

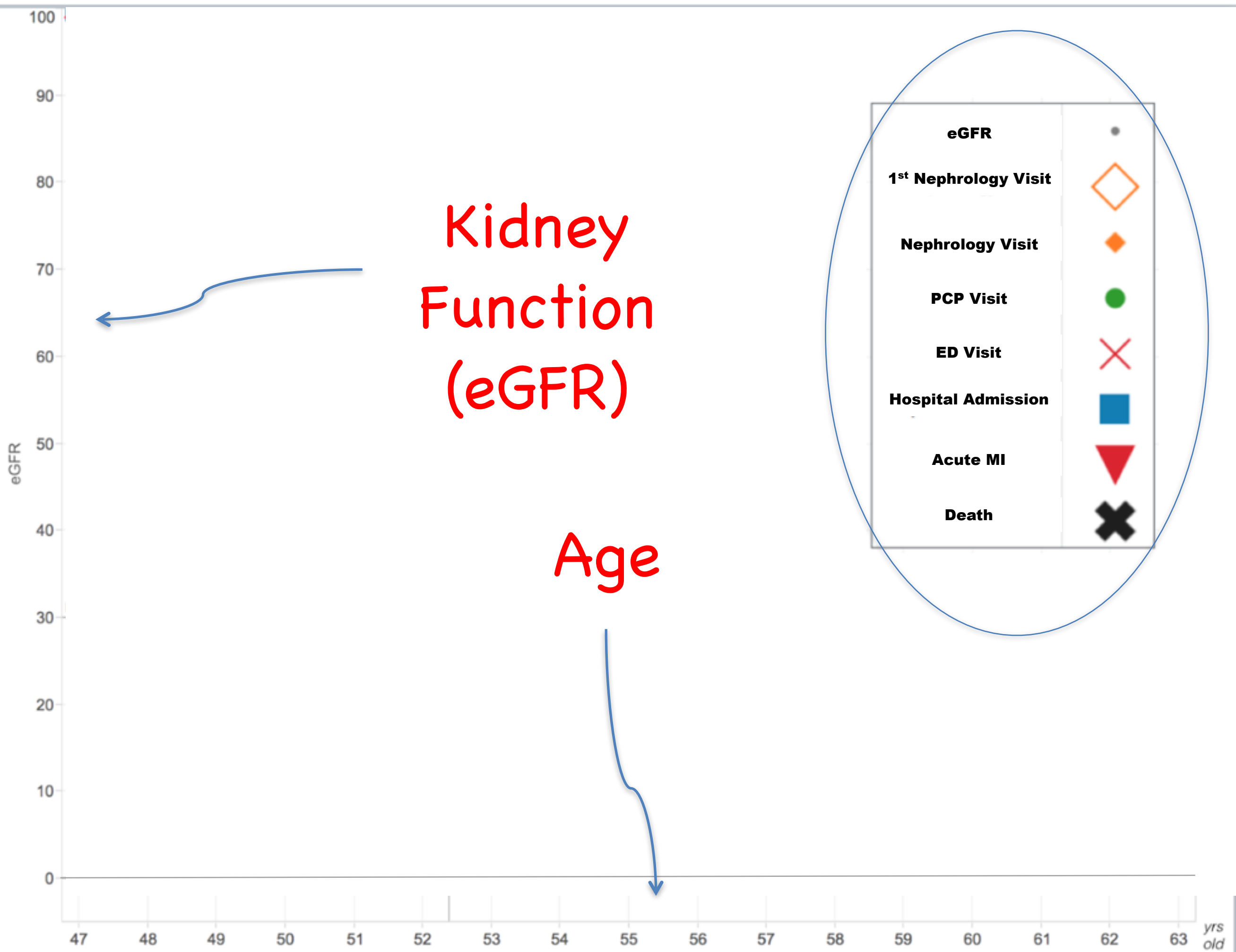
Scalable Modeling of Multivariate Longitudinal Data *for Prediction of Chronic Kidney Disease Progression*

Joe Futoma

Mark Sendak

Blake Cameron

Katherine Heller

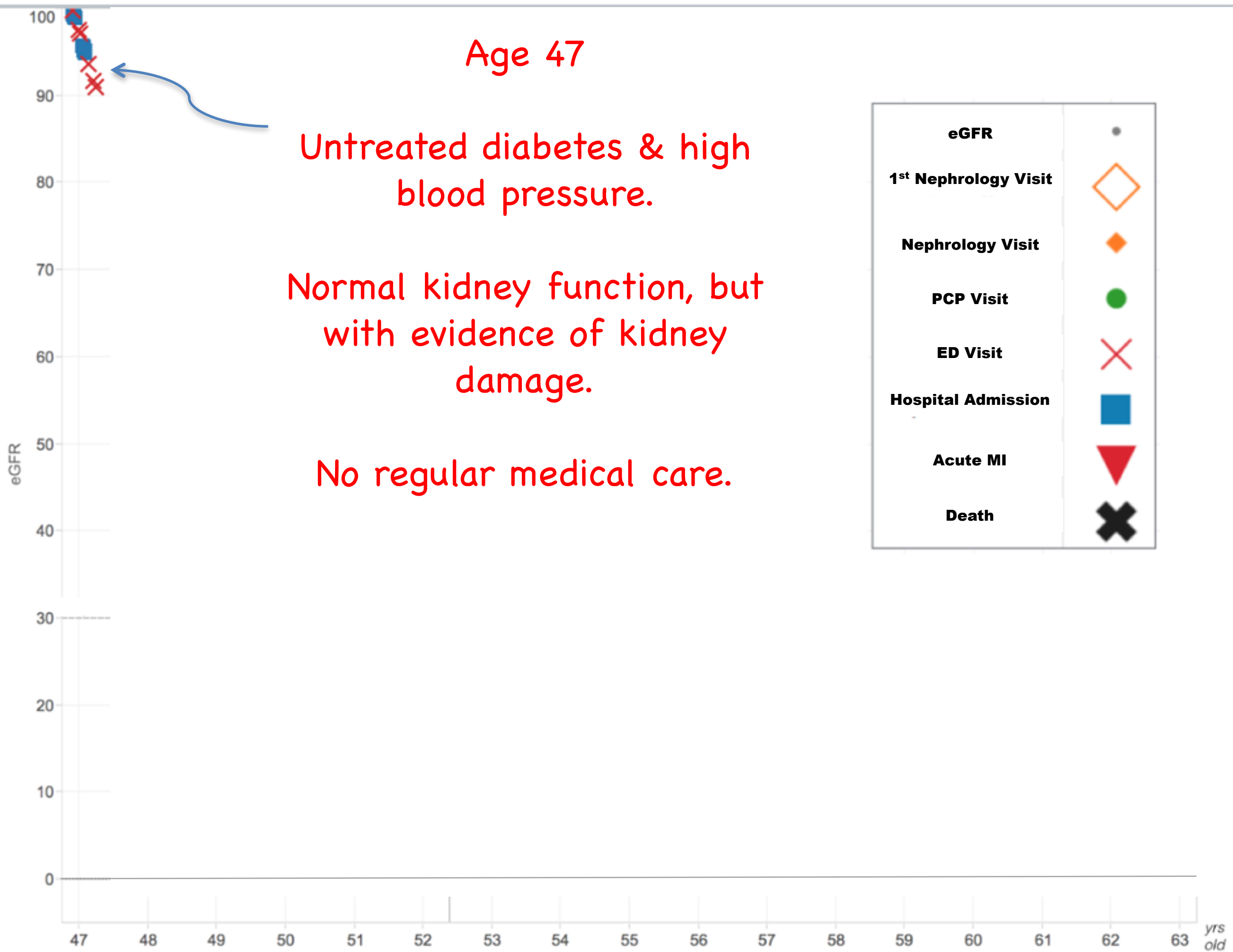


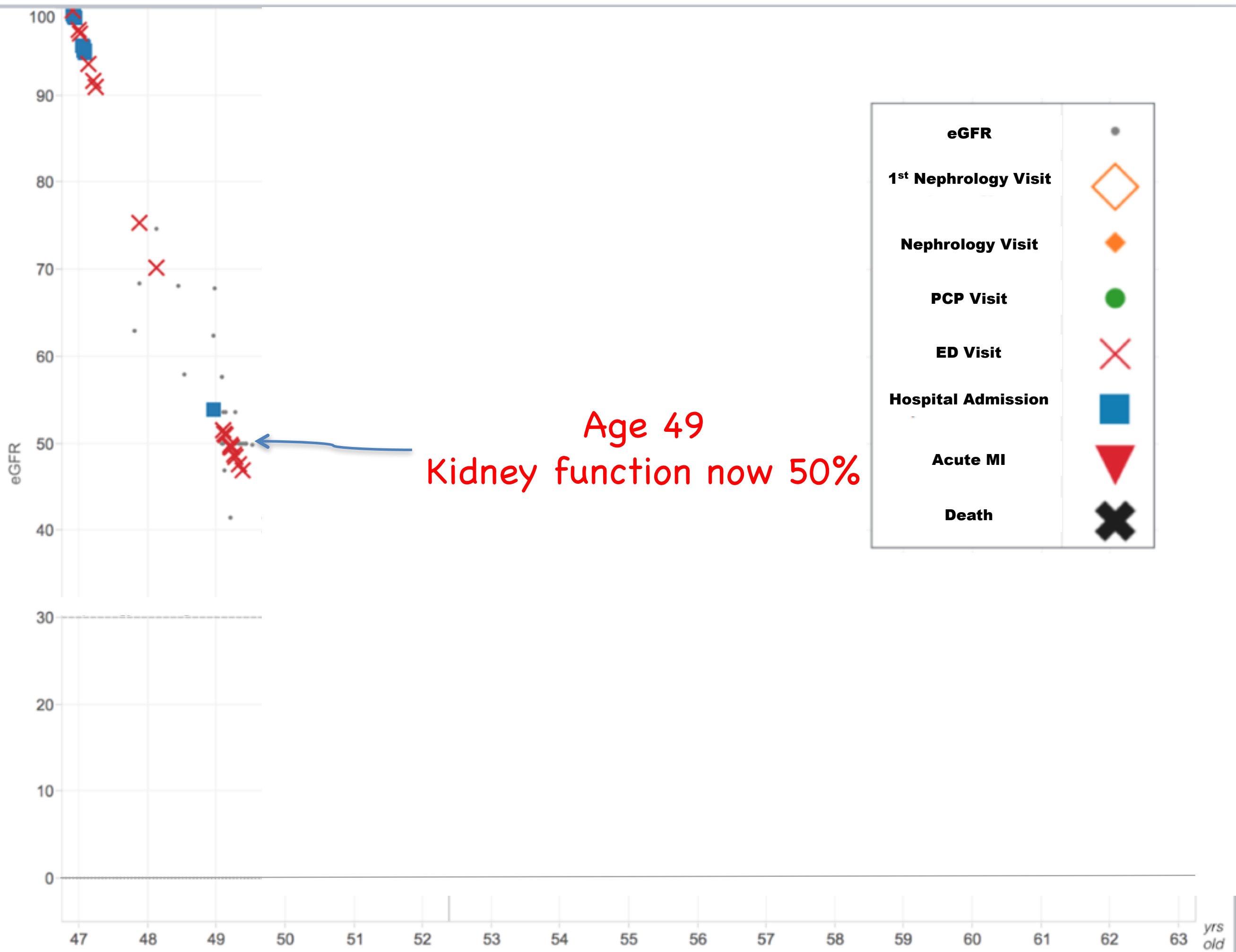
Age 47

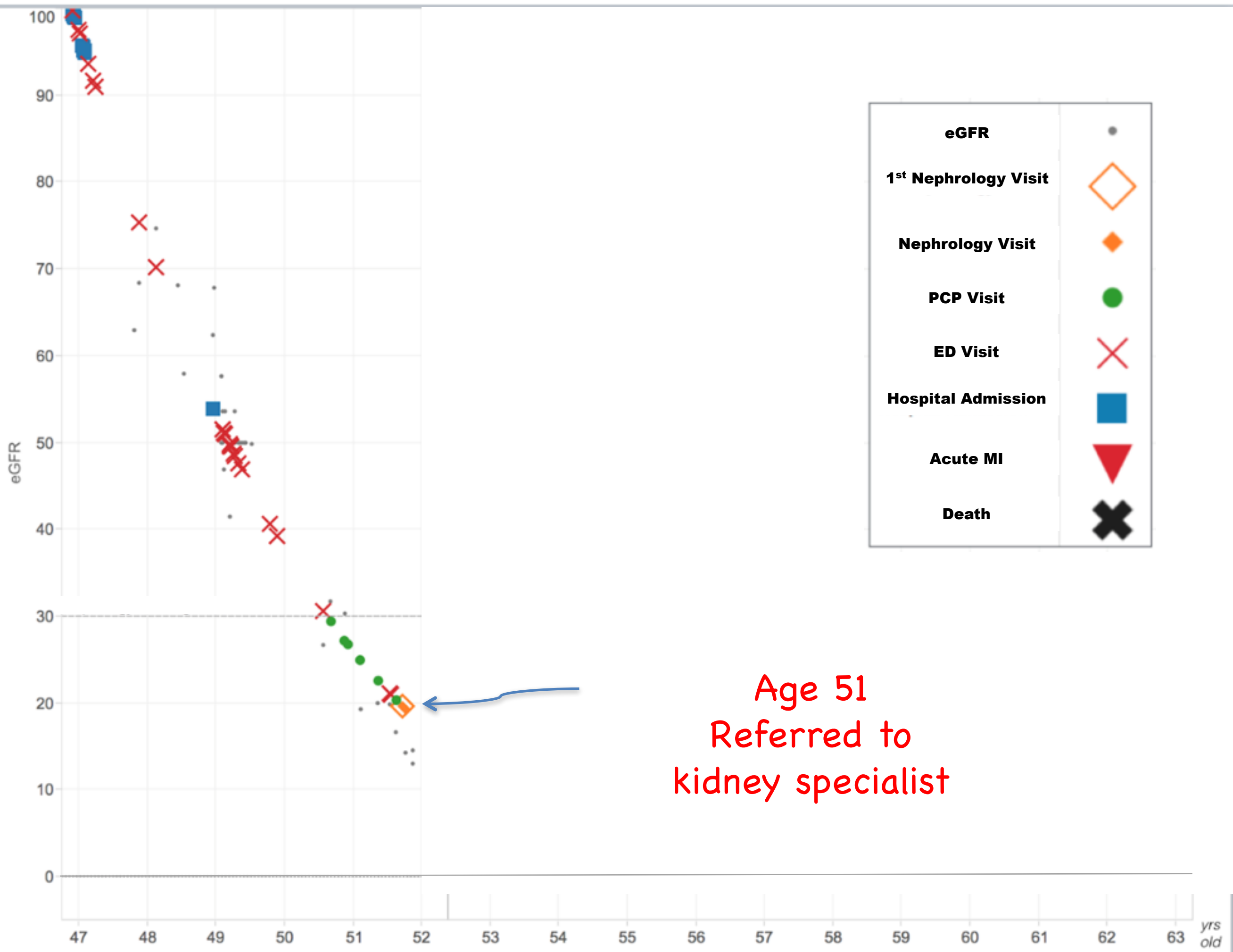
Untreated diabetes & high
blood pressure.

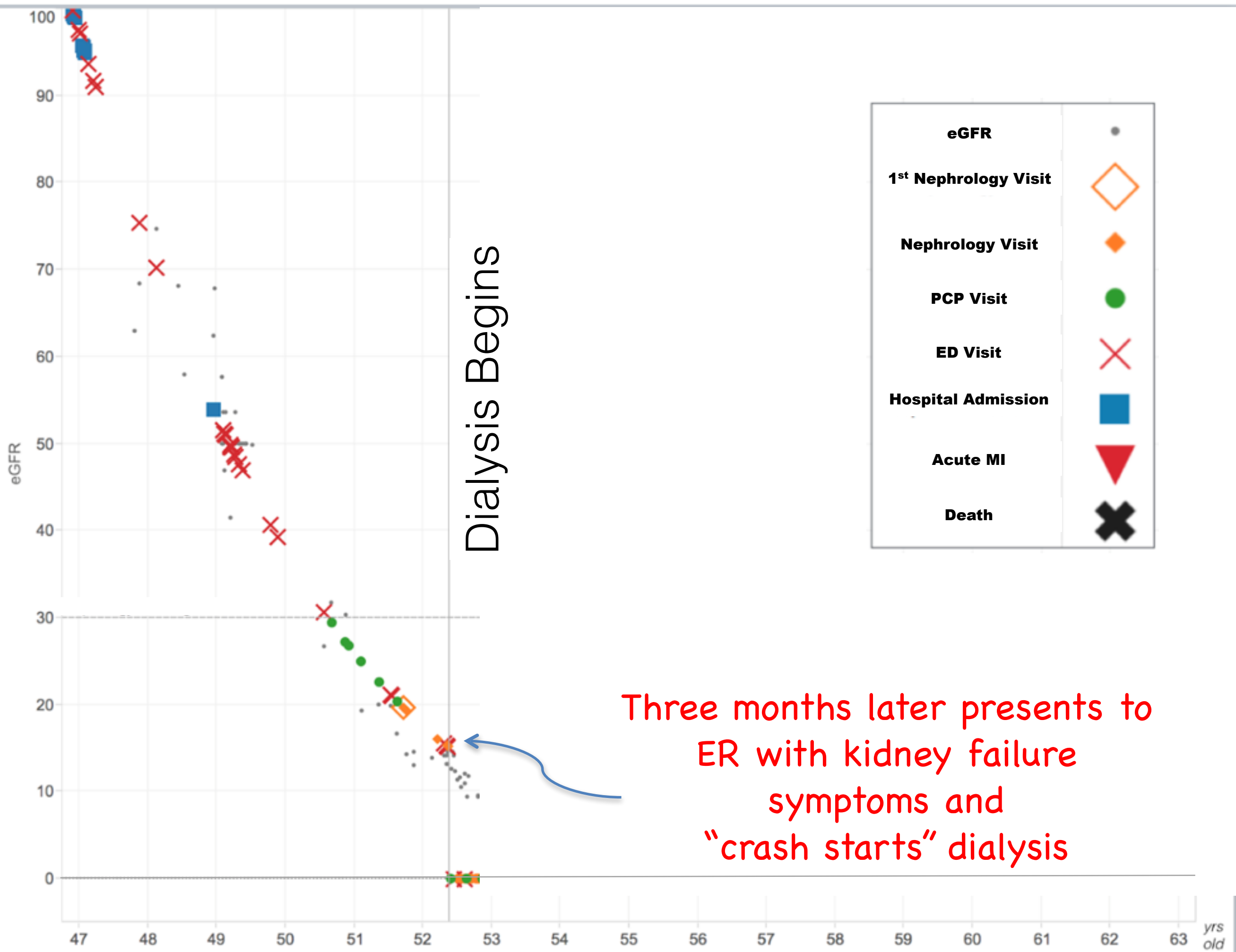
Normal kidney function, but
with evidence of kidney
damage.

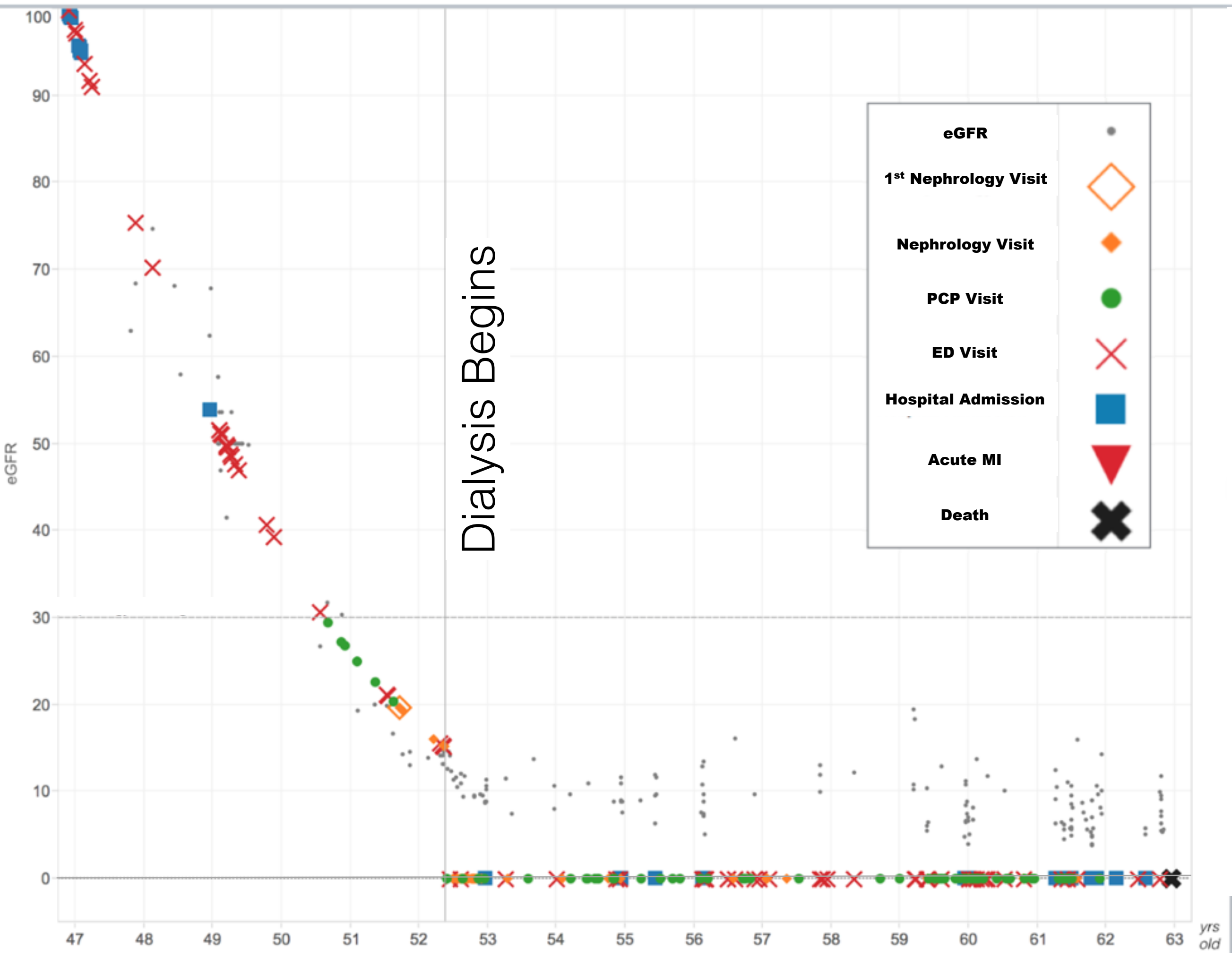
No regular medical care.

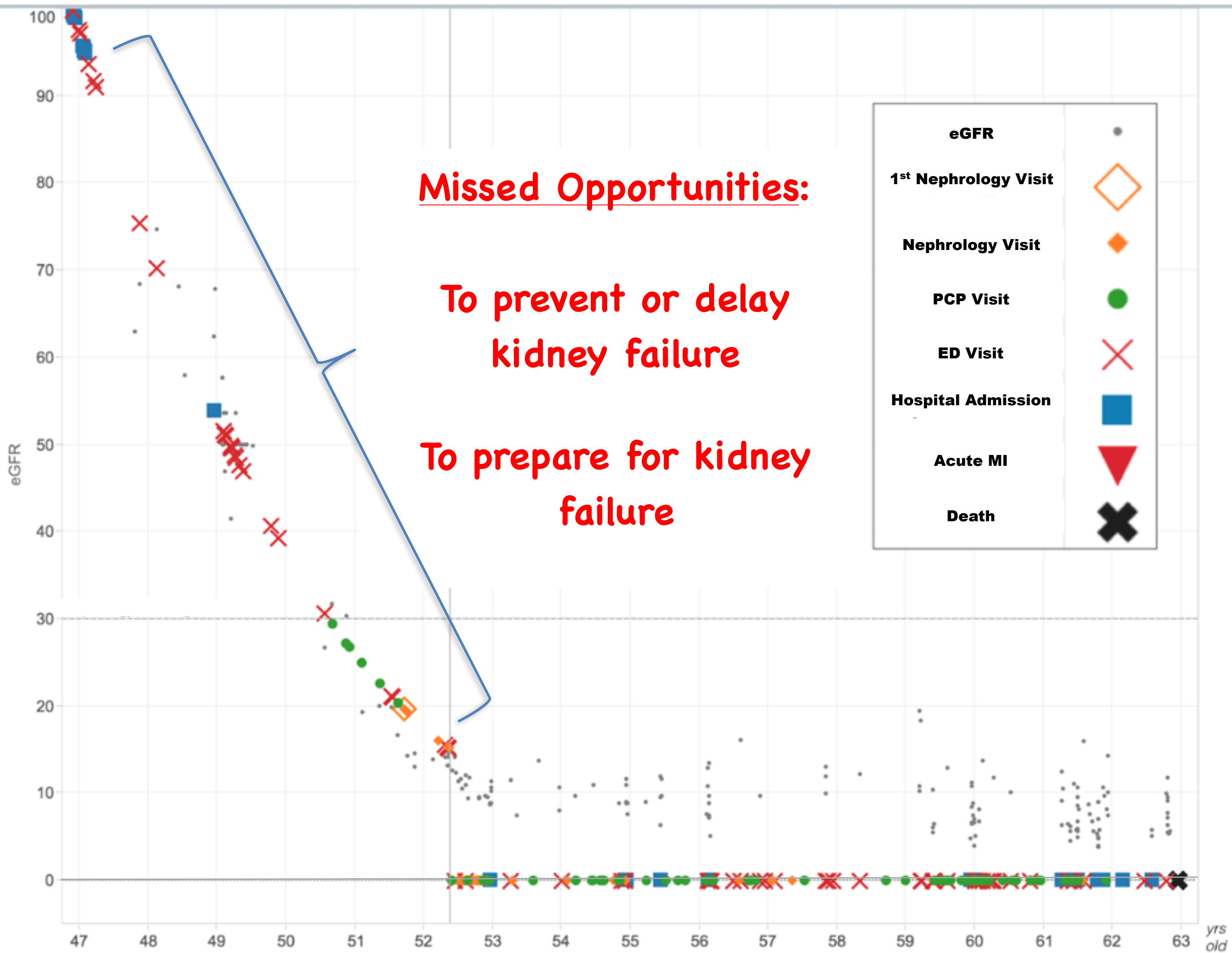














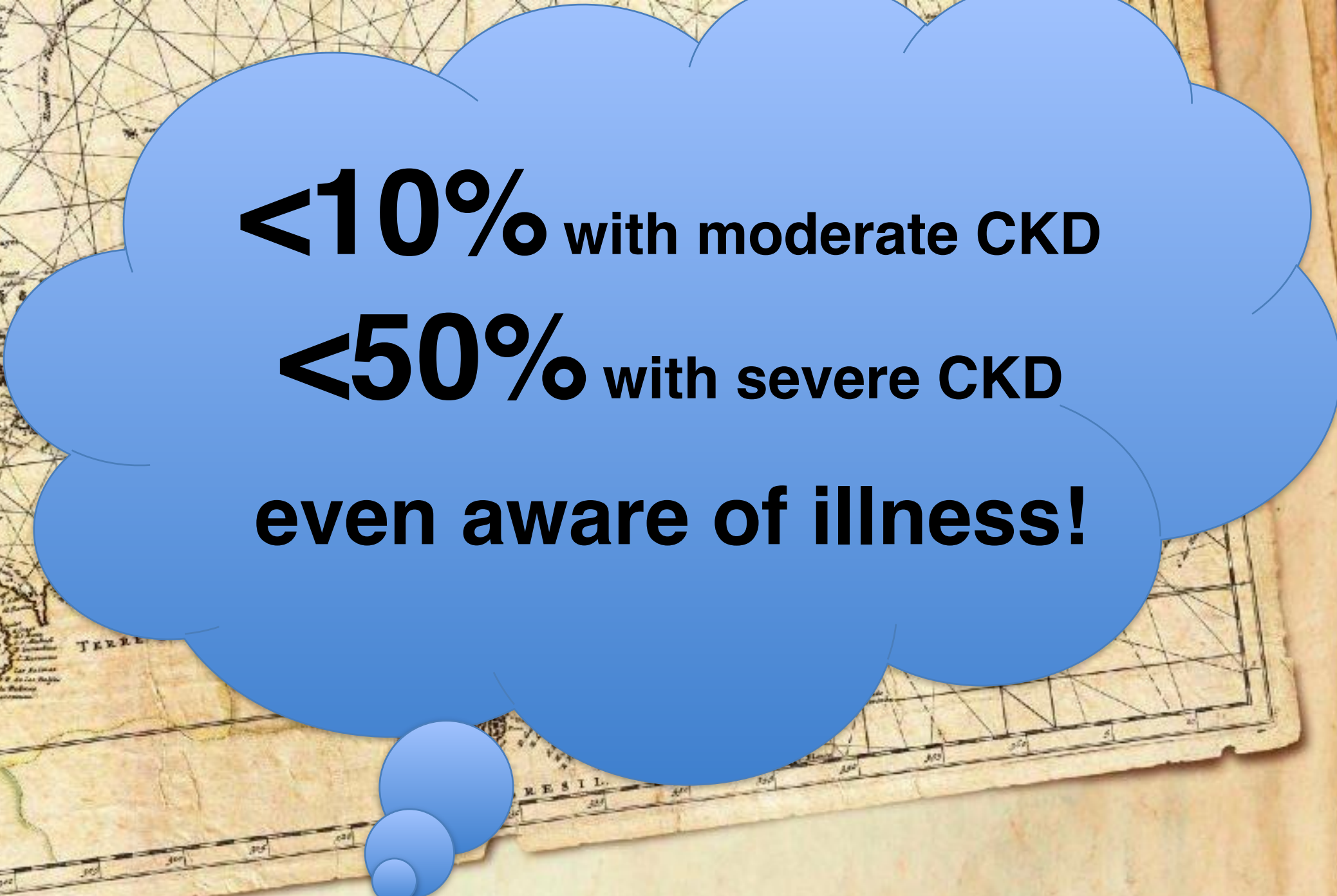
42%

**starting dialysis have
no prior nephrology
care**

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*Atlas of Chronic Kidney Disease
in the United States*

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DIVISION OF KIDNEY, UROLOGIC, & HEMATOLOGIC DISEASES



<10% with moderate CKD
<50% with severe CKD
even aware of illness!

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Renal Function Trajectory Is More Important than Chronic Kidney Disease Stage for Managing Patients with Chronic Kidney Disease

Steven J. Rosansky

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- ❖ Can we use other clinical data (labs and / or vitals) to improve prediction of disease progression?
- ❖ Goal: flexible model for multivariate longitudinal data

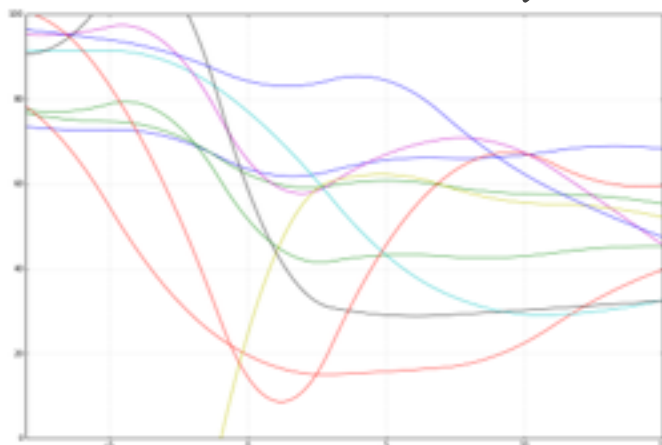
Model for a single trajectory

Conditional likelihood factorizes across P labs: $p(\vec{y}_i | z_i, b_i, c_i; x_i) = \prod_{p=1}^P p(y_{ip} | z_i, b_i, c_i; x_i)$

$$y_{ip}(t) \sim N(\mu_{ip}(t), \sigma_p^2)$$

$$\begin{aligned} \mu_{ip}(t) \sim & \mathcal{GP}(\Lambda^{(p)} x_i \\ & + \Phi_z(t)^\top \beta_{z_{ip}}^{(p)} \\ & + \Phi_l(t)^\top b_{ip}, \\ & K_p) \end{aligned}$$

Curves
per
subtype



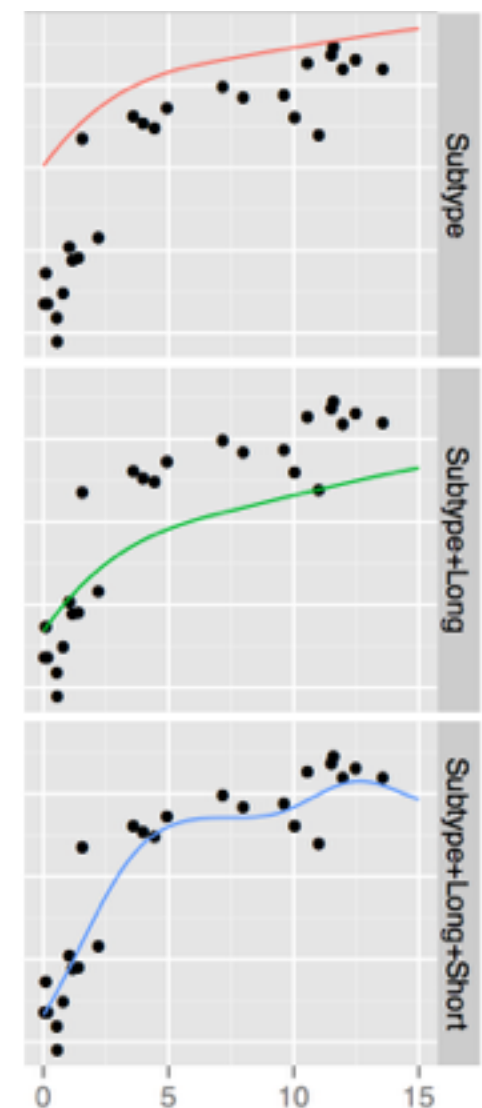
Population effect

Latent subpopulation
curve

Individual long-term
deviations

Individual transient
deviations (GP)

$$K_p(t, t') = a_p^2 \exp\{-l_p^{-1} |t - t'|\}$$



Inducing Dependence

Dependence between mean functions
for the P labs in 2 ways:

$$\mu_{ip}(t) \sim \mathcal{GP}(\Lambda^{(p)} x_i + \Phi_z(t)^\top \beta_{z_{ip}}^{(p)} + \Phi_l(t)^\top b_{ip}, K_p)$$

Long-term deviations are correlated
via multivariate normal:

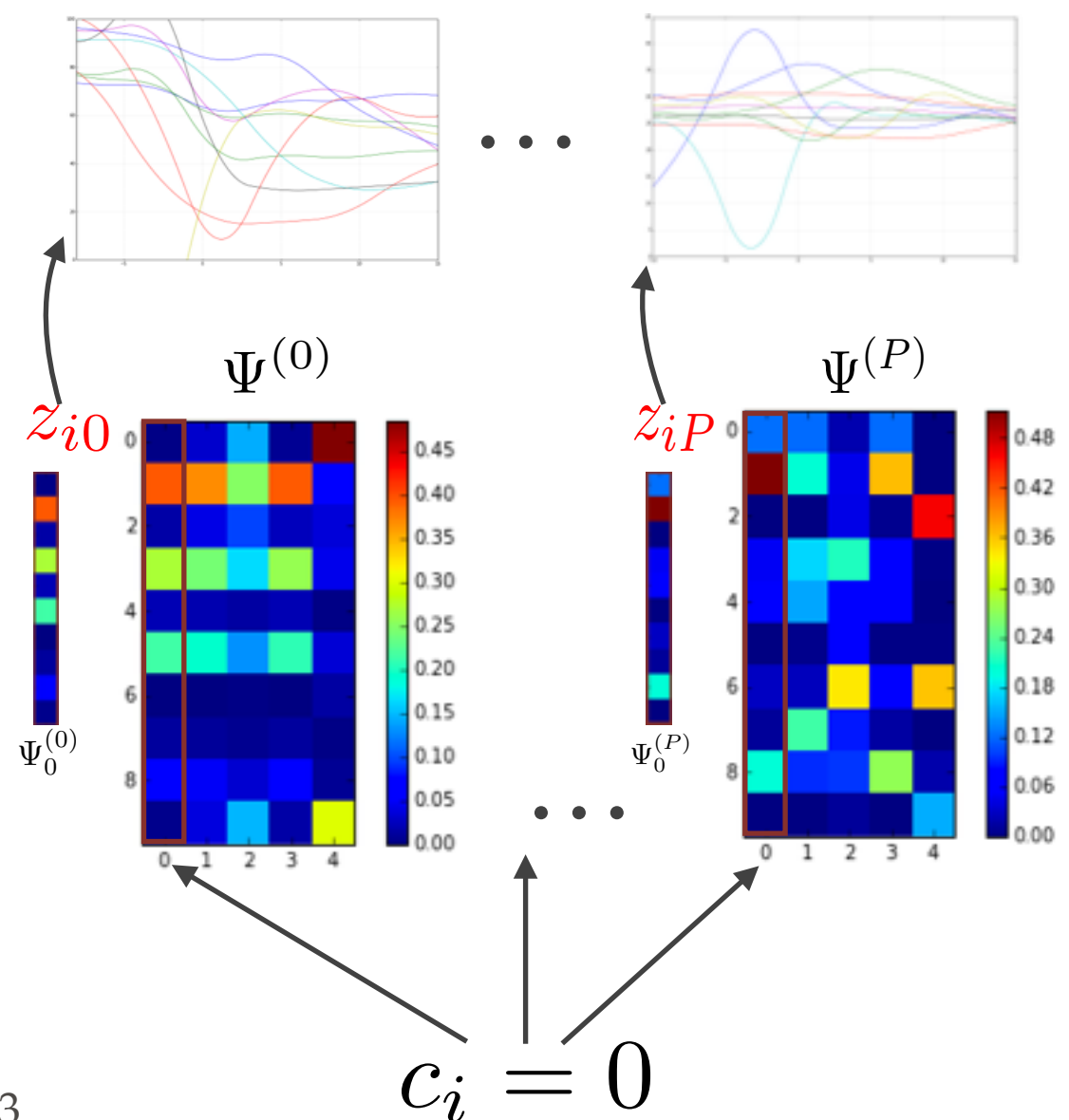
$$\vec{b}_i = (b_{i1}, \dots, b_{iP})^\top \sim N(0, \Sigma_b)$$

Subtypes / clusters per lab are correlated
via mixture of multinomials:

$$\mathbf{z}_{ip} | c_i = g \sim \text{Multinomial}(\Psi_g^{(p)})$$

$$c_i \sim \text{Multinomial}(\pi_i)$$

$$\pi_{ig} = \frac{e^{w_g^\top x_i}}{\sum_{g'=1}^G e^{w_{g'}^\top x_i}}$$



Experimental Setup

- ❖ 6 variables of interest: eGFR, 5 other labs relevant to CKD
- ❖ Cohort of 44,000 patients at Duke with at least moderate stage CKD (Stage 3+) and 5+ measurements for eGFR
- ❖ For each test patient: use data before t to predict future labs
- ❖ Evaluation for each lab:
 - ❖ average MAE across test patients, in future time windows
- ❖ Baseline: [Schulam & Saria, 2015] trained independently

Quantitative Results

Table 1: Mean Absolute Errors across all labs from 10 fold cross validation. Bold indicates p-value from one-sided, paired t-test comparing methods was $< .05$. *, **, *** indicate $p < .01$, $< .001$, $< .0001$, respectively.

Predictions with data up to...		$t = 1$				$t = 2$			$t = 4$	
Lab	Model	(1, 2]	(2, 4]	(4, 8]	(8, 19]	(2, 4]	(4, 8]	(8, 19]	(4, 8]	(8, 19]
eGFR	Schulam	8.86*	10.43*	12.05	13.69	8.84***	11.08**	13.23*	9.39***	12.29*
	Proposed	9.12	10.67	12.28	14.21	9.26	11.73	13.99	10.12	13.07
Serum Alb.	Schulam	0.59	0.79	1.09	1.53	0.60	0.88	1.28	0.63	0.96
	Proposed	0.34***	0.39***	0.47***	0.63***	0.35***	0.45***	0.63***	0.40***	0.58***
Serum Bicarb.	Schulam	1.92	2.06	2.13	2.31	1.93	2.06	2.21	1.89	2.14
	Proposed	1.87	1.97	2.04	2.31	1.89	1.99	2.31	1.87	2.24
Serum Calc.	Schulam	0.74	1.02	1.62	2.89	0.72	1.26	2.27	0.85	1.53
	Proposed	0.37***	0.44***	0.58***	0.80***	0.39***	0.54***	0.80***	0.46***	0.73***
Serum Phos.	Schulam	1.02	1.35	1.46	1.44	1.17	1.36	1.34	1.13	1.15
	Proposed	0.57***	0.68***	0.88***	1.23	0.65***	0.88***	1.25	0.82***	1.23
Urine ACR	Schulam	1.17	1.30	1.44	1.64	1.14	1.30	1.53	1.11	1.41
	Proposed	0.92***	1.02***	1.17***	1.44	0.96***	1.13*	1.45	1.02	1.42

Conclusion

- ❖ Novel model for multivariate longitudinal clinical data
- ❖ Current clinical practice: “clinical gestalt”, no evidence-based method to inform decision-making process
- ❖ Future work:
 - ❖ More flexible dependence between labs
 - ❖ Jointly predict with events of interest (hospital admissions / high utilization, cardiac events, etc)
 - ❖ More clinically actionable metrics to evaluate models

An anatomical illustration of the human urinary system. The kidneys are highlighted: the left kidney is a bright pinkish-red, and the right kidney is a bright cyan blue. The rest of the urinary system, including the ureters, bladder, and urethra, is shown in a light blue, semi-transparent style. The background is a light gray with a faint, larger-scale anatomical outline of the torso.

Thank you!

Acknowledgments

- ❖ Contact: jdf38@duke.edu
- ❖ Joint work with:
 - ❖ [Mark Sendak](#), M.P.P./M.D. Candidate
 - ❖ C. Blake Cameron, M.D.
 - ❖ Katherine Heller, Ph.D.



Presenting tomorrow
at clinical talks!

