	September 27, 2010					
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2	MEETING					
3	OF					
4	EVIDENCE-BASED TREATMENT DECISIONS IN TRANSPLANTATION,					
5	THE RIGHT DOSE & REGIMEN FOR THE RIGHT					
6	PATIENT/INDIVIDUALIZED TREATMENT					
7	Conducted by Renata Albrecht, MD					
8	Thursday, September 27, 2018					
9	8:04 a.m.					
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12	Food & Drug Administration					
13	White Oak Campus, Building 31					
14	10903 New Hampshire Avenue					
15	The Great Room Section A					
16	Silver Spring, MD 20993					
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18	Reported by: Michael Farkas					
19						
20	Capital Reporting Company					
21	1250 Eye Street, NW, Suite 350					
22	Washington, D.C. 20005					

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1	APPEARANCES	1	Yan Wang, PhD, F	
2		2	Maria P. Hernandez-Fue	ntes, MD, PhD
3	Renata Albrecht, MD, FDA	3	Head of Translation Biolog	y for Immunology
4	Roslyn B. Mannon, MD	4	UCB Celltech	
5	University of Alabama at Birmingham	5	Edward Chong, MBC	ChB, MRCP
6	Birmingham, AL	6	Chief Medical Officer,	Vitaeris
7	Mark Stegall, MD	7	Marc Cavaille-Coll, Ml	D, PhD, FDA
8	Mayo Clinic, Rochester, MN	8	Krista Lentine, MD,	PhD
9	Ameeta Parekh, PhD, FDA	9	Saint Louis University	Hospital
10	Inish O'Doherty, PhD, C-Path	10	St. Louis, MO	•
	Katherine A. Hollinger, DVM, MPH, (DACVPM CAPT, USPHS)	11	David Axelrod, MD	. MBA
12	FDA	12	Lahey Clinic, Burling	
		13	Margaret Mooney,	
13	John Michael Sauer, PhD, C-Path		Chief, Clinical Investigat	
14	Gary Steven Friedman, MD, Pfizer	14		ions branch
15	Michael M. Abecassis, MD, MBA	15	Larry	
16	Northwestern Medicine, Chicago, IL	16	Rhia	
17	Josef Coresh, MD	17	Shannon Woodward, Ph	
18	Johns Hopkins University	18	Robert Woodward	d
19	Ulf Meier-Kriesche, MD, FAST	19		
20	Veloxis Pharmaceuticals - TTC Workgroup Co-Chair	20		
21	Alexandre Loupy, MD, PhD	21		
22	CHU Necker, Paris, France	22		
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	SPEAKER	PAGE	1	honored we are to be able to present this open public
	Alexandre Loupy, MD	256	2	workshop on the FDA campus today and thank all of you
	Yan Wang, PhD	299	3	for attending.
	Ken A. Newell, MD, PhD	300	4	Before we start, a few housekeeping rules.
	Maria P. Hernandez-Fuentes, M.		5	You can order boxed lunches at the kiosk outside the
	Edward Chong, MBChB, MRCF	328	6	room, and there's snacks and coffee available
	Marc Cavaille-Coll, MD, PhD Krista Lentine, MD, PhD	300	7	throughout the day. If you have any questions during
0	367		8	the day, there are conference room staff outside, and
Q	David A. Axelrod, MD	378	9	there will be staff in the room to assist you.
	Mark D. Stegall, MD	389	10	So the focus of the first day is going to be
11	Margaret Mooney, MD	407	11	biomarkers. This (inaudible) a series of four
	Shanon Woodward, PharmD, Ol		12	sessions. And in the fifth session, we'll talk about
13				transplant center practices.
14			14	At or near the close of the first day, we'll
15			15	have an open public comment period. There's a sign-up
16			16	sheet at the registration desk for the available time
17			17	for that session. So please, if you're interested, do
18			18	sign up. And we know we have a number of folks that
19			19	already have.
20			20	The second day, we'll only do two sessions on
21			21	the patient-focused drug development. And as
22			22	moderators during that day, Dr. Everly and I will talk
		Page 7		Page 9
1	PROCEEDINGS		1	about the goals of that second day as well.
2	DR. ALBRECHT: Let's go ahead	and get started.	2	Finally, a comment on the format of this
3	Thank you all for coming. My name is Renata Albrecht.			meeting. Each session will have about three to five
4	I'm from the Division of Transplant and	Ophthalmology	4	formal presentations lasting about 15 minutes, at the
5	Products. To the to my right is Dr. Inish			end of which we'll have a question-and-discussion
6	O'Doherty, my co-moderator, and also the	ne Executive	6	period. During that period, there will be questions
7	Director of the Transplant Therapeutics Consortium.			shown on the slides. And what we ask is that we invite
8	It is our distinct pleasure to welcome all of			everyone in the audience as well as the panel to
9	you to the FDA. And we particularly ap	preciate your	9	participate in that discussions. We find those very
10	taking the time to participate in what we	hope to be	10	beneficial.
11	one of many milestone meetings in our f	ïeld.	11	So with that, let me go ahead and start our
12	Unlike or previous FDA workshop	o, this one was	12	meeting. So I'm going to ask Dr. Ros Mannon to please
13	planned by FDA in close collaboration v	with the recently	13	come to the podium and tell us about the call to
14	formed Transplant Therapeutic Consorti	um and the	14	action, addressing unmet needs in transplantation.
15	Critical Path Institute. You'll hear about	the history	15	Dr. Mannon.
16	of this public-private partnership from D	r. Ros Mannon,	16	DR. MANNON: Thank you, Renata, Inish, members
17	Dr. Mark Stegall, and Dr. Ameeta Parek	h at the FDA.	17	of C-Path that have been instrumental in making this
18	Also, during the day, you'll meet i	many of the	18	probably one of the most collaborative workshops that
19	people who are part of this effort in acad	emia,	19	I've participated in. And also, you made me very
20	industry, government, and other stakeho	lders, including	20	nervous because I have a lot to do.
21	21 our patient guests.			But anyway, these are my disclosures. So I
22	So I'll limit my remarks to say how	w happy and	22	think that, as a new faculty member and attend
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- 1 working with Allan Kirk in the NIH in the early 2000s,
- 2 I was excited about the blossoming transplant pipeline
- 3 shown on the left that Flavio wrote about -- what's
- 4 new, what's hot. There were many drugs, many
- 5 opportunities. And within about six years, that
- 6 pipeline seemed to be dead. And I mean, how many talks
- 7 have most of us attended where we've seen a slide that
- 8 Flavio shows of the graveyard of transplant
- 9 therapeutics?
- 10 And it became clear to me as, through my
- 11 personal interactions, that there was a lot of biologic
- 12 therapy as immunosuppressants being used in other
- 13 fields, but it was not coming to our field anymore.
- 14 And again, when you think about new drug applications
- 15 over the last, I don't know, 15 years, the really only
- 16 novel agent that has been approved was in 2011, was
- 17 Belatacept, or Nulojix. But the only other approvals
- 18 have been sort of congeners, or variants of current
- 19 therapies.
- There are also really critical, unmet needs.
- 21 These are the ones that I think about almost on a daily
- 22 basis -- increasing the number of organs and improving
 - Page 11
- 1 function of non-ideal organs and new therapies to
- 2 affect that; improving our patients' long-term outcomes
- 3 after any type of transplant; improving the function of
- 4 those grafts; immunosuppression medications that
- 5 minimize comorbidities and improve the quality of life
- 6 of the patient; trying to avoid viral diseases and
- 7 cancer, which are prevalent; and then also thinking
- 8 about what's going to happen for the really critical
- 9 areas, specific indications such as antibody-mediated
- 10 rejection, delayed graft rejection, potentials for
- 11 tolerance and treatments for recurrent diseases post-
- 12 kidney transplant.
- So I wasn't really familiar with private-
- 14 public partnerships. I knew a lot about cardiac
- 15 safety. It had been initiated at Duke. I was at Duke
- 16 quite a bit of my training in my early years. And it
- 17 was Rob Califf's launch to look at adverse events in
- 18 these very large cardiology interventional trials.
- But in January 2012, Bob Gaston was unable to
- 20 attend the dinner at the American Society of Nephrology
- 21 Board. Ron Falk said I could attend because I was the
- 22 incoming president. He thought it was okay.

- Page I
- 1 And Ron's from UNC. He's chief of nephrology.
- 2 And he discussed with me this goal of improving kidney
- 3 disease therapeutic pipeline. And he had this amazing
- 4 vision where he was going to execute a memory of
- 5 understanding with FDA through an individual called
- 6 Patrick Archdeacon, who's known here, who was in, I
- 7 think, in public policy. And they created what was
- 8 called the Kidney Health Initiative in October 2012.
- 9 This initiative, they were specifically
- 10 requesting participation by AST, but the depth of the
- 11 participation and interaction in that initiative of
- 12 transplantation was not clear. And after discussions
- 13 with Patrick, it became clear that it would have,
- 14 really, a very limited scope and not really the vision
- 15 of transforming our field.
- 16 However, I do want to say there was a success
- 17 story that we created, a series of data standards with
- 18 CDISC and CFAST and want to thank Dan Brennan and Rita
- 19 Alloway myself, who served on that group.
- Around this time, right before that meeting,
- 21 we had the famous, or perhaps infamous, 2012 endpoints
- 22 meeting in downtown Silver Spring. And after watching
 - Page 13
- 1 all the HLA Lab directors throw their shoes at each
- 2 other, it came clear that there were key themes. One
- 3 is drug safety and the risk of new therapies and how to
- 4 transform the field when there's a concern about
- 5 patient safety.
- 6 Thinking about this over the next few months,
- 7 I participated and requested a presence at a public
- 8 hearing. This was an FDA public hearing here in
- 9 February of 2013 presenting transplantations unmet
- 10 needs. This was a hearing about rapid drug approval,
- 11 predominantly focused on anti-infectives in special
- 12 populations.
- And I really did feel out of place until one
- 14 of the breaks when Dr. Cox, who runs the office, came
- 15 down from the podium of infected -- infectious -- he
- 16 actually is the office that directs the Transplant
- 17 Ophthalmologic Division. And he came down. And he
- 18 said, you know, that was a very compelling argument,
- 19 and we'll be in touch.
- 20 And sure enough, a couple weeks later, I
- 21 participated in a call with some AST staff. Renata
- 22 Albrecht was on the call, Patrick Archdeacon

- 1 representing Kidney Health Initiative and public
- 2 policy, and then tried to raise the awareness for
- 3 therapeutic advances. Where would transplant fit into
- 4 Kidney Health Initiative? It wasn't clear. But it was
- 5 clear that we needed a position statement. We needed a
- 6 compelling argument and needed to be supported by data.
- 7 So I recruited my colleagues -- Rita Alloway,
- 8 Tim Schroeder from CTI, and Flavio Vincenti -- to help
- 9 me draft what we call the Call to Action, the Reviving
- 10 of the Pipeline of Transplant Therapeutic Agents. And
- 11 we called it a therapeutic initiative, not consortium,
- 12 because it was just four of us writing about the field.
- We highlighted again that patients following
- 14 transplantation who returned to dialysis, their five-
- 15 year survival is not any better than some of the
- 16 patients with cancers. And when you -- when -- I went
- 17 into this field not to be taking care of patients that
- 18 were going to die. I was determined to make a
- 19 difference, and these data are kind of startling.
- We also recognize that we take for granted
- 21 many of the side effects that impair daily living --
- 22 diarrhea, headaches, tremors daily, and difficulty
- Page 15
- 1 thinking -- and then the comorbidities that develop or
- 2 worsen after transplantation and, God forbid, the
- 3 return to dialysis. And there's been some amazing work
- 4 by Allison Tong looking at standardized outcomes in
- 5 transplantation through the SONG Network.
- 6 In the letter drafted to Renata's office, I
- 7 provided -- we provided in the document a historical
- 8 background of the status of transplant and unmet needs,
- 9 a blueprint for action, harnessing other things like
- 10 information technology and the regulatory demands on
- 11 investigators and companies in terms of patient safety,
- 12 and then a potential approach for therapeutic and
- 13 device development.
- 14 And I mention this -- and this was really the
- 15 focus of my address in 2013 in Seattle. I reminded
- 16 everyone that how did we get here. And you talked to
- 17 one group, and they'd say, oh, it's FDA. You talk to
- 18 another group, and they say, well, it's industry. And
- 19 I said the biggest problem is us, that we as physicians
- 20 and scientists have allowed this to continue. And we -
- 21 you know, to see and look at a patient day to day and
- 22 say, well, this is the best I can do for you, your

- 1 graft's going to fail, it's unacceptable.
- 2 So it took a while after that document was
- 3 drafted. And we did get a response back. And about a
- 4 few months later in August 2013, we met here with the
- 5 Office of Translational Science. This is an office
- 6 responsible for promoting innovation and drug
- 7 regulatory review across CDER and was really
- 8 implemented by the Critical Path Initiative amongst
- 9 other charges.
- 10 And Dr. Buckman-Gardner read the document, had
- 11 a strategy session. I outlined three potential avenues
- 12 for us to get to where we are today, recommended an
- 13 individual named Arthur Holden, who works with the
- 14 iSAEC, Adverse Events Consortium, meeting with Martha
- 15 Brumfeld and -- from Critical Path, and also talking to
- 16 the Biomarker Consortium with Steven Hoffman because it
- 17 was clear that we needed some biomarkers.
- 18 Though I was off, I was no longer president
- 19 but past president, we had monthly calls, we discussed
- 20 options, and we spent a tremendous amount of time
- 21 reaching out to these individuals meeting by phone, but
- 22 also meeting in person to discuss how they would
- Page 17
- 1 foresee this kind of opportunity for transplantation.
- 2 And we would regularly check in with OTS. But to be
- 3 honest, while they were supportive, they weren't going
- 4 to tell us what to do. They were hands off, allowing
- 5 us to make these decisions.
- 6 Several months later, we had our first
- 7 organizational meeting. Arthur Holden then, that CEO
- 8 of the international consortium, facilitated gratis.
- 9 There were a few companies that attended. We had a
- 10 mission statement and goals and discussion of funding.
- And this was followed by a second meeting.
- 12 These were both at AST, a public policy office, Bryan
- 13 Cave offices downtown. This was co-chaired now by the
- 14 new joint steering task group for TTC, co-chaired by
- 15 Mark Stegall and myself. We had much more industry
- 16 representation. FDA and OTS -- transplant and OTS both
- 17 attended.
- And we came up with two core projects. We
- 19 wanted to address the barriers to the new therapeutic
- 20 development almost immediately, typically by a consent
- 21 -- not a consensus paper, but a white paper, and then
- 22 identify and evaluate new predictive -- transplant

- 1 predictive technologies that could effective identify
- 2 rejection phenotypes earlier and maybe help in
- 3 developing novel drug -- not -- in other words, drug
- 4 development tools and transplantation.
- 5 It's really hard. It was very slow. And at
- 6 times, I really almost kind of wanted to give up. And
- 7 I think it's when you're transforming the field you
- 8 have this naivete that everyone's going to jump on and
- understand what you're doing, but people don't.
- 10 And despite monthly calls, there was a lot of
- 11 discussion about which path we were going to take; was
- 12 an individual going to help us get there? I contacted
- 13 C-Path again in January of 2015, presented that option
- 14 to the board, thinking that this was really the way to
- 15 go, that AST was a small organization. This was an
- 16 opportunity to take and leverage what they had done.
- 17 At that time, Neonatal had just joined them,
- 18 polycystic kidney disease, TB. I mean, these were
- 19 opportunities for us, and I thought that they had the
- 20 bandwidth to do this. And they presented, and I
- 21 attended the board meeting in May 2015.
- 22 Later that fall, we had an exciting and

- 1 committee with Anil Chandraker, who was then the 2 incoming president; and Ken Newell sitting here; the
- 3 immediate past president, Mark Stegall, who's here; and
- 4 I think I saw Dixon Kaufman as well.
- 5 Steve Broadbent then several months later had
- 6 the third -- or I call it the third organizational
- 7 meeting. He presented the C-Path overview. And I
- 8 either -- I credit this to him, but it was somebody in
- 9 the room who said -- and I wrote this in my notes --
- 10 "Theory is easier than practice, consensus takes time,
- 11 and structure is critical." And he -- you know, it's
- 12 really true. And so when you hear that, you say, okay,
- 13 you're impatient, but maybe it does have to take some
- 14 time.
- 15 At that time, there were additional attendees.
- 16 NIAID actively participated. The KHI/ASN came, and
- 17 there were multiple additional potential industry
- 18 partners. And so finally, you know, I use the date
- 19 April 26, but I think officially it was March 2017.
- 20 The consortium was created as a private-public
- 21 partnership through C-Path. These are the current
- 22 partners most recently updating to include CSL Behring

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- 1 exhilarating endpoints workshop. The outline is shown
- 2 here of the different directions that we were taking.
- 3 And this was followed very quickly by an international
- 4 group of investigators the next morning from the
- 5 Transplantation Society, led by Philip O'Connell and
- 6 Dirk Kuypers, where we talked about changing and
- 7 transforming clinical transplantation studies, again,
- 8 looking at the notion of surrogate endpoints for
- 9 approval, looking at how well oncology had advanced and
- 10 maybe using that as a potential model to advance the
- 11 field.
- 12 Later on, the charge that we had at our second
- 13 organizational meeting to write about barriers was
- 14 published in 2016. This is the paper by Mark Stegall
- 15 where we talked about general barriers and the
- 16 misconceptions of understanding the state of the field,
- 17 the regulatory issues that are involved, potential
- 18 funding issues from the biopharma industry,
- 19 perspective, and then the transplant community -- no
- 20 blame, just highlighting the issues.
- So things really got started in February 2016.
- 22 The two societies, AST and ASTS, created a co-steering

- 1 and CareDx, who have recently joined the group. And
- 2 our FDA liaison is Renata Albrecht.
- 3 It makes me very proud to go to the C-Path
- 4 page and see that we're part of the many consortium of
- 5 organ diseases and also the thing that this
- 6 organization can do. And you'll hear more about it
- 7 shortly.
- 8 Lots of feedback.
- 9 And then I want to thank the people that
- 10 aren't in this room -- Susan Nelson, who is our exec of
- 11 AST; Bill Applegate, our director of public policy. I
- 12 mean, these two individuals for two and a half years
- 13 really supported me doing this. It was a tremendous
- 14 amount of staff time, and they were great.
- 15 And another person who I know is in this room,
- 16 Kim Gifford of ASTS -- you know, it's unusual when an
- 17 individual from one society crosses to the other asks
- 18 for help. Kim, you did a marvelous job, and you were
- 19 really helping at a time when we were undergoing a
- 20 leadership transition within AST.
- 21 My other colleagues, Rita, Randy Morris,
- 22 Randall -- Randy, Flavio, Tim Schroeder, some of whom

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- 1 are here, and then the FDA for really maintaining this, 1 to where we are today.
- 2 inspiring us, and continuing us to move forward. And 2
- 3 my colleagues in the overseas societies that I maintain 3 we need the TTC? People could still ask that question.
- 4 close contacts with, particularly Nancy Ascher, who
- 5 strongly supported the notion of getting in on the
- 6 ground level with this organization.
- And finally, you know, where's my passion? So 7 in the field. And we all believe that we have to
- 8 last week, up in Florence, Alabama, or, actually, west
- 9 of that. I attended a wedding. And you can see the
- 10 bride there. She's lovely. And the person of interest
- 11 is this chickee here, and this is her twin sister.
- 12 She's also my patient. She allowed me to show you
- 13 this. And she's really struggling with a failing
- 14 kidney allograft.
- 15 And for me to come into the room every few
- 16 months and say, well, your kidney function's a little
- 17 bit worse, and we're going to try this blood pressure
- 18 medicine, she -- she's very young. I want her to be a
- 19 bride. And I want her to have a family just like her
- 20 sister's going to go on to. And so that's the thing --
- 21 the kind of things that drive me on a daily basis to
- 22 move forward.

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- Thank you very much. 1
- 2 (Applause.)
- 3 DR. ALBRECHT: Thank you, Dr. Mannon.
- 4 Next, we'll have a presentation by Dr. Mark
- 5 Stegall on the Transplant Therapeutic Consortium
- 6 current workgroups and undertakings.
- 7 DR. STEGALL: All right. So again, thanks for
- 8 inviting us and allowing us to put this effort together
- 9 the last few years. So these are my disclosures.
- And the main reason I really want to get up
- 11 here this morning is to thank everyone that's worked on
- 12 this in the last couple of years. The societies
- 13 definitely have worked on this, I think, quite closely,
- 14 which I think is a good thing for the societies to do.
- 15 And I think that really is the -- one of the main
- 16 reasons why it has been successful, the aforementioned
- 17 Kim Gifford in -- on our side; members of the TTC as it
- 18 continues to grow -- now we're up to 10 industry
- 19 members of the group, and I think that's a good sign
- 20 that people are understanding that this actually might
- 21 turn out to be something; and, certainly, the FDA and
- 22 C-Path have played an instrumental role in getting us

- And so I guess just to go back and -- why do
- 4 It's been said before, just recently, the transplant's
- 5 not perfect. There's still many unmet needs. And this
- 6 sometimes, I think, is still not believed by everyone
- 8 improve outcomes. We have to have new therapy.
- 9 And so what we decided that had to happen was
- 10 that a collaborative effort that rethinks the entire
- 11 drug development process, unmet needs, biomarkers,
- 12 endpoints, safety is what is really needed. And
- 13 working all together, I think that we can do this.
- 14 But what really became apparent, as was just
- 15 mentioned, is that the people within transplantation
- 16 needed help from people who have done this sort of
- 17 thing outside of transplantation. And that's where we
- 18 are today. We have C-Path and members of the FDA who
- 19 have gone through this process before.
- 20 How did we get there? Well, we had the
- 21 history that Ros put together. But also, there was a
- 22 period where we actually took a pause. And I think Ken

- 1 was one of the very big proponents of this, is to talk
- 2 to people outside of transplant and ask them what they
- 3 think, actually, we should be doing, especially
- 4 industry. I think there was a good back-and-forth
- 5 discussion with industry about what would be important
- 6 for them in getting more interest in developing drugs
- 7 for transplant patients.
- 8 We also decided -- we made some very big
- 9 decisions early on that set us down the pathway that we
- 10 are going down today. We decided to start with kidney
- 11 transplantation. For one, it's the largest number of
- 12 transplants being done. But also, there is the most
- 13 data in kidney transplant patients. Most drugs are
- 14 first approved in kidney transplant patients. But
- 15 there are a few things that the TTC wants to do, and
- 16 one of the things that it wants to do is to include
- 17 other organ transplants as we go down the pathway. And
- 18 so there is -- there -- what we're going to do now and
- 19 what we're planning to hopefully be able to do in the
- 20 future.
- 21 From the very beginning, we decided to do the
- 22 yin and yang of drugs. So there is a -- two

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- 1 workgroups. One is the efficacy in workgroup, which is
- 2 endpoints and biomarkers. And the other looks at drug
- 3 safety and profiling and characterization. And we
- 4 became a public-private partnership with the FDA. And
- 5 there were some of us that didn't think that that would
- 6 actually ever happen, and it really did. It was good.
- As mentioned, there are now 10 members of
- 8 this, and this is kind of our -- you'll see this slide
- 9 many, many times. But the idea is that we can sit now
- 10 and have discussions in what is termed the
- 11 "precompetitive space." And I think that that's a very
- 12 healthy thing to do. We can have back-and-forth
- 13 discussions with FDA, with members in the
- 14 transplantation community, and move forward.
- 15 The summary here is the current direction that
- 16 we are going is that we are developing novel drug
- 17 development tools. And that is a term that may be very
- 18 familiar to some people in this room and totally
- 19 unfamiliar to other people in this room. But you're
- 20 going to hear that a lot.
- 21 So what is the TTC doing? We're going to
- 22 develop basically in the next four years two new drug

- 1 comes to moving the needle of healthcare in the United
- 2 States. It's important to us. But truly, it's not --
- 3 95 percent of the patients in the world don't need a
- 4 transplant. But it's an important field, and it's
- 5 important for us. And it's important for us to do drug
- 6 development right.
- 7 And therefore, I think the FDA has agreed with
- 8 us because we did make the list of public-private
- 9 partnerships. And actually, when I gave this talk last
- 10 time, we were at the very bottom. So we're not even
- 11 the (inaudible) kid on the block. The worldwide
- 12 innovation network, which is -- it's now below us. So
- 13 there you go. So we're kind of old kind of school
- 14 right now.
- 15 And I think this is important. I think this
- 16 is really significant that we're not just off in a
- 17 corner screaming at -- you know, howling at the Moon
- 18 that are no new drugs. But we've actually tried to
- 19 incorporate ourselves into the process of drug
- 20 development and move within that.
- 21 So the industry priorities, how we move this
- 22 way, industry said they wanted drug development tools

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- 1 development tools in transplant. And what we're going
- 2 to end up with is we're going to have one drug
- 3 development tool that's going to be a safety,
- 4 basically, benchmarking tool based on standard of care.
- 5 And then we'll have another drug development tool
- 6 that's more of an efficacy tool that basically takes
- 7 post-transplant data that predicts the likelihood of
- 8 graft loss. And that post-transplant data is based on
- 9 things like a biopsy, renal function, proteinuria, DSA,
- 10 those parameters that, basically, everyone can measure
- 11 and agree upon that exists. And that has been part of
- 12 some of the predictive models that people have worked
- 13 on in the last few years. And the specific one we're
- 14 looking at employing is the iBox tool.
- 15 And so that's really where we are. Potential
- 16 future directions would be to possibly develop
- 17 validated biomarkers and PRO measures and expand to
- 18 other types of organs, all right?
- 19 So again, I think we hit this at sort of the
- 20 right time. The FDA, as I read this, have developed
- 21 public-private partnerships in other areas. And
- 22 transplant, you know, is a pretty small field when it

- 1 that would aid in drug development. And mostly, I
- 2 think they were talking about efficacy tools. And so
- 3 we took that into advisement.
- 4 And you can see the two workgroups, which a
- 5 bit now are a bit passe because we've already figured
- 6 out what we're going to do. But out of those
- 7 workgroups came the -- those two concepts about drug
- 8 development tools.
- 9 And Workgroup 1, which I believe Ken is --
- 10 been chairing, primarily, with Ulf, has -- basically is
- 11 to develop a tool that looks at -- drug development
- 12 tool looks at new ways of looking at efficacy of drugs.
- 13 But basically, as I mentioned, it's looking at post-
- 14 transplant data that would be predicting long-term
- 15 graft survival, mostly one-year post-transplant data.
- 16 And those details of that model that has been looked at
- 17 are there. And the process that we will be doing -- I
- 18 will show you -- is the same for both of these drug
- 19 development tools, how we will develop them.
- 20 The other one is a group that I've been
- 21 working with, with Troy Somerville, who is my co-chair
- 22 from Sanofi. And it's been very clear to us that

- 1 transplant patients have a lot of serious adverse
- 2 events. And that can be something that's hard to
- 3 quantify, but also could be off-putting to industry and
- 4 getting involved in transplantation and developing new
- 5 agents because there's just so many adverse events in
- 6 transplant patients. But we actually don't have a tool
- 7 to figure out what those adverse events are and how
- 8 common they are.
- 9 And I think that -- so that's what this is
- 10 about. And there are -- what was the nice thing about
- 11 this is, as soon as we were starting to think about
- 12 this, there are people within C-Path who have worked on
- 13 drug safety profiling and could take that expertise and
- 14 rapidly apply it to the data that we have from
- 15 transplant patients.
- So that was the synergy that we were able to
- 17 work on almost immediately kind of like, you know, I
- 18 think we should do this. And you know, and he said I -
- 19 oh, we can do that. I think -- you know, let me just
- 20 send you a few slides from Klaus (ph), and he'll work
- 21 on that. And the -- I think that energy that C-Path
- 22 brings and the expertise both have been -- really help
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- 1 us a lot.
- 2 Yeah. So we wrote yet another white paper.
- 3 And not -- as Ken says, he doesn't think white papers
- 4 change the world. They probably don't. But at least
- 5 they get my mind cleared up about what we should be
- 6 doing. And so hopefully, this white paper will be in
- 7 the literature looking at this issue of drug safety.
- 8 And I believe, also, there will be an FDA letter
- 9 commentary on the paper, too, to clarify all these
- 10 issues and, if nothing else, to help us with the
- 11 terminology.
- The TTC, I think, now is really about data.
- 13 That's what we're going to talk about. In fact, that's
- 14 the talk about now and talk about in the afternoon.
- 15 It's about data. And data will allow us to do a lot of
- 16 things, but it's not the kind of data that is a poster
- 17 at ATC kind of data. This is going to be data that's
- 18 going to be much more rigorously collected and gone
- 19 through than other datasets.
- And so what happens in this process and the
- 21 way that we're going to develop these two drug
- 22 development tools is that we will develop this

- 1 integrated database from data that we have collected
- 2 from multiple datasets. But the primary datasets that
- 3 we will be looking at are Phase 3 randomized multi-
- 4 center clinical trials. I believe a lot of that data
- 5 actually already exists here at the FDA because they
- 6 were FDA trials. And so I think that that would be
- 7 data that we can definitely look at validating or,
- 8 let's say, testing, the iBox first tool, and also
- 9 looking at serious adverse events, which are actually
- 10 quite detailed caught by that.
- 11 I believe that Mike advocates that your CTOT
- 12 study is part of the data that was sent. We appreciate
- 13 that. And then there will be a couple of single-center
- 14 data that actually fit the profile of iBox. One of
- 15 them is Paris (ph), obviously -- I hope that fits the
- 16 profile -- and data from our group here at Mayo, also,
- 17 because that was part of that.
- So the way that this works is you put all the
- 19 data together, and you can start looking at these
- 20 different two drug development tools and seeing if they
- 21 really do turn out to be what we hoped that they would
- 22 be.

- 1 And if I'm running out of time, I'll go and
- 2 say that the Transplant Therapeutics Consortium has
- 3 actually accomplished a lot in the last couple of
- 4 years. I would even say in the last year it has really
- 5 taken form. And we have a very clear idea, I think, of
- 6 where we are going in the next three to four years.
- 7 And I don't think we're going to take on any more
- 8 projects in the next three to four years. But
- 9 hopefully, at the end of this, we will have those two
- 10 drug development tools developed and then possibly be
- 11 able to look forward to more projects in the future.
- 12 And the announcement I would like to make is
- 13 that the -- there has been a broad agency announcement,
- 14 which is basically a contract between FDA and the TTC,
- 15 which provides some funding for these endeavors and,
- 16 also, of course, the membership and the continued
- 17 funding there. And C-Path has also taken some of their
- 18 money and put into this, also. So we have enough
- 19 money. We have some ideas.
- 20 And as Ros said, you know, good things take
- 21 time to get right. I have -- so these are apples,
- 22 actually, that we just harvested from our yard. It

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- 1 took about five years for the trees to make apples for
- 2 us. And I don't even like apples. But my wife does,
- 3 so we have a bunch of apples. So probably give -- some
- 4 of you may be getting, you know, baskets of apples in
- 5 the future. Who -- it's a nice gift.
- And I know a little bit something about
- 7 processes that are painful and take a long time. This
- 8 was the kidney allocation system that was changed in
- 9 the U.S. I wrote this paper five years into the
- 10 process, and it still was another five years before it
- 11 finally got programmed and put into place. And people
- are still complaining and arguing about that.
- 13 So I think that the fact that this started in
- 14 2013 and it's only 2018 and we're getting along today,
- 15 these things do take time to get going forward. And
- 16 you have to find the right people. And so there are a
- 17 lot of reinventing of ideas that were good ideas at the
- 18 beginning, and now they're great ideas -- so very
- 19 optimistic about the future about this.
- 20 Thank you.
- 21 (Applause.)
- 22 DR. ALBRECHT: Thank you, Dr. Stegall.

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- 1 And the last presenter for the introduction
- 2 session is Dr. Ameeta Parekh from the Office of
- 3 Translational Science here at FDA. And she'll talk to
- 4 us about the role of public-private partnerships in
- 5 catalyzing the critical path.
- DR. PAREKH: Well, good morning, everyone. I
- 7 do want to thank Renata and Inish for giving me this
- 8 opportunity to talk to you all.
- 9 And I'm from the Center for Drug Evaluation
- 10 and Research at FDA, CDER. And I'm going to talk about
- 11 the PPPs, the public-private partnerships.
- 12 So it's interesting how Dr. Mannon and Dr.
- 13 Stegall really laid out the need, the unmet need, for
- 14 the transplant and the fact that such -- I don't know
- 15 if I want to call it high-hanging fruit -- but it's
- within the reach, and it's within reach if we work
- 17 collectively and collaboratively.
- 18 And we at CDER, we have extensive experience
- 19 now. We have multiple partnerships that are already in
- 20 place. And thanks to Dr. Stegall and his slide, there
- 21 are -- he showed the glimpse of about four or five
- 22 consortia that are listed on our public-private

1 partnership website. He also showed the support that

- 2 Dr. Woodcock has for these endeavors. And below that
 - 3 list, the four or five that he showed, there are a
 - 4 total of about 40-plus consortia that we are currently
 - 5 collaborating with. And we have considerable
- 6 experience now, and we've gained this over the years.
- 7 We've stumbled. We've learned. But we know that it
- 8 works. And I'm going to give you some examples of the
- 9 role of public-private partnerships in innovation and
- 10 drug development.
- 11 My disclaimer -- so a general outline, I'm
- 12 going to talk about the challenges in drug development.
- 13 So drug development is not new. We've been doing this
- 14 for many, many years. But we've been learning as we
- 15 go, and we improve on our previous model as we go.
- So what are the challenges that we are facing? 16
- 17 And what do we need to do to address these challenges?
- 18 And how do we address this?
- 19 So innovation through collaboration is one of
- 20 the solutions, and one model for this innovation and
- 21 collaboration is the public-private partnerships. I
- 22 would like to share with you some success stories. And

- 1 the key to this -- the three examples and many, many
- 2 examples that I want to share and that I would ask you
- 3 to read about is sharing. And I think that's the
- 4 message behind the success of collaboration through
- 5 PPPs.
- 6 You've seen this before many, many times. And
- 7 again, every time I see this slide, I get a different
- 8 message out of this. But basically, what is the slide
- 9 telling you about drug development? Many compounds in
- 10 the pipeline, but they fail. And there are failures
- 11 throughout. And even late in Phase 1, Phase 2, Phase
- 12 3, there are failures.
- 13 So what's the issue here? The issue is the
- 14 uncertainty that we face throughout the drug
- 15 development pipeline. And we all have seen this in
- 16 different forms or shapes as either reviewers or drug
- 17 developers or patients, or what have you. And
- 18 basically, this is telling us, you know, the standard
- 19 conventional approach, it works. It's a very strong
- 20 model. But it's costly, and it may not work for
- 21 everything. And the challenging questions that we have
- 22 in this day and age -- maybe we need a different

- 1 approach. And with the technological advances that are
- 2 available to us in this day and age, maybe we do need
- 3 to consider other approaches.
- 4 And what am I thinking of in terms of these
- 5 other approaches? Maybe we need new clinical trial
- 6 endpoints, maybe novel trial designs, maybe novel and
- 7 better response predictors. Drug development tools
- 8 have already been talked about -- biomarkers, for
- 9 example, as drug development tools for safety and
- 10 efficacy. And Dr. Stegall already talked about his
- 11 plan for TTC with two drug development tools to be
- 12 developed.
- All of these things can be done by a single
- 14 entity. It's -- it takes effort. It takes sharing.
- 15 It takes sharing in a precompetitive space. And Dr.
- 16 Stegall mentioned that as well.
- 17 So what is needed? One of the models, again,
- 18 that we have experience in is this consortium model,
- 19 the innovation through collaboration, and one example
- 20 being public-private partnerships.
- What is public-private partnerships? So I've
- 22 kind of defined it here, the definition that we have

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- 1 used more recently in our manual of policy and
- 2 procedures. It's a consortium. It's a collaborative
- 3 group. It's managed by a convening or coordination
- 4 organization. It involves multiple stakeholder
- 5 organizations. It includes at least one nonprofit and
- 6 at least one for-profit organization. And it takes
- 7 multiple stakeholders to be at the table to share -- to
- 8 share their experience, to share their expertise, to
- 9 share their resources.
- And what are the benefits? The benefits are
- 11 you share the benefits. But you also share the cost.
- 12 So the cost is you -- one single entity doesn't bear
- 13 the cost of whatever it takes to get a product through.
- 14 And I thought there was a very interesting
- 15 message in Dr. Mannon's slide, and it really fits very
- 16 well here. And I made a note of it. "Theory is easier
- 17 than practice, consensus takes time, and structure is
- 18 important."
- And I think as she was reading that and as I
- 20 was reading that slide, I thought, oh, my gosh, that's
- 21 PPPs, and that's the collaborative effort that goes
- 22 into all of the practical aspects. There is a whole --

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- 1 you know, the guidance, the process that's laid out for
- 2 PPPs. And I think TTC with Inish has the lead and the
- 3 Critical Path Institute with their experience in 15 or
- 4 so consortia I think, hopefully -- I have my fingers
- 5 crossed -- and we can move forward safely in this
- 6 arena.
- 7 From the FDA side -- again, Dr. Stegall
- 8 already introduced this -- this is a very strong
- 9 message from the FDA -- we are very supportive of this.
- 10 And on this same -- this is a public website for the
- 11 public-private partnerships and consortia. And it has,
- 12 again, a list of many consortia that we are
- 13 collaborating with.
- 14 If you go and click on each of these links,
- 15 the consortia links, you'll see how different they are.
- 16 One is doing this while the other is addressing a
- 17 totally different issue. And all of these issues that
- 18 these consortia are addressing are really unmet needs
- 19 in product development and drug development.
- 20 And one of the things that comes with this
- 21 that Dr. Woodcock and Dr. Scott Gottlieb have been
- 22 pushing is, to be able to achieve these unmet needs,

- 1 there needs to be modernization. And in fact, very
- 2 recently -- I think August -- Dr. Gottlieb has FDA
- 3 Voice, a blog calling for organization. And Dr. Janet
- 4 Woodcock had a similar thing from CDER for
- 5 modernization of the drug development, the whole
- 6 strategic drug development process at CDER. And both
- 7 these documents are on FDA Voice. And they are blogs
- 8 from our leadership, basically supporting collaboration
- 9 and working together. So I would encourage you to look
- 10 for that and see the message that they are driving.
- 11 So I mentioned that there are multiple
- 12 consortia that we are currently partnering with, 40-
- 13 plus. And this didn't happen overnight. If you recall
- 14 -- and I think Dr. Stegall mentioned, and I kind of
- 15 maybe disagree with him on one aspect -- and he
- 16 mentioned white papers don't get you too far, but they
- 17 do. And the result of the 2004 Critical Path
- 18 Initiative, which was a white paper in my mind, led to
- 19 a lot of partnerships and a lot of juices flowing and a
- 20 lot of thinking. And that's back in 2004, and that
- 21 white paper led to a lot of thinking, a lot of
- 22 collaboration. We need to change our model of our

- 1 routine drug development. Maybe we need to engage more
- 2 stakeholders, patients, regulators, academicians,
- 3 industry. We all need to be at this table to address
- 4 these unmet needs.
- 5 So a result of that white paper was a lot of
- 6 partnerships, a lot of initiatives. And about a couple
- 7 years back -- it was 10 years since that white paper,
- 8 the critical path initiative -- we published. We
- 9 thought, wait, it's been 10 years. What have we gained
- 10 from these partnerships? And we talk about 40-plus
- 11 partnerships today. So we published a couple years
- 12 back on the consortia the role of public-private
- 13 partnerships in catalyzing the critical path.
- 14 And I'm going to take three examples out.
- 15 There are many, many examples. And they keep growing.
- 16 If you go to each of those consortia websites, it's
- 17 really awesome to see how everyone is working together
- 18 in advancing this whole collaborate -- collaborative
- 19 model. And so I'm going to give you three specific
- 20 examples. And interestingly, there's one common
- 21 denominator that I see across all of these examples and
- 22 not just these three -- across all of the initiatives

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- 1 that are going on right now. And that is sharing.
- 2 So this one -- the first example that I want
- 3 to share with you -- and I'm just going to give you a
- 4 quick glimpse. I -- if you're interested, please go to
- 5 the website. This one is data sharing, and there's
- 6 different types of sharing. This one is sharing of
- 7 data. So this is through the consortium, the Critical
- 8 Path for Alzheimer's disease consortium, which is also
- 9 under the Critical Path Institute. Sharing of
- 10 Alzheimer's disease clinical trials data across the
- 11 consortia partners and working in this precompetitive
- 12 space, they were able to develop a quantitative disease
- 13 drug trial model. And this simulates -- so what's the
- 14 point of this model, right?
- So every drug development tool and that --
- 16 you'll hear more and more about it throughout
- 17 today and tomorrow -- every tool that is developed has
- 18 a context of use. Keep that in mind. You can't just
- 19 get on this path and say I'm going to develop this and
- 20 this and this and this. Before you get onto that path,
- 21 ask yourself what is the context of use, how is it
- 22 going to be useful because that's -- so -- context of

1 use and that drug development tool is a means to an

- 2 end. And that means to an end, the end is kind of
- 3 captured in the context of use. And you'll hear more
- 4 about it in the biomarker realm and maybe in the COA
- 5 realm tomorrow.
- 6 So this -- so what's the context of use, or
- 7 COU, if I may call that? It -- what's the COU for
- 8 this? What's the purpose of this? This simulation
- 9 tool helps with the design and planning of mild to
- 10 moderate Alzheimer's disease clinical trials and for
- 11 every context of use. Whether it's a simulation tool,
- 12 a biomarker, a COA, anything, you need to have that
- 13 context of use because you want to have a purpose for
- 14 addressing the unmet needs to this -- the question.
- 15 And this disease progression model was submitted. The
- 16 whole package was submitted to the FDA a few years
- 17 back, and FDA established it as fit for purpose for --
- 18 and a dynamic tool that's -- that went through the
- 19 regulatory acceptance pathway.
- 20 So thank you, C-Path for doing this, and you
- 21 really paved the path for models and ancillary
- 22 approaches to addressing complex questions in clinical

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- 1 trials.
- 2 Talking about complex questions in clinical
- 3 trials, I'm going to shift the gears to a very novel
- 4 approach, the master protocols. We've seen, you know,
- 5 the standardized, prospectively designed, randomized
- 6 clinical trials. And some master protocols is a novel
- 7 trial design approach. It's one overarching protocol
- 8 designed to answer multiple questions.
- 9 And going all the way down to the last bullet
- 10 on this slide, this master protocol, the -- through the
- 11 I-SPY 2, it was basically a Phase 2 adaptive design in
- 11 1 51 1 2, it was basically a linase 2 adaptive design i
- 13 biomarkers as a tool, a drug development tool, for

12 breast cancer. And it basically used two more

- 14 screening new treatments. And basically, this I-SPY 2
- 15 approach and the master protocol approach evaluated
- 16 multiple therapies across multiple tumor subtypes. And
- 17 when there was promising drugs, they moved forward into
- 18 the next stage of drug development.
- 19 The next example that I want to tough on is
- 20 biomarkers. And the biomarkers -- again, going back,
- 21 we've talked about biomarkers. Let me give the
- 22 definition and read it out to you. It's a defined

- 1 characteristic that's measured as an indicator of
- 2 normal biological processes, pathogenic processes, or
- 3 response to an exposure or intervention. And there are
- 4 many types of biomarkers.
- 5 And FDA has a pathway, actually three
- 6 pathways, for getting -- or integrating biomarkers into
- 7 drug development. The first two are the conventional
- 8 pathways that many of you are familiar with, the first
- 9 one being R&D pathway. It goes individual drug
- 10 development pathway, and it's through the discussions
- 11 with the specific division, specific therapeutic
- 12 product, and the context of specific drug development
- 13 program.
- 14 The second one is the scientifically supported
- 15 community implementation, examples such as serum
- 16 creatinine or blood pressure. These are biomarkers
- 17 that have been used for years because the experts have
- 18 accepted it. And they are broadly, widely used, and
- 19 appropriate scientific support exists for their use by
- 20 experts in the community.
- The third one, which is what we were
- 22 discussing earlier -- and John Michael is going to

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- 1 really expand on it and put a lot of effort into
- 2 explaining what this entails -- is the FDA's biomarker
- 3 qualification program. This is relatively new as
- 4 compared to the other two, but not so new. We've
- 5 learned over the years. We did a pilot, and we worked
- 6 over the years. And we experimented with this.
- 7 And we are finding that this is a good pathway
- 8 where a group of consortium, for instance, can review
- 9 and can pull together the data, share the data, and
- 10 pull together the evidence that's needed. And the
- 11 evidence that's needed, again, the -- it pivots on the
- 12 context of use, and the consortium model really helps
- 13 to drive this forward.
- 14 And one example, a successful example, is that
- 15 of predictive safety testing consortium. They had the
- 16 first biomarker qualified back in 2008, and this was a
- 17 nonclinical qualification. Since then, there have been
- 18 several qualifications, nonclinical as well as clinical
- 19 qualifications. And there is a paper, a recent paper
- 20 and going back to the context of use. What evidence do
- 21 we need for biomarker qualification? And we have FDA
- 22 leaders in this field who published this paper. So I

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- 1 would encourage you to go to this paper and check it
- 2 out.
- 3 The principles -- I don't want to spend too
- 4 much time on it. I know John Michael is going to
- 5 really, really explain every step. But before you
- 6 start to construct a biomarker roadmap, our drug
- 7 development tool roadmap, the need statement, the
- 8 context of use. What is the benefit of being right?
- 9 What is the risk of being wrong? And all of those
- 10 things basically help decide what is the evidence
- 11 that's needed.
- 12 And fortunately, the biomarkers, there can be
- 13 many types of biomarkers. And two collaborative
- 14 efforts between NIH and FDA and other groups, other
- 15 experts, we have come up with this BEST Glossary that
- 16 defines the different types of biomarkers. And when
- 17 you think of context of use, you can think, hmm, is it
- 18 going to be a diagnostic? Is it going to be a
- 19 monitoring biomarker? Am I going to use it for patient
- 20 selection? Is it going to be enrichment? Is it going
- 21 to monitor safety? Is it going to monitor efficacy?
- 22 So there are different types of biomarkers. And again,

- 1 I would encourage you to look at the BEST Glossary
- 2 before you decide where am I headed with these drug
- 3 development tools.
- 4 Just stepping back, biomarker qualification is
- 5 what we've been talking about and we will talk about
- 6 later today. And again, there will be examples of the
- 7 three pathways, the R&D pathway, the acceptance through
- 8 expertise, and the qualification throughout the day
- 9 today. There will be examples by different speakers.
- But as an example, the biomarker qualification
- 11 process, it's a multi-step process. It takes several
- 12 steps of evidence generation, and it requires resources
- 13 and expertise and collaborative efforts of the things
- 14 that can facilitate the sharing. And there's different
- 15 types of sharing, and you learn that as you work with
- 16 TTC and as you hear John Michael in his talk on what
- 17 kinds of sharings go into this model.
- And the role of consortia really ties it all
- 19 together. The -- for the -- in this case, for
- 20 development and qualification of biomarkers, they
- 21 provide a neutral environment. They have timelines.
- 22 They have partnering. They have the rules and the

- 1 agreements that are laid out. And the best thing about
- 2 these consortia effort that FDA works with is really
- 3 getting everything out there in the public domain.
- And Dr. Janet Woodcock is very supportive of
- 5 these PPPs, and she is really supporting the
- 6 collaborative partnerships and through our -- the
- 7 recent blog that I mentioned earlier, modernization of
- 8 the drug development processes and the strategies are
- 9 changing and her approach, the infrastructure, is
- 10 changing. And I would encourage you to see that blog.
- 11 It was June 4th blog from Dr. Janet Woodcock and FDA
- 12 Voices. And she's basically sending the message out
- 13 that we need to work together to achieve such unmet
- 14 needs.
- 15 Thank you.
- 16 (Applause.)
- 17 DR. ALBRECHT: Thank you. Thank you very
- 18 much, Dr. Parekh.
- 19 And now we'll move to Session 1. And I'll
- 20 introduce -- or I'll have Dr. Inish O'Doherty and Dr.
- 21 Kathy Hollinger, who is from FDA, introduce themselves
- 22 and take over Session 1.

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- DR. O'DOHERTY: So hello. My name is Inish
- 2 O'Doherty from the Critical Path Institute. I'm the
- 3 executive director for the Transplant Therapeutics
- 4 Consortium.
- 5 Thank you again for everyone coming here
- 6 today. I think it's -- as both Dr. Stegall and Dr.
- 7 Mannon worked very well to explain, it's taken a long
- 8 time to get here. These things take time. There's a
- 9 certain amount of churn. But we're making progress.
- 10 We do it together. It takes time to have community
- 11 consensus. So having you all here today is -- you
- 12 know, it's standing room only in the room is a great
- 13 achievement for that.
- 14 We're going to be going through Session 1.
- 15 I'll just give a brief overview of how that fits into
- 16 the course of the day. You know, we're not always
- 17 saying that Day 1 is biomarkers. And this Session 1 is
- 18 really focused at giving a level set to the audience
- 19 and saying, yes, biomarkers exist in the community.
- 20 We're not doubting that. And they're being used even
- 21 in clinical decision-making. But how can one make the
- 22 transition from using a biomarker in clinical

1 considerations and clinical practice to be able to use

- 2 it for regulatory decision-making in drug development?
- 3 And these two things don't need to be mutually
- 4 exclusive. But if you're not aware that there's
- 5 differences that need to be considered, you're going to
- 6 miss the mark when you want to be able to incorporate
- 7 this into a regulatory decision process for drug
- 8 development.
- So you know, and another big thank you goes to
- 10 the speakers for all these sessions and the planning
- 11 calls and, you know, taking it on board that we're
- 12 asking people to think about this a little bit
- 13 differently than they do on a daily basis,
- 14 understanding that there's going to be a great body of
- 15 work done. But how do we translate that into a drug
- 16 development setting? That's what we're looking to be
- 17 able to do here today.
- 18 So we're not always going to do it exactly
- 19 right. There might be a misstep in nomenclature, but
- 20 we're bringing the community forward together, working
- 21 together on these new principles of how it's going to
- 22 be applied to drug development, ultimately to get new

- 1 tools.
- 2 So as I said, Session 1 is going to be focused
- 3 on kind of level-setting with the audience,
- 4 understanding how to, in this case, qualify a
- 5 biomarker. And it doesn't mean that every biomarker
- 6 needs to be qualified. Dr. Ameeta Parekh talked about
- 7 the idea that there's other pathways. But really, what
- 8 the first talk's going to look at is how do you create
- 9 a framework to look at the considerations that one
- 10 should when examining a biomarker for a regulatory
- 11 process, so the context of use statement, the unmet
- 12 need, and the evidence that needs to go in that.
- 13 So that's really a theme that we're working on
- 14 throughout today to try to apply to biomarkers that
- 15 exist in the community to think about how they can move
- 16 into drug development.
- 17 So at a high level, we're going to work
- 18 through those, the biomarker presentations, from pre-
- 19 transplantation. As you'll see in the agenda, it goes
- 20 to early post and then late post-transplantation. And
- 21 you'll see that theme we want to carry from the Session
- 22 1 throughout that idea of the progression of transplant

1 and how they may be used.

- 2 So again, a great pleasure to have you all
- 3 here today. I'll let Dr. Kathy Hollinger introduce
- 4 herself as well.
- 5 DR. HOLLINGER: Thank you, Inish.
- 6 Hi. My name is Kathy Hollinger. I'm a
- 7 veterinarian and an epidemiologist in the Biomarker
- 8 Qualification Program. I joined that program a year
- 9 ago, and biomarkers have been worked on here at FDA for
- 10 about a decade, if I understand the history correctly,
- 11 Ameeta. You've been working with them longer. And
- 12 there may be other people here in the room from FDA who
- 13 have worked on biomarkers as well.
- 14 What I want to say is, in my short tenure in
- 15 the program, I have worked with some folks on
- 16 submissions for biomarker qualification. And kind of
- 17 turning your mindset from a clinical perspective into a
- 18 regulatory drug development tool perspective is going
- 19 to help you very, very much. And the more specific
- 20 your request or your submission is and focused on that
- 21 drug development aspect, the better we can help you and
- 22 the more focused our recommendations can be back to you

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- 1 on how to build the evidence that you need to get it to
- 2 move toward qualification.
- 3 So I look forward to the panel discussion, and
- 4 I look forward to working with many of you in the
- 5 future.
- 6 Thank you.
- DR. O'DOHERTY: So without further ado, I'd
- 8 like to introduce Dr. John Michael Sauer. He's a
- 9 program officer at the Critical Path Institute and
- 10 executive director for the Predictive Safety Testing
- what evidence is required to qualify a biomarker.
- 13 DR. SAUER: Great. Thanks a lot for the
- 14 introduction, Inish. And I'm really happy to be here
- 15 today. This is going to be a fun talk.
- 16 My objective is to really help you understand
- 17 the biomarker qualification pathway. I'm going to use 17 regulatory review. In other words, we know how the
- 18 a lot of the same slides that Ameeta actually used.
- 19 I'm going to go into a little bit more depth.
- 20 And the reason that I'm using those same
- 21 slides -- it's not by accident -- we need to make sure
- 22 that we're all on the same page in the words that we

- 1 use and how we think about this because there is now a
- 2 codified process by which biomarkers are accepted by
- 3 the FDA. And so it's best if we follow the process to
- 4 be successful.
- 5 So again, Ameeta already showed you this.
- What's the definition of a biomarker? I'm not going to
- 7 read it out loud, but, I mean, it's important that we
- 8 all understand what this statement means and what it
- 9 doesn't mean. And many times, what happens is we get
- 10 into qualifications, and we work with partners. And
- 11 they begin to think that the assay is being qualified
- 12 or the assay is the biomarker. That's not right. It's
- 13 not the assay. It's the actual, you know, molecular,
- 14 histological, radiographic, or physiological thing that
- 15 is being measured that's actually the biomarker. And
- 16 that's an important aspect, right? So we're on the
- 17 same page there with biomarkers.
- 18 Ameeta showed this slide. I'm going to
- 19 concentrate on the biomarker qualification program.
- 20 Now, I think when we look at this slide and we look at
- 21 these different ways of introducing biomarkers,
- 22 sometimes we're drawn to that community consensus

- 1 approach. Believe it or not, that's actually a longer
- 2 approach than actually doing qualification.
- 3 What we do in qualification is we basically
- 4 take the 50 or so years it takes to reach community
- 5 consensus, and we push that down into 4 or 8 years,
- 6 right, and do the right science so that we can then
- 7 convince ourselves as scientists and the regulatory
- 8 folks that, indeed, these biomarkers do what we say
- 9 they do.
- 10 Again, so what is biomarker qualification? So
- 11 Consortium. And he's going to be talking today about 11 it's a formal regulatory review and an acceptance
 - 12 process of biomarkers to be used in drug development.
 - 13 So as is on the FDA website, a qualification is a
 - 14 conclusion that, within the stated context of use, the
 - 15 biomarker can be relied upon to have specific
 - 16 interpretation to application and drug development and

 - 18 biomarker works, and we're sure that it works that way.
 - 19 We understand the caveats associated with it and when
 - 20 we can and cannot apply that biomarker in drug
 - 21 development.
 - 22 Again, scientific and -- scientific acceptance

1 and regulatory certainty -- that's what we're looking

- 2 at, right, so that we can stand up in front of the
- 3 audience like this and say this is what the biomarker
- 4 does, these are the conclusions that I'm going to draw
- 5 from it.
- 6 So the exciting part for drug developers is
- 7 that when they now use a qualified biomarker in drug
- 8 development, they're going to know what the FDA is
- 9 thinking and how they're going to interpret that data.
- 10 Likewise, cut points, clinically significant cut
- 11 points, those are already being determined, right, and
- 12 they're predetermined in many cases. Likewise, the
- 13 quality of the analytics that are required to measure
- 14 the biomarker have already been accepted.
- Now, one thing that's important to remember,
- 16 and to differentiate from how we think about in vitro
- 17 diagnostics and other approaches, qualification does
- 18 not mean that that assay that's being used to measure
- 19 the biomarker is an in vitro diagnostic, right? It can
- 20 be, but it doesn't have to be. And likewise, just
- 21 because you qualify a biomarker, it doesn't
- 22 automatically give it that status or its assay that
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- 1 status.
- 2 I think an important aspect, also, is that
- 3 qualification just isn't biomarker discovery or
- 4 clinical validation. They're both a part of it.
- 5 There's no doubt about it. But it's taking that entire
- 6 package and being able to then convince the community
- 7 and to convince regulators how that biomarker works.
- 8 And so it's very analogous to drug development
- 9 in many ways. The documents are very similar. And how
- 10 they go through the quality, if you will, the biomarker
- 11 and the data behind that biomarker.
- 12 So what is really objective as a
- 13 qualification? Once a biomarker is qualified, it's
- 14 available. It's available to the public, right? It's
- 15 not a proprietary approach, right? And that's
- 16 important because that's what we're trying to do
- 17 because we're trying to change drug development overall
- 18 by introducing these various approaches.
- 19 These biomarkers are meant to streamline drug
- 20 development and speed the review process. A biomarker
- 21 that's used for regulatory decision-making that's not
- 22 qualified, basically, you're going to have to prove to

- 1 that regulatory agency that, indeed, it's performing
- 2 the way it's performing. But if the biomarker is
- 3 qualified, that's already been done for you.
- 4 Again, the biomarker process, you know,
- 5 provides a framework -- and that's what I'm going to go
- 6 into next -- of how, basically, DDTs, these drug
- 7 development tools, are accepted by the FDA.
- 8 So it all starts with a drug development need.
- 9 So you want to solve a problem. What is that problem?
- 10 And how are you going to solve it, and how could a
- 11 biomarker potentially solve that problem for you?
- 12 So what you do is you go ahead and you figure
- 13 out what you want to do with that biomarker very
- 14 specifically. And that's what the context of use is --
- 15 how that biomarker is going to be used within drug
- 16 development.
- 17 Then what comes from there is there's a level
- 18 of evidence that needs to be met, and that's really a
- 19 discussion with the agency around what this package is
- 20 going to look like for the acceptance of the biomarker.
- 21 Then the actual acceptance happens, and then hopefully
- 22 that drug development need or gap is then solved.
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- 1 This has all been codified by law by the 21st
- 2 Century Cures Act. Section 507 actually goes deeply
- 3 into the qualification of drug development tools. This
- 4 law was put in place about two years ago, and it really
- 5 codifies the approach that needs to be used in order to
- 6 interact with the FDA and to gain approval of these
- 7 biomarkers or endorsement of these biomarkers.
- 8 So here goes the process kind of drawn out,
- 9 right? It's not graphically drawn out, but I'll show
- 10 you that later. How to think through the road map, if
- 11 you will.
- So what's the gap? How can you state what the
- 13 need is? Develop your context of use, which is the
- 14 concise description of the biomarker's specific use in
- 15 drug development. Understand the benefit to patients,
- 16 right, and also the risk associated with the biomarker
- 17 being wrong because that's all going to then feed into
- 18 what the evidence that's required. It's a pretty
- 19 simple map, but the nice part what it does, it creates
- 20 a conversation piece for requesters, folks trying to
- 21 qualify biomarkers, to be able to communicate with the
- 22 FDA and use the same language.

- 1 So another way to think about this context of
- 2 use statement, it's like a drug label, right? How is
- 3 this biomarker going to be applied in drug development?
- 4 And there's really two elements to any context of use.
- 5 The first is the class of the biomarker. Is it a
- 6 diagnostic biomarker, a prognostic biomarker, or is it
- 7 a clinical trial endpoint?
- 8 And this has all been outlined in the BEST
- 9 Glossary. So if you ever have time, take a look at the
- 10 BEST Glossary, and it allows you to understand how to
- 11 characterize these different biomarkers and how they
- 12 can be used.
- 13 The second part of the context of use is
- 14 really what question is the biomarker intended to
- 15 address, right? So what is its fit-for-purpose use?
- 16 So here are the different classes of
- 17 biomarkers. I'm not going to go through them one by
- 18 one, but you can see on these slides that there are a
- 19 number of different classes that biomarkers can fit
- 20 into. You know, I think everybody's drawn to the one
- 21 from the second from the bottom, the reasonably likely
- 22 surrogate endpoint, but it's the hardest one to get to.
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- 1 And we'll talk a little bit about that with the level
- 2 of evidence. Probably the easiest one to get to is a
- 3 diagnostic biomarker, and we can talk a little bit
- 4 about that.
- 5 The next thing, you know, we need to think
- 6 about is, you know, what is now that biomarker intended
- 7 to actually address. Why do you want that qualified?
- 8 Why do you want to use that biomarker? And there's
- 9 some pretty defined terms out there -- so inclusion,
- 10 exclusions, right, criteria; you know, stopping a
- 11 patient in a clinical trial; you know, establishing
- 12 proof of concept in a given patient population. So
- 13 there's multiple uses for these biomarkers. So it's
- 14 very important that we clearly state how we're going to
- 15 use these biomarkers.
- Now, Ameeta showed this slide previously. But
- 17 really, what it does is it links the different
- 18 categories, really, to the intended uses. So the nice
- 19 part, those need to correlate, right? So -- and then
- 20 that's how you really define then the biomarker
- 21 category or class that you're going to end up in and
- 22 then be able to link that then to the use of the

- 1 biomarker.
- 2 So again, in the templated guidance documents
- 3 that are associated with the biomarker qualification
- 4 and creating a context of use, the -- as I said,
- 5 there's two important categories to creating a context
- 6 of use, right -- the category of the biomarker and then
- 7 its drug development use.
- 8 Now, that seems like it's going to be a one-
- 9 sentence thing. But as you can see from this example
- 10 from our Polycystic Kidney Disease Outcome Consortium
- 11 for total kidney volume, you know, it's also very
- 12 descriptive, right? There's no doubt that it includes
- 13 those two important pieces -- in this case, a
- 14 prognostic enrichment biomarker that's to be used for
- 15 the -- as an enrichment factor in clinical trials.
- 16 So -- but what it also does, this context of
- 17 use, allows users of the biomarker to also then
- 18 understand how this fits in and how they can apply it
- 19 to their given trial or their drug development program.
- 20 Probably, you know, dealing with consortia,
- 21 the place where we face the largest amount of anxiety
- 22 is actually around how much evidence is required in
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- 1 order for be -- for us to be successful. And that's a 2 conversation that can't happen in the absence of the
- 3 regulators. There has to be alignment around that.
- 4 But here's a couple things to think about.
- 5 This is where qualification differs from drug
- 6 development. When we think about the level of evidence
- 7 that's required to register a drug for broad usage, we
- 8 look at a preponderance of data to support that drug
- 9 development.
- But when we look at biomarker qualification,
- 11 we're really looking at a correlation. In other words,
- 12 does the biomarker actually mimic and correlate with
- 13 the gold standard. It's a really important aspect
- 14 because it changes your entire statistical approach and
- 15 how you think about gathering data, et cetera.
- The nice part is that, you know, we do have a
- 17 framework to work from and to drive the conversation
- 18 with regulators, right? You've seen this before.
- 19 You've also seen this before from Ameeta. I mean, some
- 20 people learn graphically; some people like words. I'm
- 21 a graph guy.
- I mean, so you think about it. You know, you

- 1 have a given statement, a need statement, what you want
- 2 to do, what you want to solve. You create that context
- 3 of use. You go ahead then and talk about the benefit,
- 4 risk. And then from there, you can have a very robust
- 5 discussion around what the evidence is required to go
- 6 ahead and then meet qualification.
- 7 So one thing to think about is let's say you
- 8 have a biomarker that you believe could be a surrogate
- 9 endpoint. But you also know that this is a response
- 10 biomarker that can be used in clinical trials as an
- 11 endpoint. Likewise, you know there could be a
- 12 prognostic biomarker to go ahead and actually use for
- 13 patient enrichment.
- 14 It's a heck of a lot easier to start at the
- 15 prognostic biomarker point. You don't have as robust
- 16 of a context of use as you would for a reasonably
- 17 likely surrogate endpoint. And therefore, the data
- 18 expectations, the regulatory expectations, the
- 19 evidentiary expectations are much lower. It's going to
- 20 be easier to be able to begin to use that biomarker,
- 21 and they're going to increase as you move towards a
- 22 response biomarker and then towards a surrogate
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- 1 endpoint.
- Now, I realize this is a generalization. But
- 3 it's going to hold true regardless, right? It's just
- 4 where the expectations are because, in order to achieve
- 5 that context of use, you're going to need that much
- 6 more evidence.
- We can break down the evidence component
- 8 pretty easily. There's two major areas that we need to
- 9 think about -- first, the analytical validation, the
- 10 assay that's being used, and the performance
- 11 characteristics of that assay.
- The other side of the coin is really around
- 13 the clinical validation and whether or not this
- 14 biomarker actually correlates to the gold standard or
- 15 not and how well it does, right? Does it do what we
- 16 want it to do?
- We published a paper. I believe last year it
- 18 came out, and this was around a workshop that was held
- 19 around defining, really, how we go ahead and codify
- 20 this process, right, of discussion -- of discussing
- 21 what evidence is really required to support biomarker
- 22 qualification.

- 1 We used safety biomarkers as the example
- 2 within this publication. And the reason was, was that
- 3 was the most advanced biomarkers that were moving
- 4 through the qualification process. And Gary Friedman
- 5 is actually going to talk a little bit about some
- 6 kidney safety biomarkers that we've recently qualified
- 7 and how that was done.
- 8 But let me make it more complex for you.
- 9 Sorry. I have to do this. So if you look at it, when
- 10 we break down those two features, the clinical
- 11 validation as well as the analytical validation, we can
- 12 break it down in the subcategories that need to be met
- 13 to various degrees, depending on what category of
- 14 biomarker you choose and what the use of that biomarker
- 15 is -- in other words, the context of use.
- 16 So assay performance -- the validation of the
- 17 assay is absolutely important, right? You need to make
- 18 sure that when you measure a given biomarker that you
- 19 can do that repeatedly, right? Now, we know that most
- 20 early biomarkers we don't have reference standards,
- 21 different aspects like that. So you know, sometimes
- 22 that accuracy aspect will be we can't address all the
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- 1 time. But again, we have ways of dealing with that.
- 2 So characterizing the relationship of the
- 3 biomarker to the clinical outcomes, or whatever that
- 4 gold standard is, you know, the biological rationale
- 5 for a biomarker is very important, especially when
- 6 you're talking to the regulators, right? This is why
- 7 we think this biomarker is doing what it's doing. Is
- 8 that always needed? Maybe not. Maybe not. Sometimes
- 9 it just correlates, and you don't understand why -- but
- 10 again, an important conversation.
- Also, then think about how you're going to
- 12 achieve your qualification, what datatypes you're
- 13 actually going to utilize. So in every case, we have
- 14 to have a prospective analysis, right? But it doesn't
- 15 have to be prospective data. It could be retrospective
- 16 data where there's now a new prospective analysis
- 17 associated with it. So that's something to think
- 18 about. I mean, do you want to conduct a new trial, or
- 19 do you want to use data that already exists?
- 20 Data reproducibility -- this is a very
- 21 important aspect of qualification. It's learn and
- 22 confirm. It's exploratory data followed by

1

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- 1 confirmatory data. Use the exploratory data to set
- 2 your cut points and set your hypothesis. Allow that to
- 3 then be confirmed in a different data set.
- 4 Again, comparison to the current standard --
- 5 of course, that has to happen. But let's face it.
- 6 That can sometimes be an issue. If you're having a
- 7 biomarker that is more sensitive than the current
- 8 standard, then all of the responses from your new
- 9 biomarkers are considered false positives. So you
- 10 sometimes have to reach beyond the current standard and
- 11 discuss, really, what is the truth that this biomarker
- 12 is demonstrating.
- 13 Pre-specified statistical analysis and then,
- 14 of course, the strength of the evidence, right? In the
- 15 end, it's always the strength of the evidence, right?
- 16 We're scientists. That's what we're driven on.
- 17 Here goes just for fun. I put -- very good.
- 18 Just for fun, I put in two contexts -- I put in a
- 19 context of use here, and I put in two different
- 20 possibilities. So in this context of use, we're using
- 21 some kidney safety biomarkers in individuals with
- 22 normal renal function. Well, there's a certain base
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- 1 level of evidence. How can we look at where we need
- 2 more evidence? Well, what if we now apply this to this
- 3 kidney -- these kidney safety biomarkers now to both
- 4 individuals with normal renal function, but also
- 5 individuals with the disease, a chronic disease? Well,
- 6 of course there's going to have to be more evidence.
- 7 Your baseline of these biomarkers may be different.
- 8 The response of these biomarkers to additional insult
- 9 to the kidney may be different.
- A second one is, if you look at this context
- 11 of use closely, we're using these biomarkers in
- 12 conjunction with the conventional kidney safety
- 13 biomarkers -- serum creatinine, BUN, and cystatin C.
- 14 What if we decide to go ahead and remove those
- 15 biomarkers and these new biomarkers overtake that? Of
- 16 course, once again, a higher level of evidence is
- 17 required. And so that's why it's very important that
- 18 you craft your context of use such that you're able to
- 19 obtain that with the data you have or the data that
- 20 you're looking at generating.
- 21 Well, I'll stop there and say thank you.
- 22 (Applause.)

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DR. O'DOHERTY: Thanks, John Michael, for

- 2 giving a background there, kind of looking at the high-
- 3 level landscape of, you know, what do we talk about
- 4 when biomarkers are being considered for drug
- 5 development, and, also, what do the regulators
- 6 consider.
- 7 So next up, we have Dr. Gary Friedman, who's
- 8 actually at Pfizer, but a member of the Predictive
- 9 Safety Testing Consortium. And he's going to be
- 10 talking about biomarker qualification but with a
- 11 specific example, working through the process John
- 12 Michael just worked through, looking at kidney safety
- 13 biomarkers.
- 14 Now, these are biomarkers for drug-induced
- 15 injury. They're -- you know, we're not saying that
- 16 these are the biomarkers for transplant. What we're
- 17 saying is look at the process. This is a worked
- 18 example of how you navigate that process using this
- 19 framework.
- 20 So Gary, over to you from here.
- 21 DR. FRIEDMAN: Inish, thanks very much.
- 22 Dr. Albrecht, members of the FDA, we're
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- 1 grateful for your support throughout this long
- 2 development process. Inish, John Michael, we would not
- 3 have gotten to where we are without your being good
- 4 shepherds. So thank you very much.
- 5 So without further ado, we're going to take
- 6 this from the theoretical to the actual. Here are my
- 7 disclosures. And I've had the good fortune of being
- 8 part of both the Predictive Safety Testing Consortium
- 9 based here in the U.S., but also the honor and pleasure
- 10 of being part of the safer -- well, SAFE-T has a
- 11 different acronym now. So I'll forgo that one.
- 12 But the processes that we have worked through
- 13 in conjunction with FDA, with EME, and the Critical
- 14 Path Institute, we could not be here without their
- 15 guidance, their flexibility. And they're supporting us
- 16 through some pretty dark days.
- 17 And I'm here at this podium speaking. But
- 18 behind me, actually, are a couple hundred individuals
- 19 who have been participating in this throughout the EU,
- 20 throughout the United States, academic centers,
- 21 pharmaceutical companies, and the like. And I believe
- 22 we've got everybody on this slide, but I may have left

- 1 off somebody. So I'll apologize for having left
- 2 anybody off. But this is an acknowledgement that I'm
- 3 here as a representative of the Predictive Safety
- 4 Testing Consortium, and we could not be where we are
- 5 now without each and every one of these members.
- 6 So cutting to the chase in November of 2016,
- 7 the SAFE-T Consortium achieved this -- the issuance of
- 8 this letter of support. And this was issued by the FDA
- 9 as well as a separate letter was issued by the EMA.
- 10 And I want to share with you that one of the most
- 11 exciting and amazing aspects was being in the room here
- 12 in Silver Spring with members of FDA and EMA or being
- 40 777 4 61 1 7 1 1 1 4 7 7 7 7
- 13 at Westferry Circus in London with members of EMA and
- 14 FDA all working in concert and, again, with our good
- 15 shepherds at the Critical Path Institute helping us
- 16 along.
- 17 So here you see the biomarkers that John
- 18 Michael was referring to just a few moments ago and
- 19 each of the steps in the process that were required to
- 20 get to where we are. I'm going to touch on those right
- 21 now. It's a bit difficult to consolidate all that
- 22 information concisely in the next 15 minutes.

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- But the piece de resistance was just about six
- 2 weeks ago where you see this qualification
- 3 determination letter issued by individuals within -- in
- 4 the room here. And it is really as we move toward the
- 5 adjudication of the two prospective studies. And that
- 6 adjudication process will begin imminently. We expect
- 7 to be able to deliver that data to FDA and to EMA
- 8 within the next quarter. And that will be the next
- 9 step as we move potentially toward full qualification
- 10 of these biomarkers.
- So before you run out of the room screaming,
- 12 know that everything that was described earlier in
- 13 terms of the processes -- so the FDA and the EMA, each
- 14 taking the gaps that they perceive in terms of drug
- 15 development steps and the ability to move from early
- 16 preclinical development all the way to drug approval,
- 17 each of the steps -- and you heard the acronym BEST,
- 18 biomarkers endpoints testing, each of the learnings and
- 19 the growth that FDA put together in place before us
- 20 should take what you see in front of you and
- 21 potentially contract those timelines.
- Going back, however, to 2006 and then moving

1 forward all the way to 2017-'18 are what I'm going to

- 1 forward an the way to 2017- 18 are what I'm going to
- 2 tell you about in summary right now. But each of these
- 3 steps, as we move through them, we move through them
- 4 with FDA, with EMA, with Critical Path Institute
- 5 guiding us every step of the way.
- 6 Some of the authors of this publication may or
- 7 may not be in the room here. But they -- in this
- 8 publication in 2010, there were 10 articles that were
- 9 produced -- that provided the roadmap, really, for
- 10 where we are as of this moment. And the -- this first
- 11 publication that you see here describes well FDA and
- 12 EMA perceptions of where the gaps are.
- And then on the right side of this slide, it
- 14 describes the creation of a Critical Path Initiative.
- 15 And you see incarnate those representatives here to my
- 16 right. Furthering that publication, the universe of
- 17 potential biomarkers all the way from the glomerulus,
- 18 all the way to the collecting duct, you see a
- 19 smattering of the couple dozen of potential biomarkers
- 20 that we could consider as we move forward.
- You may recognize quite a number of the names
- 22 there. And you'll notice that, while some of them are

- 1 from academia, others are clearly from pharma,
- 2 particularly in this case. Two of the authors are from
- 3 Novartis. And a number of you in this room have
- 4 probably interacted with each of these investigators,
- 5 whether the academic side or the pharma side.
- 6 Again, the sharing of data that was emphasized
- 7 before, you have within the Predictive Safety Testing
- 8 Consortium, you have for the drug injury -- drug-
- 9 induced kidney injury work stream, working group. You
- 10 have members from Pfizer, from Novartis, from -- you
- 11 name it. They're all present, and they're all sharing
- 12 information and working closely with ac (ph) admissions
- 13 who are bringing their acute kidney injury patients or
- 14 their normal, healthy volunteers to our focus so that
- 14 then normal, hearting volunteers to our focus so that
- 15 we can obtain the requisite samples.
- And what was done is, as we move through the
- 17 approximately 60-plus biomarkers from the glomerulus to
- 18 the collecting duct, we did the ROC analyses. And
- 19 those things that fell below the diagonal line were
- 20 clearly dispensed with. And fortunately, you can see -
- 21 in the upper quadrant, you can see -- without going
- 22 into the data in specific, you can see the number of

- 1 biomarkers that exceeded the 50 percent area under the
- 2 curve. You can see the biomarkers that, if you look
- 3 closely here, you'll notice that there is a very light
- 4 -- my wife says I'm color-challenged -- but there is a
- 5 light mauve curve there. And above that are all of the
- 6 biomarkers that meet or exceed serum creatinine. And
- 7 so with this evidence, we move forward in that learn-
- 8 and-confirm strategy that was referenced earlier.
- 9 So what we did was, in terms of within SAFE-T
- 10 and within PSTC, the preclinical data that were derived
- 11 from various animal models in animals exposed to
- 12 cisplatin, aminoglycosides, and other tubular toxins,
- 13 including cyclosporine and tacrolimus, we began to look
- 14 at some of those biomarkers that ended up in the urine
- 15 samples.
- And with the preclinical learnings, we then,
- 17 within the EU at a number of sites -- for instance, in
- 18 Paris, in Barcelona, and in London and in Dublin --
- 19 recruited healthy volunteers as well as individuals
- 20 with malignancies or with infections and then began to
- 21 capture those samples that really compose the outputs
- 22 of the learning phase.

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- 1 From there, we then designed here within the
- 2 United States two prospective trials where almost 300
- 3 subjects have been enrolled. All of their data has now
- 4 been captured. All the samples have been analyzed, and
- 5 the data have now been locked. And we will now have an
- 6 adjudication process by six expert nephrologists who
- 7 will be independently looking at all of the
- 8 information.
- 9 I'm not going to go into this in detail, but
- 10 suffice to say, this is our favorite picture, clearly,
- 11 by the preceding speakers. So in this specific
- 12 instance, you see the red-highlighted box. So this
- 13 SAFE-T Consortium, the Predictive Safety Testing
- 14 Consortium, with the urinary biomarkers all normalize
- 15 for urinary creatinine. We selected to go with the
- 16 path of a safety biomarker. And the context of use you
- 17 can see there as in terms of looking at the presence or
- 18 the extent of toxicity related to intervention or
- 19 exposure.
- And in a nutshell, there were approximately
- 21 150 subjects, either normal, healthy volunteers, or
- 22 clinical subjects who were exposed to a known

rage o

- 1 nephrotoxin. And you can see that what SAFE-T and what
- 2 PSTC did, there was some harmonization in terms of the
- 3 collection points of all of those data. So you can see
- 4 prior to exposure, during exposure, and after exposure.
- 5 We can see the rise and fall of each of the biomarkers
- 6 that ultimately were outlined in that letter of
- 7 support.
- 8 I'm not going to go through this in detail.
- 9 But suffice to say that, from 2009 to 2018, we've gone
- 10 from the garnering of preclinical data for each of the
- 11 biomarkers, done the analysis to see with area under
- 12 the curve which of those biomarkers we should consider
- 13 and which we should discard. And subsequently, the
- 14 letters of support were issued by EMA and FTA.
- But really, where we are right now is at this
- 16 moment. We are about to read out two prospective
- 17 studies of individuals exposed to cisplatin and
- 18 individuals exposed to aminoglycoside, and individuals
- 19 that are matching controls. And those will be read out
- 20 over the next quarter. And then subsequently, as those
- 21 individual adjudications are completed and they're
- 22 completed independently, those data will then be

- 1 collated and then submitted to FDA and to EMA.
- 2 And I'm going to stop right there and really
- 3 thank you for your time and attention.
- 4 (Applause.)
- 5 DR. O'DOHERTY: Thanks, Gary, for going
- 6 through that.
- 7 And I think it -- it's nice to be able to see
- 8 that, you know, certain consortia have really paved the
- 9 way and have been the vanguard of working through this
- 10 qualification process with FDA. You know, we've had
- 11 multiple planning calls to say that qualification is an
- 12 evolution and -- in its processes within the FDA and
- 13 EMA. And I think that's clearly evidence through this
- 14 process.
- 15 So a bit of a change of gears on this one.
- 16 We're going to have Dr. Josef Coresh presenting on GFR
- 17 decline as an endpoint in clinical trials and CKD.
- 18 Now, this wasn't a qualification process but, rather,
- 19 more along the lines of scientific community consensus
- 20 using a very well-established measure that already
- 21 existed in the community. So still the same principles
- 22 of understanding the data that's necessary to garner

- 1 this endorsement, but a bit of a shift of gears
- 2 regarding changing from qualification.
- 3 DR. CORESH: Thank you. I want to thank you
- 4 for the opportunity to come, listen, and present and
- 5 congratulate you on this important undertaking.
- 6 So we looked at GFR decline as an endpoint in
- 7 clinical trials of CKD, and we did this using the CKD
- 8 Prognosis Consortium and other collaborations that I'll
- 9 tell you about the next 15 minutes.
- 10 In terms of the outline, I wanted to talk for
- 11 one slide about the criteria for assessing a surrogate
- outcome in CKD, and you've heard about that already. I
- 13 wanted to emphasize that our approach was to use data
- 14 to make progress. And I think you've seen a lot of
- 15 that, and I think the increased emphasis on data,
- 16 collaboration, consortia coming together in
- 17 longstanding undertakings is really important.
- 18 I think the other thing that we've contributed
- 19 is in thinking about surrogates for clinical trials.
- 20 We realize the data within trials in CKD was limited.
- 21 So we added data from observational studies and from
- 22 simulations. And I'll show you that, and I think that
- 1 helped sort of reach the threshold, which is not a
- 2 simple threshold to know what thresholds you need.
- 3 These, you know, build on the 2012 FDA
- 4 workshop, and I'll give you the conclusion at the end
- 5 so you can think about it. And hopefully, you're
- 6 somewhat familiar with it. It's been published in
- 7 2014. And that is that using estimated GFR change as a
- 8 surrogate outcome, going from a doubling of serum
- 9 creatinine, which is a 57 percent reduction in
- 10 estimated GFR, to a lower threshold of 30 to 40 percent
- 11 reduction is a useful surrogate. And the useful thing
- 12 is, by looking at data, we could quantify the major
- 13 caveats, which really related to an acute effect that
- 14 can nullify the whole paradigm, right? So I think,
- 15 often, it's both getting to the conclusion and knowing
- 16 when the conclusion can and cannot be applied.
- 17 In terms of related work, we've continued this
- 18 work sort of, yeah, you're right there award for
- 19 finishing something in science is you have three new
- 20 questions, right? And hopefully, you actually get to
- 21 pursue them thoughtfully. And we finished a related
- 22 FDA workshop in 2018 on changing in albuminuria and on

- 1 GFR slopes as a more refined way to look at change in
- 2 GFR. And I'm happy to discuss that. The papers for
- 3 that will be presented at the ASN. And then two are
- 4 going to be published shortly, and two more will be
- 5 submitted after that.
- So I think it's helpful for me in chronic
- 7 kidney disease to start with the KDIGO guidelines,
- 8 which define CKD as an abnormality of kidney structure
- 9 or function present for three or more months. The
- 10 staging since 2013 is by cause, GFR category, and
- 11 albuminuria, right? And the colors are sort of a heat
- 12 map of risk. The lower the GFR, the higher the risk.
- 13 The higher the albuminuria, the higher the risk. But
- 14 it's important, especially for this meeting, that cause
- 15 is important. And within transplantation, you have
- various nuances of the different pathologic processes
- 17 going within this cause.
- 18 It's also important to note that, when the
- 19 guidelines were published, progression data were very
- 20 limited. So we made some statements with limited
- 21 evidence that decline in GFR category or a drop by 25
- 22 percent or rapid progression slope of more than 5 ML
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 - 1 permitted per year were, you know, reasonable things to
 - 2 do. But the evidence was limited, and the confidence
 - 3 is dependent on the number of years and number of
 - 4 measures you had. And in terms of albuminuria, we
 - 5 noted that small fluctuations are common, but we didn't
 - 6 have all the evidence to really talk about what level
 - 7 of change was going to be useful.
 - 8 In terms of assessing a candidate's surrogate
 - 9 endpoint, right -- so now when we get to a biomarker
 - 10 and we want to use it as a surrogate, we really need
 - 11 sort of the highest level of evidence, right? The
 - 12 categories are clear -- so biologic plausibility,
 - 13 strength and consistency of epidemiologic observational
 - 14 data, and, most importantly, prediction of the
 - 15 treatment effects on the clinical outcome from the
 - 16 surrogate. And within that, there are categories in
 - 17 the BEST document which are very useful of a candidate
 - 18 surrogate, a reasonably likely surrogate, and a
 - 19 validated surrogate.
 - 20 And it's clear that, for the validated
 - 21 surrogate, which would allow drug approval based on the
 - 22 surrogate, you need high evidence, right? But we found

- 1 it a little bit frustrating that it's not easy to know
- 2 what is high evidence. And maybe it will never be
- 3 fully defined, but it's a bit of a challenge to
- 4 continue to write as people try and, you know, sort of
- 5 clear that highest obstacle as to what it would be.
- 6 So what did we do, right? So this is the
- 7 summary of a number of years of work. And we were
- 8 fortunate that we had the CKD Prognosis Consortium,
- 9 which was born in 2009, out of a controversy. And
- 10 again, when we succeeded in resolving the controversy,
- 11 we were given yet another task in forming a consortium.
- 12 And formally -- fortunately, it builds to progress.
- 13 The consortium has continued to grow over the last now
- 14 10 years. It's amazing. You look back at all these
- 15 timelines, and you think, oh, we're moving fast. And
- 16 then, boom, it's a decade. We're moving fast. Boom,
- 17 it's another decade. But hopefully, we've done
- 18 something.
- And at this point, we've got 70 cohorts that
- 20 regularly participate. They're allowed to opt in or
- 21 out into every analysis. So there's no guarantee.
- 22 They could all disappear tomorrow if they don't like

- 1 perspective, that if you started two patients in an
- 2 equal starting point, we're going to adjust for the
- 3 first point. And we -- the question is: Is more rapid
- 4 CKD progression from Path B compared to Path A
- 5 associated with higher subsequent risk of ESRD? So we
- 6 divided it into a baseline period in which we assess
- 7 the rate of progression or the change, and then we said
- 8 does that predict the future.
 - And in many ways, if you look at this, you'll
- 10 be, like, saying, well, it may be obvious. If their
- 11 GFR's lower at the beginning of the end of the
- 12 baseline, of course they'll get the ESRD faster. But
- 13 that suggests that you believe in GFR being useful,
- 14 right?
- 15 It is important to distinguish that this is
- 16 different from the diagram on the right, right? That -
- 17 clinicians often see patients at the last measurement
- 18 because they use all of their data. And they say,
- 19 given two patients with the same last measurement, is
- 20 the past slope predictive of future? And it turns out
- 21 that's a much harder question. We address that as well
- 22 in papers. But for the surrogacy, it's really the left

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- 1 what we do. But basically, almost everybody
- 2 participates. And with larger datasets and health
- 3 systems, we've got up to 10 million participants
- 4 globally.
- 5 And I'd like to acknowledge Morgan Grams,
- 6 who's the co-PI of the consortium; and Andy Levey, who
- 7 does a lot of the helping, thinking, and editing; Ron
- 8 Gansevoort in the Netherlands. And this is a group of
- 9 all the leading investigators we meet annually to
- 10 pursue the different topics.
- 11 This is a list of the investigators and key
- 12 cohorts. It's just always good to acknowledge that
- 13 people have done, really, decades of work and then
- 14 share their data. And it is a tricky balance in that
- 15 you don't want to just take their data and run with it.
- 16 You have to sort of really give back something, even if
- 17 it's just scientific credit, collaboration, and the
- 18 ability to succeed locally, right, where, often, you
- 19 really can't pay for any of this stuff.
- 20 So what did we do in terms of CKD progression,
- 21 right? We decided to focus on evidence and on future
- 22 risk. So observationally, we took the clinical trials

- 1 question that we address.
- 2 And we analyze participants in each cohort.
- 3 In each cohort, we model the percent change in
- 4 estimated GFR using a spline. We meta-analyzed across
- 5 cohorts using a random effect meta-analysis. And then
- 6 we examined the heterogeneity using forest plots and
- 7 meta regression, right? And the advantage is, if you
- 8 see both a result and strong consistency across the
- 9 globe, you are much more confident in terms of
- 10 concluding that you have something that is really
- 11 biologically important, consistent, and predictive.
- 12 So what did the data show for the
- 13 observational studies, right? So basically, this is
- 14 the baseline characteristics and follow-up. And you'll
- 15 see that we had 19 cohorts with a GFR less than 60, 9
- 16 cohorts with a GFR above 60, lots of patients. We
- 17 looked at one- and two- and three-year baseline
- 18 periods. We had a number of serum creatinines at two
- 19 years of about three, and that's the result I'll show
- 20 you -- lots of ESRD events so we can look at things
- 21 with precision and about 2.4 years after the two-year
- 22 baseline period, right? And the mean GFR for below 60

1 was 48 and for above 60 was 90.

- 2 This is the risk curve. For a GFR less than
- 3 60, we saw that, if you look at percent change in
- 4 estimated GFR and you use 0 percent as the reference
- 5 point, then the lower percent change with a doubling of
- 6 serum creatinine, which was already used by the FDA,
- 7 the doubling of serum creatinine resulted in a 31-fold
- 8 greater risk of ESRD subsequently.
- 9 And in a way, I was very happy because when we
- 10 prepared for this meeting, we met with Ed Lewis (ph)
- 11 and some of the other people who established this
- 12 surrogate. And it turns out about 30 years ago or so
- 13 when you establish a surrogate, you know, it's a cab
- 14 ride to the FDA where the senior statistician and the
- 15 senior scientist talked and said, so what's a good
- 16 surrogate? And then they presented something. And if
- 17 it worked, it worked. And the amount of data available
- 18 was a lot weaker. It turns out they chose very good
- 19 reasonable things. And maybe everybody made the right
- 20 decision and didn't need 10 years of data. I think now
- 21 we actually need the data to show it.
- 22 And the good thing is, I think, in this day

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- 1 and age, we shouldn't take surrogates for granted.
- 2 We've had some very complicated stories with HDL
- 3 cholesterol, et cetera.
- 4 So the established surrogate worked. And then
- 5 the question was: Could you back down from that? And
- 6 what we did was sort of emphasized that, if you looked
- 7 at a 30 percent decline in GFR, basically, you saw 5-
- 8 fold subsequent risk of ESRD, which was substantial
- 9 risk. And it was impressively 6.6-fold at GFR greater
- 10 than 60, very consistent, right?
- We also saw that an increase and a decrease
- 12 weren't exactly symmetric, so that was important. And
- 13 then, importantly, the percentage of the population
- 14 that had an attributable risk was much higher. So in
- 15 some sense, when you back off to a lesser criterion,
- 16 you get less or relative risk -- you know, 5-fold
- 17 rather than 30-fold, but the percentage of the
- 18 population that experienced this and explained the
- 19 event was much higher. So the clinical trials with
- 20 smaller size could actually reach adequate power.
- In terms of consistency, it was quite
- 22 impressive for this outcome, right? I mean, basically,

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- 1 if you look at increased risk, every study showed
- 2 increased risk -- one wasn't significant, but that was
- 3 a smaller study -- and higher GFR, a little more
- 4 heterogeneity, but, still, very impressive consistency
- 5 for the results.
- 6 Then we -- basically, where did we go from
- 7 there? What we did was we wrote up the result in the
- 8 cohorts, and that was published shortly after the
- 9 workshop. We wrote up the results for the
- 10 observational analysis of clinical trials, the
- 11 intention to treat analysis of clinical trials. And
- 12 I'll show you that result briefly. We did simulations,
- 13 and then Andy Levey drew up a summary of all of this.
- 14 And then there were commentaries by both the FDA and
- 15 the EMA about their interpretation of the level of
- 16 evidence. And then since then, we've been sort of
- 17 gratified that a number of companies have taken this
- 18 evidence and built it into their drug development
- 19 pipeline, right?
- 20 I don't think we have a guarantee in a
- 21 document that this will always work, as in a guidance
- 22 itself. But instead, we have a body of evidence, a set

- 1 of publications, and, I think, an understanding of how
- 2 things work.
- This is the data for the clinical trials. And
- 4 Leslie Inker worked hard on this for a long time to get
- 5 all the trials. There were 37 randomized trials. But
- 6 really, data were still limited. Here, they're plotted
- 7 by drug category, and you can see that, even within the
- 8 categories of interventions, the standard errors are
- 9 quite wide.
- 10 You also need -- in order to get surrogacy,
- 11 what you want to see is that a good correlation across
- 12 studies between the hazard ratio of the alternative
- 13 outcome really plotted on the X-axis here the surrogate
- 14 trying to predict the hazard ratio of the established
- 15 outcome. So if something is very protective on the
- 16 alternative outcome here, meaning showing less
- 17 reduction in GFR, it's less likely -- it should also be
- 18 protective on the definitive outcome, which was end-
- 19 stage renal disease or doubling of serum creatinine,
- 20 right? And then drug categories that worked less well
- 21 on the alternative would work less well on the trial.
- You need a range of results, from studies that

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- 1 work very well to studies that work poorly, to get a
- 2 good correlation. And then you actually have to do
- 3 some pretty sophisticated tools for all sorts of
- 4 adjustments for inherent correlations within the
- 5 studies.
- 6 So I think the trials alone were completely
- 7 consistent, but I don't know they're completely
- 8 convincing without the observational studies.
- 9 We also did simulations. And they, again,
- 10 supported the use of a 30 to 40 percent decline.
- 11 That's been published separately. I won't go into the
- 12 details. But they did nicely point out that, if you
- 13 have no acute effect, then you really get a Type 1
- 14 error (ph) that's success -- acceptable, and the power
- 15 is improved.
- 16 If, on the other hand, you're looking for the
- 17 long-term effect on GFR, but within the first month or
- 18 two you actually have an acute hemodynamic effect that
- 19 changes your GFR by more than a few milliliters, that
- 20 actually alters your ability to look at the long-term
- 21 effect, right? So actually, it gave us a major caveat
- 22 in thinking about this. And it limits the use, but it

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- $1\,$ should limit the use to the appropriate cases where it
- 2 is useful.
- 3 So the summary of the evidence from all the
- 4 sources, observational studies, trials, and simulations
- 5 was that, based on a series of metanalyses of the
- 6 cohorts, clinical trials, and simulations of trial
- 7 designs and analytic methods, the workshop concluded,
- 8 including a whole discussion, all the scientists from
- 9 various stakeholders that confirmed -- so this last
- 10 endpoint of decline -- it's useful if you repeat it,
- 11 and it turns out that that increases the power a fair
- 12 amount -- decline an estimated GFR of 30 percent or 40
- 13 percent over 2 to 3 years may be an acceptable
- 14 surrogate endpoint in some circumstances. But the
- 15 pattern of treatment effects on GFR must be examined
- 16 specifically. Acute effect on estimated GFR are an
- 17 issue. So statements are a little bit nuanced, I
- 18 guess, in trying to show the example.
- 19 And the conclusions are basically that
- 20 meaningful CKD progression can be understood in the
- 21 context of its prediction of future risk in surrogacy.
- 22 And I gave you the conclusion for 30 to 40 percent

- 1 decline. Within transplant, I think we'll have to look
- 2 at sort of different acute effects and drugs, different
- 3 short-term variability, so the actual context for this
- 4 specific use, right? I said I would give this talk if
- 5 I presented the data we have, not the data we don't
- 6 have.
- 7 Ongoing work -- so, you know, once we did
- 8 this, a number of years later, the FDA talked with the
- 9 National Kidney Foundation. And they said, well, what
- 10 about slopes and integrating all the different data
- 11 points. And I actually was a little bit, you know,
- 12 thinking we already did all this work; we already did a
- 13 bunch on the slopes; it's all in these 50-page
- 14 supplements; maybe we don't have to do it. But I was
- 15 quite interested in albuminuria change, which we hadn't
- 16 tackled. We tackled a decade before that.
- 17 And so we did both topics. And actually,
- 18 interestingly, the slopes were very powerful. And
- 19 you'll see some of those results presented, and I'm
- 20 glad to discuss them in questions.
- 21 And finally, surrogacy speaks only to
- 22 efficacy, not safety, I think, which may be related to

- 1 off-target effects. So in some sense, if you get a
- 2 surrogate that's very specific to what you need and you
- 3 get it to move in the right way, if it's strong, it
- 4 should predict the clinical outcomes. But the
- 5 surrogate isn't necessarily likely to capture off-
- 6 target effects on other pathways, and that's where
- 7 safety data needs to be assembled in a complementary
- 8 fashion.
- 9 So in closing, I wanted to acknowledge that it
- 10 really takes a lot of people to do this. The CKD-EPI
- 11 collaboration -- and this is a picture at the FDA
- 12 workshop in 2018; the CKD Prognosis Consortium -- and I
- 13 give you the definition of consortium, which I think is
- 14 a neat thing. This is our group at Hopkins that does
- 15 data coordination, and this is the group of
- 16 investigators for that. And really, the NKF-FDA
- 17 workshop attendees, international collaborations, co-
- 18 investigators, it really -- you know, to get to a
- 19 consensus, it takes a lot of people and listening to
- 20 everybody.
- 21 So thank you.
- 22 (Applause.)

1 DR. O'DOHERTY: Thank you for that great

2 presentation. I think it really shows, you know, going

- 3 after an unmet need through a structured process,
- 4 although not qualification but still very data-driven,
- 5 you can see the similarities that really cross-
- 6 pollinate there.
- So in the final presentation, we're going to
- 8 have Dr. Ulf Meier-Kriesche from Veloxis, who is a co-
- 9 chair of Workgroup 1 and the TTC, which is a biomarkers
- 10 and endpoints workgroup. And he'll be talking about
- 11 clinical biomarkers versus qualified biomarkers for
- 12 uses, endpoints, and clinical trials of therapeutics.
- 13
- 14 Inish.
- 15 We have heard now from three different
- 16 speakers how daunting of a task it can be to get an
- 17 endpoint, let alone a surrogate endpoint into
- 18 therapeutic space. Nevertheless, the kidney space has
- 19 made dramatic progress. And in transplantation,
- 20 suddenly, we are trying to learn from the other areas
- 21 of where progress has been made in order to potentially
- 22 accelerate the timelines we have heard about one
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- 1 decade, two decades, right? We are trying to make
- 2 something happening a little bit earlier.
- 3 But where do we really come from? Why is
- 4 acute rejection graft loss, death and loss to follow up
- 5 our endpoint? A lot of people have pointed out that
- 6 this is really less than ideal. Yes, it is the
- 7 ultimate verification of whether a therapy works or
- 8 not. But again, it's very difficult to develop trials
- 9 for this endpoint.
- 10 But if we step back at wherever we are coming
- 11 from, historically, acute rejection loss actually
- 12 really important. A lot of patients lost their grafts
- 13 due to acute rejection in the last century. Graft
- 14 survival in the beginning was 50 percent at a year.
- 15 Patient survival was dismal, too. And so the loss to
- 16 follow-up has always been and will always have to be an
- 17 assessment just because of potential of bias in the
- 18 assessments.
- 19 But there has been, obviously, a lot of
- 20 change. From 1950 when transplantation started to now,
- 21 outcomes have changed dramatically. And with that, the
- 22 relevance of our endpoint has changed. So now that, I

- Page 100 1 mean, graft and patient survival exceeds 95 percent,
- 2 now that rejection rates are very low and the impact of
- 3 rejection certainly has changed over time, our endpoint
- 4 is really -- I'm not going to say not applicable
- 5 anymore, but certainly it is something very difficult
- 6 to measure with the number of patients we have
- 7 available in our therapeutic space.
- So now the burning question is, obviously, why
- 9 has this endpoint never been updated. We have had that
- 10 for a long time. We have complained about for -- for a
- 11 long time. Why hasn't it changed?
- 12 To make it very clear, it is not the FDA's

DR. MEIER-KRIESCHE: Yeah. Thank you so much, 13 mandate to come up with new endpoints. It is really up

- 14 to the transplant community to drive new endpoints.
- 15 And while the community has come up with a lot of
- 16 endpoints which can be clinically useful, we have not
- 17 really undertaken a concerted effort to drive new
- 18 endpoints through a biomarker qualification process.
- 19 And this is changing now. So with this
- 20 public-private partnership, we are trying to recognize
- 21 the steps we have to take to qualify biomarkers which
- 22 potentially can be used for endpoints in

- 1 transplantation.
- 2 And certainly, there have been very
- 3 authoritative voices in the field of transplantation
- 4 pointing out how big of a problem for drug development
- 5 this is. We all know that we have a fairly dried up
- 6 drug development pipeline in transplantation, and that
- 7 is because our population is relatively small. We have
- 8 a standard of care which produces good one-year
- 9 results. We have a significant unmet need, but that is
- 10 in the long term. So again, it's difficult to measure.
- 11 So how can we bridge all of this?
- 12 There is clearly not one specific solution for
- 13 the transplant community, but we're going to have to
- 14 start somewhere. Certainly, one would want to be in
- 15 oncology, right? We would like to have surrogate
- 16 endpoints, and you have heard how difficult that is.
- 17 We would like to have clinical trial networks, novel
- 18 clinical trial designs, adaptive trial designs. These
- 19 are all things we can explore. But certainly, we have
- 20 to start somewhere.
- 21 So to this end, you have heard the Transplant
- 22 Therapeutics Consortium was launched in March 2017,

- 1 first of all, identify the areas where we all agree
- 2 upon we can make a difference and then trying to drive
- 3 specifically these initiatives forward.
- 4 You have seen this slide. This is how the
- 5 Transplant Therapeutics Consortium is constructed,
- 6 importantly, to point out that the societies are really
- 7 leading the way here. They originally really brought
- 8 this into our space. Importantly, the FDA and NIH are
- 9 part of it, but also the industry stakeholders. So it
- 10 is in the precompetitive space where we can have all
- 11 discussions and agree on things which make sense for
- 12 our therapeutic area to improve drug development.
- 13 So how can the C-Path model, which obviously
- 14 has been tried in quite a few instances successfully,
- 15 be applied to transplantation? As a first step, we
- 16 identified key challenges. So we set biomarkers and
- 17 endpoints as clearly one of the key challenges. So we
- 18 established a workgroup for that. And as Mark
- 19 explained, although we established another workgroup
- 20 for drug and safety profiling in transplantation.
- 21 Step 2 then is to specifically develop drug
- 22 development tools. And so we are going to develop one
 - Page 103
- 1 drug development tool to start out with as an endpoint
- 2 in transplantation and one safety drug development
- 3 tool.
- 4 How to we gain regulatory acceptance? There
- 5 are different pathways, and I'm not going to belabor
- 6 this here. We can either go through the regular
- 7 qualification process, or we can get endorsement
- 8 through the fit-for-purpose process. Which way we'll
- 9 ultimately go depends a lot on the data we produce and
- 10 the ultimately context of use we are seeking.
- 11 The structure of the consortium, again, to
- 12 point out that there's a lot of input from the
- 13 societies. We have two workgroups which share the
- 14 data. They are going to bring in a lot of data.
- 15 That's really where the tactical working part is, to
- 16 coordinate the data, house the data. And fortunately,
- 17 for both workgroups we will have similar data needs.
- 18 Ken and I are chairing the biomarkers and
- 19 endpoints workgroup. What we are going to try to do
- 20 is, as we have heard a lot, we need a context of use.
- 21 We are going to establish that. We are going to look
- 22 at the datasets available, predominantly phase III

- Page
- 1 clinical trials in the space. And the basic idea is to2 take the one-year data from these clinical trials, look
- 2 take the one year data from these entirear trials, look
- 3 at a constructed endpoint, which I'm going to talk a
- 4 little bit more in a moment, at a year and then see
- 5 with long-term follow-up data from the public
- 6 registries what the long-term outcomes of these
- 7 patients are and see if this candidate endpoint is
- 8 actually predictive.
- We are going to put this into a modeling plan
- 10 and ultimately get agency feedback. Then we are going
- 11 to produce all the data, submit the patient-level data,
- 12 and then hopefully at a certain point get endorsement
- 13 for the biomarker.
- 14 This slide you have already seen. It's just
- 15 to point out that the process we are proposing for the
- 16 TTC Workgroup 1 is very -- well-aligned with the
- 17 general framework for biomarkers within the FDA.
- So clearly, the unmet need we have talked
- 19 about is the drug development process where we need new
- 20 endpoints. There are other things which, of course,
- 21 obviously being done. And as I have talked about, we
- 22 are also going to look at biomarkers. Eventually, we
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- 1 may look at clinical trial designs. But again, the
- 2 primary objective right now is to find a new endpoint
- 3 in transplantation.
- 4 Specifically, one of the challenges in the
- 5 endpoints is to have biological plausibility for these
- 6 endpoints, and we have been really lucky that Alex
- 7 Loupy in France has been working for many years on the
- 8 idea to combine clinically meaningful parameters, which
- 9 most of us in the field actually believe in and try to
- 10 model them into a composite score. And the reason why
- 11 that gives us a little bit of a head start -- we do not
- 12 have to go in and explain why renal function and the
- 13 measurement of renal function itself is significant --
- 14 same for DSAs and proteinuria.
- 15 So essentially, the iBox Alex has developed
- 16 will give us a scoring system at a year after
- 17 transplantation, and we are going to try to reproduce
- 18 what he has already shown, that that correlates to
- 19 long-term outcomes.
- To further refine the goals, specifically, we
- 21 are going to try to predict five-year graft survival.
- 22 But that's because we probably have that data available

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- 1 for most of the data, we are going to bring in. And
- 2 certainly, this has to be supplemented with strong
- 3 mechanistic and epidemiologic rationale.
- 4 If this ultimately leads to what we would like
- 5 to have, which is a reasonably likely surrogate
- 6 endpoint, this can be instrumental in clinical trials
- 7 because it could lead to an accelerated approval
- 8 process, granted, with post-marketing follow-up. If we
- 9 wanted something which gives us approval without a
- 10 post-marketing follow-up, then we will need a surrogate
- 11 endpoint. (inaudible) is really the reason we like the
- 12 surrogate endpoint. Once a lot of trials are going to
- 13 be conducted with that, eventually, we may have enough
- 14 data to seek, really, to obtain a surrogate endpoint.
- 15 So the next steps is really to perform the
- 16 data landscape analysis, and we have already done that,
- 17 in large part, bring the data in, standardize the data,
- 18 put them into a data warehouse, and then, again,
- 19 connect them to the long-term outcomes data developing
- 20 a modeling plan.
- Here are some of the datasets where we are in
- 22 negotiation with the pharmaceutical companies who have

- 1 then the quantitative platform and ultimately the
- 2 submission for regulatory endorsement.
- 3 Here's a little bit of the progress we have
- 4 made. You have heard we have started in 2017. There
- 5 have been a lot of different meetings which have really
- 6 driven forward the understanding of us as a limited
- 7 community, but also the broader community of what we
- 8 are really doing. And it's really taking very nice
- 9 shape this year with several presentations at public
- 10 meetings. We are going to seek advice from the FDA,
- 11 and that will really guide our path forward in
- 12 developing the -- this as our hopeful final product of
- 13 the surrogate endpoint.
- 14 And I think, with that, we are up to the end
- 15 of this session. And we are going to go into the
- 16 questions. Thank you.
- 17 (Applause.)
- DR. O'DOHERTY: So as you can see in the
- 19 agenda, there's a number of questions that are there as
- 20 guidance on -- to stoke conversation should there not
- 21 be questions from the floor. But knowing that, you
- 22 know, the transplant group is always a talkative bunch,

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- 1 these large datasets. Again, and I have to thank
- 2 everybody who has worked on this on both sides, on the
- 3 C-Path side and on the industry side, because this is a
- 4 lot of work to create data-sharing agreements and
- 5 create data catalogs. And -- but again, there has been
- 6 a lot of progress, and we know that there is a lot of
- 7 data available which will be instrumental in testing
- 8 the iBox, which has already been modeled by Alex Loupy
- 9 in France.
- 10 So you have seen that there are a lot of
- 11 different biomarker categories. And in
- 12 transplantation, we also could think about several
- 13 different ones. But what we ultimately really would
- 14 like to get to is a reasonably likely surrogate
- 15 endpoint because that would allow us to discriminate
- 16 new therapies, have potentially lower patient numbers
- 17 needed to show differences, potentially a shorter trial
- 18 duration. And that will ultimately incentivize
- 19 industry stakeholders to come in and look at the space
- 20 more favorably.
- So the worker (ph) goal -- obviously, we need
- 22 to acquire the data we talked about that will support

- 1 I'm sure there will be a few. So we invite folks to
- 2 come up to the mics and pose questions, but also those
- 3 that are sitting on the table if they would like to be
- 4 able to jump and ask any questions on the individual
- 5 talks or on any of the specific ones that are laid in
- 6 on the screens at this point in time.
- 7 And if there is not an abundance of people to
- 8 stand up straightaway, maybe I can, you know, ask for
- 9 perspective from a fellow C-Pather and also for folks
- 10 who are involved in the Biomarker Qualification Program
- 11 at the FDA.
- 12 I think the first one there, you know, the
- 13 idea of how do we know when a biomarker is ready to
- 14 start the qualification process -- John Michael, I know
- 15 you've dealt a lot with consortia in their fledgling
- 16 stages to understand how they're thinking about this
- 17 process, but, you know, kind of giving that perspective
- 18 from the third-party entity.
- 19 DR. SAUER: Yeah, absolutely. Thanks, Inish.
- 20 That's a really good question.
- I mean, what we go through C-Path is a process
- 22 called regulatory readiness, if you will. And what we

- 1 try to do is understand around the given biomarker that
- 2 we want to pursue exactly what data is behind it, so
- 3 the status, right, because when we're thinking about
- 4 qualification, we're not thinking about doing biomarker
- 5 discovery, right? We want to make sure that there's a
- 6 pretty solid package around that biomarker before we
- 7 bring it to FDA if we have that opportunity.
- 8 So I think that's the important part. When
- 9 you're thinking about we want to take a biomarker
- 10 through qualification, where is it actually at? And do
- 11 a legitimate assessment of that biomarker because
- 12 that's what the Agency is going to be looking for.
- 13 That way, you can have a very direct conversation about
- 14 what else needs to happen along this biomarker pathway.
- DR. O'DOHERTY: Thanks, John Michael.
- And I know, Kathy, as co-moderator and working
- 17 the biomarker program, you see a lot of different
- 18 efforts, not asking to talk about any of those
- 19 individual particular efforts, but kind of general
- 20 thematic viewpoints of the Agency when they're looking
- 21 at these considerations and early submissions.
- DR. HOLLINGER: Okay. Thank you, Inish.

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- 1 What I want to get down to is some of the
- 2 process focus as well because the 21st Century Cures
- 3 Act mandated a three-step process, or stage process
- 4 that's starting with a letter of intent and then moving
- 5 to a qualification package and then to -- or sorry --
- 6 plan, and then a full qualification package.
- And you know, when you ask the question how do
- 8 you know when you're ready to start the process, you
- 9 would be starting that process at the letter of intent
- 10 stage. And that stage is a pretty light-weight place
- 11 to start. It's simply asking you what is your
- 12 biomarker, what's your drug development need, do you
- 13 have a feasible way to measure it, and what are you
- 14 proposing as your context of use with knowledge, full
- 15 knowledge, that context of use can change throughout
- 16 this qualification process and would change, basically,
- 17 based on the data that you are providing at the
- 18 subsequent stages the qualification plan and the full
- 19 qualification package to reflect what substantiation
- 20 you have provided for that context of use.
- So you're ready to start maybe before you have
- 22 all of the data that you need because you want to start

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- 1 working with the FDA fairly early so that we can help
- 2 shape what your plan might look like. And what you get
- 3 in response to that first stage, the letter of intent
- 4 stage, is a letter that tells you whether FDA accepts
- 5 your proposal or your concept into the biomarker
- 6 qualification program. And in that letter, we provide
- 7 you with a number of recommendations or suggestions for
- 8 how to move into your next stage.
- 9 So if you come to the table with what might --
- 10 you might feel is a fully prepared qualification
- 11 package and you're starting with an LOI, you might find
- 12 that FDA has some other thoughts or considerations that
- 13 might reroute your pathway forward. And so please
- 14 don't hesitate to start if you know what your biomarker
- 15 is, if you have a feasible and reliable way to measure
- 16 that biomarker, and you clearly have a sense of where
- 17 that will fit in your drug development context of use
- 18 statement.
- 19 And use is basically -- when you look at what
- 20 your context of use is, you may have started with where
- 21 is your drug development need. And sometimes your drug
- 22 development need is where are your biggest problems,

- 1 where are your roadblocks, where are your challenges.
- 2 DR. SAUER: I would like to add one point in
- 3 that the interactions with FDA for qualification are
- 4 different than with drug development. It is really a
- 5 partnership, a scientific partnership, of how to get
- 6 that biomarker qualified. And so you have to work
- 7 together.
- 8 And what you'll find is that the meetings are
- 9 a bit more relaxed. I remember when I was in, you know
- 10 -- in a drug company. I mean, we really didn't have
- 11 some of those basic scientific discussions that we get
- 12 to have within the realm of qualification. And so
- 13 that's an important thing to remember. I mean, it
- 14 truly is a partnership in trying to get these drug
- 15 development tools out because everybody wins. FDA
- 16 wins. The drug developers win. So that's why I think
- 17 that partnership is that way.
- DR. NEWELL: I was going to ask a question I
- 19 fear I know the answer to, but it's related to
- 20 procedure.
- 21 And so, if I understand from John Michael,
- 22 there's different types of biomarkers. So there's

- 1 prognostic. There are those that predict responses to
- 2 interventions, and there are surrogate endpoints. And
- 3 they require different levels of evidence. And those
- 4 would be driven by the context of use, I'm sure.
- 5 But so if you said I have -- and as she said,
- 6 there could be a biomarker or a candidate biomarker
- 7 that fulfills many of those. So if you say I have
- 8 something that hits all three of those or some of the
- 9 others, when you go forward, you're going to say I'm
- 10 going to propose a reasonably likely surrogate
- 11 endpoint, and the context of use will be this. If the
- 12 evidence in the end isn't quite there, is it possible
- 13 without restarting the process all over to say it
- 14 doesn't quite meet this bar, but it meets a somewhat
- 15 lower bar and then to say, okay, and if we get more
- 16 evidence down the road, we can go back under the same
- 17 kind of application and have it move up to a, you know,
- 18 more stringent biomarker?
- 19 DR. HOLLINGER: Absolutely. And that's what I
- 20 mentioned when I was saying that the context of use can
- 21 evolve throughout this process. And it will be based
- 22 on what data you've presented to support your context

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- 1 of use. Sometimes we find that, you know, that
- 2 biomarker needs to be used in conjunction with certain
- 3 other factors, whether it's a clinical evaluation or
- 4 whether it's other tests, to be able to be used for a
- 5 specific context of use. So that's one way you might
- 6 modify it.
- 7 Or you might actually modify the actual use of
- 8 it. So rather than using it as an endpoint, you might
- 9 use it as an enrichment factor or for, you know,
- 10 identifying certain treatment arms or some other way to
- 11 apply it in drug development. And then you can come
- 12 back to the table with another qualification effort to
- 13 get to the place you want to go to when you have --
- 14 when you're looking at getting the data that will help
- 15 support that use.
- DR. NEWELL: And you could use the data from
- 17 the original submission to support the revised
- 18 submission.
- 19 DR. HOLLINGER: Absolutely.
- DR. ALBRECHT: Kathy, let me go ahead and ask
- 21 you -- when you receive a letter of intent, I assume
- 22 they're not always perfect. So what is your process

1 age 11

- 1 for interaction -- sorry. I just want to make sure we
- 2 get sort of the iterative discussion. What is your
- 3 process with interacting with the person -- or the
- 4 group that submitted the letter in helping guide them
- 5 along?
- 6 DR. HOLLINGER: So it is a bit of a dialogue.
- 7 And so the first kind of thing that we do is look at
- 8 the submission from the requester. And the requester
- 9 is the person making that submission. And we review
- 10 and try to understand what the concept is and whether
- 11 it's well presented and whether they are adding all the
- 12 elements that people need to look at in their
- 13 assessment of that letter of intent.
- 14 Basically, before we send it to our subject
- 15 matter experts, we want to make sure that it has an
- 16 opportunity at success and getting good recommendations
- 17 from that review division or the various reviewers that
- 18 will be looking at the submission.
- 19 So for example, if I wrote myself a list here,
- 20 Elements of the Successful Submission, because I think
- 21 that's very, very helpful. Number one, it's a
- 22 receptive requester because we will be working with

- 1 you. And you know, if we say to you, you know, the
- 2 biomarker description is lacking or the context of use
- 3 or you didn't give us a good drug development need or
- 4 we need references in this document, please be
- 5 receptive to that because the reason we are asking is
- 6 that, further downstream, someone will have to look at
- 7 it. And we have many different disciplines reviewing
- 8 that letter of intent.
- 9 So let's say I have a statistician or I have a
- 10 clinical expert in pulmonary disease or -- you know,
- 11 they will probably want to go to a certain set of
- 12 references that might be different from the different
- 13 discipline.
- 14 So if you're making statements in your
- 15 document, make sure they've been referenced -- they can
- 16 be referenced with your research; they can be
- 17 referenced with longstanding research. But make sure
- 18 you've put your references in there.
- 19 Keep it very focused. Sometimes we get
- 20 submissions that are not focused. They might be
- 21 promotional and saying this is, you know, the best
- 22 thing since sliced bread. Not only does it do this,

5

11

12

1 we ever find the disparity there.

So you know, and those are just some little

DR. FRIEDMAN: And I would just like to

DR. HOLLINGER: Well, I thank you for that.

It feels bad to tell you that -- you know, we

3 kind of hints on how to get to where you want to go.

8 not a grand inquisition process. This was very much

9 collegial interaction that was a learning process for

10 all of us. And we truly can confirm what you said.

4 And we look forward to working with all of you.

6 confirm -- and I know there are speakers at the

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1 but it does these 10 other things -- excuse me -- does

2 these 10 other things. We realize you work really hard 2

3 on these, and we realize that this might be step one in

4 the first bite out of the pie. But it doesn't help.

5 It distracts our experts from looking at the specifics

6 and giving you a really good focused set of

7 recommendations. The recommendations can be as all 7 microphones -- but I just want to confirm that this was

8 over the map as the submission, and then where do we

9 end up as a group? We don't end up in a good place.

10 So keep it focused on what is your biomarker,

11 what are your analytics, and what is your context of

12 use. And we really haven't addressed analytics yet.

13 But analytics validation is also a very important

14 piece. And a good part of that occurs in that middle

15 step, that second step during the QP phase.

We want to see that it's feasible and reliable

17 in the LOI phase, but you're going to probably be

18 presenting a lot of data on your analytic in the second

19 stage, the qualification plan because the qualification

20 plan is then going to focus on the clinical validation

21 and making sure that you have all your data together

22 that will allow us to accept the biomarker for that

14 says, you know, your submission is not reviewable.15 Well, that's disappointing. I'm certain that people

13 now have a little memo sometimes that goes out and

16 find that that's disappointing. But I think that if we

17 do that at that stage and then get it to a place where18 we can get a really good set of recommendations for you

19 -- and sometimes you'll see that not reviewable two or

20 three times. It's happened. And so don't lose faith.

21 We will get there, but that's just part of the process.

DR. O'DOHERTY: So we have a speaker on the

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1 context of use.

2 Make sure that you define terms in your

3 submissions. So if you're talking graft reduction,

4 what does that mean? How are you defining that in your

5 studies? Or how will you be using your data to

6 demonstrate graft reduction?

7 And remember, also, that under the 21st

8 Century Cures Act that there is a requirement for

9 transparency. So that letter of intent will be posted

10 on the internet with our decision letter and

11 recommendations. It does also protect confidential

12 commercial trade secret and proprietary information,

13 and those we're suggesting you put in attachments and

14 don't necessarily reference the attachments that you

15 feel are confidential or trade secret in the body of

16 your letter of intent. But certainly mark your

17 attachment. Where you feel it is trade secret, mark it

18 such that it is trade secret or commercial

19 confidential. And we will have a legal review to make

20 sure that we aren't violating the terms of the 21st

21 Century Cures Act by withholding information that could

22 be made public, and we will have a dialogue with you if

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1 floor as well.

2 UNIDENTIFIED MALE SPEAKER: Yeah. I'm going

3 to introduce a comment, and I would like to get

4 Katherine's and Ameeta's and Renata's reaction.

5 So it seem -- when you were developing a drug,

6 you started by defining the desired target profiles,

7 and then you -- one-year (ph) plan for preclinical and

8 clinical developments to meet that desired target

9 profile. It seems to me like, in this case, what

10 you're saying is, if you are thinking about a drug

11 development tool, you start by defining your desired

12 context of use. And then you hone in the plan to meet

13 the context of use. So in the end, a statement could

14 be, just as drugs have labels, drug development tools

15 have context of use statements. Would that be a fair

16 representation of the similarities between the two

17 processes?

18 DR. HOLLINGER: Yes. And I don't want to

19 leave out the drug development need because that's

20 going to define your use and how you apply it. Your

21 biomarker and where it fits in this whole drug

22 development process, whether it's used to enrich a

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- 1 clinical trial or whether it's used as an endpoint,
- 2 those will be varying levels of evidence and, you know,
- 3 applications for those tools.
- 4 UNIDENTIFIED MALE SPEAKER: Can I ask a
- 5 question? I'm sorry.
- 6 DR. HOLLINGER: Go ahead.
- 7 DR. ABECASSIS: So I just wanted to try to
- 8 clarify something, and I realize that drug development
- 9 is, you know, front and center. And when I was putting
- 10 my talk together, which I'll give later, our biomarker
- 11 has nothing to do with drug development, right? So it
- 12 was kind of really hard to -- so I guess what I'm
- 13 asking is: Is there a definition of drug development,
- 14 A; and if the purpose of the biomarker has nothing to
- 15 do with drug development, how does it fit into all of
- 16 the frameworks that you guys have very nicely and
- 17 kindly provided for us?
- DR. HOLLINGER: So very often, we are working
- 19 with people who work mostly in a clinical realm. And
- 20 what we need to do, if you're intending it to be
- 21 qualified, is make sure that we're focused on a drug
- 22 development use. And I've had one submission where I

- 1 that you're looking at. Maybe you're going to add
- 2 proteinuria in the mix. And it's good to see that
- 3 there's something related sort of to kidney. And we're
- 4 doing kidneys, also, but just in a different context.
- 5 And maybe I -- I think when learning this
- 6 process is what other people have gone through is
- 7 helpful for us. So how did it get to be, after a
- 8 million patients, it's still 30 to 40 percent and 2 to
- 9 3 years? Because, you know, we're transplant people,
- 10 so we're going to make it really, you know -- I'm a
- 11 surgeon, too, so there has to be some sort of, you
- 12 know, direct kind of input. And where are you kind of
- 13 in this process then, you know?
- DR. CORESH: So I appreciate the question.
- 15 First of all, when you say you did a million patients,
- 16 well, I think the distinction is important because that
- 17 may actually be part of my question to Ulf Meier-
- 18 Kriesche and the TTC Consortium as to whether they're
- 19 thinking about the observational data in transplant
- 20 patients. And I'll expand on that in a bit, but I'll
- 21 answer my question first.
- 22 Right. So first of all, right, not only did I

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- 1 had to work toward that. And we had to figure out
- 2 where is the best place to put this, and how can we
- 3 qualify it to have the greatest versatility and
- 4 application in the drug development space. So we could
- 5 work with you to try and figure out how the biomarker
- 6 will benefit drug development, and that's what we're
- 7 here for.
- 8 DR. STEGALL: So I have a question -- maybe a
- 9 comment on that is that I think that the way I look at
- 10 this, the way this works in transplant, we're kind of
- 11 building this highway, and a lot of things are going to
- 12 go down it and maybe a subsequent biomarker validation
- 13 process for something else definitely. But if we don't
- 14 get this part right, one-year patient and graft
- 15 survival is not going to allow anything to get -- so I
- 16 think that's where we're kind of headed with this.
- 17 But I have a question for Dr. Coresh, is that
- 18 -- so you have -- and don't get me wrong. So you have
- 19 done a million patients, something like that, which
- 20 we're never going to do, and looked at them very
- 21 carefully. And it seems like to me that still 30 or 40
- 22 percent and still 2 to 3 years. And there's one thing

- 1 not do it, it isn't even in research studies only,
- 2 right? So the idea is we've harnessed all of the
- 3 clinical population. So Geisinger, for example, has
- 4 followed for over 15 years all of their participants
- 5 with and without kidney disease and were harnessing all
- 6 the clinical data in that, right?
- Now, when you go to larger health systems, the
- 8 common denominator of that meat grinder kind of slide
- 9 that people have shown several times for the data
- 10 becomes lower, right? So the richness of the data
- 11 becomes lower.
- 12 DR. STEGALL: Okay.
- 13 DR. CORESH: But you have that
- 14 generalizability party, which is actually quite nice.
- 15 So that's one point.
- So it may not be as bad as it seems. And both
- 17 the million and the decade because you can go a decade
- 18 backward, right -- and in some sense for epidemiology
- 19 and data analysis, going backwards is a lot more
- 20 efficient than going forwards because waiting another
- 21 decade is a lot worse. I really like getting things
- 22 done as well.

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1 In terms of moving for our 2018 meeting, we

- 2 looked at slopes. It's interesting. If you look at
- 3 slopes quantitatively in the clinical trials and you
- 4 look at even one-, two-, and three-year slopes, on the
- 5 individual patient, the slopes and change in
- 6 albuminuria are quite variable and not that
- 7 informative. But averaged over a group, the slopes, in
- 8 particular, were highly correlated with the long-term
- 9 outcomes of the trials, right?
- 10 So there actually is quite a bit of hope, more
- 11 than I had thought about even one- and two-year
- 12 results, even one-year results, for detailed slopes
- 13 with this caveat that acute effects can really be an
- 14 issue. And it's the fact that it's actually kind of
- 15 amazing that a slope change in one year, really, from
- 16 minus 5 MLs to minus 4 MLs, of only 1 ML, has been
- 17 highly predictive of the future outcome when measured
- 18 in a group precisely. But you can tell. If the drug
- 19 had an acute effect of one to two ML, it would turn
- 20 everything on its head. So you have to model that, and
- 21 we did detail work about that modeling.
- 22 So maybe that helps you. I think we still

1 Okay. Thanks.

- 2 DR. STEGALL: Okay. Thanks.
- 3 DR. CORESH: But I think I had a question as
- 4 to -- in terms of the trials, right, in the TTC, is
- 5 there enough heterogeneity of treatment effects that
- 6 you think you'll be able to look across trials at the
- 7 effect on the surrogate and the effect on the trial?
- 8 Or is it more of an observational analysis of all of
- 9 these data within trials of one-year outcomes
- 10 predicting long-term outcomes?
- And either way, what do you think about the
- 12 idea of are there data in observational datasets that
- 13 might be useful in some way.
- DR. MEIER-KRIESCHE: Yeah. So again, we are
- 15 going to do, obviously, both, right? We are going to,
- 16 first of all, assess the overall effect, whether the
- 17 marker at a year is predictive of, let's say, five-year
- 18 outcomes. But then the next step, as you rightfully
- 19 point out, will be to assess across drug-treatments,
- 20 across patient populations. It's this constant.
- 21 And we are -- we got a significant head start.
- 22 And I'm going to punt this a little bit to Alex. I

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- 1 need better biomarkers, better insights, better
- 2 understanding of pathology, better subsetting of
- 3 disease subtypes, potentially better understanding of
- 4 pathophysiology. But it's also useful to have the
- 5 large common denominators. And sometimes you may need 5
- 6 quite a bit of this for the safety data as well, right,
- 7 because if you get too efficient, you may not know
- 8 safety as much.
- 9 DR. STEGALL: And you used estimated GFR,
- 10 right --
- 11 DR. CORESH: Yes.
- 12 DR. STEGALL: Okay.
- DR. CORESH: Now, we -- you know, we work a
- 14 lot on sort of improving the estimates, actually. And
- 15 some people have criticized that, you know, good
- 16 enough. The people who said it wasn't good enough now
- 17 say it's good enough.
- And it turns out that it'll depend on whether
- 19 your drug affects the creatinine itself. But
- 20 otherwise, I don't know that, by measuring, you're
- 21 going to get a lot further on the GFR. You may need to
- 22 look at other domains, as much as I'm a fan of GFR.

- 1 mean, they have done fabulous work in France and in
- 2 Europe, in general, on validating the iBox in their
- 3 patient populations and have done all this work to do
- 4 it across populations, across treatments.
- 5 So we have the good fortune that we will be
- 6 able to use this fact-finding and this preliminary data
- 7 to now go into a validation phase where we can
- 8 actually, in an untouched dataset where we take all the
- 9 clinical trials and link them to long-term outcomes,
- 10 test what Alex has done in a separate setting. Again,
- 11 there we're going to look across drug treatments,
- 12 across populations. And hopefully, that will give us
- 13 the required evidence.
- Now, obviously, there can be always context of
- 15 uses which come up subsequently which haven't been
- 16 tested in both trials. You wouldn't be able to cover
- 17 those. But at least you get a general idea how robust
- 18 your marker may be. But maybe Alex can expand on that
- 19 a little bit more.
- DR. LOUPY: Yeah. Of course a very important
- 21 component of validating the models, we're to go inside
- 22 randomized trials and do some post-work (ph) analysis.

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- 1 So we needed some published randomized clinical trials
- 2 with sufficient follow-up to the actual events, graft
- 3 loss, and the capability of having, like, a one-year,
- 4 or whatever, if it was two-year, rescore evaluation
- 5 that we could calibrate and compare the assessment of
- 6 the risk. And the predictive probability of failure
- 7 was due to actual events observed within these trials.
- 8 And it was also important for us, as you
- 9 mentioned, to study different clinical scenarios --
- 10 minimization of treatment, rejection treatment, T cell-
- 11 mediated rejection, antibody-mediated rejection. That
- 12 was a very important component, randomized clinical
- 13 trials. And as you mentioned, also, a very important
- 14 part of the analysis was to add a lot of heterogeneity
- 15 in the system to validate the scoring in geographical
- 16 distant, you know, and different practice across
- 17 centers in France and U.S. and also South America and
- 18 other countries.
- 19 So it's the -- both are -- we used both
- 20 approaches because we think they are like providing
- 21 heterogeneity and also some kind of understanding of
- 22 how the model can be transported.

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- UNIDENTIFIED MALE SPEAKER: And just to add to
- 2 that, the approach that we're taking with the -- basing
- 3 it off of what Alex has done, and to your comment about
- 4 the structure of the model, what we want to do is turn
- 5 what Alex has done and turn it into a drug-disease-
- 6 trial model, which is what Ameeta described as we did
- 7 for the Alzheimer's effort that we coordinated on C-
- 8 Path. But then that's going to provide the necessary
- 9 foundation for the sponsors to be able to adopt the
- 10 endpoint through the fact that we've quantified the
- 11 aspects that are (inaudible) about disease progression,
- 12 the drug effects, and of course the clinical trial
- 13 realm aspects -- you know, dropouts and allocations and
- 14 these -- and things like that. So that's kind of the
- 15 gist of the core of the effort that we want to
- 16 undertake.
- 17 DR. ALBRECHT: So we had a question online as
- 18 what does it take to get a biomarker ready to be used
- 19 for clinical decisions. And I think what you've been
- 20 discussing is the level of evidence and the reiterative
- 21 evaluation and analysis of the data so that you're
- 22 confident that it does do what it's purported to do.

1 Thank you.

- 2 UNIDENTIFIED MALE SPEAKER: Inish, I had a
- 3 question -- or a comment. First of all, the speakers
- 4 in the slides often use the word "qualify" biomarker.
- 5 And I just want to emphasize for the audience that, as
- 6 one slide shows, there are two routes to designate a
- 7 biomarker -- qualification and fit-for-purpose. So
- 8 when we use the word "qualify," we should understand
- 9 that, subsumed under that, are the two routes for
- 10 biomarker designation.
- 11 The question I had for was for Gary --
- 12 DR. ALBRECHT: I just want to clarify because
- 13 qualification is a process that was mandated under the
- 14 21st Century Cures Act that is the three-step process.
- 15 The other approach where you go to the review division
- 16 and have a dialogue and say we want to use this in our
- 17 drug development program for a particular program, that
- 18 would be another method, or another approach, for use
- 19 of a biomarker, but it wouldn't be a qualified
- 20 biomarker.
- 21 The status or designation that is a
- 22 qualification effort comes after it goes through those

- 1 three stages and is made public so that anyone can use
- 2 a qualified biomarker.
- 3 So once you have qualification as your status
- 4 for your biomarker, it's qualified for that particular
- 5 use, and it's made publicly available so anyone could
- 6 use it in their drug development program. In the first
- 7 fit-for-use example, that is for a specific drug
- 8 development program and dialogue within the review
- 9 division for that particular project.
- 10 And then the third way -- there is a third
- 11 way, and that's more from a scientific consensus that
- 12 that's being used, that biomarker is being used, in
- 13 drug development -- I'm guessing not only in drug
- 14 development, but it's in clinical use.
- DR. MORRIS: And then if Ameeta can also
- 16 comment on the fit-for-purpose initiative, which is not
- 17 related to individual drug development submissions, but
- 18 it's handled by the Office of Clinical Pharmacology
- 19 specifically for quantitative drug development tools.
- 20 And you can have a quantitative drug development model
- 21 that supports the qualification of a biomarker, or you
- 22 can have the model itself be put through the fit-for-

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1 purpose initiative with OCP.

2 DR. ALBRECHT: Thank you.

3 DR. PAREKH: And the best part of all this is

4 the transparency that we have currently. So if you do

5 a search for qualification drug development tools FDA,

6 you'll see that you have the list of biomarkers that

7 are qualified. You have seven biomarkers as of

8 yesterday that are listed on that document. There are,

9 I think, four COAs that are listed as qualified

10 clinical outcome assessment tools, qualified. And

11 there's a whole range of submissions that are in the

12 process. I think there were more than 30 that I

13 counted yesterday for COAs. So that's the

14 qualification, two pieces -- the biomarkers and the

15 COAs.

16 The fit-for-purpose is also on the website.

17 So the fit-for-purpose designation that we are giving

18 as of right now is also for drug development tools, but

19 it's more ancillary tools or methodologies that don't

20 fall under the defined biomarkers and COAs. And

21 currently, we have two fit-for-purpose tools, the

22 Alzheimer's disease ancillary model and the MCP mod,

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- 1 which is a simulation tool that determines dose --
- 2 early dose -- or dose determination. So those are the
- 3 two items that are listed under the formal fit-for-
- 4 purpose pathway. But they are all through the FDA's
- 5 regulatory endorsement, the review pathway.
- DR. MORRIS: Thank you for that clarification.
- 7 I had a question for Gary Friedman. And that
- 8 is: How applicable are the nephrotoxic biomarkers you
- 9 described for a wide variety of renal insults? How do
- 10 we know that data from particular insults you have
- 11 looked at are applicable to a brand new drug with a
- 12 mechanism off target that we may never -- can never
- 13 even anticipate until we see it?
- 14 DR. FRIEDMAN: Great question. And I think
- 15 that going, step-wise, we've looked at the -- these
- 16 biomarkers which are 8 out of about 65 that we
- 17 initially looked at in the preclinical space and then
- 18 moved into the clinical space. As we now look to move
- 19 into use in patients who have an underlying disease and
- 20 maybe have normal GFR or have an underlying disease and
- 21 maybe an abnormal GFR, there -- the data are going to
- 22 emerge. And there is -- as was referred to earlier,

1 not only is there a discovery of the biomarker and

- 2 validation, but then there's calibration.
- 3 So this is the part that keeps on going that,
- 4 as we generate more and more data and have data on
- 5 subsets, whether based on gender, ethnicity, and the
- 6 like, there is going to be a continuous reevaluation
- 7 and recalibration of the full changes from baseline.
- In specific in transplant, when you consider
- 9 the variety of transplants that are done, one of the
- 10 discussions that we've had internally within PSTC as
- 11 we've thought about transplant but not taken action on
- 12 it yet, you may actually have "normal, healthy
- 13 volunteers," meaning, as you look across your clinics,
- 14 you have patients who have intentionally or
- 15 unintentionally informed you that they stopped taking
- 16 their immunosuppression and their creatinine is 1.1.
- 17 So you have a number with transplant tolerance,
- 18 whatever that my mean. And so you may have patients
- 19 with GFRs that are in the normal range on known
- 20 nephrotoxic drugs. That may be a place to define
- 21 whether or not these biomarkers that we've seen in
- 22 normal, healthy volunteers or subjects with normal GFR,

- 1 that may be one of the translation points in solid
- 2 organ transplantation.
- 3 DR. O'DOHERTY: I think that's a -- maybe
- 4 we'll just have to pause it there and wrap up the
- 5 conversation for this session. There will be more Q&A
- 6 after each other session, but we're going to hit a
- 7 morning break at this point in time. We'll ask folks
- 8 to be back in the room by 10:45. And then as well, if
- 9 you're ordering lunch, still -- it's the last order at
- 10 the kiosk outside in front to be able to do that.
- 11 And thanks again for the discussion. We look
- 12 forward to welcoming you back after the break.
- 13 (Break.)
- 14 DR. VELIDEDEOGLU: I think we still have some
- 15 people out in the hallway. I just want to give a few
- 16 more minutes before we start the second session of the
- 17 workshop.
- 18 Good morning, everybody. My name is Ergun
- 19 Velidedeoglu, one of the medical officers here at the
- 20 FDA. Dr. Ulf Meier-Krieschea and I will be moderating
- 21 this session, which is the second session of this
- 22 workshop titled Potential Biomarkers to Identify

- 1 Alloimmune Risk in Patients Pre-transplantation. Up
- 2 until now, we heard great presentations regarding the
- 3 overview of the subject potential biomarker
- 4 development, and then we have seen one excellent
- 5 example from CKD patients. Now we are going to start
- 6 getting into the specifics of the subject.
- 7 Our first speaker is Dr. Peter Nickerson from
- 8 the University of Manitoba, and the title of his talk
- 9 is HLA molecular Mismatch A prognostic biomarker for
- 10 primary alloimmunity.
- 11 DR. NICKERSON: Thank you very much. I want
- 12 to thank the organizers for the kind invitation to come
- 13 and share our work. And what I'm going to be focusing
- 14 on is, when I say molecular mismatch, these sub amino
- 15 acid zones on the whole molecule that are mismatched
- 16 relative to the recipient and the donor as opposed to
- 17 the whole entire molecule. And so you'll see this
- 18 image over and over again.
- 19 Disclosures -- I have some consulting in
- 20 honoraria. I will not talk off label or
- 21 investigational use.
- 22 So the starting premise is that primary

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- 1 alloimmunity is a major cause of allograft loss. And
- 2 in this publication we put through in 2012, which is a
- 3 consecutive cohort, and we looked at 10-year median
- 4 survival. What we saw is that those patients that were
- 5 developing a de novo HLA donor-specific antibody had a
- 6 significantly lower graft survival at 10 years compared
- 7 to those patients that did not develop an antibody.
- 8 Now, a de novo donor-specific antibody
- 9 indicates T and B cell allorecognition for that
- 10 antibody to develop. In fact, it's a very coordination
- 11 immunologic response that has to be intact for this
- 12 antibody to develop as an IgG donor-specific antibody
- 13 in the serum.
- 14 And once we looked at -- and getting into
- 15 functional aspects, we looked at the estimated EGFR
- 16 rate of decline in our cohort. We looked at those
- 17 patients who were stable throughout the entire course.
- 18 So this group of patients up here in the average rate
- 19 of decline was minus 0.43 mils per minute per year.
- 20 And in those patients that were going to develop a de
- 21 novo DSA as an indicator of primary alloimmunity, they
- 22 were already losing function at a faster rate before

1...50 1.

- 1 the antibody showed up, and it accelerated in its loss
- 2 of function after the antibody showed up. And so we
- 3 took this to indicate that the de novo DSA is really a
- 4 biomarker of a process that's underway. And you're
- 5 going to hear more about DSA later in this -- today.
- 6 So from there, we were interested in what DSA
- 7 were specifically important. And what we saw was that
- 8 Class 2 HLA versus Class 1 HLA allorecognition is a
- 9 dominant pathway. And if we look at -- this is the
- 10 graft survival in those patients without an antibody in
- 11 orange. Those that only developed a de novo Class 1
- 12 antibody in red had a graft survival curve that was no
- 13 different from the patients without antibody. Those
- 14 with isolated Class 2 or those with Class 1 and Class 2
- 15 are the ones that did poorest.
- 16 In terms of causality, where HLA mismatching
- 17 fits in, well, HLA mismatching is really the initiator
- 18 of the primary immune response leading to allograft
- 19 loss. And so we conceptualize that this mismatch
- 20 really is what's driving T cell mediated rejection,
- 21 whether it's subclinical or clinical. And you'll hear
- 22 a lot about that later today. And it's also the driver

- 1 of de novo DSA that leads to ABMR, again, subclinical
- 2 or clinical. And these can be smoldering processes,
- 3 ultimately leading to fibrosis and graft loss.
- 4 Minimization and nonadherence interacts with
- 5 the mismatching in the sense that it's really taking
- 6 the brakes off the immune response and allowing it to
- 7 progress more rapidly.
- 8 From causality, if we can go to the next
- 9 slide, which it doesn't want to go now -- can you
- 10 advance the slide? There we go.
- The corollary here is that HLA identical
- 12 transplantation should lead to improved graft survival.
- 13 And here we have the classic experiment in humans where
- 14 we take twin transplants, and we didn't need any
- 15 immunosuppression back then to have excellent graft
- 16 outcomes.
- 17 The more recent data through UNOS and SRTR
- 18 shows us that if you have a zero mismatched HLA graft,
- 19 you actually have a graft survival advantage of about
- 20 five years compared to any degree of mismatching. The
- 21 problem here is that only 8.5 percent of transplants
- 22 have a zero mismatch, and 93 percent have one or more

- 1 mismatches. And so the question becomes how can we
- 2 grade risk within this 93 percent, and can we get more
- 3 granular.
- 4 And that really leads us to this statement,
- 5 which is we must now prepare for a second phase in
- 6 which more sophisticated measures of HLA compatibility
- 7 should be developed for a more accurate prediction of
- 8 outcome. And I think that's what we're really talking
- 9 about when we're talking about biomarkers. And this
- 10 statement was made only 46 years ago, so we haven't
- 11 really come a long way in the last 46 years in
- 12 advancing this concept.
- So that really got us to the star working
- 14 group. And the star working group is a joint AST-ASHE
- 15 (ph) consensus forum where we're trying to look at
- 16 immune risk assessment pretransplant for clinical
- 17 purposes, but really getting it into, ultimately, how
- 18 do we define this at a mechanistic level. And that
- 19 could be developed for clinical use.
- 20 And so we're focused, and what we recommended
- 21 was two types of risk assessment -- an immune risk
- 22 assessment for memory and immune risk assessment for
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- 1 primary alloimmunity, which is what I'm talking about
- 2 today.
- 3 And when we got to primary alloimmunity, we
- 4 said that, really, molecular mismatching is probably
- 5 one of the areas that needs to be developed if we're
- 6 going to think about clinically how to assess primary
- 7 alloimmune risk.
- 8 So taking that, the next step forward, HLA
- 9 molecular mismatch really induces the B cell receptor
- 10 allorecognition event as well as a T cell receptor
- 11 allorecognition event. And the biological basis of
- 12 this is that you have epitope-paratope structural
- 13 relationships between an antibody, which is the B cell
- 14 receptor on a B cell, recognizing the donor HLA
- 15 molecule. And it does that through a paratope-epitope
- 16 relationship.
- 17 And what's been identified is that there's a
- 18 core area on the epitope which Rene Dekesnoy (ph) has
- 19 termed for no other reason to call it an applet (ph).
- 20 It has no other meaning than Rene liked that term. But
- 21 it's thought to be that this central amino acid
- 22 polymorphisms that exist on the donor HLA are the

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- 1 predominant bonding domain of the CDRH3 region on the
- 2 antibody. And it's felt that this region determines
- 3 specificity of the antibody, in large.
- 4 Now, when you look at comparing donor and
- 5 recipient HLA molecules -- and he's developed the
- 6 computational software called HLAMatchmaker to do this
- 7 -- we can talk about a -- in this example DR beta 10405
- 8 (ph) as a 1DR mismatch to this patient's HLA-DR
- 9 molecule. But if you look at it at the molecular
- 10 level, the number of surface amino acid differences
- 11 that exist in this molecule between the donor and the
- 12 patient, there is up to 11 different areas where you
- 13 could have potential alloreactivity by an antibody,
- 14 compared to this HLA-DR beta 1 mismatch where there's
- 15 only one amino acid difference between the donor and
- 16 the recipient.
- 17 But we treat this, and we've classically
- 18 treated this as equivalent. This is a 1 DR mismatch.
- 19 This is another 1 DR mismatch. But they're clearly
- 20 different at a molecular level in terms of their
- 21 relatedness between the donor and the recipient. And
- 22 when you compare this in a whole population, you can
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- 1 say that here's a 1 DR mismatch in our whole cohort.
- 2 There's a whole range of applet mismatches or molecular
- 3 mismatches that exist for that 1 DR mismatch in
- 4 different patients.
- 5 So if you were to take two recipients, here's
- 6 a Recipient A who has a 1 DR mismatch by our
- 7 traditional whole protein mismatching, and they have
- 8 very many applet mismatches, compared to Recipient B,
- 9 who we think of as worse because they have a 2 DR
- 10 mismatch, who has very few applet mismatches between
- 11 donor and recipient. So the traditional way of looking
- 12 at things really has a loss of information as compared
- 13 to a molecular method of looking at relatedness.
- And we put this into a multivariate model and
- 15 look at DR de novo DSA or DQ de novo DSA as our
- 16 endpoint and what are the hazard ratios for --
- 17 independently for developing these DR DQ DSAs. What we
- 18 see is that recipient age -- the older you are, the
- 19 less your risk, but the younger you are, the higher
- 20 your risk. If you're not taking your meds, well,
- 21 clearly, that puts you at risk. If you are on
- 22 cyclosporin versus tacrolimus, you are at a higher

- 1 risk. And then for every 10 applet mismatches for DR
- 2 or every 10 applet mismatches for DQ, you are at
- 3 increased hazard specifically of getting a DR or a DQ
- 4 de novo DSA.
- Now, is applet mismatching and matchmaker the
- 6 only computational method for doing this? No. Others
- 7 have developed other methods. So we did a head-to-head
- 8 comparison of these other HLA molecular mismatch
- 9 methods to look at whether they were better at
- 10 predicting HLA immunogenicity.
- 11 And we looked at amino acid mismatching or
- 12 electrostatic mismatching. The first thing we did was
- 13 we correlated it with applet mismatching. And you can
- 14 see there's a very tight correlation by any of the
- 15 three methods in terms of looking at relevant
- 16 mismatchedness between donor and recipient, if that's a
- 17 term.
- And when you put it into the multivariate
- 19 models, you find that the same four factors always come
- 20 up in predicting the outcome. And then the question
- 21 becomes how can you compare these different models
- 22 using these different methods. And so we used the AIC
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- 1 scores as a way of comparing the overall quality of
- 2 that model. And comparing the AIC scores between
- 3 models, you can get a sense of relative quality of the
- 4 model. The lower the AIC score, the better the model.
- 5 And so the applet mismatch had the lowest scores for
- 6 both DR and for DQ. And whether this translates into
- 7 clinically improved predictability has not been
- 8 determined. But at least at a statistical level, the
- 9 applet one performs well and at least on par with the
- 10 others if not a little bit better.
- Okay. So now we want to try and get to some
- 12 way of quantifying and categorizing patients into
- 13 levels of risk. So we look at whole antigen
- 14 mismatches. And really, apart from zero mismatch, 1
- 15 and 2 really has no improvement in terms of predicting
- 16 a DSA-free survival. And if you look at DQ, in fact,
- 17 two DQ mismatches perform better than one DQ mismatch.
- So again, I think that what we're seeing here
- 19 is that, if you look at ADCs (ph) and predicting zero
- 20 versus one or more, the ADCs are quite poor. It's 0.58
- 21 and 0.54 with very poor sensitivity. And so we don't
- 22 want that kind of a biomarker.

- If we look at the molecular mismatch for DR
- 2 and DQ, we're able to separate into three different
- 3 groups -- 0, 1 to 11, and 12 to 41 for DR and similar
- 4 for DQ. And what we see here is that the AUCs now have
- 5 improved to 0.73 and 0.72 when we're looking at 1 -- 0
- 6 to 11 versus 12 or more. So we're starting to have
- 7 better resolution of predicting immunogenicity of a
- 8 given mismatch.
- 9 So the context of use of such a prognostic
- 10 molecular mismatch score would be a prognostic
- 11 biomarker termed at the time of transplant in
- 12 conjunction with baseline antibody testing to rule out
- 13 preformed alloimmunity -- so we're talking about
- 14 primary alloimmunity -- categorizing kidney transplant
- 15 recipients as high, intermediate, or low risk for de
- 16 novo DSA graft rejection or graft failure with
- 17 categories to be used independently, in pairs, or they
- 18 could even be used as triplet-risk categories to enrich
- 19 Phase 2, 3 clinical trials with patients based on risk
- 20 category in evaluating novel drugs. And so really,
- 21 it's about prognostic biomarker, categorizing patients,
- 22 and then using enrichment strategies.
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- 1 The benefit of this is you get improved
- 2 efficacy in clinical trials versus the current standard
- 3 of primary alloimmune risk assessment, which, right,
- 4 today we use low risk being based on PRA. It's only on
- 5 DR mismatching at the whole antigen level and race.
- 6 And these criteria are used frequently in inclusion,
- 7 exclusion, and stratification tools in drug
- 8 development.
- 9 The risk of using this score would be
- 10 misclassification as high risk. You would have
- 11 exposure to increased immunosuppression, potentially,
- 12 when not warranted, or misclassification as low risk
- 13 where you could expose to inadequate immunosuppression
- 14 when it's not warranted. And you could be qualifying a
- 15 drug in only a subpopulation of kidney transplant
- 16 recipients when, in fact, there's a benefit of the drug
- 17 to the entire population. So these would be the risks
- 18 that you would want to take into account.
- 19 And in terms of the evidentiary criteria grid,
- 20 if we think about the assay and analytical validation,
- 21 what is unique about HLA is it's universally available
- 22 in accredited clinical laboratory. So this is not

- 1 limited to one lab, but, in fact, anywhere in the world
- 2 can do this.
- 3 HLA-typing anolytes, HLA-typing devices, and
- 4 HLA-typing analytic software is all 510(k) FDA-approved
- 5 at this point. So we're not looking at trying to
- 6 rederive these aspects. I've called it fit-for-
- 7 purpose, which is what the evidentiary criteria grid
- 8 uses as language. The computational analysis for HLA,
- 9 DR, DQ, and DP matching is -- we've been using a
- 10 Version 2 of the software, which is a locked version of
- 11 the software. So I think, in that sense, we're not
- 12 continually modulating this software as we're using it.
- 13 In terms of scientific understanding, I think
- 14 the biological rationale is present. The causal
- 15 biological links establishing HLA mismatch and the
- 16 primary alloimmune response is well established in
- 17 terms of understanding molecular mechanism. I'd say
- 18 here there's still some room for improvement. The
- 19 structural biology of antibody binding to its HLA
- 20 target is being further refined. And understanding
- 21 TCMR allorecognition is another area of being further
- 22 defined.

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- In terms of biological performance
- 2 expectations, sensitivity to change, it could be -- it
- 3 is a continuous variable of risk. And consistency of
- 4 the biomarker response -- I didn't show the data, but
- 5 we've seen consistent magnitude of effect when
- 6 adjusting for immunosuppression levels. And in terms
- 7 of specificity, well, it is donor-specific response.
- 8 We're looking at an antibody against its target. I
- 9 don't think you can get much more specific.
- 10 In terms of the types of data and samples
- 11 around establishing qualifications, so far, we've been
- 12 using a prospective study that's a consecutive cohort.
- 13 We have a retrospective study as well and a prospective
- 14 cohort. And we have a small RCT that Dr. Heeger is
- 15 going to talk a little bit about next, and so I won't
- 16 go into that.
- 17 In terms of statistical considerations, the
- 18 relationship of the biomarker to clinical outcomes,
- 19 it's an independent correlative of de novo DSA graft
- 20 rejection, mariolopathy (ph), and graft loss. And I
- 21 didn't show you all that data today.
- 22 Usefulness of the threshold for decision-

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- 1 making -- well, we've gone from an AUC of 0.45 and 0.58
- 2 to 0.72 and 0.73.
- 3 Additional considerations -- there's further
- 4 refinement in the HLA molecular mismatch score that's
- 5 now in place that we've been developing using the
- 6 software. Further validation in retrospect of analysis
- 7 cohorts and RCTs is underway, and we have further
- 8 validation and prospect of RCTs underway as well.
- 9 So where are we at today? Well, in terms of
- 10 being a prognostic biomarker for primary alloimmunity
- 11 in kidney transplantation, we're refined our approach.
- 12 And that's now in submission for publication. But our
- 13 AUC has now gone up to 0.85 from 0.73 in terms of
- 14 predicting de novo DR or DQ DSA. And we can stratify
- 15 low risk, intermediate, and high risk where this
- 16 represents, actually, 25 percent of all transplants, 35
- 17 percent and 45 -- 40 percent, respectively. So you
- 18 have a nice segregation of the population into
- 19 different subsets.
- Now, DSA is a molecule, but it doesn't
- 21 translate into rejection. So what about rejection?
- 22 Well, here's ABMR showing that these three categories

- 1 give a step-wise gradation of risk for developing ABMR
- 2 in the first 10 years post-transplant. And in the
- 3 high-risk group, you're seeing a lot of that in the
- 4 first five years.
- 5 More importantly, it's also stratifying for
- 6 TCMR in the first year. So this is over the first 12
- 7 months of the transplant, and you're able to identify a
- 8 low-, intermediate-, and high-risk group for developing
- 9 a T cell mediated rejection, which we've been
- 10 classically using as one of our clinical endpoints in
- 11 drug design trials.
- 12 So I think this tool could be used as an
- 13 enrichment tool in clinical trial design to get the
- 14 smaller ends so that we could actually have more
- 15 effective and smaller trials.
- 16 And that -- I'll stop, and I'll just recognize
- 17 this is a lot of work. Chris Weeb (ph), Denise
- 18 Pachenko (ph) in our labs been one of the drivers
- 19 between the work -- behind the work that I've been
- 20 showing. We've been collaborating with Vascillis
- 21 Cosmolioptis (ph) in Cambridge. We've had key
- 22 collaborations with Peter Heeger in the CTOT Consortia,

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- 1 Arthur Matas in the DCAF (ph) Consortia, and a close
- 2 collaboration with the STAR Consensus Working Group
- 3 with Anat Tambur and her leadership in bringing this
- 4 forward.
- 5 Thank you very much.
- 6 (Applause.)
- DR. MEIER-KRIESCHE: So our next speaker is
- 8 Peter Heeger from Mount Sinai Medical School. And he
- 9 is going to talk to us about biomarkers to assess a
- 10 risk for kidney allograft injury during CNI withdrawal.
- DR. HEEGER: Great. Thanks for the 11
- 12 opportunity to come here, and thanks for paying
- 13 attention while there's much more drama down the street
- 14 in Capitol Hill at the moment. But this is
- 15 interesting, anyway.
- 16 So we'll talk about biomarkers. I don't --
- 17 you know, I have a couple of research grants, but
- 18 nothing that's relevant to this.
- 19 So long-term transplant outcomes we now have
- 20 understood are suboptimal. And what's interesting for
- 21 those who don't think about this is immunosuppression
- 22 is basically done by protocol at center-specific

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- 1 practices. Some patients do well and could tolerate
- 2 less immunosuppression. Others have poor outcomes
- 3 despite absence of clinical risk factors. And we're
- 4 not really making decisions individually. So if we
- 5 could find ways to individualize, that could improve
- 6 outcome, and it could also provide a way to enrich for
- 7 patients to look -- to put into studies, specifically,
- 8 that are relevant to new drug assessments.
- So risk assessment permits at-risk population
- 10 enrichment that can guide management. Who's most
- 11 likely to do badly? And we heard something just now
- 12 from Peter Nickerson. And maybe if we had better
- 13 biomarkers and better evidence, we could -- I -- put
- 14 people in the right trials.
- 15 Who's most likely to tolerate decreased
- 16 immunosuppression? And I think that's something we16
- 17 don't always think about. But as was noted earlier
- 18 today, there are a lot of off-target effects from
- 19 immunosuppression. So if you could find the low-risk19 pretransplant assay was telling us something about what
- 20 people and then put them into clinical trials, that
- 21 would be important.
- 22 Noninvasive diagnosis of graft injury you're

1 going to hear about later. We'll tough on that a

- 2 little bit. But that could prevent the morbidity of a
- 3 biopsy. And if you could detect subclinical or
- 4 incipient injury, that might be, you know, an important
- 5 safety net for withdrawal studies and help you get
- 6 around other morbidities. And again, you're going to
- 7 hear from my colleagues about that.
- 8 You know, we've been doing clinical trials and
- 9 biomarkers, and we're very interested in validation and
- 10 standardization. And I think this is just to show that
- 11 if you're doing a clinical trial, it's important to try
- 12 to standardize your assay so you can get them out to
- 13 people, which is sort of a step to getting approval to
- 14 use them in this -- in the processes that we're talking
- 15 about today.
- 16 So one of the things that we've been
- 17 interested in now for almost 20 years is studying donor
- 18 reactive T cell immunity by ELISpot. And this could be
- 19 a predictive marker for post-transplant risk
- 20 stratification. This is an assay where we take the
- 21 recipient cells, test them against the donor cells and
- 22 then make interferon gamma as a read-out. And it's a

- 1 measure of memory immunity. So it's a way to sort of
- 2 say that I have already an immune response against my
- 3 donor. And that's not something that was studied
- 4 previously. And again, if you could use this kind of
- 5 assay to stratify, then maybe you could pick people at
- 6 higher or lower risk for, you know, drug studies.
- 7 So in an initial publication, we showed that
- 8 if you did not have this assay, if it was negative, the
- 9 risk of acute rejection was low. And if the -- if you
- 10 had a positive test, the risk was high. And the kidney
- 11 function was actually lower at one year in people who
- 12 had a positive test versus the lower -- a negative
- 13 test. And that turned out to be independent of all
- 14 these other -- several other, you know, clinical risk
- 15 factors.
- And although -- and here's just another
- 17 statement that, independent of delayed graft function
- 18 or developing acute rejection of this assay, the
- 20 was happening at 12 months in terms of glomerular
- 21 filtration rate.
- 22 Now, we didn't do formal validation initially

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- 1 ourselves, but I think it's important that other people
- 2 picked up on this assay. And so around the world now,
- 3 people have tried to do this and have found very
- 4 similar results that taking this assay can give you
- 5 some information about post-transplant outcomes,
- 6 categorize the people as high or low risk.
- 7 And here's just another example of a multi-
- 8 center study that we did through CTOT where the
- 9 patients had -- who had -- were positive had a higher
- 10 evidence of acute rejection and a lower EGFR at 12
- 11 months.
- So you know, the issue here is that there is
- 13 evidence that this assay could be used to identify
- 14 transplant patients at an elevated post-transplant
- 15 risk. We don't know yet, of course, whether altering
- 16 therapy based on the results if going to improve the
- 17 outcome. The complexity is that this is a multi-step
- 18 asset that requires donor cells to assess donor-
- 19 reactive responses. And as such, it's going to be very
- 20 difficult, I think, to employ broadly, you know, in the
- 21 clinic, although it's possible. And it's been
- 22 standardized, but we haven't gone through this type of

- 1 one of these chemokines is relevant.
- 2 And just to show you a little bit of data,
- 3 what we're looking at here is can we diagnose acute
- 4 rejection in a patient who has an elevation in serum
- 5 creatinine post-transplant. And the data here
- 6 demonstrate that there's a much higher level of this
- 7 chemokine, CXCL9, and people who have acute rejection
- 8 versus those have other causes of injury or even
- 9 infection. And the area under the curve was really
- 10 quite reasonable -- 0.856. And the false positives are
- 11 actually not false positives. They're positives
- 12 because people have urinary tract infections or BK
- 13 virus infections which can be detected noninvasively.
- 14 So actually, you can tell injury here.
- 15 Right. So we also noted that the values in
- 16 these -- this is when the patient had rejection. The
- 17 values were higher before the rejection, up to 30 days
- 18 before, which suggests maybe it could be useful as a
- 19 prognostic or detecting the evidence for rejection
- 20 before we saw it clinically, right?
- 21 So again, there's evidence that these -- from
- 22 our group and many others that chemokines can detect

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- 1 approval. And it's, I think, therefore, difficult to
- 2 commercialize.
- 3 And you can imagine if you're doing a deceased
- 4 donor transplant, how are you going to do this in the
- 5 middle of the night and get a result? That's not so
- 6 straight-forward. But nonetheless, I think under
- 7 certain circumstances there's some evidence that will
- 8 be important.
- 9 We've also been looking at chemokine
- 10 measurements as a noninvasive diagnostic. We've all
- 11 heard of chemokine kidney transplant inflammation and
- 12 rejection. And again, you're going to hear more about
- 13 these kinds of assays, including molecular assays
- 14 later. Just for those who don't really know about what
- 15 chemokines do, interferons release during these immune
- 16 responses that cause these chemokines to be released
- 17 that then attract more T cells to come into the area.
- 18 And so there's a biologic plausibility for using this
- 19 kind of analysis, particularly in the kidney where you
- 20 can measure chemokines in the urine. I'm not the first
- 21 one to do this, but we've been interested in it. And
- 22 we did a validation study to sort of look at whether

- 1 clinical and subclinical transplant rejection, which I
- 2 think puts it on a pathway for this kind of validation
- 3 that we were talking about this morning. It has
- 4 implications for both clinical care and for trials
- 5 because you could use this to diagnose -- potentially
- 6 diagnose rejection subclinically.
- 7 There are available kits for research
- 8 purposes. There aren't really any commercial offerings
- 9 yet, although there is one company that I know of that
- 10 has had some IP in this area.
- And ideally, the best way I see this as being
- 12 used is if we could develop a pregnancy test like
- 13 dipstick, which was -- you could give to the patients
- 14 and sort of say you could follow this at home and see
- 15 if that has a clinical utility, not necessary directly
- 16 relevant to the clinical trials that we're talking
- 17 about.
- 18 So to take -- I want you to see this because
- 19 we tried to put all these things in context in a study
- 20 that we did -- it was just alluded -- with the idea we
- 21 wanted to try to withdraw potentially toxic calcineurin
- 22 inhibitors in stable kidney transplant recipients and

1 then use the biomarkers to see whether we could predict

2 or diagnose what might happen.

3 And so our concept was that tacrolimus is

4 good, but maybe it has long-term bad side effects. And

5 so what we did was we took living donors, and we

6 treated them with induction therapy and three drugs --

7 tacrolimus, MMF, and prednisone. These were low-risk

8 patients by a clinical criteria to begin with, and we

9 let them go for six months on this standard

10 immunosuppression, relatively standard. And if they

11 had no rejection, no DSA, and they had a surveillance

12 biopsy that was absolutely normal, we decided they were

13 at as low a risk as we could detect, right? These were

14 people who were doing great on all these drugs, and we

15 couldn't find anything. And so we decided we would try

16 to randomize them to come off the drug or to stay on

17 calcineurin inhibitors, right?

And so the main lesson of this came out very

19 quickly. And that is that we had to stop the study

20 after we randomized 21 patients. Now, I said -- we

21 actually enrolled 50, but we only got half of them to

22 the randomization standpoint because we had to be so

ive

1 There were two patients here who had positive

2 tests once, and when we repeated them and looked for

3 evidence of infection, they had infection. So we

4 didn't do anything, and they didn't have acute

5 rejection. So you know, a small study, it -- so it's

6 proof of principle that this might work.

7 And then we went back to ask about the

8 pretransplant biomarkers to ask the question maybe our

9 risk stratification pretransplant could tell us what's

10 going to happen to these patients when we withdrew.

11 And so, you know, this is the Peter Nickerson data

12 showing -- reminding me that -- reminding us that this

13 epitope mismatch load can tell you something about

14 who's going to develop DSA, right?

So we applied it to our transplant group with

16 Peter's help. And what we found was that all the

17 people who developed DSA had the high epitope

18 mismatches, and none of the people who had the low

19 epitope mismatches developed DSA, which, you know,

20 further sort of suggests that this pretransplant test

21 is really giving you some indication of risk

22 assessment.

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1 strict. And despite that, we had to stop the study

2 because of the outcomes.

3 And so this is just to show you that in our

4 patients who had withdrawal, this is when the drug

5 withdrawal started. This is what -- when it was ended.

6 And we could develop DSA or acute rejection in about

7 half the patients right around the time that the drugs

8 were withdrawn. And in the patients who did not have

9 drug withdrawal, they all did fine. Basically, one had

10 a late DSA, and one had a low-level DSA to start with.

So we wanted to understand whether we could

12 tell who was going to get these abnormalities. And we

13 were measuring these chemokines. And when you look at

14 -- and here, we have the same colors, but I want you to

15 know that the rejections are now the red and the CXCL9

16 positivity in the urine, which we serially measured

17 during this time, came up positive in all of the

18 patients right before they developed the rejection.

19 This is 30 days. This is about a week. This is 3

20 days. So serially measuring this chemokine over the

21 course of the withdrawal was actually informative. We

22 didn't act on it, but it was informative.

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1 And then we also looked at whether or not the

2 patient had pretransplant ELISpot positivity. And

3 also, rejections and the bad outcomes hurt -- happened

4 in the patients who had this pretransplant ELISpot

5 positivity.

6 So I think it raises some really interesting

7 things about what we could -- what kinds of tests we

8 could use for enriching patients to -- for clinical

9 trials. Those who have these positive tests might be

10 the ones you want to enrich for the highest risk for

11 studying patients who we want to try new drugs in.

12 From a clinical standpoint, right, we

13 currently sort of give drugs as induction therapy, and

14 we decrease our immunosuppression over time. And we

15 don't really know who's going to develop things. And

16 ideally, what we would do is come up with some sort of

17 a biomarker profile that would tell us who's at the

18 highest risk early, do a series of tests that might

19 include urinary or blood transcriptome analyses over

20 time and try to make decisions to individualized

21 patients that way.

22 And I think that when I think about doing

- 1 this, I want to incorporate these biomarkers into
- 2 clinical trial designs to test whether biomarkers --
- 3 biomarker base changes in therapy can detect
- 4 subclinical injury and improve outcomes. And so you
- 5 sort of have to do a study where there's a standard of
- 6 care arm and an arm where you treat or do something
- 7 different based on biomarker status and ask whether you
- 8 end up with a better outcome in that group. And I know
- 9 there's several people in this room who are interested
- 10 in doing those kinds of things.
- So I'm going to stop there, and I'm happy to
- 12 answer questions later. And this was work done by many
- 13 colleagues. So thank you.
- 14 (Applause.)
- DR. MEIER-KRIESCHE: Our third speaker in this
- 16 session is Dr. Roslyn Mannon from the University of
- 17 Alabama. And the title of her talk is Genomic single
- 18 nucleotide polymorphisms biomarkers of alloimmune
- 19 risk?
- 20 DR. MANNON: Thank you so much and for
- 21 nominating me to give this talk. This is part of my
- 22 STAR AAST AASHE (ph) initiative to look at pre-immune

initiative. This is with enryeisity of miniesota and

- 1 risk. And some of you, this is a very broad overview
- 2 because I have 15 minutes. And even though I can talk
- 3 fast, I had to cut it down.
- 4 These are my disclosures that are not
- 5 relevant.
- 6 So I think the hot topic these days for all
- 7 patient care in clinical trials is this precision
- 8 medicine. This is the monograph in the National
- 9 Academy of Science. It -- if you read the whole
- 10 report, it really kind of gives you the foundation of
- 11 what some of the NIH initiatives are in terms of the
- 12 one -- you know, (inaudible) everybody and also the
- 13 NIDDK initiative where they're obtaining pathology,
- 14 linking it to diagnosis, linking that diagnosis to --
- 15 potentially to Omix Technologies and developing sort of
- 16 a very granular database to allow them for patient
- 17 management. And I think, again, oncology has been sort
- 18 of a leader in developing this.
- But again, we have a really more -- much more
- 20 complex system. And it would be great to say that the
- 21 genes of the recipient tells you everything about
- 22 what's going to happen. This is a figure from a grant,

- 1 not funded. But I point it out because we were doing
- 2 all these things to sort of understand what are these
- 3 plant -- pre- and post-transplant risks. And it's much
- 4 more complicated than just putting the kidney, and the
- 5 donor has a significant input to this process.
- 6 And so when we're thinking about genome
- 7 analysis, there are clear pharmacogenomics. And I'm
- 8 not going to delve deeply because I think Teun van
- 9 Gelder will do this at a later session, particularly
- 10 for CNI or calcineurin inhibitor metabolism and also
- 11 for mycophenolate metabolism that have some important
- 12 data.

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- 13 There is recipient genomics. Some of you in
- 14 the room have looked at immune modification and immune
- 15 risk of individuals and then the donor genomics, which
- 16 I really won't describe today.
- 17 So just as a flavor about associations with
- 18 calcineurin inhibitor toxicity, this is a GWA study of
- 19 tacrolimus concentrations of over 3,000 kidney
- 20 transplant patients. This was part of work of DCAF
- 21 genomics and geno 3 (ph), which is an NIAID-funded
- 22 initiative. This is with University of Minnesota and

- 1 several transplant centers, including our own.
- 2 You can see the Manhattan plot on the left
- 3 identifies one particular snip in this GWAS. It was
- 4 associated with tacrolimus trough concentrations. And
- 5 this was over CYP3A5.
- 6 And we've also been able to identify a series
- 7 of loss of function mutations, which are also present
- 8 in African-American, although not as commonly as
- 9 European-Americans. And as shown in the panel on the
- 10 right, you know, when you look at mean dose-adjusted
- 11 tap (ph) levels, the number of these loss of function
- 12 alleles really affect the dose that you need in order
- 13 to reach your target.
- 14 Again, the naysayers will say, well, does
- 15 genotype dosing affect outcomes. There's been a couple
- 16 of studies that Teun may bring up. They haven't been
- 17 conclusive. But certainly, in our research and what
- 18 we've published is that, if levels are low early, the
- 19 trend is that they tend to stay low. It really takes
- 20 effort to get those levels up. And all three variants
- 21 in the loss of function in clinical factors only
- 22 account for about half of the variation that we see in

1 tac trough. So there's clearly other factors that are

2 out there.

3 Nonetheless, the clinical pharmacogenomics

4 implementation consortium has guidelines for CYP3A5

5 genotype and tac dosing. I only know, like, one center

6 and a half that actually use this. We don't. We wing

7 it. And there's also a tac dosing equation based on

8 the geno 3 data that are published. And so the

9 consideration is maybe this is really a more

10 appropriate way for drug dosing.

There has been data on the genetics associated

12 with mycophenolate hematologic toxicity. The GI

13 toxicity has not been conclusive. But in this study of

14 about 1,000 individuals in the geno 3 DCAF genomics

15 cohort, 23 percent were African American. We used a

16 variety of platforms. We were able to identify SNPs

17 associated with anemia as well as leukopenia.

So we were asked to sort of look at the unmet

19 therapeutic needs. And so I think having a specific

20 dosing strategy to read a therapeutic trough and the

21 shortest and fastest period to minimize activation of

22 alloimmunity is one unmet need, but, also, to identify

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1 those at risk for specific PRO (ph) measures, which is

2 part of Workgroup 2, to either provide reduced dose at

3 the onset or avoid that toxicity and may have to switch

4 completely to a different class in terms of maintenance

5 therapy.

6 In terms of the context of use, the potential

7 for pharmacogenomic SNPs, I think, could be used as

8 safety biomarkers. The -- for the people that like

9 graphs, I put the graph on the right. And the people

10 that like words, the words are on the left. So I

11 thought, rather than being redundant and having two

12 slides, it does sort of give you a sense that the

13 safety is on the bottom shown here, a biomarker. And

14 then the monitoring biomarker is shown at the top,

15 really, sort of to measure and assess the treatment

16 effect. So those are two possibilities.

17 And if you wanted -- you asked me to draft a

18 context of use statement. So I came up with these, and

19 you can debate them. I'm not here to say this is it.

20 But you could do testing -- pharmacogenomic testing for

21 CYP3A5 as a safety biomarker for patients treated with

22 tacrolimus to assess for under-dosing of

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1 immunosuppression and increased risk of acute

2 rejection. And the MPA may not be prime time, but

3 intriguing in terms of PRO measures, such as anemia,

4 leukopenia, that cause us to make therapeutic changes.

5 Switching to the topic that I was also asked

6 to talk about is immune response SNPs. And this is

7 just a summary of a few studies. Barbara Murphy just

8 left, but she's contributed to this literature. And

9 again, this is in the recipient, whereas different

10 genes alleles are associated with rejection. And you

11 can see a variety of things up at the top -- CTLA4.

12 IL-17 genes have been published. ICAM and vascular

13 cell proteins have been associated in the past.

14 But also, groups have also looked at other

15 SNPs for immune quiescent things like IL-10, which may

16 have immunosuppress qualities or TGF beta. And then

17 these have not been conclusive. And if you read

18 through the literature, some of this is the patient

19 size or the population and also the platform that was

20 used.

21 And indeed, other groups have looked at can

22 you determine and associate certain SNPs by GWAS and

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1 determine who's going to have allograft function and

2 failure. This is a 326 kidney transplant recipient

3 cohort from Ireland. Inish, I included this for you.

4 But it is good data -- and they are -- again,

5 similarity of ethnicity, so maybe not helpful in

6 defining a very diverse -- ethnically diverse

7 population that exists in the U.S., or at least in the

8 Southeast United States, identifying a number of SNPs

9 in genes that are sort of all -- a little bit all over

10 the place but seem to track closely with graft failure.

11 In the so-called DCAF cohort, decline in

12 kidney allograft function-funded cohort -- in genomics,

13 this is a paper with Ajay Astrani (ph) that we

14 collaborated with. We were unable to confirm 23 prior

15 SNPs for risks of kidney transplant rejection. So we

16 made an effort to do that. I think we had the patient

17 population. But we also identified 15 new SNPs that

18 are associated with cellular rejection. And those are

19 shown in the table, which you may not read, but my

20 slides are on publically.

21 And we found a couple things. One, there was

22 a significant-center to center variation in rejection.

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- 1 So this DCAF genomics cohort consists of seven
- 2 transplant centers. And one center, such as ours, is
- 3 predominantly a deceased donor population with African
- 4 Americans, whereas Minnesota's population is more
- 5 Caucasian, and the opposite two-thirds are living
- 6 donors.
- 7 There also have been something new and
- 8 intriguing. And in doing my work for STAR, I came -- a
- 9 couple of publications I thought that I'd share. And
- 10 one is that of complement polymorphisms. This is a
- 11 very comprehensive review paper by Michael Senetal (ph)
- 12 from Utrecht (ph) from -- and published in the American
- 13 Journal of Transplant in 2017. You can't really read
- 14 this because you just -- I mean, you need slide and
- 15 slide.
- But the important aspect is that we have to
- 17 think about complement activation. In its crosstalk
- 18 with alloimmunity, this is a really significant part of
- 19 antibody-mediated injury. And again, complement also
- 20 acts as a co-stimulator. It was this group's
- 21 recommendation to look at SNPs in CD-46. CD-46 is a
- 22 co-factor for Factor I and facilitates degradation of

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- 1 complement proteins C3b and C4b, which are important in
- 2 AMR.
- 3 And I also point to you that they have some
- 4 preliminary data that looks very promising that's on
- 5 frontiers of immunology that's an online publication --
- 6 so, again, not just thinking about T cell mediated
- 7 rejection, but complement.
- 8 And finally, another interesting papers --
- 9 series of papers I came across, and that are with SNPs
- 10 within CD16a at the Fc gamma receptor 3 alpha. Again,
- 11 the idea here is that maybe gene polymorphisms and IgG
- 12 effector functions may affect complement activation and
- 13 antibody-dependent complement cytotoxicity,
- 14 particularly, in this case, (inaudible) K cells.
- 15 Interestingly, there's a paper -- and I forgot
- 16 to put the reference in for you all, but it's -- you
- 17 know, there's a genotype-associated response in
- 18 lymphoma to rituximab. Never thought about looking at
- 19 that because we use rituximab sometimes quite
- 20 frequently and sometimes don't see responses. There
- 21 are preliminary data in kidney transplant patients
- 22 showing differences in this recipient SNP affecting

- 1 outcome.
- 2 And a very interesting paper that is published
- 3 in circulation in 2019 -- 2018 is shown here on the
- 4 right. This is in heart allografts with an association
- 5 of vasculopathy associated with SNPs. And I won't go
- 6 through which one is which. But again, it probably
- 7 needs additional validation.
- So the unmet need is defining high immune
- 9 risk. I think Peter Nickerson shows you sort of the
- 10 more sophisticated levels, but this is what a lot of us
- 11 use -- DSA crossmatch negative or positive. In the
- 12 intact (ph) study, one of the most recent clinical
- 13 trials published, it was African-American race re-
- 14 transplant, and it calculated PRA of 20 percent. And I
- 15 think these are sledgehammers. This is not fine tools.
- 16 And we need fine tools.
- 17 So the context of use, again, a susceptibility
- 18 risk marker, would be the role for genomic immune
- 19 response SNPs. And -- or on -- and you can see that
- 20 graphically on the right -- or as predictive markers to
- 21 identify individuals who may or more likely experience
- 22 the undesired effects. So you may be able to define a

- 1 trial if you believe the validation.
- 2 And that's my final point. To date, the
- 3 results of these analyses have been somewhat ambiguous
- 4 and controversial. Hence, for me to provide you a
- 5 definite context of use statement I think is a bit
- 6 premature. I don't want to say which gene. Rely --
- 7 you know, we need reliable validation. And again, is
- 8 this really too complicated for the transplant field
- 9 because of this interaction between donor and
- 10 recipient?
- And with that, I'll acknowledge the many -- my
- 12 lab, who keeps me sustained even when I'm running
- 13 around like a lunatic; the CTOC Consortia; the DCAF
- 14 Consortia, which I'm a member of; and also, the STAR
- 15 initiative by Anat Tambur and Peter Nickerson that have
- 16 really been helping us define immune risk.
- 17 Thank you.
- 18 (Applause.)
- 19 DR. MEIER-KRIESCHE: Thank you to all our
- 20 speakers.
- 21 It's -- before moving on to the general
- 22 questions that's going to be shown on the screen

- 1 shortly, I have a short question to Dr. Mannon or
- 2 anybody else who wants to tackle.
- 3 Dr. Mannon, I've seen that you have briefly
- 4 mentioned about the CTLA4 SNPs. And this is in follow-
- 5 up to a discussion -- meeting discussion that took
- 6 place during last year's AMR workshop. And I remember
- 7 that there was a discussion that certain patients on
- 8 Belatacept based regimens do very well, whereas a
- 9 subgroup of those patients may develop treatment-
- 10 resistant rejections which don't do as well.
- 11 So as far as I looked up in the literature,
- 12 the CTLA for SNPs have been -- I don't know what the
- 13 prevalence in the general population, but have been
- 14 studied in patients who are on tacrolimus-based
- 15 regiments. So is there any merit in studying or looing
- 16 into this in Belatacept-treated patients? Or has
- 17 anybody ever looked into this?
- DR. MANNON: So Barbara Murphy is an expert in
- 19 CTLA4 SNPs. I'm calling her out. But with regards --
- 20 so I'll let her answer those first questions. But with
- 21 regard to Belatacept in our CTOT 10, 15, and 16, these
- 22 were clinical trials looking at the optimization of use
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- 1 of Belatacept-based regimens and in calcineurin and
- 2 (inaudible) free regimen, some of which were already
- 3 published. We did collect that information. The
- 4 patient populations were too small.
- 5 So we did those analyses in our lab and had
- 6 the independent biostatistician look at them, but we
- 7 did not see a relationship. And again, it may be
- 8 because, for example, CTOT 16 only had 69 patients.
- 9 And though we had a fairly high rate of rejection in
- 10 the bella (ph) arm because there were three arms, later
- 11 two arms, it just was not conclusive.
- DR. MEIER-KRIESCHE: I see. Thank you.
- 13 DR. MANNON: Barbara.
- DR. MURPHY: So the SNPs that are related to
- 15 the (inaudible off mic) are actually associated with
- 16 functional (inaudible off mic) duration as well. So
- 17 you do actually see a difference between the (inaudible
- 18 off mic) when you block the (inaudible off mic)
- 19 antibody (inaudible off mic) the individuals with
- 20 (inaudible off mic) so that you can see greater or
- 21 lesser (inaudible off mic) depending on the
- 22 immunosuppression (inaudible off mic) for those

- 1 individuals. To my knowledge and in discussions in the
- 2 past, trying to get people (inaudible off mic) to
- 3 look at this, this is (inaudible off mic).
- 4 DR. MEIER-KRIESCHE: Okay. Thank you.
- 5 Now we can move on to the general FDA
- 6 questions. And if there's anybody else in the audience
- 7 who has a specific question, please ask your question.
- 3 UNIDENTIFIED MALE SPEAKER: Yeah. This is for
- 9 Peter Nickerson. Awesome presentation. I -- it's
- 10 great to see a fellow clinician think in terms of drug
- 11 development tools, quantitative models, (inaudible)
- 12 information criteria. It confirms that I'm not alone.
- 13 Thank you.
- 14 A question for you. Are you thinking of the
- 15 idea of potentially advancing the models that you've
- 16 developed that are semi-parametric in nature to turn
- 17 them into full parametric survival models? Because if
- 18 you can do that, then, theoretically, through some
- 19 careful cross validation exercises, we could be looking
- 20 at potentially simulating clinical trial scenarios for
- 21 failure based on the biomarker.
- DR. NICKERSON: Yeah. So I think that's --
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- 1 we're trying to get to the best version of the
- 2 biomarker we think we can get to, and then we'd be very
- 3 interested in pursuing those types of simulation
- 4 modeling. I think that's sort of the next phase and --
- 5 because I think, with that, you can start thinking
- 6 about then what kind of trial designs do I really need
- 7 going forward.
- 8 UNIDENTIFIED MALE SPEAKER: Cool.
- 9 DR. NICKERSON: So absolutely.
- 10 UNIDENTIFIED MALE SPEAKER: Awesome.
- DR. MEIER-KRIESCHE: Okay. Does anybody from
- 12 the audience have any specific questions? If not, we
- 13 are going to move on to the FDA questions.
- 14 So the first question is: What are the unmet
- 15 needs in drug development and clinical practice in the
- 16 kidney pretransplant setting, and how do these align?
- 17 DR. HEEGER: So maybe I'll start with the
- 18 unmet need in drug development. I think one of the
- 19 problems -- and I think we recognized this in CTOT-09 -
- 20 was what we thought was low risk wasn't low risk.
- 21 And there is a heterogeneity of risk even within what
- 22 is traditionally called low risk. So I think that's

- 1 one of the big problems around drug development, is
- 2 you're including a lot of patients in trials who don't
- 3 necessarily need to be in the trial because they're
- 4 going to dilute out the clinical outcome that you're
- 5 looking for.
- 6 So we really need to drive towards homogeneity
- 7 in clinical trial design in patient populations to
- 8 allow the clinical trial design to be more efficient.
- 9 And I think that's where -- if we can -- and that --
- 10 you may say, well, that might get a drug qualified in a
- 11 restricted population of patients. And yes, that's
- 12 true. But then you can do subsequent trials to see how
- 13 broadly applicable it is.
- But if you can get a trial done with a much
- 15 smaller end in a more efficient time frame, then I
- 16 think you have a real opportunity. And I think we
- 17 shouldn't be thinking about just one biomarker, but can
- 18 we do some kind of an enrichment strategy for
- 19 homogeneity that you can then link to a surrogate
- 20 endpoint outcome in a clinical trial. And the two
- 21 together might give you a real efficient trial design
- 22 to qualify a drug. And then beyond that, you could
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- 1 look at broader utilization of that agent.
- 2 So I think the unmet need is precision and
- 3 risk stratification. And I think you heard three talks
- 4 about T cell memory, primary memory, SNP as immune
- 5 responsiveness or safety. And the whole intent was all
- 6 three of these can be used to get towards homogeneity
- 7 into maybe a high-risk category if that's the -- to
- 8 have a higher event rate in your standard of care
- 9 versus novel agent.
- 10 DR. MORRIS: Peter, I noticed in your two
- 11 slides where you plotted survival and ABMR and TCMR
- 12 that the slope for decreased survival was steeper
- 13 earlier in TCMR. So this, to me, indicates that a
- 14 focus for drug development for primary de novo DSA
- 15 should still be looking at controlling T cell
- 16 activation. We know just from basic biology that
- 17 primary responses are T cell-dependent, and DSA is a
- 18 signal that we're not controlling the T cells. So I
- 19 thought that was very instructive.
- DR. NICKERSON: And no, I would agree, Randy.
- 21 I think what we're seeing is that -- and many groups
- 22 around the world now have shown that TCMR early is a

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 1 subsequent markers of those at risk to getting DSA
- 2 late. And when you look at pathologies in ABMR, many
- 3 of them are mixed. They're not pure ABMR. Alex's
- 4 group in Paris had a nice paper with -- it was Ojay
- 5 (ph); I guess it was about a year ago -- that nicely
- 6 detailed the mixed nature of these rejections.
- 7 And so, yes, I think we should be looking at -
- 8 you know, and as I showed you, the EGFR was already
- 9 going down faster in those patients before they
- 10 developed the DSA. And I think what's going on there
- 11 is there's probably a subclinical cellular event going
- 12 on in the graft.
- So I believe that we still have to keep the T
- 14 cell in our sights, and trials focused on TCMR can be
- 15 very instructive. And I think that's where you'll hear
- 16 in the next session why subclinical rejection is a
- 17 really important thing to be able to diagnose as maybe
- 18 part of your trial design.
- 19 (Crosstalk.)
- 20 DR. MEIER-KRIESCHE: -- Sarwal has a question
- 21 or a comment.
- DR. SARWAL: So I just wanted to actually, I
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- 1 think, echo what Peter has said. And really, I think
- 2 the point, the challenge, for us is to really try and
- 3 stratify which patients should be selecting
- 4 pretransplant for which drug trials. And I think we
- 5 have two types of probably drug trials that are going
- 6 to come in those with equivalency for outcome but with
- 7 increased safety versus those with increased efficacy
- 8 dealing with certain things where the safety parameters
- 9 maybe are more understood.
- 10 And so I think what Peter has shown is
- 11 actually -- you know, really highlights that there is
- 12 the whole attention that has to be paid between the
- 13 donor and the recipient.
- 14 But I'd like to probably challenge the
- 15 community and say that I think we probably in the
- 16 future need to take even one step further because we
- 17 have access to such deep sequencing tools that the
- 18 future should lie for us that we are actually
- 19 developing individual donor recipient (inaudible).
- 20 So we should be looking at the recipients'
- 21 alloimmune recognition response specifically to that
- 22 donor because, right now, we are doing a pool effect

- 1 where we are looking at some of this stuff. And I'll
- 2 talk a little bit about how we can look at other
- 3 parameters, including doing this kind of sequencing for
- 4 non-HLA. But I think that's kind of the future. If we
- 5 could get there, we could really get some of these new
- 6 drugs and trial them with greater safety and efficacy.
- 7 DR. ABECASSIS: Can I make a comment on
- 8 Peter's?
- 9 DR. MEIER-KRIESCHE: Please.
- 10 DR. ABECASSIS: So I think what -- first of
- 11 all, your work is fantastic, really exciting.
- But I think there's a danger to doing clinical
- 13 trials that are so narrow that, you know, by the time
- 14 you're done, you know, 100 years later, all you can
- 15 draw is a conclusion about a very specific patient
- 16 population. And I agree with Minnie. You know, we
- 17 have the ability to come at data later on and be able
- 18 to look at -- you know, predictors of failure or, you
- 19 know, predictors of whatever.
- 20 And I've always been of the mind that, you
- 21 know, you want to just go wide, go big, and then come
- 22 back and look at data, as opposed to, you know, there's
- - Page 187
- 1 a temptation to do a smaller trial, very focused. But
- 2 then the outcome is just based on that very narrow
- 3 population.
- 4 DR. NICKERSON: So I think you make a good
- 5 point, Mike. And I think the other opportunity you
- 6 have besides enrichment would be a stratification
- 7 design where, basically, you'd use your markers as
- 8 stratification tool, and then you could look for is
- 9 there a differential effect in the different
- 10 populations of your drug afterwards or as part of your
- 11 statistical analysis plan of that drug development.
- 12 And then you could see whether or not -- whether the
- 13 drug is most efficacious in one subcohort or another.
- 14 And in fact, that's exactly what they're doing in
- 15 oncology now, right, with a lot of the targeted drug
- 16 therapies.
- 17 UNIDENTIFIED MALE SPEAKER: And I would also
- 18 add that there's -- we need to kind of step away from
- 19 that perception that because if we use a drug
- 20 development tool that helps us enrich the clinical
- 21 trial and increase the probability of success, that's
- 22 really what gets drugs approved. Going too wide just

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- 1 because of a perception that the target population2 might be wider has not been as successful, and I think
- 3 history shows that. So that's -- I means, it's
- 4 striking amounts.
- 5 Just because you get a biomarker qualified
- 6 that can enrich a clinical trial doesn't mean that,
- 7 first of all, you have to use it every single time.
- 8 And second, you have to put it into context as to what
- 9 that means to the individual drug development programs
- 10 in the pipeline.
- DR. SARWAL: Could I just comment on the
- 12 statement you made that you cannot do trials in a very
- 13 narrow population? I think times have changed. And
- 14 the example is the master protocol. And on one of my
- 15 slides, I gave the reference to a paper last year, I
- 16 think, with Janet Woodcock and Lisa Lamonge (ph).
- 17 And they are using -- so currently, they have
- 18 -- so the master protocol is multiple therapies,
- 19 multiple patient subtypes. And they -- recently, I
- 20 read somewhere that they have approved drugs -- you
- 21 can't even say a drug -- using the master protocol.
- 22 You genotype the patient, multiple patients with this
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- 1 test that's approved. And then you can -- based on the
- 2 outcome of that test, you can treat the patient with
- 3 one of umpteen drugs. This is all under one trial.
- 4 So the concept of one randomized clinical
- 5 trial prospectively designed to answer one question
- 6 applies. It's great for certain things. But for
- 7 complex situations such as what you just mentioned,
- 8 think there are options that FDA is looking into and
- 9 has embarked on.
- 10 DR. STEGALL: I have a comment.
- DR. MEIER-KRIESCHE: Stegall.
- DR. STEGALL: So there's a -- I look around
- 13 the room, and they -- the pharma that are here, a lot
- 14 of them are doing studies in post-transplant patient
- 15 populations where they've identified a problem post-
- 15 populations where they we identified a problem pol
- 16 transplant and are doing what I would call rescue
- 17 therapy. And so I don't know if that's -- it turns out
- 18 that those studies are pretty hard to enroll, also.
- 19 They are actually -- their patients already has an
- 20 identified problem, which is associated with graft
- 21 loss, right? And (inaudible technical difficulty)
- 22 finding more and more of those patients on one-year

1 biopsies and all the rest.

2 But I think there has to be some sort of

3 discussion around what are the best biomarkers for

4 post-transplant intervention, which is truly an

5 enriched population already. And that truly avoids --

6 I mean, the easiest patient to enroll is pretransplant,

7 right? And that's an easy transplant population. And

8 yes, there are novel trial designs that might enhance

9 that.

But when you already have a patient post-

11 transplant who has declared themselves a problem

12 patient, which is what iBox does, that's -- I think we

13 need to sort of think more on that way of thinking.

14 And it may be, because there's going to be some more

15 talks about, you know, monitoring patients, but

16 monitoring for DSA or monitoring for peripheral blood

17 assays, but also the histology and what we already kind

18 of -- markers we already know something about very

19 clearly. And I think that seems to me just, also, too,

20 as a person who does these trials, there's a lot of

21 heterogeneity endpoints and inclusion criteria in those

22 studies right now, and it would be really nice to have

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1 that -- conversations about trying to get our heads

2 around, like, for example, just clearly post-transplant

3 ABMR. And so -- and that's not, you know, CTOT

4 anything. That's just, unfortunately, what we see.

5 DR. NEWELL: Just one comment here I want to

6 make is that, I mean, prognostic enrichment in clinical

7 drug trials (inaudible) the legitimate strategy. I

8 mean, if you take the acute rejection example with the

9 current drugs or which -- with the potential drugs

10 which are in the works, it may not -- we may not be

11 able to show a difference for the acute rejection

12 endpoint, just as an example, because the -- if we

13 enroll all comers or low-risk patients as generally has

14 been done in trials.

But if we apply a strategy of prognostic

16 enrichment and enroll patients who are at higher risk

17 for acute rejection, then we may be able to show a

18 difference. So that's one potential hypothetical use

19 for prognostic enrichment.

20 UNIDENTIFIED MALE SPEAKER: I was going to

21 say. As I try to reconcile the two statements, you're

22 actually trying to achieve very different things. And

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2 So I think what Peter is saying is, if you got

3 a very selected population, then you might be able to

1 it's probably the companies who would see it that way.

4 better risk-adjust and show more meaningful differences

5 for the therapy. But if your marker is so narrow that

6 it only identifies 1 percent of the population and then

7 you go to your context of use statement -- and I think

8 most pharmaceutical companies already say transplant's

9 small -- and if you can now only use the drug in 1

10 percent of the transplants we do in the country, it

11 would be in some ways helping them, but in some ways

12 hurting them because no one's going to go after that

13 population.

14 I think what Mike was saying is that it's

15 useful to have studies set up where you can capture

16 more of the population. And so how you transition

17 from, yes, it works in the small subset of patients

18 that's very carefully defined to assessing whether it

19 works in a larger population is, I think, the

20 intersection of what you're talking about.

21 DR. MEIER-KRIESCHE: I think Dr. Nickerson

22 wants to response.

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1 DR. NEWELL: Yeah. So --

2 DR. MEIER-KRIESCHE: And then Dr. Murphy.

3 DR. NEWELL: So I think that's the point that

4 I was trying to illustrate on the last slide, which

5 was, in fact, these three risk categories partition 25,

6 35, and 40 percent of the cohort, right, which is all

7 comers. So in fact, none of the one category is going

8 to really partition you into 1 percent of the

9 population. It's giving you, actually, a big whack of

10 the population.

11 DR. NICKERSON: I was just saying, rather than

12 as an enrichment strategy, I liked it better as a risk

13 stratification because then you leverage the strength

14 of your tool, but you don't restrict it.

DR. MEIER-KRIESCHE: Dr. Murphy.

DR. MURPHY: Just to follow up on Ken's point,

17 though, the idea of being too restrictive, that's the

18 very way that cancer actually started moving forward.

19 I mean, if you think about how they identified an -- 10

20 percent of individuals with a certain type of lung

21 cancer and managed to get approval for that drug -- and

22 slowly but surely they started making a difference.

- 1 And I think we need to be careful about being afraid to
- 2 be too -- being afraid of being too restrictive.
- 3 DR. SARWAL: And I want to give the example of
- 4 cystic fibrosis drugs. The first one was approved for
- 5 a sliver and then bigger. And then the concept that
- 6 you're raising is let's give up before we start. And
- 7 all the rare diseases -- I mean, there are patients out
- 8 there, you know. We could be patients at some point.
- 9 And I think we need to have that consideration. And
- 10 there are pathways at the FDA, the breakthrough
- 11 therapies, and, you know, all of that whole area. And
- 12 it's laid out in the Cures Act, in PDUFA, that we'll
- 13 work with you on that, and we find ways to get across
- 14 or get there because these are huge unmet need areas.
- DR. MEIER-KRIESCHE: Dr. Mannon.
- DR. MANNON: Just to go back to the big versus
- 17 little studies, I mean, I thought that one of the
- 18 reasons these have merit is because we could narrow the
- 19 population numbers we need to find the endpoint that
- 20 we're mystically looking for. And if we had -- you
- 21 know, I mean, why do people -- you know, the biggest
- 22 problem I have with old trials is, like, why did people

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- 1 fail? Why didn't people do well? And we usually can't
- 2 go back and look.
- 3 So I think there is total merit to this
- 4 because it's obviously more than HLA mismatch. It's
- 5 obviously more than where you live and how much money
- 6 you have and whether you have insurance. And so the
- 7 ability to consolidate many of these factors I think is
- 8 important moving on. I don't think narrowing the
- 9 population will affect the sales pitch. I think that
- 10 you could then use that drug if it's approved, perhaps
- 11 even in a broader context because if you say I'm taking
- 12 the high risk and they do well, potentially, we could
- 13 develop it and expand it to say this is good for all
- 14 humans with transplants.
- DR. MEIER-KRIESCHE: Okay. I think someone in
- 16 the audience wants to --
- 17 MR. FOWLER: Yeah, I --
- DR. MEIER-KRIESCHE: Please, go ahead.
- 19 MR. FOWLER: I'd just like to add a
- 20 perspective. My name is Kevin Fowler with the Kidney
- 21 Health Initiative.
- 22 And going back to what Dr. Murphy was saying

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- 1 about look at oncology, I think if you look at what's
- 2 happening in kidney disease, everyone was looking at
- 3 diabetic kidney disease. And now they're going to make
- 4 some progress. But really, where the impact is being
- 5 made in kidney disease was in rare disease.
- 6 And I guess my sense is you can debate going
- 7 back and forth, but you've got to get someplace to get
- 8 started to show some success to pharma, to patients,
- 9 and the larger community. That's just my two cents
- 10 from my experience in that area.
- DR. MEIER-KRIESCHE: So one quick comment to
- 12 the usefulness of the stratification biomarkers, I
- 13 think it's very clear from the development prospective
- 14 they're extremely important. And we are kind of
- 15 discussing the different (inaudible technical
- 16 difficulty), which may apply to individual projects.
- 17 Whether you use them for enrichment or whether you use
- 18 them for de-risking (ph) your trial or whether you're
- 19 go into large, small, it doesn't really matter. It
- 20 gives you the opportunity to discuss this so you have a
- 21 more flexible way forward.
- 22 And I think Peter's data is actually really

- 1 amazing because there's a trial which failed which
- 2 could potentially have succeeded if that stratification
- 3 variable was available before this trial. And this is
- 4 exactly the example -- one of the examples where
- 5 something like this can be useful and then obviously
- 6 can be useful in terms of increasing the number of
- 7 events. And obviously, you have to strategically think
- 8 through how you can make that applicable eventually to
- 9 the larger population.
- 10 But bottom line, having something like that
- 11 can really prevent you from making missteps. And
- 12 sitting on the end of really having to try to bring a
- 13 new therapy into a population, that's really what keeps
- 14 me up at night, that I may have variability in the
- 15 population which drives outcomes which I cannot
- 16 control. So very clearly, in some way, this is going
- 17 to be extremely helpful, no matter which way we are
- 18 going to employ this.
- 19 UNIDENTIFIED MALE SPEAKER: I think, to echo
- 20 Ulf's point -- I was going to try and make it, but I
- 21 think you made it very well -- it's the idea that these
- 22 are tools, right? These aren't defining the strategy

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2 can be applied to specific strategies in scenarios

1 of pharmaceutical organizations. These are tools that

- 3 which we can't control. We can't control market
- 4 factors. We can't control all these other things
- 5 outside of here. But what we can control is developing
- 6 a toolkit to design and optimize clinical trials such
- 7 that you have reduced the heterogeneity to have a
- 8 better shot and goal (ph). And the better you can do
- 9 that consistently, the more likely you are to succeed.
- 10 So it's -- so the specific application and
- 11 strategy is a great conversation to get into and
- 12 features into the context of use portion. But clearly
- 13 being able to reduce the heterogeneity within -- with
- 14 regard to your patient populations is a great first
- 15 step in that aspect.
- 16 UNIDENTIFIED MALE SPEAKER: I would only say,
- 17 to beat a dead horse, not reduce the heterogeneity, but
- 18 account for it.
- 19 UNIDENTIFIED MALE SPEAKER: Exactly. Yeah.
- 20 DR. MORRIS: I have a comment just generally
- 21 about drug development. If your drug in a trial fails
- 22 to meet the endpoint and it's not approved, it's a dead

1 disease, then the payor may not have to pay for that

- 2 drug. It didn't work. It's like getting a -- paying
- 3 for a car that won't run. Who would pay for that?
- 4 So value-based pricing then gets back to
- 5 narrowing the population in such a way that you're more
- 6 likely to have a drug that is effective in that
- 7 population.
- B DR. MANNON: So following up on Kevin's point,
- 9 we actually have an online question from someone who
- 10 writes, "I'm a transplant recipient and rare disease
- 11 patient. For patients pre- and post-transplant, do you
- 12 believe that a more specific approach needs to be
- 13 taken? For patients with particular strong immune
- 14 systems who have rare diseases, will biomarkers be
- 15 enough?"
- And I know we have limited time, but the
- 17 question does say pre- and post-transplant. So perhaps
- 18 in subsequent sessions, we can talk about rare disease
- 19 and strong immune responses. I don't know if one or
- 20 two people may want to make comments now, or we can
- 21 reserve this for the following session, given that we
- 22 are, I think, getting close to noon.

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- 1 drug. If you do design a trial with the goal of a very
- 2 broad claim for a large market and large revenue and
- 3 you win, you win big. But if that trial seeks to
- 4 fulfill an endpoint with a very broad claim and you
- 5 fail, then you don't have usually any more chance
- 6 usually in pharma to recover from that failure.
- 7 So I think that there are two factors that are
- 8 beginning to influence the way we're thinking about
- 9 designing trials. One is that, if you design a trial
- 10 with a narrower claim and you succeed in meeting the
- 11 endpoint, you may have a lower initial revenue. But we
- 12 all know that drugs are complicated. And once they're
- 13 in the clinic, you learn how to use the drug. And from
- 14 that knowledge, you broaden your understanding, and you
- 15 can do another trial with a broader claim and increase
- 16 the revenue.
- 17 No drug, no money. Small market, some money.
- 18 Knowledge, bigger market, more money. That's number
- 19 one.
- Number two is the current trajectory toward
- 21 value-based pricing, meaning that if a drug fails to
- 22 provide the therapeutic effect in a patient for that

- 1 UNIDENTIFIED MALE SPEAKER: The only comment I
- 2 would say is that it's probably not going to be one
- 3 biomarker. I think that you need many because there
- 4 are many different reasons why people have a bad
- 5 outcome.
- 6 And so in the end, you're going to synthesize
- 7 finding multiple biomarkers to correlate with some
- 8 surrogate endpoint and individualize based on those
- 9 results. That is the most likely scenario.
- 10 DR. MEIER-KRIESCHE: I mean, the time is 12:00
- 11 o'clock. I think we need to close the session here.
- 12 And we will reconvene sharp at 1:00 p.m. for the next
- 13 session after the lunch break. Thanks.
- 14 (Lunch break.)
- 15 DR. BALA: Okay. All right. It's time for
- 16 the Session 3 now, which is Potential Early Post-
- 17 Transplant Biomarkers of Alloimmunity or Risk for Graft
- 18 Loss.
- 19 I'm Shukal Bala with the FDA, and my co-
- 20 moderator is Dr. Peter Nickerson from University of
- 21 Manitoba, Canada,
- 22 Our first speaker for today is Dr. Minnie

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- 1 Sarwal from University of California San Francisco, and
- 2 her talk is going to be Noninvasive immune monitoring
- 3 for subacute rejection in kidney transplantation.
- 4 DR. SARWAL: Thank you so much. It's actually
- 5 my pleasure and privilege to talk today about, really,
- 6 the things -- the kind of thinking that we want to
- 7 bring together in this room to address what subclinical
- 8 monitoring -- so sorry -- what monitoring for
- 9 subclinical rejection and inflammation in the context
- 10 of graft injury could actually look like.
- 11 These are my disclosures with not much
- 12 relevance to the talk today.
- 13 So I wanted to start off with this
- 14 introductory slide and actually fashion the talk around
- 15 this in the next 15 minutes. But before I start, I
- 16 just wanted to actually give you one factoid, which I
- 17 think is quite startling for the community, is that we
- 18 -- our reliance on graft injury, our reliance on graft
- 19 rejection, is based on a transplant biopsy.
- 20 But yet if you actually pull a group of
- 21 transplant pathologists and you take the same slide and
- 22 you send them -- send it across to them -- and this has
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- 1 been done in the context of Banff meetings; this has
- 2 been done, actually, by Peter Ferness (ph) in some of
- 3 his very well-published articles -- the concordance
- 4 rate for -- across pathologists for that same biopsy
- 5 slide will range anywhere from about 20 to 30 percent.
- 6 And we are yet relying on that kind of read for what we
- 7 are driving the management of our patients.
- 8 So I'm not even going to talk about that
- 9 issue, but it'll come out as to why getting better
- 10 biomarkers to harness and understand subclinical
- 11 information and injury in a transplanted organ becomes
- 12 critical for us to actually look at.
- 13 So the kind of management gaps that I'm going
- 14 to talk about today is really -- I -- understanding the
- 15 identification of the at-risk population of patients.
- 16 And I'm going to talk about before transplant because
- 17 that very transplant period -- before transplant,
- 18 immediately after transplant -- is really going to
- 19 impact long-term graft survival. And we have data
- 20 previously from (inaudible) from the (inaudible)
- 21 journal that talks about that if you have more than two
- 22 rejection episodes, you can actually lose something

- 1 like nine years of allograft life over time. And
- 2 there's plenty of data around that, so we know that
- 3 that's a bad thing.
- 4 The second part of the talk is going to talk
- 5 about, really, the post-transplant, noninvasive kind of
- 6 application of biomarkers. And this is important for
- 7 us because we want to identify injury before the drift
- 8 in serum creatinine, which is our current gold standard
- 9 for noninvasive or minimally invasive monitoring. And
- 10 we know that that can sometimes rise when more than 60
- 11 percent of that allograft is injured, so we really want
- 12 to move earlier.
- 13 Avoiding the late detection of injury -- and
- 14 that's actually what we're looking at with biopsies
- 15 that are triggered by clinical graft disfunction, so we
- 16 really want to address that. And the minimizing
- 17 invasive biopsies -- so we're trying to address this
- 18 currently by doing protocol biopsies. But that means
- 19 we are trying to do protocol biopsies in every patient.
- 20 And all of us who manage our kidney transplant
- 21 patients, we know that they are actually not very
- 22 excited about doing that. And only probably about 20

- 1 percent of the U.S. transplant programs are doing that.
- 2 So really, why do we want to do this? Because we want
- 3 to give the right drug at the right dose to the right
- 4 patient.
- 5 So let's look at the first problem. So I --
- 6 and Peter Nickerson gave a fabulous talk about looking
- 7 at DNA in the context of HLA disparities and then
- 8 looking at it in a more final microscope and looking at
- 9 things like applet mismatching. So I'm going to talk
- 10 about that and say that it -- that is an extremely
- 11 important focus for us. And for drug trials, looking
- 12 at the patient prior to transplant and stratifying
- 13 which patient they're going to select, I think it's
- 14 extremely important. But can -- but should we even be
- 15 moving a little beyond HLA?
- And so to try and do that, I'm actually just
- 17 going to give you a concept study that we actually
- 18 started at Stanford with Mike Snyder over a cup of
- 19 coffee, and then it actually came to reality and is now
- 20 funded by the catalyst program at QCSF. They basically
- 21 help score kind of high-risk, high-gain kind of
- 22 inventions in academia and try and get them out into

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1 commercialization.

- 2 So through this kind of proposal, we actually
- 3 chose to say that, if you look at the concept of the HY
- 4 mismatch, female recipients who actually get male
- 5 kidneys do mount an anti-HY response. So there is an
- 6 immunogenicity for donor-expressed antigens which the
- 7 recipient lacks.
- 8 So in that concept, should we be looking at
- 9 other non-HLA antigens that the donor is expressing but
- 10 the recipient lacks? And to do that, we actually did
- 11 exome sequencing of the donor as well as the recipient.
- 12 And when we did RNAseq off that donor kidney to make
- 13 sure that whatever the variant mismatch was, was
- 14 actually an expressed variant in that donor kidney. We
- 15 weren't interested if it was present just in spleen or
- 16 testes, et cetera. So it was really the transplanted
- 17 organ.
- And the concept was that if you had a variant
- 19 that actually was mismatched between donor and
- 20 recipient, it could cause a change in the transcription
- 21 factors, the metalation, et cetera, such that there
- 22 could be an immune recognition off that antigen because

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1 of that variant mismatch. Of course, the question is

- 2 what does that mean and does it actually correlate with
- 3 functional outcome.
- 4 So to try and do that, this is actually the
- 5 data. And when we did the whole exome sequencing, of
- 6 course, we can also look at HLA. And you can see that
- 7 donor recipient HLA variant mismatches, as we expect,
- 8 are higher in people who reject. And the red is people
- 9 who developed antibody-mediated rejection after
- 10 transplant, T cell mediated rejection after transplant
- 11 on new rejections. So you can see higher variant
- 12 mismatches.
- But what happens if you look at the rest of
- 14 the variants in a non-HLA part of the genome? And you
- 15 can see that, in fact, you can see this actually gets
- 16 even more enhanced. So we are missing a lot of stuff,
- 17 that, really, we're looking at the tip of the iceberg
- 18 here with the HLA. But there's a lot of stuff
- 19 happening in the non-HLA compartment that we're not
- 20 even recognizing. And you can see across all these
- 21 thousands of variants those that are enriched in the
- 22 kidney are actually much higher here.

And so this tells us if we, again, take those

- 2 HLA variants and we try and cluster our patients across
- 3 the variants with a color combination still (inaudible)
- 4 category, you can see again the mismatches that kind of
- 5 -- if you were to take a pretransplant sample, do the
- 6 donor-recipient variance on HLA and cluster of (ph)
- 7 patients, could you have told risk?
- 8 Peter is showing that, in large numbers, you
- 9 can start to see that separation after transplant. But
- 10 in smaller numbers, you're not being able to see that
- 11 kind of clean separation. Can you actually see that
- 12 with the non-HLA variance?
- 13 So we have 123 variants that will be mapped,
- 14 highly expressed in the kidney, highly expressed in
- 15 immune cells, highly expressed, also, in endothelial --
- 16 the compartment. So that's what the bioinformatic
- 17 algorithm enriched for. You can see it's actually
- 18 quite nice. You can start separating people who
- 19 developed AMR, TCMR on this kind of axis. And here are
- 20 the people who did not reject.
- 21 So the reason I put this to you is I think the
- 22 kind of technologies we have today can harness this

- 1 kind of information such that focusing on that
- 2 pretransplant selection of the patient who has maximum
- 3 risk is really important. But of course we don't want
- 4 to be doing exome sequencing and spending \$2,000 per
- 5 patient. Can you reduce this to a SNP array? So we
- 6 actually have generated a fluidigm SNP array customized
- 7 for the 123 recipients as a four hour turnaround time.
- 8 Cost of goods is about \$250 per sample. And you can
- 9 actually get pretty good data.
- 10 So this is the SNP array now, an independent
- 11 validation set. And you can see that these are
- 12 actually the SNPs. So this is a -- if it is red, there
- 13 is a donor recipient variant mismatch for the SNP;
- 14 white, there is no variant mismatch. You can see here
- 15 are the people who actually do -- antibody mediated
- 16 rejection after transplant, T cell mediated rejection.
- 17 There are few variants that are actually enriched for
- 18 people who do not reject, which may be protective.
- 19 And you can see here on the Y axis is if you
- 20 actually got -- the donor was actually related,
- 21 unrelated, and if there's race, if it's related to
- 22 African American versus Caucasian, et cetera. But you

1 can see the real prime separation is for the event

- 2 after transplant.
- 3 So I'm not going to present more data on this,
- 4 but we have actually large-scale validation on about
- 5 800 donor recipient pairs. But the idea is that you
- 6 can take these kind of custom SNPs before. You can
- 7 combine them with the HLA data that you're getting.
- 8 You can run the panel on across these non-HLA variants.
- 9 And these are the most common variants, so, really, the
- 10 low-hanging fruit. The future, of course, would be is
- 11 to customize this to each donor recipient pair, which I
- 12 think is the end of the goal here.
- But essentially, if you're getting closure --
- 14 included all these variants, you could really select
- 15 for drug trials which is that patient group that you
- 16 want to highly enrich that could be having that event
- 17 after transplant or absence of event.
- So we've talked about that. Let's look at the
- 19 post-transplant patients. So in post-transplant
- 20 monitoring, this is actually where we're managing our
- 21 patients today. So we see our patients in clinic.
- 22 They actually have a change with regards to

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- 1 proteinuria, GFR decline. We could do the iBox over
- 2 here. We could say how those people are going to
- 3 respond. But actually, you believe that maybe we are
- 4 missing stuff.
- 5 So what -- as I said, about 20 percent of the
- 6 programs will do a protocol biopsy. We actually pick
- 7 up all the subclinical rejection, and we try and treat
- 8 these patients. There is enough data about that, that
- 9 if you treat inflammation and you treat inflammation
- 10 early, you actually can improve outcome with regards to
- 11 GFR, et cetera.
- But here, I'd like to put to you is that more
- 13 are happening beneath the surface. So rather than just
- 14 relying on clinical parameters or doing a protocol
- 15 biopsy, could you actually do something else that will
- 16 give you the molecular health of the allograft? And
- 17 why is that important? That is important because if
- 18 you actually look at the protocol biopsy, when you
- 19 actually have subclinical inflammation in the graft --
- 20 and we've done a lot of this work at Stanford and at
- 21 QCSF, we've actually found that, about 30 percent of
- 22 them are actually molecularly active. Seventy percent

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- 1 of them actually could be molecularly quiescent.
- 2 So just looking at what the histology shows is
- 3 sometimes very difficult for us to actually take that
- 4 and proceed to the right kind of treatment for our
- 5 patient.
- 6 So how do we actually address this? So to go
- 7 there, we actually propose to actually take a urine
- 8 specimen over here and look at the molecular health ϕf
- 9 the allograft as reflected in the urine. I'm just
- 10 going to present you that data today and not present
- 11 you new data on blood.
- 12 And so why is this important? Because if you
- 13 actually look at the study of protocol biopsies, these
- 14 are protocol biopsies and at 0, 6 -- 0, 3, 6, 12, 24,
- 15 and 36 months as part of an NIH multi-center study
- 16 across 12 programs in the U.S. You can see that, even
- 17 in the absence of any donor-specific antibody, these
- 18 were just the patients selected who had no donor-
- 19 specific antibody, no clinical acute rejection. You
- 20 can see if you did multiple protocol biopsies, which is
- 21 not a reality for our patients, you can see there is a
- 22 progressive accumulation of injury that's occurring in

- 1 these allografts. This is injury that we do not
- 2 recognize because these patients largely have a stable
- 3 serum creatinine. How are we actually going to figure
- 4 out this injury? Because we're not going to be
- 5 biopsying our patients all the time.
- 6 So the question is: What do we do? So we did
- 7 molecular analysis off these biopsies to ask: Is there
- 8 a difference in people here who actually had a three-
- 9 or six-month protocol biopsy? Could we have done a
- 10 molecular analysis here and predicted that they would
- 11 have got there? So can we take two groups of patients
- 12 -- patients who got there really fast -- we call them
- 13 progressors; patients who got there really slowly -- we
- 14 call them non-progressors? And is there a difference
- 15 in the molecular profile? And you can see there is.
- 16 So these are patients who are progressing over -- so
- 17 you can see these are the non-progressors in blue, and
- 18 we looked at basically immune signatures that actually
- 19 drove. See, there's a gene set analysis.
- 20 So when we looked at genes involved in T cell,
- 21 B cell proliferation, natural killer cell, mast cell,
- 22 so in allo and innate immunity was increased at the

1 six-month protocol biopsy time point when they were

2 histologically normal and not differentiable. And you

3 can see over time these scores increased.

4 So take-home message is there's more fibrosis

5 occurring. There's more injury occurring. But guess

6 what. There's also more molecular inflammation

7 occurring, and that's what's driving it. And in fact,

8 the take-home message here is that if you actually look 8 standard of care? Yes. But I think it was pointed out

9 at these scores at six-month protocol biopsies here --

10 again, the progressor, non-progressor -- you can see

11 they're higher. It's -- you can see it's the same

12 signature that's occurring at the time of acute

13 rejection.

14 So what we are missing today and why we need 14

15 better biomarkers after transplant is we need to

16 uncover that subclinical injury, which is really a

17 threshold effect of what is happening at acute

18 rejection. If you can pick it up really early and you

19 can pick it up noninvasively, you can treat it, and you

20 can avoid them actually going to a full-blown acute

21 rejection.

22 So how can you actually do this? And so to Page 216

1 start to separate at the time of biopsy. We call this 2 set kind of a kidney injury test or kit. And you can

3 see that if we actually look at these biomarkers and we

4 compare them to the current standard of care in urine.

5 which is proteinuria, you can see that it -- the

6 performance is significantly better.

7 So do we have something better than current

9 earlier. The risk of these kind of biomarkers that are

10 very sensitive and specific for inflammation is that it

11 will give you that false positive, or, should I say,

12 true positive because it'll detect injury when we

13 didn't think there was injury.

So I think the best way to reflex this for

15 monitoring in the context of drug trials may be to look

16 for absence of injury. So quiescence may, in fact, be

17 the most important thing.

18 So really, this conclusion is that, to

19 evaluate drug efficacy, how do you actually treat this?

20 So I think the take-home message is, just because your

21 graft is clinically stable or histologically stable

22 doesn't mean that it is molecularly stable. So

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1 try and get to this, we've actually done extensive

2 studies. And these are published papers. I'm not

3 going to go into details. But we looked at solid organ

4 transplants undergoing acute rejection and identified a

5 common hub of genes which we called the common response 5 you're seeing as a molecular inflammation and what we

6 module. They're all highly kind of co-regulated

7 through STAT1 and NF-kappaB, et cetera. And you can

8 see they've actually reduced this kind of learning down

9 to a urine pellet isolated at the time of the biopsy

10 and actually validated these genes as being able to

11 drive the detection of inflammation in the biopsy but

12 by a urine sample.

And so you -- we've also done a lot of

14 proteomic work, and we've been lucky to have

15 consecutive funding from NIDDK to actually look at deep

16 proteomics in the urine and to try and look at panels

17 of biomarkers that can correlate of this molecular

18 injury in the graft but with a urine sample.

19 So what does this mean? So we've been able to

20 take these biomarkers and create a gene set score and a

21 protein set score. So this a combination of different

22 biomarkers. And you can see in large datasets they can

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1 therefore, inclusion of these kind of urine assays or

2 noninvasive assays to quantitate information I think is

3 extremely important. And actually, it's important to

4 recognize that there is this discordance between what

6 have not been able to recognize histologically.

7 And I think, again, in the post-transplant

8 setting, how can we use this? We can use this for

9 monitoring drug efficacy in trials that are actually

10 using novel treatments as well as for quiescence.

11 And so this is my last slide to show you. We

12 are doing some of this at UCSF. So this is some kind

13 of trials that are being run through NIAID-funded,

14 CTOT-21 trials led by Flavio Vincenti, who is a PI. So

15 we actually got regulatory (ph) T cells that are being

16 infused at the time of subclinical inflammation, as

17 recognized by a six-month protocol biopsy. And we are

18 also trying to give (inaudible) map to block the IL-6

19 access at the time of subclinical inflammation

20 recognized by a protocol biopsy.

21 The preliminary data with (inaudible) map

22 suggests that it's very difficult for us to just look

- 1 at the biopsy and say this is subclinical inflammation.
- 2 So we are actually combining this with these kind of
- 3 urinary biomarker studies to actually provide us a
- 4 better way to assess selection of the patient for that
- 5 drug and then also to look at efficacy when that noise
- 6 of what is inflammation is actually very little. And
- 7 you're going for that very early period post-
- 8 transplant.
- 9 So I think this is just to say that I think
- 10 this is what we have been wanting to take some of these
- 11 biomarkers for. I tried to actually put them on this
- 12 slide and say that, yes, we need assessment. We can do
- 13 assessment of transplant rejection risk before
- 14 transplant. We can mainly potentially have, like, a
- 15 drug that's being used to diminish transplant fibrosis
- 16 or treat AMR. And we know we have companies here that
- 17 are interested in bringing these trials forward. We
- 18 can use the kind of DNA and protein biomarkers to
- 19 select before as well as to stratify the efficacy of
- 20 the drug and safety of the drug after transplant.
- 21 I'd like to really recognize the many, many
- 22 people in our community that helped us, funding from
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- 1 all these -- I just put up a picture of the people in
- 2 my lab who have been integral for a lot or the work
- 3 that has been shown today.
- 4 Thank you so much.
- 5 (Applause.)
- 6 DR. NICKERSON: Thank you, Minnie.
- 7 Our next speaker will be Dr. Michael Abecassis
- 8 from Northwestern Medicine -- Medical School in
- 9 Chicago.
- 10 Mike.
- 11 DR. ABECASSIS: I want to thank the organizing
- 12 committee for the opportunity to present our work. I'm
- 13 going to focus today on findings from CTOT-08, which is
- 14 a NIAID-funded study.
- 15 First, disclosures. I'm a co-founder,
- 16 shareholder, clinical, and scientific advisor to a
- 17 company called Transplant Genomics Incorporated, which
- 18 does this test. Also, I shamelessly used a bunch of
- 19 material provided during the planning sessions from my
- 20 talk today, as I see most other people did as well.
- 21 So the data that I'm going to present today
- 22 has recently been published. And I want to acknowledge

- Page 22
- 1 John Friedewald, who is obviously the -- not only the 2 site PI at Northwestern, but the protocol PI for the
- 3 entire consortium. And I'm only going to present data
- 4 today from that study that focuses on subclinical acute
- 5 rejection, which Minnie has done such a wonderful job
- 6 introducing.
- 7 So our definition was histologic evidence of
- 8 rejection on a protocol or surveillance biopsy. As a
- 9 matter of fact, greater than 90 percent of our
- 10 subclinical rejections in this cohort were borderline.
- 11 And also, stable renal function -- and this was defined
- 12 as less than 20 percent change compared to the average
- 13 of the previous 2 to 3 values and a creatinine less
- 14 than 2.3.
- 15 This is a diagram illustrating the study. And
- 16 the important thing is that all patients underwent
- 17 surveillance protocol biopsies at either 3 or 6 months,
- 18 12 and 24 months and also a serial biomarker
- 19 monitoring, including at the same time as they got a
- 20 biopsy. Patients also had for-cause biopsies, et
- 21 cetera, et cetera. And again, the focus here was
- 22 subclinical rejection.

- 1 So this is a busy slide. The left panel shows
- 2 our algorithm for the analytics of the study. Just to
- 3 briefly go over this, we first looked at about 3,000
- 4 differentially expressed genes. These were mapped
- 5 using three different softwares and mapped very nicely
- 6 to genes related to rejection.
- We then took these and put them through a
- 8 random forest model, used Genie for importance and
- 9 reran them through a random forest model. This allowed
- 10 us to create our model that had 61 probe sets that
- 11 mapped to 57 genes. We had a discovery set that
- 12 included 530 paired samples. These were surveillance
- 13 biopsies and peripheral blood sample. And then we had
- 14 a validation cohort, which was from the Northwestern
- 15 University Biorepository. And we started out with 138
- 16 patients who met the criteria of stable and
- 17 surveillance protocol biopsy and that -- then used 129
- 18 that met precisely the definition that was used in the
- 19 CTOT study.
- 20 And so in our discovery set, the AUC was about
- 21 85. We purposely identified a threshold that gave us
- 22 more specificity than sensitivity. And I'll come back

- 1 to that. And then we locked down the algorithm. We
- 2 locked down the model. We locked down the threshold.
- 3 And then we tested each sample as an unknown in the
- 4 validation study.
- 5 And so the table at the bottom shows the
- 6 performance of the biomarker in both the discovery and
- 7 the validation cohort and then the subcohort. And the
- 8 reason for doing those two is one was clinically what
- 9 we would consider a stable patient, and the other one
- 10 was what the protocol required to be called a stable
- 11 patient. As you can see, there weren't many patients
- 12 that fell out of that second group.
- 13 So this was a prevalent population. There
- 14 were 400 of these had met the definition of no
- 15 rejection, stable creatinine, and 130 met the
- 16 definition of stable creatinine and rejection, which
- 17 was subclinical rejection. We used exactly the same
- 18 threshold to determine whether the test was positive or
- 19 negative. And you can see here the MPV on discovery
- 20 was 88 percent, and it was 78 to 80 percent in the
- 21 validation cohort. And then the PPV was 61 percent in
- 22 the discovery and 47 to 51 percent in the validation
 - Page 223

- 1 cohort.
- 2 The important other number to consider here is
- 3 that the test was calling positive approximately the
- 4 same proportion of patients that had the phenotype. So
- 5 we didn't way overcall one phenotype or the other.
- 6 So in terms of what this all means, we had
- 7 designed the study to, obviously, capture a whole bunch
- 8 of clinical data. By the way, this was all reviewed by
- 9 Roe (ph), which was the DCC, by the NIH, by the
- 10 steering committee. These data were reviewed by
- 11 everybody prior to even being allowed to present a
- 12 single bit of it.
- And what this shows -- at least it wasn't a
- 14 surprise to us, but I think it might be a surprise to
- 15 some -- that the biomarker -- I'm sorry -- that the
- 16 clinical phenotype, which is based on the biopsy, if
- 17 you looked at people that had no episodes or one or
- 18 greater episodes of subclinical rejection, there was a
- 19 statistically significant association with a -- both a
- 20 clinical composite endpoint that consisted of acute
- 21 rejection, clinical acute rejection, with renal
- 22 disfunction. It consisted of a delta EGFR greater than

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- 1 10 between 4 and 24 months and Grade 2 or more IFTA on
- 2 the 24-month biopsy. So we used that as a composite,
- 3 and we also found a clear association with both Class 1
- 4 and Class 2 de novo DSA. And this was a clinical
- 5 phenotype. So this is no biomarker. This is just a
- 6 clinical phenotype.
- Then we went and looked at the biomarker
- 8 independent of the clinical phenotype and asked the
- 9 question: How does the biomarker associate with these
- 10 exact same endpoints? And again, we found statistical
- 11 significance with the composite clinical endpoint as
- 12 well as with de novo DSA almost identical to what we
- 13 found with the clinical phenotype, even though there
- 14 wasn't 100 percent concordance, as you saw from the
- 15 performance of the biomarker between the clinical
- 16 phenotype and the biomarker.
- 17 This was kind of interesting. I thought this
- 18 was the most interesting part of the study. So I show
- 19 you the design again because what we asked was that,
- 20 when a patient had subclinical rejection on a protocol
- 21 biopsy and whether they were treated or not by the
- 22 center, we followed that patient with biomarker
- Page 225
- 1 determination every two weeks. And at eight weeks, we
- 2 demanded a repeat biopsy. So this was not easy for
- 3 centers to accept, but the centers that enrolled
- 4 accepted to do this.
- 5 We did say that this was only allowed once per
- 6 subject. We didn't want subjects to have to do this
- 7 more than once because, not only were they getting a
- 8 surveillance biopsy, but they were getting an eight-
- 9 week repeat surveillance biopsy and only if the serum
- 10 creatinine remained stable.
- And in order to analyze these, we had to have
- 12 all blood samples in both biopsies. And centers were
- 13 allowed to treat per their standard of care. And the
- 14 amazing thing was, first of all, that greater than 50
- 15 percent of patients treated for subclinical rejection
- 16 did not respond histologically at the eight-week
- 17 biopsy. The biopsy was either persistent or worse.
- And when I went around and asked my colleagues
- 19 at Northwestern to give me a guess, they all said 80
- 20 percent would respond, 90 percent would respond. You
- 21 know, it's subclinical rejection. Of course they're
- 22 going to respond. It turns out that was not the case.

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1 So this was very important.

2 The second part that was very important -- I

3 don't know what just -- the second part that was very

4 important was that you could predict who was going to

5 respond histologically and who wasn't going to respond

6 histologically based on the biomarker at four and eight

7 weeks. Interestingly enough, at baseline, even though

8 we had 23 patients with a positive biopsy, 13 had a

9 positive test and 12 had a negative test. And of the

10 patients who had a negative test, they all resolved.

11 And of the patients who had a positive test, 75 percent

12 did not resolve.

13 So we started to think that maybe, you know,

14 the test was giving us more information, which is, I

15 think, what Minnie was alluding to, than the actual

16 biopsy. So this was a really important and surprising

17 result.

18 So the summary is that, in patients with

19 stable renal function -- and I emphasize that again --

20 where you think everything's fine, there's nothing

21 going on, right now, the only way to detect subclinical

22 rejection is a surveillance biopsy. So these were all

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1 paired samples. We used microarray. We used 3,000

2 differentially expressed genes that map to relevant

3 pathways, the rejection, and populated the random

4 forest models. I showed you the performance. And we

5 showed a clear association between both the clinical

6 phenotype and independently the biomarker with clinical

7 endpoints known to be associated with poor long-term

8 outcome. And also, as I said, it showed that less than

9 50 percent of patients treated for subAR demonstrated a

10 histologic response.

Okay. And so now, I tried to take all of this

12 and put it into the framework that we were given and

13 asked to try to reconcile with our data. So you've

14 seen this now, and I'm not going to go over it. So I

15 constructed a context of use statement.

16 So first, the need statement. I think Minnie

17 just said this. SubAR, or silent rejection, is bad for

18 long-term graft outcomes, which have not improved in

19 decades. The only way to currently diagnose this is

20 through empirically scheduled surveillance biopsies.

21 But 80 to 85 percent of these empirically scheduled

22 surveillance biopsies are negative, which means that

1 the test, this invasive biopsy, was unnecessary and

2 exposed patients to unnecessary risk.

3 Also, the only way to currently diagnose

4 persistent subclinical rejection following treatment,

5 which we know happens in greater than 50 percent of

6 patients, is to repeat yet another invasive biopsy.

7 Therefore, there is a clear need for noninvasive

8 biomarkers to inform the use of surveillance biopsies

9 in patients with stable renal function following kidney

10 transplants.

11 So the context of use would be to serially

12 monitor patients following kidney transplant with a

13 blood-based biomarker that can be used in ruling out

14 subAR, identifying patients with adequate exposure to

15 immunosuppressant, immune-quiescent patients, at a

16 lower risk of harboring subclinical rejection, which we

17 all know forms part of the arc of chronic rejection.

18 Therefore, the objective would be to use the biomarkers

19 to guide the stratification or enrichment of patients

20 into a group that might more predictably or

21 prognostically benefit from a surveillance biopsy to

22 detect subclinical rejection or inadequate

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1 immunosuppression in order to better individualize the

2 management of kidney transplant.

3 So again, I stole another figure, and I used

4 it to go through CTOT-08 data and go through the

5 checklist that was provided and put a checkmark next to

6 where we thought -- where I thought we had evidentiary

7 -- or evidence.

8 So the relationship of the biomarker to

9 clinical outcome -- well, I showed you that that was

10 the case. Biologic rationale for use of the biomarker

11 -- I showed you that that was the case.

12 The data and study design -- this was an

13 observational study. This was a prevalent population.

14 All samples were paired. I think, as far as design is

15 concerned, you know, for an observational study, it was

16 as well designed as it could have been -- serial

17 samples.

18 The reproducibility of data was demonstrated

19 through an independent cohort. There's a comparison to

20 the gold standard. Whether we like it or not, the

21 biopsy is the gold standard.

22 The assay performance I showed you very

- 1 importantly. When you're doing a performance of an
- 2 assay, it's essential to have a prevalent population.
- 3 If you have a phenotype that's 20 percent and it's 50
- 4 percent in your validation set, you're going to
- 5 increase your PPV. And also, prespecify statistical
- 6 analysis -- so these were off-the-shelf software
- 7 programs that everybody knows and uses. We did not
- 8 have best-fit algorithms.
- 9 So I also tried to think about this biomarker
- 10 in the context of BEST. And I found myself struggling
- 11 a little bit. And so I tried to put a solid circle
- 12 where I thought that it sort of fit and a dotted circle
- 13 where I thought that maybe it fit but I wasn't sure.
- 14 And so when I tried to define what type of biomarker
- 15 this was, I wasn't really that sure. It seemed to fit
- 16 into more than one category. And this goes back to my
- 17 earlier comment that this isn't for drug development.
- 18 So this is a way to monitor patients. So I wasn't
- 19 sure, and I'd sure love some help trying to figure out
- 20 what kind of biomarker this is.
- In terms of the level of evidence, it's
- 22 important to look at potential benefits and risks.
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- 1 Potential benefits -- obviously reducing the number of
 2 indiscriminate or empirically scheduled surveillance
- 3 biopsies that are invasive by stratifying or enriching
- 4 patients with stable renal function and then
- 5 stratifying patients into lower or higher risk of
- 6 harboring subclinical rejection on a protocol biopsy,
- 7 reducing the number of negative or unnecessary
- 8 biopsies, and stratifying patients treated for
- 9 subclinical rejection with stable function who may not
- 10 -- who may show histologic response or nonresponse to
- 11 treatment.
- 12 Potential risks -- well, you could argue that
- 13 you could increase the number of surveillance biopsies,
- 14 especially in programs that do not currently use them.
- 15 You could increase the risk of monitoring biopsies
- 16 because no one does them now. And you could over-
- 17 immunosuppress secondary unmasking of subAR, but we
- 18 just all finished saying that that's a good thing. But
- 19 it is a risk.
- 20 I wanted to acknowledge Dan Solomon (ph)
- 21 without whom none of this work would ever have
- 22 happened. You all know him, and he's here with us

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- 1 right now. And so I wanted his picture to be up there
- 2 and I wanted to quote him. "The promise of precision
- 3 medicine will only be achieved when molecular
- 4 diagnostics detect actionable differences operating in
- 5 individual patients that can inform management and
- 6 change clinical outcomes."
- 7 And so to that end, I just wanted to give you
- 8 a glimpse about a randomized control trial that we are
- 9 planning. And it's hard to see, but on the left is the
- 10 standard of care. This would be compared only to
- 11 patients that get surveillance biopsies, so it would be
- 12 done at centers where patients get empirically
- 13 scheduled surveillance biopsies. And then the bottom
- 14 line is that either a single negative screening, a true
- 15 graft test -- that's what the test is called -- or two
- 16 negative tests following a positive test would be
- 17 required to forego a surveillance biopsy. So the
- 18 surveillance biopsy is the default, which is what would
- 19 be done in the standard of care arm.
- 20 And if anybody has any questions about this,
- 21 I'm happy to answer them. And that's it.
- 22 So acknowledgments -- I want to acknowledge,

- 1 as I mentioned, John Friedewald and all the members of
- 2 the CTOT-08 Consortium. This was a five-center study
- 3 funded by NIAID date. Roe (ph) was instrumental in all
- 4 of the data, acquisition, analyses and all the co-
- 5 authors of the manuscript.
- 6 I also want to thank all the transplant
- 7 coordinators at all the sites -- the research services
- 8 corps (ph), care providers, et cetera -- and also the
- 9 steering committee of CTOT, including Dr. Bridges (ph).
- 10 And as far as funding support, here are the sources --
- 11 and Transplant Genomics as well as the Northwestern
- 11 and 11anspiant Genomics as well as the 1vorthwestern
- 12 University Comprehensive Transplant Center.
- 13 Thank you very much.
- 14 (Applause.)
- DR. BALA: Thank you, Dr. Abecassis.
- 16 Our next speaker is Dr. Barbara Murphy from
- 17 Mount Sinai School of Medicine New York. And her talk
- 18 is going to be on genomic approach to immune
- 19 stratification.
- 20 DR. MURPHY: Thank you very much. I'm
- 21 delighted to be here today to present our data. And
- 22 thank you very much to the organizers for, first of

1 all, organizing this and also for inviting me.

- 2 So I want to -- my disclosures on several
- 3 DSMBs. Also, I just want to point out Renalytix, which
- 4 is a company formed in collaboration with Mount Sinai,
- 5 which is a licensing agreement with the patents that we
- 6 have on these studies here.
- So the results that I'm presenting today are
- 8 from the study funded by the NIH, the NIAID, called
- 9 Genomics of Chronic Allograft Rejection. This is a
- 10 prospective multi-center study that included five
- 11 clinical sites -- Mount Sinai, Northwestern at Ann
- 12 Arbor, Wisconsin, and Sydney Westmead Hospital in
- 13 collaboration with Brigham and MDH, also.
- 14 And this was really -- we enrolled 588 renal
- 15 transplant patients over a period of three years,
- 16 following them for two years doing baseline biopsies,
- 17 baseline blood sampling for RNA, DNA, and then
- 18 (inaudible) biopsies at 3 months, in some cases 6
- 19 months -- 12 month -- and then in all sites 12 months
- 20 and 24 months. And this really was to look at genomic
- 21 prefile -- profiling pre- and post-transplantation to
- 22 determine whether we could predict outcomes or diagnose

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- So as I said, this is blood from a recipient 1
- 2 before they have seen the transplant. And what we did,
- 3 we -- a total of 247 patients had RNAseq performed, and
- 4 163 of those had biopsies be at -- before six months.
- 5 Eighty-two had biopsies after six months. So we had
- 6 clinical indication biopsies as well as protocol
- 7 biopsies. In the patients with biopsies before six
- 8 months, we had a discovery set of 81 patients,
- 9 validation set of 74, and then the second validation
- 10 was using the later time point for acute rejection.
- 11 What we looked at was early acute rejection,
- 12 i.e., rejection before six months. We eliminated from
- 13 the analysis initially. When we were developing the
- 14 gene set, we eliminated BK, and I'll come back to that.
- 15 And so that reduced the validation set to 74 and 80.
- 16 And what you can see here from our -- on the
- 17 left-hand side form the discovery set was that we were
- 18 able to -- the 23 -- we identified the 23 genes. And
- 19 there's an AUC of 0.8 with an MPV of 0.875, PPV of 0.7.
- 20 And this compares to clinical factors, these clinical
- 21 factors in this population with an MPV of 0.7 and a PPV
- 22 of 0.5, so, clearly, outperforming that.

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- 1 outcomes in transplantation. And it really is learning
- 2 set to identify MRNA biomarkers, which would then
- 3 validate it in multiple independent datasets.
- 4 And I'm rushing because what I'm trying to do
- 5 today is show you three of the assays that we have
- 6 developed. And what I will do is go quite quickly
- 7 through them. I'm not giving you all of the data
- 8 related to them, but I really just want to give you a
- 9 sense of what we're doing in the lab. And if there's
- 10 further data that you would like to hear, I can answer
- 11 any questions or tell you afterwards.
- 12 So the first of the assays that we have
- 13 developed is a pre-transplant assay in recipient blood, 13 these risk score in individuals that had four or less
- 14 which has identified 23 genes. It -- the needs
- 15 assessment or -- of -- with regards to this is really
- around the lack of our ability as we've discussed to
- 17 stratify immunological risk in patients prior to
- 18 transplantation. And the context of use is risk
- 19 stratification prior to transplantation and potentially
- 20 patient selection and clinical trials. I suggest that
- 21 this biomarker is prognostic and also fits into the
- 22 risk stratification section for biomarkers.

- 1 When you look at the validation set, so this
- 2 was all comers. We didn't break them out into looking
- 3 at patients who had acute rejection versus those who
- 4 had no acute rejection. This is looked at as a
- 5 continuum. And you can see here we broke -- they broke
- 6 out into turtiles (ph).
- 7 What we -- I -- what we did find, when you
- 8 brought in donor variables, the only donor variable
- 9 that was additive to this recipient risk index was HLA
- 10 mismatching. So if an individual had five or six
- 11 antigen mismatches, it improved the AUC to 0.89. If
- 12 you look down at the bottom here, when you look at
- 14 mismatches, you can clearly break out those who have --
- 15 ultimately have no acute rejections versus those who
- 16 are very high risk for acute rejections with a PPV of
- 17 75 -- 0.75 and an MPV of 0.1.
- 18 Oops. When you look at the risk score, it
- 19 also identifies individuals at risk for graft loss at a
- 20 later time point -- and when you -- shown on the left-
- 21 hand side, and also then looking at AUC for risk of
- 22 graft loss by two years with an AUC of 0.9, and then in

1 pink the risk for graft loss by five years of 0.82.

- 2 This is where you bring everything together.
- 3 And it's looking at the gene risk score in the top --
- 4 the gene expression in the top panel, looking at the
- 5 continue based on probability, breaking out into
- 6 turtiles of high, intermediate, and low risk, and then
- 7 in the bottom panel looking at early acute rejection,
- 8 late acute rejection, ABMR, de novo DSA, and graft
- 9 loss. And you can see how, really, I could actually
- 10 move that line over and break it into two groups, which
- 11 clearly differentiate those at individual -- those
- 12 individuals at risk for an event post-transplant versus
- 13 those who will be extremely unlikely to have an event
- 14 post-transplant.
- What's interesting, when we went back and
- 16 looked at the individuals that developed BK, they all
- 17 fell into the lower-intermediate risk, suggesting that
- 18 if we had avoided induction therapy in these
- 19 individuals, certainly in the low-risk group, we
- 20 potentially could have avoided BK.
- 21 So when we look at the clinical validity
- 22 clearly with the training set, the validation set, and

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- 1 then when you look at gene set plus HLA mismatch, the
- 2 AUC, the PPVs, the MPVs, sensitivities, specificities
- 3 are all extremely high-performing compared to the
- 4 clinical factors alone, which we have discussed earlier
- 5 on as being problematic.
- 6 The second assay that we have been developing
- 7 is similar to the two presenters previous with some
- 8 variable -- variabilities. Looking to diagnose
- 9 subclinical acute rejection, it also has been shown to
- 10 diagnose clinical acute rejection. This is a 17 gene
- 11 set, really, developed from three month -- by blood in
- 12 -- both of the baseline and this assay are using RNAseq
- 13 at -- this is, in this case, at three months post-
- 14 transplant, the context of use being immune monitoring,
- 15 diagnosis of subclinical or acute rejection and which
- 16 are currently things that were not -- that are not
- 17 feasible clinically as a biomarker. It would suggest
- 18 it is diagnostic versus an alternative endpoint, though
- 19 we've also been discussing the idea that we need to --
- 20 I'll get back to -- understand how to actually withdraw
- 21 immunosuppression even in studies where we are using
- 22 new novel agents. We still are left with the fact that

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- 1 we are tapering our standard immunosuppression at the
- 2 same rate, and this may be a way of monitoring to guide
- 3 immunosuppression withdrawal irrespective of whether
- 4 it's new or old medication that we are using.
- 5 So this is a GoCAR cohort again -- 191
- 6 patients. The initial discovery set was done with
- 7 RNAseq and microarray with overlap between those two,
- 8 so 127 patients, some overlap of about 7 -- 4 -- 17
- 9 patients to demonstrate technical (ph) validity between
- 10 the two platforms. We would then used the 17 genes
- 11 that we identified to go on and develop a targeted
- 12 sequencing using MiSEQ or the TREx assay, which is an
- 13 FDA-approved platform for an assay. There is 113
- 14 patients in the training set and 110 patients in the
- 15 validation set, 64 from GoCAR and 46 from an
- 16 independent cohort from Belgium.
- What we show here is, in the training set in
- 18 AUC of 0.982 on the 127 patients, a PPV of 0.77, an MPV
- 19 of 0.967. We validated then three external cohorts.
- 20 So what's important about these? These are clinical
- 21 acute rejection, and they are from biopsies taken at
- 22 multiple time points, which would suggest that this

- 1 performs over time. And we've also used it at a six-
- 2 month time point in our cohort in GoCAR.
- This is data from the TREx assay showing that
- 4 we can validate it just with the targeted sequencing of
- 5 the 17 genes on a third platform. This is the training
- 6 set for the TREx showing an AUC of 0.83, an MPV of
- 7 0.786 and -- a PPV of 0.786, MPV of 0.977, so very
- 8 high-performing. And again, you see this continuum
- 9 when you look at it based on probability score.
- This is the independent validation set at 3
- 11 months on 110 patients. What's really interesting is
- 12 you look at that intermediate group, and you think look
- 13 at all these patients that are falling in there.
- 14 They're not in a high-risk group. What's going on?
- 15 There are patients in there with no acute
- 16 rejection. There are patients with acute rejection.
- 17 When you look at them, they actually have a higher risk
- 18 for graft loss than the high-risk group. In fact, what
- 19 happens is the high-risk group are more likely to go on
- 20 to develop clinical acute rejection, whereas the
- 21 intermediate group do not. And I would surmise that
- 22 they are individuals that get on -- go unnoticed and

- 1 actually go on. We've shown that they have higher
- 2 caddy (ph) at a later time point, higher rate of graft
- 3 loss. And they're individuals that go undiagnosed.
- 4 And it's not just skewed by the individuals
- 5 with acute rejection. Those with no acute rejection
- 6 perform the same as those with acute rejection and
- 7 clearly very well able to differentiate individuals
- 8 with no risk for acute rejection, no underlying
- 9 rejection.
- 10 So I think it's -- we validated this in
- 11 multiple cohorts, multiple platforms, and currently
- 12 have developed a TREx assay and validated that. And
- 13 it's an FDA-approved platform, and we're in the process
- 14 of doing that for our baseline assay, also.
- 15 I think I'm going as fast as I can.
- And lastly, this is actually published data.
- 17 The other two are just submitted. And this is an assay
- 18 which predicts at -- on a three-month biopsy the
- 19 likelihood for developing fibrosis at 12 and 24 months
- 20 and going on to lose your graft in biopsies that look
- 21 good. Pathologists can't tell who with -- from those
- 22 people will develop fibrosis. The clinical factors
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- 1 don't differentiate them. The AUC for that is pretty
- 2 much like flipping a coin.
- 3 So these are individuals that we would expect
- 4 to do well, and they go on to develop fibrosis and lose
- 5 their kidneys. And this is an assay that identifies
- 6 those individuals at a time when we could potentially
- 7 intervene and prevent graft loss. This is -- a
- 8 learning set was of 101 patients, a validation set of
- 9 45, and two publicly available datasets. Context of
- 10 use is identifying individuals that were high risk for
- 11 graft loss. And currently, the number of patients
- 12 required to study or identify an agent that would
- 13 prevent graft loss or impact graft loss are too large,
- 14 and this would -- could be used as a potential
- 15 alternative endpoint.
- 16 It's also maybe for risk stratification of
- 17 individuals within clinical trials. So I suggest that
- 18 this is, as I said, potentially a surrogate endpoint
- 19 biomarker or risk stratification biomarker.
- This is outlining some of what I mentioned
- 21 before, outlining the validation cohorts. This is
- 22 looking at clinical factors for prediction of fibrosis

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 1 and graft loss both in individuals that had fibrosis
- 2 versus -- and individuals that did not have fibrosis on
- 3 their three-month biopsies, basically showing that we
- 4 do a very poor job of predicting.
- 5 This is the training set with an AUC of 1,
- 6 which is also a little concerning. But we did
- 7 everything that we were meant to do around overfitting
- 8 and demonstrated again in a second cohort -- sorry --
- 9 second cohort here by PCR with an AUC of 0.99 -- 0.91.
- 10 And that -- in the paper, we have all the MPVs, PPVs,
- 11 sensitivities, specificities, et cetera in there. And
- 12 then we validated this on two publicly available
- 13 datasets, demonstrating that it also performed well,
- 14 all of which goes to demonstrate that this is not --
- 15 there isn't a problem with (inaudible) overfitting in
- 16 this.
- 17 And when you look at principle component
- 18 analysis to stratify individuals based on this risk --
- 19 gene risk score, we clearly did -- it forms nicely both
- 20 on the GoCAR cohort and this public data set, so very -
- 21 performs highly at stratifying individuals for
- 22 further risk of -- for risk of graft loss.
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- 1 So what I would suggest is that we have a
- 2 panel of assays that, A, identify an individual at risk
- 3 up front, a recipient that is a high-risk individual.
- 4 And we've actually identified a cellular profile that
- 5 suggests that this -- that is also identified in
- 6 individuals who have autoimmunity. And we're working
- 7 on that at the present.
- 8 We clearly -- if we added in the donor factor
- 9 of HLA typing, high-risk mismatch, I suggest that maybe
- 10 if we work with Peter around incorporating epitope
- 11 mismatching, this might be very interesting -- so a
- 12 recipient risk factor combined with a donor risk factor
- 13 to identify individuals that are high risk prior to
- 14 transplantation and then I -- well, a gene risk score
- 15 that identifies underlying inflammation within the
- 16 graft, subclinical inflammation, even borderline
- 17 subclinical inflammation, subsequent risk for -- and
- 18 subsequent risk for graft loss, and then, as I said,
- 19 identifying individuals who have good kidneys who are
- 20 at risk for going on to develop fibrosis and graft
- 21 loss. So I think the potential for application to drug
- 22 development in the multiple ways that I point out with

- 1 regards to classification of biomarkers are potentially
- 2 interesting.
- 3 So thank you very much. I want to thank the
- 4 GoCAR Consortium and the multiple centers that were
- 5 involved in that, the principle investigators, Phil
- 6 O'Connell (ph), Ajay Jamale (ph), Millie Samonego (ph),
- 7 Lorenzo Gallon (ph), Bob Colvin (ph), and Nader (ph),
- 8 and all of the transplant teams who were involved in
- 9 getting all of the biopsies and blood samples that were
- 10 involved in this really large study and my lab,
- 11 obviously. So thank you very much.
- 12 (Applause.)
- DR. NICKERSON: Thank you very much, Dr.
- 14 Murphy.
- Our next speaker will be -- needs no
- 16 introduction, really -- Dr. Roslyn Mannon talking about
- 17 protein versus gene expression as a diagnostic
- 18 biomarker of alloimmunity.
- 19 DR. MANNON: So I had actually changed the
- 20 topic, and I'm presenting on behalf of my colleagues,
- 21 Karen Keslar and Rob Fairchild (ph). Rob is heading to
- 22 the AST fellows meeting and could not make a stop in
- the number of genes. And each count is giving you an
- 22 approximate copy.

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- 1 D.C.
- 2 So another caveat is that we developed this.
- 3 This is very early data that has not been published.
- 4 It's only been discussed in abstract form, and it's
- 5 based on the Clinical Trials and Organ Transplant, or
- 6 CTOT, consortia. And this was really from a clinical
- 7 application perspective. We were not initially
- 8 developing this as a drug development tool, and it's
- 9 currently undergoing validation.
- These are my disclosures, and Rob has none.
- 11 So again, setting the context for immune
- 12 monitoring, we use allograft biopsy. It's subject to
- 13 sampling and observer bias. It's -- you know, the
- 14 histological analysis is quite difficult in some cases,
- 15 and there's lack of -- there's intra-patient
- 16 variability. It's invasive. Patients don't like it.
- 17 There's increased risk. And it's been coupled with, as
- 18 you heard, transcriptomic analysis to potentially
- 19 enhance the diagnosis or help us identify or create new
- 20 phenotypes using that information.
- But as a nephrologist, we've always been
- 22 trained to look at the urine. And about more than a

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- 1 decade ago, Sue Anthron's (ph) lab identified the
- 2 transcription using quantitative PCR of urinary
- 3 pellets, identifying gene transcripts such as CXCL9 and
- 4 CXCL10, granzyme B is being able to distinguish
- 5 individuals that had rejection on biopsy versus not as
- 6 (inaudible) being a diagnostic strategy.
- 7 But these transcripts (inaudible) regulated in
- 8 other inflammatory conditions, and it gets difficult to
- 9 utilize them when you have patients infected with, say,
- 10 viral nephropathy such as BK polyomavirus.
- 11 The other issue with urine is that RNA is not
- 12 great quantity, and the cells that are in the urine
- 13 oftentimes can be degenerated and breaking down. And
- 14 so we decided to try the use of the nanostring
- 15 technology platform. The advantage here is that you
- 16 don't do an amplification step. You bind the RNA with
- 17 gene-specific reporter and capture probes. Those that
- 18 are hybridized to the RNA fall -- or locked onto a
- 19 platform, and then that platform is read -- you
- 20 actually read the platform and actually have counts for
- 21 the number of genes. And each count is giving you an

- 1 So we hypothesize that we could use this
- 2 nanostring platform to look at -- to measure MRNA
- 3 expression in the urine, look -- looking at individuals
- 4 that had stable allograft function versus those that
- 5 had acute rejection and, as I'll show you, also those
- 6 with BK polyomavirus nephropathy.
- 7 Our data set includes RNA urine, pellet RNA
- 8 isolated from patients in the CTOT-10, 15, and 16
- 9 studies. These were studies looking at the
- 10 optimization of Belatacept. So the control arm had
- 11 tacrolimus. The Belatacept arm was tacrolimus and CNI
- 12 and a steroid-free arm. Both trials were stopped for a
- 13 number of reasons. But for 10, it was a rejection
- 14 issue and, for 16, similarly, a kidney transplant
- 15 rejection. 15 is a kidney-pancreas study. And the two
- 16 samples that are in there are kidney transplant, not
- 17 pancreas rejection.
- We had 29 individuals that had stable
- 19 function. And we had to actually add an additional BK
- 20 nephropathy. Our rate of BK nephropathy was not that
- 21 high.
- We used the 795 target genes that are part of

- 1 the nanostring (inaudible) cancer immunology code set.
- 2 So we did not have a -- we just used their standard
- 3 code set. We did not create our own custom.
- 4 Shown on the left is the heat map and, on the
- 5 right, the volcano plot distinguishing acute rejection
- 6 versus control. There were about 45 upregulated genes,
- 7 and I think 39 downregulated genes shown there.
- 8 And then using this elastic net -- and I won't
- 9 even pretend to know -- elastic net penalized
- 10 (inaudible) methodology. A 24 gene set was identified
- 11 that could distinguish between patients with acute
- 12 rejection. The genes are shown on the horizontal
- 13 access, and the extent of expression is shown on the
- 14 vertical access. The middle panel shows you the box
- 15 plots showing performance for no injury on the left and
- 16 then injury on the right.
- 17 Now, why did I say injury? Because
- 18 inadvertently, two patients had BK polyomavirus when we
- 19 were doing the initial analysis and fell in there. And
- 20 then we realized that, though the AUC showed good
- 21 distinguishing from individuals that were stable, we
- 22 had some contamination of those samples.
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- Be that as it may, we took this initial gene
- 2 signature and collaborated with Mike Abecassis' and
- 3 John Friedewald's group as a validation cohort. So in
- 4 addition to all the sample collection, they had also
- 5 isolated urine pellet as well. And you can see that
- 6 our transcription -- this is the heat map. These are
- 7 no rejection, and these are clinical rejection. Don't
- 8 ask me what those are because I can't explain it. I
- 9 know what they are, but I don't want to tell you
- 10 because I'm just working it out.
- 11 And then shown here is the specific assessment
- 12 of those samples. We went ahead and looked at the
- 13 samples, randomly pulled samples out to see if we could
- 14 classify rejection. And indeed, we could.
- 15 The -- again, the acute rejections had higher
- 16 scores with our gene signature, and the box plots are
- 17 here, identifying the rejection individuals -- and this
- 18 is true rejection, not BK -- versus nonrejection
- 19 individuals.
- But it's interesting to note that there were a
- 21 lot of genes expressed by both -- in both T cell
- 22 mediated rejection shown on the left and also BK. And

- 1 I had actually demonstrated this in intragraft biopsies
- 2 probably more than a decade ago. Oftentimes, it's the
- 3 magnitude of difference. But here, you can see that
- 4 there are 34 genes upregulated that are shared by both
- 5 and one downregulated gene.
- 6 I just show you these box plots because Karen
- 7 Keslar provided them to me -- but again, identifying
- 8 the sort of significant overlap between acute rejection
- 9 and BK, which are the left two bars here at each box --
- 10 at each doplot (ph) and the stable patients. So they
- 11 look very similar, and they're significantly elevated
- 12 compared to controls.
- But utilizing this data, we have also been
- 14 able to identify uniquely expressed genes that are
- 15 unique to both -- to either T cell mediated rejection
- 16 shown on the left and BK. We were able to identify 21
- 17 genes upregulated in acute rejection that are unique
- 18 with 39 downregulated and about 80 -- 75 or 80
- 19 upregulated and about 70 downregulated shown here.
- 20 And again, using elastic net regression, we
- 21 have now developed a new gene set of 55 genes that are
- 22 predominantly upregulated. But as you can see, some

- 1 are downregulated and the performance and the training
- 2 that is shown here comparing acute rejection versus BK
- 3 with a fairly significant area under the curve.
- 4 So we have been able to demonstrate using this
- 5 as a noninvasive approach. You're comparing patients
- 6 that are stable compared to those that have T cell
- 7 mediated rejection or BK nephropathy. I would skip the
- 8 last part because I don't think we're there yet.
- 9 But in terms of what is the unmet therapeutic
- 10 need, you've heard this repeatedly. We need diagnosis
- 11 -- diagnostic tools that don't involve an invasive
- 12 procedure, particularly for patients who are being
- 13 monitored and, you know, that -- just whether we're
- 14 doing surveillance or not, it's still kind of a
- 15 struggle with biopsies. And it's relatively easier
- 16 than doing a native kidney. But we need a noninvasive,
- 17 accurate, not expensive, rapid turnaround time
- 18 procedure. And we need an accurate method to monitor
- 19 patients, if you've heard. And we've heard different
- 20 platforms identified here.
- When you think about the context of use, if I
- 22 have to force this into a drug development tool, this

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- 1 could be potentially, if properly validated, be a
- 2 diagnostic marker measuring disease presence or status
- 3 to confirm specifically acute rejection or, in cases of
- 4 BK, the BK diagnosis or use for monitoring to avoid
- 5 repeated allograft biopsy. I think this is
- 6 predominantly, in my personal thinking, was a
- 7 diagnostic strategy.
- 8 I was asked to draft conflict -- oh, God --
- 9 conflict of you -- you know, got that on my head -- but
- 10 COU statement examples. So as a diagnostic biomarker,
- 11 the urine nanostring panel of RNA expression would be
- 12 used as an alternative method to diagnose acute
- 13 rejection or BK nephropathy. And then as a monitoring
- 14 biomarker, the urine nanostring panel of RNA will allow
- 15 for surveillance of allograft responses to new
- 16 therapies. Say we have trials where we have withdrawal
- 17 of agents such as CTOT-09 where we saw significant
- 18 rejections or, importantly, intolerance trials where
- 19 we're conditioning and then removing all their drugs.
- 20 So moving forward, we clearly need to continue
- 21 our external validation with the CTOT-08 samples.
- 22 There are several hundred samples that have been well

Our next speaker is Dr. Alexandre Loupy from

- 2 Paris, France, and the topic of the talk is going to be
- 3 risk prediction score for allograft loss in kidney
- 4 transplant recipients.
- 5 DR. LOUPY: Good afternoon, everyone. And
- 6 thank you very much for the kind invitation. I'm
- 7 really pleased to share these data with you.
- 8 And I will start with this question mark. So
- 9 in the biomarker world, do we necessarily have to use
- 10 fancy tools to prognosticate risk of long-term
- 11 allograft loss? So it's easy to make this statement
- 12 because I'm the last speaker of the session now. And
- 13 the thing is that I'm also, and the team, looking into
- 14 detailing to transcriptogenomics or noninvasive
- 15 biomarkers. It's not to say it's not useful. It has a
- 16 very important interest for many components on the way
- 17 we take care of patients.
- But we have to maybe step back and wait and
- 19 take the lessons for our ancestors. And you know
- 20 (inaudible). In France, he wrote the (inaudible). And
- 21 he said that probably sometimes the best is the enemy
- 22 of good.

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- 1 phenotyped. We needed to perform studies to determine
- 2 whether -- and because we have serial samples from that
- 3 cohort, we are determining whether we can actually
- 4 identify increased upregulation of our 24 gene set
- 5 prior to the onset. We also have all these subclinical
- 6 rejection samples that are in the pot as well.
- We're excited and considering using different
- 8 structured code sets to look at antibody-mediated gene
- 9 expression in the urine of patients. This would be
- 10 particularly helpful at a center like mine where we do
- 11 ABO incompatible and HLA incompatible where we are
- 12 doing rather frequent biopsies and, similarly, trying
- 13 to develop a profile to develop graft fibrosis and
- 14 progression.
- Obviously, Rob and I want to thank the
- 16 Clinical Trials and Organ Transplant, an NIAID-funded
- 17 consortium. But we also have considerable
- 18 collaboration in this room, including Northwestern,
- 19 Mount Sinai, University of Maryland, and Emory as well.
- 20 Thank you.
- 21 (Applause.)
- DR. BALA: Thank you, Dr. Mannon.

So today's topic is really to try to

- 2 understand the fact that, as we need a robust validated
- 3 integrated system for predicting long-term kidney graft
- 4 failures, we may already have something good that we
- 5 could use as the demonstration that it could be
- 6 actually usable for prognostication.
- 7 So we do have probably good biomarkers or good
- 8 stuff to prognosticate risk of long-term allograft
- 9 loss, but we do have a lot of issues to overcome. Our
- 10 task is really difficult because we have to face the
- 11 low level of detail of transplant registries. They are
- 12 useful, but they are not primarily designed to address
- 13 risk stratification and do not contain key prognostic
- 14 parameters.
- Number two is the small number of patients in
- 16 the more detail cohorts -- the lack of complex
- 17 integration of data; the lack of generalization (ph) of
- 18 some scoring system to other transplant systems; the
- 19 lack of transportability of the scoring system, which
- 20 is time of assessment; the lack of demonstrated
- 21 performance in different declinations just because we
- 22 need readily accessible tools allowing its use in

- 1 different medical-economic settings and different
- 2 clinical trials; and last but not least, there is no
- 3 current system validated in the setting of therapeutic
- 4 interventions. So you see that we have these big seven
- 5 steps to overcome.
- 6 So what is the iBox strategy started back 15
- 7 years ago? And I will just give you some details. We
- 8 wanted back in 2004 to have a study that could address
- 9 prognostication. So that was a hypothesis. And this
- 10 is how we built what we call the Paris Group
- 11 Multidimensional (inaudible) Database System. And I'm
- 12 going to spend a little bit of time here because our
- 13 approach was a very holistic approach. We did not make
- 14 any assumption that one parameter could be very helpful
- 15 or not. And it's our multidimensional database system,
- 16 and the structure is just summarized here. Our goal
- 17 was to deconstruct the barriers between specialties,
- 18 and we wanted to have the real transplant life.
- 19 So it's an (inaudible) register database. Our
- 20 database has external audits every year. We have
- 21 prespecified protocols, curated pipelines that make,
- 22 you know, automatic import of data within different
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- 1 platforms in our network. This is a very important
- 2 point. It's a completely unselected cohorts. Any
- 3 patients who get a kidney transplant will be entering
- 4 into the database system, and we'll actually stay
- 5 forever just because, in France, the transplant
- 6 populations have a (inaudible), meaning that when they
- 7 get a transplant in the centers, the patient will come
- 8 over and over again. And we don't have a lot of
- 9 patients lost to follow up.
- 10 So it allows us to have a prospective (ph)
- 11 assessment of prognostic parameters, to have
- 12 (inaudible) follow up in events (ph). And not to
- 13 restrict the prognostic parameters into the
- 14 pretransplant period or post-transplant period or one
- 15 year or two years or five years, we have all these
- 16 data. So the goal is really to have an appraiser with
- 17 a holistic approach of (inaudible) parameters and just
- 18 to align them and integrate them in some kind of
- 19 prognostication system that will assess long-term risk
- 20 of allograft loss.
- 21 So this is the way the database is structured.
- 22 And of course, when we run the model for assessing

- Page 260 1 risk, we have to test the exportability. So there is a
- 2 huge validation (ph) cycle that I'm going to be
- 3 describing later on. And also an important component
- 4 is how the risk stratification will be interfaced and
- 5 available for calculating every patient individual
- 6 profile of allograft loss.
- 7 So this is the study design, the iBox risk
- 8 generation and validation. It's an international
- 9 study. These are patients who receive a kidney
- 10 transplant across 11 centers in Europe and North
- 11 America. You will see that new centers are coming in
- 12 the process. If you want to have more detail about the
- 13 inclusion-exclusion criteria in our study design, you
- 14 can just go onto clinicaltrial.gov because the study
- 15 registered.
- 16 So the participants, as I said, it was very
- 17 important for us to generate the model in the Paris
- 18 transplant (inaudible) cohort and test exportability in
- 19 independent validation cohorts and also to validate our
- 20 scoring system in three randomized clinical trial
- 21 covering distant clinical scenario.
- So inclusion time was 2000 to 2014, and the
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- 1 median time follow-up was eight years after risk
- 2 evaluation.
- These are the iBox participating centers, and
- 4 it has been updated just, you know, today. To show you
- 5 that now the consortium is about 18 centers, 23,000
- 6 patients, 150,000 patients (inaudible) for randomized
- 7 clinical trials. What was important for us was to add
- 8 as many -- as much heterogeneity as we could. In other
- 9 words, the goal was to add more and more centers with
- 10 completely different allocation (ph) system, completely
- 11 (inaudible) practice pattern, different
- 12 immunosuppressive regimen to test the robustness of the
- 13 risk stratification system and probably to be able
- 14 after a while to adjust it. This is where
- 15 heterogeneity in such (inaudible) number can be
- 16 transformed from a weakness to a major strength. And
- 17 I'm going to show you more details about that.
- 18 So of course, this big collaboration needed to
- 19 have a step-by-step data exchange protocol, manual,
- 20 dictionary, template, a context of use statement, and
- 21 also to build some kind of heterogeneity map because,
- 22 as you guess, not all centers have the same platforms,

- 1 the same assessment for proteinuria. So we had to take
- 2 that into account, and that was -- which actually took
- 3 us many and many years to achieve.
- 4 So to make a long story short about the
- 5 (inaudible) factors, we examined (inaudible), as I
- 6 said, 42 prognostic parameters from -- starting from
- 7 day zero, you know, doing a quality, ethnicity,
- 8 whatever. We have, as I said, (inaudible) database who
- 9 have treatment, who have injury, who have protocol
- 10 biopsy, biopsy (inaudible), assessments and
- 11 (inaudible).
- 12 So what we do, it was very important. When
- 13 you study so many prognostic parameters, you have to
- 14 (inaudible) for the (inaudible), the independency. We
- 15 don't want to overfeed the models. So we paid
- 16 particular attention for performance, discrimination,
- 17 calibration, validation. We'd use competing (ph) risk
- 18 approach and the adaptability of our system.
- 19 And last but not least, we are not expecting
- 20 and I'm not going to show you here today a perfect
- 21 system because you can think about that it's real-life
- 22 data. So the prognostication system cannot be perfect.
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- 1 That's just impossible.
- 2 So then we apply the final model. So
- 3 importantly, there is no big surprise. But I want to
- 4 remind you that every single parameter here has been
- 5 adjusted and the quantification of the amplitude of the
- 6 independent variables here in this model. And you can
- 7 see that the first is time from transplant to risk
- 8 evaluation. It was very important for us to provide a
- 9 system that can be performed at one year post-
- 10 transplant, but also three months, six months post-
- 11 transplant or three years just because we know that the
- 12 clinical trials would have different endpoints. And we
- 13 just know that the patient's status can change over
- 14 time. So you need the system to be adaptable and
- 15 updatable according to the fact that the patient status
- 16 will change over time.
- 17 EGFR -- we've been talking a lot about EGFR --
- 18 it's obviously an important component in the equation;
- 19 protein-creatinine ratio; and also, as you can see
- 20 here, some what we call invasive biomarkers, which is
- 21 basically, again, no real surprise; the degree of
- 22 interstitial fibrosis and tubular atrophy; injury,

- rage 2
- 1 which is defined by micro circulation, inflammation,
- 2 (inaudible) transplant (inaudible); and the presence
- 3 and (inaudible).
- 4 Using that output of the model, again,
- 5 starting from many prognostic parameters, we kind of
- 6 think that the most important is the assemblage, the
- 7 way we assemble these things in the models, and to
- 8 achieve a very good performance defined by the C-Stat
- 9 (ph) of 0.83 that you can see here.
- 10 Is that enough? Of course not. You have to
- 11 calibrate the model. In other words, you have to see
- 12 whether your risk assessment performed after transplant
- 13 could fit between the predictive probability of failure
- 14 of your model and the failures observed. So these are
- 15 the calibration curves that shows that it's a very good
- 16 feed between what the model measures very early on
- 17 after transplant and the three, five, and seven years
- 18 graft failure rate.
- 19 Another important aspect was the timeline of
- 20 risk evaluation and transportability. It was very
- 21 important for us to make the model dynamic, meaning
- 22 that you can update the model and recalculate the

- 1 score, as I said, just because the patient status
- 2 changes over time.
- 3 So this is in the derivation set, the density
- 4 plots of time of risk evaluation in development cohort.
- 5 So you can see that most of the risk evaluations were
- 6 performed within the first year post-transplant. Why
- 7 the first year? Because this is when, you know,
- 8 important events can occur, and this is some kind of
- 9 time point where a lot of centers can perform protocol
- 10 evaluations. It could be also useful for clinical
- 11 trials.
- 12 So the take-home message of this slide is that
- 13 the iBox accuracy is confirmed when measured at
- 14 different time points after transplantation, which
- 15 permits to a data score based on new events.
- An important aspect was also the validation of
- 17 the score. I do -- I'm not describing here the
- 18 internal validation procedure like bootstrapping. And
- 19 I've been focusing on the validation in geographical
- 20 distant systems, as you can see. And as I said before,
- 21 it was very important for us to see that the centers
- 22 are really different from one country to another. But

- 1 it's some major strengths, I believe, here. And you
- 2 can see that, in some centers, that the iBox
- 3 distribution score can vary between the center. But
- 4 again, not only the score perform well, but also it was
- 5 well-calibrated in any single validation cohort from
- 6 the consortium.
- Another step which is very important was to
- 8 quantify whether histology added to the performance of
- 9 the score irrespectively of the pure functional
- 10 assessment. So if you ask me, is GFR important? Of
- 11 course. Is GFR slope important? Of course.
- 12 Is the integrative score more important than
- 13 the simple component of GFR alone or proteinuria alone,
- 14 of (inaudible) or (inaudible) alone? Yes. You can see
- 15 here that you can reclassify the patient in term of
- 16 risk. In other words, when you combine all these
- 17 things together, it gives you more performance, more
- 18 power, and a reclassification possibility, which
- 19 improves your scoring system.
- 20 So what about the adaptability now of the
- 21 system? And we're working the past two years very hard
- 22 on that. The question was that: How can the iBox be
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- 1 fitted into less-informed (ph) data set and also
- 2 available clinical trials, so ongoing clinical trials
- 3 and different (inaudible) system?
- 4 First of all, you saw that in the iBox we
- 5 stuck with the benefit of national classification
- 6 lesion grading, as we all know is not perfect, but at
- 7 least we are all speaking the same language when we see
- 8 about IFTA score or (inaudible). We know what we're
- 9 talking about.
- 10 So when we substitute was the fact that we
- 11 used the diagnosis instead of the lesion grading. We
- 12 also at -- made some adaptation of the algorithm for
- 13 datasets in which this information was lacking on MFI.
- 14 We also used different algorithm to take into account
- 15 that, in some centers, they don't have P and C ratio.
- 16 So we use dipstick gram per liter or gram per 24 hours.
- We generated four centers which actually are
- 18 not performing protocol biopsies, and we would like to
- 19 follow their patient base on (inaudible) monitoring of
- 20 GFR, DSA, or proteinuria, a pure functional score that
- 21 you can see here in this mammogram (ph).
- 22 And we also pay particular attention for

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- 2 learning procedures that can account to missing
- 3 parameters.
- 4 So the last component of the iBox system was,

1 missing data. This is how we implement some machine

- 5 as I said, to test its movements within therapeutic
- 6 intervention. So we used these three trials that we
- 7 have on site, which has -- some of treatment of
- 8 (inaudible); some of get treatment of T cell mediated
- 9 rejection and patient converted to Belatacept. So
- 10 three intervention, three different clinical scenario,
- 11 and this is here, the pre- and post-treatment iBox
- 12 movement.
- So you see that some patients are in blue. It
- 14 means that they are decreasing their iBox score. It
- 15 means that they should respond to therapy. But also,
- 16 you have the red patients who actually are increasing
- 17 the iBox score. So again, in those three trials, the
- 18 calibration was very good, meaning that you could
- 19 assign the patient at the time of treatment the
- 20 probability of seven years graft failure, which is in
- 21 the patient -- the patient 83 percent. And you can see
- 22 that the graft loss probability after treatment here in
 - Page 269
- 1 these patient you can reapply, recalculate the iBox
- 2 score is 49 percent. And again, the calibration was
- 3 good.
- 4 And last but not least -- and you know, my
- 5 student -- my PAD (ph) student working on that on the
- 6 clinical trial spent two years for doing one table. So
- 7 sometimes you say, Alex, two years for one table; are
- 8 you kidding me? No. It's just to focus on the fact
- 9 that, when you gather data from a clinical trial, then
- 10 you have to update, you have the clean the data, you
- 11 have to ask the different participating center for
- 12 updates on histology and everything. It takes a lot of
- 13 time.
- And to make a long story short, it was very
- 15 important for us induce (ph) randomized clinical trial
- 16 to do post (inaudible) analysis -- in other words,
- 17 apply the iBox score very -- at early period or at the
- 18 time of the therapeutic intervention, and you can see
- 19 that the C-Stat (ph) again was very good or fair in
- 20 those clinical trials. And importantly, the projected
- 21 time that you would have saved for having actually the
- 22 good assessment of the long-term failures, the time

1 saved was 5.1 years in the (inaudible) trial and 5.3

- 2 years in the (inaudible) trial.
- So just to conclude, these are some example of
- 4 the iBox use. You can use these coefficients in the
- 5 parameters. You can assess a patient at the time of
- 6 transplant. This patient has an iBox risk assessment
- 7 and at the time of treatment for possible (inaudible)
- 8 mediated rejections. So then you have the time post-
- 9 transplant in years, the estimated allograft survival,
- 10 and you have a second assessment of your treatment.
- 11 And you can show the projection of this patient on a
- 12 long-term run and show that the iBox score after this
- 13 therapeutic intervention will have translated to an
- 14 updated survival probability to a certain number.
- 15 And this is how some people, you know, started 15 inflammation, which currently, by standard of care, is
- 16 asking us to project their patient in their trail for
- 17 long-term follow-up. This is the (inaudible) study.
- 18 And you know, (inaudible) called us and said, okay, I
- 19 have one-year data for all the patients. So now what
- 20 would you be able to project every single patient in
- 21 (inaudible) trial for the seven graft loss? So this is
- 22 an example where you see that the one-year data will

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- 1 the FDA, but we have an open mic as well. So if
- 2 anybody has any questions they want to raise or address
- 3 or comments --
- 4 DR. MORRIS: Yeah, Peter, I have a question
- 5 for Minnie.
- 6 On your interventional -- where is Minnie?
- 7 Oh, there she is. On your interventional very small, I
- 8 know, early trial where you're treating with TREx or
- 9 tofacitinib (ph) for subacute (ph) rejection, are you
- 10 including a negative control where you don't treat, and
- 11 are you including a positive control where you treat
- 12 with steroids?
- 13 DR. SARWAL: Yeah, so that's a good question.
- 14 We are actually choosing in this trial subclinical
- 16 not being treated. So it's not randomized to three
- 17 arms. The standard of care is do nothing because,
- 18 these kind of changes, they're really kind of not even
- 19 Banff-graded kind of -- not a Banff -- it's like
- 20 really, you know, very subclinical, non-Banff-graded
- 21 inflammation.
- 22 So because that is currently not being

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- 1 actually translate to iBox code, which will actually
- 2 translate to seven years allograft survival
- 3 probability.
- 4 So in conclusion, the novelty here in the
- 5 system, this is a true integrative system, dynamic
- 6 validating (inaudible) of unselected cohorts in similar
- 7 independent population in three randomized trials.
- 8 The performance of the models are improved
- 9 when you combine (inaudible) the parameters to
- 10 traditional functional parameters monitoring. It
- 11 outperforms currently existing scoring system. And it
- 12 demonstrated performance in different declination. And
- 13 last -- and it's a very important task -- it's not
- 14 perfect. It can be improved with time. We have heard
- 15 a very nice presentation on emerging predictors and
- 16 biomarkers that might improve the system.
- 17 So I would like to thank you for your
- 18 attention.
- 19 (Applause.)
- 20 DR. NICKERSON: All right. That leaves us
- 21 with about 20 -- just over 20 minutes to have a
- 22 discussion. There are questions for discussion from

- 1 managed, by standard of care, it is not being managed.
- 2 So that's been basically the CTOT-21 application where
- 3 Flavio's PI was to randomize and have two studies.
- 4 Both studies would be randomized where you do nothing
- 5 versus giving TREx or nothing versus giving IL-6
- 6 receptor blockade.
- 7 And so they -- the -- what we discovered in
- 8 that is just histological classification of what is
- 9 subclinical inflammation is very difficult unless you
- 10 combine it with the molecular assessment that we're
- 11 doing by the urine testing.
- 12 DR. MORRIS: Okay. But at least you have a
- 13 control arm where you do nothing.
- 14 DR. SARWAL: Yes.
- 15 DR. MORRIS: Okay.
- 16 DR. SARWAL: Yes.
- 17 DR. MORRIS: All right.
- 18 DR. SARWAL: Yes.
- 19 DR. NICKERSON: Ros.
- 20 DR. MANNON: Yeah. So you know, I've heard
- 21 your data, like, a million times, but today it just
- 22 struck me. Do you weight the subscores for the

- 1 pathology, or are all of them given equal weight? So
- 2 is I and T more important than -- do you -- or it just
- 3 doesn't matter? You just put them all as one score.
- DR. LOUPY: No. The -- every single parameter
- 5 has weighted -- has weight in the equations, of course.
- 6 I can tell you that if you want to rank the most
- 7 important parameters from, you know, the less important
- 8 parameters, you will have to use (inaudible)
- 9 proteinuria. They are, like, very strongly associated
- 10 with risk. But still, you have some kind of
- 11 independency of INT and GPDC (ph) and DSA. That was
- 12 the -- our goal, is -- was to assign and use the Banff
- 13 scores, and these are weighted equations.
- 14 DR. MANNON: So are any of the Banff subscores
- 15 more important than the others? Like -- and if you
- 16 don't -- so if you do --
- 17 DR. LOUPY: Yeah.
- 18 DR. MANNON: Yeah, I mean, is it micro -- you
- 19 know, because we hypothesize that. Microvascular
- 20 injury is most important, blah, blah, blah, than IFTA.
- 21 But I'm just curious because you've got so many
- 22 specimens now. And then I kind of wonder for centers

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- 1 equations, you lose some kind of predictive performance
- 2 in your system.
- 3 The simple point is that why did we use the
- 4 Banff scoring instead of the diagnosis. Just because
- 5 we wanted to get rid of the interpretation of the
- 6 lesions, so we used the scoring. But as you said, some
- 7 centers send their data without Banff scoring, and we
- 8 use the diagnosis instead of the Banff scoring. BK
- 9 virus nephropathy, ABMR, TCMR, or CNI toxicity, TMA,
- 10 whatever, it was really important, as you mentioned, to
- 11 be able to show that, actually, in those situations, we
- 12 could validate the system.
- 13 DR. BALA: Alex, maybe a couple other
- 14 questions on iBox. So if you were to try and identify
- 15 the clinical phenotype of your patient at the time of
- 16 enrollment or the time of transplant -- in other words,
- 17 okay, we knew they had a DSA, right, or they didn't
- 18 have -- or we thought they were naïve or low risk for
- 19 memory -- how does your -- at what time point do you
- 20 find that you have a good predictability for
- 21 prognosticating outcomes? That's one question.
- 22 DR. LOUPY: Yeah.

- DR. BALA: The second question would be you're
- 2 looking at graft loss, which I am assuming is
- 3 (inaudible)-censored graft loss. Have you tried to
- 4 model for all-cause graft loss in your system to --
- 5 because, ultimately, in a drug development trial, you
- 6 would want to have all-cause graft loss as one of your
- 7 endpoints, right?
- 8 DR. LOUPY: So yeah, I will start with
- 9 (inaudible). Of course it's a very important question,
- 10 so we validate it in (inaudible). And importantly, we
- 11 also use competing (ph) risk (ph) approaches for our
- 12 (inaudible) they may have interfere with the
- 13 observation of losing the graft. So that was for the
- 14 second part, your second question.
- 15 For the first question, very important, what
- 16 kind of timeline should we use? And our first study
- 17 design was to stick with post-transplant parameters,
- 18 but not to get rid of pretransplant parameters. Why
- 19 did we stick with post-transplant parameters? Because,
- 20 actually, in my point of view, day zero, or
- 21 pretransplant risk scoring system, are helpful for
- 22 allocation. Be sure that your -- or your arm are

- 1 like -- I know one large medical center that doesn't
- 2 use Banff at all. They still use --
- 3 DR. LOUPY: Yeah, yeah.
- 4 DR. MANNON: -- sort of like --
- 5 DR. LOUPY: Yeah, yeah, yeah.
- DR. MANNON: -- all a caddy -- not you guys,
- 7 but it's another big center in the south, not our
- 8 center -- but that uses that. So I -- they have a lot
- 9 of data, but I don't know how you would --
- DR. LOUPY: So it was very important for us to
- 11 say, okay, there are, like, three components in the
- 12 histology part of the score. You have scarring.
- 13 Actually, scarring is very important for predicting
- 14 long-term graft loss. You have inflammation, and you
- 15 have a component of inflammation, which is (inaudible),
- 16 and the other one which is -- has a T cell mediated
- 17 component. And you have the CG (ph) lesions. Of
- 18 course, we know CG is a bad lesion to have and carries
- 19 a bad prognosis.
- 20 So this other ranking of the lesions, you have
- 21 scarring and activity (ph) and damage. And
- 22 importantly, if you remove these variables from the

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- 1 balanced. No score generated before transplant
- 2 actually have a -- has a good performance to predict
- 3 the future just because we know that, as soon as you
- 4 put the graft, some stuff will occur.
- 5 So it was important for us to have the one-
- 6 year time frame, but taking into consideration these
- 7 day zero parameters to adjust the system. It was very
- 8 important not to exclude them and they be part of some
- 9 sensitivity analysis, for example. But I think that
- 10 day zero assessment and post-transplant assessment as
- 11 some -- are different.
- 12 And also, a very important point is that what
- 13 we wanted was to be also helpful for randomized control
- 14 trial. And you can see a drug company and say, okay, I
- 15 do a randomized control trial. I have inclusion-
- 16 exclusion criteria. I randomized my patient at day
- 17 zero. So you expect it to group off balance at some
- 18 point.
- 19 But then what happens when you give drug A and
- 20 drug B? And then that's what I wanted to do. Put
- 21 yourself at one year and just project the patients and
- 22 compare the two groups. So it's different questions, I

- 1 (inaudible).
- 2 So I would say that the -- it starts to be
- 3 good at starting at two and three months after
- 4 transplant where you are in a kind of steady state.
- 5 And even (inaudible) cure-all has a (inaudible)
- 6 rejection, whatever, but then you can calculate the
- 7 risk. So that's the reason why we stick with the one-
- 8 year prerogative. Of course, if you move the iBox to
- 9 two, three, four years, then you're gaining prognosis
- 10 because you have more, you know, events in your
- 11 assessment.
- 12 DR. BALA: It's --
- 13 UNIDENTIFIED MALE SPEAKER: Can I ask a
- 14 question for Barbara? Just because I think you talked
- 15 mostly -- or the most about pretransplant risk
- 16 assessment. And most of us have sort of an inherent
- 17 guestimate as to high-risk, low-risk. And how does the
- 18 scoring system, based on the genomics that you came
- 19 sort of correlate with sort of current clinical
- 20 judgment? And is that something that you would then --
- 21 could see, you know, then categorize in people in terms
- 22 of induction treatments and that sort of stuff?

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1 think, but both are interesting.

- 2 UNIDENTIFIED MALE SPEAKER: Right. So if
- 3 you're dealing with an -- what you think is a naïve or
- 4 relatively what we've always called low-risk population
- 5 and you -- the question would be: How early could you
- 6 look to have a prognostic time? And is one year too
- 7 early? Or is -- or are you better at maybe 18 months
- 8 or two years? Like, I just don't understand the
- 9 dynamic of that environment.
- DR. LOUPY: The more you get from the
- 11 timeline, the later you get, the better your prediction
- 12 will be.
- 13 UNIDENTIFIED MALE SPEAKER: Of course.
- DR. LOUPY: Of course. So we put it at one
- 15 year, but also six months, three months, or any time
- 16 because now the centers participating in the iBox
- 17 (inaudible) just when you assess risk, whatever, just
- 18 give the data, and we project and we validate because
- 19 we want time to be adaptable.
- 20 So first of all, the iBox does not work in the
- 21 first few weeks after transplant just because GFR does
- 22 not mean anything. You have, you know, recovery and

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- DR. MURPHY: So the population that we have in
- 2 GoCAR do not include individuals that are highly
- 3 sensitized. So they were not included in it. So this
- 4 is taking a population and using the clinical data from
- 5 that population, the AUC for prediction of acute
- 6 rejection within the first six months was 0.5.
- 7 UNIDENTIFIED MALE SPEAKER: Right.
- 8 DR. MURPHY: And so -- and the interesting
- 9 thing is, when we look at it, there is actually an10 immunological phenotype associate, as mentioned,
- 11 associated with it. So it's not just -- people get
- 12 nervous when they hear genes. It's like this black
- 13 box, whatever. But there is actually a clinical
- 14 phenotype and we're actually seeing the same phenotype
- 15 in autoimmunity as well. So it's -- it seems to be
- 16 identifying a high immunological risk individual.
- 17 UNIDENTIFIED MALE SPEAKER: Which current --
- 18 under current measurement, we probably been --
- 19 DR. MURPHY: We have to --
- 20 UNIDENTIFIED MALE SPEAKER: -- treat it as a
- 21 low immunologic risk.
- 22 DR. MURPHY: Yeah.

	<i>b</i> , , , , , , , , , , , , , , , , , , ,
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1 UNIDENTIFIED MALE SPEAKER: So I think this is	1 DR. MURPHY: genomics didn't matter.
2	2 DR. LOUPY: Yeah, yeah.
3 DR. MURPHY: Yes.	3 DR. MURPHY: So
4 UNIDENTIFIED MALE SPEAKER: You know, the	4 DR. LOUPY: Two very
5 important thing about the work is that it actually	5 DR. MURPHY: it's only fair.
6 allows intervention, giving current available drugs to	6 DR. LOUPY: Two very important points. So
7 better predict those who need more aggressive treatment	7 first of all, you know, we are, like, tied as the HLA
8 and potentially the other way around. The people who	8 incompatible
9 are being treated	9 DR. MURPHY: No.
10 DR. MURPHY: Yes.	DR. LOUPY: kidney guys
11 UNIDENTIFIED MALE SPEAKER: with more	DR. MURPHY: I understand it. I'm doing
12 aggressive	DR. LOUPY: doing
DR. MURPHY: Yes. In fact, the	13 (Crosstalk.)
14 UNIDENTIFIED MALE SPEAKER:	DR. LOUPY: That's kind of true. And that's
15 immunosuppression.	15 the reason why we paid particular attention to be very
DR. MURPHY: is even better. So being able	16 careful. First of all, it's an unselected population.
17 to identify an individual who shouldn't get as high	17 So you have patients who are doing really well have
18 immunosuppression actually is even better.	18 compromised kidney
19 Actually, can I just ask Alex a question?	DR. MURPHY: But have you taken them
20 Alex, have you tested iBox in a low-risk	20 specifically and tested it?
21 population with good kidneys? And what is the	21 DR. LOUPY: And so and we did sensitivity
22 performance? Because	22 analysis because we did not want the iBox to give too
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1 DR. LOUPY: Thank you for the question.	1 much power to DSA and microcirculation inflammation and
2 DR. MURPHY: the as a nephrologist	2 everything. So we applied the score, also, in what you
3 DR. LOUPY: Thank you.	3 call low-risk patients within our cohort and in the
4 DR. MURPHY: kind of tell me	4 also the validation set, and we had a very good
5 DR. LOUPY: Thank you.	5 conservation of our performance just because I think
6 DR. MURPHY: you know, albuminuria	6 because it was generated in an unselected populations
7 DR. LOUPY: Yeah, yeah.	7 that actually contains that kind of patients.
8 DR. MURPHY: you know, biopsy, et cetera,	8 So for the second point, it's the subject of
9 one year	9 an ongoing study because I say you can expect the
10 DR. LOUPY: Yeah.	10 prognosis. So we
DR. MURPHY: tells me who's going to lose	DR. MURPHY: No, no. I'm just
12 their kidney. I kind of think I can do that myself,	DR. LOUPY: No, no.
13 but	DR. MURPHY: I'm winding you up on purpose.
14 DR. LOUPY: Oh.	DR. LOUPY: But I we do that as clinician
DR. MURPHY: But you know, the	15 every day. Every day, I see a patient. I patient, and
DR. LOUPY: Thank you again. Thank you again.	16 the patient say, okay, you have this all of these
17 (Laughter.)	17 parameters. He's one year out post-transplant, say,
DR. MURPHY: No, but since you no, I'm	18 how long will my kidney last? And like, I think
19 throwing it at you on purpose	19 DR. MURPHY: I know.
20 DR. LOUPY: Two very	DR. LOUPY: maybe 14 years. So what we
21 DR. MURPHY: because you said	21 did, we did a study comparing the human assessment, a
22 DR. LOUPY: Yeah.	22 different label, assistant professor (inaudible)

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- 1 DR. MURPHY: I actually believe you. I
- 2 believe you. I totally believe you.
- 3 DR. LOUPY: -- (inaudible) professor with the
- 4 iBox. And I can tell you that when you give to a
- 5 clinician, including myself -- oh, not myself because I
- 6 know the coefficient, so I'm a little bit biased.
- 7 (Laughter.)
- 8 DR. LOUPY: But when you give all these tons
- 9 of parameters to someone and say, okay, can you model
- 10 what -- this patient will have this kidney in three,
- 11 five, seven years or eight years, the AUC of the humans
- 12 are of 0.52. And the surprise is that the professors
- 13 are not doing better than the residents. So ...
- DR. MURPHY: But I think the important point
- 15 because I was teasing you because you said we don't
- 16 need genomics, I think it's important to remember that
- 17 (inaudible) plus genomics and other biomarkers may
- 18 actually be beneficial. And so we shouldn't throw out
- 19 genomic -- you shouldn't -- we shouldn't stick in our
- 20 lanes. We need --
- 21 DR. LOUPY: Yeah.
- DR. MURPHY: -- to understand that each of

- 1 My question kind of goes back to the part
- 2 about expectations, right? If you establish high
- 3 expectations with people, right, they may at times hit
- 4 that. And I'm just wondering because there's a
- 5 psychosocial dimension of transplant that I don't think
- 6 is really fully understood because I look at myself.
- 7 I've done better than my doctor thought, but he set
- 8 high expectations for me. So I've just met those
- 9 expectations.
- 10 So I'm really curious about the part about the
- 11 role of exercise, you know, all the other dimensions
- 12 that could impact graft life. So I just wonder if you
- 13 can comment if you've done that or, if you haven't,
- 14 maybe a suggestion.
- DR. LOUPY: Yeah. So we have a lot of thing,
- 16 you know, that we -- we have a lot of things, you know,
- 17 that are raised, but not what you are talking about. I
- 18 think it's important. And what is currently lacking in
- 19 the system is other work, like, the (inaudible) factors
- 20 that may affect transplant outcomes. And we,
- 21 unfortunately, cannot control for this aspect, but it's
- 22 the subject of an ongoing study ancillary to the iBox

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- 1 these components could enhance each other, and that's
- 2 going to be critical for us to move forward.
- 3 DR. LOUPY: And I agree with your point.
- 4 DR. MURPHY: Yeah.
- 5 DR. LOUPY: That's the reason why I think that
- 6 the system can be enhanced. But what I wanted really
- 7 to stress is that we are -- I think in transplantation
- 8 we do not have to be shy as compared to the cancer
- 9 field where prognostic scoring system have been used
- 10 widely and have poor performance. We already have
- 11 something which is pretty okay. And of course, we will
- 12 implement or improve the system and see what will be
- 13 the new noninvasive biomarkers that will be integrated
- 14 with some kind of system. And I completely --
- 15 DR. MURPHY: Agreed.
- DR. LOUPY: -- agree with your point.
- 17 DR. NICKERSON: We have a question from the 18 floor.
- 19 UNIDENTIFIED MALE SPEAKER: Yeah. This is
- 20 actually a follow-on to your comment and Dr. Murphy's
- 21 comment to Dr. Loupy. So I really enjoyed your
- 22 presentation, so thanks again for coming here.

- 1 in my institution. So I think we'll have the answer,
- 2 but it's very --
- 3 UNIDENTIFIED MALE SPEAKER: Good.
- 4 DR. LOUPY: -- important.
- 5 UNIDENTIFIED MALE SPEAKER: Good. Thank you.
- 6 DR. STEGALL: Okay. I have one more comment
- 7 on what you said -- I -- the -- or the line of thought
- 8 that you have and, I think in -- as it goes for a TTC
- 9 progress forward. So it -- there is a movement to have
- 10 something like this become some sort of drug
- 11 development tool. And they will have, hopefully, some
- 12 sort of acceptance of that, more than one year of graft
- 13 survival and patient survival. But I can see all of
- 14 these, you know, being then looked at piece by piece.
- 15 And you can see this is a nice path forward.
- And at any time point, if you found a four-
- 17 month tool that worked better than the one-year tool,
- 18 as you had mentioned, it was a loud intervention or a
- 19 specific intervention earlier. I mean, I think that
- 20 would just be the way -- you know, you can just see how
- 21 this is the -- adding things on to this might be good.
- 22 And some of this may turn out to be better for some

1 types of patients than others, right?

- I mean, one of the issues I have is that, you
- 3 know, no matter what, the graft loss rate is pretty
- 4 low. And so we have to always keep that in mind as
- 5 we're trying to put these, you know, paths forward,
- 6 right? We always want to catch the people who have the
- 7 highest rate of graft loss, include those people in
- 8 clinical trials and not, you know, do everything else
- 9 and everyone else is very, very low risk. And most of
- 10 the times, we're looking at very short-term outcomes
- 11 anyway, like, maybe five years, right?
- So yes, it's -- what do you guys say about
- 13 these are in evolution always, right -- biomarkers that
- 14 are an evolutionary thing?
- DR. O'DOHERTY: Yeah. I mean, it comes back
- 16 to that idea that was kind of outlined at the start of
- 17 the day that -- what's the current regulatory accepted
- 18 endpoint when you're talking about drug development,
- 19 right? And you don't take leaps and bounds in
- 20 regulatory science. You make incremental steps
- 21 forward.
- And you know, one reason why the iBox scoring

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- 1 system kind of percolated to the top with regard to the
- 2 TTC efforts was because it's not that bit step forward
- 3 that everyone really wants. It's an incremental step
- 4 forward based off a lot of very, you know, heterogenous
- 5 patient-level data that we can aggregate together.
- 6 So it doesn't mean that that's the finality of
- 7 it. It means it's a step forward in that direction.
- 8 Of course, other groups can keep doing their own things
- 9 and, ultimately, working together as a community. It's
- 10 how that coalesces and dovetails in that it's not just
- 11 one thing being mandated. It's the complements between
- 12 them. And if there's genetic components that are
- 13 missing here, does that further refine those -- that
- 14 model as well? So ...
- DR. NICKERSON: I think Dr. Albrecht had a
- 16 comment, and then we'll come to Mike.
- DR. ALBRECHT: We had a question from the web.
- 18 The -- this is a recipient who's had three transplants
- 19 and is at high risk for ABMR and is asking about the
- 20 role of biomarkers in switching medications.
- And I actually also want to simultaneously say
- 22 that I think Mike probably does have a drug development

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- 1 tool. We would just have to determine what context to
- 2 use it in a drug development.
- 3 But I guess I would like folks to comment on
- 4 the biomarkers and the use of them when switching
- 5 patients between medications or maybe even different
- 6 doses of medications.
- 7 DR. MORRIS: Well, picking up a little bit on
- 8 that and referring to Mike and, I think, one of the
- 9 other speakers in the session where they mentioned the
- 10 context of use as being diagnostic and Mike said, well,
- 11 it's not a drug development tool, actually, it could
- 12 well be a drug development tool for identifying
- 13 patients who have failed current first-line therapy,
- 14 just as in oncology where they fail first-line therapy
- 15 and then they're eligible for new second-line therapy.
- 16 Diagnosis of people who are at risk of losing their
- 17 grafts based on whatever markers you use could be
- 18 people who would be identified as subjects would be
- 19 included in a trial where some are treated with the new
- 20 drug; the others are on standard of care.
- 21 DR. ABECASSIS: Yeah, I agree. So with
- 22 respect to our biomarker, I want to always have to

- 1 remind myself and everybody else this has so far only
- 2 been validated on patients with stable renal functions.
- 3 So you've got somebody who's in trouble, it may be we
- 4 haven't tested it. We've got thousands of samples that
- 5 at some point we'll probably get enough money to test.
- 6 But you know, this isn't stable patients. So if you're
- 7 -- if you've got one of these distressed kidneys like
- 8 the (inaudible) kidneys, what -- we haven't tested or
- 9 validated these kidneys.
- 10 So however, I think that, you know, if you
- 11 have stable renal function and you're doing well and
- 12 you get a negative test, your immune-quiescent. You
- 13 know, you're going to be pretty sure that things are
- 14 okay. And if you wanted -- or let's say side effects
- 15 to one medication and you wanted to switch to another
- 16 medication, you could conceivably, you know, use it to
- 17 monitor that patient and make sure that you don't have
- 18 to wait for the creatinine to bump like we usually do.
- 19 You might want to just monitor that. But I -- it's
- 20 certainly not a test that's been developed or validated
- 21 for distressed kidneys.
- I had a question about the iBox and something

- 1 just comes to mind, and I have a question for the whole
- 2 group, you know. What's the right time? So you know,
- 3 we've all focused on one year, and then we always talk
- 4 about long-term outcome. If we really want to look at
- 5 a number today, 2018, that we would consider a good,
- 6 long-term outcome versus a bad long-term outcome, you
- 7 know, I struggle with what's that number.
- 8 I mean, you know, kidneys don't last forever
- 9 in anybody, right? So is it five years? Is it 10
- 10 years? Is it 15 years? What is that number? Because
- 11 I think when you start to look at surrogate endpoints
- 12 for long-term function, unless you define what long-
- 13 term function is, you know, it's impossible to identify
- 14 a surrogate endpoint because, you know, you said
- 15 something that, I mean, I chuckled at because it makes
- 16 sense, is, you know, the later you check, the more
- 17 predictive, you know, you're going to be. Sure. You
- 18 know, at 9 years, your prediction for 10 years is
- 19 pretty good.
- 20 (Laughter.)
- 21 DR. ABECASSIS: But you know, is it -- could
- 22 it be -- I mean, you know, you want to kind of move
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- 1 both goal posts, right? So you want to say if you
- 2 have, you know, a kidney at 5 years, can you predict 15
- 3 years, which you may not be able to predict at 1 year.
- 4 And you know, what are those thresholds?
- 5 Like, what are we as a community thinking should be,
- 6 you know, a reasonable long-term outcome of a kidney?
- 7 And what percent of patients do we expect or do we hope
- 8 will have good function at that time point? Is that
- 9 even an answerable question?
- 10 DR. NICKERSON: So I think -- I'm going to
- 11 try, and then Mark can try.
- 12 DR. STEGALL: Okay. Go ahead.
- DR. NICKERSON: I think it depends on what
- 14 you're trying to look at. So --
- DR. ABECASSIS: It depends on the kidney.
- DR. NICKERSON: Yeah. Right. It depends on -
- 17 again, if it's a drug development program, you're
- 18 trying to bring a new drug to market, you're going to
- 19 have to take it to a clinical outcome to ultimately get
- 20 long-term qualification. You might get qualified on
- 21 surrogate, but you're still going to have to take those
- 22 patients to a long-term outcome to qualify, get it full

- 1 ---
- 2 UNIDENTIFIED MALE SPEAKER: (inaudible off
- 3 mic).
- 4 DR. NICKERSON: Well, that's my point. So the
- 5 point is the long term will be defined by the number of
- 6 events. And it's -- and it -- you're going to have to
- 7 achieve a certain number of events difference between
- 8 the standard of care and the interventional arm. So
- 9 you're stuck based on the event rate that you're going
- 10 to have for your long term, and that may be death or
- 11 graft loss, right?
- 12 So you're stuck on that. And then the
- 13 question you have to work backwards to is how many
- 14 event differences would I need to see at this time
- 15 point to be able to predict that difference at some
- 16 time point down the road. And then it becomes a
- 17 viability question for the company. How many years am
- 18 I willing to invest to follow these patients for those
- 19 event rates in the long term?
- 20 So it's going to really differ, Mike, based on
- 21 the event rate that you're going to experience --
- 22 DR. ABECASSIS: But the reason --
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- 1 (Crosstalk.)
- 2 DR. ABECASSIS: The reason I was asking the
- 3 question, though, is so I think most of the patients in
- 4 your data set are relatively early post-transplant. I
- 5 mean, so have you looked at -- we all have patients
- 6 that are 10, 15 years out, right?
- 7 DR. NICKERSON: Yeah.
- 8 DR. ABECASSIS: And we all have -- so have you
- 9 looked at patients, you know, starting at 10 years and
- 10 then see what happens 10 years late --
- 11 DR. NICKERSON: Yeah.
- DR. ABECASSIS: -- because we have those
- 13 patients. They exist, right? So because I get the
- 14 focus is time zero to whatever, right? But it may be
- 15 if you haven't modeled it already that it's as
- 16 important to take patients at five years.
- 17 DR. STEGALL: Right. But I don't think that
- 18 the issues at one year are different. I -- really, the
- 19 issues at 1 year in a kidney transplant, based on our
- 20 protocol of biopsy data, are going to be different at
- 21 10 years.
- 22 DR. ABECASSIS: So --

- 1 DR. STEGALL: You're going to -- those are
- 2 going to -- and maybe the iBox will be able to be the
- 3 same model. But if you have glomerulitis as the major
- 4 lesion, for example, it's going to be much more common,
- 5 I would think, in the first five years. And as you go
- 6 forward -- I mean, again, I may -- minority opinion on
- 7 this -- so -- but I think that you -- the answer what's
- 8 long-term graft survival is basically until the patient
- 9 dies. That's long-term graft survival.
- 10 UNIDENTIFIED MALE SPEAKER: So I --
- DR. STEGALL: But that -- that's actually a
- 12 big question.
- 13 UNIDENTIFIED MALE SPEAKER: I can --
- DR. STEGALL: And I think the think about it
- 15 is that in -- but in a patient with a high iBox score
- 16 at one year, five years is long-term graft survival for
- 17 that patient. And I think that it's -- so that's the
- 18 reason I said it depends on the kidney. Not everybody
- 19 ends up with that kind of thing.
- 20 But I really do think the goal always is to
- 21 have the kidneys last forever. But I don't know if
- 22 some of the issues about antibody and all the rest are
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- 1 going to be the major issue at 10 years for those
- 2 patients. And I think that -- so --
- 3 UNIDENTIFIED MALE SPEAKER: Are or are not?
- 4 DR. STEGALL: Are -- they will not be as --
- 5 yeah, I think it's --
- 6 DR. ALBRECHT: So this is a very important
- 7 discussion, but we need to switch sessions. And the
- 8 good news is the next session is late post-transplant
- 9 biomarkers. And so let's continue this dialogue.
- 10 So may I ask Dr. Yan Wang at FDA and Ros
- 11 Mannon to please moderate the next section?
- 12 And sir, can you stand up right after the end
- 13 of this session, and we'll take your question at that
- 14 time?
- 15 UNIDENTIFIED MALE SPEAKER: Sure.
- DR. WANG: Certainly. Okay. Good afternoon.
- 17 Welcome to Session 4 of the workshop. In this session,
- 18 we are going to talk about potential late post-
- 19 transplant biomarkers to identify patients
- 20 immunological risk.
- My name is Yan Wang and (inaudible) at FDA, so
- 22 (inaudible) transplant product. And Dr. Ros Mannon is

- 1 the co-moderator for this session. Thank you.
- 2 And our first speaker is Dr. Ken Newell from
- 3 Emory University. He is going to talk about biomarkers
- 4 of tolerance following kidney transplantation based on
- 5 the result of the immune tolerance network studies of
- 6 tolerant kidney transplant recipients.
- 7 Thank you.
- 8 DR. NEWELL: So I would like to thank the FDA
- 9 and C-Path for organizing this and inviting me. As I
- 10 thought about it, I'm invited, as I so often am,
- 11 because I'm the poster child for what is not a
- 12 biomarker. And I'm going to show you here why this, I
- 13 think, doesn't work and how my thought process has
- 14 evolved over time.
- 15 In terms of disclosures, none of these things
- 16 affect the content of this presentation.
- 17 So I'm going to try to outline why we need a
- 18 biomarker in tolerance studies, evidentiary criteria
- 19 supporting the association between B cell and B cell
- 20 phenotypes and the tolerant phenotype, the context of
- 21 use for a B cell signature of tolerance in kidney
- 22 transplant recipients as I originally thought it would
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- 1 be, some of the barriers to why it's not, and what it
- 2 could -- what the current data could support in terms
- 3 of a context of use and what we need to do to broaden
- 4 that context of use.
- 5 So I think it goes without saying the
- 6 statement of need is that minimization of
- 7 immunosuppression, to the extent that it's safe, has
- 8 the potential to reduce the morbidity of
- 9 immunosuppressive drugs in our transplant recipients.
- 10 The problem, though, is that, in the absence of
- 11 validated biomarkers, this is a purely empiric process
- 12 where you kind of wean and hope to see nothing bad
- 13 happen, so it exposes patients to risks.
- 14 And there are a couple of papers. There's
- 15 also a paper from the group ANOT (ph) that is very
- 16 similar in what it did. But this is Peter's data, so I
- 17 won't belabor it. But as he said this morning, they
- 18 took very carefully selected patients under a strict
- 19 protocol, tried to wean immunosuppression, and 50
- 20 percent of them had an outcome that was bad for them.
- 21 Hence, the study was stopped.
- 22 So obviously, if you could use some of the

- 1 tools he described this morning to guide that so that
- 2 you went from a 50 percent success rate to a 95 percent
- 3 success rate, we'd all feel a lot better. Then the
- 4 same is true when you talk about tolerance, which is
- 5 simply weaning to the extreme.
- 6 So when you talk about is there any evidence
- 7 to suggest a link between B cells and tolerance, there
- 8 are a number of papers here. And I'm not going to go
- 9 through them all, but I am going to hit the high points
- 10 of a few. I'm going to do it fairly quickly.
- 11 So this is the first paper we wrote. It was
- 12 published in JCI, a companion manuscript, one that
- 13 Maria might mention, very similar in intent. We took
- 14 patients who were off immunosuppression for at least a
- 15 year. They had good renal function. I'll show you
- 16 what it was. It was near their baseline. And we
- 17 compared them to patients who were receiving a
- 18 conventional triple-drug immunosuppressant regimen and
- 19 tried to say what are the differences.
- 20 This is really hard to see here. But what I
- 21 would tell you is the cohort was a little unusual and
- 22 that it was predominantly recipients of living donor

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- 1 kidneys. They were really well matched. I don't think
- 2 I can get the pointer. I -- kind of I can.
- The mismatch -- where did it go? Somewhere.
- 4 Oh, right here. So they were really well matched
- 5 relative to the comparison group.
- 6 They were further out from transplant than the
- 7 other group. They were about, on average, I want to
- 8 say, 15 to 20 years out from transplant versus about 5.
- 9 So that's another, perhaps, significant difference that
- 10 we'll come back to. But they had good kidney function
- 11 with creatinines of around one. So these were people
- 12 who were quite unique in that they were, on average, a
- 13 decade out from transplant with a creatinine of one who
- 14 hadn't taken immunosuppression for quite a while, but
- 15 some important differences.
- So this is why you should not be too wed to
- 17 your hypotheses. If you went back and read my original
- 18 grant application, it said that tolerance was related
- 19 to regulatory T cells, and we were going to get samples
- 20 from patients and prove there were more T cells with a
- 21 regulatory phenotype and properties, and then we would
- 22 have a good marker.

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- 1 So we did gene arrays. And what this showed
- 2 you is -- my first thought is, out of 5,000, roughly,
- 3 transcripts we looked out, I figured there would be
- 4 hundreds that were differentially expressed, and it
- 5 would be impossible to sort it out. And there were
- 6 only 30 that were really differentially expressed. Of
- 7 those, about two-thirds were related to B cells. This
- 8 says B cell-specific. That's probably not correct.
- 9 It's related to B cells.
- 10 So to show you how wrong I was, our original
- 11 flow cytometry panels didn't even have B cell markers
- 12 in them. We were so sure that B cells were irrelevant
- 13 So then we went back and redid the flow panels and
- 14 showed that, also, by flow cytometry -- and I'll show
- 15 some of the data -- there are more B cells, and there
- 16 are different types of B cells. Their phenotype isn't
- 17 the same.
- This is often overlooked by everybody besides
- 19 Sue Than (ph), who points it out. And it's in one of
- 20 his recent reviews. We looked at gene expression in
- 21 urinary sediment pellet cells. And again, the only
- 22 gene that was differentially expressed was CD20, a B

- 1 cell marker. And so it says that not only are there
- 2 more B cells in the peripheral blood, but there are
- 3 more B cells in the shed cells from the kidney and,
- 4 hence, probably in the kidney, which if you believe
- 5 that, you know, cells should be the site of action to
- 6 have an effect, then these B cells are in the kidney,
- 7 perhaps.
- 8 This is Maria's paper. I'm not going to
- 9 belabor it -- a different cohort of patients, slightly
- 10 different study design, slightly different assays, but
- 11 still kind of a similar surprising finding.
- 12 This is from the group ANOT. They went a
- 13 little further, and they found more B cells. But they
- 14 also said these B cells had different surface markers,
- 15 fitting with the fact that it's not just more of
- 16 regular B cells, but it might be different numbers of a
- 17 unique B cell subset.
- And they argued in another paper that these
- 19 are transitional B cells. These B cells produce more
- 20 IL-10. We'd shown that in our first paper. When you
- 21 stimulate the maxrebo (ph), why is that important? IL-
- 22 -10 is a potentially immunoregulatory or

- 1 immunosuppressive cytokine. There was an extensive
- 2 data that I was totally unaware of from autoimmunity
- 3 experimental models and then clinical models that there
- 4 are B cells with regulatory properties.
- 5 So when you start talking about is there a
- 6 biologically plausible reason why having more B cells
- 7 of this transitional type are good, or could be
- 8 protective, yes, there is a potential biologic fit for
- 9 this if they're the right type of cells.
- 10 And then they also showed that there was a
- 11 developmental defect here that prevented terminal
- 12 differentiation of these B cells. So again, they don't
- 13 develop into plasma cells. They're not going to
- 14 produce high amounts of antibody, perhaps. Maybe they
- 15 produce immunoregulatory cytokines. So it kind of fits
- 16 as a model.
- 17 So the next thing we did is we tried to say,
- 18 if this signature is going to be relevant, it should be
- 19 stable over time. If the B cell signature -- and I
- 20 should say this B signature to go back -- I'm moving
- 21 kind of quickly -- but it's based on the expression we
- 22 reduced it to three genes that are all B cell receptor
- - Page 307
- 1 genes. And they're B cell receptor genes that are not
- 3 cell.
- 4 So we looked at these three genes, and we
- 5 tried to say is it stable over time because, if one
- 6 time they're predicted to be tolerant based on these
- 7 three genes and another they're not but their clinical
- 8 phenotype hasn't changed, it's not very useful as a
- 9 tool, right? Conversely, if their clinical phenotype
- 10 has changed, then the test continues to predict them
- 11 with the same phenotype they started with. It's not
- 12 very useful.
- 13 So what this shows you is, over a time period
- 14 of about three years, the blue, tolerant patients,
- 15 clinically tolerant by phenotype, maintain about the
- 16 same B cell expression for the two most predictive
- 17 genes. What's kind of interesting is that, over time,
- 18 the control cohort begins to merge with them,
- 19 suggesting they're acquiring the same type of thing.
- 20 And this becomes important to say, does this reflect a
- 21 change in their immune status, or is it just a function
- 22 of time since transplant? And those are some of the

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- 1 things we can't answer. But certainly, in the liver
- 2 transplant world, when you look at tolerance, the most
- 3 powerful predictor of developing tolerance is time from
- 4 transplant.
- 5 This goes into more detail. And this was done
- 6 by Naki Sans (ph), but more detailed phenotyping. And
- 7 the biggest difference between the tolerant patients,
- 8 their B cell repertoires, and the nontolerant has to do
- 9 with the maturational status. So the naïve and
- 10 transitional T1 and T2 B cells really distinguished the
- 11 tolerant from the nontolerant. It wasn't simply that
- 12 there were just globally more B cells of all types.
- 13 This shows it another way. So this is B cell
- 14 number here. So we rank-ordered all the patients based
- 15 on how many B cells they had. And this is by the
- 16 percentage of T1, T2, and naïve. So it's kind of
- 17 saying, what's more important? The number of B cells
- 18 or the phenotype of the B cells. And you can't see it,
- 19 but this is the clustering. And actually, the
- 20 composition of the repertoire, or the maturational
- 21 status of your B cell population, predicts tolerance
- 22 better than just the number of cells -- of B cells.

- 1 This is more work from the group ANOT. They
- 2 very commonly expressed, I'm told, on your average B 2 took six different studies and tried to do a meta-
 - 3 analysis and found out that, although the genes were
 - 4 subtly different, the most commonly differential
 - 5 expressive genes, many of them were related to B cells.
 - 6 So it's, again, just another way of looking and saying
 - 7 it's not one study.
 - 8 So I'd say that there's a fair amount of
 - 9 evidence that B cells -- and I haven't shown you some
 - 10 of the functional data that the B cells are actually
 - 11 functionally different. They're able to suppress
 - 12 donor-specific responses when you take tolerant --
 - 13 these regulatory -- or the -- I should say the
 - 14 transitional B cells from tolerant patients can
 - 15 suppress T cells in vitro, arguing that they have some
 - 16 function.
 - 17 So I've tried to make the argument that
 - 18 there's a fair amount of data supporting this. So what
 - 19 would this tell us? Oh, and then this is also
 - 20 important. This is from the ANOT group. They -- you
 - 21 can't see it, but they tried to take gene expression
 - 22 data and then mix it with clinical, somewhat more like

- 1 the iBox, you know, where you're trying to put together
- 2 different types of data to get a predictive model. And
- 3 as they add things such as age at collection of the
- 4 sample, age at transplant, and renal function as
- 5 determined by creatinine, they can increase the
- 6 predictive power of the model, so moving more towards a
- 7 drug development tool, perhaps, by adding other types
- 8 of data.
- 9 So then the next study we did, we tried to
- 10 say, look, if this is only expressed in 1 out of 1,000
- 11 patients, even if it's 100 percent accurate, it's
- 12 worthless. It's got to be in a high enough percentage
- 13 of patients to be clinically useful as a tool, and yet
- 14 it's got to -- if it's in 80 percent of patients, I
- 15 know I can't stop immunosuppression in 80 percent of
- 16 kidney transplant recipients, so it's probably not
- 17 useful.
- 18 So this was done by NIAID and the ITN
- 19 together, enrolled 249 patients. And over time, we
- 20 looked at -- over a three-year period, we said, how
- 21 many by the two genes we're using now would you predict
- 22 to be tolerant? To predict -- these are all patients
- Page 311
- 1 receiving immunosuppression of some sort.
- 2 So what you can see is 25 to 30 percent for
- 3 any given visit had the signature. But then you say,
- 4 well, remember, it's got to be stable over time. So we
- 5 took the patients who had it at all three time points
- 6 versus those who never had it. And that was 17
- 7 patients always had it; 71 never had it. So those are
- 8 the most extreme phenotypes, if you will. And we said,
- 9 how do those two look?
- The most interesting thing is I can't tell you
- 11 if they're tolerant. We didn't try to wean any
- 12 immunosuppression. But this is kidney function. Now,
- 13 what it shows you is, whether you look at creatinine or
- 14 EGFR, the group that has these B cells has
- 15 significantly better renal function over time. They
- 16 start out the same at transplant. But as you go
- 17 further, they begin to diverge. And I would point out
- 18 that this is about the same difference in renal
- 19 function that you see with Belatacept. So it's not a
- 20 trivial difference, again, arguing that, perhaps, the B
- 21 cells have a role.
- This just says that the signature has

- 1 different prevalences, depending on your
- 2 immunosuppression. So if you say what when I first saw
- 3 this data would I say this meant, I'd say that, as far
- 4 as the context of use, the ITN B cell signature of
- 5 tolerance can be used to identify tolerant kidney
- 6 transplant recipients who can undergo some degree of
- 7 partial or complete weaning if they meet certain
- 8 criteria. That's totally wrong.
- 9 And I have to wrap up here, so I'll go really 10 quickly now.
- But the point is we never attempted weaning.
- 12 We don't know that the group that doesn't have the
- 13 signature doesn't contain tolerant patients in it.
- 14 It's the wrong comparison and control groups.
- 15 Maria will talk about this. Immunosuppression
- 16 is a confounder. And this is just from another group.
- 17 And it shows you here that immunosuppression has
- 18 profound effects on B cells. I don't think this is the
- 19 sole thing because, if you look at tolerance in liver
- 20 transplant, they get the same drugs, and yet they don't
- 21 have a B cell signature when you stop their
- 22 immunosuppression. So I think there are some reasons
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- 1 we can debate later.
- 2 But then I tried to say I think -- and I'll
- 3 conclude with this maybe -- that what you can say from
- 4 this is patients who are out from transplant doing well
- 5 without DSA, without rejection, who are taking no
- 6 immunosuppression, perhaps if they have the signature,
- 7 you can believe that they will continue to do well
- 8 without drug. So it might tell you that it's safe to
- 9 do this, and, that way, it may be -- what's the word
- 10 I'd want -- it may help diagnose a tolerant state once
- 11 they exist. It tells you nothing about how you get
- 12 there. So I think that's the real limitation of this.
- 13 This is nowhere near a drug development tool, as best I
- 14 can tell.
- 15 And I think I'll just quit there. Thank you.
- 16 (Applause.)
- 17 DR. WANG: Our next speaker is Dr. Maria
- 18 Hernandez-Fuentes from UCB Celltech. The title of her
- 19 talk is Biomarkers of Tolerance in Kidney
- 20 Transplantation: Are We Predicting Tolerance or
- 21 Response to Immunosuppressive Treatment?
- Thank you.

- DR. HERNANDEZ-FUENTES: Thank you very much to
- 2 the FDA for bringing me here and giving me the
- 3 opportunity to participate in what I think is a very
- 4 interesting and a very important discussion. And I
- 5 think it is very important to bring academy and
- 6 industry and our leaders in the same room and trying to
- 7 think about how to move this forward.
- 8 So I do have a disclosure. I moved into the
- 9 industry (inaudible) two years ago. But all of the
- 10 data that I am going to show is -- has been generated
- 11 in -- as an academic whilst I was in full time in
- 12 King's College London.
- 13 So I am very in the privileged position that
- 14 Ken Newell has talked before, and he's set the stage
- 15 of, well, what is it that we're looking. And the idea
- 16 of the -- when we started was to identify whether we
- 17 could make sure that we could identify the patients
- 18 that were not necessarily already in a good position to
- 19 not be very immunosuppression-dependent.
- 20 So I did do the exercise of, if I wanted to
- 21 use these biomarkers, what is it that we needed. And
- 22 as -- I agree with Ken. What we need is maybe we could
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- 1 identify patients in (inaudible). We could withdraw or
- 2 at least decrease immunosuppression. And therefore, we
- 3 think that has some benefits in the long term.
- 4 And this in -- this is contributing to
- 5 personalizing poor stress plant management. How do we
- 6 transfer that into a specific drug development
- 7 programs? It's a complicated issue because the drug
- 8 development programs in transplantation is not going to
- 9 be a single drug. It is going to be the (inaudible)
- 10 drug on the context of all of the other drugs. But
- 11 that's my side point.
- 12 And the context of use is to use them in that
- 13 context, and that's how we've been thinking about it
- 14 and developed that program.
- Of course, the benefit is, if it is through
- 16 the patient (inaudible) would control the immunity
- 17 against the transplant, but there needs a lot less
- 18 immunosuppression, we would decrease the risk of
- 19 infection to more nephrotoxicity and cardiovascular
- 20 disease that immunosuppression brings.
- 21 So Ken has mentioned that we did a study which
- 22 we published (inaudible). We had a set of biomarkers

- Page 316 1 and also, coincidentally, with him, we had a set of
- 2 genes that were B cell-related. They were different
- 3 biomarkers, but we used, again, a microarray, and it
- 4 was a surprise when we initially interchanged
- 5 information. You know what? The B cells are more
- 6 important than the D cells.
- 7 And I have the same bias in -- we have the
- 8 same bias in initial design. And we also had some
- 9 biomarkers that it was flow cytometry and B cell flow -
- 10 you know, the percentage of CD19 cells. And briefly,
- 11 it was important to differentiate the total recipients
- 12 from the rest of the group that were in the comparator
- 13 group.
- 14 So we did this initial study, and we had a
- 15 very good sensitivity and a specificity. And
- 16 importantly, for the discussion afterwards, we had the
- 17 group of healthy controls both in the test set and the
- 18 training set. And for the training set, we were really
- 19 fortunate to interchange sample from the Immune
- 20 Tolerance Network. And we did (inaudible) the same
- 21 assays, the flow cytometry, we had a functional assay
- 22 and (inaudible) and the gene expression, we got very
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- 1 good sensitivity and specificity in that cohort as
- 2 well.
- The statistician thought that it would be a
- 4 more clinically applicable parameter if we could
- 5 calculate the probability of being tolerant for each of
- 6 the patient included in the trials that are in the
- 7 studies that we were doing. And therefore, she went on
- 8 and did that. And of course, the differentiation in
- 9 the training set is very good. And then, importantly,
- 10 in the validation set, it's also very good.
- 11 So we did have some patients with a stable
- 12 function. That had a cut-off above -- that were
- 13 similar to those that were identified as operationally
- 14 intolerant.
- So with that, we (inaudible) and did the same
- 16 validation assay that Ken (inaudible) did with the
- 17 (inaudible) study because it is very important to
- 18 identify what is the prevalence of that signature in
- 19 the stable patients in your population. But also, we
- 20 needed another ancillary validation of that signature.
- 21 All of those gene expression was done on microarrays.
- 22 We needed to do the platform transformation to

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- 1 something that more -- was more close to the point of
- 2 care, which is RT-PCR.
- 3 So we used fluidigm (ph) because we still were
- 4 looking at a lot of genes. We did do the stability
- 5 (ph) of signature. If you want, I have the data, but
- 6 I'm not going to show you.
- 7 And we did have a proof of concept group,
- 8 which were patients that were undergoing a steady
- 9 withdrawal for clinical reasons, not because they had
- 10 any biomarkers. And we wanted to see what happened
- 11 before and after.
- This is the cohort. We had 14 completely new
- 13 total (inaudible) recipients that have not participated
- 14 in the initial studies. They were a slightly better
- 15 match, but not as well matched as the other ones. And
- 16 we have (inaudible) donors there.
- We had 190 patients with stable function
- 18 longer than three years. That's less than 50 percent
- 19 variation in the creatinine function. And of course,
- 20 they were on different immunosuppression levels. And
- 21 we had the group of patients that have had a biopsy
- 22 that indicated a certain degree of immune damage that

- 1 those that are off prednisone.
- 2 Once you adjusted for the other use,
- 3 cyclosporine and tacrolimus did not seem to have a very
- 4 strong influence on that probability of being tolerant.
- 5 Importantly, the patients that were on steroids, when
- 6 they themselves came off steroids, their probability of
- 7 being tolerant changed. And we did not see a
- 8 difference here between the tolerant and the healthy
- 9 controls
- 10 And as Ken Newell has explained, we were
- 11 looking at B cells. And here, we already knew about
- 12 the B cells, so we looked at different subset of B
- 13 cells. And the general B cells have a (inaudible), the
- 14 subset that is most affected by the immunosuppressants
- 15 is the transitional B cells. And these are the high CD
- 16 -- 38 CD24 subset that I can describe.
- 17 Again, so (inaudible) has a very strong
- 18 effect. Patients on (inaudible) have very low
- 19 frequency of those B cells. Patients of prednisone
- 20 have lower than the ones that are out of prednisone.
- 21 Your CNIs have no effect on the transitional B cells,
- 22 and the tolerant recipients have the same level of

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- 1 was immune-driven. And we call that chronic reaction.
- 2 Of course, because it is a retrospective
- 3 collection, which is the necessity in kidney transplant
- 4 recipients, all of the -- these are all of the stable
- 5 patients. We have 17 different treatment groups. And
- 6 we didn't consider that here because this was -- most
- 7 of them were five years after transplantation. So we
- 8 didn't consider the induction protocol, part of that
- 9 because we didn't have that information in the clinical
- 10 records, believe it or not.
- And so this was the -- (inaudible) is the
- 12 statistician that did this analysis. She calculated
- 13 the probability of tolerance that she had done in the
- 14 other study. You've seen those 10 genes that were
- 15 identified that had a strong B cell marker. And what
- 16 happened is that the patients in -- and these are the P
- 17 (ph) values suggested for the fact that all of the
- 18 patients are in different treatments. So they are not
- 19 straight away -- and -- but you have -- you -- what you
- 20 can see is patients on a -- as a (inaudible) have a
- 21 much lower probability of being tolerant. The patients
- 22 that were on prednisone have a lower probability than

- 1 transitional B cells of healthy control. So it's not
- 2 like they go overboard.
- 3 And this is what I think it is more important.
- 4 The same patients that are -- when they were on
- 5 steroids, some of these were fairly low, like, two
- 6 milligrams a day of prednisone. When they came off of
- 7 steroids, this is six to eight months later. All of
- 8 them except one increased their percentage of
- 9 transitional B cells in (inaudible).
- 10 So because we wanted to use the signature to
- 11 select patients to change the immunosuppression, we
- 12 thought it would rather (inaudible) to have a signature
- 13 that is dependent on the immunosuppression because if -
- 14 then if you change the immunosuppression, you'll know
- 15 if that signature has changed just because you changed
- 16 the immunosuppression or because they are not tolerant
- 17 anymore. And how do you then handle the clinical
- 18 follow-up?
- 19 So the statistician went back to square one,
- 20 went back to the instances of tolerance arrays, did a
- 21 study that -- the (inaudible) is used to control for
- 22 confounding factors. She did a logistic regression,

- 1 and she calculated for each one of the genes in the
- 2 array, the immunosuppressant-independent expression.
- 3 And you've seen that. She derived the difference
- 4 between the tolerance and the rest, and she came up
- 5 with the sets of nine genes that would differentiate
- 6 between the tolerance and the patients and the healthy
- 7 controls.
- 8 And now the genes are more transcription
- 9 factor and general uses. It is not that they're not
- 10 completely B cell-independent. There are two of them
- 11 that are in the B cells, and then there is one that is
- 12 quite B cell-specific. This we didn't know when we
- 13 published, but it is now being described in plasma
- 14 cells but not in healthy B cells.
- So now we have a new set of genes. And then
- 16 does it matter what the immunosuppression (inaudible)?
- 17 So we used those same samples. And here you can see a
- 18 probability of being tolerant using those set of genes
- 19 in the same patients that I have shown you before. And
- 20 now you can see that there is no difference of whether
- 21 you are on (inaudible) or MMF, on CNIs, on prednisone.
- 22 You have, more or less, the same probability before or
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- 1 after withdrawal, and that's -- the tolerance have a
- 2 higher probability than the healthy controls. That
- 3 makes us feel a bit better. Whether that's completely
- 4 (inaudible) or not is a different matter.
- 5 So this is what I think we need to think
- 6 about. The gene expression of a patient in a certain
- 7 time point is the consequence of several things that we 7
- 8 need to distill. There is some certain biology that is
- 9 viewed to the immunosuppressant effects or being for
- 10 years in immunosuppressants. And there is a certain
- 11 biology that has to be referred to the tolerant
- 12 (inaudible).
- We think that using the strategy that we have
- 14 used, we have highlighted these versus the other. But
- 15 it shows the use of the effect.
- One of the consequence of not using these, so
- 17 the -- it's we need robust statistical methods to
- 18 analyze the gene expression because there is a lot of
- 19 factors that are influencing the patients. And again,
- 20 we think that we have this identified. But of course,
- 21 this is the (inaudible).
- What happens if you don't use this? So this

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 1 is the patients -- the -- all of the stable patients.
- 2 So if we use the old signature without a control, we
- 2 50 if we use the old signature without a control, we
- 3 identified 25 patients in -- within a 190. That could
- 4 be identified as tolerance and would be the ones that
- 5 we would suggest for winning. Using the new one, we
- 6 identified 20 patients. And then there's only two
- 7 patients that are the same between one and the other.
- 8 And if you can see the -- in the initial
- 9 signature, there is a higher proportion of patients on
- 10 tacrolimus. It's interesting. The proportion of
- 11 patients in (inaudible) is very low, and prednisone is
- 12 not low. But if we then go and use the
- 13 immunosuppression-independent, those percentage of
- 14 patients in -- that are taken in each one of those
- 15 drugs is different. So we do select different
- 16 patients. This is an analysis that has been given by
- 17 Sophia Aristacooney (ph), which is the (inaudible)
- 18 statistician working in this.
- We did take -- we undo (ph) the -- both genes.
- 20 We took the gene that -- one of the genes of
- 21 (inaudible). I can't remember why we didn't do the
- 22 other one. Anyway, the gray bars are the -- this is
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- 1 the percent -- the number of patients that I've
- 2 selected from the Gambita (ph) study using the
- 3 expression of that gene that are not on prednisone nor
- 4 that (inaudible) on prednisone. Gray bars are, if we
- 5 don't correct for immunosuppression, and the black bars
- 6 are if we correct for immunosuppression.
 - So I think the bigger difference (ph) -- and I
- 8 think you found this as well -- there are quite a few
- 9 patients on tacrolimus with (inaudible). If we correct
- 10 for immunosuppression, there are less patients on
- 11 tacrolimus that we select with those genes.
- 12 So I think we need to -- if we are going to
- 13 use these for patient selection for immunosuppression
- 14 with (inaudible), I think we would need to do this
- 15 correction. So the context of use will drive, I think,
- 16 these decisions.
- 17 So the way we were going to do this is, of
- 18 course, is a clinical trial where you would have
- 19 patients understand their therapy. And then you would
- 20 have patients identified that have these tolerant
- 21 genes. And half of them, you would do partial winning
- 22 (ph), and half of them should stay on therapy. And we

1

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- 1 have calculated how many we needed to find differences,
- 2 and it was -- you know, we needed to screen about 1,000
- 3 patients. So it's not a minor trial to be taken into
- 4 account. This hasn't been done yet. I've asked two or
- 5 three times for money to do this, and I have been
- 6 unsuccessful, you know, in getting that.
- 7 Okay. So the statement of need and the
- 8 context of use -- we have talked about it. The benefit
- 9 to the patients is, in theory, decrease the risk for
- 10 infection, tumors, nephrology. But the risk is very
- 11 different in these tests of false positive than a false
- 12 negative. So a false positive of the test means that
- 13 you've selected a space (inaudible) to increase their
- 14 immunosuppression. And then the (inaudible) situation
- 15 (inaudible) will use the transplant, whereas the false
- 16 narrative test is the same as we are now. So they will
- 17 not be (inaudible) on immunosuppression. And I think
- 18 that has to be taken into account when you calculate
- 19 the threshold.
- 20 And I still think that, of course, it is an
- 21 intellectual jump to say that patients that have the
- 22 same signature of patients that have come off the

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- 1 immunosuppression for a while may be suitable to select
- 2 for lower immunosuppression. That's the demonstration
- 3 that we neither -- we don't need to do.
- 4 I think that they could be identified as a
- 5 diagnostic of the subset, or as Newell has mentioned,
- 6 diagnostic of the tolerant recipient. And whether we
- 7 can use those -- and that's another big jump -- is a
- 8 likely (inaudible) endpoint in those (inaudible) using
- 9 trials that are proliferating, that needs also to be
- 10 demonstrated as well.
- And I have to thank a lot of people. So the
- 12 (inaudible) of Tolerance Network and the Immune
- 13 Tolerance Network, this was for the initial study. The
- 14 Gambita Consortium, which is in the last five years,
- 15 has been included a lot of groups within the UK, but
- 16 also in Europe. And the two statisticians have had a
- 17 central point in the analysis of the studies, but
- 18 there's been a large number of technicians, project
- 19 managers, research nurses. And these are the funding
- 20 bodies that have allowed this validation.
- Thank you very much.
- 22 (Applause.)

Page 328 DR. WANG: Our third speaker is Dr. Edward

- 2 Chong from Vitaeris. He is going to talk about a
- 3 backwards approach to identifying a predictive
- 4 surrogate endpoint for chronical antibody-mediated
- 5 rejection.
- 6 DR. CHONG: Thank you very much. Good
- 7 afternoon, ladies and gentleman. My name is Eddie
- 8 Chong. I am the chief medical officer for Vitaeris.
- 9 And I would like to thank the Transplant Division and
- 10 the TTC to invite me to speak on behalf of my
- 11 colleagues.
- So let's -- I'm going to change gears
- 13 slightly. I'm not going to show you any slides of geno
- 14 array readouts or protein readouts. But what I'd like
- 15 to do today is to describe the process that we went
- 16 through and the work that we did for a pivotal trial
- 17 that we are intending to start early next year.
- This slide here summarizes the three pathways
- 19 that one could under -- could follow to identifying and
- 20 looking up a surrogate endpoint for clinical trial. So
- 21 the first bullet is the Biomarker Qualification
- 22 Program, and you've heard a lot about it already.

- 1 The second pathway is through an expert
- 2 consensus. And some of -- the examples of some of the
- 3 surrogate endpoints are listed here. And these have
- 4 all been validated through large clinical outcome
- 5 study. And therefore, you could use this endpoint for
- 6 a pivotal trial for regular approval.
- 7 But what I'd like to discuss is the third
- 8 route that we took, and this is through the R&D route
- 9 as part of a drug development process whereby we -- you
- 10 know, at this point I'd like to take the opportunity to
- 11 thank the Transplant Division for their help and
- 12 support and the useful advice they gave us whilst we
- 13 were working through this process to arrive at this
- 14 pivotal trial that we -- as -- that I said that we are
- 15 intending to start next year. And if this trial is
- 16 positive on the surrogate endpoint, we would hopefully
- 17 be able to use this as a basis for accelerated
- 18 approval.
- 19 So before I discuss the work we did, a bit
- 20 about the condition that we tried to develop our
- 21 therapeutic drug for. And this is for chronic
- 22 antibody-mediated rejection. As most of you will know,

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1 it is now recognized as the leading cause of long-term

- 2 allograft loss after kidney transplantation. It's
- 3 recognized to be a rare and serious life-threatening
- 4 condition with no approved or effective treatment.
- 5 And studies, therefore, to demonstrate
- 6 clinical benefit, this is one of the major problems
- 7 that we face in transplantation, is that studies
- 8 requiring to show clinical benefit would be large and
- 9 would take a long time.
- So -- and when you think about the possible
- 11 surrogate endpoints that one could use for accelerated 11
- 12 approval, there are many. And you could think about
- 13 biopsy data, DSA, proteinuria, or some measure of
- 14 rental function.
- 15 And all of these have been shown to
- 16 significantly correlate with the risk of allograft
- 17 loss. But unfortunately, correlation does not make a
- 18 surrogate endpoint, as we all know, because what we
- 19 lack is quantitative data to relate the surrogate
- 20 endpoint with the risk of graft loss, i.e., you need to
- 21 be able to quantify the change in the surrogate
- 22 endpoint with the change in the risk of the clinical

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- 1 benefit endpoint, i.e., allograft loss. And without
- 2 data to show this quantitative relationship, it's very
- 3 difficult to design a trial and also to convince the
- 4 FDA that the surrogate endpoint is reasonably likely to
- 5 predict clinical benefit. Therefore, there is -- there
- 6 -- up to now, there has not -- no surrogate endpoint
- 7 has been used for accelerated or full approval by FDA
- 8 for this condition.
- 9 So some -- a couple of slides -- you've seen
- 10 this slide. I think man of us have seen this slide
- 11 before. It shows the correlation between DSAs and
- 12 graft survival or graft loss here. There was people
- 13 with de novo DSA with clinical renal disfunction have a
- 14 higher risk, and this is people without de novo DSA and
- 15 no renal function. So you've seen this. So this here
- 16 again shows the significant correlation between a
- 17 potential surrogate endpoint, i.e., DSA and allograft
- 18 survival.
- 19 Again, another slide here, this shows that --
- 20 the same thing. You see a significant correlation,
- 21 statistically significant correlation between DSAs and
- 22 graft -- and risk of graft loss. And here again, with

1 biopsy data, this is risk of graft loss.

- 2 But there is some data in the literature that
- 3 shows the quantitative relationship between here, the
- 4 GFR renal function decline and the risk of allograft
- 5 loss. And this is a publication by Clayton (ph)
- 6 (inaudible) Group in Australia. It showed the -- it
- 7 has the -- as the EGFR declined, you get a higher risk
- 8 of graft loss. But this isn't de novo transplant
- 9 patients, not in the patients with chronic antibody-
- 10 mediated rejection.
- 1 And the panel on the right here, as you can
- 12 see, has the decline in EGFR from baseline over --
- 13 well, the baseline here is years 1 to 3. The higher
- 14 the decline in EGFR for -- you get a higher risk of
- 15 graft failure and also overall patient survival.
- So in our study, what we plan to use is EGFR
- 17 as a predictive surrogate endpoint for our trial. EGFR
- 18 is an attractive surrogate endpoint that one could use.
- 19 It's -- the decline in EGFR is the clinical consequence
- 20 of chronic rejection, antibody-mediated rejection, and
- 21 on the direct pathway to allograft loss.
- So if you can reduce the slope in EGFR by an

- 1 intervention, this should reflect the beneficial effect
- 2 of the intervention on the disease process and also on
- 3 allograft function and, hopefully, allograft survival.
- 4 Again, it's easy to measure and quantify. As I said
- 5 earlier, it's not a validated surrogate endpoint for
- 6 use. It has a basis for full approval except, as was
- 7 discussed earlier this morning, it has -- it's accepted
- 8 for CKD for chronic kidney diseases, but not for
- 9 chronic antibody-mediated rejection. But -- and it's
- 10 potentially useful as a surrogate endpoint for
- 11 accelerated approval.
- 12 As I mentioned earlier, if we can see a
- 13 positive effect on the slope of EGFR decline, this
- 14 should reasonably likely to predict clinical benefit.
- The problem, as I mentioned earlier, there is
- 16 limited data on the quantitative relationship between
- 17 the slope of EGFR decline and the risk of allograft
- 18 loss. And in the literature, I -- the only paper I
- 19 could find is a publication from Peter's group in
- 20 Manitoba.
- 21 So what we did to -- as a workup to supporting
- 22 and persuading the FDA to -- that -- you know, that

- 1 EGFR decline can be used as a surrogate endpoint, an
- 2 interim surrogate endpoint for accelerated approval for
- 3 a clinical trial, is to do a modeling exercise. This
- 4 modeling exercise is a noninterventional historical
- 5 perspective cohort study. And as I mentioned, the
- 6 primary objective is to validate the functional
- 7 relationship between the change in EGFR following
- 8 diagnosis of active ABMR and the risk of allograft loss
- 9 in the subsequent years.
- The inclusion-exclusion criteria that we use
- 11 to select the patient population reflects the selection
- 12 criteria that we intend to use in our clinical trial.
- So what we -- basically, what we did was we --
- 14 patients with active ABMR, using the Banff 2015
- 15 criteria, this one-year transplant with a minimum of
- 16 three-year serial data on (inaudible) and graft status
- 17 were selected. And thanks to the collaboration from
- 18 Peter, Dr. Jamale (ph), who's in the audience, and two
- 19 investigators in Barcelona, we were able to get about
- 20 200 patients. They identified patient-level data to do
- 21 this modeling exercise.
- And I'm not a statistician, but the change in

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- 1 EGFR across time was model using a linear mixed-effects
- 2 model. And the relationship between the change in the
- 3 EGFR, the slope of decline, and the risk of our
- 4 allograft loss was examined using this Jung (ph)
- 5 modeling framework.
- 6 And the Jung modeling framework predicted
- 7 that, you know, there's a -- not surprising, that the
- 8 baseline EGFR and its rate of decline -- and this is
- 9 defined as the EGFR slope change per month, following
- 10 active ABMR, diagnosis, significantly predicted the
- 11 risk of allograft loss of the -- close (ph) to five
- 12 years.
- And we could then hypothesize the treatment
- 14 effect of your intervention and ensure what this
- 15 intervention -- what this treatment effect will have on
- 16 the clinical meaningful endpoint, which is the
- 17 reduction of allograft loss over five years. And then
- 18 looking backwards, you can look at the slopes and see
- 19 in an earlier time point what the difference in the
- 20 slopes would be. And then you could also then quantify
- 21 it as difference in the slope, which is reasonably
- 22 likely to predict the risk benefit over five years.

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- 1 And with this information, therefore, you will
- 2 be able then to calculate the sample sizes for the --
 - 3 for both endpoints, for the early interim surrogate
 - 4 endpoint and also for the final clinical benefit
 - 5 endpoint.
 - 6 So based on this modeling exercise, the -- I'm
- 7 -- the FDA has accepted the study design that we plan
- 8 to initiate next year. And if positive, if we see
- 9 positive results on the interim EGFR surrogate endpoint
- 10 -- and hopefully that will be the basis for accelerated
- 11 approval. And then full, regular approval will then
- 12 obviously depend on the results of the final analysis
- 13 on the allograft loss endpoint.
- So I think that's the end of my slide. So
- 15 thank you very much.
- 16 (Applause.)
- 17 DR. ALBRECHT: So that brings us to the end of
- 18 this session. And I didn't know if anyone had any
- 19 questions.
- We had a question from the audience that we
- 21 didn't honor. Perhaps you could start.
- 22 UNIDENTIFIED MALE SPEAKER: Thank you.

- 1 (inaudible off mic).
- 2 DR. ALBRECHT: It may be on.
- 3 UNIDENTIFIED MALE SPEAKER: Okay. I'm
- 4 (inaudible off mic). The question I wanted to ask at
- 5 the last transition was prompted by (inaudible off
- 6 mic) a question about how long is long term. And then
- 7 there were several opinions from, I think, the point of
- 8 view of drug development. Long term for clinical trial
- 9 for a pivotal trial (inaudible off mic) long term I
- 10 would say to two years.
- Now, (inaudible off mic) challenge that.
- 12 But the logistics of recruiting in big trial or two big
- 13 trials and then following it up and maintaining
- 14 (inaudible off mic) participation and avoiding
- 15 premature dropouts, the -- they -- just from a
- 16 practical point of view (inaudible off mic), et
- 17 cetera. To go beyond two years is really not
- 18 (inaudible off mic) challenge (inaudible off mic)
- 19 therapeutic areas, perhaps (inaudible off mic).
- 20 And in terms of long-term allograft survival,
- 21 two years is not long term at all for (inaudible off
- 22 mic). So somehow, in order to apply these same needs

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- 1 (ph), which I'm very impressed (inaudible off mic),
- 2 we have to (inaudible off mic).
- 3 DR. ALBRECHT: Here we go.
- 4 UNIDENTIFIED MALE SPEAKER: We'd have to find
- 5 a way --
- UNIDENTIFIED MALE SPEAKER: We can hear you 6
- 7 better now.
- 8 UNIDENTIFIED MALE SPEAKER: Yeah.
- 9 (Laughter.)
- 10 UNIDENTIFIED MALE SPEAKER: It was in the way.
- 11 UNIDENTIFIED MALE SPEAKER: -- we have to find
- 12 a way to apply these exciting techniques --
- 13 DR. ALBRECHT: Yeah.
- 14 UNIDENTIFIED MALE SPEAKER: -- in a way that
- 15 we have a surrogate marker or a surrogate endpoint,
- 16 preferably of less than two years, but I would say, as
- 17 a starting point for discussion, more than two years.
- 18 That's long term to me.
- 19 DR. O'DOHERTY: I think maybe just to follow
- 20 up on the idea as well that, you know, I think Dr.
- 21 (inaudible) walked through that example of hoping to go
- 22 through an accelerated approval process so that there

- 1 be executed today, have better prediction of what's 2 going to happen with clinically (inaudible) endpoints
- 3 farther out in time. That's a -- that might sound like
- 4 a nuanced concept, but it's critically important if we
- 5 really want to transform the paradigm for drug
- 6 development in the transplantation.
- 7 Now, the other thing I -- and thank you. That
- was awesome. Thank you for sharing that.
- 9 The concept of joint models is something that
- 10 FDA is embracing. And it's in PDUFA. It's in the 21st
- 11 Century Cures Act. It's all about model-informed drug
- 12 development. Joined models are a conduit to make that
- 13 happen. We use that same approach for the first
- 14 imaging clinical biomarker. And this is an example in
- 15 kidney disease, polycystic kidney disease. That's the
- effort that Steve led. And that is extremely powerful.
- 17 Now, those models are data-hungry. So getting
- 18 it back to the conversation about this morning, we need
- 19 to get the data together. So ...
- 20 DR. ALBRECHT: It goes back to the meat
- 21 grinder.
- 22 Kevin.

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- 1 are different conduits, I will say. I'm not speaking 2 of the FDA if other folks want to join in -- but to be
- 3 able to propose different approval processes where you
- 4 might get with the surrogate a -- to market approval
- 5 for which you have to define a very specific post-
- 6 marketing strategy defined with the sponsor and the FDA
- 7 for that individual therapy in which you are on the
- 8 market as long as you ultimately meet those hard
- 9 endpoints, if you will, as well. And then it's kind of
- 10 a different, you know, novel scenario in which you're
- 11 able to consider that part.
- 12 DR. ALBRECHT: The man at the mic.
- UNIDENTIFIED MALE SPEAKER: Thanks. So yeah,
- 14 I agree with the previous comment in the sense that we
- 15 need to bring these back to drug development. We need
- 16 to separate this a little bit from individual patient
- 17 care. As much as it may be painful to the community,
- 18 we need to focus this on drug development.
- 19 And one of the things that we're saying is
- 20 we're not necessarily trying to lengthen the duration
- 21 of the trials, but find the tools that, in the
- 22 appropriate duration of the trials that are feasible to

- MR. FOWLER: Yeah. I'd like to go back to Dr. 2 Abecassis' comment about what's long term. So the
- 3 simple answer is what Dr. Stegall said, right? You
- 4 live forever with it, and you -- or you die with it,
- 5 right, simply.
- I would just maybe approach this from a -- I
- 7 think a little more of a complex issue. You know, Dr.
- 8 Newell and I have had a conversation about there's
- 9 people like myself that have a transplant, and it's
- 10 been a great experience. Other people have a
- 11 transplant, and it's not as great an experience.
- 12 And someone here is nodding. And I think you
- 13 can probably get a lot of information from the
- 14 patients. Doctor -- or I'm sorry -- Ellison Tom (ph)
- 15 is doing a paper -- I'm one of the contributing authors
- 16 -- about life, participation, and transplant. I would
- 17 encourage you to look at that when it becomes
- 18 published.
- 19 The other thing I would say, too, is that just
- 20 there's an absence. Like -- and I think if you go back
- 21 to her work, too, I'm more afraid of dialysis than
- 22 dying. That's the truth of it.

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- And the truth of it is, too -- and I think --1
- 2 try to get you to think about this in more of a
- 3 holistic way is that, you know, I just was involved
- 4 with a project reviewing a LDO and their education.
- 5 There's no communication about risk of dialysis. And
- 6 so I think that's part of the larger picture that this
- 7 needs to become part of, is understanding that.
- And when Dr. Cooper (ph) and I were talking
- 9 about this earlier, two of the (inaudible) conference,
- 10 these risk discussions aren't occurring. And I've
- 11 shared them with the FDA, and they were very surprised
- 12 of my perspective.
- 13 So I think it's a much more richer perspective
- 14 to look at that -- these different areas. But I was
- 15 just thinking that the simple thing is I really am
- 16 afraid more of dialysis than dying, truthfully.
- 17 Dialysis is death.
- 18 DR. NEWELL: So I wanted to comment on that,
- 19 build on Mike's carry-over from the other, and then ask
- 20 our last speaker a question as well where I think I
- 21 don't understand it. But I think when you say how long
- 22 is long term, it might not be the right question.

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- 1 I think what we need to do as a field is
- 2 describe what is a successful transplant. That varies
- 3 depending on the source of the kidney, the age of the
- 4 recipient, the type of the organ. But I think, as that
- 5 becomes better defined -- and certainly, survival will
- 6 become a component of that, but also quality of life
- 7 and things like that. But then you can still use
- 8 things like the iBox or any of these other models to
- 9 say does it impact that -- what is successful.
- So I think to think just in terms of long
- 11 term, I think from a practical standpoint, I'd say
- 12 right now one year is a whole lot better than -- or I
- 13 mean five years is a whole lot better than one year.
- 14 So I like the iBox because I think, you know, if you
- 15 can't get to five years, it's probably not a good
- 16 treatment.
- 17 So I do think that that's important. But we -
- 18 I think that, in five years, we won't be sitting
- 19 around here saying is three years long enough, is two
- 20 years, is five years. We'll be talking about a much
- 21 more complex endpoint that brings in patient-reported 21 think is the truth, which is chronic rejection and not,
- 22 outcomes, quality of life, cost, utility.

So that's just my perspective. And I know

- 2 that there are some groups that are taking this on over
- 3 the next year or so trying to talk about that.
- 4 The question I had about using EGFRs and
- 5 endpoint, when we were discussing this as part of the
- 6 TTC, there were several people who didn't like that
- 7 endpoint. They made the simple statement I can convert
- 8 from a nephrotoxic drug like a CNI to a non-nephrotoxic
- 9 drug, and all of a sudden, I get a bump in GFR. But
- 10 does that really equate to a better long-term outcome?
- 11 And there are confounders. You know, if I have an
- 12 episode of BK nephropathy, I'm going to take a hit.
- 13 And so is it possible to take something that
- 14 isn't really -- a lot of the studies we've heard about
- 15 are very specific to studying alloimmunity. Those are
- 16 the biomarkers. And you say something that's linked to
- 17 alloimmunity is a good predictor of a treatment to
- 18 prevent alloimmunity. I understand that. This is a
- 19 kind of -- something that's linked to kidney injury.
- 20 It's specific for chronic antibody-mediated rejection.
- 21 And do you think you'll have so much noise that other
- 22 things could confound that?

- 1 DR. CHONG: Yeah. It is a good point you're
- 2 making. But in the trial that we are planning to do,
- 3 obviously, we will try and control for the background
- 4 immunosuppression.
- 5 And again, it's important to emphasize that
- 6 we're looking at the rate of decline in EGFR over time.
- 7 So these patients coming into the study will have --
- 8 will be known to have this slowly progressive decline
- 9 in renal function. So I think that, you know,
- 10 hopefully, you know, we would overcome that problem.
- UNIDENTIFIED MALE SPEAKER: So I want to -
- 12 can I make a quick comment?
- So EGFR -- you could have a worse EGFR because
- 14 you have chronic rejection, or you could have a worse
- 15 EGFR because you're taking too much calcineurin
- 16 inhibitor. And the last time I did a little survey,
- 17 informal, our community was still divided right down
- 18 the middle as to whether kidneys died because of
- 19 chronic rejection or because they died -- now, I think
- 20 it's swinging more and more and more towards what I
- 22 you know, the fact that we're getting them -- so I

- 1 think in these studies we're testing drugs, and we're
 2 veing substitutes for what we know to cort of he the
- 2 using substitutes for what we know to sort of be the
- 3 best T cell activation drug that we have.
- 4 You know, sometimes a bump in EGFR I the right
- 5 direction may be a great short-term gain for a bad
- 6 long-term outcome if you're setting somebody up for
- 7 chronic rejection. And I just kind of ask myself: How
- 8 far have we swung towards, you know, all of us
- 9 believing that kidneys die from chronic rejection and
- 10 not from, you know, using calcineurin inhibitors?
- 11 DR. SARWAL: I just --
- 12 UNIDENTIFIED FEMALE SPEAKER: (inaudible off
- 13 mic).
- 14 DR. SARWAL: Yeah, sorry. I just wanted to
- 15 add to something, actually. I -- I mean, I really
- 16 agree with, I think speaker from the floor that
- 17 actually raised this issue. You know, we've become so
- 18 focused on looking at loss and injury that I think
- 19 that's become such a paramount endpoint for us, that
- 20 should we be really thinking about looking at this
- 21 slightly differently?
- I mean, we're looking at cancer-free survival.

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- 1 Why don't we look at injury-free existence? I mean, at
- 2 what point are we going to say that we should be
- 3 looking at the day-to-day performance of that allograft
- 4 in a state of health?
- 5 People do like PTT (ph) values because they're
- 6 trying to optimally dose their patients. We really
- 7 don't even have a yardstick to be monitoring the
- 8 efficacy of how we're dosing these drugs so that they
- 9 stay in that environment of stability. So now that
- 10 we've learned so much about injury and we got so much -
- 11 I mean, we got a little bit better with survival --
- 12 should we be trying to look at these -- at selection of
- 13 drugs and using them on a day-to-day basis by looking
- 14 at better readouts of daily immune quiescence and
- 15 inactivity of injury?
- DR. MANNON: So that may be -- you guys could
- 17 continue to argue. But with regards to the trial that
- 18 he is presenting --
- 19 DR. SARWAL: No, that's --
- 20 DR. MANNON: -- I think it's actually
- 21 valuable. I mean, I never imagined that -- when they
- 22 were proposing to do this, I thought there's no way

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- 1 that the -- that they'll allow them to do this. But if
- 2 you have a steady level of tac coming into the study,
- 3 all right -- and again, everybody's a little bit
- 4 different -- and you have depressed GFR to begin with
- 5 but not too low because you'll see no effect, I don't
- 6 think it's unreasonable. FSGS studies have looked at
- 7 slope of GFR. I mean, I think you have to start
- 8 somewhere.
- 9 But your point is well taken. I mean, you
- 10 know, nobody wants to -- I agree. I mean, the Song
- 11 initiative has indicated that patients and caregivers
- 12 would rather have their (inaudible) rather be dead than
- 13 go back on dialysis and that dialysis fear. And I
- 14 think it's tough to manage them. And so maybe being
- 15 injury-free is the right model.
- 16 But I think for this study, I think it's -- I
- 17 mean --
- DR. SARWAL: Yeah, this study --
- 19 (Crosstalk.)
- DR. SARWAL: So that's different. But I'm
- 21 just talking about newer drugs that come in. I mean,
- 22 maybe the focus should be about absence of injury

- 1 rather than all the time looking at loss and, you know,
- 2 negative outcomes.
- 3 DR. HERNANDEZ-FUENTES: Can I make a comment?
- 4 One of the problems that I think we have is we do have
- 5 a marker for kidney function, which his EGFR. And it
- 6 has all the confounders. What we don't have is
- 7 (inaudible) marker of level of immunosuppression. And
- 8 drug doses we know do not reflect the patient
- 9 individual immunosuppression, and that's a jump that we
- 10 need to make in all of the drug development studies
- 11 because we need to do immunosuppression. We think we
- 12 are, more or less, immunosuppressing the majority of
- 13 the population, and all of the results are based on
- 14 population and studies how many acute rejection
- 15 patients have, but not on individual immunosuppression.
- 16 How -- we don't have a measure.
- 17 And we've tried to do that in some of the
- 18 assays we've done, the Elispot assay, the -- but it
- 19 doesn't give you a single -- you know, a single
- 20 parameter to say that's how much. And that's the term
- 21 that we all need to (inaudible) and to overcome.
- 2 And I agree with you that maybe we need to

1 change. And I don't know what is the step because

- 2 so I know working in the pharmaceutical industry, and 2 space of biomarkers. You know, when we started the TTC
- 3 when you start talking the people that are signing the
- 4 trials off, you see an endpoint that nobody has used
- 5 before. They all go because they think that when
- 6 you're talking then to the -- you come to discuss with
- 7 the FDA and the whole regulatory authorities, it's
- 8 never going to fly because this is an endpoint that
- 9 nobody has used before. And I don't know how do we 9 the kind of molecular component.
- 10 change this.
- 11 So this is one of the reasons why I'm very
- 12 happy that we are here together and say how -- I'm
- 13 asking now the -- how do we change the endpoints?
- 14 DR. SARWAL: And we are ignoring two big
- 15 factors here. When we're only talking about -- we're
- 16 ignoring the factor that patients are -- can be
- 17 nonadherent, not Kevin. But, like, there are patients
- 18 that are nonadherent. And then they're sporadically
- 19 nonadherent even though they take their drugs at night19 it's a full and accurate description of everything by
- 20 and they have a good level -- a (inaudible) trough
- 21 level.
- 22 And the second thing is systemic factors.

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- 1 transplant community but, you know, working in the
- 3 effort and that kind of conception of saying how do you
- 4 make that step forward, how do you overcome this
- 5 challenge where maybe you want to go from, you know,
- 6 the kidney function, ultimately, to maybe what you were
- 7 talking about in your presentation. You had that nice
- 8 breakdown of, you know, injury, I think morphology and
- 10 And you know, with the aspiration to be able
- 11 to move to that molecular component where maybe you can
- 12 describe an absence of injury, it goes from how much
- 13 would it take to move the regulatory science needle in
- 14 that space, knowing that -- if that is the ultimate
- 15 goal. And the assessment that we did through some of
- 16 the effort so the -- prioritizing the idea of the iBox
- 17 was because it's -- it seems real -- it's going to be
- 18 straight-forward in a lot of its components, not that
- 20 any means.
- 21 But I think, you know, the aspirational idea
- 22 of how you would move that idea forward is an

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- 1 We're dealing with increasing problems with obesity
- 2 worldwide, and we're dealing with hypocholesteremia and
- 3 hypertension. And all of those things damage the
- 4 transplanted kidney just like they damage the native
- 5 kidney. And so reading out absence of injury kind of
- 6 may be the most important way for us to go back and
- 7 manage that patient holistically.
- 8 DR. HERNANDEZ-FUENTES: I would agree to try
- 9 and implement that. And I don't know whether -- you
- 10 know, I'm asking now the FDA people. Would you want to
- 11 see it in parallel? Would you want to see unique?
- 12 Would you accept it as a secondary outcome, some
- 13 exploratory outcome?
- 14 DR. MANNON: So we've heard, like, all of this
- 15 different kind of technology and assessments. And the
- 16 question we're asked is can we speculate on which of
- 17 these biomarkers, or are there other biomarkers that
- 18 predict long-term graft stability? And I throw that
- 19 out to the experts because I'm not answering it. I
- 20 mean, I have my own ideas, but --
- 21 DR. O'DOHERTY: And maybe I can add a bit of
- 22 context as someone who's, you know, new to the

- 1 absolutely valid point. And how do you -- knowing if
- 2 that's the strategy, how do you build it into a
- 3 regulatory strategy? And what's the right process? Is
- 4 it qualification, or is it through a sponsor-driven IND
- 5 submission? And that's really up to the resources that
- 6 are available and the people who are involved to be
- 7 able to move that conversation forward.
- 8 DR. SARWAL: Absolutely. I think it may take
- 9 us into an uncomfortable area where we think we're
- 10 doing really great. And as we start doing more and
- 11 more molecular analysis, we may realize that our margin
- 12 of who we think is stable and the creatinines are fine
- 13 and the slope of the EGFR is fabulous are actually
- 14 patients that are not actually fine. And you know, we
- 15 would need to wait for 10 years to see that, yes, they
- 16 had worse outcome, and they will develop DSAs over
- 17 time.
- 18 So I think we have to -- we may go through an
- 19 area of discomfort where we will uncover this group --
- 20 you know, what may be the burden of molecular injuries.
- 21 And then the task will be to us what do we do. So if
- 22 we've got a new drug that's coming in and then we're

Page 354 1 picking up molecular injury, do we actually dose it 2 differently to actually suppress that appropriately? 3 And that becomes then the new surrogate. 4 DR. NEWELL: I was going to say it seems to me 5 and I struggle with this but I used to think that 6 biomarkers endpoints is all kind of related to 7 biomarker (inaudible). But so, like, if you take 8 Peter's example, he shows very clearly the applet 9 mismatching. The degree of applet mismatching is a 10 powerful factor. But if I only have one donor and 11 that's it, it's or you know, it's going to predict a 12 worse outcome for me. But it's not really actionable, 13 short of getting a different donor paired exchange, 14 maybe a different immunosuppressive regimen. I don't 15 know. 16 Then Minnie talks about things that are 17 designed to diagnosis early inflammation under the 18 assumption that that will decrease long-term outcome. 19 Those are both useful. But to me, your context of use 20 would not really have anything to do with guiding 20 associated 12 UNIDENTIFIED MALE SPEAKER: So 2 DR. ABECASSIS: Maybe I'm missing 3 DR. ABECASSIS: Maybe I'm missing 2 DR. ABECASSIS: - something. 5 DR. ABECASSIS: But isn't a bad biopsy a 7 biomarker of a bad outcome? I mean, Mark, didn't you 8 write a paper that says and what am I 9 DR. SARWAL: That's 10 DR. ABECASSIS: Like, am I just having a 11 moment or 12 DR. SARWAL: No, I'm having a moment, too, 13 because you I what I keep feel like we're 14 we keep on missing the point that three groups here, 15 and there's several other groups around the world. And 16 we can have identified subclinical acute rejection, 17 borderline subclinical acute 18 DR. ABECASSIS: On a biopsy. 20 associated 20 associated 21 DR. SARWAL: rejection on a biopsy 21 associated 22 DR. SARWAL: rejection on a biopsy
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at the second of
21 therapy to increase long-term graft survival, per se. 21 DR. ABECASSIS: As a biomarker
22 It would be very hard to show that in the foreseeable 22 DR. SARWAL: with long-term
Page 355 Page 3:
1 future. 1 DR. ABECASSIS: outcome. What are we
2 I think what I like about the iBox is that's a 2 missing?
3 tool that, today, can be used. And it does respond to 3 DR. SARWAL: We've been publishing on it since
4 therapeutic interventions. So as Inish said, it's 4 for the last 10 years, and we do nothing about it
5 closer to being ready. 5 because it's inconvenient to do a biopsy. And
6 And so it seems to me that all these are good. 6 DR. ABECASSIS: But if you had
7 It's just how we use them and how quickly we can roll 7 DR. SARWAL: And then we look at the injury
8 them out. Yours might be the, you know, surrogate 8 DR. ABECASSIS: Right.
9 endpoint of the future. But I would think that it 9 DR. SARWAL: related to the long-term
10 would have to go through something before that to say I 10 inflammation and say
11 just that, you know, you can use it to adjust DR. ABECASSIS: But to say that you don't have
12 immunosuppression. 12
DR. SARWAL: Absolutely. I mean, so we're 13 DR. SARWAL: you do badly.
14 using things like drug levels. And don't we get a low DR. ABECASSIS: As to say that you don't
15 drug level and adjust the immunosuppressions? I think 15 have a surrogate is wrong. You have a I'm sorry
16 it's a thinking change. It's like what additional 16 to say you don't have a biomarker is wrong. You do
17 information. And you're absolutely right, of course. 17 have a biomarker. It's called a biopsy, okay?
18 What are the stages of validation, and, you know, how 18 So to say you have an invasive biomarker and
To what are the stages of variation, and, you also will not be to say you have an invasive ordinarior and
19 do we get it to that point of confidence that you can? 19 you need to make it noninvasive would be correct. But
19 do we get it to that point of confidence that you can? 19 you need to make it noninvasive would be correct. But

- 1 that was raised in the quorum might be also that is --
- 2 we have a biomarker for quiescence; do we have a
- 3 biomarker that projects overimmunosuppression beyond BK
- 4 virus and the incidence of that, which I think --
- 5 UNIDENTIFIED MALE SPEAKER: Biopsy is a
- 6 biomarker --
- 7 DR. ALBRECHT: So if I can jump in --
- 8 UNIDENTIFIED MALE SPEAKER: Yes, but the other
- 9 way around, over --
- 10 DR. ALBRECHT: This is sort of foreshadowing
- 11 tomorrow's day. But we were fortunate to have two
- 12 meetings in which patients participated. And Ken made
- 13 a very strong statement that he takes death over
- 14 dialysis. The patients, when they were hearing about
- 15 these routine biopsies, one patient said I don't want
- 16 to be a pin cushion. We would love noninvasive tests.
- 17 So I think that's the reason to do more because the
- 18 biopsy, we heard, is also, you know, morbidity,
- 19 potentially injury, et cetera.
- 20 But urine biomarkers, blood biomarkers, I
- 21 think patients would be very happy with that based on
- 22 what we heard. And the we have our patients here as
- Page 359
- 1 well. So I invite you to make comments, if you'd like.
- 2 We will hear from them tomorrow in more detail.
- 3 DR. NICKERSON: So maybe I'll just make one
- 4 comment to Ken in response. So I agree that we can
- 5 monitor the grafts with these diagnostic tools that
- 6 you've heard from multiple groups which will tell you
- 7 that you have quiescence or you don't have quiescence.
- 8 And I think that's a major step forward that --
- 9 especially if it was noninvasive. And then you can
- 10 adjust immunosuppression up if it's not quiescent.
- What you don't know is can you adjust it down
- 12 when it's quiescent. And the CTOT-09 study that Peter
- 13 presented suggested that all of those post-transplant
- 14 tools held no utility to predict the safety of
- 15 minimization. They told you that they post-transplant,
- 16 that they -- that you were losing control because the
- 17 inflammation started. But they didn't tell you who
- 18 could go down. And the tests that predicted who could
- 19 go down were the pretransplant tests, the molecular
- 20 mismatch. And it may even be in Barbara's type of
- 21 model with the genomic -- there immune responsiveness.
- And so I think that gets to a point that you

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- 1 were making, which can you use that knowledge at the 2 time of transplant to dial in how much drug you need.
- 3 And in fact, I would argue you may use that to
- 4 understand that. In fact, you may not need a lot of
- 5 the aggressiveness that we currently do to everybody.
- 6 In the next session, we're going to hear about
- 7 there is center effect as to who gets what, as opposed
- 8 to a risk-stratified effect as to who gets what. And
- 9 so I would argue that the risk stratification at the
- 10 time of transplant, the hypothesis would be that that
- 11 could be used to predict how much drug you really need.
- 12 DR. NEWELL: I don't understand yet how you'd
- 13 use it as a drug development tool other than making
- 14 sure you had the right balance of patients in a study.
- 15 So you know, if you say how does that lead to drug
- 16 development, that's the thing I'm blocking on. So ...
- 17 DR. NICKERSON: Yeah. So I would argue --
- 18 (Crosstalk.)
- 19 DR. NICKERSON: -- is what stratification is
- 20 blocked -- (inaudible) -- stratification, as you talked
- 21 about, and then you could look at is there a response
- 22 differential across the new drug. Or ultimately, you
 - Page 361
- 1 might be able to use it as a way of saying, okay, I can
- 2 avoid this. If you do the trial as a drug-dosing trial
- 3 and say I need this drug dose in this cohort, I need
- 4 this dose drug in this subcohort of risk, and so you
- 5 could actually do that trial and use it as a dose-
- 6 ranging exploratory drug development.
- 7 (Crosstalk.)
- 8 DR. NEWELL: -- I'm kind of fixated on trying
- 9 to get it to a reasonably likely surrogate endpoint.
- 10 And so I think -- I don't see how that works, but we
- 11 could talk about it --
- DR. CHONG: I just want to make a --
- 13 (Crosstalk.)
- DR. CHONG: I just want to make a --
- DR. NEWELL: -- see it as a drug development.
- DR. CHONG: I just want to make a point, you
- 17 know. There is a lot of biomarkers out there, you
- 18 know, and a lot of people have presented data showing
- 19 biomarkers. It shows a correlation. But to use that
- 20 biomarker for drug trial, you need to be able to show a
- 21 quantitative relationship between that biomarker and
- 22 your clinical benefit endpoint so that you can then

1

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- 1 define a change in this biomarker; how does it change
- 2 the risk of graft loss? So that's the step that is
- 3 missing from all the discussions that we've had today.
- 4 So without that information, you can't design a
- 5 clinical trial using that biomarker.
- 6 DR. MANNON: Kevin and then Randy and then --
- 7 oh, my gosh. I'm sorry, Maria. I didn't see you
- 8 because we're going to need to wrap up soon.
- 9 MR. FOWLER: Yeah. So just -- I want to
- 10 amplify what Dr. Albrecht said about the need for a
- 11 noninvasive monitoring test. I think it just gets to
- 12 the point like to the conversation with Dr. Stegall, is
- 13 that you get to the point you're asking yourself what
- 14 else can I do.
- 15 And then I think the -- also, the value that
- 16 those noninvasive tests have is they also -- it could
- 17 be also used for adherence and other behavior aspects
- 18 that could impact outcome. So here, here for
- 19 noninvasive diagnostics. Bring more to the market.
- 20 Bring innovation.
- DR. MANNON: I've never heard of a patient
- 22 say, oh, I don't want to pee in the cup. But

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- 1 everybody, they're like, whatever, take it.
- 2 MR. FOWLER: Who cares?
- 3 DR. MANNON: But you know, certainly.
- 4 Randy.
- 5 DR. MORRIS: Yeah. Certainly, diagnostics are
- 6 nice. But I think that one of the things I didn't have
- 7 time to comment on after Alex Loupy's talk was this was
- 8 an example of a biomarker showing a therapeutic effect
- 9 and regardless of what you're planning to do --
- 10 interventional trials, prevention trials, whatever
- 11 biomarker you feel is diagnostic or prognostic.
- 12 Ultimately, you have to show that treating that
- 13 biomarker then causes a true clinical event later on.
- 14 And that's the obligation of all the noninvasive
- 15 people. It's not easy to do.
- 16 The last thing I want to do -- there's not
- 17 enough time -- but it's for Ken and Maria. It's hard
- 18 enough to develop a drug when you know how the drug --
- 19 when you know the actual molecular structure of the
- 20 drug, you actually know the target, and you think you
- 21 know how the drug works. I'm curious to know how
- 22 tolerance really works at a molecular level.

- DR. HERNANDEZ-FUENTES: So am I ...
- 2 (Laughter.)
- 3 DR. HERNANDEZ-FUENTES: Another point we
- 4 haven't discussed, and I've --
- 5 DR. MORRIS: Don't evade the question there.
- 6 DR. HERNANDEZ-FUENTES: No, no, no, no.
- 7 So one of the issues when we are developing
- 8 these biomarker signatures and all of that is when I
- 9 have the discussion with the statistician how that she
- 10 select the markers that are a better indicative of the
- 11 difference between that group and that group. She says
- 12 that she needs to, A, get rid of all of the markers
- 13 that are negative in our small group of patients
- 14 because then she cannot calculate the mathematical
- 15 algorithm. It doesn't work.
- And then she -- we've heard about elastic net.
- 17 Elastic net selects those markers that are not
- 18 correlated to each other to give you the better
- 19 significance.
- When I hear this and then I hear people asking
- 21 is this biologically relevant, I think we -- or at
- 22 least in my point of view, the markers I have selected

- 1 are not to explain the biological relevance. If I
- 2 wanted to understand the biological relevance, I
- 3 wouldn't ask her to use those markers that correlate to
- 4 each other and belong to different pathways. And then
- 5 I can see a picture of what it is. I don't think of
- 6 (inaudible). So I don't know what tolerance look like.
- 7 DR. NEWELL: I think, Randy, when -- and I
- 8 always struggle with -- so, like, some of the things
- 9 Maria showed are, like, expressed in spinal cord. And
- 10 I'm trying to think, is how is a protein expressed only
- 11 in a spinal cord relevant to tolerance.
- 12 I think when you think about mechanisms of
- 13 tolerance, part of the problem is, at least
- 14 experimentally, they're very different. And they also
- 15 change over time. The late Charlies Oros (ph) pointed
- 16 that out and -- or he hypothesized, and Meghan Sykes
- 17 (ph) has shown it that, you know, a mechanism that's
- 18 operative at three months might not be operative at
- 19 nine months. So it makes it even more complex because
- 20 your assays may need to evolve over time.
- 21 DR. MORRIS: Yeah, but the mechanisms are all
- 22 phenomenological. They're not molecular. Ask Meghan,

- 1 molecularly, how one patient is tolerant versus
- 2 another. What are the actual mechanistic pathways at
- 3 the molecular level? And if she gives you an answer,
- 4 I'll pay you \$100.
- 5 (Laughter.)
- 6 DR. NEWELL: Well, what's the mechanism of
- 7 rejection at the molecular level?
- 8 DR. ALBRECHT: All right. All right. On that
- 9 challenge note, I'm going to let everybody use the
- 10 restroom, wake up a little, and we resume at 4:15 p.m.
- 11 (Break.)
- 12 DR. ALBRECHT: Hello. If everybody could take
- 13 their seat, we're going to go ahead and get started
- 14 with the next session.
- 15 DR. CAVAILLE-COLL: Good afternoon. My name 15 we know, despite apparently effective
- 16 is Marc Cavaille-Coll. I'm a medical officer and
- 17 reviewer of products for solid organ transplantation.
- 18 I'll be co-chairing this session with Dr. Randall
- 19 Morris. And this session is called the Challenges of
- 20 Developing Data Across Transplant Centers.
- 21 Our first speaker is Dr. Krista Lentine from
- 22 Saint Louis University Hospital, St. Louis, who will be

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- 1 framing, a key theme that we are trying to address 2 again is how to balance efficacy and morbidity and
- 3 immunosuppression choice. And as we all know, advances
- 4 in immunosuppression have substantially reduced the
- 5 risk of early acute rejection in patients undergoing
- 6 immunologically compatible kidney transplantation such
- 7 that the current incidence of acute rejection in the
- 8 first-year post-kidney transplant is now less than
- 9 about 10 percent. And rejection rates are also quite
- 10 low in contemporary liver transplant.
- 11 But this marked reduction in acute rejection
- 12 has come at the cost of rising rates of
- 13 immunosuppression-related complications, including
- 14 infection, cancer, and cardiovascular disease. And as
- 16 immunosuppression, the chronic immunologic injury also
- 17 limits long-term allograft survival. It's known that
- 18 immunosuppressive agents vary somewhat in their
- 19 toxicity profile. But again, how to balance the
- 20 question of not enough versus too much at the patient
- 21 level is often elusive.
- 22 There are guidelines for kidney transplant

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- 1 speaking to us about the epidemiology and the variation
- 2 of both induction and maintenance therapy in kidney and
- 3 liver transplantation.
- 4 Dr. Lentine.
- DR. LENTINE: Well, thank you very much. And 5
- 6 I'd really like to thank the organizers for the
- 7 opportunity to join you today.
- The data that I have to share is different
- 9 than a number of the presentations that we've been
- 10 hearing. It's an epidemiologic framing piece, and I
- 11 hope that we can use the information in that context.
- 12 And specifically, I've been asked to share
- 13 about work that I've done in partnership with Dr.
- 14 Axelrod on variation in induction and maintenance,
- 15 immunosuppression, and national U.S. practice.
- 16 And my disclosures -- the most relevant is NIH
- 17 funding that supported the three studies that we are
- 18 going to review.
- 19 So again, reviewing the -- oh, these slides
- 20 are not advancing, sir. What do I need to do? There
- 21 we go. All right. Thank you.
- 22 So again, reviewing the problem, scope, and

- 1 immunosuppression practice. For example, 10 years ago,
- 2 the 2009 KDIGO guideline recommended that all patients
- 3 receive induction therapy. IL-2 receptor antibodies
- 4 are advised as first-line, whereas lymphocyte depleting
- 5 agents were advised for so-called high immunologic-risk
- 6 patients.
- 7 The guideline also offers recommendations on
- 8 maintenance immunotherapy, favoring use of calcineurin
- 9 inhibitors, specifically, tacrolimus as first-line and
- 10 anti-metabolite with mycophenolate as first-line and
- 11 suggesting that if steroids are discontinued, the
- 12 discontinuation be conducted within the first week.
- 13 Notably, the guideline also suggests tailoring
- 14 immunosuppression to the patient's risk profile but is
- 15 not detailed on how to tailor.
- 16 And further, the International Liver
- 17 Transplantation Society issued a very recent statement
- 18 that -- concluding that current immunosuppression
- 19 regimens and agents are highly effective in minimizing
- 20 graft laws due to acute and chronic rejection but can
- 21 also produce a substantial array of toxicities. And
- 22 the group noted that utilization of the

1 immunosuppression varies widely and believes that this

2 contributes to the wide disparities in post-transplant

3 outcomes between transplant centers.

4 So Dr. Axelrod, myself, and our colleagues

5 became interested in describing the national landscape

6 of immunosuppression prescribing. Our approach is

7 grounded on patient-level linkages of the national U.S.

8 transplant registry with other information sources,

9 which combines the value of confirmed patient status,

10 demographic and clinical traits of recipients and

11 donors as recorded in the registry with additional

12 exposure and outcomes information. And specifically,

13 here we use a pharmacy claims linkage as real-world

14 measures of prescribed medications.

We also link Medicare billing claims, which

16 can be used as measures of diagnoses for clinical

17 complications, as Dr. Axelrod will discuss next.

18 Regarding measures, again, we draw the

19 recipient donor and transplant information from the

20 national SRTR registry. We categorize induction as IL-

21 2 receptor antibodies, thymoglobulin, Alemtuzamab, or

22 no induction. We look at maintenance immunosuppression

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1 in periods of 0 to 6 and 7 to 12 months post-transplant

2 and categorize as triple therapy, including tacrolimus,

3 MMF, and steroids, steroid-sparing, anti-metabolite-

4 sparing, mTOR inhibitor-based or cyclosporin-based.

5 We describe the unadjusted variation in

6 regimen use with stacked bar plots describing use by

7 both transplant center and within UNOS region. And we

8 use hierarchical modeling with patient and donor case

9 factors as Level 1 and center as Level 2. And these

10 models compare each alternative regimen to a referenced

11 regimen.

12 The empirical Bayesian estimates compare the

13 adjusted proportion of use of a regimen of interest

14 with the reference regimen incorporating the clinical

15 case adjustment from the model. And the interpretation

16 is that, if the 95 percent confidence interval for a

17 centers-adjusted use of a regimen does not include the

18 median national rate of use, then the prescribing

19 pattern is significantly different from the expected

20 use for that regimen.

The heterogeneity measures from the these

22 models include intraclass correlation, which quantifies

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1 the proportion of variance in regimen use accounted for

2 by center.

3 Medians odds ratios is another measure that

4 quantifies the median of the odds that patients with

5 identical characteristics will receive the regimen of

6 interest when two centers are drawn at random. For

7 example, a median odds ratio of two means that a

8 patient with a given set of characteristics has, on

9 average, twice the odds of receiving that regimen of

10 interest at one of the randomly selected centers than

11 at the others. In other words, higher median odds

12 ratios equate with greater variation.

13 The models also produce adjusted odds ratios

14 describing associations of case factors with each

15 regimen of interest versus the reference accounting for

16 center effect.

17 So the first study we want to share relates to

18 kidney transplant induction practice. And for

19 induction therapy, there are currently only two

20 approved and accessible choices, as we know -- IL-2

21 receptor antibodies, specifically, basiliximab versus

22 thymoglobulin. And induction indication for

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1 Alemtuzumab is complex, given its manufacturer. And

2 there are no other new induction agents on the

3 immediate horizon.

4 Notably, the use of induction has been

5 increasing in recent cohorts. More than 80 percent of

6 patients receive induction therapy, including

7 thymoglobulin in 46 percent, IL-2 receptor antibodies

8 in 22 percent, and Alemtuzumab in 13 percent. Use does

9 vary by clinical immunologic risk profile, as defined

10 by that KDIGO, but does not completely follow the KDIGO

11 guideline.

12 Notably, proportion of the patients receiving

13 induction regimens vary widely across centers from 0 to

14 100 percent. Accounting for center, there were case

15 factor correlation that make sense. Use of

16 thymoglobulin or Alemtuzumab versus IL-2 receptor

17 antibodies was less common for older patients but more

18 common on with black race and sensitization. Self-pay

19 patients were less likely to receive induction

20 treatment and more likely to receive Alemtuzumab.

21 Re-transplant, status, sensitization, and

22 receipt of a nonstandard deceased organ were associated

- 1 with depleting agents versus IL-2 receptor antibodies.
- 2 And use of depleting agents increased over time,
- 3 whereas induction-free transplant declined over time in
- 4 the hierarchical models.
- 5 These themes will recur, but this is the
- 6 quantification of center-level variation. Many centers
- 7 variation -- varied from the expected use after
- 8 adjustment for donor and case factors. And this is
- 9 shown in the so-called caterpillar plots. Each point
- 10 reflects a center, and we're looking at the 95 percent
- 11 confidence intervals in relation to the adjusted
- 12 expectation. Center explained about 60 percent of the
- 13 variation in regimen choice in these induction models.
- 14 The median odds ratios from case factor-
- 15 adjusted models range from 7.5 to 11, also supporting
- 16 very large differences in the likelihood of induction
- 17 choice based specifically on the center, whereas case
- 18 factors explained a smaller proportion of observed
- 19 variation.
- We applied a similar methodology to assess
- 21 variation in the use of kidney transplant maintenance
- 22 immunosuppression. These are data for regimen among 7
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- 1 to 12 post-transplant. Here the center-level variation
- 2 was not as strong as for induction but still
- 3 substantial with median odds ratios of 2 to 5. And
- 4 center explained approximately 15 to 50 percent of the
- 5 variation in maintenance choice, whereas measured case
- 6 factors explained 5 percent or less.
- 7 Accounting for center, there were case factor
- 8 correlations that make sense. Minimized regimens were
- 9 more common in older patients compared to triple
- 10 therapy, but less common in black patients and prior
- 11 transplant recipients. And minimized regimens were
- 12 also less common in sensitized patients, but more
- 13 common in those using cash pay.
- 14 Our most recent study looked at maintenance
- 15 therapy in liver transplant recipients. And note this
- 16 article was just highlighted in the Transplant Society
- 17 Newsletter last month and that, not surprisingly, we
- 18 found again that liver immunosuppression shifts with
- 19 time after liver transplant with 42 percent receiving
- 20 triple therapy in the first six months and then
- 21 shifting to more common antimetabolite or steroid-
- 22 sparing regimens for liver patients.

- 1 Briefly, we again found that center explained
- 2 more variation than the case factors. But there are
- 3 also clinical correlations that make sense. For
- 4 example, a hepatocellular carcinoma as a cause of liver
- 5 failure, cancer within six months, and a low estimated
- 6 GFR less than the 30 at six months were associated with
- 7 mTOR inhibitor use compared with triple
- 8 immunosuppression.
- 9 So regarding what we know now,
- 10 immunosuppression regimens do vary in potency and side
- 11 effect profiles in that tailoring immunosuppression
- 12 regimen balance (ph) the risk of acute and chronic
- 13 rejection versus toxicity of over immunosuppression may
- 14 improve long-term patient and graft outcomes and is a
- 15 recommended goal of chair -- of care and is, in fact,
- 16 the objective of this workshop.
- 17 But at this time, immunosuppressant regimen
- 18 choice does appear to vary dominantly by center
- 19 practice. Some patient and donor care -- factors were
- 20 associated with choice, for example. Factor associated
- 21 with clinical rejection risk correlate with more potent
- 22 regiments. However regiments are strongly clustered by
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- 1 center, and center effect is -- explains more variation
- 2 than case factors. And cost and patient resources may
- 3 also be a consideration.
- 4 What we don't know yet is, really, how to
- 5 optimally tailor immunosuppression choice. And so the
- 6 needs include the developing these robust risk
- 7 stratification and monitoring tools that have been
- 8 discussed today as well as a need for developing a
- 9 large clinical trial -- clinical consortia and trials
- 10 and networks in our field.
- And so we -- what we should do now is continue
- 12 to try -- strive to answer the call and to continue to
- 13 -- continue efforts to -- continue to define sources of
- 14 variation, I believe, are useful to help frame the
- 15 call. And we can build on integrated secondary data
- 16 analyses through linkages to more granular information,
- 17 such as laboratory results, pathology, and biomarkers,
- 18 and also explore the development of a clinical
- 19 consortia and trials and networks to improve the
- 20 evidence base for patient-centered treatment choice.
- 21 I'd like to thank the collaborators in our
- 22 research group and now move on to my colleague, Dr.

- 1 Axelrod, who will discuss the clinical and economic
- 2 implications of this type of clustered practice.
- 3 (Applause.)
- 4 DR. AXELROD: So I would also like to thank
- 5 the moderators for inviting us to participate in this
- 6 session. And in some ways, I think this session should
- 7 have been at the beginning and, perhaps, not at the end
- 8 of today, as it really frames a lot of the discussions
- 9 that we've had.
- 10 I thought I'd spend a few minutes talking
- 11 about what the implications of what Dr. Lentine just
- 12 described and why we should care that the variation in
- 13 practice is significant.
- 14 As this audience well knows, effective
- 15 management of cellular and humoral rejection is the
- 16 cornerstone of successful solid organ transplantation.
- 17 Current immunosuppressant protocols vary markedly
- 18 across centers, as Dr. Lentine has just shown you, and
- 19 that regimen choice is explained dominantly by center
- 20 practice rather than clinical and donor factors. And
- 21 that really reflects the fact that our field continues
- 22 to evolve and has, you know, been a cottage industry

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- 1 for many, many years. It is, perhaps, remarkable that,
- 2 you know, in a town like Boston where I was just
- 3 working, management of the same kidney transplant
- 4 recipient getting a similar organ can vary, you know,
- 5 and differ across all seven centers even though we're
- 6 caring for nearly similar patients.
- 7 And it suggests that the choice of
- 8 immunosuppression is far from uniform nationally,
- 9 providing, in fact, a national experiment to examine
- 10 the impact of immunosuppression choice on clinical and
- 11 economic outcomes while controlling for the variety of
- 12 factors that we recognize are part of solid organ
- 13 transplantation, including, as Krista defined as case
- 14 factors, post-patient and recipient and donor
- 15 characteristics.
- 16 This project is part of immunization
- 17 optimization project, which aims to develop evidence-
- 18 based selection of immunosuppression induction and
- 19 maintenance regimens, which balance patient survival
- 20 and graft survival with the need to minimize long-term
- 21 complications for immunosuppression. This requires a
- 22 rich real-world data set that allows us to deal with

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- 1 the variety of different and markedly impactful
- 2 differences in the care of our patients.
- 3 It's infrequently been answered by the large
- 4 controlled trials, given the need to balance
- 5 interpretable conclusion next to -- inclusion criteria
- 6 and the inherent size limitations. And therefore, we
- 7 really need systems that balance immunosuppressive
- 8 complications with benefits of reduction that reflect
- 9 the real-world practice for our patients.
- Finally, I think if clinical outcomes are
- 11 largely similar, then we have to recognize that we are
- 12 functioning within a relatively cost-constrained world.
- 13 And the cost-effective regimen -- that the most cost-
- 14 effective regimen should be employed.
- 15 The impact of regimen selection will be
- 16 reviewed for its impact on patient and graft outcomes
- 17 on post-transplant medical complications and, finally,
- 18 on the cost of transplant and follow-up care.
- 19 The analytic methods were largely outlined by
- 20 Dr. Lentine for the variation in use, the additional
- 21 data in these analyses, including economic data, we
- 22 used Medicare payment data, as well as Viseon (ph)

- 1 health -- county records for transplant programs.
- 2 Viseon collects data from the majority of the large
- 3 academic and increasingly nonacademic centers.
- 4 Post-transplant complications were defined
- 5 using Medicare diagnostic claims. All categories
- 6 required at least one inpatient stay or two outpatient
- 7 stays for a diagnosis of a specific complication. And
- 8 the statistical methods included survival analysis,
- 9 both adjusted and unadjusted, in multi-variate linear
- 10 regression analysis for cost.
- 11 I'll start looking at long-term outcome. As
- 12 most people are familiar, there are a variation in
- 13 outcome associated with the use of various induction
- 14 regimens. You see here there is a graded survival
- 15 based on the use of immunosuppression induction
- 16 regimens with campath having a slightly better outcome,
- 17 perhaps, than IL-2 receptors, although we recognize, A,
- 18 the differences are small and that there will be
- 19 potentially differences in the underlying population.
- 20 These are the unadjusted numbers you see here for graft
- 21 survival. In fact, it flips on its head where IL-2
- 22 receptor unadjusted analyses are slightly better.

- 1 Again, we recognize that these are generally used in
- 2 low-risk immunologic patients, which is why you need
- 3 large studies to be able to adjust for the these
- 4 confounding factors.
- 5 In the adjusted hazard ratio, at three years,
- 6 you see that the -- compared to IL-2 receptor, which is
- 7 the reference hazard of 1, you see slightly better
- 8 outcomes and reduced death in patients who received
- 9 thymoglobulin, whereas death center graft failure may
- 10 be a little bit higher, actually, in campath and
- 11 relatively similar for all-cause graft failure.
- 12 If you look at the impact of maintenance
- 13 regimens on clinical outcomes, again, you see a spread.
- 14 This is reflected in the patient survival where you see
- 15 survival of about six -- or about five points less for
- 16 patients that didn't -- that received -- didn't receive
- 17 steroids-sparing agents.
- 18 The graft survival, again, you see a spread
- 19 over time. And when you look at the multi-variate
- 20 analyses, controlling for the differences in donor and
- 21 recipient factors, you see, in fact, that a steroid-
- 22 sparing regimen appears to have a lower risk of death

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- 1 compared to some of the other regimens, including CSA-
- 2 based regimens that have a significantly increased risk
- 3 of patient death.
- 4 When you look at death-censored graft failure,
- 5 again you see a reduction in death associated with
- 6 steroid-sparing and perhaps an increase in death
- 7 associated with CSA-based immunosuppression regimen
- 8 and, finally, all-cause graft failure with similar
- 9 patterns.
- 10 And I would point out to you that Dr. Lentine
- 11 showed it relatively quickly, but there are still areas
- 12 in centers in this country in which the majority of
- 13 their patients are receiving CSA-based
- 14 immunosuppression regimens and other that have -- the
- 15 rarely use steroid reduction protocols. And so we may
- 16 have evidence-based practice that it suggests that
- 17 there are opportunities to improve the outcomes of our
- 18 patients without even the implicate -- the development
- 19 of new immunosuppression regimens.
- 20 But it's important, as we heard from Kevin
- 21 earlier, to think about outcomes beyond death and graft
- 22 failure. And while patient and graft failure are of

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- 1 primary interest for patients, the alternative outcomes
- 2 are also important. And these include the trade-off
- 3 between immunosuppression and the incidence of
- 4 complications, including infections, malignancy, and
- 5 cardiovascular disease.
- 6 There is no available transplant registry data
- 7 set to answer these question. And therefore, we
- 8 utilize the Medicare claims for patients who had
- 9 Medicare primary insurance from the point of transplant
- 10 on.
- So you see here that you -- the differences in
- 12 the incidence of malignancy over time is associated
- 13 with induction therapy on the left and, similarly, with
- 14 infection rates over time on the right with various
- 15 types of rates over time. When you see here
- 16 summarized, when you combine the impact of induction
- 17 regimen with maintenance regimen, you see significant
- 18 differences in the incidence of specific infections --
- 19 for example, pneumonia and sepsis, non-melanoma skin
- 20 cancers, as well as the other viral cancers and NODAT.
- When you place this into the multi-variate
- 22 model, you see, again, that, for example, sirolimus-

- 1 based regimens have a higher incidence of pneumonia, as
- 2 do CSA and tac-alone-based regimens with lower rates
- 3 for steroid-sparing, similar variation in the incidence
- 4 of sepsis, pyelonephritis, other cancers. And you see
- 5 here for viral in cancers again, this sirolimus-linked
- 6 -- this sirolimus therapy seems to have a higher
- 7 incidence. And the expected association of tacrolimus
- 8 with new onset diabetes after transplant.
- 9 Finally, we consider the economic implications
- 10 of transplant immunosuppression regimen selection.
- 11 Choice of induction clearly impacts the cost of care.
- 12 Thymoglobulin is estimated to be about \$14,000 per
- 13 course, basiliximab about \$6,500. And Alemtuzumab,
- 14 based on the current issues, is free for centers using
- 15 it. But the economic impact of choice extends beyond
- 16 these initial pharmaceutical costs, and you see that
- 17 resources are needed to manage the complications, as we
- 18 talked about.
- 19 The cost analysis differed by time period.
- 20 The cost of the transplantation itself, again, used the
- 21 Viseon cost accounting data. And then we used one-year
- 22 cost data from Medicare claims from 2006 to 2013 to

- 1 look at the costs after the first period of
- 2 hospitalization.
- 3 Here you see variation in the cost --
- 4 differential cost of the transplant care by induction.
- 5 You see the increased cost of thymoglobulin compared to
- 6 IL-2 receptor and certainly compared to campath. And
- 7 you see small variations by induction regimen over the
- 8 first year.
- 9 If you look at attributable costs, it really
- 10 is thymoglobulin that increased the cost of
- 11 transplantation by about \$10,000. And for those of us
- 12 that are in the business, we recognize that use of
- 13 these agents is the best thing for our patients, as
- 14 we've heard. They clearly reduce the risk of long-term
- 15 complications. And yet there is no adjustment
- 16 currently from one of your sister parts of the federal
- 17 government for people who are getting expensive
- 18 induction at the time of their transplantation.
- 19 Similarly, you see variation in the cost of
- 20 transplant by maintenance therapy at -- over the first
- 21 year for Medicare. First, second, and third year, you
- 22 see the differential by triple therapy compared to

1 So in conclusion, induction and maintenance

- 2 immunosuppression are associated with differential
- 3 incidents of complications and cost of care during both
- 5 merdenes of complications and cost of care during so
- 4 the kidney transplant and post-kidney transplant5 period. Higher initial cost savings of some regiments
- 6 -- for example, thymoglobulin induction appear to be
- 7 followed by later costs savings likely driving by lower
- 8 rates of rejection. Additional work is needed to
- 9 determine the optimal regimen based on the donor and
- 10 recipient characteristics. And development of a
- 11 predictive calculator to provide patients and providers
- 12 with informed choices about immunosuppressant-related
- 13 outcomes is crucially important and will best be
- 14 developed by consortium, as you'll hear about from Dr.
- 15 Stegall.
- 16 There's a desperate need for multi-center
- 17 prospectively collected datasets with richer capture of
- 18 post-transplant outcomes and, particularly, those
- 19 beyond just the well-controlled -- randomized
- 20 controlled trials using the pivotal trials for the
- 21 immunosuppression.
- So I -- again, I appreciate the opportunity to

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- 1 steroid-sparing and higher cost for people getting mTOR
- 2 and CSI-based therapy. Again, attributable cost
- 3 differences vary markedly according to our choice of
- 4 immunosuppression regimen after adjustment for baseline
- 5 donor and transplant factors.
- 6 The limitation of this study is its clinical
- 7 data is limited to the elements that are currently
- 8 included in the OPTN data set. We lack detailed data
- 9 on immunosuppression exposure, dose duration, and
- 10 level. We lack clinical comorbidity capture, including
- 11 prior malignancy and development of NODAT that we would
- 12 like to be able to make these analyses richer. And as
- 13 we've heard this morning, I think we really lack a much
- 14 better understanding on a molecular level of what the
- 15 immunosuppression -- the state of immunosuppression and
- 16 the immunosuppression and rejection risks for these
- 17 patients are.
- 18 However, the post-operative complications are
- 19 currently captured through administrative data claims
- 20 and at least provides a real-world experience that
- 21 allows us to think about alternative outcomes beyond
- 22 death and graft failure.

- 1 present this work. Thank you.
- 2 (Applause.)
- 3 DR. CAVAILLE-COLL: Thank you, Dr. Axelrod.
- 4 Our next speaker is Mark Stegall from the Mayo
- 5 Clinic, who's going to be speaking to us towards
- 6 building a network of clinical centers.
- 7 DR. STEGALL: So I'm told that the next
- 8 speaker may not be here, and so I have, like, an hour.
- 9 (Laughter.)
- 10 DR. STEGALL: It's going to be awesome
- 11 because, like, I know, like, a million jokes, and it's
- 12 going to be that kind of a day, part of the day where -
- 13 this is -- Ken knows this. This is the kind of part
- 14 of the day that I'm gone, right? Usually, by this
- 15 time, just like Abecassis, blow this off.
- So I'm here. You guys are smart, man. Got
- 17 me.
- 18 So building a clinical network, it's -- and I
- 19 think I'm -- I was supposed to say this; Inish paid me
- 20 to say this -- it's all about data, right -- collecting
- 21 data. And collecting data is actually difficult and
- 22 expensive, and collecting good data is probably nearly

- 1 impossible. And I would actually say that the current
- 2 challenges, right, choice of immunosuppression,
- 3 monitoring protocols (inaudible) by centers where the
- 4 transplants are formed (ph) and not by patient
- 5 characteristics are that, actually, people are smart,
- 6 you know. It's -- when they give you something for
- 7 free, it's like how bad could it be, right? It's free,
- 8 you know, so you use it.
- But the real issue is I think there's really
- 10 no clear-cut data that has this -- a compelling reason
- 11 why you should use this. Not all those centers are
- 12 using (inaudible) and prednisone as the maintenance
- 13 immunosuppression. I mean, the field has move forward
- 14 a little bit.
- 15 So my opinion is that it's not really limited
- 16 types of inductions. There are all sorts of patient-
- 17 related issues. And I do think -- this is at least my
- 18 hypothesis. I mean, not everybody will follow
- 19 compelling data. You've not met my daughter. So --
- 20 but I think that it's a good thing.
- 21 What kind of data do we have? We have
- 22 registry data, and I think that that's what the last

- 1 much real-world data about all types of patients. And
- 2 for example, you know, Meteor has a study out now
- 3 looking at HLA-identical living donor kidney
- 4 transplants. And it turns out that none of those were
- 5 ever included in any immunosuppressive trial between
- 6 the rejection rate was so low, so nobody knows anything
- 7 about those patients. So -- and that seems to be a
- 8 recurrent theme in just about every trial you want to
- 9 start.
- 10 I guess the folks in Vitaeris had the same
- 11 issue, too. They had to pay four centers to get data
- 12 that they -- in order to get a trial -- get the data
- 13 they needed for a trial. And it's unfortunate that we
- 14 have to go down this pathway every single time.
- 15 And so we need all this type of data. I don't
- 16 think there's one type of data that is -- that trumps
- 17 any other data, but I do think that that is really what
- 18 a research consortium is about.
- 19 And most transplant programs individually
- 20 don't have any long-term data. There's really --
- 21 whatever that is -- 5-, 10-year follow-up is actually
- 22 quite rare in most programs. And it's really hard to

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- 1 two talks were about, right -- registry data. And
- 2 everyone knows that you can get a lot of data from the 2 issue. Remember that? But we need to fund this in
- 3 STAR file, from -- and that's going to be very helpful
- 4 many times. But the problem is that, with that data,
- 5 of course, is there's a lot of missing data. It hasn't
- 6 really been -- there you are -- it hasn't really been
- 7 validated. And I mean, the people who put in the data, 7 way that it's set up -- or I think the classic one in
- 8 I mean, there is not a clinical research organization
- 9 that comes back around, looks at data, and makes sur 9 -- there's a centralized organizing group. The members
- 10 that it is good data. And that's a problem.
- 11 Then you have a lot of data from multi-center
- 12 Phase 3 randomized clinical trials, as we are looking
- 13 at in the TTC where we really have put a lot of money 13 effective at doing clinical trials. And it's very
- 14 and effort into developing that patient-level data.
- 15 And I think that there's a lot of great data. And if
- 16 you talk about clinical research consortia, there
- 17 actually are a lot of clinical research consortia that
- 18 exists in transplants. CTOT has put a lot of consortial
- 19 together, correct? But I think the real issue is
- 20 sustaining those consortia.
- And also, I think the last thing that I would
- 22 say is that, as we go through this, it's really not as

- 1 collect that data. It was the old unfunded mandate
- 3 many ways.
- 4 So clinical research consortium defined as a
- 5 group of medical centers or programs that are organized
- 6 to conduct clinical trials in a specific space. The
- 8 oncology -- classical ones in oncology are -- there are
- 10 agree to a standard of care and data sharing. It's
- 11 freestanding and continuous. They're not -- these are
- 12 not one-and-done consortia, and they are efficient and
- 14 common in oncology.
- 15 And talking to people who are in clinical
- 16 consortia in oncology or in diabetes, when certain
- 17 studies come out of a certain consortia, it's got to
- 18 get a good housekeeping seal of approval, you know.
- 19 They did it right. They know how to do a clinical
- 20 trial. And we know that enrollment's such a huge issue
- 21 in all trials, but especially in transplantation.
- 22 And just to say, this was mentioned, I think,

- 1 by Ken, so I put this up here, that there are many
- 2 clinical consortia worldwide, but this one is
- 3 definitely a big one and does a lot of great things.
- 4 But they have, really, a specific interest in cellular
- 5 therapy. And so they may not be the group that you
- 6 would go to find out about HLA-identical living donor 6 there's a single trial. If there's a single trial,
- 7 kidney transplants.
- And I think that the flavor of many consortia
- 9 in oncology, certainly, there are some disease-specific 9 about studying cancer, actually, because maybe that
- 10 consortia. But I think they have a little bit of a
- 11 broader approach to doing that.
- 12 So we started something called a multi-center
- 13 transplant alliance. It's primarily started through
- 14 the three Mayo sites, which the good thing about that
- 15 is that there's one bank account and there's one IRB.
- 16 So it's really helpful to get some trials going. We do
- 17 a lot of paired donors. We do have a lot of
- 18 collaboration.
- 19 And there also is a convergence of clinical
- 20 practices. So we actually do use pretty much the same 20 I got -- let me mention something. Alex actually has a
- 21 immunosuppressive regimen. It's stratified by certain 21 really good research consortia, I think, because it's
- 22 patient types and all the rest. And if you've ever
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- 1 been to Rochester, Minnesota, this logo is actually
- 2 kind of fun. I can take a second to explain it.
- 3 The IBM logo really looks like the MTA logo.
- 4 But those birds that are flying in formation are
- 5 ubiquitous in Rochester, right? It's the Canadian
- 6 geese, right? And they don't fly very far from
- 7 Rochester. They stay there all winter.
- 8 But when geese fly in formation, they actually
- 9 use less energy, right? The geese at the front -- the
- 10 goose at the front takes all the brunt. They -- that's
- 11 the coordinating center. And everybody else uses less 11 Clinic for many years. And people just were not
- 12 energy. And the idea is that's what a consortia is
- 13 about. And I think that -- I wanted to give this whole
- 14 talk why you should never start a research consortium 14 people to study ever. But it just wasn't the number
- 15 so I thought that would be the way to do it.
- 16 (Laughter.)
- 17 DR. STEGALL: Now, that's a little bit over
- 18 the top, but reality is do not do this. It's not a
- 19 good idea, right? It will kill everything else that
- 20 you want to do with your life. It saps a lot of time
- 21 and energy. There's no question about it.
- 22 It will actually only demonstrate to you and

- 1 your peers, people you know well and you thought 2 respected you, how really inept you are at group
- 3 leadership. And so if you want to do that, this is
- 4 perfect.
- 5 It's almost impossible to get funded unless
- 7 that's great. But these kind of consortia that are
- 8 freestanding, you know, we're starting to -- thinking
- 10 would help.
- 11 Then I think that collaborators are busy.
- 12 They really are busy. And they're almost -- it's too
- 13 busy even if they want to help you.
- 14 Conference calls are -- there's never a good
- 15 time. So we try monthly conference calls. And it's
- 16 kind of we're going to have them whether anyone shows
- 17 up. And we end up having two, maybe three about the
- 18 same issue.
- 19 I would say parenthetically that, you know, so

- 22 almost like what France is about, right? You guys

- 1 share data and all the rest. So that's helpful. We're
- 2 not that. We're not that. I can tell you that.
- 3 It takes a long time to be productive. And I
- 4 said -- did I say that collecting data is difficult and
- 5 expensive?
- 6 But multi-center research is really important,
- 7 and it's important for transplantation. And I think it
- 8 should go beyond just doing Phase 3 clinical trials.
- 9 It improves diversity and decreases biases in studies.
- 10 It turned out we wrote a lot of papers at the Mayo
- 12 interested in Norwegians who got living donor kidney
- 13 transplants. Now, I think they're the most fascinating

- 15 one thing in other people's -- you know, don't knock it
- 16 if you haven't tried it kind of thing.
- 17 So the other thing is that -- I told you I
- 18 know a million jokes -- resources -- it's a natural
- 19 history of studies, especially in small subgroups. And
- 20 Inish, I think, and his group are very interested in
- 21 the natural history of diseases. And we really don't
- 22 have a really great handle on the natural history of

- 1 kidney transplantation. And I can say that at least at
- 2 5 and 10 years, that area out there is a bit uncharted
- 3 territory. We have a pretty good handle the first five
- 4 years maybe.
- 5 Detailed data and specimen collection with a
- 6 single standard of care is helpful. It's amazing how
- 7 having specimens biopsy serum cells and all that come
- 8 in handy when you are answering -- trying to answer new
- 9 questions, maybe work with other people. Larger
- 10 populations for faster enrollment, faster study
- 11 enrollment, is almost an oxymoron. The study part of
- 12 it makes it hard. It makes studies possible for hard-
- 13 to-enroll groups.
- 14 Antibody-mediated rejection -- I'm going to
- 15 take a minute to talk about that because there's
- 16 several studies in that. And actually, it's collective
- 17 expertise. It turns out we're a lot smarter, you know.
- 18 We're like a genius when we work all together. And
- 19 when we work individually, not so much. And I think
- 20 it's -- probably most people worked in consortia that
- 21 good ideas come out of just sitting and talking to
- 22 other people about how things turn out, but it takes a
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- 1 lot of work.
- 2 And it -- this -- the reason it really came
- 3 out of this was not just the Norwegian issue, which was
- 4 part of the issues. But the other reason is that we
- 5 had this issue where people would say, oh, our
- 6 subclinical rejection rate is 30 percent. And these
- 7 were some of our colleagues. And I would look at it
- 8 and say it can't be 30 percent.
- 9 And so we'd have them get their data, and they
- 10 would do it. And this is Ray Halmond's (ph) group from
- 11 -- that does a lot of the deceased donors in Arizona.
- 12 And it was 14 percent in Alemtuzamab and 9 percent in
- 13 the ATG group. And that was, like, hundreds of
- 14 patients. So I think the more you get data -- the
- 15 other thing is talking to Bob Gaston and Arthur Matas,
- 16 you know, they were doing biopsies for cause. We were
- 17 doing protocol biopsies. And at some point, the
- 18 biology has to kind of merge. There has to be the same
- 19 thing that happens to a kidney transplant patient.
- 20 So I thought we should just really try to get
- 21 enough programs that would work together on. And this
- 22 is not necessarily about any one specific research

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- 1 project, but it's try to come up with a standard of 2 care and a way of doing follow-up. And we are
- 3 partially there.
- 4 And so the programs that are now in the MTAK
- 5 (ph) Consortium I could say some of these programs have
- 6 moved around because people have moved. And there is
- 7 also one in pancreas transplantation because a lot of
- 8 guys about my age thought it was time we should do
- 9 something about pancreas transplantation before we stop
- 10 doing it completely.
- And then there's -- we do about 1,500 kidney
- 12 transplants a year, about 300 pancreas transplants a
- 13 year in these consortiums. And I think the way to look
- 14 at this is that this is just one model. It's probably
- 15 just a beginning of maybe something that could be
- 16 collaborative with a lot of different people. There
- 17 are a lot of things about -- the studies were opt-in,
- 18 and we could add other sites if there were people
- 19 interested in desensitization or other things like
- 20 that.
- 21 And what's happened is that, over the last few
- 22 years, which would -- we paid for this partly out of
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- 1 some of my money that I have from my professorship, and
- 2 part of the money is paid for out of some NIH grants
- 3 and some other things. So we've enrolled 1,000
- 4 patients in observational clinical trials over the last
- 5 few years. And we went from doing 65 percent living
- 6 donors, which is what we do in Rochester. And they --
- 7 now we see -- you can see that Mayo Clinic Florida does
- 8 39 percent living donors. So we have much more of a
- 9 mix of types of transplants.
- And if you look at ethnicity, we went from,
- 11 you know, all the Norwegians to having many different
- 12 types here. And even though it's only 15 percent, 10
- 13 percent of people have no ethnicity. I didn't know
- 14 that, but what you learn. And -- but even 15 African
- 15 Americans in clinical trials, not just in people who
- 16 are transplanted, it's still, you know, a kidney biopsy
- 17 which have been scanned in our Aperio scanner, biopsy
- 18 tissues, cells, and serum, allo antibody data on 150
- 19 people at one year that could go into iBox, right,
- 20 Alex?
- 21 So what we did is we also got people to work
- 22 together. So we even got pathologists to work

- $1\,$ together. So there are two pathologists from Mayo
- 2 Clinic Rochester, two pathologists from Mayo Clinic
- 3 Arizona, and two pathologists from Mayo Clinic Florida
- 4 on this one paper. And that was actually a big deal
- 5 because reading biopsies is a big thing in what we do.
- 6 And I think Alex met some of these people when he came
- 7 to visit us this summer. So it becomes a very
- 8 collaborative group. And again, they are working hard
- 9 to make this.
- 10 Just the last thing -- I don't know if I'm
- 11 running out of time, but we want to facilitate
- 12 enrollment in Phase 3 multi-center trials. Low
- 13 enrollment is a big problem. I get a lot of phone
- 14 calls from a lot of companies how the enrollment is
- 15 going slowly. Why? And I think that it's a big
- 16 problem when you have data collection.
- 17 A big problem, too, when you get a clinical
- 18 trial is recreating the wheel every single time. Some
- 19 programs don't have standing up -- don't have a
- 20 research coordinator doing transplant full time. And
- 21 so it's really hard to start up again.
- And they may only have one person doing it.

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- 1 And then when they quit and they decide they, you know,
- 2 want to do oncology because there's so many nice
- 3 studies, they go over there. And then you have
- 4 nothing.
- 5 And then there's this issue about every study
- 6 seems to be different and even in the same area. And
- 7 transplant's a pretty complex field to run clinical
- 8 trials in. And when we ever get anybody else to help
- 9 us out, they just shake their head how complex they
- 10 are.
- But I just give you an idea about ABMR. You
- 12 know, I -- it's pretty -- it's a pretty rare event.
- 13 It's about 1 percent per year. So maybe 5 percent
- 14 cumulative incidence at 5 years. And there'd be --
- 15 there -- you know, you -- like everything else, there
- 16 are always going to be these patients. Nobody actually
- 17 meets enrollment criteria for the clinical trial. It's
- 18 so hard sometimes, especially in these complex
- 19 patients.
- 20 So if you do 5 percent of 100, you need about
- 21 2,000 kidney transplants to have been followed. And
- 22 the center performing 200 transplants will have 10

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- 1 cases in that cohort. So basically, you have to do
- 2 about 3,000 kidney transplants to get 100 patients,
- 3 right, in a clinical trial of ABMR. And that's a lot
- 4 of kidney transplants.
- 5 And if you multiply that times the number of
- 6 drugs that were are trying to use in this area, just
- 7 the physicality of doing a clinical trial -- and this
- 8 becomes a big issue -- subclinical rejection was
- 9 something we've been interested in many years. But
- 10 doing a clinical trial on subclinical rejection
- 11 requires about 3 or 400 patients almost in each arm to
- 12 show an impact on outcome. And so you have to have a
- 13 bunch of places doing protocol biopsies, and it's hard
- 14 to do.
- 15 And I want to -- I wouldn't go away without
- 16 mentioning something I think that we should talk about.
- 17 And I had a conversation this morning with someone from
- 18 the FDA who was sitting next to me. And I think that
- 19 we should really consider adaptive trial design in
- 20 clinical trials and kidney transplantation. It's a way
- 21 to learn from relatively small numbers of study
- 22 subjects. In our calculations, you may have as few as

- 1 eight patients that can be used to decide of therapy is
- 2 ineffective
- 3 Another aspect at hand is efficiency if
- 4 there's a single control group, rather than having
- 5 multiple control groups over and over again.
- 6 And the vast majority of patients then can be assigned
- 7 to an experimental group. And oncology, of course,
- 8 beat us to the punch many years before. This is -- you
- 9 should read these papers and the comments on them about
- 10 adaptive trial design. This is a Bayesian adaptive
- 11 trial design. It doesn't have to be exactly like this.
- But I think that we should truly think about
- 13 not when we're thinking about looking at the way we do
- 14 drug studies. I think that adaptive trial design is
- 15 something we really need in transplantation, especially
- 16 if we're talking about subsets of small groups of
- 17 patients.
- 18 So compare oncology to transplantation. A few
- 19 years ago, they put out an article that there are
- 20 23,000 clinical trials going on in the world today,
- 21 right? I think that, you know, that seems like I do
- 22 IRBs, and I'm still way behind that. That's a lot of

1 trials. I think 16,000 of them are in oncology.

- 2 In transplantation, maybe 20. You think there
- 3 are that many? Twenty in transplant?
- 4 And I think the lessons from oncology is they
- 5 work together. They have standing clinical research
- 6 consortia. And again, we are not a great success, but
- 7 we're trying to do it. And I'd be happy to work with
- 8 anyone else and try to make this a success in
- 9 transplantation. They commonly use surrogate endpoints
- 10 for clinical trials, and they don't give up. There's
- 11 no question. They're -- they are just persistent, and
- 12 they will tend to be successful for that.
- 13 I really think that the MTA actually is not
- 14 built for me. It's built for the junior faculty of the
- 15 place that I work at. And they're probably going to
- 16 see the most benefit from this long term. And I don't
- 17 think I'm really worried about how fast it's going to
- 18 happen.
- 19 I think we built some trust. We have some
- 20 momentum. We're showing some productivity. I would
- 21 have to thank Matt Everly, also. He's been very active
- 22 and supporting of what we're trying to do. We're

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- 1 keeping funded, but people are coming along and doing
- 2 this.
- 3 And then the real problem is that when you
- 4 have this group and it gets to be bigger and bigger,
- 5 you know, you have to keep -- take care of the people
- 6 at home, too. And this is a totally -- it's a separate
- 7 job to do this.
- 8 So that's my experience with the clinical
- 9 research consortia. Maybe in five years I can give you
- 10 a more rosy update. Thank you.
- 11 (Applause.)
- DR. CAVAILLE-COLL: Thank you, Dr. Stegall.
- Our next speaker is Margaret Mooney from the
- 14 National Cancer Institute, who's going to address
- 15 Clinical Trials Networks in Oncology A Model of
- 16 Collaboration.
- 17 DR. MOONEY: Okay. Well, thank you very much
- 18 for inviting me here today. And it actually is very
- 19 nice to listen to the differences in the problems that
- 20 you have in transplantation and thinking about clinical
- 21 trials and to realize, even though we may seem like the
- 22 100-pound gorilla in the room, even in oncology, we

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- 1 face many of the same issues. And we have to deal with
- 2 all the same challenges.
- 3 So I just want to say I have no financial
- 4 disclosures. And as a federal employee, any commentary
- 5 that I might make are my own personal opinions and not
- 6 those of the National Cancer Institute.
- 7 So I was asked to give a very brief history of
- 8 the NCI-funded (ph) cooperative group program, which is
- 9 a grant program that was started more than 60 years ago
- 10 by the NCI to evaluate cancer treatments. So I will
- 11 try to go through 60 years of history in 6 minutes or
- 12 less, so I hope you'll bear with me, and then to talk
- 13 about how we tried to transform that grant program over
- 14 the past five years into a truly national network
- 15 program.
- And then the last part of my presentation --
- 17 I'll just talk about some of the clinical trial designs
- 18 and challenges in this area of precision medicine that
- 19 we're encountering in oncology, which leaves us with
- 20 very few patients in many areas of particular cancer
- 21 subtypes. And so in that way, we really do have many
- 22 of the same challenges that you have. I'll also speak

- 1 a little bit about the way we're designing biomarker-
- 2 designated trials and using adaptive design features as
- 3 well.
- 4 So we were very fortunate that, in 1955,
- 5 actually, the U.S. Congress appropriated about \$5
- 6 million to establish a cancer chemotherapy national
- 7 service center. And at that time, NCI established a
- 8 cooperative group model of a resource -- a research
- 9 consortium to test chemotherapeutic agents. And by
- 10 1958, we had 17 cooperative groups. Now, they were
- 11 small. They were in different cancer areas, and they
- 12 were really just empirically screening drugs. They
- 13 weren't really looking at the disease and asking a
- 14 specific clinical treatment question for that patient
- 15 population.
- And it wasn't until 1966 that we kind of
- 17 separated that clinical trials activity from a purely
- 18 sort of empirical drug screening approach to actually
- 19 an independent evaluation of the cancer and looking
- 20 beyond just drugs of how we used radiotherapy with
- 21 drugs, how we used surgery with drugs, and how we
- 22 combined all three of them to approach the best

1 treatment for cancer patients.

2 But we still operated on a very independent

3 sort of one-grant-to-each-group model at that time.

4 People would propose trials. They would be reviewed.

5 They would be put into effect.

But we weren't very collaborative at that

7 time. And it wasn't until the early '80s that we

8 changed the paradigm of how we funded those trials and

9 how we worked with those cooperative groups. So it

10 really became a collaboration between the investigators

11 in the academic centers and across the United States

12 that participated in those trials and directly with the

13 physician and physician staff at NCI.

And then in 1983, there was additional funding

15 from Congress to try to expand our research consortium

16 from an academic base into the community. So we

17 started the Community Clinical Oncology Program, or

18 CCOP, now known as an NCOP, was established to ensure

19 that community physicians and their patients could

20 participate in our trials.

21 And then in 1990, that was extended to provide

22 specific grants to areas and community centers that had

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1 and then approached the whole issue of pediatric

2 oncology in a unifying fashion. And so they did merge

3 into one group in the early 2000s.

4 And you can see here this is actually a rather

5 dramatic diagram of what happened in terms of the

6 survival of children with acute lymphoblastic leukemia,

7 ALL, who were enrolled in those cooperative group

8 trials between 1968 and 2009. And back in 1968 and

9 1970, the overall 10-year survival for children who had

10 ALL was about 10 percent. But by consistently, and as

11 Dr. Stegall said, really, never giving up, they tested

12 more and different combinations of multi-agent

13 chemotherapy regimens until the survival in the early

14 2000s and now in the late 2000s is 90 percent or

15 higher.

So now the focus has shifted as we understand

17 more about the molecular biology of child cancer to

18 focus on trying to understand what the molecular

19 characteristics are that determine which children will

20 have difficulties and will recur with ALL and also to

21 back off of therapy now, particularly for children who

22 we want, hopefully, to live a long normal life and try

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1 a minority base and ethnically diverse populations,

2 again, for the same purpose -- to try to really have a

3 national program that treated all patients in the

4 United States. It also allowed us to advance and look

5 not just at treatment, but also at prevention and

6 control.

7 But as we found that we got bigger, I wouldn't

8 say our resources always got larger or more

9 substantial. And so we found that, by having so many

10 different groups looking at cancer, there was quite a

11 bit of competition and a lack of efficiency. And the

12 first place we saw that was in pediatric oncology.

13 They actually had four separate national research

14 cooperative groups. Two of them were quite large, one

15 called the Children's Cancer Group, the other the

16 Pediatric Oncology Group. And then they had two

17 smaller, very specific groups, one in Wilms tumor and

18 the other in rhabdomyosarcoma.

But again, they found that, because they were

20 filling up the patient population much more narrowly

21 among the four groups, that they felt it would be much

22 more efficient if they combined into one single group

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1 to have more and less toxic therapy and still have the

2 same equivalent survival.

3 So as I said, we were very lucky to have that

4 initial support and continued support from the American

5 taxpayers to have a really publicly funded clinical

6 trials system. And it really was rather unique, and it

7 grow -- grew into a very distinctive national system.

8 As I said, we were able to have direct involvement from

9 investigators, not just in academic centers, but also

10 community centers. We're able to expand the types of

11 trials we did, and we have a long history of

12 accomplishments from all the hard work of those initial

13 physicians and those physicians who participate today,

14 but particularly from the patients and their family

15 members who participated in those trials and continued

16 to participate in trials.

17 Many of our accomplishments are in the area of

18 drug and drug development. But obviously, we also have

19 many trials related to other types of therapeutic

20 approaches like therapeutic -- like radiotherapy and

21 surgery.

At the same time, we've had several reviews

- 1 and analysis of our program in hopes to make it better.
- 2 And I've listed just three of these that were done in
- 3 the -- between 2005 and 2010. And probably the most
- 4 significant one was the last one on the bottom in 2010
- 5 by the Institute of Medicine, who really was given the
- 6 charge from the NCI director at that time to review our
- 7 entire program and really recommend how we could make
- 8 it more efficient and more productive as we entered
- 9 into an era of precision medicine.
- 10 And out of that review by the Institute of
- 11 Medicine, they did confirm that they really felt that a
- 12 public clinical trial system was really complementary
- 13 and had a very important role in patient care and
- 14 science and that it provided public access for
- 15 important clinical questions and as well as collecting
- 16 biospecimens for future research. But it also was
- 17 important because it would address questions that often
- 18 in the pharmaceutical and biotechnical industry weren't
- 19 well addressed.
- 20 But they did say that we needed four goals for
- 21 modernization, and you'll see those listed at the
- 22 bottom. One is they felt that it had -- we had to

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- 1 speed and run our trials much more efficiently. We had
- 2 to have more innovative science and trial design. We
- 3 needed to prioritize the trials that we did. And last
- 4 but not least, we needed to really incentivize the
- 5 participation of patients and physicians in these
- 6 trials.
- 7 So at the time in 2010 when the IOM, the
- 8 Institute of Medicine, did this analysis, we actually
- 9 had 10 different cooperative groups. There were five
- 10 that were kind of multi-modality in the sense they
- 11 cross different modalities of treatment approaches in
- 12 cancer, but also different diseases. And then we had
- 13 five that were specialty.
- 14 But what was happening, even though they would
- 15 occasionally collaborate on a trial -- and we had some
- 16 centralized services such as -- we did have a central
- 17 IRB that we started at the time. We did have a central
- 18 portal by which we could put trials they wanted to
- 19 collaborate on together so they could work together.
- 20 They still were really operating very independently.
- 21 So the question was how did we get to a -- or
- 22 how could we get to a network program from these

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- 1 individual 10 different cooperative group systems.
- 2 And so what the NCI did in July of 2012 was we
- 3 put out a new RFA for the funding of the program to
- 4 make it truly a network program. We consolidated it
- 5 down from 10 different programs to 4 adult groups and 1
- 6 pediatric group. So we kind of took that separate
- 7 infrastructure, consolidated it, and streamlined it.
- We also at the same time needed to provide an
- 9 essential infrastructure that can -- that was standing
- 10 and that all those groups could use. We tried to put
- 11 procedures in place to launch the trials more rapidly
- 12 and to have user-friendly harmonization of the way all
- 13 of them ran their trials so that everyone could
- 14 participate in them.
- 15 But I think the last and maybe the most
- 16 important thing that really drove this type of
- 17 consolidation on the investigator side as well was
- 18 understanding that we really needed in an area where
- 19 breast cancer now really was 10 different types of
- 20 cancer. We were finding out that lung cancer was very
- 21 different depending on the type of lung cancer you had
- 22 and the molecular characteristics of your tumor, that

- 1 we needed to have a functional platform to really
- 2 perform large-scale testing of increasingly smaller
- 3 subsets of molecularly defined cancers. And at the
- 4 same time, we needed to continue to focus on questions
- 5 that weren't always as well supported in a commercial
- 6 environment.
- 7 So in 2014, we did start the new NCI National
- 8 Clinical Trials Network. Obviously, it wasn't
- 9 completely new. It was built on 50-plus years of
- 10 history and dedication. And all the clinical groups
- 11 that had participated before actually came in and
- 12 reorganized themselves and consolidated into the four
- 13 adult groups and one pediatric group I mentioned.
- We continued to have a well-supported
- 15 community oncology base that participated in our
- 16 trials. And it did allow us, as you'll see in a few
- 17 minutes, to continue to do large umbrella trials that
- 18 screened (inaudible) patients, depending on the
- 19 characteristics of their tumor. We continued to do
- 20 multi-modality in non-drug trials when appropriate as
- 21 well as combination trials with different types of
- 22 investigational agents combined together when

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1 appropriate.

- 2 And last but not least, we were able to have
- 3 some new initiatives where we now, for every completed
- 4 clinical trial, once the primary results have been
- 5 published, we're able to take de-identified patient-
- 6 level data and put it in a public database so
- 7 researchers can now and into the future use that
- 8 information and do investigations.
- 9 At the same time, we have since the early '60s
- 10 collected biospecimens on pretty much every clinical
- 11 trial that was conducted. We now have a reservoir of
- 12 those biospecimens that weren't ever used for the
- 13 particular translational science in a trial. And those
- 14 are now beginning to become publicly available as well
- 15 for researchers to submit proposals on -- once a trial
- 16 is completed.
- 17 So we have a lot of basic operating
- 18 principles, which I won't go into here. But I'll just
- 19 suffice to say that -- and we now make sure that it --
- 20 that everyone operates in the network. So if you
- 21 belong as a particular academic or community
- 22 institution to one of the groups that participates in a

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- 1 consortium, you can participate in any trial that any
- 2 other groups put into the network. So this really is
- 3 open to everyone.
- 4 We also have made sure that each one of the
- 5 separate research consortium or major groups actually
- 6 uses the same common data management system, the same
- 7 common data elements, and we really work together to
- 8 make sure everything is harmonized across the network
- 9 no matter which particular group is leading a trial.
- 10 At the same time, each of those groups has a
- 11 distinct personality, and they still maintain their
- 12 individual research characteristics.
- So over the last four years, we have put on
- 14 over 75,000 unique patients onto clinical trials. I've
- 15 shown here a little bit something that demonstrates, I
- 16 think, how our trials have changed in the last five
- 17 years as opposed to a decade before. We have more and
- 18 more trials now where we initially screened patients
- 19 for particular patient characteristics, but also
- 20 molecular characteristics of their tumor so that we can
- 21 determine which subset patients -- or in which
- 22 intervention a patient should go into.

So we've seen over the last five year -- four

- 2 to five years that we have more and more trials where
- 2 to five years that we have more than more than when
- 3 that's an essential component of the particular
- 4 clinical research question that we'll be doing with the
- 5 intervention.
- 6 So I'm now going to shift a little bit and
- 7 just talk very briefly of some of the recent trials
- 8 we've done in the era of precision medicine and to give
- 9 a little bit of examples of adaptive devine -- design
- 10 features that we use.
- On all our trials, we do interim monitoring,
- 12 and that's because we need to monitor for both efficacy
- 13 and futility as the trial goes along. That helps us be
- 14 much more efficient. So if we see that an experimental
- 15 therapy looks like it is never going to be shown to be
- 16 better than the control or the standard of care, we end
- 17 the trial early. And the same thing if we're seeing
- 18 various distinct and early signal that something is
- 19 going to be dramatically beneficial.
- We also are much more efficient at trying to
- 21 understand what trials will succeed and what won't so
- 22 that we end or we modify a trial early if we see we're

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1 having accrual problems.

- We also put in certain designs like Phase 2, 3
- 3 trials. So we'll look for an early signal. And if
- 4 that early signal meets a certain barrier, we will then
- 5 move seamlessly into a definitive Phase 3 trial. That
- 6 also helps us be much more efficient.
- 7 There's been a lot of discussion about
- 8 surrogate endpoints. Those are very challenging to do
- 9 even in oncology and even with all the resources we
- 10 have. And we've been misled many times about something
- 11 that we really thought was going to be a good surrogate
- 12 for overall survival or for even disease-free survival
- 13 only to find that that hasn't panned out after we got
- 14 long-term follow-up.
- 15 So we focus much more now on intermediate
- 16 endpoints. They themselves are obtained, obviously,
- 17 earlier than the definitive clinical endpoint. They
- 18 are sometimes and often influenced by the intervention,
- 19 and they're correlated with a definitive clinical
- 20 endpoint. But they aren't a pure surrogate.
- 21 So that helps us, for example, if we look at
- 22 something like pathologic complete response of a

- 1 treatment. We might look at that early on right after
- 2 neoadjuvant therapy in the surgical specimen. And if
- 3 that -- we're seeing a high rate of complete pathologic
- 4 response at a certain level, we would then move on to
- 5 continue the therapy and evaluate the more definitive
- 6 endpoint, which is overall survival or even disease-
- 7 free survival.
- 8 The other thing we found were surrogate
- 9 endpoints. And when we thought they were definitive is
- 10 when we changed the class of agent that we were using.
- 11 So when we went from chemotherapy to more targeted
- 12 agents like anti-angiogenesis agents or even now with
- 13 immunotherapy, you couldn't necessarily use the same
- 14 surrogate endpoint. We found that it wasn't -- a
- 15 surrogate for one class of agents didn't work for
- 16 another class of agents. It worked in one disease. It
- 17 didn't work in another disease. It worked in one
- 18 subtype of patients and not in another.
- So it's a very, very challenging area. And
- 20 obviously, we don't have time to talk today about all
- 21 the issues related to that. But I think it's changed
- 22 our approach in some respects in the way we design
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- 1 trials that we're looking more at intermediate
- 2 endpoints, realizing that many of them really aren't
- 3 pure surrogates for the primary endpoint of interest.
- 4 So I'm very quickly going to give three
- 5 examples of trials that we've conducted or completed
- 6 recently in the era of precision medicine. The first
- 7 one will be early-stage breast cancer where we used a
- 8 biomarker or an assay to identify a risk level for
- 9 patients in terms of whether they -- whether the breast
- 10 cancer recurs or not.
- The other is a new umbrella trial for adjuvant
- 12 therapy in early-stage cancer. And the last is a very
- 13 challenging signal-thinking, early-phase trial where we
- 14 try to match all kinds of new agents with distinct
- 15 targets to patients who have tumors with particular
- 16 molecular characteristics called match.
- 17 So many years ago, we had done a series of
- 18 cancer clinical trials in breast cancer where, in fact,
- 19 we also collected biospecimens. And we found over time
- 20 that women with early-stage what we call ER-positive
- 21 lymph node negative early-stage breast cancer that was
- 22 HER2-negative, that they benefited from Tamoxifen

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- 1 therapy. We then found that they also benefited if you
- 2 used Tamoxifen, which is a hormonal agent, with
- 3 chemotherapy.
- 4 But what we found is we also knew that,
- 5 although we were treating everyone with hormones in
- 6 chemotherapy, many patients didn't appear to need
- 7 chemotherapy. But we didn't know which patients they
- 8 were.
- 9 So biospecimens were taken from many of the
- 10 trials that were done in the 1980s and 1990s even. And
- 11 those specimens and the long-term follow-up that we had
- 12 from those breast cancer patients were used to actually
- 13 develop a particular biomarker assay on recurrence
- 14 risk. And so about 250 genes were identified that were
- 15 thought to be most highly correlated with the risk of
- 16 breast cancer recurrence. However, with a model
- 17 building, they then streamlined that down to a 21-gene
- 18 assay expression model and chose 21 genes. And out of
- 19 those, they then did a validation study on specimens
- 20 with long-term outcome that were from a previous trial.
- 21 And from that, they developed something from
- 22 oncotype DX, which is a biomarker that allows us to
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- 1 determine a patient's risk of recurrence when they have
- 2 early-stage breast cancer. We know that patients who
- 3 have a low recurrence score have a low risk of
- 4 developing recurrence and probably only need hormonal
- 5 treatment. Same thing for those who had a very high
- 6 score, that they probably needed hormonal therapy and
- 7 chemotherapy.
- 8 But the big question was what to do for the
- 9 majority of patients, about 70 percent of them, who
- 10 were in the immediate-risk area where their risk --
- 11 excuse me -- recurrent score was somewhere between 16
- 12 and 26. Should you give them just hormones? Should
- 13 you give them hormones plus chemotherapy?
- 14 And what we then did is design a very large
- 15 trial that was done between 2006 and 2010 where over
- 16 11,000 breast cancer patients underwent testing of the
- 17 oncotype DX assay to determine their risk score. If
- 18 they were immediate risk -- and that meant they had a
- 19 score between 11 and 25 -- we randomized them to
- 20 hormones plus or minus chemotherapy. The patients who
- 21 were in the other two extremes were just treated and
- 22 followed to see how well they did.

1 And just three months ago, the results of this

2 trial were announced at the annual ASCO meeting in June

3 2018. The name of the trial was TAILORx. And what we

- 4 found is that, in fact, patients who were in that
- 5 intermediate risk category who received hormonal
- 6 therapy did just as well as those who had hormonal
- 7 therapy and chemotherapy. And because of that, we are
- 8 now able to go forward and with a great deal of
- 9 confidence, based on that risk score, determine which
- 10 patients need to be treated with hormonal -- or can be
- 11 treated with hormonal therapy alone and which really
- 12 need chemotherapy and hormonal therapy.
- We're trying to do something slightly
- 14 different in early-stage lunch cancer. Here we've
- 15 identified certain types of mutations, EGFR mutations
- 16 in (inaudible) rearrangements that actually, if a
- 17 patient has those characteristics in their tumor, we
- 18 found that, with particular targeted therapies against
- 19 those targets, they do very well if they have advanced
- 20 disease.
- 21 And what we've designed is a very large trial
- 22 so that we can screen based on a -- what we call a

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- 1 multiple biomarker randomized enrich design, which is a
- 2 mouthful. But in any case, what it allows us to do is
- 3 screen a lot of patients, select the tumors of the
- 4 patients who have tumors with particular molecular
- 5 characteristics, and then randomize them to the
- 6 appropriate therapy.
- 7 So we've done that in this trial, umbrella
- 8 trial, called Alchemist where we select the patients
- 9 with a particular histology who have either EGFR or an
- 10 (inaudible) rearrangement and treat them with a
- 11 particular therapy targeted against that mutation, or
- 12 we don't give them any further therapy.
- 13 At the same time, we've combined it with those
- 14 patients who don't have those markers, and we treat
- 15 them with chemotherapy, plus or minus immunotherapy.
- 16 So that's an ongoing trial that's taking place right
- 17 now.
- And the last big thing that we've been able to
- 19 do with the new national network is really take that
- 20 model and use it, actually, in a large national signal-
- 21 finding trial. So here, what we were trying to do is
- 22 screen a large number of patients and do complete NGS,

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- 1 next-gen sequencing, of the tumors to determine whether
- 2 they have particular molecular characteristics that we
- 3 could then actually match to new experimental drugs.
- 4 So this is something that we call a multiple
- 5 biomarker signal-finding design. And essentially, we
- 6 picked the marker. And then with the screen of all the
- 7 patients, regardless of the type of cancer they have.
- 8 So it's histology agnostic. If they have that
- 9 molecular characteristic and they have exhausted other
- 10 areas of therapy, we put them in a clinical trial and
- 11 see if that particular targeted area -- agent that's
- 12 actually set up to work with their particular molecular
- 13 characteristics has an effect or not.
- 14 This trial is called Match. It's been very
- 15 challenging, but, at the same time, very rewarding
- 16 because in two and a half to three years, we were able
- 17 to screen over 6,000 patient. We were able to match
- 18 about -- between 7 to 800 of them to particularly new
- 19 experimental therapies based on the target of the -- of
- 20 their particular molecular characteristic. And we also
- 21 made a focus of the screening to really concentrate on
- 22 rare cancers as well.

- 1 So I won't go into the details here, but we
- 2 were able to, out of those 6,000 patients, just to
- 3 screen about 62 percent of them who had rare cancers.
- 4 The rest had more common cancers. We had 40 different
- 5 treatment arms in that trial. Most of them are still
- 6 ongoing, but 15 of them have completed treatment. And
- 7 their results for them have been released.
- 8 So we're hopeful that this type of national
- 9 signal-seeking screening trial will lead us to new
- 10 discoveries in oncology and new signals for targets and
- 11 for treatment.
- 12 So thank you. That was a whirlwind
- 13 explanation of what we've done for the last 60 years.
- 14 But I guess the only caveat I'd like to say is that I
- 15 think that the model of collaboration has been
- 16 extremely successful in oncology. It's also been
- 17 essential. Without that, I don't think we would have
- 18 made many of the most significant and dramatic changes
- 19 in therapy that we've been able to do all together. So
- 20 thank you very much.
- 21 (Applause.)
- DR. MORRIS: I'd like to thank all the

1 speakers in the session that is now open for questions

- 2 or comments.
- 3 DR. STEGALL: I have a question. So two
- 4 questions. How do you get two to three pharmaceutical
- 5 companies to work together on a trial? Because I asked
- 6 them, and they look at me like I'm crazy. And what
- 7 percentage of cancer trials are actually in this --
- 8 under this format? And is it, like -- is it 20
- 9 percent, 80 percent, those kind of things?
- DR. MOONEY: Okay. In terms of working with
- 11 companies, because, you know, going back to the 1950s,
- 12 I mean, really, initially, there wasn't a biotech
- 13 industry back then. So in that sense, government did
- 14 pay -- play an important role in really starting
- 15 science and research in that area. But because of
- 16 that, we kind of grew up with the drug development
- 17 field and with biotech. And so we had many
- 18 relationships with pharmaceutical companies and biotech
- 19 companies during that period.
- 20 But what we found is that we were able to set
- 21 up certain types of research agreements with multiple
- 22 companies where they viewed the government as an honest

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- 1 broker because we didn't have an investment interest in
- 2 what happened. We had a scientific interest. And so
- 3 over the last 10 years, we've developed what we call
- 4 CRADA, which are collaborative research agreements with
- 5 companies that have certain data-sharing aspects and
- 6 confidentially -- confidentiality aspects that allow
- 7 them to go in and combine their two agents together in
- 8 trials that we run through the research consortium.
- 9 At the same time, we've put in IP protection.
- 10 So that was a significant issue with all the companies
- 11 and concerns about that. And we've put that in place,
- 12 too. So it's really to -- a lot of hard work from all
- 13 the people who work in the regulatory area to set up
- 14 those kinds of agreements.
- 15 DR. STEGALL: And the percentage --
- DR. MOONEY: Oh, the percentage I have no
- 17 idea. I mean, I think what's difficult is, 60 years
- 18 ago, we could say we were doing most of the clinical
- 19 trials in oncology. Today, there's been such an
- 20 explosion, and that's really difficult to say.
- We used to say -- and I think we still do --
- 22 that we're probably the largest funder of -- public

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- 1 funder of clinical trials. But I think the explosion
- 2 in investment by biotech and all the number of trials
- 3 going on, particularly now with immunotherapy, it will
- 4 be very difficult to categorize.
- 5 DR. STEGALL: Okay. Thank you.
- 6 DR. MORRIS: I have a question. If you were
- 7 here earlier, you realize that we're very interested in
- 8 biomarker surrogate endpoints and drug development
- 9 tools. And as you mentioned, oncology has spearheaded
- 10 the area of surrogate endpoints, accelerated approval.
- 11 So I was wondering if you could give us a few
- 12 examples of surrogate endpoints that were endorsed by
- 13 the FDA and which were used by sponsors to receive
- 14 accelerated approval and that predicted a true clinical
- 15 outcome.
- DR. MOONEY: So that -- you know, again,
- 17 that's a different -- difficult question. I think for
- 18 us in oncology survival itself was always the primary
- 19 endpoint. So when we began to show differences with
- 20 certain regimens in progression-free survival in the
- 21 advanced disease setting and then disease-free survival
- 22 in the adjuvant setting, which correlated very strongly

- 1 with chemotherapy to overall survival, the FDA did take
- 2 progression-free survival in the advanced disease
- 3 setting, and they did take disease-free survival in the
- 4 adjuvant setting and did give us accelerated approval
- 5 on that within waiting for overall survival.
- 6 That's where -- in chemotherapy, because we
- 7 had a long history and a lot of data on those trials,
- 8 we really could correlate those progression-free
- 9 survival, disease-free survival with overall survival.
- 10 As we began to change the class of agents, that didn't
- 11 become so clear. When we began to realize that some
- 12 patients were really benefitting when we took everybody
- 13 together because of molecular characteristics, again,
- 15 together occude of molecular characteristics, again
- 14 that began to change a little.
- But I think, still, if we look, we've moved
- 16 even earlier in some respects in very advanced and rare
- 17 cancers where, if we show a dramatic response rate,
- 18 okay -- so not even progression-free survival, just a
- 19 response rate -- that they've been very open to using
- 20 that as an early indicator, maybe not a perfect
- 21 surrogate, and then waiting for the eventual primary
- 22 outcome of the end -- of the primary endpoint outcome

1 to get full approval.

- 2 DR. MORRIS: So can you -- can an oncologic
- 3 drug get traditional approval if it shows progression-
- 4 free survival but not any difference between the
- 5 comparator in overall survival -- or survival rate?
- 6 DR. MOONEY: So --
- 7 DR. MORRIS: In other words, the patients
- 8 don't do any better, but they have progression-free
- 9 survival. How does that work?
- DR. MOONEY: Okay. Well, I'm not from the
- 11 FDA, so they're the -- they'd be the best one. But I
- 12 certainly can give an example where, in some cases,
- 13 they have approved or given full approval based on
- 14 progression-free survival as long as there's no
- 15 decrement in overall survival.
- So there were some -- and it comes down to the 16
- 17 severity of the condition, how, you know, the fatal it
- 18 is, whether any other alternatives of therapies and
- 19 what the benefit in that progression you're seeing is.
- 20 And if the same time they see something very
- 21 significant clinically and then there's no decrement in
- 22 over survival, at least in some cases, I believe they
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- 1 have given full approval, even on that.
- We've seen a lot more early approvals in terms
- 3 of accelerated approval waiting for a more definitive
- 4 endpoint. We've also seen what they call breakthrough
- 5 approvals.
- 6 But to just give one example that they've done
- 7 in advanced disease setting very recently with
- 8 immunotherapy in what we call microsatellite
- 9 instability, so it's probably not worth going into all
- 10 the details about it. But in any case, immunotherapy
- 11 across a variety of different cancers in the advanced
- 12 disease setting seem to be particularly beneficial for
- 13 patients who had tumors with that characteristic.
- 14 So I believe it was, if someone's here from
- 15 the FDA, one of their first across histology full
- 16 approvals for use of an agents in that class of
- 17 disease. Now, again, that was very advanced. People
- 18 had exhausted other standards of care. But it was
- 19 based on, really, not long-term outcome, but it was
- 20 based on seeing a dramatic response in progression-free
- 21 survival across multiple histologies.
- DR. MORRIS: (inaudible off mic) examples of

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- 2 histological stages of disease but don't increase
- 3 overall survival. In other words, it's another way of

1 drugs that have been approved which halt progression of

- 4 looking at progression-free but here at the actual
- 5 histological level.
- 6 DR. MOONEY: Yeah. So I'm not -- are you
- 7 asking --
- 8 DR. MORRIS: Yeah. I'm asking whether there
- 9 are examples in oncology where a drug prevents
- 10 progression of a stage of disease assessed by histology
- 11 but overall the patients in both arms die at the same
- 12 rate. It's a way of looking at --
- DR. MOONEY: Yeah.
- 14 DR. MORRIS: -- progression-free --
- 15 DR. MOONEY: Yeah.
- DR. MORRIS: -- as well but at a histological
- 17 level.
- DR. MOONEY: Yeah. So certainly, most of the
- 19 trials that we've run up until more recently as we've
- 20 understood more about the molecular characteristics and
- 21 targets, we've run within histologies. So there have
- 22 been many trials where we've seen a difference in

- 1 progression-free survival that looked quite dramatic,
- 2 but then there was no difference in overall survival.
- Now, sometimes that was because there were
- 4 alternative therapies available after someone stopped
- 5 tumors stopped responding to that initial therapy.
- 6 And so there were many examples of that, actually,
- 7 where we do see a difference in progression-free
- 8 survival, but overall survival doesn't change.
- 9 DR. MORRIS: Drugs were approved --
- DR. MOONEY: Well, sometimes they were
- 11 approved; sometimes they weren't. And they were
- 12 approved, as I said, where that benefit in progression
- 13 was quite large. Sometimes they're quite small.
- 14 There's a difference, but it's not really large. The
- 15 other thing -- there can be a difference, but if
- 16 there's a lot of toxicity associated with it, then what
- 17 are you buying?
- 18 So it's a complicated assessment. Nothing
- 19 seems to be getting easier.
- DR. LENTINE: Can I ask a question, Dr.
- 21 Morris?
- So I really wanted to thank Dr. Mooney and Dr.

- 1 Stegall for those excellent presentations.
- 2 And Mark, you began by mentioning some
- 3 disincentives to consortium, why they're very difficult
- 4 to build, not just in relation to industry, but other
- 5 factors. So I just wanted to get your take on what's
- 6 your vision. How do we advance to become more like
- 7 what Dr. Mooney describes? And do you envision it's
- 8 going to take us 50 years, or is it more imminent on
- 9 the horizon?
- 10 DR. STEGALL: (inaudible off mic). So I
- 11 think that -- I mean, I'm -- I don't know what the
- 12 right formula is. We just decided to get started. And
- 13 I think that was the first thing.
- 14 And then we now are in the phase of trying to
- 15 really get studies going. We'll do kind of whatever.
- 16 But I -- we submitted, you know, things like NIH grants
- 17 and things like that. And I think that, at some point,
- 18 we would like to see -- there has to be like it's
- 19 happened with NCI. To do something like this, there
- 20 really has to be money for the infrastructure because
- 21 you just can't go year to year trying to get money,
- 22 even grant to grant trying to get money. That's not
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- 1 going to work for a consortia. It's just not.
- 2 And so I think at some point, whether we get
- 3 an endowment, whether societies pull together to do
- 4 this, whether there's a rich patient at the Mayo Clinic
- 5 that's willing to give us money, I don't think we need
- 6 the kind of money NCI does.
- We partner with other areas even in our sphere
- 8 of diseases. I mean, it seems like to me that FDA has
- 9 kind of moved a little bit out of cancer now, and
- 10 they're moving in these public-private partnerships are
- 11 in other areas. And it's great.
- 12 So I think the only thing is transplant just
- 13 needs to be at the table like we are today, be included
- 14 in the conversation. We've been pretty much early
- 15 adopters. So I think -- that's my hope.
- And then like everything else, it gets better
- 17 when there's more input. So I'd be happy to talk to
- 18 anyone in the room about maybe trying to do something
- 19 bigger. But bigger is not always better. Like you
- 20 found out, there were a lot of -- I heard about all
- 21 those horror stories, my friends, you know -- they cut
- 22 us out, you know. And if you're just not performing,

- 1 they cut you out.
- 2 So there is -- it's -- I think they found that
- 3 over 60 years -- it may take that long for all those
- 4 people with the big egos to die.
- 5 (Laughter.)
- 6 DR. STEGALL: And the collaborators -- and the
- 7 good thing is the next generation of people that I'm
- 8 training are collaborative, right? It's not a big deal
- 9 to them. They're not trying to be as famous as all the
- 10 rest of the people up here, me included.
- 11 DR. LENTINE: And the concept of including not
- 12 just academic centers, but even moving into the
- 13 community, do you think that's part of the equation for
- 14 our field or --
- DR. STEGALL: Well, transplant's not. It --
- 16 transplant's actually -- it should be really easy,
- 17 right? It's really 30 -- I think something like 80
- 18 percent of the transplants are (inaudible) 30 percent
- 19 of the programs in the country -- or 30 programs. And
- 20 I think that -- so one could do really good clinical
- 21 trials.
- 22 You don't need every single -- but I think
- Page 441
- 1 that cancer may be a little bit different. The only
- 2 thing about is getting, really, a lot of the
- 3 limitations, right? I'm sure the way we do a lot more
- 4 local therapy because people don't want to drive 150
- 5 miles every time to get an infusion, right? So there's
- 6 all those issues about just logistics of doing clinical
- 7 trials.
- 8 It would be great if we could do something
- 9 more local for patients because people travel a fair
- 10 ways to get a transplant. Does that answer your
- 11 question?
- DR. LENTINE: Yes. Thank you.
- 13 DR. STEGALL: Thank you.
- 14 DR. MANNON: I mean, I think one of the
- 15 differences between oncology that's very stark is the
- 16 division of the institute support for NIH for the --
- 17 for our patients. And there is an implicit or, you
- 18 know, a well-spoken difference in funding, that NIDDK
- 19 funds graft failure and graft CKD. And NIAID files
- 20 immunological outcomes.
- 21 And until those two things emerge -- and it's
- 22 not going to happen any time soon because we just met

- 1 with them a few weeks ago on behalf of one of the
- 2 societies -- I think there's no federal mandate. I
- 3 mean, there's -- we can't even get immunosuppression
- 4 after three years paid for, Kristine (sic). So I'm not
- 5 sure that they're going to see this as a hallmark.
- 6 I think the public, you know, was responding.
- 7 The death rates were scary. And almost -- I mean, I
- 8 think that having a line item in a federal budget is a
- 9 big difference.
- 10 I think communities are really -- you know, I
- 11 think we can't even get the academic centers to get on
- 12 board. AST tried this in 2003. I think that was the
- 13 first year I was on the clinical trials committee with
- 14 Flavio, and there was tremendous pushback. And we even
- 15 had members of the -- do you -- I mean, I don't know if
- 16 you remember. Some of you all may remember that. But
- 17 people were angry. They were like, well, I'm not going
- 18 to be included, so I'm not going to be like a blue
- 19 ribbon.
- 20 So I -- you know, I think it's something worth
- 21 exploring because I don't think that the -- like, first
- 22 of all, we have CTOT. We have -- you know, and that --
 - Page 443
- 1 it -- I hope there will be an RFA in two more years.
- 2 And that has really -- there is infrastructure, but we
- 3 could definitely use more money. And I -- you know,
- 4 and I'm hoping there's an RFA. I mean, they keep
- 5 talking about it. But I think that that's one big
- 6 difference, that we don't have the budget, the funding.
- 7 And we have smaller patient population.
- 8 So it may come from the -- again, why are we
- 9 here today? Because the societies pushed for this.
- 10 And it was in -- less threatening, and I think it's
- 11 worth going back and saying to societies let's try this
- 12 again.
- 13 DR. STEGALL: I'm sure that --
- DR. MANNON: And maybe not say blue ribbon --
- 15 you know, something more generic like cooperative, you
- 16 know.
- 17 (Laughter.)
- DR. MANNON: With junior faculty-- maybe
- 19 developing their careers that way because that would be
- 20 more open.
- 21 DR. MORRIS: Larry.
- 22 LARRY: Yeah. Mark made a comment about what

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- 1 we might call the 80/20 rule. And it's true that 802 percent of the transplants go on in about 20 percent of
- 3 the centers, more or less.
- 4 In a sense, whenever pharma does a multi-
- 5 center trial, it is establishing a collaborative study
- 6 group. So there's a lot of -- there's a template for
- 7 that and a lot of models. One of the real problems,
- 8 though, is that, even at the "busy centers,"
- 9 recruitment often does not meet expectations. So it's
- 10 typical, let's say, for a Phase 3 trial in transplant
- 11 with 6 or 800 patients.
- We might have 80 centers, and it takes too
- 13 long to recruit a trial like that with the BEST efforts
- 14 because, even the busy centers often don't meet their
- 15 recruitment targets. So we have --
- (Crosstalk.)
- 17 LARRY: They're too busy. If you tell us 20
- 18 patients in six months, we know that's 10 patients in
- 19 12 months.
- 20 DR. STEGALL: So I -- but I think that we -- I
- 21 have a hope that you could probably put together a
- 22 clinical research trials network. I know -- say it has
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- 1 to be the MTA (ph), that individuals in that network,
- 2 one of their jobs is to get patients enrolled and to do
- 3 a good job with this.
- 4 LARRY: Right.
- 5 DR. STEGALL: And it probably failed the first
- 6 couple of times. But at some point, you'd probably
- 7 find someone in there who really wanted to do that and
- 8 had time to do that. If you paid their salary and some
- 9 of the infrastructure salary of the people they worked
- 10 with, I would guarantee you that it would work better
- 11 than the current system.
- 12 LARRY: Well, I absolutely agree. I agree
- 13 with your model.
- 14 (Crosstalk.)
- 15 LARRY: But it's just an offering from the
- 16 real world, you know.
- 17 DR. STEGALL: We'd also need tissue banks and
- 18 all that sort of stuff that -- yeah.
- 19 DR. MORRIS: Peter I think is --
- 20 UNIDENTIFIED MALE SPEAKER: Peter and Mark, I
- 21 have the pleasure to work with incredibly talented
- 22 people at CareDx. I just wanted also to have a

- 1 positive note because, right now, within six months, we
- 2 have recruited 27 centers in the United States with our
- 3 registry study. It's an observational study. But 27
- 4 centers in 6 months is quite incredible.
- 5 And you know, that's the force of
- 6 transplantation. We are talking about bringing the
- 7 village together. And having the ability to recruit 27
- 8 centers in any other therapeutic area, that's pretty
- 9 astonishing, especially when you're thinking about, you
- 10 know, world-in-class tertiary care centers in the
- 11 United States.
- 12 So just on a positive, there's a lot of force
- 13 in transplantation, and we should use this because,
- 14 here around the room, if we hit our recruitment
- 15 targets, which is a 1,000 patients, within 18 months,
- 16 that's pretty phenomenal.
- 17 So I wanted to thank you for recruiting, but
- 18 please continue to recruit because it's right, Mark.
- 19 We need the recruitment targets in order to have the
- 20 right ends.
- 21 Thank you.
- 22 DR. HERNANDEZ-FUENTES: So I wanted to comment

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- 1 on the recruitment problem. In the UK, I think we have
- 2 benefitted from an initiative that the NIH have put
- 3 together where they were paying the hospitals that
- 4 included patients in clinical trials that had certain
- 5 levels of political (ph) criteria.
- 6 So for the -- in the -- in not only -- so they
- 7 were priming (ph) -- investigator led the studies, but
- 8 also the ones that have public funding like MRC (ph)
- 9 funding. So now in the UK, the hospitals get funding
- 10 that support that infrastructure, paired patient
- 11 included in one of these studies, and (inaudible)
- 12 observational studies. So they have observational
- 13 studies, clinical trials. And this is all grant-funded
- 14 but also commercially funded.
- 15 And I think it is an important totally game
- 16 changer. So in the first study, we could only recruit
- 17 70 patients, or something like that, in five years.
- 18 The second study -- I couldn't cope with the amount of
- 19 centers that wanted to participate in the study. It
- 20 was very -- you know, I had the program manager was
- 21 completely overwhelmed. It changes things.
- 22 So I think there are initiatives that the

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- 1 societies and the federal government or the federal
- 2 funding or -- there are initiatives that are able to
- 3 change the game in recruitment levels, and that would
- 4 really accelerate research.
- 5 DR. MORRIS: Rhia (ph).
- 6 RHIA: Yes. I'd like to make a comment about
- 7 the clinical trials collaborative and compare it to
- 8 what's going on in oncology. For those of us that have
- 9 worked in transplant clinical trials for so long, I
- 10 think we've learned things that make them work well.
- 11 I think, first, is having a clinical research
- 12 group embedded within your clinical team allows you to
- 13 identify the patients more quickly and more readily.
- 14 The second thing is something that's different
- 15 about oncology. You get a diagnosis of cancer, and
- 16 you're not deciding to make a treatment decision that
- 17 day. There's time that progresses. In
- 18 transplantation, certainly in the case of a de novo
- 19 transplant, you really don't have much time to decide
- 20 that you're going to put them in a de novo trial. And
- 21 even in the instances of where you have a rejection
- 22 episode, most people want to implement therapy within

- 1 24, 48 hours, which we've begun to think is
- 2 appropriate, and it is.
- 3 So having the logistics worked out that it's
- 4 going -- that -- and understanding the differences in
- 5 transplantation from some of these other cooperatives
- 6 is going to be very important. And in my opinion, it
- 7 has been having the clinical research people embedded
- 8 within the clinical teams because there's no way that
- 9 you can have all of the providers knowing exactly what
- 10 studies are open when and, basically, stopping their
- 11 decision long enough to say, hey, can we consider
- 12 enrolling them in a clinical trial. And that's
- 13 essentially what you have to do in transplantation.
- 14 DR. MORRIS: Yeah, Peter.
- 15 DR. NICKERSON: I guess I'd like to hear on
- 16 one other area that could be important, and that's the
- 17 economics of transplant care. And the economics of
- 18 transplant care in this country tends to favor very
- 19 short-term outcomes. And there are many centers. If
- 20 you take those 80 -- those 20 percent, many of those
- 21 centers are hesitant to enroll what they might perceive
- 22 as patients in the higher-risk trials because that

			<u> </u>
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1	could impact their outcomes.	1	So with that, our first speaker is Kevin
2	And I think that that's a solvable problem if	2	Fowler. Is Kevin still in the room? Nope.
	we, you know, think about how we reimburse. And I just	3	Okay. In that case, I will move on to Stanley
	was wondering if that's something people think is	4	Rose (ph). Stanley Rose?
5	relevant.	5	(Crosstalk.)
6	DR. ALBRECHT: So Peter, thank you for those	6	DR. WOODWARD: Oh, okay. Next, we have Robe
	comments. We should pause for a while because now we		Woodward. Robert Woodward.
	need to get to the open public session.	8	MR. WOODWARD: Sorry. I had earlier in the
9	And Shannon Woodward is going to moderate that		week expressed that we may give a comment, but I
	session. Do we know who the first speaker is, Shannon?		decided not to.
11	DR. WOODWARD: Hi, everyone. And thank you so		DR. WOODWARD: Thank you.
	much for hanging in there with me.	12	Next, we have Brandon Keeting (ph). Brandon
13	So right now, I'm just going to go over a		Keeting?
	couple of things to help facilitate this session for	14	(Crosstalk.)
	open public comment. So right now, the purpose for	15	(Laughter.)
١	this part of the workshop is to allow opportunity for	16	DR. WOODWARD: Oh, wow. Swapna Kakani (ph)
17	č		Swapna Kakani? No. Okay.
	comment on topics other than the main discussion topics	18	Well, this is a historically short session.
	of the workshop.	19	(Laughter.)
20	Keep in mind that neither FDA or Critical Path	20	DR. WOODWARD: I think that's proof that our
	Institute will be addressing the comments that we hear		workshop has been very interactive. So thank you all
22	during this session. But all of the comments are being	22	for your time.
1	Page 451 transcribed, and they will become part of the public	1	Page 453 (Applause.)
	record.	2	DR. ALBRECHT: Thank you, everyone. I think
3	We'd also like this to be a transparent		that concludes today's session, and we look forward to
4	process. So we encourage you to note any financial		seeing you tomorrow morning at 8:00 o'clock to start
	interest that may be relevant to your comment. And if		our patient-focused drug development day. Thank you
	you don't have any, you're welcome to state that for		very much. And thank you to all the speakers and
	the record as well.		attendees.
8	We collected sign-ups before the workshop and	8	
9	also during the breaks as well, and we currently have	9	
10	five speakers signed up.	10	
11	So as I call your name, you're welcome to	11	
12	approach the microphone here in the middle of the room.	12	
13	And also, there is a two-minute time limit for each	13	
14	speaker.	14	
15	I don't have one of those Jeopardy-style	15	
16	buzzers, and I won't be screaming at anyone too hard	16	
17	because it's the end of the day. But what I will do is	17	
18	kindly nudge you just to let you know that you're	18	
19	coming towards the end of your time.	19	
20	And if your name is called and you're no	20	
20			
21	longer interested in sharing your remarks, just let us	21	

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