

*The Geisinger DiscovEHR cohort: 233,185  
people with exome sequencing and  
longitudinal EHR data*

*Douglas R. Stewart, MD*

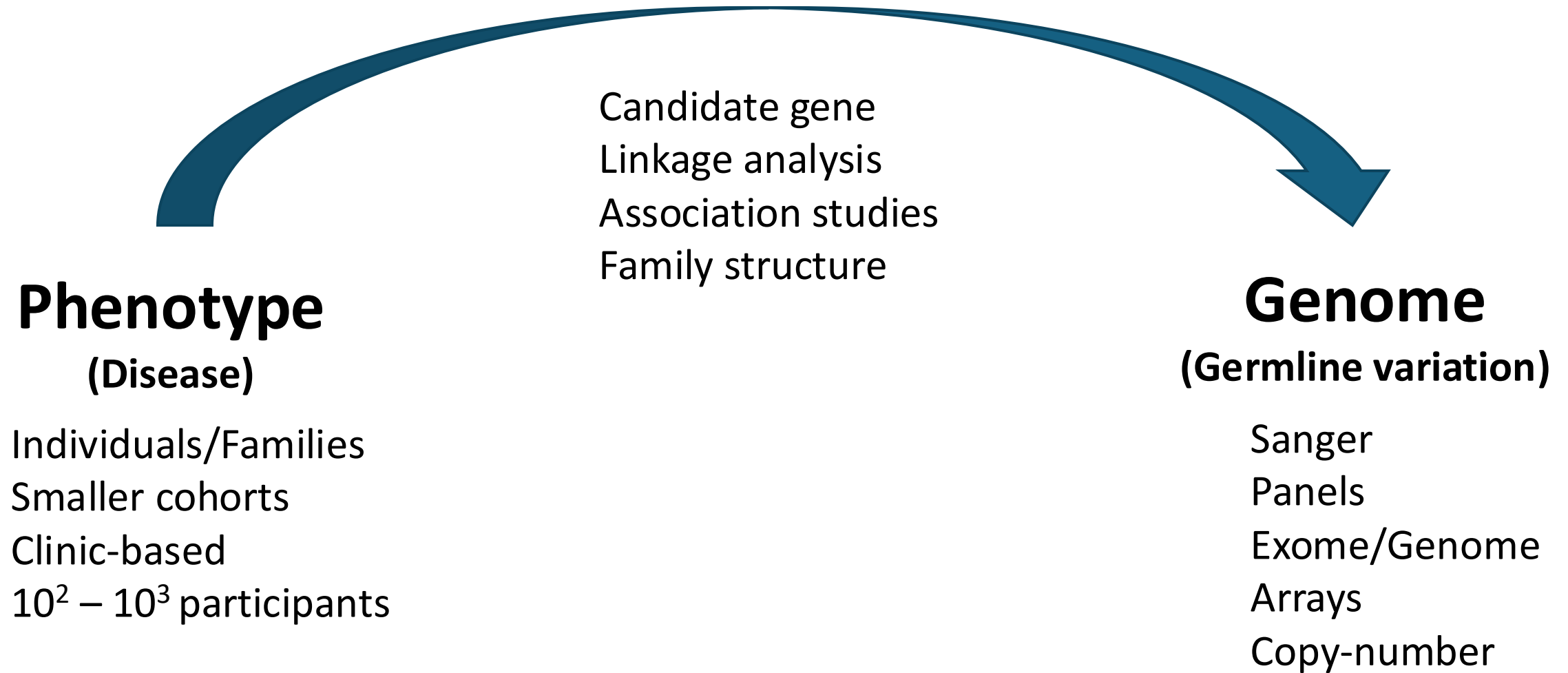
*Jung Kim, Ph.D.*

*Clinical Genetics Branch*

## Outline

1. *What is genomic ascertainment?*
2. *MyCode and DiscovEHR*
3. *CHEK2 cancer risk*
4. *RASopathies cancer risk*
5. *Lessons learned*
6. *Practical matters*

# Phenotype-first model of clinical genetics...



# Phenotype-First

“Ascertain weird phenotype *then* find genotype”

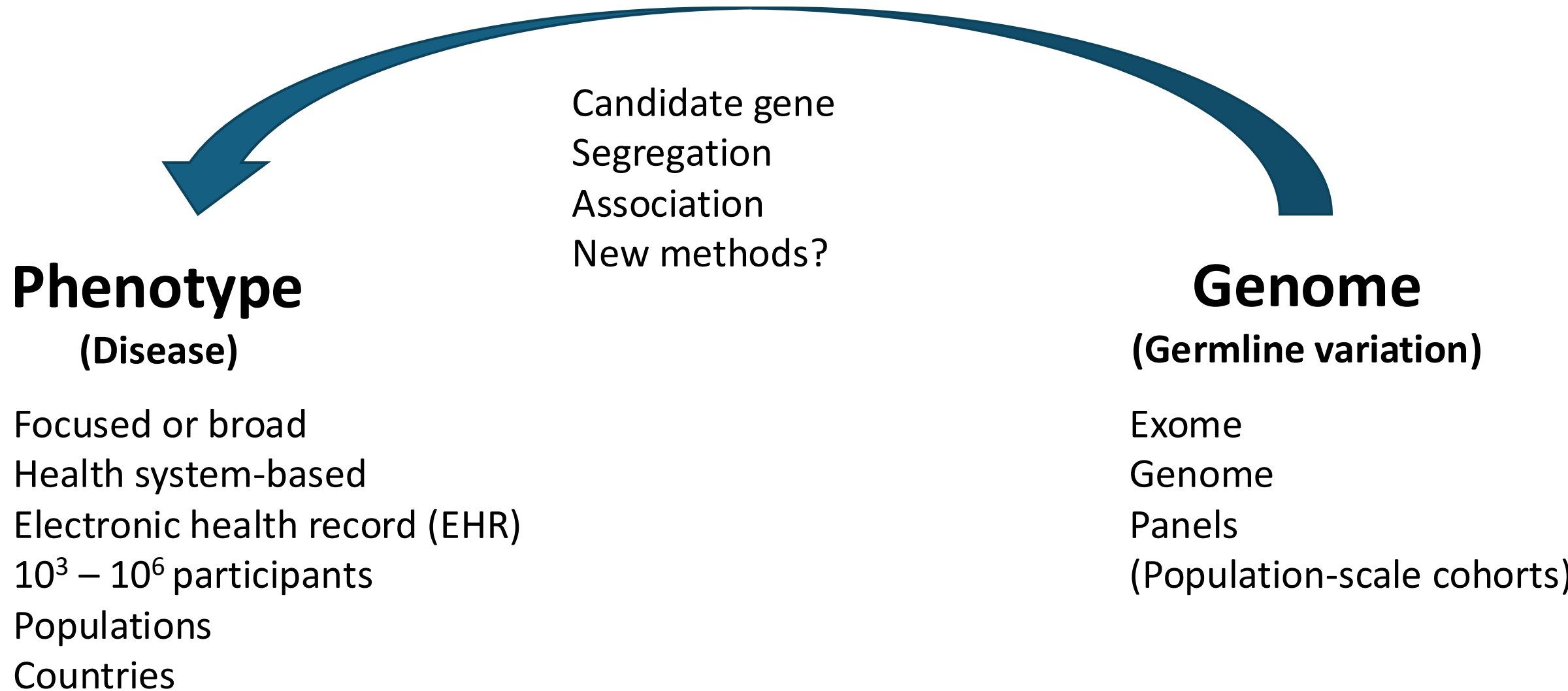
## Strengths

- “Tried-and-true” approach to rare disease
- Builds on expertise of clinical investigator (pattern/syndrome recognition)
- Well-trod recruitment strategies
- Costs can be more modest (single clinic/investigator recruiting families)

## Weaknesses

- Ascertainment biases
- Miss non-penetrant cases
- Miss rare or unknown manifestations of disorder
- May over-estimate severity of disorder
- Reactive
- Time- and labor-intensive to build special cohorts; lower throughput

# Genome-first approach to clinical genetics...



# Genotype (Genome)-First\*

“Ascertain weird genotype *then* find phenotype”

## Strengths

- See full phenotypic spectrum, especially at older ages
- Wider range of severity
- Better penetrance estimates
- Proactive
- Multiple gene/pathways
- Opportunities for syndrome discovery
- Higher throughput?

## Weaknesses

- Different ascertainment biases
- $10^{-5} \times 10^6 = 10^1$
- Infrastructure requirements
- Significant costs to build/recruit cohorts
- Bioinformatics expertise – variant classification
- Data science expertise
  - Clinical bioinformatics for phenotypes
  - Missing/sparse data (few clinical visits)
  - Quirks of medical coding
  - Medical coding: for billing, not research!

\*AKA: “Public health genomics,” “Population genomics,”  
“Reverse phenotyping,” “Genomic ascertainment”

# What are the consequences of genomic ascertainment?

- *Prevalence* of pathogenic/likely pathogenic (P/LP)\* variants is (often) greater than previously estimated
- *Penetrance* (risk from a P/LP variant) may not be as high as previously estimated
- *Phenotype* is different (may be less severe, broader)

\*Clinically actionable germline variation classified by ACMG/AMP rules (Richards *et al Genetics in Medicine* 2015)



and Genomics

Carey et al *Genet Med* 2016

# The Geisinger MyCode community health initiative: an electronic health record–linked biobank for precision medicine research

David J. Carey, PhD<sup>1</sup>, Samantha N. Fetterolf, BS<sup>1</sup>, F. Daniel Davis, PhD<sup>1</sup>, William A. Faucett, MS<sup>1</sup>,  
H. Lester Kirchner, PhD<sup>1</sup>, Uyenlinh Mirshahi, PhD<sup>1</sup>, Michael F. Murray, MD<sup>1</sup>, Diane T. Smelser, PhD<sup>1</sup>,  
Glenn S. Gerhard, MD<sup>2</sup> and David H. Ledbetter, PhD<sup>1</sup>



Geisinger Medical Center, Danville, Pennsylvania  
Opened 1915 as Geisinger Hospital

Geisinger

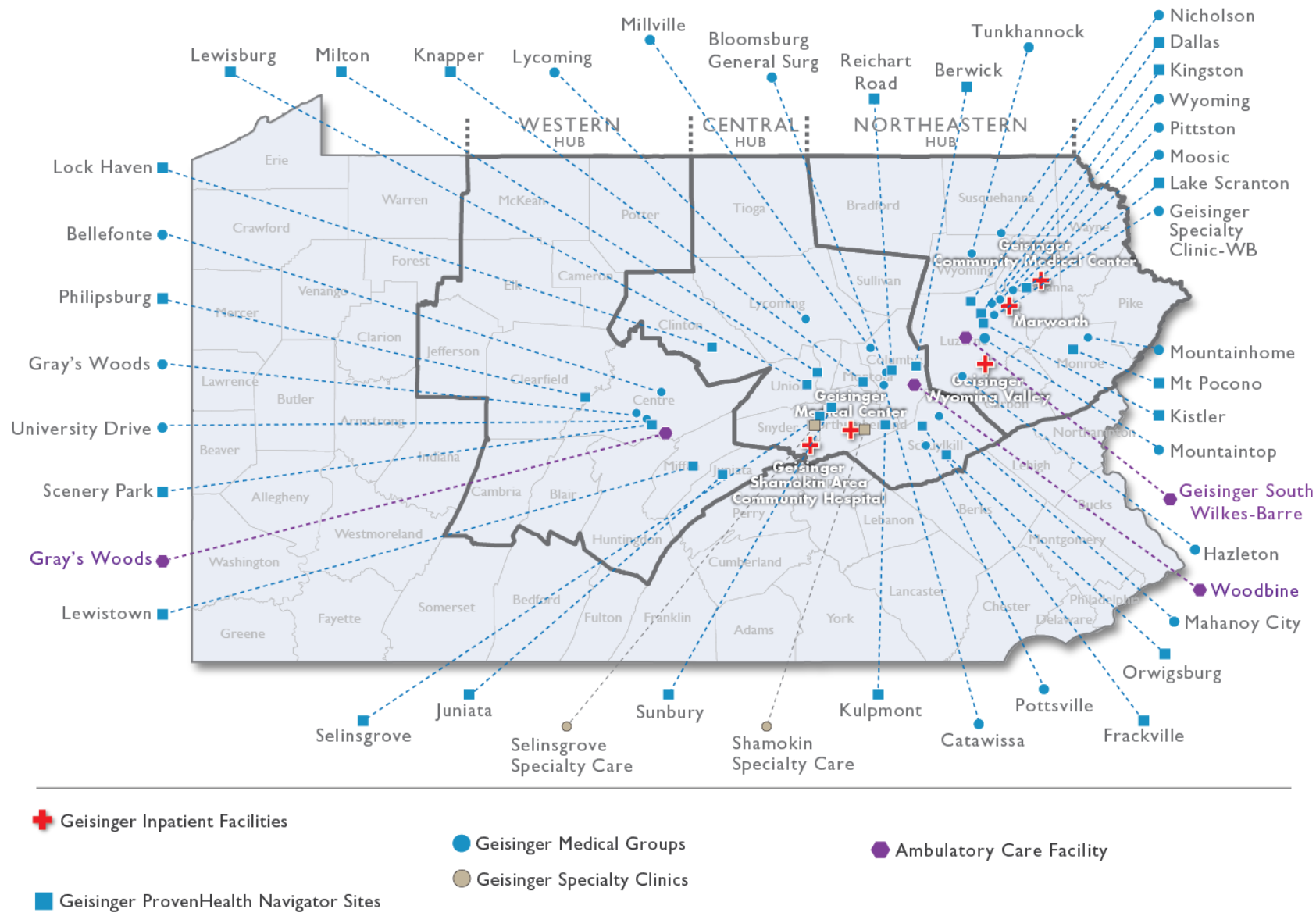
Abigail Geisinger  
1827 - 1921



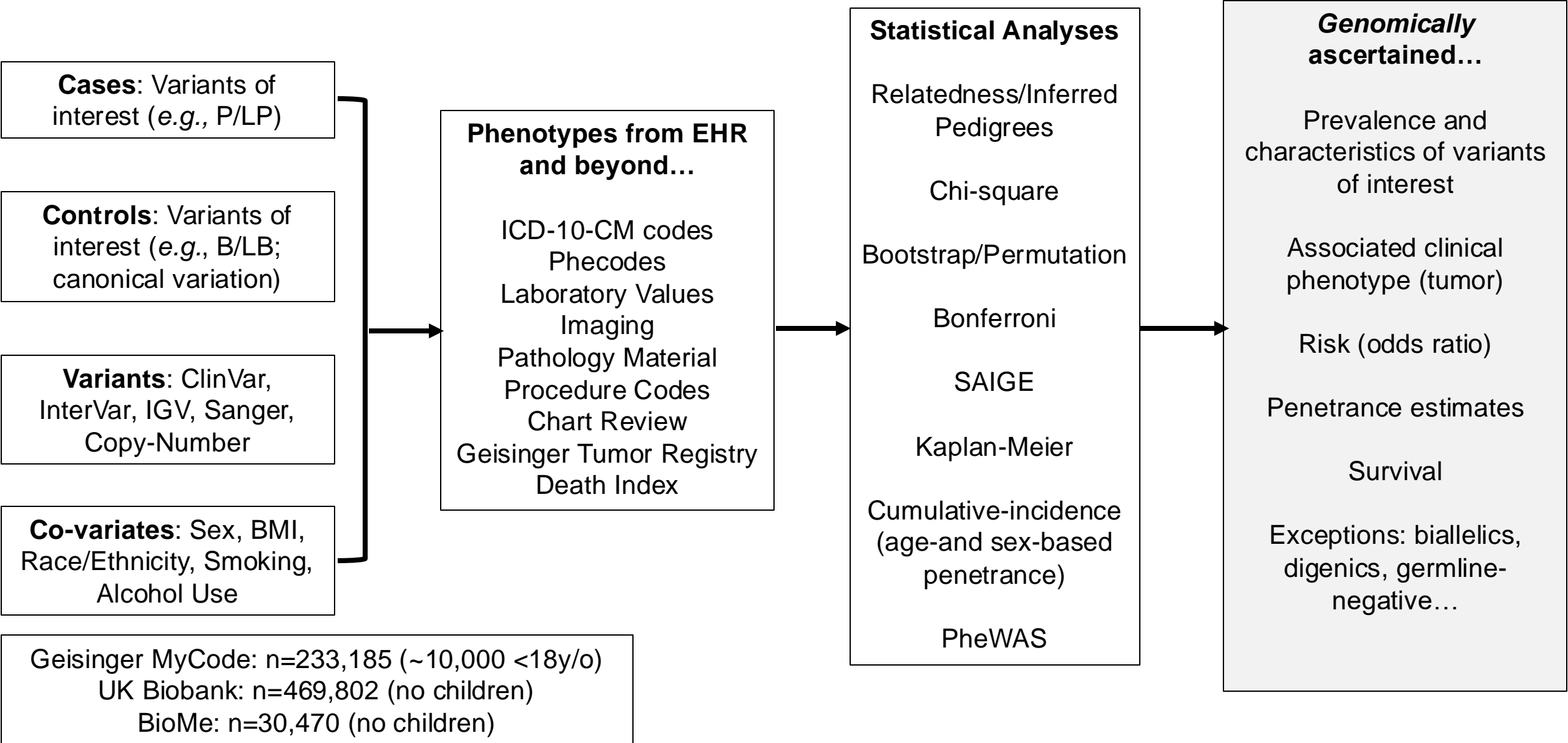
# Genome-first approach using population-scale sequencing linked to electronic health records

## Geisinger

- Serves >3M people
- Relatively non-transient; many multi-generation families; low in/out migration
- EHR since 1995
- 233,185 exomes (+/-arrays) (1/2025; with Regeneron)
- 5-year (2021-2026), DCEG-funded contract to investigate monogenic tumor predisposition disorders using the genome-first approach



# Implementation of a genome-first approach in three population-sized, exome-sequenced, EHR-linked cohorts



Genome-first approach of the prevalence  
and cancer phenotypes of pathogenic  
or likely pathogenic germline *TP53* variants

Kelvin C. de Andrade,<sup>1,7,\*</sup> Natasha T. Strande,<sup>2</sup> Jung Kim,<sup>1</sup> Jeremy S. Haley,<sup>2</sup> Jessica N. Hatton,<sup>1</sup> Megan N. Frone,<sup>1</sup> Payal P. Khincha,<sup>1</sup> Gretchen M. Thone,<sup>2</sup> Uyenlinh L. Mirshahi,<sup>2</sup> Cynthia Schneider,<sup>3</sup> Heena Desai,<sup>3</sup> James T. Dove,<sup>2</sup> Diane T. Smelser,<sup>2</sup> Penn Medicine BioBank,<sup>6</sup> Regeneron Genetics Center,<sup>6</sup> Arnold J. Levine,<sup>4</sup> Kara N. Maxwell,<sup>3</sup> Douglas R. Stewart,<sup>1,5</sup> David J. Carey,<sup>2,5</sup> and Sharon A. Savage<sup>1,5</sup>

Genetics in Medicine (2024) 26, 101042

A genotype-first approach to exploring Mendelian  
cardiovascular traits with clear external manifestations

Brittany M. Wenger, BS<sup>1</sup>, Nihir Patel, MS<sup>2</sup>, Madeline Lui, BA<sup>1</sup>, Arden Moscati, PhD<sup>3</sup>, Ron Do, PhD<sup>3</sup>, Douglas R. Stewart, MD<sup>4</sup>, Marco Tartaglia, PhD<sup>5</sup>, Laura Muñoz-Mosquera, MD, PhD<sup>6,7</sup>, Julie De Backer, MD, PhD<sup>7,8</sup>, Amy R. Kontorovich, MD, PhD<sup>2,9</sup> and Bruce D. Gelb, MD<sup>2,10</sup>



Genetics in Medicine Open (2024) 2, 10

Research



JAMA Dermatology | Brief Report

Estimated Prevalence, Tumor Spectrum, and Neurofibromatosis Type  
1-Like Phenotype of *CDKN2A*-Related Melanoma-Astrocytoma Syndrome

Michael R. Sargen, MD; Jung Kim, PhD; Thomas P. Potjer, MD, PhD; Mary E. Velthuisen; Arellis E. Martir-Negron, MD; Yazmin Odia, MD; Hildur Helgadóttir, MD, PhD; Jessica N. Hatton, MS, CGC; Jeremy S. Haley, MS; Gretchen Thone, MS, CGC; Brigitte C. Widemann, MD; Andrea M. Gross, MD; Marielle E. Yohe, MD, PhD; Rosandra N. Kaplan, MD; Jack F. Shern, MD; R. Taylor Sundby, MD; Esteban Astiazaran-Symonds, MD; Xiaohong R. Yang, PhD, MPH; David J. Carey, PhD; Margaret A. Tucker, MD; Douglas R. Stewart, MD; Alisa M. Goldstein, PhD

## ARTICLE

A genome-first approach to characterize *DICER1*  
pathogenic variant prevalence, penetrance and  
cancer, thyroid, and other phenotypes in 2  
population-scale cohorts

Jung Kim<sup>1</sup> , Jeremy Haley<sup>2</sup> , Jessica N. Hatton<sup>1</sup> , Uyenlinh L. Mirshahi<sup>2</sup> , H. Shanker Rao<sup>2</sup> , Mark F. Ramos<sup>1</sup> , Diane Smelser<sup>2</sup> , Gretchen M. Urban<sup>2</sup> , Kris Ann P. Schultz<sup>3,4,5</sup> , David J. Carey<sup>2</sup> , Douglas R. Stewart<sup>1,\*</sup>

## BRIEF REPORT

Most Fanconi anemia heterozygotes are not at  
increased cancer risk: A genome-first DiscovEHR  
cohort population study

Joseph Deng<sup>1</sup> , Burak Altintas<sup>1,2</sup>, Jeremy S. Haley<sup>3</sup>, Jung Kim<sup>1</sup>, Mark Ramos<sup>4</sup>, David J. Carey<sup>3</sup>, Douglas R. Stewart<sup>1</sup>, Lisa J. McReynolds<sup>1,\*</sup>



Research

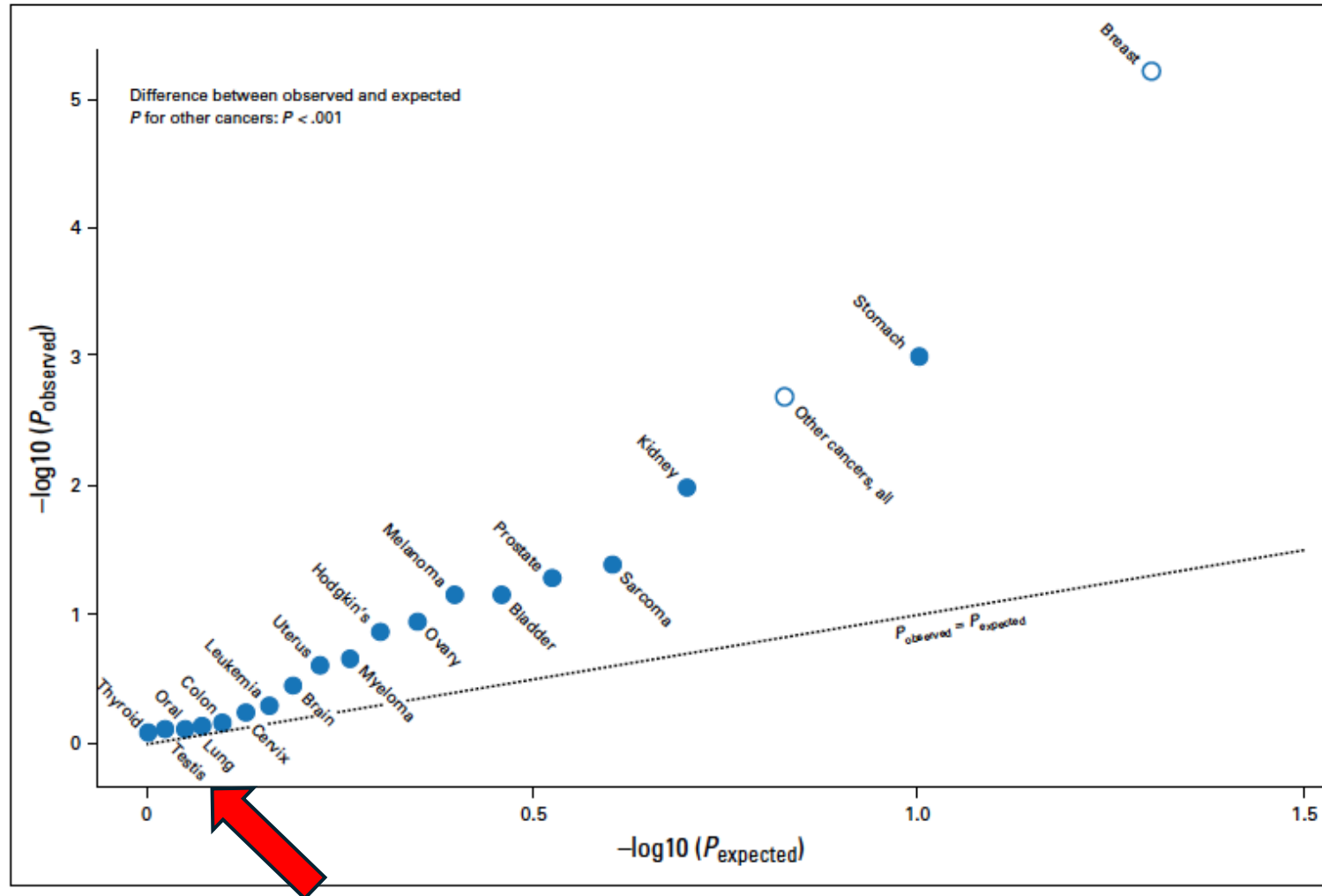
JAMA | Original Investigation

Estimated Prevalence and Clinical Manifestations of *UBA1* Variants  
Associated With VEXAS Syndrome in a Clinical Population

David B. Beck, MD, PhD; Dale L. Bodian, PhD; Vandan Shah, MD; Uyenlinh L. Mirshahi, PhD; Jung Kim, PhD; Yi Ding, MD, PhD; Samuel J. Magaziner, MPhil; Natasha T. Strande, PhD; Anna Cantor, MS; Jeremy S. Haley, MS; Adam Cook, MS; Wesley Hill; Alan L. Schwartz, MD, PhD; Peter C. Grayson, MD; Marcela A. Ferrada, MD; Daniel L. Kastner, MD, PhD; David J. Carey, PhD; Douglas R. Stewart, MD

# ***CHEK2* is a low-to-moderate risk multi-tumor-predisposition gene**

## **Risk of individual cancer types in *CHEK2* 1100delC heterozygotes**



86,975 people from the Copenhagen General Population Study

Recruited 2003 – 2010

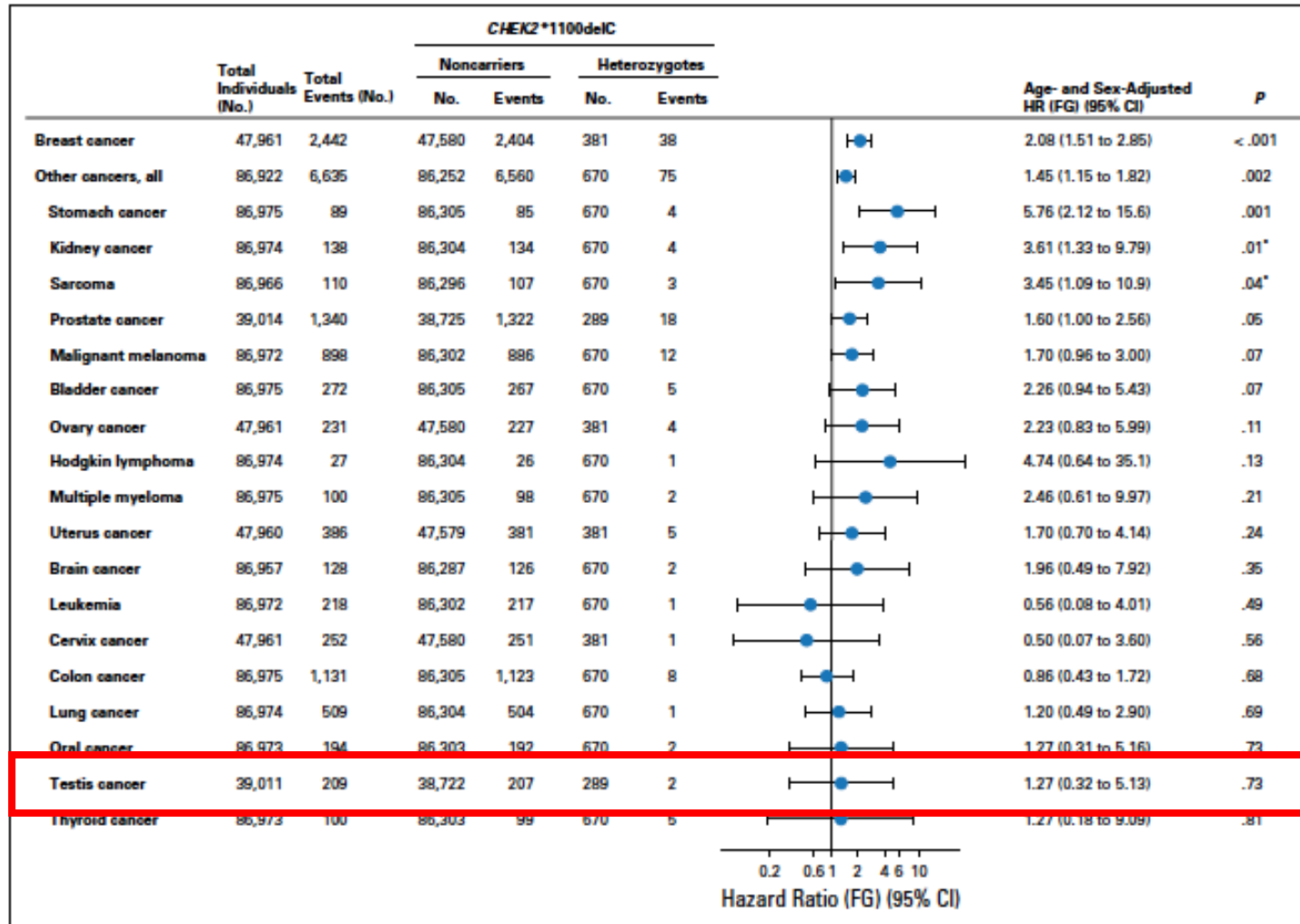
Linked to Danish Cancer Registry (1943 – 2011)

Open circles: *a priori* hypothesized cancers

Closed circles: exploratory analyses

# *CHEK2* is a low-to-moderate risk multi-tumor-predisposition gene

Risk of individual cancer types in *CHEK2* 1100delC heterozygotes




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## Genomic ascertainment of *CHEK2*-related cancer predisposition

Sun Young Kim, Jung Kim, Mark Ramos, Jeremy Haley, Diane Smelser, H. Shanker Rao,  Uyenlinh L. Mirshahi, Geisinger-Regeneron DiscovEHR Collaboration, Barry I. Graubard, Hormuzd A. Katki, David Carey, Douglas R. Stewart

**doi:** <https://doi.org/10.1101/2024.08.07.24311613>


**This article is a preprint and has not been peer-reviewed [what does this mean?]. It reports new medical research that has yet to be evaluated and so should not be used to guide clinical practice.**

Posted August 08, 2024.

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Jung Kim, Ph.D.  
Clinical Genetics Branch



Sun Young Kim, MD, Ph.D.  
Cincinnati Children's

# *CHEK2* heterozygotes (cases) and controls

## Genomic ascertainment of cases and controls

### Geisinger

- “Goldilocks” build; ABHet: 0.2-0.8; GQ>30; Depth > 5
- n= 167,050; age>18 yrs; mean 56.6 yrs
- *CHEK2* P/LP heterozygotes: 3,153
- 5 bi-alleleics with 2 common variants excluded
- Controls: individuals without *CHEK2* variation or B/LB: 152,662

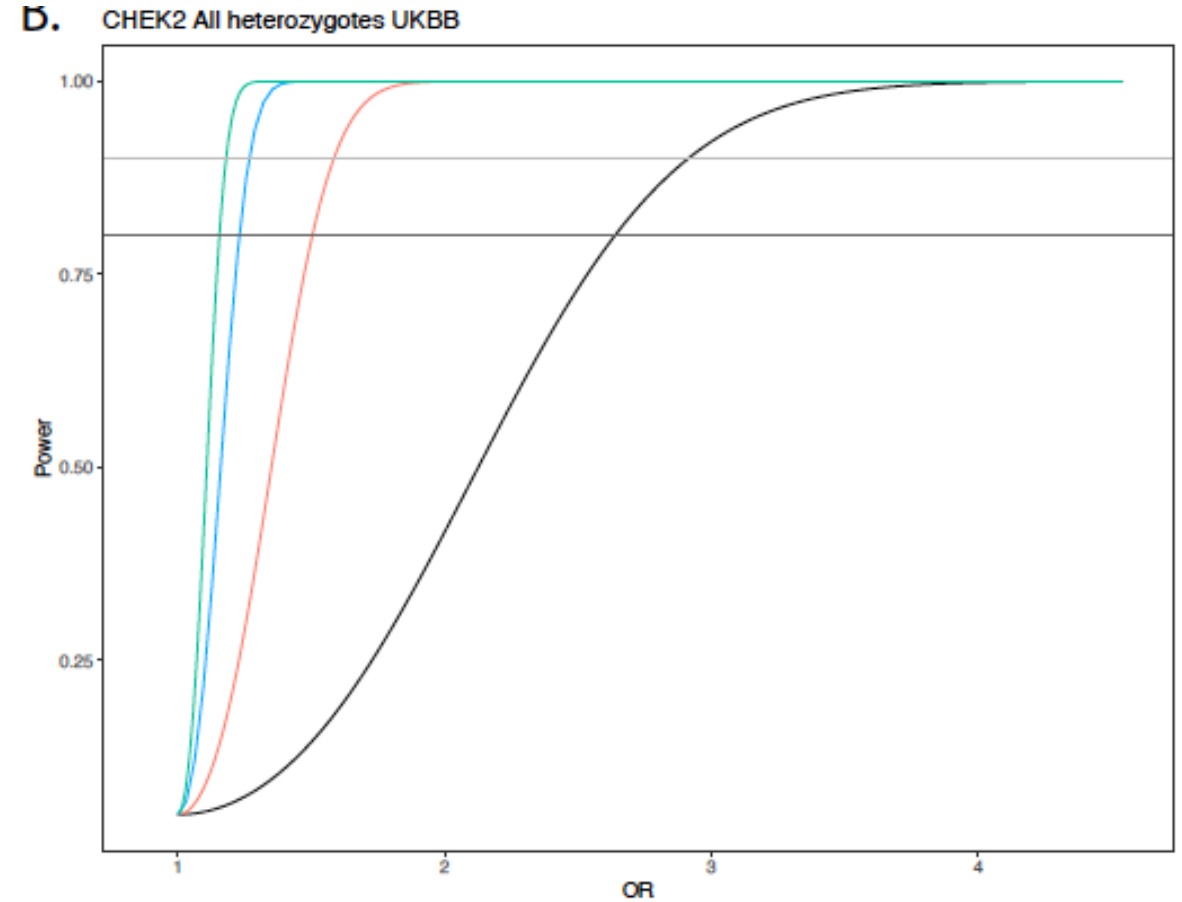
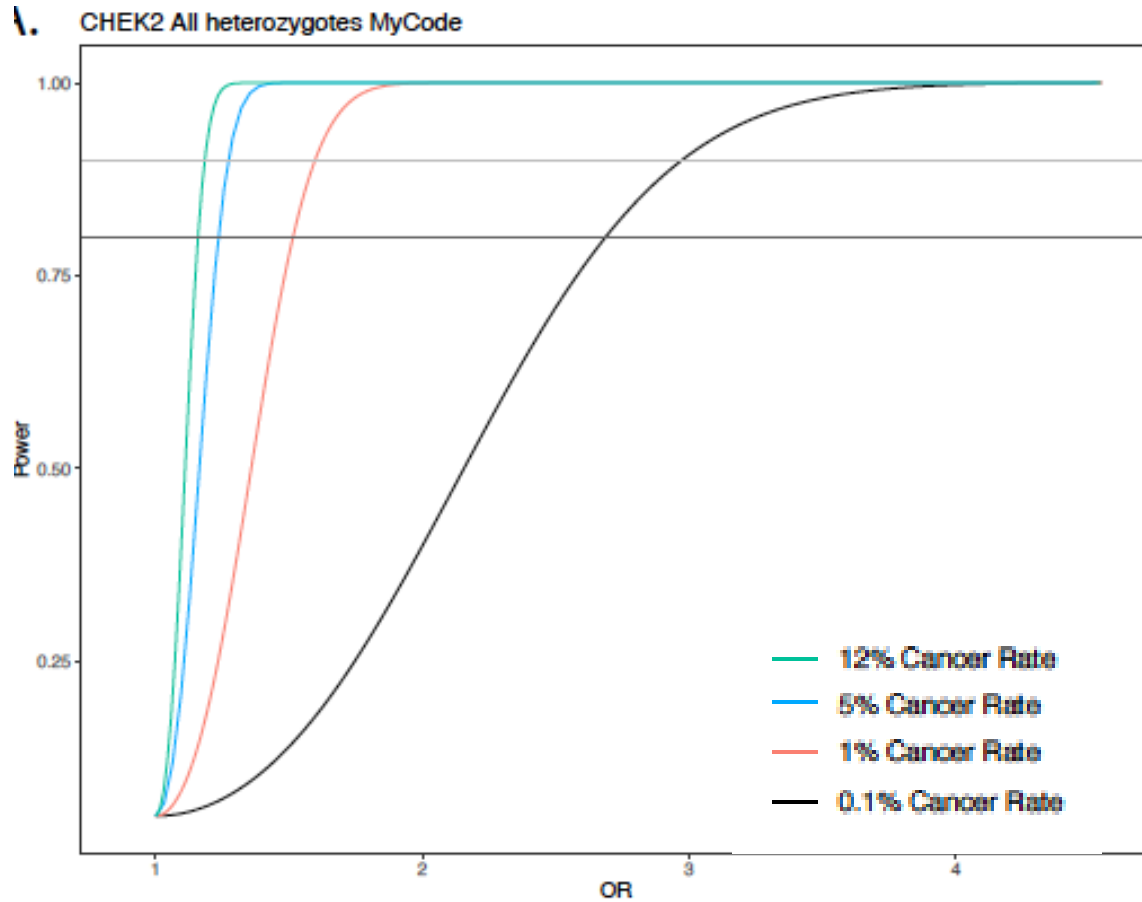
### UK Biobank

- Data-field 23157
- n=469,681; age>18 yrs; mean 56.5 yrs
- *CHEK2* P/LP heterozygotes: 3,232
- Includes 8 bi-alleleics but none with 2 common variants; not excluded
- Controls: individuals without *CHEK2* variation or B/LB: 305,330

# Prevalence of All, pathogenic truncating variants (PTV) and pathogenic missense variants (PMV) in *CHEK2* in adult heterozygotes in UK Biobank and Geisinger MyCode.

Cohort	Individuals/Prevalence (95%CI)	All <i>CHEK2</i> P/LP Variants	Pathogenic Truncating Variants (PTV)	Pathogenic Missense Variants (PMV)
UK Biobank – related and unrelated (n=469,765)	Number of individuals	3,232	1,847	1,290
	Prevalence	1/145 (1/140 – 1/150)	1/254 (1/243 – 1/266)	1/364 (1/344 – 1/384)
UK Biobank – unrelated (n=437,645)	Number of individuals	3,171	1,825	1,268
	Prevalence	1/138 (1/133- 1/142)	1/239 (1/229- 1/251)	1/345 (1/326- 1/364)
MyCode – related and unrelated (n=167,050)	Number of individuals	3,153	913	2,221
	Prevalence	1/52 (1/51 – 1/54)	1/183 (1/171 – 1/195)	1/75 (1/72 – 1/78)
MyCode – unrelated (n=109,730)	Number of individuals	2,489	728	1,751
	Prevalence	1/43 (1/41 – 1/44)	1/150 (1/140- 1/162)	1/62 (1/59-1/65)

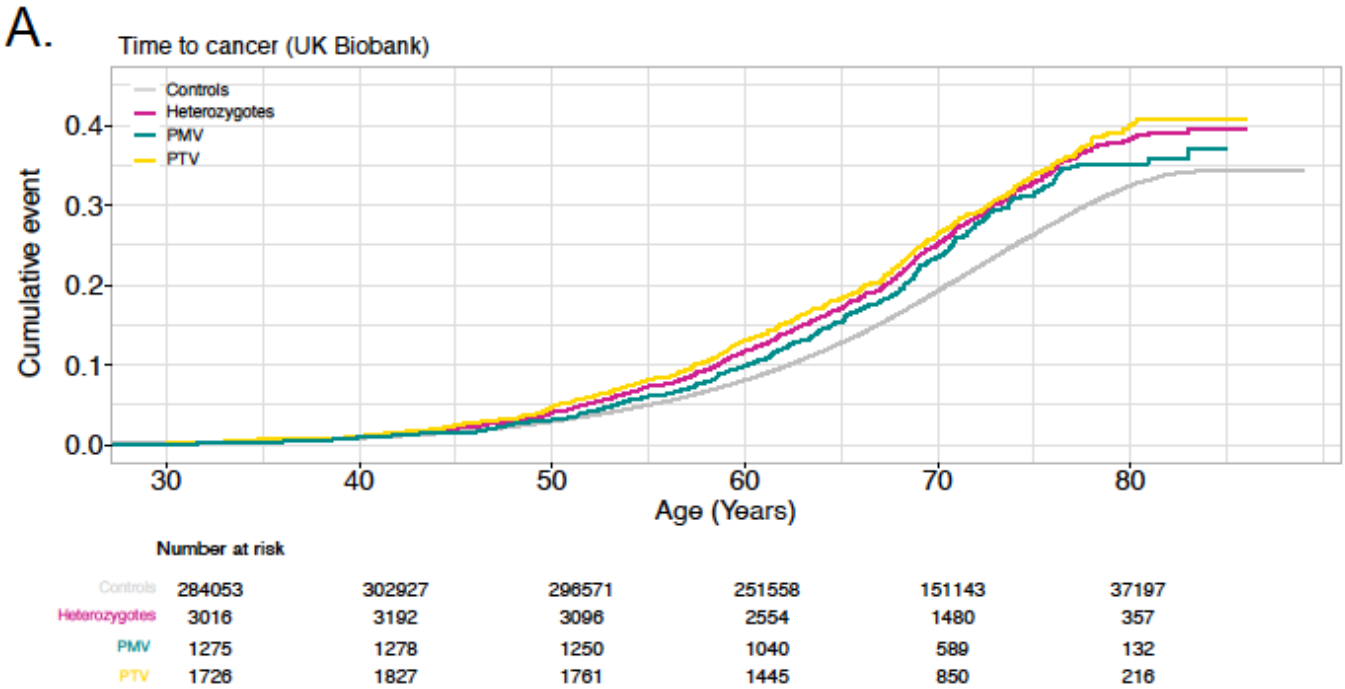
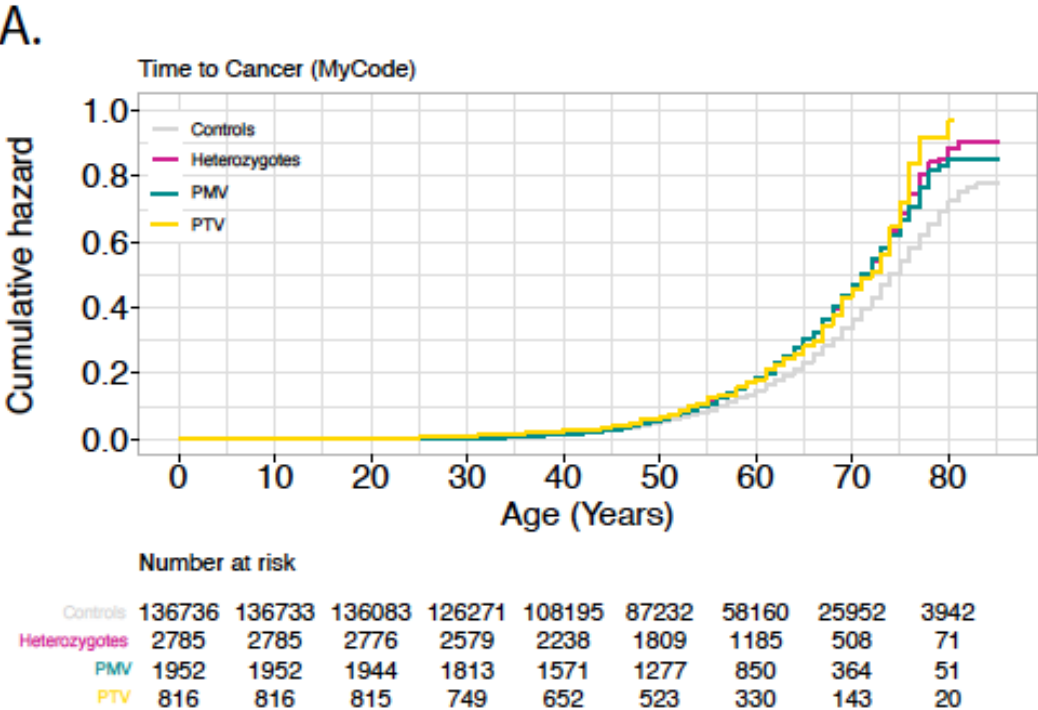
# Power as a function of risk (odds ratio) in MyCode (left) and UK Biobank (right) for a range of cancer rates



Dark gray line: 80% power; light gray line: 90% power

Kim, Kim *et al.* Submitted.

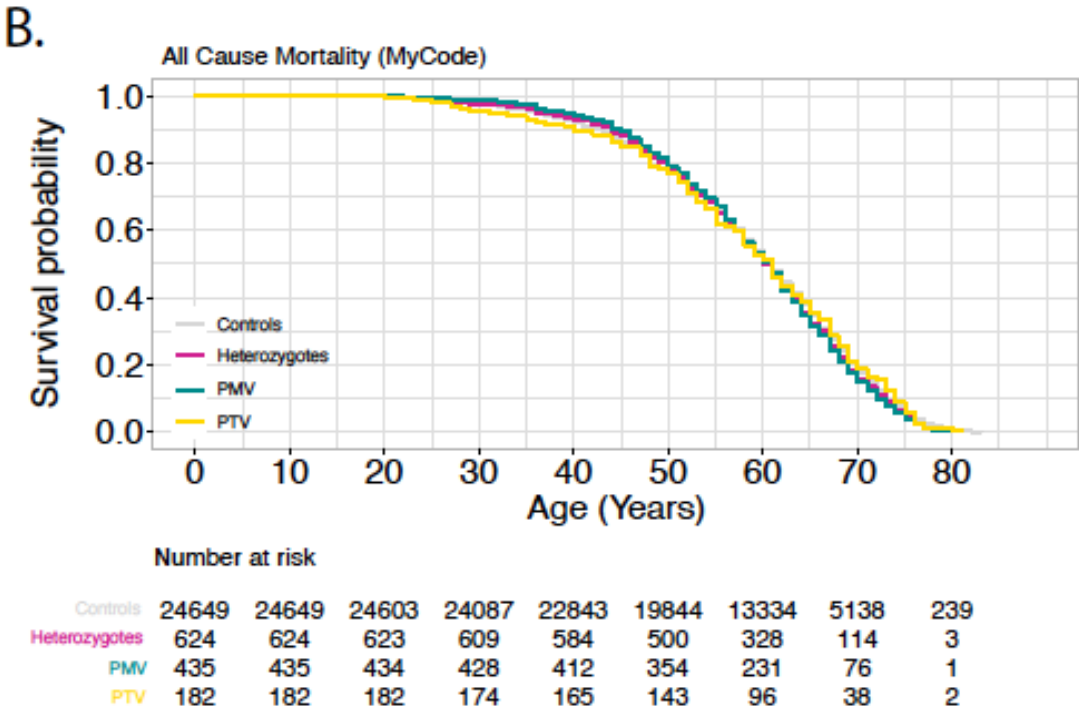
# Age-dependent penetrance of pathogenic *CHEK2* variants for all cancers. Left: Time-to-cancer (penetrance) in Geisinger MyCode; Right: Time-to-cancer (penetrance) in UK Biobank



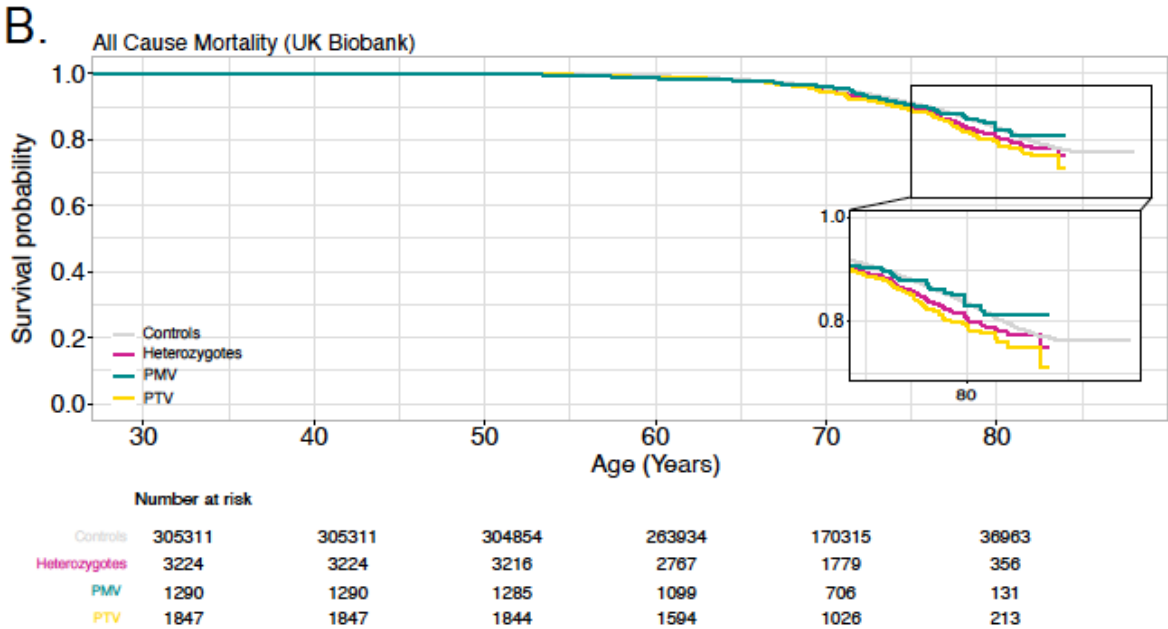
MyCode (adjusted HR: 1.26 [95%CI 1.16-1.37], *P*-value: 3.2x10<sup>-8</sup>)  
(No significant difference between PMV and PTV)

UKBB (adjusted HR 1.31 [95%CI 1.24-1.40], *P*-value: 2x10<sup>-16</sup>)  
(No significant difference between PMV and PTV)

# Age-dependent penetrance of pathogenic *CHEK2* variants for all-cause mortality. Left: All-cause mortality in Geisinger MyCode; Right: All-cause mortality in UK Biobank

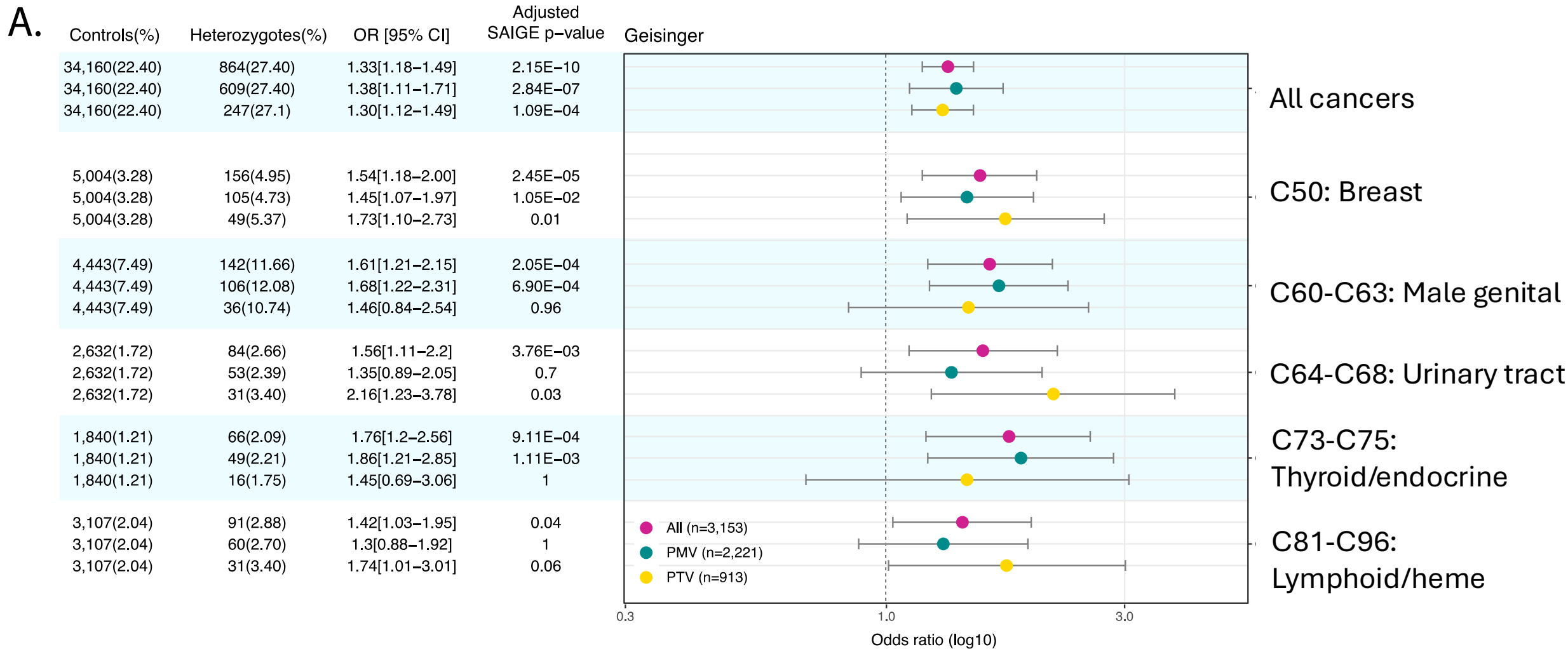


No significant differences in Geisinger MyCode  
adjusted HR 1.09 [95%CI 0.96-1.24], *P*-value: 0.20)  
(No significant difference between PMV and PTV)



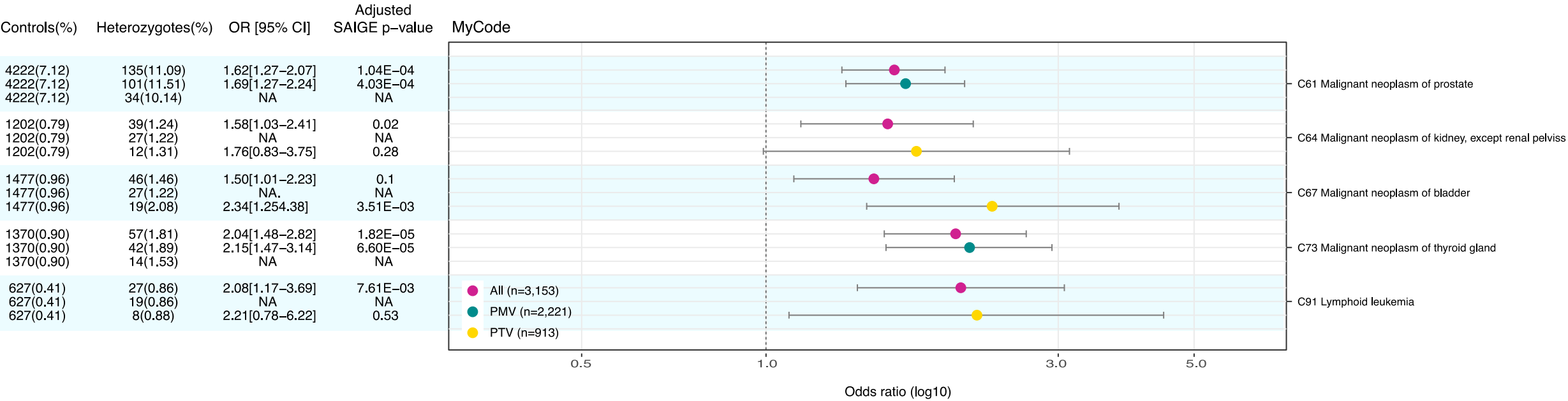
Significantly increased in All heterozygotes in UKBB  
adjusted HR 1.21 [95%CI 1.08-1.37], *P*-value: 1.51x10<sup>-3</sup>  
(No significant difference between PMV and PTV)

# Odds ratio for All, PTV and PMV *CHEK2* heterozygotes for organ system groupings of cancer ICD codes with a significant excess of risk in Geisinger MyCode



# Odds ratio for All, PTV and PMV *CHEK2* heterozygotes for specific cancers in the organ system groupings of cancer ICD codes with a significant excess of risk in Geisinger MyCode

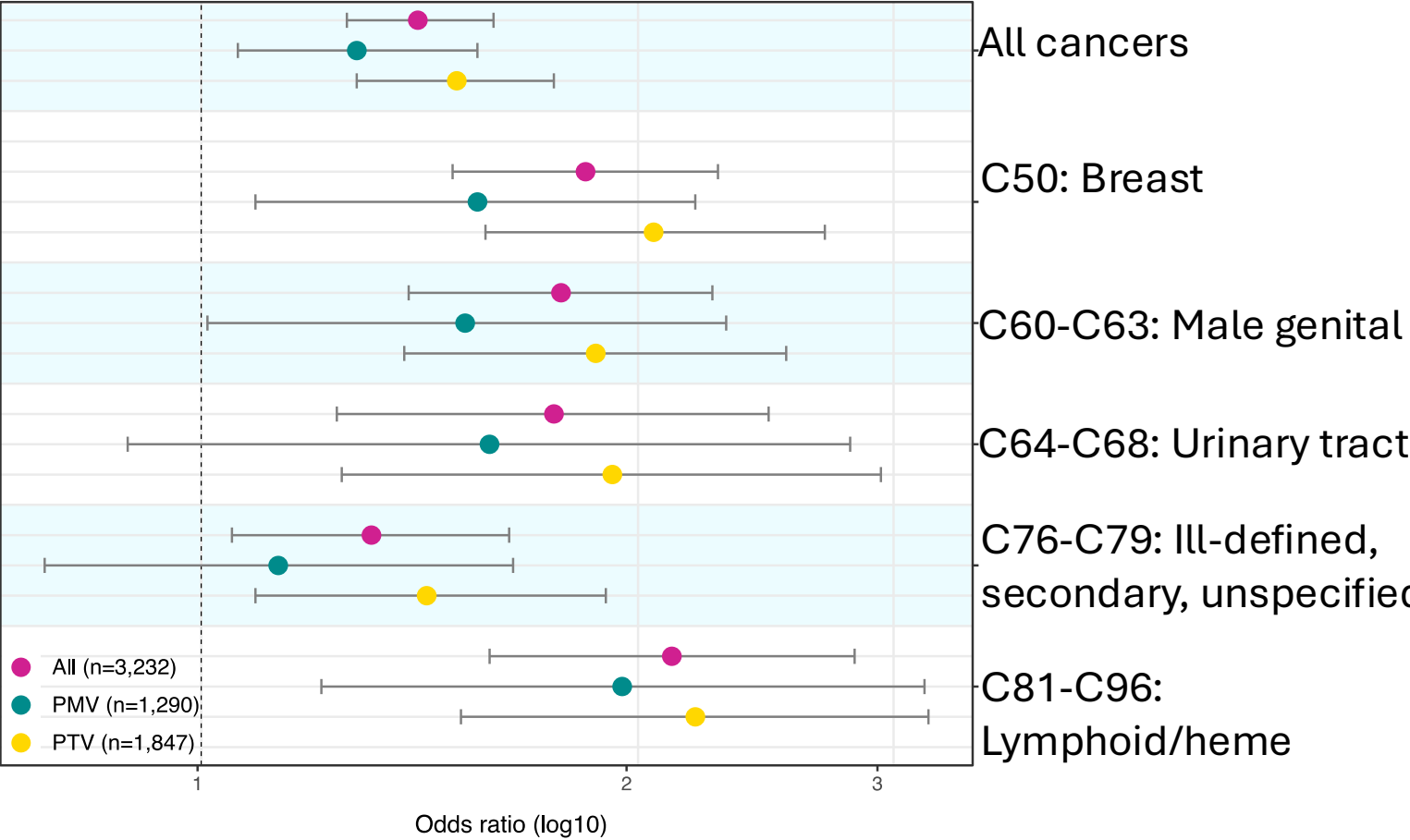
A.



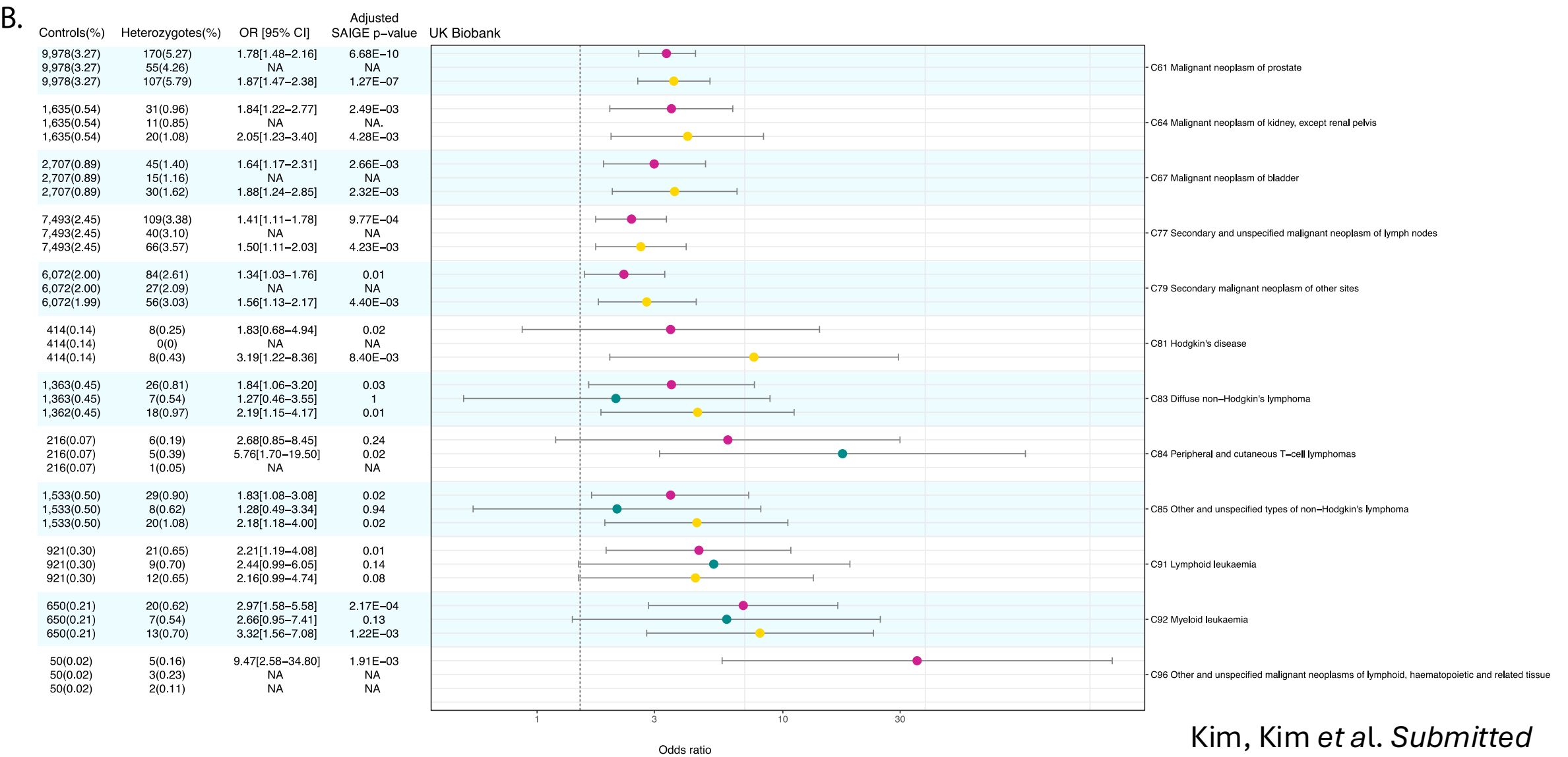
# Odds ratio for All, PTV and PMV *CHEK2* heterozygotes for organ system groupings of cancer ICD codes with a significant excess of risk in UK Biobank

B.

Controls(%)	Heterozygotes(%)	OR [95% CI]	Adjusted SAIGE p-value
69,836(22.87)	934(28.90)	1.41[1.26–1.59]	6.05E–15
69,836(22.87)	344(26.67)	1.28[1.06–1.55]	2.19E–04
69,836(22.87)	562(30.23)	1.50[1.28–1.75]	9.56E–12
12,439(4.07)	227(7.02)	1.84[1.49–2.27]	2.47E–12
12,439(4.07)	80(6.20)	1.55[1.09–2.19]	1.41E–02
12,439(4.07)	139(7.53)	2.05[1.57–2.69]	4.49E–10
10,557(3.46)	179(5.53)	1.77[1.39–2.25]	3.64E–09
10,557(3.46)	58(4.50)	1.52[1.01–2.30]	0.14
10,557(3.46)	113(6.12)	1.87[1.38–2.53]	4.13E–07
4,351(1.43)	77(2.38)	1.75[1.24–2.46]	1.01E–04
4,351(1.43)	27(2.09)	1.58[0.89–2.80]	0.84
4,351(1.43)	49(2.65)	1.92[1.25–2.94]	2.68E–04
14,339(4.70)	192(5.94)	1.31[1.05–1.63]	4.68E–03
14,339(4.70)	66(5.12)	1.13[0.78–1.64]	1
14,339(4.70)	120(6.50)	1.43[1.09–1.90]	2.95E–03
5,030(1.65)	108(3.34)	2.11[1.58–2.82]	3.45E–09
5,030(1.65)	39(3.02)	1.95[1.21–3.15]	4.70E–03
5,030(1.65)	65(3.52)	2.19[1.51–3.17]	8.74E–07



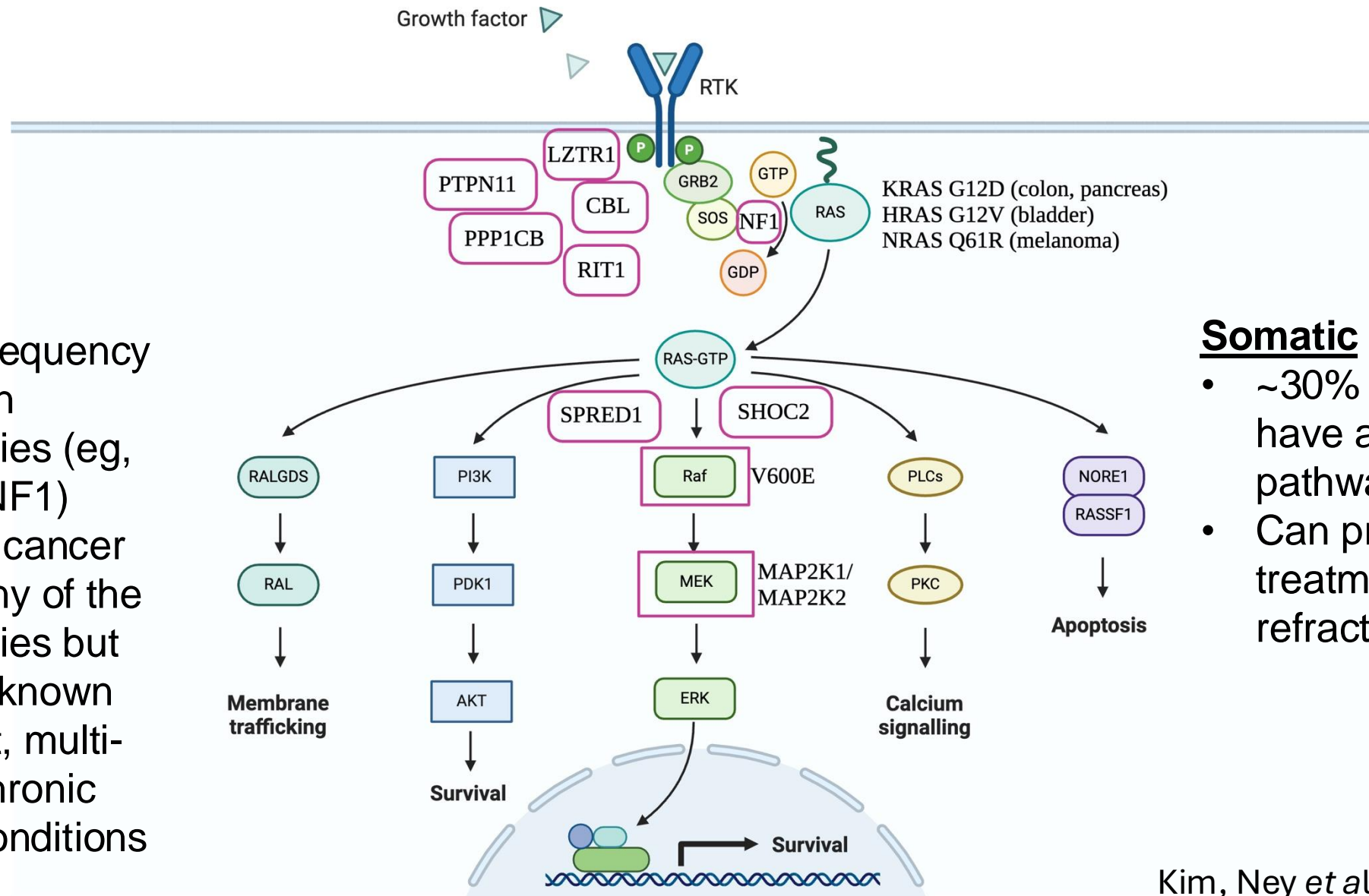
Odds ratio for All, PTV and PMV *CHEK2* heterozygotes for specific cancers in the organ system groupings of cancer ICD codes with a significant excess of risk in UK Biobank



# Genomic ascertainment of *CHEK2* heterozygotes

- Relatedness-adjusted, Bonferroni-corrected genomic ascertainment of two population-based, exome-sequenced, EHR-linked cohorts
- High power to detect elevated risk ( $OR > 2$ ) in all but the rarest cancers
- Confirms the significantly increased risk for breast and prostate cancers (as well as all cancers, collectively)
- Observed risk tends to be even lower ( $OR < 2$ ) than previous estimates, especially for PTV
- In neither cohort was a significant excess risk for “malignant neoplasms of digestive organs” observed, despite numerous studies in which a modest excess risk has been reported
- Substantial evidence from both cohorts of significant increased risk for kidney cancer, bladder cancer and CLL (lymphoid leukemia).
- Significant excess of malignancies of thyroid and other endocrine tumors (C73-C75) was observed in MyCode but not UK Biobank
- For some rarer cancers (male breast, testicular) the two cohorts were likely underpowered for others (sarcoma, stomach) there may be both a power issue and a survival bias in ascertainment given the aggressive nature of these cancers

# RAS/MAPK Pathway



## Germline

- ~1:2000 frequency of common RASopathies (eg, Noonan, NF1)
- Increased cancer risk in many of the RASopathies but degree unknown
- Significant, multi-system, chronic medical conditions

## Somatic

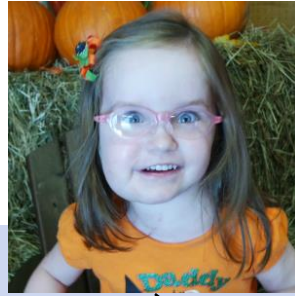
- ~30% cancers have altered RAS pathway
- Can predict treatment refractoriness

# The RASopathies

SYNGAP1



NF1



Cap-AV Malformation



Costello Syndrome



Legius Syndrome



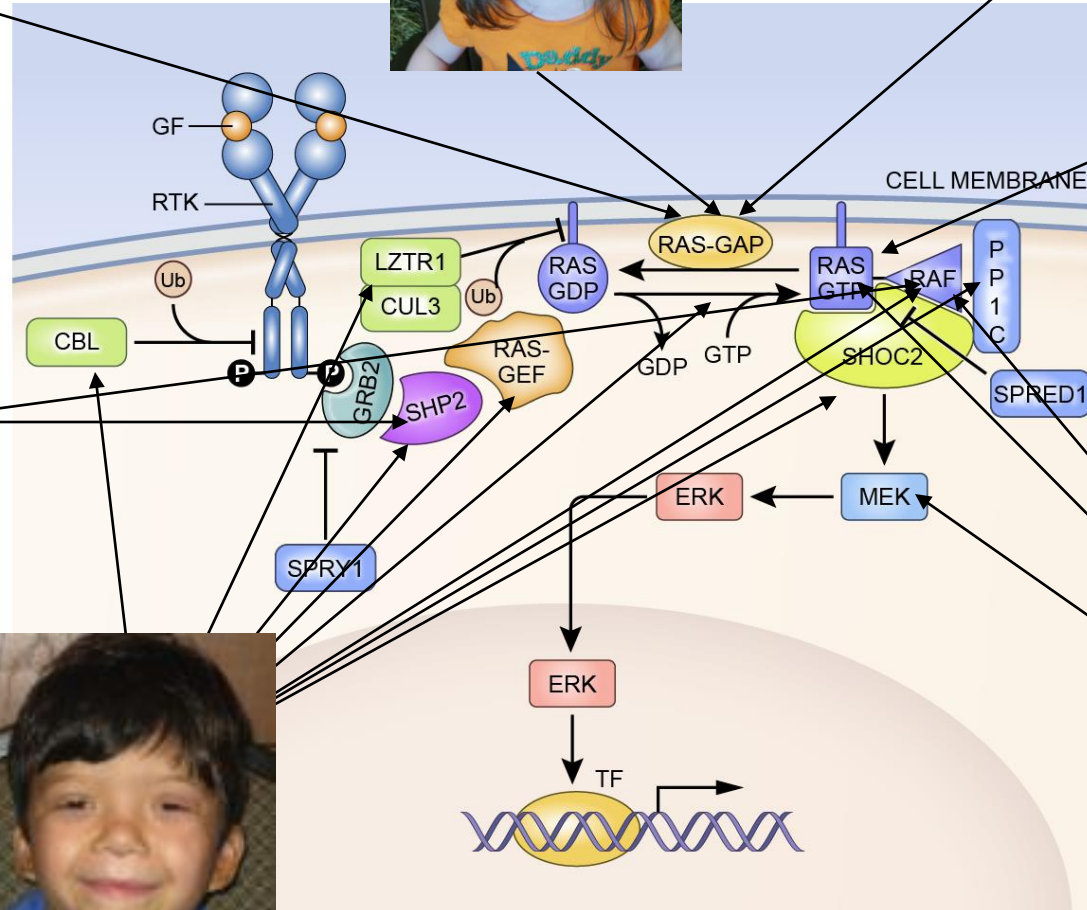
Cardiofaciocutaneous Syndrome



Noonan Syndrome  
Multiple Lentigines



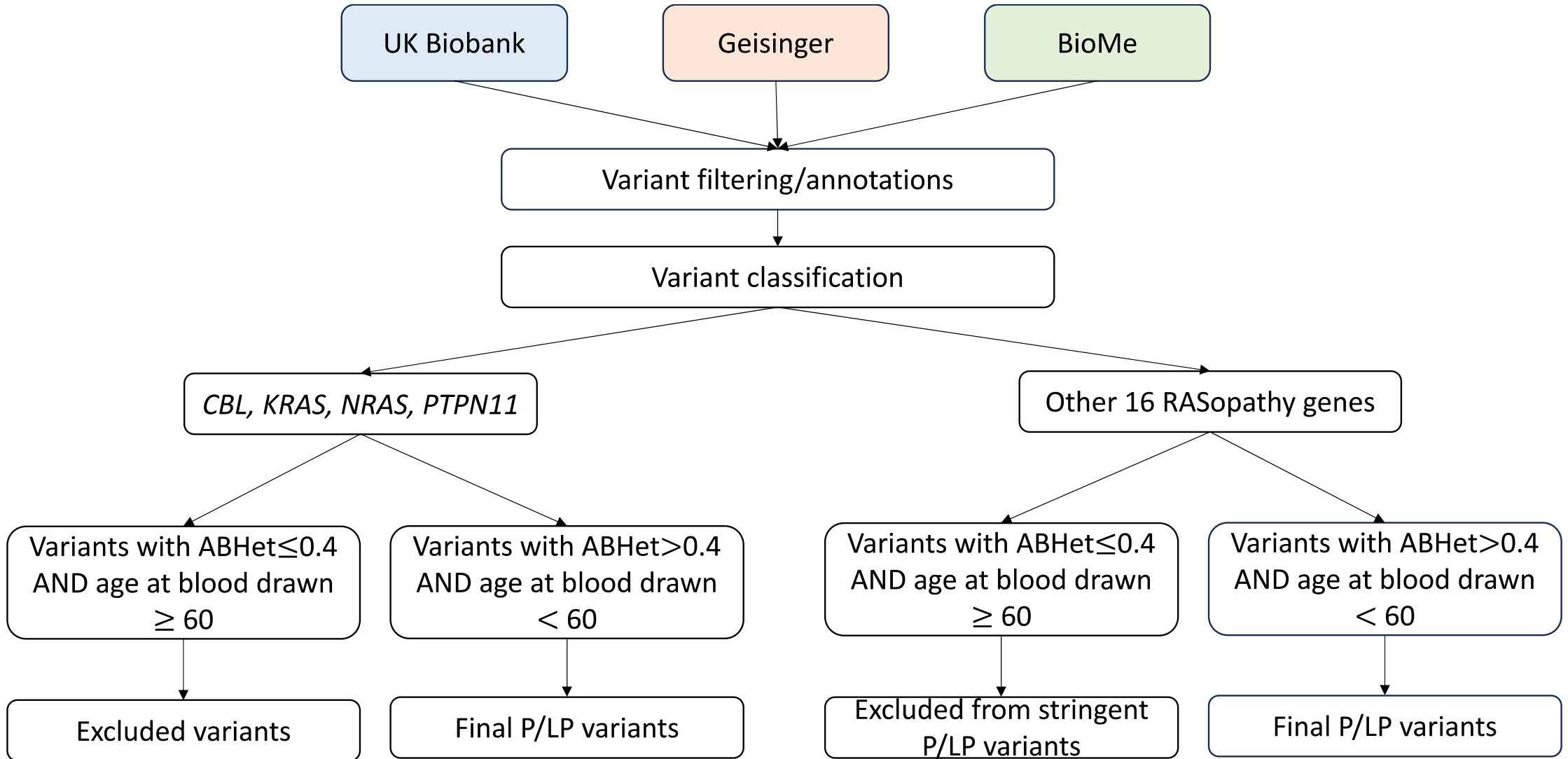
Noonan Syndrome



# Genomic ascertainment of RASopathies

- Cancer risk well documented in childhood and adolescence
  - From phenotypic and family ascertainment
  - Costello: bladder, rhabdomyosarcoma, neuroblastoma
  - High-risk variants in Noonan: JMML, rhabdomyosarcoma, neuroblastoma
- Cancer risk in CFC and Legius syndrome unclear throughout lifespan
- Despite case reports of cancer in adults with germline P/LP in RASopathy genes, cancer risk is unknown
- Interrogate the exome sequence of individuals in three large biobanks to quantify germline P/LP variant prevalence, cancer incidence, and survival of adults with non-NF1 RAS/MAPK genes

# Flow diagram of variant classification and application of filtering to limit clonal hematopoiesis (CH) variants and develop a range of germline prevalence estimates.



# Frequency of RAS/MAPK variants in UKBiobank, Geisinger, and BioMe

		UK Biobank (469,618 exomes)		Geisinger MyCode (167,050 exomes)		Mount Sinai BioMe (30,129 exomes)	
Gene Syndrome		count	frequency	count	frequency	count	freq
<i>CBL</i>		14	1:33,544 (1:19,982–1:56,309)	8	1:20,881 (1:10,581–1:41,207)	0	-
CFC	stringent	9	1:52,179 (1:27,453–1:99,178)	3	1:55,683 (1:17,474–1:215,605)	0	-
		10	1:46,961 (1:25,509–1:86,453)	4	1:41,762 (1:15,185–1:130,367)	0	-
Noonan	stringent	141	1:3,330 (1:2,824–1:3,927)	68	1:2,456 (1:1,938–1:3,113)	15	1:2,008 (1:1,217–1:3,314)
		149	1:3,151 (1:2,684–1:3,700)	73	1:2,288 (1:1,820–1:2,876)	17	1:1,772 (1:1,106–1:2,838)
NSML		21	1:22,362 (1:14,627–1:34,188)	7	1:23,864 (1:11,560–1:49,264)	1	1:30,129 (1:4,639–1:577,181)
Noonan without NSML	stringent	120	1:3,913 (1:3,273–1:4,679)	61	1:2,738 (1:2,132–1:3,517)	14	1:2,152 (1:1,282–1:3,612)
		128	1:3,668 (1:3,086–1:4,361)	66	1:2,531 (1:1,989–1:3,219)	16	1:1,883 (1:1,159–1:3,058)
Legius ( <i>SPRED1</i> )	stringent	24	1:19,567 (1:13,150–1:29,116)	3	1:55,683 (1:17,474–1:215,605)	0	-
		24	1:19,567 (1:13,150–1:29,116)	4	1:41,762 (1:15,185–1:130,367)	0	-
Costello		0	-	0	-	0	-

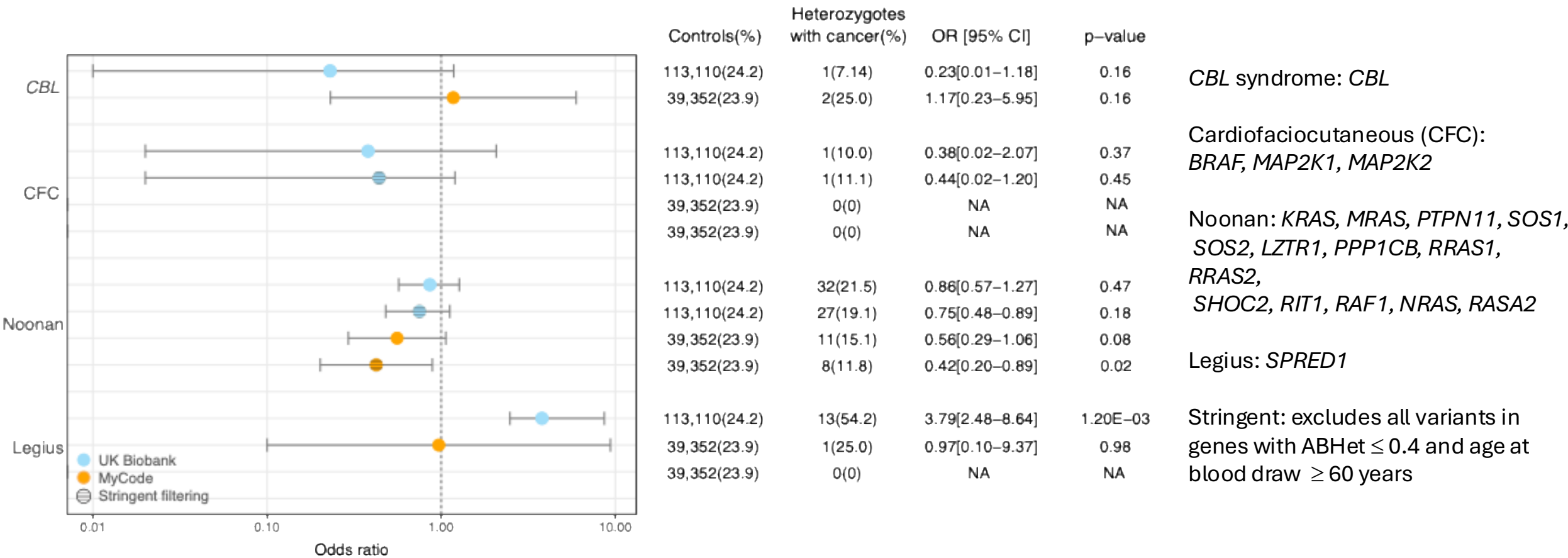
Noonan – *KRAS*, *MRAS*, *PTPN11*, *SOS1*, *SOS2*, *LZTR1*, *PPP1CB*, *RRAS1*, *RRAS2*, *SHOC2*, *RIT1*, *RAF1*, *NRAS*, *RASA2*

Cardiofaciocutaneous (CFC):  
*BRAF*, *MAP2K1*, *MAP2K2*

NSML: Noonan syndrome with multiple lentigines: select variants in *PTPN11*

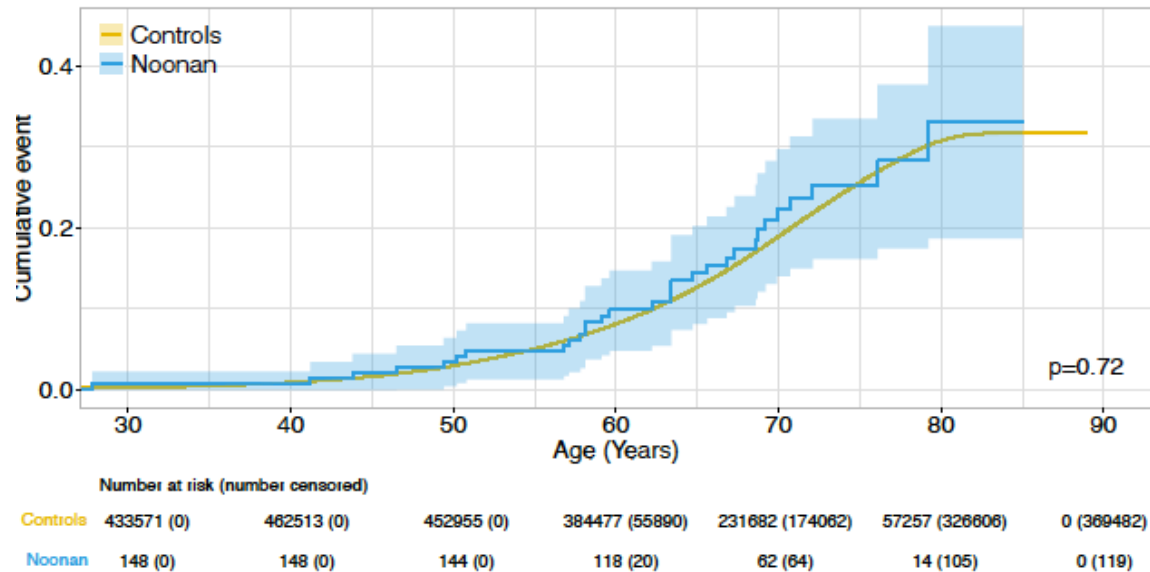
Stringent: excludes all variants in genes with ABHet ≤ 0.4 and age at blood draw ≥ 60 years

# Cancer prevalence calculated as Odds Ratio in individuals with germline Pathogenic/Likely Pathogenic variants in RASopathies versus controls in UKBB and Geisinger cohorts

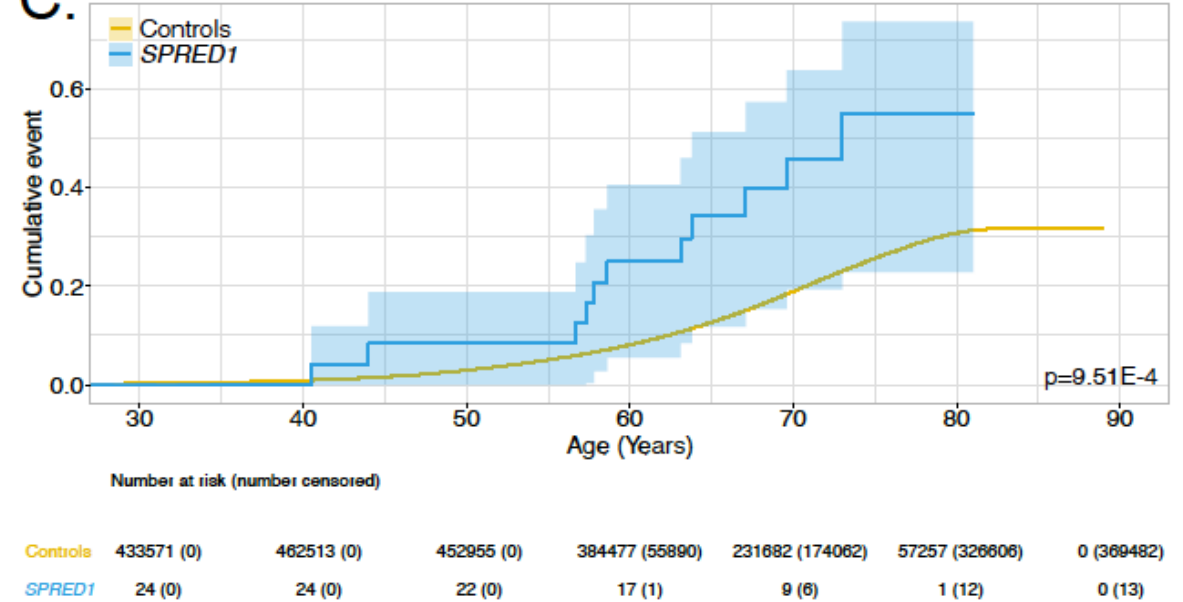


# Time to cancer in UK Biobank in Noonan-associated genes (panel A) and in individuals with Pathogenic/Likely Pathogenic variants in *SPRED1* (panel C)

A.

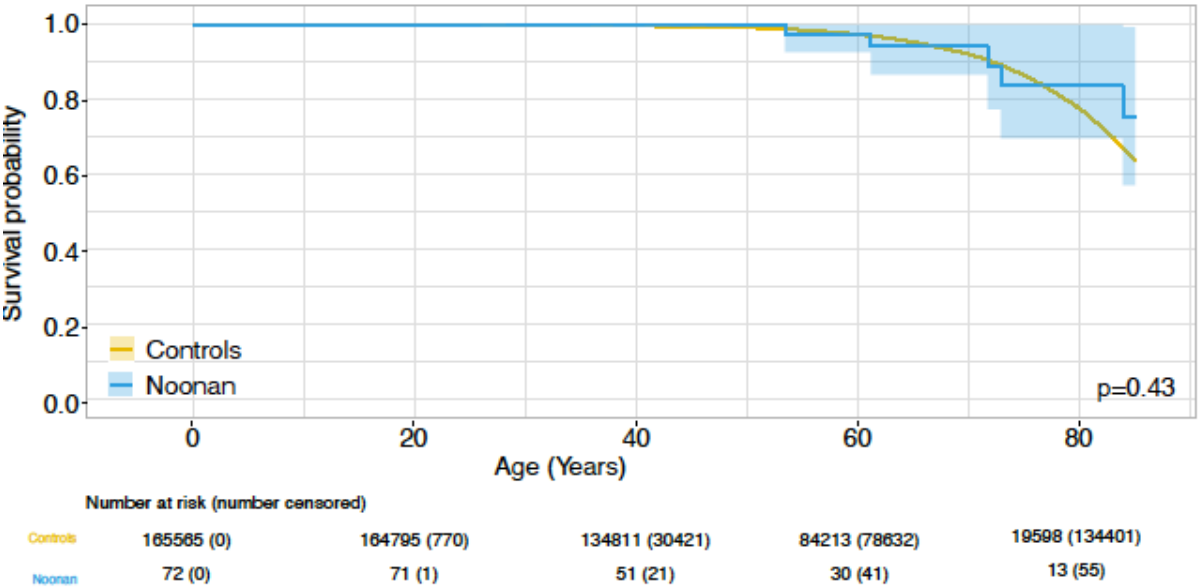


C.

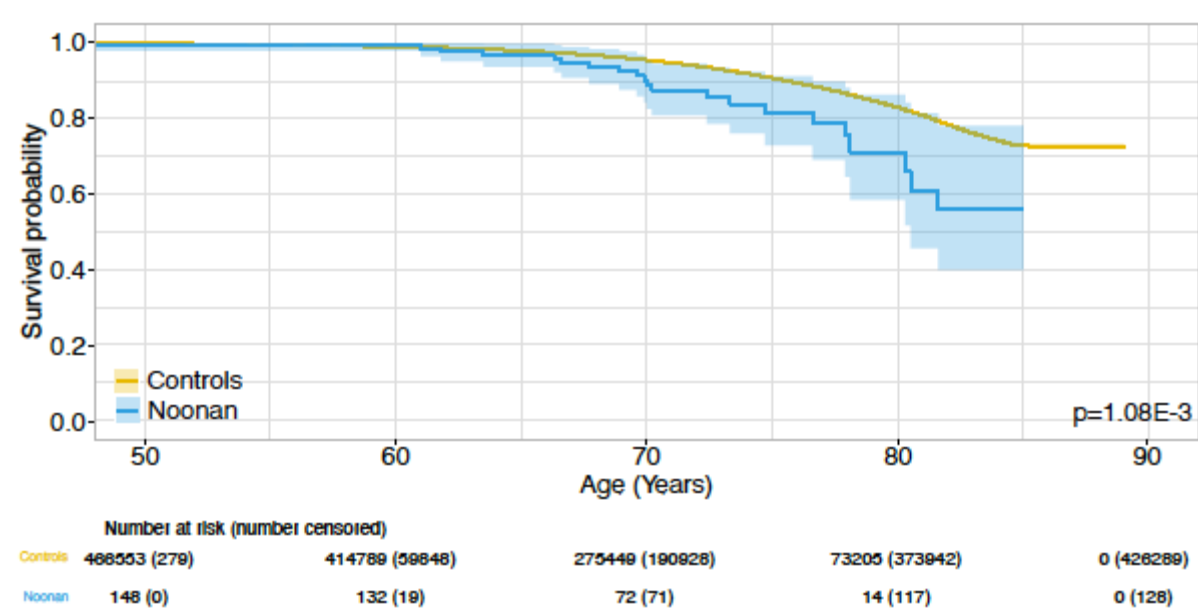


Time-dependent survival is not significantly different in Noonan-heterozygotes vs. controls in Geisinger MyCode (panel A) but is less favorable vs controls in UK Biobank (panel C)

A.



C.



## Using Genomic Ascertainment to Explore Prevalence and Cancer Risk in Adult Individuals with Pathogenic and Likely Pathogenic Germline Variants in RASopathy Genes

- P/LP variants in Noonan syndrome-associated genes were the most common
- P/LP variants in Noonan syndrome-associated genes were not associated with an increased cancer risk in adults
- In UK Biobank, P/LP variants in *SPRED1* were associated with a 4-fold higher risk of cancer compared to controls in adults and had earlier cancer onset
- In UK Biobank, P/LP variants in Noonan syndrome-associated genes were correlated with increased all-cause mortality and cancer-related mortality

# What are the consequences of genomic ascertainment?

- *Prevalence* of pathogenic/likely pathogenic (P/LP)\* variants is greater than previously estimated
- *Penetrance* (risk from a P/LP variant) may not be as high as previously estimated
- *Phenotype* is different (may be less severe, broader)

\*Clinically actionable germline variation classified by ACMG/AMP rules (Richards *et al Genetics in Medicine* 2015)

# Lessons learned from the genome-first approach (so far)– part I

- *Genome-first approach holds enormous promise, however...*
- Complements “phenotype-first” approach
- Manual EHR review is messy, incomplete and labor-intensive
  - Often query of ICD codes tells you what you need to know
- Large cohort x rare disease = modest numbers
  - More sequencing: DCEG Connect, NIH All of Us, UK Biobank ...
  - Usefulness of phenotype-first cohorts
- Characteristics of cohorts matter and bring their own biases
  - Health system vs. healthier volunteer
- Outcome studies are easier to do than etiology studies

# Lessons learned from the genome-first approach (so far)– part II

- *Genome-first approach holds enormous promise, however...*
- Large number of matched controls a blessing and a curse (inflated p-values)
  - Work with a good biostatistician
- Variant interpretation is relatively easier
  - We focus on ACMG/AMP classification of pathogenicity (for now)
  - Work with a good variant scientist
- Phenotype work is relatively harder
  - Pick your phenotypes with care and keep simple: height, cancer registry, blood glucose
  - Work with a clinical bioinformatician who knows ICD coding and phecodes
  - Phecodes as a way to simplify use of ICD codes
- Medical coding is an art and science
  - Multiplicity/redundancy of codes for the same thing
  - Institutional coding cultures
  - Awareness of diagnoses: breast/colon cancer family hx vs renal cancer family hx

# What's next?

- Analyze larger and larger cohorts
  - All of Us (NIH)
    - Goal of 1 million participants
    - Reflects diversity of the US circa 2024
- Analyze genome (not “just” exome) data
  - Wide variety of pathogenic variants
  - All of Us releases genome data – available on ~250,000 people now
  - UK Biobank release of genome data on 500,000 people
- Recruitment using genomic ascertainment
  - Reverse Phenotyping Core (NHGRI/Les Biesecker)
  - All of Us (NIH/Josh Denny)
- Incorporate findings into surveillance and variant interpretation guidelines
- Overall goal: improve “cancer interception”: grape vs. grapefruit

# Practicalities using MyCode data

- Use: genome-first, GWAS, ExWAS (rare-variant association)...
- Available data: ~233K exomes (arrays) with linked demographics, ICD codes, labs, imaging, chart review, pathology (samples and reports), medications, visit type, orthogonal sequencing
- Includes ~9000 pediatric exomes
- Access: through Jung and Doug
- Scheduled calls
- Proposal form
- Cost (CGB)
- Logistics of running analyses