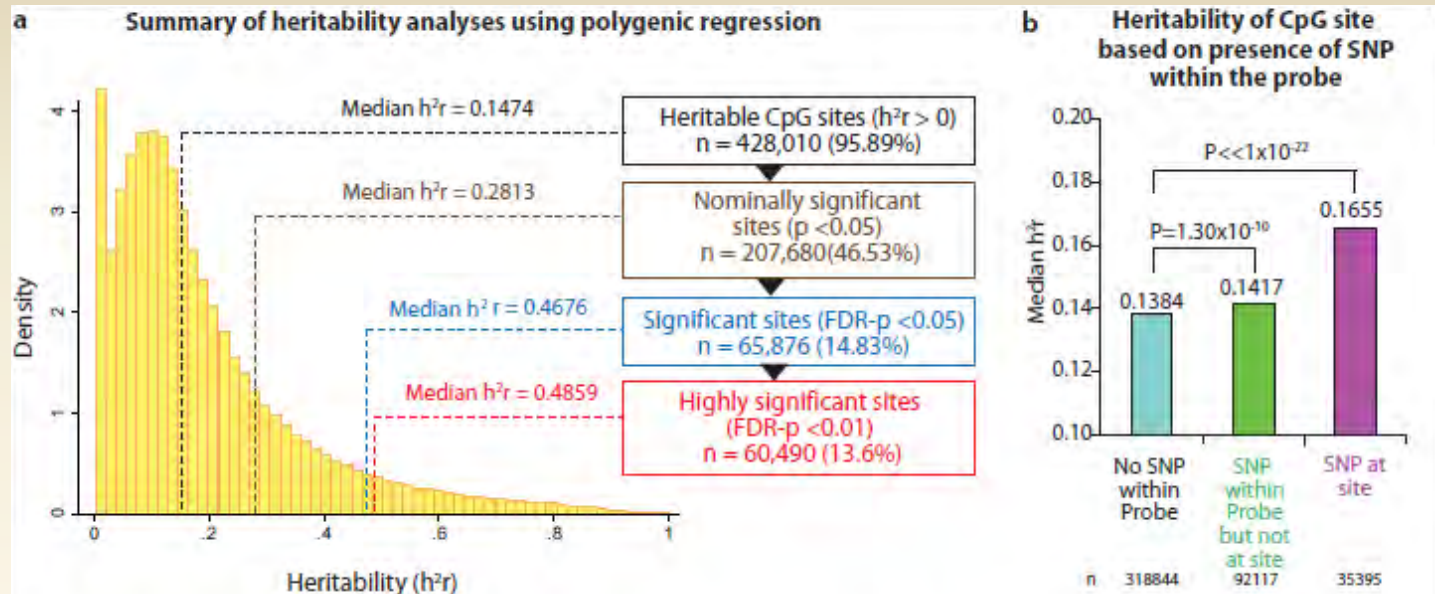


Figure 1 – Epigenetic silencing of gene expression. DNA methyl-transferases carry out the methylation of CpG dinucleotides, which triggers the process of gene silencing by recruitment of methyl binding domain (MBD) and Histone deacetylases (HDAC) to bind to the methylated DNA. This results in histone deacetylation and chromatin condensation leading to loss of transcription factor binding and subsequent repression of transcription.

Study Design

- ✎ Whole-genome methylation profiling (Illumina 450k BeadChips)
 - ✎ 859 individuals from visit 3
 - ✎ 341 individuals from visit 2
 - ✎ 241 of these overlap
- ✎ Normalization and quality control:
 - ✎ Probes normalized to control probes on array
 - ✎ Beta-mixture quantile normalization to correct probe bias
 - ✎ Inverse normalization to ensure normal distribution
 - ✎ Correction for cell counts, age, sex, medication, etc
- ✎ Assessed.....
 - ✎ Heritability of DNA methylation and meQTLs (Visit 3)
 - ✎ Age- and sex-associated CpG sites (Visit 3)
 - ✎ CpG sites associated with MetS risk (mostly Visit 3; Visit 2)

Heritability and Genetic Regulation of DNA Methylation



meQTLs defined as $\pm 50\text{kb}$ from CpG site

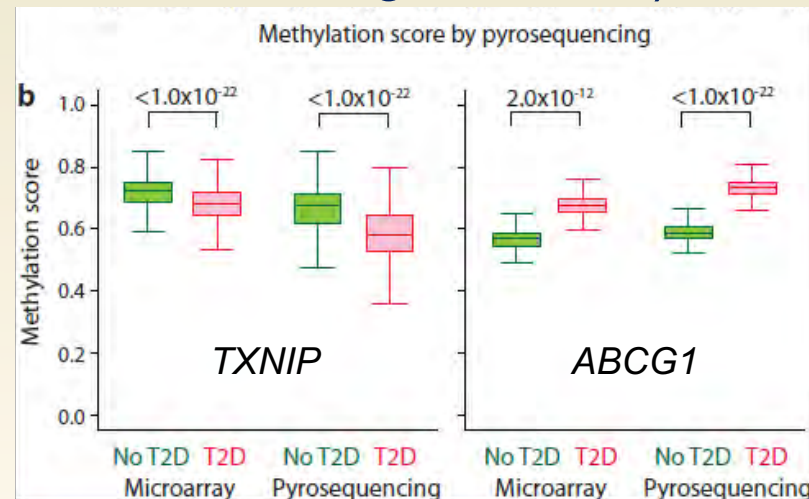
- 14.3% of CpG sites are significantly associated with at least 1 SNP (average 10.3 significant SNPs per site)
- Heritability was improved by 0.64% for each additional significant SNP
- Number of significant methylation-SNP associations explained 12.47% of the variability in heritability

DNA Methylation is Associated with Age and Sex

- ✎ 22.3% of sites associated with age
 - ✎ 38.4% of these show increased methylation with age
 - ✎ Pathways associated: neurological disorders/neuronal system/neuronal transmission/long term potentiation, inhibition/regulation of insulin secretion, energy metabolism, cell communication and cell signaling pathways
- ✎ 2.8% of sites associated with sex
 - ✎ 85.6% of these hypermethylated in females
 - ✎ Pathways associated: nuclear receptor transcription, NOTCH and IGF1 pathways

DNA Methylation Influences Diabetes

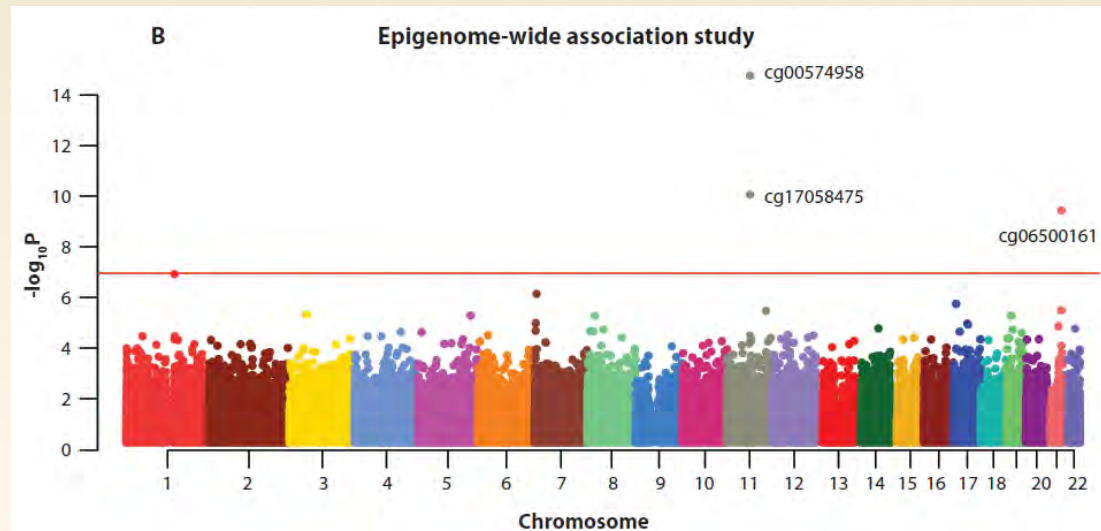
- ✎ T2D/FG/HOMA-IR: 51/19/24 significantly associated sites
- ✎ 53 CpG sites had a composite significance score $p < 0.017$
 - ✎ Top 5 associations accounted for 7.8% of the heritability of T2D (*TXNIP*, *ABCG1*, *SAMD12* and 2 intergenic sites)
 - ✎ CpG sites in *TXNIP* and *ABCG1* were validated by pyrosequencing



- ✎ Biological candidates: *TXNIP*, *ABCG1*, *SREBF1*, *LOXL2*, *CPT1A*, *SOCS3*, *CALHM1*, *ICA1*, *ZBTB7A*, *CUX1*, *NFE2L3*, *LDLRAP1*
- ✎ Gene enrichment analysis implicated pathways in insulin signaling, and those related to lipid signaling and transport

DNA Methylation Influences Obesity

- Hypertriglyceridemic waist (HTGW)
 - 3 significant associations (2 sites in *CPT1A*, 1 in *ABCG1*)
 - Accounted for 9.52% of the variability in HTGW
 - Top *CPT1A* site validated by pyrosequencing and also associated with Visit 2 data



Mamtani *et al* 2016, *Clin Epigenetics* 8:6.

- Obesity measures
 - BMI: 8 associations
 - WC: 3 associations
 - Obesity: 12 associations
 - Biological candidates: *APOL1*, *CPT1A*, *NOD2*, *PHGDH*, *SOCS3*, *TNFSF10*

DNA Methylation Influences Lipids and Blood Pressure

👉 Lipid Phenotypes

- 👉 Total cholesterol: 2 significant associations
- 👉 HDLC: 32 significant associations
- 👉 LDLC: 11 significant associations
- 👉 Triglycerides: 10 significant associations
- 👉 Biological candidates: *CPT1A*, *TXNIP*, *CALHM1*, *ABCG1*, *TNIP2*, *KLF13*, *KCNQ1*

👉 Blood pressure

- 👉 Only suggestive significance: *CAMTA1*, *GALNT2*, *NOTCH4*

MetS-Associated DNA Methylation Changes

- ✎ Metabolic syndrome
 - ✎ 3 significant associations: *CPT1A*, *TXNIP*, *ABCG1*
- ✎ *TXNIP*: Glucose/insulin tolerance; triglyceride concentration in diabetics; mediates diet-induced obesity¹⁻³
- ✎ *CPT1A*: Involved in fatty acid oxidation, implicated in regulation of feeding⁴, obesity and lipid levels (methylation)⁵⁻⁷
- ✎ *ABCG1*: Involved in glucose and lipid homeostasis⁸, failure to identify genetic variation associated with T2D⁹, methylation within this gene implicated in obesity⁶, plasma lipid levels¹⁰ and insulin resistance and diabetes¹¹⁻¹²

1. Jo *et al* 2013, *Diabetologia* 56:2723-32.

3. Blouet *et al* 2012, *J Neurosci* 32:9870-7.

5. Aslibekyan *et al* 2015, *Obesity* 23:1493-501.

7. Gagnon *et al* 2014, *J Lipid Res* 55:1189-91.

9. Schou *et al* 2012, *Diabetes Care* 35:2600-6.

11. Hidalgo *et al* 2014, *Diabetes* 63:8101-7.

2. van Greevenbroeck *et al* 2007, *Diabetes Med* 24:498-504.

4. Mera *et al* 2014, *PLoS One* 9:e97195.

6. Demerath *et al* 2015, *Hum Mol Genet* 24: 4464-79.

8. Mauldin *et al* 2008, *Circulation* 117:2785-92.

10. Pfeiffer *et al* 2015, *Circ Cardiovasc Genet* 8:334-42.

12. Chambers *et al* 2015 *Lancet Diabetes Endocrinol* 3:526-34.

DNA Methylation Changes Associated with Development of Diabetes and Obesity

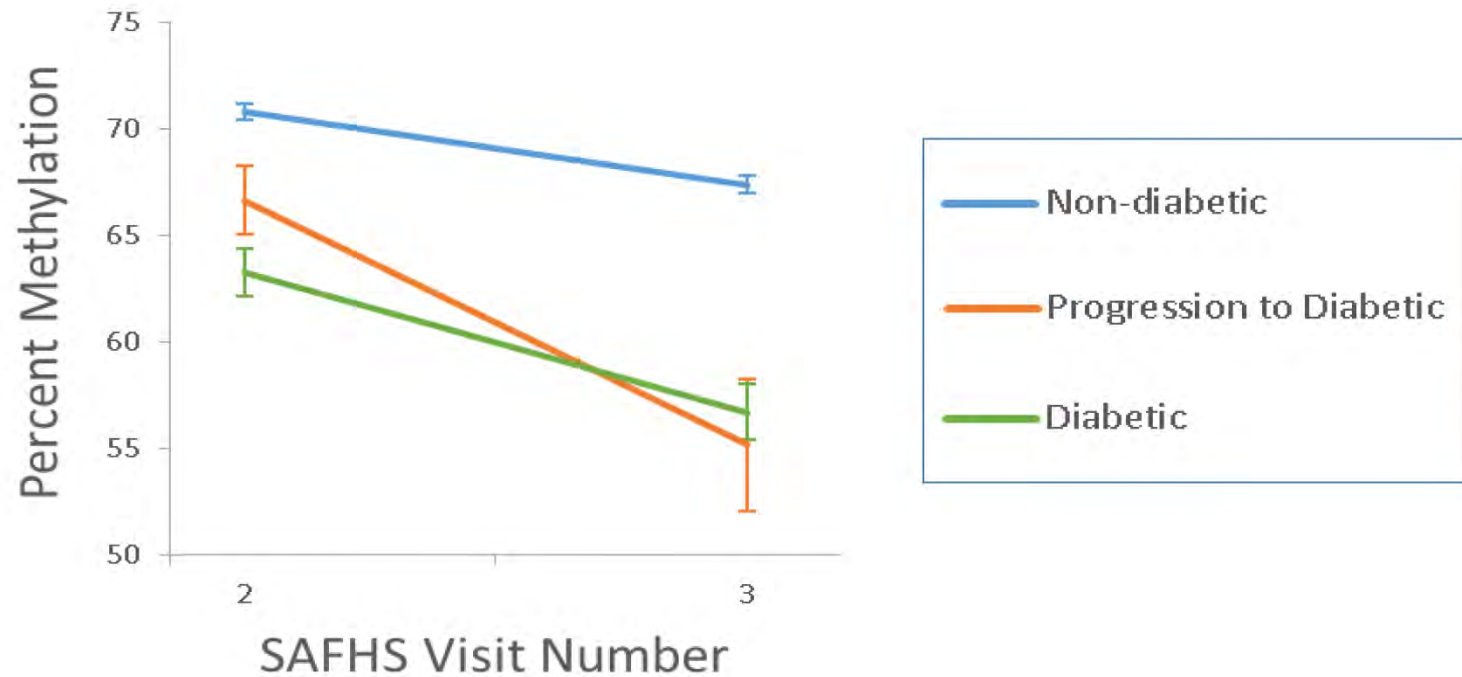
Assessed candidate regions for differences in DNA methylation over time

Visit 2 vs visit 3; n=241 individuals

TXNIP, ABCG1, CPT1A, SREBF1, LOXL2, SOCS3, CALHM1

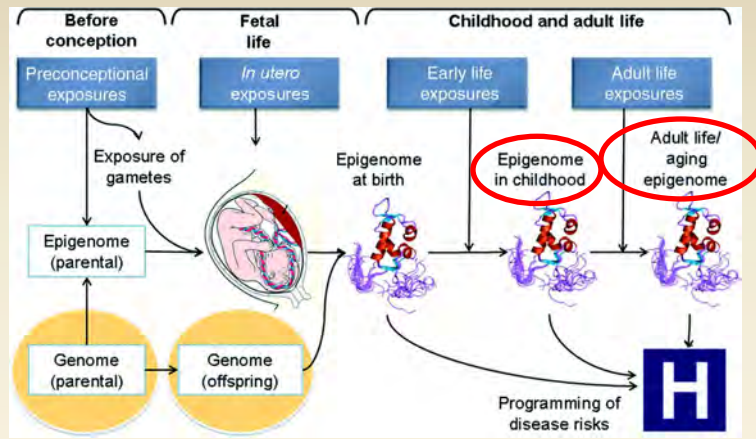
Phenotype	Gene	P-value
Fasting Glucose _{Diff}	TXNIP	1.07×10^{-4}
	CPT1A	1.28×10^{-3}
	LOXL2	2.86×10^{-3}
Obesity _{Diff}	ABCG1	4.47×10^{-3}
Waist Circumference _{Diff}	CPT1A	5.33×10^{-3}
% Body Fat _{Diff}	CPT1A	6.78×10^{-3}

DNA Methylation changes in *TXNIP* may Precede Diabetes Onset



What Next?

Early Intervention???

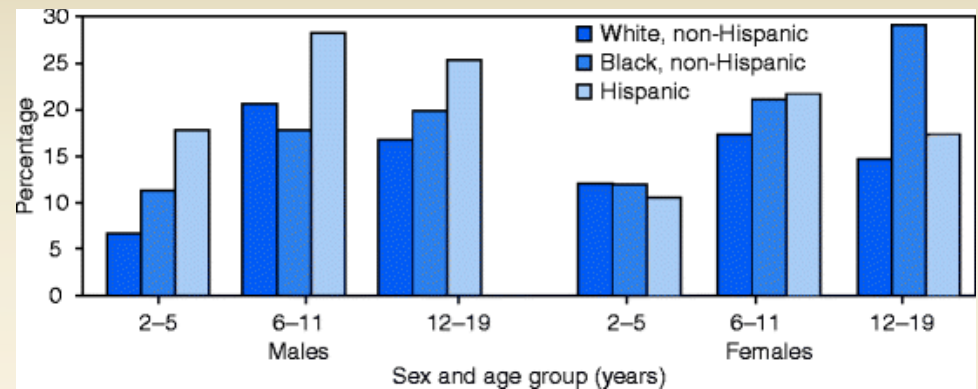


Prevalence of metabolic syndrome varies greatly in children, based on diagnostic criteria

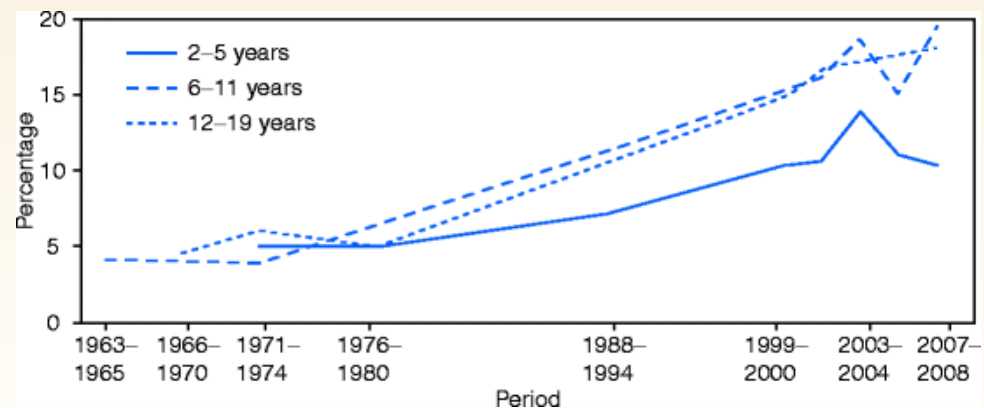
- Median prevalence in non-obese/non-overweight children 0-1%
- Median prevalence in overweight children 2.8-29.3%
- Median prevalence in obese children 10-66%

Friend et al (2013) *Metab Syndr Relat Disord* 11:71-80.

Prevalence of obesity in children



Prevalence of obesity among children and adolescents by sex, age group, and race/ethnicity, United States, 2007-2008 (Reprinted from Centers for Disease Control and Prevention)



Messiah et al (2012) in *Pediatric Metabolic Syndrome* pp37-55.

Focus on obesity/energy homeostasis nexus

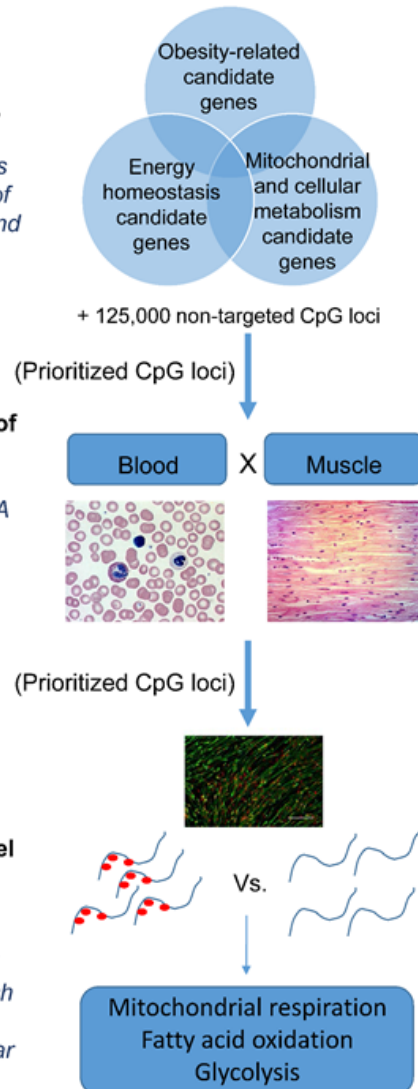
Aim

1. DNA methylation signatures of energy homeostasis and obesity.
Targeted and non-targeted sequencing library to assess association with measures of energy intake, expenditure and storage, and obesity.

2. Establish the relevance of peripheral biomarkers to energy-producing tissue.
Examine correlations of DNA methylation levels between blood and skeletal muscle.

3. Develop an *in vitro* model system to study energy homeostasis and bioenergetics.
Using epigenetic editing of muscle cells, we will establish the importance of energy homeostasis genes to cellular energy metabolism.

Study Design



Study cohort

Viva la Familia
 916 Hispanic children with high levels of obesity; extensive phenotypic information related to energy homeostasis.

Cohort 1
 22 blood-skeletal muscle tissue pairs (Caucasian adults)

Cohort 2
 Six blood-skeletal muscle tissue pairs (Hispanic adults)

Cohort 3
 Six blood-skeletal muscle cell pairs (Hispanic children)

iPSC Repository
iPSC-derived muscle cells from six Hispanic children.

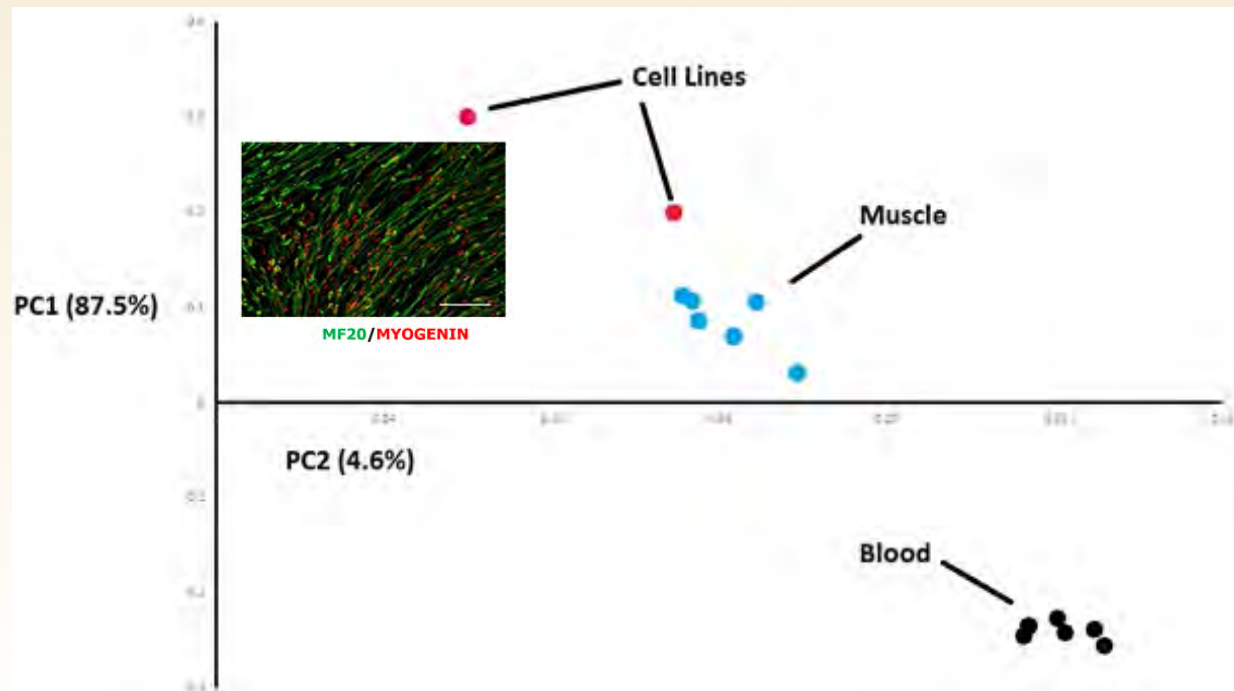
Viva la Familia (VIVA) study

PI: Shelley Cole/Nancy Butte

Anthropometry
Body composition
Energy intake
Total energy expenditure
Basal metabolic rate
24 hour respiratory quotient
Protein/fat oxidation
Physical activity (accelerometers)

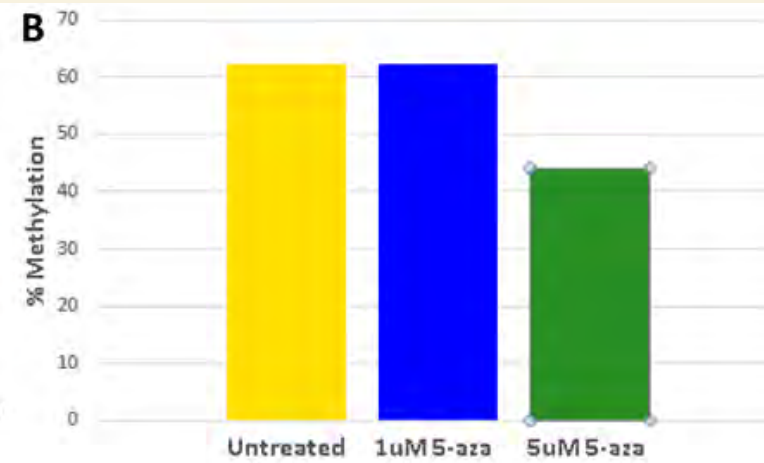
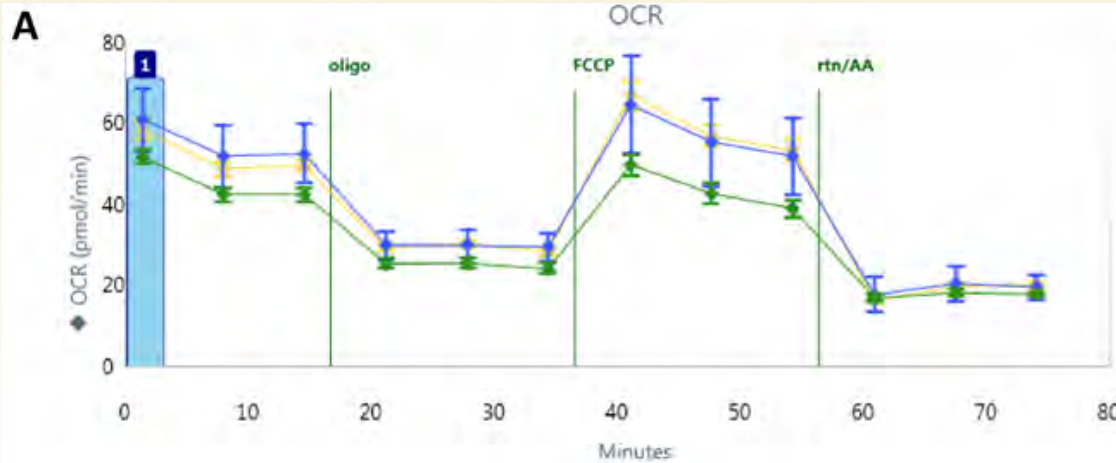
DNA Methylation in Muscle

- Whole-genome methylation sequencing
 - Overall correlation between blood and muscle 0.84-0.89 ($p=2.2 \times 10^{-16}$)
 - PCA analysis indicates similarity between ES/iPSC-derived muscle cells and muscle tissue



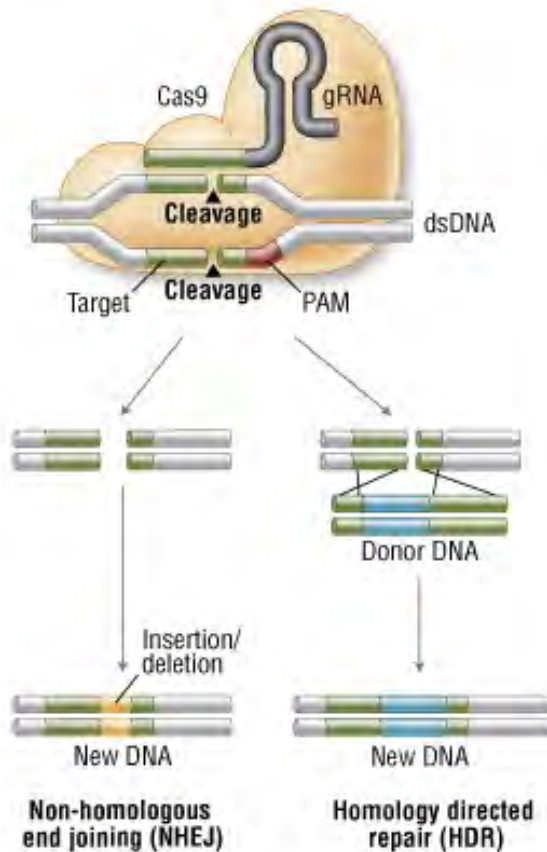
DNA Methylation and Mitochondrial Function

- Seahorse mitochondrial stress test assay
 - Human skeletal muscle cells treated with 5-azacytidine
 - Global demethylation decreases basal (86%) and maximal (66%) respiration, ATP production (91%), and proton leak (70%) compared to control cells

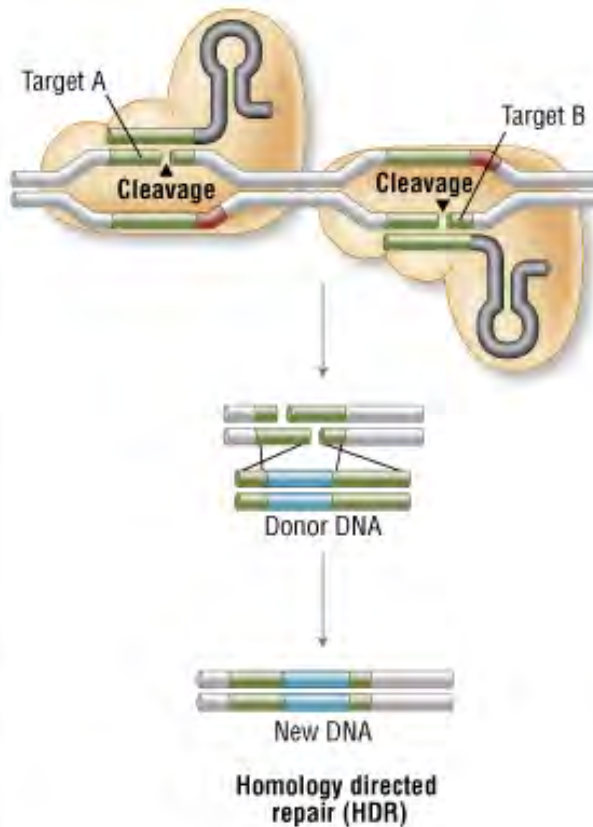


CRISPR: Cas9 Variants

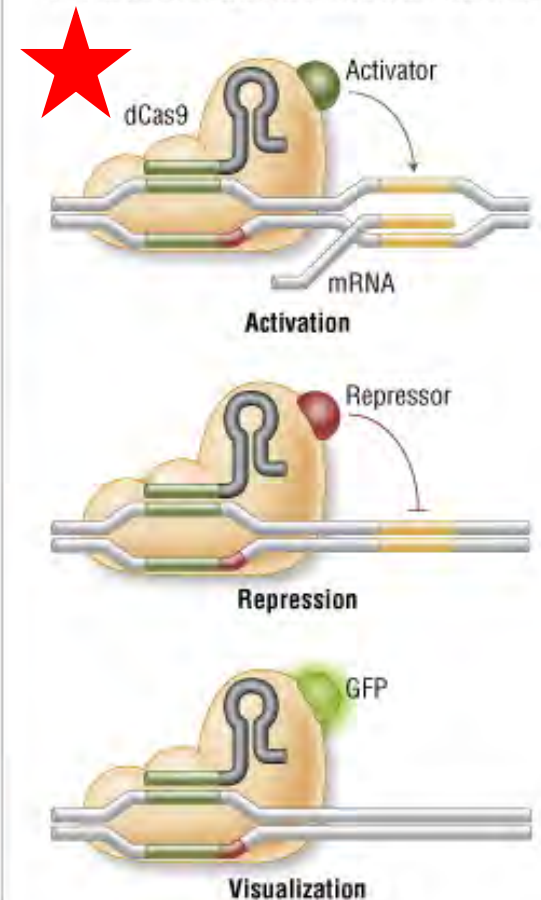
A. Genome Engineering With Cas9 Nuclease



B. Genome Engineering By Double Nicking With Paired Cas9 Nickases



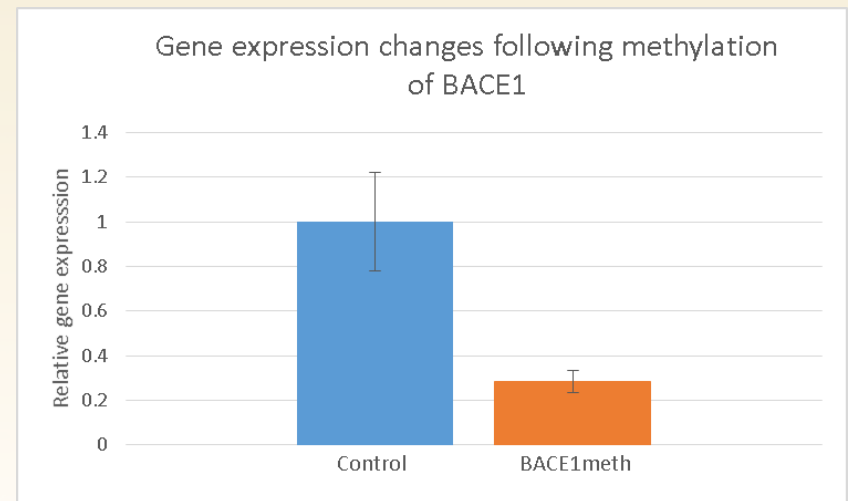
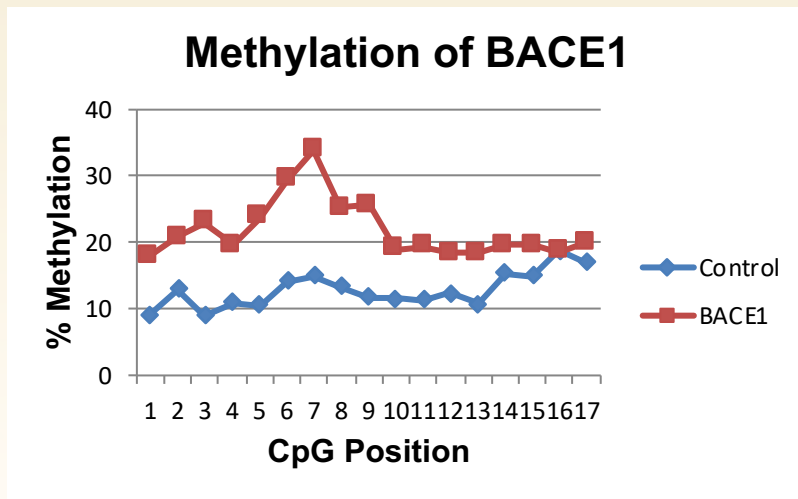
C. Localization With Defective Cas9 Nuclease



Stable Methylation of iPSCs

To bypass editing of terminally differentiated muscle cells, we developed a platform to alter DNA methylation in iPSCs at specific sites using CRISPR-dCas9 system

- Generated stable iPSC lines for methylated *BACE1* promoter using 3rd generation lentiviral system (methylation retained > 40 days)
- Associated with a significant decrease in gene expression



Will use this system to understand function of altered methylation related to obesity and energy homeostasis

Collaborators

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Rio Grande Valley

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Joanne Curran

Tom Dyer

University of Alabama

Bertha Hidalgo

Howard Wiener

Baylor College of
Medicine

Nancy Butte

University of Texas Health
Sciences Center San Antonio

Yidong Bai

The University of Arizona
Health Sciences

Dawn Coletta

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Owens Foundation

Looking for postdocs

***Expertise in stem cells, genetic/epigenetic editing,
and/or data analysis/bioinformatics!!!***