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3	FOOD AND DRUG ADMINISTRATION (FDA)
4	CENTER FOR DRUG EVALUATION AND RESEARCH (CDER)
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6	PUBLIC WORKSHOP:
7	FACILITATING ANTIBACTERIAL DRUG DEVELOPMENT FOR
8	PATIENTS WITH UNMET NEED
9	AND DEVELOPING ANTIBACTERIAL DRUGS THAT TARGET A
10	SINGLE SPECIES
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12	Monday, July 18, 2016
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1	PROCEEDINGS
2	8:30 a.m.
3	WELCOME AND INTRODUCTIONS
4	DR. COX: Good morning. Good, the
5	microphone's on. Welcome, everybody. I'm Ed Cox.
б	I'm director of the Office of Antimicrobial Products.
7	And can folks here me? We're good? Okay. I just
8	want to start out by welcoming everyone. I'm still
9	getting myself oriented here at the podium a little
10	bit to our public workshop on facilitating
11	antibacterial drug development for patients with unmet
12	need. And just so that folks, you know, understand, I
13	mean, this is a workshop. It's not an advisory
14	committee. So it really is an opportunity for
15	discussion. It's not really an exercise in achieving
16	consensus.
17	We do provide conflict of interest
18	information, which I think is available at a table out
19	front, if folks are interested in seeing that. And
20	we'll also, later on in the day, have an open time for
21	comments for anyone who wishes to provide their
22	viewpoints. And I thought what we'd do first is just

1	go around the panel and have folks introduce
2	themselves this morning so that folks know who is on
3	the panel. And maybe we'll start on my left with
4	Kert. And please just introduce yourself and use the
5	microphones so that folks, both on the webcast and in
6	the room, can hear you.
7	DR. VIELE: Hi. I'm Kert Viele, from Berry
8	Consultants. I'm a statistician.
9	DR. RUBIN: Good morning. I'm Dan Rubin, a
10	statistical reviewer at FDA.
11	DR. AMBROSE: Hi. I'm Paul Ambrose, from
12	the Institute of Clinical Pharmacodynamics, a PK/PD
13	guy.
14	DR. FRIEDLAND: Ian Friedland. I'm the
15	chief medical officer at Achaogen.
16	DR. REX: John Rex. I'm an internist and ID
17	specialist at AstraZeneca Pharmaceuticals.
18	DR. KARTSONIS: Nick Kartsonis. I'm an
19	infectious disease clinician and I work at Merck.
20	DR. CAVALERI: Marco Cavaleri, head of anti-
21	infectives and vaccines, European Medicines Agency.
22	DR. MARKS: Lynn Marks, infectious disease

Page 10 specialist at GlaxoSmithKline. 1 2 DR. NAMBIAR: Sumathi Nambiar, director of the Division of Anti-Infective Products, CDER, FDA. 3 4 DR. BORIO: Lu Borio, ID clinician and an acting chief scientist. 5 DR. DUDLEY: Mike Dudley, from The Medicines 6 7 Company and head of research and development. 8 DR. LARSEN: Joe Larsen, acting deputy director at BARDA. 9 10 DR. LOUIS: Tom Louis, Johns Hopkins, 11 biostatistics. 12 DR. DIXON: Dennis Dixon, NIH, NIAID. 13 MR. DANE: Aaron Dane, statistical 14 consultant. 15 SESSION 1: GENERAL CONSIDERATIONS FOR UNMET NEED 16 PROGRAMS 17 EFFECTIVENESS STANDARDS INCLUDING ORPHAN 18 PRODUCTS 19 DR. COX: Great. Thanks, everybody. And we appreciate all that have come to join today and all 20 21 the panelists that have also traveled far and wide to 22 come and join us. And let me just -- I'll just

1	briefly walk through I think folks have the agenda,
2	so I'll briefly walk through some nuts and bolts.
3	This morning, we'll talk about general considerations
4	for unmet medical need development programs. We'll
5	have a series of talks, you know, describing different
6	pathways. And then, as we move on in the day, we'll
7	actually hear from a couple of folks that have, you
8	know, tried to venture into this area. They'll share
9	with us their experiences to date, what's worked, what
10	they've run into as far as the challenges in doing
11	such programs. So we appreciate their willingness to
12	provide us with those details. I think that'll be
13	very helpful.
14	And then, later in the afternoon, we'll have
15	some discussion about statistical considerations for
16	developing antibacterial drugs using an unmet need
17	paradigm. So I just want to provide a little bit of

background and some context. You know, we typically find that as we're preparing for a workshop, 19

18

oftentimes there's a lot of very rich discussions 20 during the course of the preparations for a workshop. 21 So what I'm going to try and do -- my talk 22

1	is a little bit disjointed. But I'm going to try and
2	touch on a number of the issues that came up as we
3	prepared for today's meeting because I think that may
4	be helpful. You know, folks know that the
5	antibacterial drug development area is particularly
6	challenging. Scientific reasons make it difficult.
7	You're not exactly sure what the patient's diagnosis
8	is. The patient may need other overlapping therapy
9	that can obscure the assessment of the drug that's
10	being tested. There's a lot of drugs out there, but
11	there are still patients who for whom those drugs
12	are not good options because of the development of
13	resistance.
14	Economically, it's also challenging, not
15	within the scope of what we'll be talking about today,
16	but there has been a lot of important work looking at
17	the economic issues for antibacterial drug
18	development. And also though it's not really parsed
19	into these two poles, but more of a continuum, we do
20	see antibacterial drug development in terms of
21	standard development programs. These are the more

22 traditional development programs where there are

1	molecules that are being developed using sort of
2	traditional NI margins, traditional study approaches.
3	And then, on the other end of the pole is the area of
4	unmet need development programs. So these are
5	development programs that are characterized typically
6	by a greater degree of uncertainty and it's not a
7	decision per se to go one way or the other based on
8	the absence of information about the drug. Actually,
9	the drug and its characteristics are very important in
10	determining which pathway one might choose.
11	For a molecule that is pursuing an unmet
11 12	For a molecule that is pursuing an unmet need development program, there really has to be a
12	need development program, there really has to be a
12 13	need development program, there really has to be a particular characteristic that make it a reasonable
12 13 14	need development program, there really has to be a particular characteristic that make it a reasonable choice, such as it's a molecule that operates via a
12 13 14 15	need development program, there really has to be a particular characteristic that make it a reasonable choice, such as it's a molecule that operates via a new mechanism of action. It's otherwise stable to
12 13 14 15 16	need development program, there really has to be a particular characteristic that make it a reasonable choice, such as it's a molecule that operates via a new mechanism of action. It's otherwise stable to resistance mechanisms that would otherwise chew up a
12 13 14 15 16 17	need development program, there really has to be a particular characteristic that make it a reasonable choice, such as it's a molecule that operates via a new mechanism of action. It's otherwise stable to resistance mechanisms that would otherwise chew up a molecule or it's paired with a resistance inhibitor or

22

21

happened over the last several years that have helped

some, with passage of GAIN, the qualifying infectious

1	disease product legislation that came in place, which
2	provides for fast-track designation, priority review
3	and an additional five years of exclusivity for drugs
4	that qualify. And the QIDP designations so far are up
5	to 63 different unique molecules, probably the more
6	important number. The 107 is sort of a factor of how
7	you split up if you look for different formulations
8	or different indications. So 63 is probably the
9	number to index off of here. And then, we have to
10	keep in mind that, in general, most drugs that enter
11	into Phase I are not ultimately shown to be safe and
12	effective. So although these numbers sound quite
13	large, you know, some of them may some of them
14	won't make it we know just based on experience.
15	And it's also important to keep in mind too
16	that when we think about bacterial diseases and
17	antibacterial drugs, that the response that a patient
18	experiences is not just the antibacterial drug, but
19	there's also the immune system, tissue repair and
20	other events going on that happen as the patient moves
21	from being ill to being better. I won't spend much
22	time on this slide. But folks are aware of some of

1	the recent approvals for antibacterial drugs and I've
2	included in here also a drug for TB. And unmet need,
3	so if we think about unmet need, how do you get there.
4	Well, if you have a less than robust antibacterial
5	drug development pipeline, it provides an opportunity
6	for resistance to essentially get a little bit ahead.
7	And so, a situation where you have unmet need is
8	actually something that you prefer to avoid. You
9	don't want to end up in a situation where you have
10	bacteria that are resistant to multiple drugs such
11	that you have patients who lack good therapeutic
12	options.

13 So ideally, if you have ongoing development that's robust, you can have agents already available 14 15 that have already been shown to be safe and effective 16 prior to the point in time that you need them. And we 17 know already that it's difficult to react in a timely 18 fashion once an unmet need has arrived -- has arisen. 19 You know, it may take 5 to 10 years to develop a new antibacterial drug. So a resistance mechanism that 20 pops up today, to embark upon a program at that point 21 22 in time is really not a timely way to respond.

1	Sumathi will go into a little more detail on
2	trial design options for unmet need. But here's some
3	of the different options that you might think about, a
4	non-inferiority trial design. You can do it in a body
5	site of infection. Superiority trial in one body site
6	or you could do something pooled across multiple body
7	sites. And Kert will talk some about some of the work
8	that his group has been doing on this a little bit
9	later today. Nested NI superiority trial designs
10	based upon the patient's baseline isolate. And we've
11	also seen development in the area oflactams that
12	have been previously approved paired with new
13	lactamase inhibiters. In this situation, you can rely
14	upon the previous finding of safety and efficacy for
15	the previously approvedlactam drug. Another area
16	too where there's some activity is that of showing
17	superiority of an adjunctive therapy with standard of
18	care over standard of care.
19	And let me talk some about non-inferiority

20 trial designs. You know, this is an issue that comes 21 up. It's a topic of which there's really much 22 discussion. And Sumathi and I and some others wrote

1	on this even a couple of years back. I think it was
2	in 2014, in the summertime. If you think about it and
3	what the circumstances that you need to have in order
4	to be able to show superiority, it's likely time-
5	limited. It really is dependent upon enrolling
6	patients with, you know, resistant phenotypes for
7	which you have inadequate options. And this could be
8	really challenging, particularly if, you know,
9	patients who have, you know, few options are you
10	know, if the frequency is not that high.
11	And if you think about it, if this is a very
12	difficult paradigm to follow, you could take a good
13	drug, an effective drug and run into challenges and
14	difficulties in conducting the clinical trial. So
15	you're not really just testing the drug. You may also
16	be testing the test. And if the test is one that
17	really is not achievable, the drug may fail because
18	the test can't be performed, not because the drug
19	the test can t be performed, not because the drug
19	wouldn't have otherwise been shown to be effective.
20	
	wouldn't have otherwise been shown to be effective.

1	I mean, some would argue if that's the
2	circumstance that you've gotten yourself into, you've
3	not done well. And we have to keep in mind too that
4	when you're studying best available therapy and trying
5	to show superiority over best available therapy, best
б	available therapy may actually have some effect.
7	Resistance is not a binary, you know, hundred percent
8	or zero percent. It's a continuum. So you may have a
9	lesser likelihood of response. But it's not going to
10	be zero. So best available therapy may have some
11	effect which may make showing superiority somewhat
12	challenging. What I mean by that is it's not that the
13	new drug isn't better. But the effect size may be not
14	so not as large as you might expect initially
15	without sort of putting more thought into this.
16	So the trial may be one of considerable
17	size. And if you think about a trial that's designed
18	to show superiority and the reason that you can show
19	superiority is that the options currently available
20	are not that good, once a new standard of care has
21	been demonstrated, the ongoing trials would, from an
22	ethical standpoint, need to include that standard of

1	care. So there may be a certain degree of
2	unpredictableness/uncertainty that may accompany doing
3	a superiority trial.

4 So just thinking about, you know, if you take a non-inferiority approach, the drug that you 5 study, you may not actually elicit all of the 6 attributes of the drug in a non-inferiority trial. 7 8 There may be mechanistic reasons that the drug will have utility and preserve its activity; again, certain 9 10 resistant isolates that may not be enrolled in the 11 non-inferiority trial because patients in that trial 12 would generally be ones in whom you would want the 13 comparator drug to be effective. We can talk more about the nested superiority/non-inferiority. 14

15 And then, just one last final point and that is as we think about where the drugs that we use today 16 came from, including the drugs that we use to treat 17 18 patients who have resistant organisms, they were --19 many were studied at a time when the resistant phenotypes of concern didn't even exist. So, and 20 21 superiority trials, you know, I'm trying to get to 2.2 sort of the practical issues here. There's no

question superiority trials provide clear evidence of efficacy and that they are easy to interpret and that they don't have some of the trappings of a noninferiority trial.

5 But they can be challenging to conduct, as I've just discussed. And through the course of the 6 7 presentations today, I think you'll hear some more 8 details on this. We understand that some folks are 9 interested in such claims. You know, and we're more 10 than happy to work with folks that are wanting to do, 11 you know, superiorly trials. But we think it's 12 important that folks think about this and, you know, 13 balance some of the issues with achievability, you know, so that the drug can be studied if you run into 14 15 particular challenges if you're trying to pursue 16 something in the area of superiority. And some have 17 raised too issues with regard to generalizability 18 using a non-inferiority approach. And that's 19 something we can talk about a little bit more today 20 too.

21 And so, here I'm jumping around a little 22 bit. But you know, just thinking about some of the

1	challenges that we face in antibacterial drug
2	development, if you contrast serious acute bacterial
3	diseases with oncologic conditions, HIV, hepatitis C,
4	rare metabolic disorders, and go through sort of a
5	couple of different characteristics and I'll just
6	do this informally. I don't know that it's engraved
7	in stone or that I've got it completely correct. But
8	I'd welcome your thoughts on this too.
9	But if you think about it, identifying
10	patients well, for serious acute bacterial
11	diseases, it can be really any of a number of
12	different folks across the globe who may show up with,
13	you know, an acute infectious disease caused by
14	bacteria. And they'll show up, you know, quickly,
15	whether they're already in the ICU or they present to
16	the emergency room. You know, and for an oncologic
17	condition, usually you're going to have a tissue
18	diagnosis. You're going to know who these patients
19	are; likewise, for HIV and hepatitis C. For rare
20	metabolic disorders, the patients may be in a registry
21	of care at a referral institution. So it's a much
22	more defined population.

1	So that's one issue that can make studying a
2	drug for an acute bacterial disease quite challenging.
3	The disease course over time for most serious acute
4	bacterial disease, it starts, you know, quickly and it
5	ends fairly quickly. So the period of time to either
б	enroll a patient in a trial or, you know, study an
7	intervention is very limited. It makes it, again,
8	very challenging. And that's not quite the case I
9	mean, the other disease you know, you may want to
10	intervene within a relatively short period of time.
11	But the time pressure is much different, in my
12	opinion.
13	Diagnostic certainty for the patient with
14	a serious acute bacterial disease, is it pneumonia, is

a serious acute bacterial disease, is it pneumonia, is ± 4 15 it heart failure, is there something else going on 16 You know, just think about the patient in the here. 17 ICU with HAP/VAP and the challenges of making that 18 diagnosis. And you know, again, for these other 19 conditions, typically you have a fair degree of 20 diagnostic certainty. We've already talked about the 21 urgency of the situation. For acute infectious 22 diseases too, there may be considerable variability in

outcomes. You know, when I talk with my colleagues in the oncology group, they oftentimes will tell me, you know, that the tumor won't shrink. It simply doesn't happen.

So if you have a lights-on/lights-off 5 phenomenon, you know, an ammonia level that's going to 6 7 stay up here absent an effective therapy -- things 8 could be quite different in an acute bacterial disease and it could make things fairly challenging. Also the 9 10 opportunities for rescue for serious acute bacterial 11 disease, the opportunities for rescue may be really 12 quite limited. You know, you may jump in there. But 13 given the serious nature of the disease, the rapidity with which it can progress -- and for some of the 14 15 other conditions, there are opportunities to jump in 16 there and come in with another therapy.

17 So you know, a credit to all the folks that 18 are, you know, here today working on what is an 19 important but also a very challenging area of 20 antibacterial drug development. Clinical trials 21 continue to teach us new things, many of which we 22 didn't necessarily expect and that we would have hoped

1 to have avoided. So I think it's important -- and I won't go through these, but I thought it would be helpful just to have them out there, all based on information that's out there in the public. You know, we see that some drugs didn't pan out in certain conditions. Some drugs didn't appear to work as well as their comparator.

8 And some of these things are surprising to We see some that work in some indications and 9 us. 10 then some that have troubles in others. So you know, it may be intrinsic characteristics of the drug. 11 Ιt 12 may be the dosing of the drug. There may be other 13 things going on here that weren't necessarily expected. And again, I'm jumping around a little bit. 14 15 But one of the things we hear sometimes is that there 16 isn't much going on in HAP/VAP and HAP/VAP is really challenging to study. There's no question about that. 17 I don't think there's any debate. 18

But if you go to clinicaltrials.gov, you can actually see there are a handful of studies going on in HAP/VAP and that's good news. So and typically what we're seeing is that folks are doing, you know,

1	complicated intra-abdominal, complicated UTI
2	indications and then subsequently moving on to the
3	more challenging indication of HAP/VAP. So if we
4	think about antibacterial drug development too, it's
5	important that we continue to advance the science.
6	This is a challenging area. You can tell we're
7	dealing with a fair degree of uncertainty in some
8	situations in order to, you know, have drugs that can
9	be studied, that can be available for patients.
10	But it's also important too that we continue
11	to tend to the science. And the folks at the FNIH
12	have been working on developing and evaluating
13	endpoints. The folks at CTTI are doing important work
14	looking at trial efficiency and design. They have a
15	very important project, in my opinion, in HAP/VAP,
16	trying to figure out how they can make HAP/VAP trials
17	more efficient and they're progressing well on that.
18	And the Duke-Margolis Center has been looking at
19	overarching issues in antibacterial drug development
20	and, you know, has a conference following this on
21	economic development. We work at our colleagues at
22	EMA and we're very glad that Marco came over to

1	join us you know, through our confidentiality
2	agreements. And we've found those interactions to be
3	very helpful. It gives us a chance to share opinions
4	on development programs and on approaches to
5	development. And I think really an important theme
6	here is that curating the science supporting clinical
7	trial design and endpoints is key both here in the
8	United States and for harmonizing available approaches
9	internationally. And there's no reason, if the
10	science is there, that we shouldn't be able to do
11	similar things.
12	You know, whenever somebody holds a
13	workshop, it's an opportunity to talk about all the

issues that we face. And I think it's important to 14 15 recognize right from the start that it's important 16 that, you know, we recognize the multifaceted nature 17 of the challenges that we face. And FDA plays an 18 important part here. But I think there's also a lot 19 of other groups that are involved. And you know, I've 20 listed a variety of the different areas and I think folks will recognize, you know, resistance 21

22 surveillance for the prevention of infection, a lot of

work of colleagues in stewardship, a lot of colleagues
 at the CDC research and development. We're glad that
 Dennis could join us here from NIAID.

4 And there's an important role of academia, industry and government, hospitals, patients, society 5 in general because of the issues around antibacterial 6 drug use. Professional societies publish treatment 7 8 guidelines and provide, you know, other advice to practicing physicians. Public-private partnerships 9 10 and payers all play a role here. And I think it's important that we keep that in mind as we work through 11 12 the day. So to overcome these challenges, we'll need 13 a variety of different solutions to deal with the multiple different factors that we're facing and the 14 15 challenges of antibacterial drug development, the use 16 of these drugs, antimicrobial resistance.

17 It's important that basic science, R&D 18 continue to feed and develop new lead molecules for 19 early development that then progresses through 20 advanced development. Again, colleagues from NIAID, 21 Joe Larsen from BARDA is also here with us today. And 22 I think too, you know, the value of new antibacterial

drugs, you know, if we look at some of the economic 1 reports -- and I've cited the RG report here -- you 2 know, the societal value of having a new antibacterial 3 4 drug exceeds its private value. So there's a little bit of an imbalance here that suggests the need for, 5 you know, continued work on incentives to try and be 6 7 able to get things in balance with regard to the value 8 of these drugs to society.

Another very important area I think that 9 10 could help advance the science in this area is that of 11 a clinical trial network. And our colleagues from 12 BARDA recently put out a request for information to 13 understand a little bit more about what might be involved in developing a clinical trial network. 14 And 15 when we talk about a clinical trial network, at least 16 in my mind we're talking about infrastructure so you 17 avoid having to start up each time. So you know, you 18 do a HAP/VAP trial, you're not just starting from square one and the last group that did one just sort 19 of deflated all their infrastructure. 20

This should allow for the development of expertise, the lab support being in place and ideally

1	there'd be a common protocol that would be used for
2	each of the several drugs. It could also allow for
3	the concurrent study of a couple of drugs at the same
4	time. And it also may serve important roles too for
5	developing diagnostic tests, another important area.
6	I mean, if diagnostic tests can be developed, that
7	could transform the way that antibacterial drugs are
8	utilized out there and used more prudently and could
9	also help some with clinical trials too.
10	And just if folks are unfamiliar with sort
11	of a common protocol or master protocol idea, here's a
12	schematic of what one might look like. You have a
13	control group on top and the control group is shared
14	between the drugs that are enrolled during the same
15	time period and you can see drug A in blue is the
16	first experimental drug. So during that initial
17	period, it's drug A and the control, to which patients
18	are randomized. Drug B is introduced in that second
19	segment and there control patients are shared between
20	drug A and drug B. And then, subsequently drug C pops
21	in and all three share the control group. So you have
22	three drugs being studied concurrently. Drug C is

1 monitored and stopped early for futility and drug B
2 continues on to be studied throughout the duration
3 there. Drug A finishes a little bit early and is
4 analyzed.

So there are certain efficiencies here, 5 certain development of degrees of expertise that could 6 7 be gained with a master protocol. There's no question there's fixed costs. There's a lot involved in 8 setting up such an infrastructure. But it seems like 9 10 there's an area where such approaches might help. So 11 I want to stop there. I know it was a little bit 12 disjointed. But I wanted to cover sort of a variety 13 of different topics that have come up, done so in sort of a whirlwind fashion. 14

15 And now, I want to introduce Sumathi 16 Nambiar. Sumathi is the director of the Division of 17 Anti-Infective Products and also a very good 18 colleague. And she will be providing us a talk on --19 let me make sure I get my classes on here -- trial considerations for unmet medical need. So she'll be 20 21 walking us through some of the nuts and bolts of unmet 2.2 medical need development. So Sumathi, it's all yours.

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1	TRIAL CONSIDERATIONS FOR UNMET NEED
2	DR. NAMBIAR: Thank you, Ed. Good morning,
3	everybody, and welcome you to this two-day workshop.
4	Can you hear me okay? All right. Okay. I'm going to
5	try and build upon some of the principles that Ed has
6	laid out in his talk. So here are some criteria that
7	typically drugs have to be met can you hear me?
8	Sorry. This is better? This is right in my face.
9	All right. Okay. It sounds like you can hear me.
10	All right.
11	So these are some of examples of types of
12	antibacterial drugs that might be suitable for an
13	unmet need development pathway. This is not an all-
14	exhaustive list. But if you have a product that acts
15	via a new mechanism of action or has an added
16	inhibitor that can neutralize a mechanism of
17	resistance or the activities preserved in setting of
18	resistance to other antibacterial drugs would appear
19	to meet an unmet need. I just want to emphasize this
20	point because more recently we are seeing proposals
21	for bridge [ph] programs without a real good
22	justification for why one thinks the product actually

meets an unmet need. So one needs to spend a little bit of time and effort to really justify and make it clear as to why a proposed product has the potential to meet an unmet need.

So in general, for unmet need programs, 5 smaller data packages are acceptable and hence such 6 programs, there will be greater uncertainty about 7 8 risks and benefits. Single, adequate and wellcontrolled trial may be adequate. We need good 9 10 support of evidence to support that single trial. And it's very important that this thorough evaluation of 11 12 the activity of the drug in vitro and in animal models 13 of infection to support the smaller clinical data package. Healthcare communities should be aware of 14 15 the uncertainty, both around risks and benefits, and 16 these risks and benefits and the shortcomings will be communicated appropriately and labeling. And labeling 17 18 from such programs will include a limited use 19 statement.

20 We expect adequate in vitro data and 21 activity in relevant animal models of infection, 22 adequate evaluation of PK/PD relationships from animal

1	models of infection. It's very important, and I
2	cannot emphasize this enough, that understanding the
3	PK in patients with renal or hepatic impairment early
4	in development is very important because this will
5	facilitate enrollment of such patients, as they often
б	have important comorbidities. And you'll see this
7	theme come up in subsequent presentations. I think it
8	comes up in Dr. Friedland and Dr. Dudley's talk, where
9	how patients with unmet medical need are in fact a
10	little different from patients who typically enroll in
11	some of these trials. So I think this is very
12	important. And also it's important to collect PK data
13	in clinical trials.
14	I just want to remind everybody that drugs
15	being developed to address upmet medical need must

15 being developed to address unmet medical need must 16 meet the statutory standard for effectiveness where 17 substantial evidence is defined as evidence consisting 18 of adequate and well-controlled investigations. And 19 an adequate and well-controlled study is described in 20 21 CFR 314.126. Since the passage of FDAMA, you know, we are allowed to -- I think they sort of clarified 21 22 that we could consider data from one adequate and

well-controlled clinical investigation confirmatory
 evidence to constitute substantial evidence. And
 every often in discussions that come up that the
 standards might be different for products which are
 designated as orphan and orphan drug products do still
 need to meet these statutory requirements.

7 So we go through some trial design options. 8 I think as Ed has already mentioned, we are of the opinion that well-conducted non-inferiority trials are 9 10 important to maintain a robust pipeline of 11 antibacterial drugs to meet patient needs. Treatment 12 options should be available before new mechanisms of 13 resistance emerge, and if we are in a situation where these trials are in fact easy to do because levels of 14 15 resistance are so high, then antibacterial drug 16 development has not kept pace with emergence of 17 resistance.

A well-conducted non-inferiority trial will provide evidence of a drug's efficacy in a given body site of infection and in general these trials will be limited to situations where the baseline organisms are susceptible to both the test and comparator drug. So

1	these trials often enroll few or no patients infected
2	with multidrug-resistant phenotype organisms. But
3	the evidence for this activity against those
4	particular phenotypes comes from the drug's activity
5	in vitro and in animal models of infection.

6 So what might be some options if one wants to conduct a non-inferiority trial? A single trial at 7 8 any one body site would be acceptable. As I mentioned earlier, it's important to enroll patients with 9 10 severity of illness or comorbidities which might be 11 similar to those seen in patients with unmet need. We 12 are willing to accept a wider non-inferiority margin 13 than one would accept for a traditional development Data from such a trial could be supplemented 14 program. 15 with data from a study in patients with infection due 16 to the specific phenotype of interest. From such a 17 study, one can obtain PK data and in a sicker 18 population or patient population that has 19 comorbidities. And it also provides some clinical experience in patients with infections due to these 20 21 specific organisms, which we've heard from our 22 clinical colleagues is very valuable to them.

1	We've certainly had a lot of discussion
2	amongst ourselves whether it's possible to do a non-
3	inferiority trial pooled across body sites. We do
4	think that poses additional challenges, but we'd
5	certainly be interested from thoughts from attendees
6	at the workshop. I think some of our main concerns
7	have been that the magnitude of treatment effect can
8	vary across the infection types that one is attempting
9	to pool. The endpoints are highly variable. And I
10	think, very importantly, such a trial may not
11	demonstrate if there's a potential deficit in
12	treatment effect across the different infection types
13	that are pooled. And we've seen examples of drugs
14	that have worked in one or more body sites and not
15	worked in other body sites. And Ed had shown us a
16	slide which sort of gave examples of recent
17	experiences.
18	One can certainly do superiority trials. It
19	provides a clear finding of efficacy. But we do think

20 it poses -- it is extremely challenging to do one of 21 these trials. And again, this will come up in 22 discussions and presentations during the course of the

1	day. We think the ability to rely on superiority is									
2	likely time-limited because once a new therapy becomes									
3	available, an ongoing trial which is designed to									
4	demonstrate superiority of a standard of care would									
5	likely become unethical because now you have other									
6	options available. And subsequent trials would need									
7	to be non-inferiority trials. Superiority trials									
8	could be at a single body site or one can pool across									
9	certain body sites, as long as you have a									
10	representative sample from each type of infection.									
11	In a superiority trial, you can attempt to									
12	demonstrate superiority over active comparator. And									
13	I've said earlier, it's usually dependent on the									
14	comparator of the trial representing suboptimal									
15	treatment. In other words, it's very hard with the									
16	currently available therapies to demonstrate									
17	superiority. It does happen, but not very frequently,									
18	where an antibacterial drug is actually able to									
19	provide additional benefit over active standard of									
20	care. One recent example was a trial in complicated									
21	UTI with ceftolozane/tazobactam where superiority of									
22	ceftolozane/tazobactam over levofloxacin was									

demonstrated. It's important to note that just over quarter of the baseline isolates in the comparator arm were levofloxacin non-susceptible. So this raises questions about whether one can in fact repeat such a trial, going back to the same study sites where the prevalence of levofloxacin non-susceptible isolates is that high.

There has been a lot of discussion and some 8 interest in potentially using external controls in 9 10 demonstrating superiority of external controls. And 11 the challenges in using external control data are 12 well-described in ICH E10. There's always a question 13 of comparability between the treatment and control groups because they can differ not only in what we 14 15 know -- so the known risk factors, but also in 16 unrecognized or inadequately measured risk factors. And it's very well-documented that untreated historic 17 18 controls tend to have worse outcomes than an 19 apparently similarly chosen control group in a randomized trial, possibly reflecting a selection 20 21 bias. As a third option for superiority trial would 2.2 be a product that is being administered in addition to

standard of care, some kind of an adjunctive therapy 1 within the test drug plus standard of care is compared 2 to standard of care versus placebo. 3

4 So again, I mentioned this earlier in superiority trials. We're willing to consider pooling 5 across body sites. So for a Gram-negative drug, 6 7 pooling, you know -- pooling across cIAI, cUTI and 8 HABP/VABP is acceptable. We do recommend that at least half the patients have HABP/VABP because this is 9 10 one indication where we've seen deficits in performance of antibacterial drugs. There's been more 11 12 than one example. In such a trial, patients with 13 document infections due to a certain resistant phenotype would be enrolled; for example, 14 15 carbapenemase production. Best available therapy 16 would be used as a comparator. All-cause mortality or disease-specific definition of clinical success is 17 18 acceptable. And we've considered allowing the use of 19 one-sided alpha of 0.05, given that the comparator regimen will have some treatment effect. And again, 20 21 you'll see this in an example later in the day. 2.2

One other option, which I know we've all

discussed a fair bit, but we've really not seen a 1 2 proposal come forth is a nested noninferiority/superiority trial design where in a 3 4 subgroup of patients that have the -- of a resistant phenotype, one can attempt to demonstrate superiority. 5 So you remonstrate non-inferiority in the population 6 7 susceptible to comparator and superiority in the 8 subset of patients that have baseline organisms resistant to comparator. Here if a superiority is not 9 10 demonstrated, it does not in fact impact the 11 conclusion of non-inferiority.

12 So I thought what I would do next is just 13 walk you through maybe three or four potential scenarios of what development programs can look like. 14 15 Again, I think it's very important to note that it's 16 really not a one-size-fits-all and these are general 17 approaches. But we do have to make adjustments 18 depending on the specific drug and the specific 19 program. so in this example, if a drug has a -- it's a Gram-negative drug and it has a spectrum of activity 20 that includes Enterobacteriaceae and P. aeruginosa. 21 22 We have activity that demonstrates that this drug

works against ESBL-producing organism including serine
 carbapenemases.

So your potential options could be a single 3 4 non-inferiority trial at any one body site. You could choose cUTI. You could choose cIAI. The benefit 5 there is you could test the drug as monotherapy. 6 7 Should you be interested in developing the drug for 8 HABP/VABP, I think one really needs to address how the concomitant therapy that's used to treat P. aeruginosa 9 10 and its impact on assessing treatment benefit will be addressed. And again, I think this is a topic that's 11 12 going to come up hopefully today, but certainly in 13 tomorrow's discussion. Again, superiority trials are an option. This could be done at a body site, any of 14 15 the body sites that I have listed above or a 16 superiority trial where one pools across body sites. And a third option would be a nested non-17 18 inferiority/superiority trial.

A second example is if you have an
antibacterial drug that only is active against a
single species; for example, P. Aeruginosa, A.
baumannii. We understand there is interest in

developing such drugs and we will spend a whole day
 tomorrow talking about this. So I'm not going to go
 into further details.

4 A third example, and we do see a fair bit of this particular option, is a new ß-lactamase inhibitor 5 which has been combined with an approved ß-lactam 6 antibacterial drug. And under section 505(b)(2) of 7 8 the Food, Drug and Cosmetic Act, we can rely in part on our previous finding of safety and effectiveness 9 10 for the corresponding approved indications for the ß-11 lactam drug. And this can provide part of the 12 evidence needed for the BL-BLI combination.

13 Again, as I said early on, it's very important that if you are using this sort of an 14 15 approach, that you provide adequate justification that the addition of the ß-lactamase inhibitor addresses an 16 17 unmet need. We need robust evidence of the 18 contribution of the ß-lactamase inhibitor in restoring 19 the activity of the ß-lactam and this can come from in vitro studies and from animal models of infection. 20 We 21 need adequate dose rationale, including the

22 appropriate ratio of the ß-lactam and the ß-lactamase

1 inhibitor. And importantly, we need -- even though we 2 can rely to a great extent on what we know about the 3 ß-lactam from previous approval, we need adequate 4 safety data for the ß-lactamase inhibitor and the 5 combination product.

The clinical data package for such a drug 6 7 could vary. It really depends on the approved 8 indication for the ß-lactam. So it depends on which ß-lactam you are choosing, what that is approved for 9 10 and the indications in which the BL-BLI have been 11 studied. So you could consider doing a single, 12 adequate and well-controlled non-inferiority trial in 13 a body site of infection and such a trial does not need to be enriched for organisms that are non-14 15 susceptible to the chosen &-lactam. We've also considered smaller trials in indications for which the 16 17 ß-lactam is approved, as in the example of 18 ceftazidime-avibactam that was approved last year. 19 And such a trial ideally should include some patients with infections due to the ß-lactamase-producing 20 21 organisms.

22

Lastly, if one is looking to develop a

1	product that will be administered as adjunctive
2	therapy to standard of care, some examples would
3	include inhaled antibacterial drugs being developed
4	for ventilator-associated bacterial pneumonia, immune
5	modulators, monoclonal antibodies targeting a specific
6	organism. The trial design would need to be a
7	superiority trial where the test drug plus the
8	standard of care is compared to the standard of care.
9	So in summary, we've laid out some potential
10	development pathways for a drug that has a potential
11	to address an unmet need. One could do a non-
12	inferiority trial at a single body site. We're
13	willing to accept a wider non-inferiority margin. And
14	one could include a nested superiority option, if
15	desired. If one wants to pursue a superiority trial,
16	such a trial could be done at one body site or you
17	could pool across relevant body sites. And the drug -
18	- the test drug is compared to the best available
19	therapy.
20	If the drug is being used as an adjunctive
21	therapy, then you add it to the standard of care and

22 compare it to standard of care plus placebo. And if

1	it's a new ß-lactamase inhibitor being developed
2	that's being combined with an approved ß-lactam
3	antibacterial drug, one could rely in part on Agency's
4	previous finding of safety and effectiveness of the
5	approved ß-lactam. Thank you.
б	[Applause.]
7	DR. MARKS: Thank you, Ed and Sumathi. What
8	a great start in terms of the clarity with which the
9	regulatory environment in the U.S. has evolved, where
10	I think many of us see the Agency as being part of a
11	solution clearly as we try to deal with this difficult
12	issue. And now, similarly on the other side of the
13	ocean, we have Marco Cavaleri, head of anti-infectives
14	and vaccines at the European Medicines Agency talking
15	about the regulatory pathways and approaches to unmet
16	need. And I would give a similar comment about Europe
17	as well in terms of being part of the solution. Thank
18	you.
19	REGULATORY PATHWAYS AND APPROACHES TO UNMET
20	NEED
21	DR. CAVALERI: Thank you very much, and good
22	morning. I would like to really thank Ed and Sumathi

1	for the invite. It's a great pleasure for me to be									
2	here and to present the perspective of the EMA. And									
3	as Ed said, I think it's important to stress also the									
4	fact that the EMA and FDA has been continuously									
5	discussing over the last years about options for									
6	developing of new antibacterial agents and									
7	particularly for those that might address unmet									
8	medical needs related to multidrug resistance. So									
9	again, it's a great pleasure for me to be here and									
10	presenting the European perspective and discuss with									
11	you options.									
12	I was asked to start with to describe to you									
12	I was asked to start with to describe to you									
12 13	I was asked to start with to describe to you very briefly what is what are currently the									
12 13 14	I was asked to start with to describe to you very briefly what is what are currently the approval pathways according to European legislation									
12 13 14 15	I was asked to start with to describe to you very briefly what is what are currently the approval pathways according to European legislation for medicinal products that could also apply to									
12 13 14 15 16	I was asked to start with to describe to you very briefly what is what are currently the approval pathways according to European legislation for medicinal products that could also apply to medicinal products that address unmet medical needs.									
12 13 14 15 16 17	I was asked to start with to describe to you very briefly what is what are currently the approval pathways according to European legislation for medicinal products that could also apply to medicinal products that address unmet medical needs. So one option is a full marketing authorization and									
12 13 14 15 16 17 18	I was asked to start with to describe to you very briefly what is what are currently the approval pathways according to European legislation for medicinal products that could also apply to medicinal products that address unmet medical needs. So one option is a full marketing authorization and maybe it's important here to also add that recently in									
12 13 14 15 16 17 18 19	I was asked to start with to describe to you very briefly what is what are currently the approval pathways according to European legislation for medicinal products that could also apply to medicinal products that address unmet medical needs. So one option is a full marketing authorization and maybe it's important here to also add that recently in Europe Union there has been approved a									

study or post-authorization efficacy studies,
 particularly in order to address uncertainties that
 are considered key to the benefit-risk of the
 medicinal products.

And then, I will talk more about conditional 5 marketing approval and approval under exceptional 6 circumstances which are the regulatory tools that we 7 8 have in those circumstances where we feel they might be needed or would be expected that an approval based 9 10 on less than normal level of evidence could be done. Then, the last option is the Article 58 scientific 11 12 opinion for use only outside of the EU, which will not 13 apply in this setting and therefore I will not bring you any further details on this. 14

So as said, one option that we have in order to come to, as we called it earlier, approval is the conditional marketing authorization. This will be based on a less comprehensive data package and subject to specific obligation in the post-approval phase.

The scope -- so the products that will be in scope for this pathway will be products that address serious debilitating diseases or life-threatening

1	diseases or products that are to be used in emergency
2	situations, like pandemic influenza, or for orphan
3	medicine or products. And the criteria which all have
4	to be met is that the risk-benefit balance is positive
5	for the product and is likely that the applicant will
6	be in a position to apply comprehensive clinical data
7	after approval and also that the unmet medical need
8	will be at least in part fulfilled and here of course
9	the wording is a bit strong. But of course it will
10	have at least a clear impact on addressing an unmet
11	medical need and also importantly that the benefit to
12	public health for the immediate availability on the
13	market of the medicinal product concerned outweighs
14	the risk inherent in the fact that additional data are
15	still required.
16	The other option that we have is called

16 Interother option that we have is called 17 under exceptional circumstances. And as the European 18 law says, in exceptional circumstances and following 19 consultation with the applicant, the marketing 20 authorization may be granted subject to certain 21 conditions, in particular relating to the safety of 22 the medicinal product. And also, it goes on saying

1 that the marketing authorization may be granted only 2 when the applicant can show that he is unable to 3 provide comprehensive data on the efficacy and safety 4 of the medicinal product under normal conditions of 5 use.

And the grounds are set out in Annex I in 6 which situations this might be applicable. In any 7 8 case, it will be linked to an annual reassessment of the conditions. So and here are the grounds as per 9 10 Annex I of the directive. So it has to be an 11 indication for which the product in question is 12 intended -- is rare, so that the applicant cannot be 13 reasonably expected to provide comprehensive evidence or in the present state of scientific knowledge, 14 15 comprehensive information cannot be provided or it 16 would be contrary to generally acceptable principles of medical ethics to collect such information. 17

So to summarize the differences between conditional MA and MA under exceptional circumstances, in this slide I will try to summarize. So the conditional MA, full conditional MA comprehensive data are expected after authorization with the idea to

1	later switch to a full marketing authorization, while
2	for MA under exceptional circumstances, comprehensive
3	data are deemed not possible to gather and therefore
4	is supposed to remain such indefinitely. The
5	conditional MA is valid for one year only with annual
б	renewals that have to take place, while the MA under
7	exceptional circumstances has the normal validity of
8	any other marketing authorization and goes through an
9	annual reassessment procedure. The conditional MA
10	applies only to centralized procedures while the under
11	exceptional circumstances MA is possible in all
12	registration procedures.

13 Now, a few words on the PRIME scheme, which is something brand new the EMA brought forward. 14 And 15 this is a scheme that is aimed to foster the 16 development of medicines with major public health 17 interest, so building on the existing framework and 18 with an eligibility program that is according to the 19 existing accelerated assessment criteria. And the idea here is to reinforce scientific and regulatory 20 advice to developer in order to foster and facilitate 21 22 earlier interaction, optimize development for robust

1	data generation, indeed try to work together with the
2	developer in order to have an efficient development
3	plan, and also enable accelerated assessment at the
4	level of the CHMP.

5 So from this principle, this boils down essentially to first of all having a written 6 7 confirmation of PRIME eligibility from the EMA 8 following a submission of a request and the potential for accelerated assessment, an early CHMP rapporteur 9 10 appointment during development, kickoff meeting with multidisciplinary expertise from EU network and 11 12 enhanced scientific advice at key development 13 milestone/decision points, including also the option to discuss with technology assessment bodies. 14 There 15 will be an EMA-dedicated contact point and fee 16 incentive for small and medium enterprises and academics will be provided for their scientific advice 17 procedures. 18

19 So now I give you a bit of an overview of 20 the entire regulatory framework in Europe. And now, 21 we will move more directly into the area that is 22 discussed today and tomorrow, which is around the

1	development specifically for MDR pathogens in area of									
2	unmet need. And the position of the EMA is summarized									
3	in the Addendum to the Guideline On the Development of									
4	Agents to Treat Bacterial Infection and I would say									
5	that the position of the EMA has not changed since the									
6	issue of that document in 2013, even if of course we									
7	are having a lot of interaction with developers and we									
8	may amend or fine-tune some of the options that were									
9	provided in there.									
10	So I will start describing you very briefly									
11	what is in that document and what are the main points									
12	that we would consider for developing new									
13	antibacterial agents in area of unmet medical need.									
13 14	antibacterial agents in area of unmet medical need. Well, first of all, these products have to be eligible									
14	Well, first of all, these products have to be eligible									
14 15	Well, first of all, these products have to be eligible for the acceptance of limited clinical development and									
14 15 16	Well, first of all, these products have to be eligible for the acceptance of limited clinical development and that might not be straightforward in all cases. First									
14 15 16 17	Well, first of all, these products have to be eligible for the acceptance of limited clinical development and that might not be straightforward in all cases. First of all, there has to be demonstration that the									
14 15 16 17 18	Well, first of all, these products have to be eligible for the acceptance of limited clinical development and that might not be straightforward in all cases. First of all, there has to be demonstration that the investigational product has the potential for treating									
14 15 16 17 18 19	Well, first of all, these products have to be eligible for the acceptance of limited clinical development and that might not be straightforward in all cases. First of all, there has to be demonstration that the investigational product has the potential for treating infection for which there are few remaining									

1	focusing	g on	a f	ew c	of the	main	ones	as	that	is	not
2	telling	you	the	ent	irety	of th	ne sto	ory.			

3 So it's important that the microbiology and 4 the PK/PD is already there to address the fact that this agent has the ability to address an unmet medical 5 And if the product is active only on single 6 need. 7 genus or species, there should be justification that 8 indeed the organism is problematic. So the possible scenarios will be from the rather easy one of a new 9 10 drug in a new class or let's say new mechanism of 11 action. That should be fairly straightforward. Or it 12 could also be new drug of an existing class with a 13 novel spectrum. Of course, the data, the micro data and the PK/PD data will be important here, or could be 14 a new or known drug of an existing class which is 15 16 coupled with a new protective agent. And the example of a ß-lactam with a ß-lactamase inhibitor is an 17 18 obvious one, but might not be the only one.

Now, there is a range of possible clinical programs that could be considered here, depending on the properties of the agent assessed or whether it's limited or broader spectrum and also, importantly,

1	what is the aim of the developers in terms of level of
2	claims and SmPC. And an example would be whether a
3	specific indication for a certain type of infection is
4	looked at plus an unmet medical need indication or
5	only a claim for using circumstances of unmet need.
6	It's important to stress, as I said before, that
7	further evidence of safety and efficacy post-approval
8	will be expected.
9	In the future, we might be more and more in
10	the situation in which requirement for post-approval
11	commitment will take place. This may come from
12	pivotal studies that are already planned for
13	additional site-specific indications by the developers
14	or that also could be a rather easy one or could be
15	prospective uncontrolled studies that might be needed
16	depending on what are the uncertainties in the
17	benefit-risk evaluation or observational data from
18	registries. And again, also here to stress that at
19	the EMA there are a lot of efforts to try to
20	understand how much can be gathered from observational
21	data, how much can be gathered from real-life data and
22	to what extent such data could have an impact on

regulatory decision, which I think we are just at the
 beginning of that journey. But it's important not to
 forget about these aspects.

4 So one of the pillars in the development specific for MDR pathogens will be to conduct an 5 extensive microbiology and PK/PD program to fully 6 document expectations for the products in order to 7 8 support the dose regimen to be tested, support plans for regimen adjustment in patient subject, to support 9 10 the anticipated efficacy against the target multidrug 11 resistant pathogens and to identify any type of 12 infection in which it should not be used or may need a 13 different regimen -- as an example, could be penetration in the ELF or binding with the surfactant, 14 15 but there could be many other examples -- and then, 16 confirm the regimen using PK data from patients and conducting exposure-response analyses during the 17 18 clinical trials. So this is an important area where 19 it might be difficult to gather conclusive evidence, but still efforts are expected to be put in place. 20 21 So I think it's important for me to stress 2.2 that in the addendum and in the EMA guidelines, we are

1	not demanding for a single specific approach to be
2	followed. But we are highlighting the potential
3	option for clinical development. So in a way, we are
4	kind of framing what are the possibilities that will
5	be acceptable for the EMA in terms of development in
6	the area of unmet need. And indeed, the goal has been
7	to enlarge the portfolio of acceptable clinical
8	development options besides the standard approaches in
9	light of the unmet medical needs.
10	So the addendum illustrates circumstances
11	which would allow either an indication for unmet need
12	or both an indication for unmet need and a standard
13	type of indication and also stress the importance to
14	put efforts to collect data with target pathogens.
15	Clearly there is an expectation from the CHMP that
16	efforts are put there, particularly for the target in
17	an unmet need indication. But of course we have to be
18	realistic and pragmatic and the prevalence will drive
19	the ability to collect such data at the end of the
20	day. So we should not forget that. And also, last
21	but not least, it's important of discussing with
22	European regulators the specificities of the proposed

program. And as I said, we are putting effort of discussing this whenever there is an application that goes both to the EMA and the FDA also with colleagues at the FDA to see what could be the potential way forward.

So in the addendum, essentially we are 6 giving some examples of what could be way forward in 7 8 the context of unmet need related to MDR. And the scenario one that we are bringing forward is not far 9 10 from what Sumathi was describing before. So a single randomized non-inferiority study in one indication, 11 12 that for Gram-negative targets should be studying 13 HAP/VAP or intra-abdominal with standard alpha and non-inferiority margin expected or alternatively a 14 15 study in UTI provided the PK extrapolation to other 16 body sites possible. And the data with the MDR pathogens may derive from a limited controlled or 17 18 uncontrolled studies. And in this sense, if the 19 results are supportive and the evidence sufficient to draw conclusions on the benefit-risk, it will be 20 21 possible then to grant an indication for both the 2.2 unmet need and the selected type of infection that was

1 studied.

A second scenario would be in case the 2 target is really the unmet need indication only. 3 So 4 it would be a randomized study in mixed infection types with a target organism, excluding infections 5 likely to need different regimen or where PK is 6 lacking, like meningitis, osteomyelitis as an example. 7 8 Superiority, we don't believe it will be feasible, at least if we look at endpoint that will be the standard 9 10 endpoint that we would require for type of infection. And the non-inferiority is also not possible as it 11 12 will be impossible to define a non-inferiority margin 13 in such context and with this mixed type of infection study. So what we would recommend in this case is not 14 15 powered for formal inferential testing. At the same 16 time, we would recommend that some comparison to look into superiority on secondary clinical endpoints could 17 18 be explored nevertheless. Control therapy might need to be flexible, so best available therapy and this can 19 be discussed and also tomorrow we will have a chance 20 21 to discuss a specific case. And the use of 22 experimental rapid diagnostic testing to enrich

1	enrollment	would be	fully s	upported.	In this	case,
2	the indicat	tion woul	d be for	the unmet	need.	

3 A third scenario would be just to conduct an 4 uncontrolled study confined to target organisms using historical and external controls. The justification 5 would be based on the rarity of the target pathogens. 6 The use of rapid diagnostic testing to enrich 7 8 enrollment here would seem rather necessary. This would be the least preferred option and the data would 9 10 need to be convincing. But of course we are not 11 ruling out this and it could be well-justified that 12 this is the only way forward. And in this case, the 13 indication would be for the unmet need.

So at the end of the day, in terms of what 14 the label will look like, what we are saying in our 15 16 guidance document is that the indication in section 4.1 of the CMPC will read something like for the 17 18 treatment of infection due to the specific pathogen --19 let's say to the example before, Gram-negative aerobes -- in patients with limited treatment options. 20 We referenced to section 4.4 and 5.1, which is the 21 2.2 warning section and the section of pharmacodynamics

2	Consideration should be given to official
3	guidance on the appropriate use of antibacterial
4	agents. And also, in section 4.2, we would state that
5	it is recommended that the new agent should be used to
6	treat patients that have limited treatment options
7	only after consultation with a physician with
8	appropriate experience in the management of infectious
9	diseases, which would also lead to in the opinion to a
10	status of restricted prescription medicinal product.
11	And I think this is all. Thank you.
12	[Applause.]
13	DR. COX: Great. Thanks, Marco. And now,
14	our next speaker is John Rex, from AstraZeneca. And
15	as many folks know, John's been a thought leader in
16	the area and done a lot of work and we're grateful for
17	his willingness to join us today and all of his
18	contributions to preparing for the workshop too. So
19	thank you, John. The podium is yours.
20	DEVELOPING ANTIBACTERIAL DRUGS FOR UNMET
21	NEED AND SO THAT WE STAY AHEAD OF THE
22	EPIDEMIC: POINTS TO CONSIDER FOR DEVELOPERS

1	DR. REX: Thanks, Ed. And thanks to the
2	organizers for the chance to be here. Am I loud
3	enough in the back? It sounds okay to me. So these
4	are my affiliations and my disclosures. If you know
5	me at all, you know that I'm an internist who went
6	into industry a little over a decade ago because I was
7	seeing bacteria that I didn't know how to treat. And
8	so, that's what I work on now. I'm going to cover
9	several topics. They're somewhat orthogonal to each
10	other and to the presentation's we've had today. But
11	it will all come together into a clear message at the
12	end: pathways for registration, economics, some
13	common mistakes and some conclusions.
14	So pathways to registration there are
15	five ideas that I'd like to be sure that you walk away
16	understanding. I'm going to cover the first four in
17	detail in my talk. Joe Larsen will pick up on the
18	fifth one in his. Let me just now just start walking
19	through them. The first topic has to do with
20	language. And we've struggled for a long time with
21	the problem that a year ago we finally sort of tumbled
22	into a partial solution to, which is the problem that

we understand how to talk about MDR and XDR. We also
understand the idea of wild type. But there's
something in between wild type and MDR that's really
important and that's the proposal is for a label
called UDR usual drug resistance.
And what UDR means is that it's what you
expect. It doesn't mean susceptible. It doesn't mean
that it's susceptible to everything. So if I'm using
a carbapenem as my comparator in a clinical trial,
then UDR is anything that a carbapenem would cover.
You know, and so it means I can study every kind of
resistance but a carbapenem in a UDR's group. But are
they really MDR? Well, it depends on your
perspective. Okay, so that's the idea of UDR. UDR
and the real implication is that in a clinical trial,
I can pick a single blinded comparator that I can use
globally comfortably.
When you get into MDR and XDR, the
comparator just gets harder and it could be that XDR,
there's no such thing as a single standard comparator.
Every patient may need a different comparator. UDR

penicillin was invented and active against S. aureus,
 S. aureus was UDR to penicillin. But then, MRSA
 emerged and then it was the DMR nightmare bug. In the
 1960s, we found a lot of papers about the horror of
 MRSA and then vancomycin appears. And so, now it goes
 back to being UDR.

7 The other message is that if an organism is 8 susceptible to the novel test agent, it's susceptible to the novel test agent. The response is independent 9 10 of whether it is UDR, MDR, XDR to other drugs. Here's 11 another way to see that. In theory, UDR is relatively 12 common and XDR is relatively rare, if we're doing a 13 good job. And the notion is that when it's UDR, I can pick a global comparator relatively easily and that 14 15 the activity of the drug is independent of the other -- of its status relative to other drugs. 16

17 So with adequate PK, data in a UDR setting, 18 which remember doesn't mean wildly susceptible, it 19 could be resistant to lots of other things. But data 20 in a UDR setting tells you a lot about how it's going 21 to work even when it's susceptible to almost nothing 22 else. But it only tells you how it's going to work on

1	the infection and that's an important thing to
2	remember as well. People who have XDR or super XDR
3	killer bugs often have had a lot of health care
4	exposure for some reason. The antibiotic will not
5	cure their cancer, motor vehicle accident-related
6	trauma and whatever else they've got, their underlying
7	immune deficiency. It can only cure an infection.
8	This matters because, as you're going to
9	hear, it is much, much harder to do prospective,
10	randomized registration quality studies in patients
11	with infections due to MDR or XDR isolates than UDR.
12	Our internal data is that it's at least twice as slow
13	and twice as costly, if you can do it at all. A
14	number of reasons you'll hear some of them today
15	but I'm going to only mention some of the ones that
16	I've seen most commonly. First, patients have to
17	present at a study site, as referral is hard.
18	Infections move rapidly. Therapy has to start now.
19	And if you say if you call up your hospital
20	administrator and say, I want to transfer somebody
21	into my hospital that has the most resistant
22	Klebsiella that anyone has ever seen in the world,

1 they're goin	g to say,	really?
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And actually, sites work really hard to make 2 those isolates rare, which is why your administrator 3 4 is going to think you've gone daft. No site wants to be a center of MDR, XDR excellence. Think about that 5 billboard in front of your hospital. So chasing 6 7 MDR/XDR is really an exercise in Lasagna's law. For 8 those of you who don't know him, Louis Lasagna was a pharmacologist who noted some years ago that the 9 10 incidence of patient availability sharply decreases 11 with a trial begins and returns to its original level 12 as soon as that trial is completed. So the bottom 13 line is we want MDR/XDR rates to be low. If it's easy to do a study in this space, we as a community have 14 15 done something terribly wrong.

16 Number two, superiority versus non-17 inferiority. New antibiotics are going to be, and 18 indeed must be mainly developed in a non-inferiority 19 setting for comparison versus an existing agent in the 20 setting of UDR pathways. But I say again, UDR doesn't 21 mean susceptible to everything. It can be resistant 22 to lots of things. It's just susceptible to the

1	comparator. The reason for this is that as a
2	designer, I have to design my trial to actually avoid
3	superiority. I cannot, should not and I will publicly
4	shame anyone who seeks to enroll patients where we
5	know that resistance is likely to the test or the
6	comparator. That's not fair to the patient.
7	It's very unlikely to you're just not
8	it's really rare to see superior efficacy over a fully
9	dosed modern comparator when the pathway is
10	susceptible to same. I mean, when the carbapenems
11	work and you fully dose them, they're good drugs.
12	It's very hard to be superior on toxicity. We're only
13	treating for 10 to 14 days. You know, most tox
14	signals take longer than that to develop. And again,
15	MDR/XDR is rare, we hope. Superiority is a high
16	stakes gamble for a novel agent. As Ed has said,
17	you're testing the drug and the test. You could lose
18	a drug because you gamble on this. If your primary
19	aim is superiority and the study fails, that's it.
20	You're done. The study result says failed. You
21	cannot go forward. But if you see superiority by
22	accident in a non-inferiority study or in a subset,

-					_
1	VOU	can	claim	that	result.
-	you	Cull	CIUIU	CIICC	TCDUTC.

2	Simpler pathways, LPAD and tier B/C. We
3	spend a lot of time discussing simpler ideas and
4	there's a consensus and it makes sense that PK/PD-
5	based dose selection should make it possible to
6	register in somewhat smaller data sets. But actually
7	doing this has turned out to be very hard. LPAD is an
8	idea that was created for in the U.S. some legislation
9	to kind of help with this about approval based on
10	combinations of data plus some safeguards. But the
11	bottom line is that LPAD really seems to be unlikely
12	in the U.S. and it actually would have been only for
13	the U.S. anyway.

14 And in fact, what we have now is a very 15 practical implementation, as you have been hearing, 16 about what -- of the tier B and tier C ideas that 17 appeared a couple of years ago. And I'll say that the 18 tier A, B, C, D nomenclature is not something that you 19 will ever see in a guidance document. It's not needed 20 but it is useful in presentations to have a feel for it along this pathway. It basically corresponds to 21 22 example one and example two that you heard Marco and

1 Sumathi present.

2	So tier A is the classic setting where you
3	can do two big trials. That's what we've always done.
4	It's nice and easy. Tier D corresponds to this idea
5	called the animal rule more discussion about that.
6	But basically it's a setting where you can't do
7	efficacy studies in man, like anthrax. I hope I can
8	never do that trial. And then, in between, there are
9	some stair steps. And the easiest way to explain B
10	and C is to see some examples.
11	So here are hypothetical tier B and tier C
12	drugs. Tier B is a drug that has a spectrum that
13	covers an entire syndrome. You'd be happy using it as
14	monotherapy for complicated intra-ab. So what you
15	should do is one standard Phase III study of drug B
16	versus a standard comparator at a standard body site.
17	This will be focused on UDR pathogens, no super, super
18	MDR/XDR. But if you choose your comparator well, you
19	can cover a lot of resistance ground. This study will
20	provide a crystal clear view on safety and efficacy of
21	drug B. And then, you put with that a little study
22	that's not pivotal. It gets as much as it gets. It's

1	an open label salvage study, might be randomized,
2	might not, where you play go-fish for really, really
3	hard pathogens and you acquire some data.

4 Tier C, this is a drug that is -- one version of this is a drug that's narrow spectrum, 5 perhaps only one organism, perhaps only P. aeruginosa. 6 7 What are you going to do here? Well, the problem is 8 that P. aeruginosa, as we're going to discuss in great detail tomorrow, is a relatively uncommon pathogen. 9 10 So here, because of that difficulty, the idea is 11 you're going to do something prospective and 12 randomized, the best you can, and you're going to be 13 doing it versus whatever is the best available therapy for that drug which means it's almost certainly going 14 15 to have to be open label. You may have to go to open 16 body sites to get enough numbers. So you may end up with sort of this really small data set where no part 17 18 of it individually is satisfactory. You might also 19 run an open label salvage study where there's no best available therapy. And you might even do an 20 21 observational study of inadvertent, ineffective 2.2 therapy for the target pathogen that might estimate

placebo response if it's a pathogen that is so
 resistant that you do that. It might apply to
 Acinetobacter.

4 Forward -- am I doing something wrong? There we go. The good news is that tier B works. 5 The quidance from the FDA and EMA, as you've clearly 6 7 heard, both describe a tier B-like idea as entirely 8 acceptable. The candidate must address unmet need and the label will include language in the form of 9 10 patients with limited treatment options. It makes perfectly good sense. We're not yet there with tier C 11 12 and that's the purpose from my chair of today and 13 tomorrow is to sort of wrangle with this notion. And it's the problem of limited statistical testing. 14 And 15 you know, I can say that for the FDA it's a sticky 16 point because there's a statutory requirement for substantial evidence based on adequate and well-17 18 controlled investigations. We heard from Marco that 19 the EMA is willing to consider it. It's not entirely clear to me yet if it could be the only indication 20 21 you've got, but maybe so.

22

But clearly they're using a language in the

1	form of treatment of infections due to x in situations
2	where you can't gather much data. But let me say
3	that, you know, if you phrase it as a regulatory
4	issue, you're making a mistake. It isn't a regulatory
5	issue. Actually it's an all of us issue. What do you
б	as a doc want to know? Well, I want to see something
7	that shows me that it gets to the site of action. I
8	want to see something that shows me that it at least
9	cures a few people. I want something. So in many
10	ways, what you're seeing here is sort of an advanced
11	declaration of what you as a doc are going to say
12	about it when it hits your doorstep. So don't phrase
13	this as a regulatory hurdle. I think that is a wrong
14	way to look at it. Really what we have to come up
15	with as a community is what's acceptable. You know,
16	what's workable and don't make the perfect the enemy
17	of the merely good.
10	

So my practical transaction is that for a single pathogen, tier C drug, it's going to have to be non-inferiority. But you're going to have to make some -- do some wiggling around, and tomorrow you'll see some examples of that kind of wiggling around.

1	Build the largest data set you can at plausible body
2	sites. Adjust some wide margins. Maybe do more than
3	one experiment. Maybe triangulate on this thing.
4	Look, superiority is always acceptable, but see above.
5	I just think that's a very high risk gamble.

6 Pressing button, but nothing is happening. 7 I have to wave my hands. Let's see. There must be 8 another button. No? Yes? Would someone advance the 9 slides for me? I'm going to retreat to that. Thank 10 you. A little disambiguation, pathogen-focused. The 11 phrase is tier C and pathogen-focused pathways can be 12 I want to make it clear at least what I'm confusing. 13 talking about. Here are the three ways you could read this language. Truly narrow, Acinetobacter only. 14 15 Broad-spectrum, but includes a rare pathogen; or any 16 spectrum, but you focus it on some subset of difficult bugs. Like it covers all the Enterobacteriaceae but 17 18 you can also treat CRE.

When I talk about pathogen-focused pathways and I think most of the time when we're discussing it over the next day or two, we're really talking about number one in in this. It's so narrow that you don't

1	have the choices implicit in versions two or three of
2	these conceptual drugs. Next slide. All right. The
3	implications of some of this, and the future economics
4	of antibiotics all collide. Next slide, please. So
5	the current economic model for antibiotics is broken.
6	The current approach is that we develop a new drug.
7	Everyone is delighted to have the new drug. They clap
8	you on the back and say, wow, that's fantastic. Thank
9	you for doing all that hard work. Matter of fact,
10	this is so important as a drug, we're not going to use
11	it. And as a consequence, it's entirely rational
12	stewardship, hold the drug back. You know, that's
13	really what we as a community should do. It's what I
14	did when I was a hospital epidemiologist.
15	From an economic perspective, of course,
16	you've just spent \$500 million bringing that drug to
17	market and that's a financial loss. And many analyses
18	show exactly the same thing. It is not it is
19	irrational to start antibiotic R&D under the current
20	development models. And the problem that underpins
21	all this is that we have a basic what amounts to a
22	pay per use model that reimburses for only one portion

of what an antibiotic does. Next slide, please. So I'd like you to think about antibiotics as the fire extinguishers of medicine or sometimes another way to think of them is think of them as the firemen of medicine, the firepersons of medicine, to be genderneutral.

7 So think about fire extinguishers. They 8 have two roles. One is to put out fires, obviously. But the other role is to make it safe to be in a large 9 10 commercial building like this one. So how often have 11 any of you used a fire extinguisher? I hope it's 12 zero, except in training, which is kind of fun. But 13 in real use, I hope zero. And yet, would you be happy to be in a building without a fire extinguisher? 14 You 15 haven't needed it all these years. Would you be happy Think about the firemen down at the 16 to forego it? corner fire station, which isn't too far away. When 17 18 should you pay the firemen? Per fire? No, obviously 19 So if you think of antibiotics as being the fire not. extinguishers or the firemen of medicine, they have 20 21 the same two uses. You use them to put out fire, but 22 equally you use them to make it rational to go into

the hospital, get your hip replaced, get your cancer treated, take care of the premature baby, all those things that antibiotics make available so that every day you walk in and you look at the antibiotics on the shelf and you gaze at them lovingly and say, boy, I'm glad I'm not going to use that today but I'm glad it's up there.

8 Next slide. So the buzzword here is delinkage and we have to find economic models that 9 10 separate reward from usage. There's a big project 11 going on in Europe called DRIVE-AB that's working on 12 this idea, things like lump sum access fees, 13 insurance-like models. In the United States, the presidential advisory council has taken up the charge 14 15 to try to sort this out and I know that others in this 16 room are very interested in this topic. Don't yet have an answer to this. But we have to find ways to 17 18 pay for the value -- both values of the fire 19 extinguisher.

20 Next slide. Now, there's an implication for 21 the developers in the room. Fire extinguishers come 22 in different categories and you actually need one of

1	each. If you've had fire training, you've learned
2	that for paper, wood and plastic, you use certain
3	kinds of fire extinguishers. But for electrical
4	equipment, you use another kind. Antibiotics are much
5	the same way. Incremental extensions of fire
6	extinguishers are nice. This one's a little lighter
7	or something, whatever. But that only gets you so
8	far. The real value is when you create a kind of fire
9	extinguisher for a category that doesn't yet have a
10	fire extinguisher. So think about that. Strong
11	scientific value, novelty in mechanism, lack of cross-
12	resistance. This is the best way to get your fire
13	extinguisher bought in the future.
14	Next slide. Some common mistakes, and so
15	now I'm going to weave this back into some of the
16	themes I've been pointing at. Next slide. So lack of

16 themes I've been pointing at. Next slide. So lack of 17 dose justification. Paul Ambrose is about to give a 18 talk on this that you're going to enjoy. But let me 19 just say that my version of this history is you can't 20 do too much. One animal model plus one isolate equals 21 inadequate. You need clear data on the PD driver, 22 clear data on the PD index magnitude, use those

1 preclinical data to conclusively rove you have a dose 2 that gives the right exposure and then the last line, 3 please, do not forget to prove that you can get that 4 exposure in the target population. I got it right, 5 Paul?

Next slide. Misreading regulatory feedback. 6 For Phase I and Phase II studies, this is important to 7 8 know that the agencies will only tell you to stop if you're likely to hurt somebody. You're free to use 9 10 any endpoint you'd like for dose finding. You want to 11 look at cytokines, you want to look at toenail color, 12 anything you want. But acceptance of that exploratory 13 endpoint does not endorse that endpoint for a pivotal trial. The other aspect of this is that following 14 15 regulatory advice, as I heard someone once say, is an 16 underused strategy. Go talk to the agencies. Thev really will make time to help you, and listen closely. 17 18 It is very tempting to hear what you want to hear. We have all been guilty of this. I have definitely been 19 quilty of this. Pay close attention when you hear the 20 21 words sponsor risk. They see more stuff than any of 22 us see. Listen closely.

1	Next slide. Unrealistic expectations,
2	expecting superiority over a fully dosed comparator
3	that is really pushed pharmacodynamically to its max.
4	This better be rare and you must, must, must not
5	deliberately enroll subjects whose infection is likely
6	due to a comparator-resistant isolate, unless of
7	course there are no other options. But then, in that
8	case, it's Ebola and we've failed as a community.
9	Also do not chase the really hard indications first.
10	Yes, I know endocarditis would be a great indication
11	to have. But you'd really better learn something
12	about your drug in a more ordinary setting before you
13	cast all of your fortunes on that very difficult
14	pathway.
15	Next slide. I want to be labeled for the
16	treatment of CRE. I want everybody to understand that
17	that never happens. Instead, your drug will be
18	indicated for the treatment of infection X caused by
19	strains of Y that are susceptible to your drug. It
20	won't say that are resistant to other drug and that's
21	because, especially across compound classes,
~ ~	

22 resistance to one drug doesn't have a one-to-one

1	linkage to susceptibility to another drug. So the
2	fact that it the fact that it is resistant to a
3	carbapenem, does it make it susceptible to your drug?
4	No, of course not.

5 Next slide. Some conclusions. Next slide. So my key points. Seek novelty. Get it registered. 6 7 Justify the dose. Lots of preclinical PK/PD data. Ιf 8 at all possible, do a standard non-inferiority study 9 for a standard comparator versus a strong -- a 10 standard indication versus the strongest comparator 11 you can come up with because, remember, even though 12 I'm calling that UDR, if you use a carbapenem, it can 13 be R'd to everything but that carbapenem and that covers a lot of ground. Seek the super difficult bugs 14 15 on the side. Don't make this pivotal. And finally, 16 keep it simple. The required number of miracles should always be less than one. Thank you. 17

18

[Applause.]

DR. MARKS: Thank you, John, for that points-to-consider approach across a broad range of things. I especially like the fire extinguisher model. That seems to be evolving nicely as an

1	analogy. I think all of us keep looking for that dry
2	chemical approach. But the organisms stay ahead of
3	us. You also talked about the importance of PK/PD.
4	So next, we're going to have Paul Ambrose, who's the
5	president of the Institute for Clinical
6	Pharmacodynamics, has some approaches in here which
7	clearly outline and show the predictable failures and
8	successes. The title of his talk is "Pharmacokinetic
9	Considerations in Unmet Need Programs." Thank you,
10	Paul.
11	PHARMACOKINETIC CONSIDERATIONS IN UNMET NEED
12	PROGRAMS
13	DR. AMBROSE: Thank you. It's certainly my
14	pleasure to be here today. Here are my disclosures.
15	I'm happy to talk about those to anyone who cares.
16	This doesn't advance? Advance. So I brought in my
17	talk to pharmacometric considerations in programs of
18	unmet medical need. I felt pharmacokinetics just too
19	constraining. Next slide, please.
20	So let me start off by saying we haven't
21	been doing a really good job at picking doses for our
22	Phase III antibiotic development programs. And the

1	goal of my talk here today is to share with you a way
2	of thinking so that we can do a better job in the
3	future, right? And so, what's really critical to
4	remember is that antibiotic development programs fail.
5	It's loss often about bad drugs and much more often
6	about bad decisions. And that's a really bold
7	statement for me to get up here and say, but it's
8	really true. Consider our place in drug development.
9	As a group, we have participated in many, many of the
10	drugs that have reached regulatory approval over the
11	last decade or so and also some of the failures. And
12	we've been behind the scenes looking at how decisions
13	are made. And so, I think we have a perspective that
14	not many people really have.
15	So from our perspective okay, advance,
16	please. It's hard to do it without the slides. So a
17	lot of folks in rooms like this really focus on
18	superiority versus non-inferiority over time. That's
19	what really the focus has been. And for me, that's an
20	important question, but it's the wrong question. It's
21	the less important question. The more important
22	question is how do I ensure that my antibiotic is

dosed correctly so that the drug not only makes it 1 2 through the regulatory process, but reaches the hands of clinicians and helps save patient lives. 3 That's 4 really the most important question. And I feel if we spent half of the time arguing about how to get the 5 dose right as we've spent arguing about inferiority 6 versus non-inferiority, I think by the end of today's 7 8 presentation, you'll agree with me that we'd have more antibiotics on the market today to treat sick patients 9 10 than we do at the moment.

11 So let me show you what I mean. Superiority 12 can be found on an exposure-response function. So 13 this is just a made-up drug. You see drug exposure is a logit function there. And you see the relationship 14 15 between AUC to MIC ratio in response. The green data 16 represents a dose of this drug, which happens to be 17 three times the dose of the red dosing regimen. You 18 can see the green regimen is up on the plateau of the exposure-response relationship and the red data -- the 19 red distribution of patient exposures is down on the 20 21 The green regimen is superior to the red curve. 22 regimen, right? It's associated with a much better

probability of response than the red regimen. This is
 really what I'm talking about.

We need to push our doses up that exposure 3 4 response curve. And the further you push them up the exposure-response curve, the harder it is to prove 5 superiority, right? Right? More and more cures, 6 fewer and fewer failures related to study drug. 7 8 That's the result. And sadly, it's very rare that we actually do this in our clinical trials. 9 But 10 occasionally, we do. Most recently, The Medicines 11 Company studied meropenem-vaborbactam, a brand new ß-12 lactamase inhibitor, a complicated urinary tract 13 infection. You can go to the Web and see the results of that trial. 14

15 They enrolled hundreds of patients. How 16 many failures? Four. Four failures. They optimized 17 meropenem not only with dose but with duration of 18 infusion. Four failures, or 1.6 percent. I'm not a statistician, but I'll tell you it's got to be 19 thousands of patients to show superiority to that 20 21 regimen, right? So the further we push up that dose-22 response curve, the harder it is to prove superiority.

1	Unfortunately, we don't often pick doses that sit on
2	the plateau of our exposure-response functions. We
3	pick them on the slope, in the middle of that slope
4	and sometimes towards the bottom.

5 Next slide, please. So if my hypothesis is correct that this pharmacology underlies all of this 6 7 stuff, right, our successes in drug development as 8 well as our failures, then we should be able to predict our failures as well as our successes. 9 So can 10 we predict our failures? Yes, and right now, I'm 11 going to take you to some uncomfortable places. 12 Before we get on how to do it better, we're going to 13 visit some uncomfortable places. We're going to go to those programs that failed. And by going there, my 14 15 goal is not to point fingers at anybody in the 16 audience or cast aspersions on anyone. My goal is to set the groundwork on how we can do this better in the 17 18 So first, you have to believe -- first, I future. 19 have to demonstrate for you so that you can believe that pharmacology underpins all of this stuff. 20 21 Next slide, please. So this is daptomycin

22 and this is the exposure-response relationship for

1	daptomycin in the animal model. It happens to be the
2	neutropenic mouse thigh infection model, the data
3	generated by William Craig. And you can see AUC-to-
4	MIC ratio is the PK/PD driver for daptomycin on the x-
5	axis there and change in log10 CFU on the y-axis. And
6	you can see as you drive exposure up, more and more
7	bacterial killing. We all remember that daptomycin
8	was studied versus ceftriaxone in patients with
9	community-acquired pneumonia and we all remember that
10	trial was stopped for lack of efficacy in the
11	daptomycin arm. So let's take a look at that.
12	Next slide, please. The red distribution of
12 13	Next slide, please. The red distribution of AUC-to-MIC ratios is a simulation of the exposures in
13	AUC-to-MIC ratios is a simulation of the exposures in
13 14	AUC-to-MIC ratios is a simulation of the exposures in those patients. You can see the median, the 25th and
13 14 15	AUC-to-MIC ratios is a simulation of the exposures in those patients. You can see the median, the 25th and 75th percentiles defined by the edges of the box and
13 14 15 16	AUC-to-MIC ratios is a simulation of the exposures in those patients. You can see the median, the 25th and 75th percentiles defined by the edges of the box and the bar and whisker plots for the range of data. You
13 14 15 16 17	AUC-to-MIC ratios is a simulation of the exposures in those patients. You can see the median, the 25th and 75th percentiles defined by the edges of the box and the bar and whisker plots for the range of data. You can see that the exposures lie wow, they lay on the
13 14 15 16 17 18	AUC-to-MIC ratios is a simulation of the exposures in those patients. You can see the median, the 25th and 75th percentiles defined by the edges of the box and the bar and whisker plots for the range of data. You can see that the exposures lie wow, they lay on the bottom of the exposure-response curve. I'm sure
13 14 15 16 17 18 19	AUC-to-MIC ratios is a simulation of the exposures in those patients. You can see the median, the 25th and 75th percentiles defined by the edges of the box and the bar and whisker plots for the range of data. You can see that the exposures lie wow, they lay on the bottom of the exposure-response curve. I'm sure Cubist thought they'd be near the top. But they sit

1	But how? Well, it's the same dose they used
2	in skin infections, where the dose worked. They also
3	noted that they were much more active against
4	pneumococcus than S. aureus. In fact, they were
5	eightfold more active, right? And they had a couple
6	of animal models. They had Bill Craig's mouse thigh
7	model. They also had a hematogenous pneumonia model.
8	But what they didn't have is they based their
9	decisions on the wrong model. They didn't use the
10	standard murine lung pneumonia model. Had they used
11	that model, they would have seen the impact of binding
12	to pulmonary surfactants in that animal model and they
13	would have seen that it didn't work versus ceftriaxone
14	in that animal model and they would have had the
15	opportunity to abandon the program, even before it
16	started. Instead, they executed that model post-
17	mortem.
18	Next slide. So ladies and gentlemen, I
19	think the daptomycin program was entirely predictable.
20	Their fatal mistake was using the wrong animal model.
21	Next slide. What about tigecycline? This
22	is again data from Dr. Bill Craig, set up identically

1	as before. As drug exposure goes up in the mice
2	this happens to be Acinetobacter you see more and
3	more bacterial killing. We all remember that
4	tigecycline was studied in hospital-acquired and
5	ventilator-associated pneumonia. Next slide. And it
6	failed versus meropenem. Here are the observed
7	exposures, the observed AUC-to-MIC ratios from these
8	patients. You can see the median AUC-to-MIC ratio was
9	just a little bit short of net bacteriostasis in the
10	animals. And a large number of patients stretching
11	with AUC-to-MIC ratios towards zero. Well, this can't
12	be good, right? Tigecycline did not meet the criteria
13	for non-inferiority. Why did they pick this dose?
14	Why did Wyeth pick it? Well, they worked in skin
15	infections. It worked in intra-abdominal infections
16	and their sponsor perceived they had a safety concern.
17	So they were going to go with the maximum predicted
18	dose.
19	Well, next slide, their critical mistake in
20	all this was the maximum tolerated dose was just
21	insufficient, right? Don't go forward with a dose
22	just because it's safe but your preclinical data might

suggest you've got a long way to go. So again, ladies
 and gentlemen, tigecycline's failure was completely
 predictable.

4 Next slide. What about ceftobiprole? This is again data from Dr. Craig, same as before. More 5 drug in the mice, more time we see it in the mice, 6 more effect for ceftobiprole. Next slide. Here's the 7 8 distribution of time above MIC in patients treated with ceftobiprole. You can see they're not -- their 9 10 median value is not even at stasis. Well, how did 11 this happen, right? Well, in Dr. Craig's animal 12 model, he noted -- he noted that the time above MIC 13 needed for efficacy was the same in pneumonia and in thigh models which suggested that you were getting 14 15 very strong lung penetration or very strong ELF 16 penetration. In fact, some number approaching a hundred percent, right? 17

18 So what did the sponsor do wrong? Well, 19 they elected -- they elected, against the counsel of 20 their advisors, to do their ELF penetration study in 21 people concurrently with their Phase III program. And 22 why? The why was to save time. They were warned.

1	They were warned that penetration of cephalosporins
2	into ELF is highly variable, going anywhere from 20
3	percent to a hundred percent. That was until they set
4	a new low. Their drug penetrated 15 percent into ELF
5	and this is the expected exposure distribution.

Next slide. It should be no surprise,
ceftobiprole was predictable. But had they done their
ELF study before launching their pneumonia programs,
they would have had the opportunity to change dose,
change interval or abandon the program altogether.

Next slide. 11 Doripenem, again, exposure-12 response in the thighs of mice, data from Bill Craig 13 again, same as before. You drive exposure up, good things happen. Doripenem was studied versus meropenem 14 15 in ventilator-associated pneumonia. Let's look at 16 their exposures on the next slide. A little bit better here, right? 17 The median exposure is associated 18 with bacterial killing. But look at the variability 19 and drug exposure at the dosing regimen study. Ιt 20 stretches towards zero. This isn't good, right? You 21 can't have that many patients with exposures that 2.2 stretch towards zero and expect that you're going to

1	be approved. So again, next slide, their fatal
2	mistake was not accounting for drug clearance.
3	Increased drug clearance in VAP patients was just not
4	accounted for in their dose regimen selection.
5	Next slide. So here we come to meropenem.
6	These are data from, this time, George Drusano's
7	laboratory and this is in mice. It's an ELF of mice.
8	So it's an ammonia model this time. And as you drive
9	time above MIC for meropenem up in the ELF of mice,
10	you get more and more bacterial killing. Now let's
11	look at meropenem. Next slide. Is it any wonder?
12	This is a 2 g dose every eight hours with a standard
13	infusion of meropenem. The median exposure is up on
14	the plateau of the exposure-response relationship, as
15	are most of the patients that would be simulated.
16	Notice the variability of penetration into lung
17	tissue. Very high. So you get that little tail that
18	goes towards zero. But the vast majority of people
19	sit up on top.
20	This, by the way, ladies and gentlemen, is
21	why you should be thinking of combination therapy in
22	patients with hospital-acquired pneumonia because you

1	will always have this subset of people with poor
2	exposures down low. So combination therapy is the way
3	to go. So this is what you want your drug if
4	you're developing something for hospital-acquired
5	pneumonia or ventilator-associated pneumonia this
б	is what you want your drug to look like. You want it
7	sitting up on top of the exposure-response curve, not
8	halfway down, not at the bottom, but at the top if you
9	want to do the best for patients and the best for your
10	program. Next slide. So meropenem, it's predictable
11	it would be successful. It's really clear why doctors
12	used this drug so much and in such severely ill
13	patients.
14	Next slide. So just in case you thought I
15	may have cherry-picked and just picked those four
16	drugs, I picked them because they were in ventilator

drugs, I picked them because they were in ventilator and hospital-acquired pneumonia programs. These are data that we presented a few years back at ICAAC, when it was called ICAAC, and we looked at the probability of PK/PD target attainment based on Phase I data and microbiology data available at the time that doses were picked versus the probability of approval by the

U.S. FDA. You can see as the drug exposure goes up or
 the probability of target attainment goes up, so does
 the probability of approval. And there's a mix of HAP
 and VAP programs in this particular collection of
 studies. There are 20 studies involving 17 drugs, 14
 failures and six successes.

7 So you might note that little red circle on 8 the bottom, all the way towards 100 percent target 9 attainment on the bottom. There are no guarantees. 10 That drug happens to be garenoxacin. You might 11 remember garenoxacin developed for community-acquired 12 pneumonia. It failed, not because it had insufficient 13 efficacy. It failed because it had safety issues. But there are no guarantees. But the further you 14 15 drive your target attainment up, the better your 16 chances are.

Next slide. So hopefully I've convinced you that failure is predictable and now we're going to answer the question, well, I've got my shiny new drug, how am I going to keep my NDA on track. Next slide. I think it's a proven approach and it's PK/PD embedded in your development program from the very beginning

1	with a very deep collection of animal studies, PK/PD
2	in design. It's getting PK early and throughout your
3	development program. It's learning at each step and
4	reassessing your beliefs about your drug and adjusting
5	dose as necessary. And if you do all those things,
6	you'll succeed. But I can tell you that our problems
7	are sometimes much more basic than that, and I'll
8	point out two challenges that we see when we talk to
9	sponsors we work with all the time.
10	The first one is, well Paul, we didn't work
11	in the animal model. That's because our drug's got a
12	unique mechanism of action. The laws of pharmacology
13	don't apply to us. And they don't say it that way,
14	but it's essentially what they're saying. Well, let
15	me assure you I haven't seen an antibiotic yet that
16	the laws of pharmacology simply don't apply. So if
17	you're thinking that your drug is special, it's
18	probably not. It really is just about killing
19	bacteria. That's what it does. If it's not killing
20	bacteria in the animals, you've got a big, big
21	problem.
22	The second problem is people want

1	checklists. We all want checklists, right? And
2	people, they feel good about checklists. They don't
3	have to think. But I'm sorry, drug development
4	requires thinking, right? I've got a checklist. I've
5	got my MIC data. I've got my animal model. I've got
б	my Monte Carlo simulation. I'm ready to start three,
7	Phase III. No, you're not. Well, I don't want to do
8	those studies, Paul. They're not required by the FDA.
9	The EMA doesn't make me do them, so I don't want to do
10	them. I can save time. Well, I hope I can show you
11	in a little bit that this is a very foolish approach
12	to drug development. It's actually very high risk.
13	Next slide. So let's start off with the
14	MIC. Pathogen susceptibility, the patient population
15	matters. These are data from Dr. Ron Jones. They
16	were actually developed after the workshop that the
17	FDA put on, on HAP/VAP a number of years back. But
18	it's looking at the percent susceptible in patients
19	with hospital-acquired pneumonia versus ventilator-
20	associated pneumonia. And the first number is always
21	hospital-acquired pneumonia, followed by, after the
22	slash, ventilator-associated pneumonia. You notice

1	all of them bolded, many of them bolded. That's
2	telling you that there's greater than 5 percent less
3	susceptibility in the ventilator-associated pneumonia
4	patients. So patients with ventilator-associated
5	pneumonia oftentimes have higher MICs than those that
6	don't. Now, this seems really obvious to any
7	clinician that treats patients that treats
8	patients. But I don't think we always fully
9	appreciated this. This happens across pathogens.
10	Next slide. What about pharmacokinetics?
11	Pharmacokinetics also differs on patient population.
12	Many drugs are renally cleared. So here's creatinine
13	clearance in 600 or so patients with hospital or
14	ventilator-associated pneumonia. The red represents
15	ventilator-associated pneumonia and the yellow or
16	gold, hospital-acquired pneumonia. And you might
17	notice that there's a cluster of patients. There's
18	more red at higher creatinine clearance values. These
19	patients the subpopulation of patients that are
20	really pushing drug through their clearing organs,
21	right? So they're getting rid of drug fast. That
22	means there's low AUCs in these patients, right?

1	And there's certainly an ICU subpopulation
2	that are hyper-clearers, right? People that have had
3	motor vehicle accidents and so forth clear drugs very,
4	very fast. So you have to account for these
5	differences in clearance. And this may look subtle to
б	you and those MIC shifts I showed you may look subtle
7	to you. But they do make a difference. Consider the
8	next slide. This I showed to you before. This is
9	tigecycline in patients with hospital-acquired and
10	ventilator-associated pneumonia. Next figure. This
11	is those same patients stratified by whether they had
12	ventilator-associated pneumonia or hospital-acquired
13	pneumonia. The difference in the box plots, notice
14	the hospital-acquired pneumonia patients did better,
15	higher exposures than the ones with ventilator-
16	associated pneumonia. In fact, if you remember the
17	clinical trial, tigecycline did about as good as
18	meropenem in patients with hospital-acquired pneumonia
19	but really tanked in those patients with ventilator-
20	associated pneumonia. I say it's no wonder. Look at
21	the difference in MIC to AUC ratios in these patients.
22	Next slide. So as you're going through and

building your dose justification, I can't encourage you enough to pressure test your dosing regimens. A lot of sponsors, they just want to do that -- they just want to do that mouse study. They want to get their PK/PD target and that's it.

I encourage you to put into very challenging 6 systems, like the hollow fiber infection model, where 7 8 you can test your drug at high inocula, much higher than you can do in the -- generally do in the animals 9 10 for long periods of time, certainly longer periods of 11 time than you can do in any animal system and look at 12 the relationship between drug exposure and resistance 13 emergence on therapy. And select your doses, if you can -- if you've got this safety headroom to select 14 your doses to shut that down, that'll increase the 15 16 lifespan of the drug and increase your chances of success from an efficacy perspective in your clinical 17 18 trials.

19 Next slide. So an NDA that arrives to the 20 FDA on time but with empty boxcars is useless. People 21 are in a really big hurry. They just want to get done 22 as fast as possible. I mentioned before they want to

1	skip studies.	If it's not required, I'm not doing it.
2	Let's go, full	bore ahead. I hope, again, to
3	emphasize that	this is a foolish proposition.

4 Next slide. Here's a typical Gantt chart that we see from some companies these days with these 5 accelerated clinical programs. What do you see? 6 Let's start off. You've got a SAD study, right, that 7 8 they're probably doing ex-U.S. And then, when that finishes, they're going to file the NDA and they're 9 10 going to tell the FDA the dose, right there. There's 11 our dose, right? Well, what's wrong with that? You 12 haven't done your MAD study yet. You haven't done 13 your multiple dose study. You don't know if you've got nonlinear pharmacokinetics or any other 14 15 pharmacokinetic issue. And by that time, you're 16 filling your vials for your clinical trial already. You're blasting ahead. By the time you finally find 17 18 out it's nonlinear pharmacokinetics, there's no way 19 you're going to change your dose. You're going to say, well, we're already too far down the road. We're 20 21 going to go. That's exactly what's going to happen. 2.2 And then look what else they do. They put

the BAL study, the epithelial lining study. 1 Thev stack it right on top of the Phase III program. 2 Ι already showed you how it's like running across the 3 4 street and eventually you'll get hit by a bus if you run back and forth enough times. But this is exactly 5 what we're seeing. And I also think most importantly, 6 look at the time durations between steps. You don't 7 see any time for thinking. Everybody's in a really 8 big rush. No one's stopping, thinking, analyzing 9 10 their data.

11 As a group that analyzes data for a living, 12 I can tell you that people think that this is going to 13 be done and you push a button and it's done in a week, It's not. Data analysis and looking at -- and 14 right? 15 letting data drive your decisions takes time. I think we all need to slow down and take a deep breath and 16 make sure our studies are being done sequentially, in 17 18 a way that makes sense. And concurrently, if we can -19 - if it makes sense to do, but just not race to the end because you could just be running off a cliff. 20 21 Next slide. So finally, a warning. Develop

22 the drug you have, not the one you wish you had. You

-	
1	know, when you hear people come up with their new
2	drug, and you're laughing but it's true. Think of all
3	the drugs out there. My drug treats resistant CRE,
4	quinolone-resistant DAP, ß-lactam-resistant DAT. It
5	works in lung, urine, feces, everywhere. It's
6	wonderful. Come on. There's no drug like that. So
7	you sell it to your investors on these false premises.
8	You get a lot of money and it drives you to do really
9	stupid things. So slow down, develop the drug you
10	have, not the one you wish you had. And with that,
11	nest slide, thank my colleagues who continue to inform
12	my thinking. Thank you very much.
13	[Applause.]
14	DR. MARKS: All right. Thanks, Paul.
15	Thanks for sharing your insights over your years
16	working in the field. And now, I'd like to invite Joe
17	Larsen up to the podium. Joe is the deputy director
18	for BARDA, the Biomedical Advanced Research and
19	Development Authority. And Joe's I'm sure probably
20	everybody in the room is familiar with Joe. BARDA has
21	played a very important role in the space of
22	antibacterial drug development, both from the

1	standpoint of product development and also pushing
2	forth the science in the field in general and looking
3	at new and novel ways to develop new antibacterial
4	drugs. And he's going to tell us a little bit more
5	about that. Thanks for joining us here today, Joe.
6	BARDA'S MARKET RESEARCH FOR A CLINICAL TRIAL
7	NETWORK FOR ANTIBIOTICS
8	DR. LARSEN: Thanks, Ed. And good morning,
9	everybody. Can I get the next slide, please? So I'm
10	an employee of the U.S. federal government. Uncle Sam

1 has vetted me for any conflicts of interest. Next 11 So as Ed said, BARDA's been involved in 12 slide. 13 antibacterial drug development since 2010. We basically form public-private partnerships for the 14 15 development of new antibacterial drugs. We've been involved in one way or another in Phase III clinical 16 17 trials for a number of the companies that we support, 18 and we plan to be involved in Phase III clinical 19 development of other -- with additional companies in 20 the future.

21 Next slide. So the problem that we see with 22 this is that every single time BARDA goes out to do a

1	clinical trial, it sets up that clinical trial de novo
2	and pays for all to build and pay for all the
3	infrastructure needed to conduct the trial each time
4	we want to do one. So we wondered if there was a
5	potential for efficiencies to be built into the
6	system, perhaps through the development of a clinical
7	trials network, to do regular registrational Phase III
8	and Phase II clinical trials.
9	Next slide. So Ed already showed another
10	diagram in his talk he stole a little bit of my
11	thunder, that but his diagram I think, frankly, was
12	a little bit better than mine but talks about the
13	way that this would potentially work. And it would be
14	that there would be a clinical trials network for a
15	standard body site indication that would be
16	continually running the standard enrolling the
17	standard of care as the control arm in that trial.
18	And then, over time, investigational products would be
19	incorporated into the clinical trials network and
20	compared to that common control arm. And this is a
21	diagram a notional diagram of how this potentially
22	would work.

1	Next slide. So as a first step in trying to
2	understand this and this is a really great
3	opportunity here to be speaking about this publicly
4	because BARDA's perspective on this is that, A, we
5	want to really hear from industry if this is something
б	that people think is needed and would be helpful. B,
7	we also want to understand from both a technical and
8	cost perspective, you know, what this would cost and
9	some of the challenges that would exist for us to be
10	able to implement this. But we also want to hear from
11	industry some things that we're not thinking about.
12	And so, I'm going to highlight today other concerns
13	and risks that have been brought up. But we are
14	BARDA very much wants to hear from industry related to
15	this to make sure that we're thinking about this in an
16	appropriate way.
17	So when the government wants to understand

so which the government wants to understand something in the market, we do market research and we issue something called a request for information. And so, we issued a request for information on February 4th, received responses back on April 11th, and we received 11 responses, eight of which were through

	_
1	standard CROs that gave us technical approach and cost
2	data on how they would establish this network. And
3	I'll share that information with you all today in a
4	way that's been scrubbed for the individual responding
5	companies. But we also received three responses from
6	antibiotic developers, which were immensely helpful
7	and those weren't providing technical or cost data.
8	They were providing narratives of saying, hey, if
9	you're if, BARDA, you're going to go forward with
10	this, you need to be thinking about the following
11	things. And that was extremely helpful to us. And
12	again, this is something that we would encourage
13	additional industry partners to come forward with and
14	have that conversation with BARDA.
15	Next slide. So what did we assume? So we
16	issued this request for information and we assumed a
17	10-year period of performance. We assumed there would
18	be an initial setup period for about a year and that
19	three investigational antibiotics would be brought in
20	to the network and then compared to a common control
21	arm. We sought information for complicated urinary

22 tract infection, complicated intra-abdominal infection

1	and nosocomial pneumonia. We told the respondees that
2	rough orders of magnitude we didn't need things
3	down to a dollar and cent, but just to a general level
4	of what they felt this would cost. And we bucketed it
5	in two different kind of levels of patients, 500
б	patients and 1,000 patients for cUTI and cIAI and 3600
7	and 600 for HAP/VAP.

8 Next slide. So every single time you do something like this, you realize all of the things 9 10 that you should have specifically asked for. And so, there's some important caveats to this information 11 12 that need to be taken into consideration. And so, not 13 everybody followed the instructions or provided the level of information that we would have liked. 14 15 Indirect rates weren't provided in many different 16 responses and that basically could increase cost by 17 about 35 percent. Different responses use different 18 assumptions in terms of how the network would work and 19 what we were asking for. And investigator site costs 20 were not included in certain responses and BARDA's clinical staff also felt that that would increase the 21 2.2 cost by about 40 to 60 percent. So you're going to

1	see in a few minutes lower numbers. And then, at the
2	end, I'm going to basically put out what we what
3	BARDA thinks this entire endeavor would cost.

4 Next slide. So this is the summary of the various costs. And I've averaged them up and then I 5 also provided the max and minimum values to give you a 6 sense of the level of variability in the responses 7 8 that we received. But in general, the average cost was about \$20 million for cUTI, cIAI and HAP/VAP at 9 10 the lower levels and then approximately, you know, \$25 11 to \$35 million for the thousand patient levels.

12 Next slide. Also we wanted to understand 13 the cost of this, just to maintain the infrastructure. And so, we called that warm-based cost. 14 That would be 15 just having the network, just enroll the control arm so that it would be operational. And the mean cost 16 17 there, it ranged a little bit by the number of 18 patients people felt would be enrolled into the 19 standard of care, was about \$40 to \$55 million with the maximum values being about \$82 million and the 20 21 minimum values being \$22 million.

22

Next slide. Also, just to give you

1	additional sense as to some of the variability in the
2	information that we received, this is the number of
3	clinical trial sites, which I think is directly
4	proportional to the cost that was reported out in the
5	responses. One response thought that just 75 sites
6	total would cover it. One respondee did not report
7	the number of clinical trial sites that would be
8	required. But on average, for the lower levels, it
9	was about 100 to 125, 130 and for the larger bucket it
10	was around basically around 175, 180 sites.
11	Next slide. So one of the questions that
12	came in, in some of the responses from industry, was
13	really a lot of questions about how this would be ran
14	and who would govern this. And also, there was some
15	questions related to if this could be adapted to drug-
16	resistant pathogens exclusively to do those type of

20 pathogens for all the reasons that I think we've heard 21 today already.

22

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18

19

We are envisioning that this would be an

trials. And I think our opinion at this point is that

if this was to go forward, it would focus on standard

non-inferiority trials and not focus on resistant

1	ACRO that would be administering this. Some questions
2	felt that they questioned who should lead this
3	effort and some of the respondees felt that it should
4	be led by a group of academic investigators. We were
5	actually walking into this thinking that BARDA would
6	actually lead this effort. But that's of course open
7	for discussion as things evolve. And then there was
8	the overall question of what would be the
9	organizational structure. And I would say several of
10	the CROs in the responses did provide an
11	organizational structure and a governance structure as
12	part of their proposals. But I think that's getting
13	down to a level that's a little too deep for us to be
14	presenting here in public.
15	Next slide. So what are the overarching
16	challenges of setting something like this up? In my
17	mind, the number one is financing, right? If we're
18	going to build this infrastructure, it has to be
19	maintained because ultimately if this is kind of
20	ultimately, it would be an economic incentive for an
21	antibacterial development because efficiencies will be
2.2	built in by having a common control arm. But if

22 built in by having a common control arm. But if

industry can't rely on that as a network as being
 there and being operational, then it's not a
 functional incentive.

4 I think initially in order to gain interest into a network like this, BARDA or other partner 5 organizations would have to finance the clinical 6 trials in its entirety to show that the network itself 7 8 was competent and could actually execute. And then, over time, I could envision a model where we would 9 10 then switch to a fee-for-service where companies would 11 pay themselves to actually tap in and utilize the 12 network. But of course, because of some of the 13 efficiencies that would be realized, their clinical trial may be less experience or may be able to be done 14 15 more rapidly.

16 One of the big questions we also have is 17 that are there sufficient products in development to 18 warrant this investment. There are not a lot of 19 antibiotics in clinical development. And if you look 20 down to the preclinical pipeline, I would not describe 21 it as vibrant and robust. But nevertheless, I think 22 there probably is enough to support standing up and

1	having a network. And once that network was also in
2	place and operational and demonstrating to be
3	competent, it may spur others to enter into the field
4	to start doing antibacterial drug development because
5	they saw that there was a favorable clinical landscape
6	for development.

7 The big risk -- you know, the big risk for 8 us is uncertainty, right? If we build it, will industry participate? Because the last thing I think 9 10 any of us wants is what's going to end up being, you 11 know, a several hundred-million-dollar white elephant. 12 And so, it's going to need to be -- again, as I 13 mentioned, we would have to pay probably for the first few drugs to go into this network to demonstrate its 14 competence and then switch to a fee-for-service-type 15 16 model.

Next slide. So just to be transparent in the responses from the three companies that responded -- and they cited a number of different challenges with this. And I would bifurcate those challenges into two buckets, one related to the protocol and how the trial would be designed utilizing a common

clinical protocol and the second being bucketed in
 terms of operational challenges of actually being able
 to run a network like this.

4 So there was a lot of questions about the flexibility of the master protocol itself and all of 5 these questions were basically around how can I 6 position my drug in the most favorable light related 7 8 to the specific, you know, circumstances of my product, which are understandable. There were 9 10 questions about how regulatory updates, auditing and 11 compliance would be conducted. I would suggest that 12 they would be conducted the same way for any other 13 regular CRO. The selection of the standard of care was cited as being problematic. 14

15 One suggestion was to create a global standard of care map to suggest an aid to management. 16 17 And they also submitted that getting sites to agree 18 globally would be a significant challenge in the 19 standard of care. Endpoint selection was cited as a challenge, also coordination between FDA and EMA was 20 21 cited as a challenge and something that was needed to 2.2 be addressed -- could be addressed perhaps through a

network like this. Questions over the data monitoring
 committees, whether it was the network or the sponsor
 that would be involved in this.

4 I mentioned again addressing product specific safety and efficacy objectives. Data 5 blinding was a concern, how to handle dose 6 7 adjustments. IV to oral switches was cited as a 8 concern. And also, this last piece I think is really important and it is something that I don't think we 9 10 thought heavily enough about when we put out this RFI, which was related to the handling of proprietary data. 11 12 And basically, the construction of all the IT 13 infrastructure that would be necessary to go into something like this we didn't even really put anything 14 15 in there related to that. And the last thing that we 16 would want to happen is a government-sponsored clinical trial network, you know, fumbles with some of 17 18 the proprietary data and that would be a really quick 19 way for anybody -- everybody to lose confidence in this type of incentive going forward. 20

21 Next slide. So after factoring in some of22 the variability that we received in our responses, I

would say the annual cost to establish this infrastructure is probably somewhere between \$60 to \$100 million annually. I think we probably would be comfortable subscribing about \$75 million to -- and that accounts for the fact that some of these things doesn't account for startup costs or investor site costs.

If I were to finance this at a level that 8 included standard of care in three investigational 9 10 drugs to cover all of the risk and the things that we haven't thought about to date, I would think that this 11 would need to be financed at a level of about \$200 to 12 13 \$250 million per year. And I think that, you know, going forward, there's a number of key challenges that 14 15 we're going to need to think through and discuss with 16 our industry partners too before something like this would be implemented. 17

18 Next slide. So there are some alternative 19 approaches that are being discussed and a lot of these 20 discussions are going on in the EU. So you know, we 21 asked for a large, standalone network to do

22 registrational trials that would be functioning, you

1	know, explicitly on that. And the challenge there, in
2	my mind, is one the most significant one to me is
3	getting the level of financing required to actually be
4	able to launch this. And the question is are there
5	other models that could be examined that wouldn't
б	require as big of a financial lift.
7	And there's some discussion in the EU with
8	some folks that are suggesting that instead of
9	building a gigantic, you know, standalone network,
10	could you utilize existing networks and, you know,
11	have them be governed in a common way, operating under
12	I guess a common strategic network to be able to do
13	this type of work without having to recreate the
14	infrastructure. I don't know the answer to that. But
15	I would say I think then the coordination of all of
16	those different parties then becomes the challenge and
17	I think those are equally challenging. There's also -
18	- you know, I'm looking forward to the discussion
19	about innovative clinical trial designs later today.
20	Maybe that's the answer to some of this.
21	Next slide. So for next steps for us, we

21 Next slide. So for next steps for us, we 22 first need to think able to the pathway to financing

And there's currently a working group that's 1 this. being ran out of the Wellcome Trust where we're having 2 a lot of discussions on the protocol, the operational 3 considerations and as well as the financing 4 considerations and they're having a meeting in October 5 where we're going to begin to discuss many of these 6 things. And there's clearly other partners besides 7 8 BARDA that are looking to try to finance something like this. And if we could all come together, it 9 10 might be a much easier path to being able to finance something like this. 11

12 The information that we've received to date 13 is very helpful. We'd be very open to receiving additional information from folks in industry because 14 15 we really need -- if this is going to go forward, we 16 need to begin to think about what a potential request for proposals would look like and the RFI was helpful 17 18 in that regard, but I don't think we're all the way 19 there yet. We need to continue to discuss and think about the ways that we can overcome the challenges 20 21 that were provided to us and highlighted to us. And 22 then, we also need to think about the most appropriate

	Page 110
1	governance structure to run something like this.
2	Next slide. So again, I just would say that
3	we are very interested in hearing from industry
4	related to this and would appreciate all of your
5	feedback. My email and phone number is there. Don't
6	hesitate to reach out to me if you want to discuss
7	anything that I've presented today. Thank you.
8	[Applause.]
9	DR. MARKS: Thank you, Joe. I think a very
10	fertile area for questions and conversation when we
11	get back from break. We're thinking about maybe
12	coming back from break around 11:20 and then add
13	hopefully a few minutes onto your lunch break to
14	facilitate interaction and dialogue among various
15	stakeholders. So why don't we come back around 11:20?
16	Sorry?
17	DR. COX: 10:50.
18	DR. MARKS: I'm sorry, 10:50. What did I
19	say? 10:50, sorry. Yeah, why don't we do that, or
20	come back around noon, you know? 10:50. Thank you
21	very much, and we'll kick off with Ian, yeah.
22	[WHEREUPON, the foregoing went off the

Facilitating Antibacterial Drug Development for Patients with Unmet Neudy 18, 2016 Page 117 record at 10:23 a.m., and went back on the record 1 2 at 10:57 a.m.] 3 DR. MARKS: So we'll get started again very 4 shortly. Thank you. 5 DR. COX: So maybe just to get started, one sort of logistical issue first. An ounce of 6 7 prevention is worth a pound of cure. We found this 8 behind the podium. If you're wondering what it is, it's a hotel card. So if people might just check 9 10 their pockets, if somebody was up in the vicinity of the podium, if they're missing their hotel card, come 11 12 to me and I will get it back to you so that you're not 13 locked out of your room when you get back there. DR. MARKS: All right. Thanks for --14 15 DR. COX: If somebody doesn't have a hotel and they're interested in a hotel, come up and talk to 16 17 me. 18 [Laughter.] 19 DR. COX: No, I'm kidding. 20 CLARIFYING QUESTIONS (PANELISTS AND 21 AUDIENCE) 22 DR. MARKS: Thanks, everyone, for coming

1	back promptly. We're going to move into the questions
2	section. And just taking moderator's prerogative, I
3	thought I'd start off with the first one. We hear a
4	lot about regulatory harmonization and the need for
5	the U.S. and the EU to work together in terms of
6	antimicrobial resistance. So I thought maybe Ed and
7	Marco, you could share with us sort of what you do
8	now, your thoughts about where this might go in the
9	future, and if you could share that with us, start off
10	with either Marco, you want to start first or
11	DR. CAVALERI: Yeah. I think, as I said, in
12	the context of TATFAR but also behind TATFAR itself in
13	the recent years we had more and more chances of
14	discussing the way forward on the development of new
15	antibacterial agents between FDA and EMA. And also,
16	we established regular contact with those, clear
17	recommendation in the TATFAR set of recommendation
18	around having a regular teleconference.
19	So what is happening is that every month we
20	sit down for a conference between FDA and EMA in which
21	we discuss development plans that have been proposed
22	to both agencies or one agency but maybe with the

1 knowledge that the other agency will be involved later
2 on in which we touch base around what is the current
3 view of each agency with respect to the development
4 plans and how much we can converge into finding, you
5 know, a single, settled requirement for the developer,
6 at least how we can define the boundaries around what
7 can be acceptable and what not.

8 And I think this has really been important and efficient in, you know, cross-fertilizing the 9 10 views between Europe and the U.S. and helping us in having a common understanding of the way forward but 11 12 also of what would be the scientific basis and the 13 evidentiary standards that would be required in both the regions. And maybe to add that we do recognize 14 15 that in certain type of infection indication, we are 16 requiring different primary endpoints.

And for the time being, we found a solution by way of different statistical analysis plan, which so far works very well and in deed there has not been a single case to our knowledge in which a company had to redo a pivotal clinical trial in order to satisfy the requirement of the FDA or the EMA. But save that,

1	I think we are putting efforts into looking into the
2	future of building more rigorous scientific
3	understanding of how to assess the benefit of an
4	antibiotic and antibacterial agent in the context of
5	this type of infection in order maybe to come up in
6	the future with some primary endpoint that could be
7	agreed by both agencies.

8 So it's a journey. But I think we are -- we understand the value of that and we are putting 9 10 efforts in order to do the best we can to convert today and also with a view that in the future there 11 12 might be more chances of converging once new ideas and 13 new options for primary endpoints on how to design clinical trials in these types of infection and also 14 15 for unmet need will come up. So I don't know, Ed --

16 Yeah. No, thanks, Marco. DR. COX: Verv 17 helpful and very complete. You know, just to sort of 18 reiterate, so you're hearing the same thing from both 19 folks. I mean, agreed TATFAR has been a helpful 20 vehicle for us to interact. And as Marco said, you know, within TATFAR, I think the first version of that 21 2.2 report, we noted that in fact the clinical trials that

1	are used in Europe are essentially, you know, the same
2	clinical trials used here and if there's an instance
3	where there's different endpoints, then we would find
4	a way to make those clinical trials useful for both
5	places by a different statistical analysis plan.

6 And as Marco's noted, we continue to work on 7 the endpoints. And I think, you know, a number of 8 folks in the room here today have been involved with the efforts through the FNIH to work on endpoints. 9 10 And you know, we see this as an area where, you know, 11 the science, you know, will essentially, you know, 12 bring us to the set of options that, you know, we 13 think will be, you know, helpful to the future and get us to a greater degree of common understanding because 14 15 if the science is there, it should work really for 16 both groups.

We also -- just to add a couple of things, we share guidance documents in development, which is helpful too so that we, you know, have both the scientific exchange and the opportunity to learn from each other. Similarly, with regards to development programs, we're sharing comments, you know, with each

1	other and also having, you know, the opportunity to
2	discuss the comments. Sometimes the comments are very
3	clear, but having that opportunity to talk with each
4	other, you know, can be even more helpful.
5	We're able to do that under a
6	confidentiality agreement and we do for those that
7	choose to take sort of a formal approach, there is
8	also parallel scientific advice that is available to
9	those that do it. And we've done a few of those and
10	worked with Marco and his group on that and very much,
11	you know, appreciate those opportunities to work
12	together in that formal approach when people choose to
13	go that way. And maybe I'll stop there, but yeah.
14	DR. MARKS: Thank you, Ed and Marco. Maybe
15	now we'll open it up to the panel for questions.
16	Aaron?
17	MR. DANE: Yeah. So it's probably mainly
18	for Marco and Sumathi, but partly for John in terms of
19	the so when you were talking about when we get into
20	the unmet need and the sample sizes are smaller, so
21	clearly we can't do the traditional statistical
22	criteria that we usually do and apply. Sometimes we

1 can still do something. But if we're in a situation 2 where the numbers are even smaller than that and all 3 of you outlined that, how do you see that data being 4 used? Because I guess it's -- we get some data and 5 then we've got to figure out when does it help us feel 6 better and when does it concern us if we're only 7 dealing with a handful of cases.

DR. CAVALERI: Yeah. I think it will have 8 to be looked at on a case-by-case basis. I think it's 9 10 very difficult to say this is the threshold. Below this number it will be impossible to draw conclusion 11 12 about if we can do that because it will vary. And of 13 course, here we're entering into a bit of uncharted territory in the sense that indeed we are talking 14 15 about very small trial with a very heterogeneous 16 population. And so, the interpretation of the data might be a challenge anyway. What we are trying to do 17 18 is to come up with the idea that it will be 19 challenging, but it will not be impossible.

And therefore we are opening to consider, in light of the unmet need and the potential benefit that would derive despite the uncertainties, it might still

be possible to draw a conclusion on a positive 1 benefit-risk despite a data set that is very small. 2 So yeah, I think it's difficult to reason in terms of 3 4 absolute numbers here. And you know, each pathogen will have different considerations. The data may show 5 something different. Of course, the PK/PD package is 6 essential and that will be, as I said, one of the 7 8 pillars of the evaluation of antibacterial agent in the context of this unmet medical need with limited 9 10 clinical development.

11 DR. DUDLEY: Yeah. I think maybe along 12 those lines of what Marco was talking about -- Paul, 13 I'm going to kind of surprise you on this a little Maybe you could talk a little bit about how the 14 bit. 15 approaches that your group has taken, with taking 16 smaller data sets and modeling exposure-response, 17 which then does give an idea of the magnitude of 18 treatment effect. And I'm thinking of some of the tigecycline work that you guys did a few years ago 19 where you looked across the various exposures of 20 21 tigecycline and were able to sort of quantify the 2.2 treatment effect that was seen in a variety of

infections and whether that will help with these small
 data sets.

Sure. We did a couple of 3 DR. AMBROSE: 4 analyses, both involving tigecycline, but one of a more frequentist nature and one a more Bayesian in its 5 thought process. And not surprisingly, with the 6 7 frequentist approach, with an exposure-response 8 relationship, your confidence bounds get really, really, really wide. And we were able to calculate 9 10 sample sizes and they were quite large based on that 11 approach.

12 But when we took a more Bayesian approach 13 and we acknowledged -- we allowed some of the animal data to inform our exposure-response analyses of the 14 15 clinical efficacy data, such as the direction of the 16 exposure-response relationship, we were able to 17 tighten those confidence bounds I think quite a bit 18 that allowed for the calculation of a much smaller 19 sample size with which to do those studies. So I think those things are possible to open to other 20 statistical approaches. And it looks like by this 21 22 agenda, we are.

1	MR. DANE: Yeah, and I think for me, it's
2	just so I'm not misunderstood, I'm not thinking we
3	need any statistical traditional statistical
4	criteria. It's just that idea of assuming we rely
5	more heavily on the PK/PD information, assuming we
6	count all these other things, how are we going to use
7	the data that we do generate, because it is difficult
8	and it's just having that feel for what how are we
9	going to react to whatever we see as we're trying to
10	plan a study.
11	DR. COX: Sam, do you want to
12	DR. BOZZETTE: change directions so
13	John, I mean, your tier C drugs, it seems like there's
14	going to be a mix, no matter what control arm you pick
15	there's going to be a mix of organisms that are
16	resistant and sensitive. So I'm wondering if you
17	could say a little more on what those trials would
18	look like. Do you need different control arms based
19	on the sensitivities? Do you enroll people right away
20	
	or do you wait until sensitivities are available,
21	or do you wait until sensitivities are available, which unfortunately takes a while unless you have a

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1 look like?
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2	DR. REX: So your first question was about a
3	mixture of susceptible and resistant in the control
4	arm, susceptible and resistant to the control
5	comparator to the chosen comparator. And what I'd
6	argue here is that you should there are very few
7	organisms for which I can't design an active control
8	arm. It's actually pretty rare right now, you know,
9	which is good, okay? So in the most general case
10	like tomorrow, we're going to discuss at some length a
11	pseudomonas-specific drug. You know, most of the
12	time, pseudomonas, if I put one I can pick one
13	thing and probably put something else with it and it'd
14	be pretty rare that my comparator regimen for that a
15	pseudomonas would be inactive.
1.0	

So in that circumstance actually, you know, my problem really is that pseudomonas is just not all that common as an organism. And so, I end up with relatively small numbers. And that actually leads -so the question from just a moment ago where somebody said to Paul, can't -- well, if I use

22 pharmacodynamics, can I prove to myself that the

1	magnitude of the effect size relate to placebo is
2	larger, which will let me use a smaller study, right.
3	The problem that you get into is let's pretend we
4	actually say, well yeah, the effect size without a
5	drug, it's you know, there's like an 80 percent M1.

6 So let's actually have a really big effect 7 size and design a small trial. When you get down into 8 groups of like -- the denominator's 50 and 50 on each side of the equation, the problem there is that if 9 10 both are active and you're expecting them both to be 11 active, then you have almost no wiggle room for a 12 little bit of heterogeneity. We'll actually show that 13 tomorrow, that a movement of one patient from success to failure can actually dramatically alter your view 14 15 of the data set. So you don't get out of the box by 16 arguing for a smaller data set. You get into another 17 box. You get into another problem.

So the difference -- so you know, that's how I think about this. And so, different control arms, well, I'm not too fussed about it being -- if I do drug A -- tier C drug versus per patient design therapy, if every one of those patients is on active

1	therapy, I think that's actually perfectly fine
2	because that's what you do in the real world anyway
3	and I'm expecting them all to be good and I'm not
4	expecting to beat that therapy. It's a little
5	messier. They're going to be the AE profile stuff
6	may be harder to interpret. But it doesn't both me
7	that much, provided that you believe that most of the
8	time the comparator was an active drug. I see that
9	Paul wants to jump in on this.
10	DR. AMBROSE: Yeah, a little bit of
11	sideways direction, like PK/PD often hits people. You
12	can show pre-clinically in any number of models that
13	it's not the resistant determinant that predicts
14	efficacy. In other words, if you hit the right
15	exposure, AUC-to-MIC is big enough, you kill the
16	susceptible bug just like you kill the resistant bug.
17	There's nothing magic about that. I can't think of
18	examples at all where that relationship really begins
19	to break down over clinically achievable
20	relationships.
21	What's different in the patients with
22	infected infected with MDR or XDR is a different

1	patient population. They're often much sicker and
2	there are other comorbidities or other reasons they're
3	dying. But again, as John pointed out, you can't do
4	much about that. So to me, optimize your dose and I'm
5	less concerned with the numbers of patients you have
6	in XDR or MDR study, as long as you've already
7	demonstrated that it's drug exposure that matters, not
8	its label.

9 DR. COX: Maybe another question for Paul. 10 So Paul, just in follow-up to your presentation, you were talking about patients who have low exposure to a 11 12 particular drug, arguing for, you know, maybe going in 13 with a couple of drugs. And I'm wondering can the patient that -- you know, your thoughts on predicting 14 15 the patient who's likely to have a low exposure to a 16 particular drug and I didn't know if you were 17 suggesting, you know, doing a TDM or just sampling a 18 And then, beyond that too, if you do have a level. 19 drug that, you know, the patient's got a low exposure, 20 should you keep the drug around? Should you stop the 21 drug? Thoughts on that? And then, if you're going to 22 pick a second drug, how do you avoid having the same

1	problem with the second drug, you know, if this is a
2	patient characteristic that they're clearing the drug
3	a little more quickly? If you pick a second drug
4	that's maybe not that's secreted similarly or has a
5	similar metabolic profile. So any other thoughts on
6	that? I thought that

7 Sure, and you'll probably have DR. AMBROSE: 8 to remind me of some of the questions that I miss in that list of them. But to start off with the first 9 10 one, I think which is am I talking about needing TDM 11 because of variability in drug exposure. Well, 12 certainly if your drug's got unpredictable clearance, 13 TDM long-term is a useful thing. But the reality is I think the outcome of an infection is dictated by early 14 15 drug exposures. That first 48 or 72 hours, I think 16 all doctors all instinctively know this.

And so, it's really important to have the right dose up front and that means pushing the drug exposure. We're not really going to have that much time for TDM. The event window's too short. It's not like HIV where we're going to be treating for years and we can move the drug concentrations up and down at

	5
1	will, right? It happens all too fast. So especially
2	for, you know, pseudomonas pneumonia, where half the
3	patients that are going to die are dead within the
4	first 48 hours or so. So to me, it's pushing that
5	exposure up front. I won't argue against TDM for
6	certain drugs. But I would push back and say pushing
7	dose is probably your safer bet.
8	The second question was
9	DR. COX: Can you predict who's going to
10	have these problems?
11	DR. AMBROSE: Yeah. You know, if it's a
12	renally cleared drug, that's your first hint. So if
13	you've got someone that's really hyperdynamic, they
14	might be a patient that's very high creatinine
15	clearances, they might be a patient that's going to be
16	at risk. It'll be simple things like that. And
17	oftentimes our doses are not selected to cover those
18	patients, right? We start with normal renal function
19	and we kind of match our AUCs going downward into
20	various renal function categories in a downward
21	direction. But we don't go in an upward direction.
22	So maybe that's something that we could think of.

1	And the second the last one I think was a
2	question related to if you've got a drug that's got
3	variable exposure, what is it that you do. You stop
4	the drug or try to add something else. I think you
5	put them on the drug that has probably the least
6	variability that you can get to that has a dose that
7	can account for that variability, number one. And
8	number two, in some effect sites, like the meropenem
9	slide I showed, I think that's really important for
10	everyone to recognize there was this tail of exposures
11	that approached zero, even with this close to
12	pharmacodynamically optimized drug and why. And
13	that's the high variability and penetration into the
14	lung.
15	So the only way to overcome that is protect
16	that fraction of patients as a second drug. You may
17	have to begin to think about inhalation as an
18	alternative route, you know, breaking on through from
19	the other side. But I'm not aware of any data where

20 people have two drugs into a patient, measure the ELF 21 and see where varying levels of penetration of drug A 22 influence drug B at all. I don't think any of that

1 data even exists. So at this point, you know, I think 2 that's an open field. But I think that data is a 3 clear argument for combination therapy in some 4 indications. 5 DR. COX: Ian? 6 DR. FRIEDLAND: I had a question for Sumathi

7 and maybe Marco can also answer this. Of those 8 different study designs that you outlined, can you give us some indication of which of those -- you know, 9 10 maybe in order of frequency, which of those responses 11 actually have undertaken? You know, so have people 12 actually done nested superiority trials? Are people 13 doing superiority trials? Are people doing external control trials, for example? 14

15 DR. NAMBIAR: The vast majority really have been non-inferiority trials. There's been one person, 16 17 maybe two who've attempted to do superiority trials. 18 But really the vast majority is non-inferiority. We 19 really have not used external controls. We haven't seen a lot of proposals for external controls. We've 20 21 used external controls more recently in the context of 22 an anti-fungal drug that was approved over a year ago.

1	But I think the vast majority are non-
2	inferiority trials. And for Gram-negatives, it's
3	usually intra-abdominal and UTI, either or both.
4	HAP/VAP typically has been the second indication,
5	which I think makes sense. I think, you know, you at
6	least have the evidence that it works among the other
7	body sites. And those trials are certainly a lot
8	easier to do than a HAP/VAP trial. So most of the
9	HAP/VAP programs have been the second indication that
10	people use.
11	DR. COX: Marco, anything to add? You're
12	seeing a lot of the same programs we're seeing, so I'm
13	guessing it's fairly similar, but
14	DR. CAVALERI: Yes. It's fairly similar.
15	Of course we're seeing some proposals around MDR
16	pathogens and in novel approaches as we were proposing
17	in the addendum. But I agree with Sumathi the
18	majority are still in the non-inferiority.
19	DR. COX: And Nick?
20	DR. KARTSONIS: Yeah. I had sort of a
21	follow-up question to the non-inferiority question to
22	Sumathi, which is now that sponsors have come with

1	these non-inferiority margins, have there been
2	situations where you've allowed a wider margin? And
3	if so, can you give us some guidance in terms of what
4	a wider margin means?

5 DR. NAMBIAR: I was hoping that wouldn't come up. But yes, we have -- we have allowed wider 6 non-inferiority margins and I think some of that 7 8 information is available in the public domain. So there's no secret here. I think particularly we've 9 10 done it in the context of complicated urinary tract 11 infections. We've allowed for a non-inferiority -- I 12 mean, traditionally it would be 10 percent.

13 But in an unmet need program, we've allowed up to 15 [percent]. But I think the important point 14 15 is that we need an adequate justification for why you 16 think the product meets an unmet need. It's not just a question of widening the margin because someone 17 18 wants to get the trial done in a shorter period of 19 time. And I think more recently, I think Ed and I keep saying there are many flavors of unmet need. 20 21 More and more we are seeing people, you

22 know, make -- it'll be a very tiny incremental benefit

1	and they'll say, here, I'm able to address an unmet
2	need and the answer to that is no. We're not willing
3	to. I think you also have to keep in mind safety
4	concerns. So widening the non-inferiority margin,
5	getting a smaller sample size might be one solution to
6	the problem.

7 But we do come across products where you've 8 seen a safety signal and in that instance, you know, a smaller program is not appropriate. So it's less 9 10 about the number. I think a lot of it really depends on what the drug has to offer and whom you are trying 11 12 to study. So and for HAP/VAP, again, we have allowed 13 margins of up to 12.5 [percent] that we consider as wider margin and programs that do such trials will 14 15 have a limited use statement in labeling.

DR. COX: Aaron? Yeah.

16

MR. DANE: Yeah, again, it's a follow-on to a comment you made around external controls, where I can see, particularly in the resistant pathogen area, that there really isn't any data out there to be able to use. But I mean, what's your view on using external controls if you're in one of the body site-

1	type approaches, and there are recent clinical trials
2	that could be used in that way? So is that something
3	that you would be amenable to doing? Because that
4	could make trials a lot more feasible if that control
5	arm data could be used across the trial in that way.

6 DR. COX: I'd welcome thoughts from other 7 people on this. But you know, for non-inferiority 8 trials, I mean, people have been successfully doing those in a variety of different areas. So I mean, I 9 10 don't think there's any tremendous barrier to doing 11 that. I mean, you know, we do see as we look across 12 trial to trial, we do see variation. And I guess the 13 question is are you reducing or increasing variability or, you know, what is the comparability of the 14 15 external control compared to the patients that are 16 actually in the trial.

And you know, when people do external controls, I mean, we talk about the importance of, you know, having a protocol that would essentially enroll patients in the externa control that would be, you know, similar to the trial that you had been enrolling the test drug patients into. So there's a lot of

1 things to think about. But, you know, ICH E10 talks 2 about historical controls and some of the issues 3 around them.

4 So you know, trying to overcome those and, you know, one of the topics that's come up too in the 5 context of the clinical trial network discussion would 6 be is this would sort of be an ideal sandbox to try 7 8 and work through these issues because there's an opportunity to have the same protocol in place over a 9 10 period of time and really try and examine and explore 11 what's really going on. You know, are the patients 12 behaving, you know, sufficiently similar with regards 13 to outcome when a similar protocol is applied. It'd be interesting to see that, how do things change. A 14 15 new drug gets approved. It might change the standard 16 of care. Does that change what we see and how do we 17 figure all that in? So probably more questions to 18 your question than answers, but --

MR. DANE: Well, no --

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2.2

20 DR. COX: -- I think those issues are, you 21 know -- are out there.

MR. DANE: I mean, in the meantime, that's

1	what I was thinking, is that, you know, if we've got
2	relatively recent trials, that's closer to that
3	network, if you like, is that, you know, rather than
4	having to rely on something from 20, 30-plus years
5	ago, if we can say, well, these trials were conducted
6	fairly recently and the designs were sufficiently
7	similar and we'd have to go through all that, does
8	that allow that information to be used, which then
9	reduces the burden on the future studies.
10	DR. COX: Yeah. Yeah, I mean, if you I
11	mean, if you look at, you know, trial A was in these
12	sites, trial B was in those sites and maybe the
13	patients are somewhat different as you move from site
14	to site, so the reason that the numbers are different
15	is not just, you know, variability but in fact patient
16	differences. So it's you know, and then, you know,
17	we see protocols and oftentimes there are subtle
18	differences or differences that exist within, you
19	know, the definition of what a success is.
20	And you know, that can change your numbers
21	significantly. So when you look at historical reports
22	in the literature for outcomes for particular disease

1	conditions, and then you look at the results of the
2	clinical trial, because of the way the endpoint was
3	defined in the clinical trial, it can lead to, you
4	know, in some instances, markedly different numbers.
5	So you know, it's a question of are you really apples
6	to apples or are you apples to oranges. And if you
7	are apples to oranges, why is that?
8	So I think there is still, you know, some
9	work to be done there. And I know I'm thinking of,
10	you know, the endocarditis trial and the definitions
11	in the literature with regard to successful
12	endocarditis and the definitions the first success
13	within the clinical trial for dapto, for right-sided -
14	- or for bacteremia, I should say, you know, really
15	led to some fairly different numbers. And so, there's
16	a lot to sort through in that. It's not just
17	MR. DANE: So it's possible. But it would
18	be difficult and there'd be a lot of steps to go
19	through I guess is the
20	DR. COX: Well, I mean, I guess I mean,
21	you can think about, you know, what is the problem
22	you're trying to solve and how big is the problem.

1	And if you're able to do, you know, well-done non-
2	inferiority trials, I mean, you know, go forth. If
3	there are issues that you're trying to solve and there
4	are you know, we'll talk about areas where it's
5	particularly difficult to do clinical trials and it
6	may be worth looking into this a little bit more and
7	trying to figure things out because you'll take a
8	problem that's insolvable and make it, you know,
9	solvable.
10	So you know, I think it's important to think
11	about the nature of the problem and where solutions
12	are, you know, most helpful and most needed and, you
13	know, try and work through it. So does that help,
14	Aaron?
15	MR. DANE: Yeah, and that's a good point.
16	So I'm thinking of the situation where it might be
17	possible to recruit maybe a couple hundred, but no
18	more. So you're halfway between a really small
19	development program and the fully powered one. And it
20	might allow you to do a different randomization ratio
21	or something like that. So this wasn't the idea of
22	you just have an uncontrolled study you'd compare it

1 with. You'd have some reference across the two that 2 you'd compare. But just trying to make those sorts of 3 situations more feasible, to get something that would 4 support approval.

5 DR. COX: Yeah, and I think we really will 6 venture into that area tomorrow, where it is very 7 difficult to actually get the patients to get to a 8 powered study. So I'm sure we'll be talking about 9 that more tomorrow. So Helen, did you want to add 10 something?

11 DR. BOUCHER: I'll just comment to add to 12 your point, Ed, about the difficulty in the bacteremia 13 trial. And I think that there are a couple of issues that we've already talked about. One goes back to 14 15 John Rex's comment about the movement of small 16 numbers. You know, that was a trial of a small number 17 of patients and there was heterogeneity, right? We 18 had different people in different buckets of 19 diagnoses. And that was something that had to be accepted to do that, to really try to complete that 20 21 trial.

22

At the end of the day, I think that one of

1	the things that was most helpful was that there was a
2	group of patients that all the patients were well-
3	characterized, but there was a group of patients in
4	whom their bad outcome was indisputable where there
5	was some treatment effect. And I think that that was,
6	at least sort of our perception of how a conclusion of
7	success could be made.

8 And so, somehow in this discussion of if you're going to have a small group, whether it's with 9 10 a wide margin or no margin, including patients, at least some patients in whom it's unequivocal that 11 12 there's impact of drug is helpful. And I think that 13 was at play in the antifungals back in 2001 and back in 2014 and Nick Kartsonis and I were there in 2001. 14 15 You know, so that notion is I think one we can all 16 agree on.

I think the challenging part comes in to what about the trials where we don't have those patients, and there's still a need? You know, there's still a need for an oral drug to treat ESBL UTIS. And as the clinician who deals with this all the time, I don't want to forget that we just don't have people

with HAP/VAP. We also have young, otherwise healthy
 people who have to come and get a PIC line for their
 ESBL UTI and they have a need as well.

4 DR. MARKS: Dennis, you wanted to make a 5 comment?

DR. DIXON: Just wanted to echo a comment 6 7 made by John Rex on the importance of speaking to the 8 regulatory agency early and having a dialogue and a discussion to learn the way forward. 9 That also 10 applies to funding agencies like NIH and BARDA. And 11 your comment, John, that there is a strong temptation 12 to hear what you want to hear, we see that too. And 13 so, I think people take the encouraging words and they don't look so much at the sentences or comments that 14 15 start with but, however and whereas and that's just so 16 important to understand the reality in moving forward.

And just to comment, I think it was a really good idea to have this workshop and to have this discussion openly so that companies out there can start to learn from others and can get a sense on what they might want to bring forward to you and have an early discussion about.

DR. MARKS: So we might -- before we go to Tom, we might just invite if there are people in the audience that have a clarifying question, just make your way to the microphone and we'll get to you right after Tom.

DR. LOUIS: Just quickly to highlight 6 7 something both implicit but somewhat explicit in 8 Paul's presentation and that is that the delivered dose isn't a number. It's a distribution and that 9 10 really I would push for distributional thinking on almost everything. In this case, the biologic effect 11 12 is really the integral of that uncertainty 13 distribution over, in this case, a nonlinear curve and things could either be much better than you think or 14 15 much worse than you think. But in either direction, 16 it's best to keep that uncertainty throughout the 17 whole system. I know that's harder than putting down 18 a number. But you'll have much better assessments and 19 better trial designs and no magical cure, but at least a sort of strategic approach. 20

21 SESSION 2: REAL WORLD EXPERIENCES IN CONDUCTING 22 SUCH TRIALS

1	DR. MARKS: Any clarifying questions from
2	the audience? I was just checking to see. Hi, over
3	here? Any questions from the audience? Okay. Is
4	that okay? All right, well, with that, we'll move on
5	to session two, real-world experiences in conducting
6	such trials. And great to have Ian Friedland, chief
7	medical officer from Achaogen. His talk is
8	"Developing Antibacterial Drugs for Patients with
9	Unmet Need: Experience and Recommendations." Thank
10	you, Ian.
11	DEVELOPING ANTIBACTERIAL DRUGS FOR PATIENTS
12	WITH UNMET NEED: EXPERIENCE AND
12 13	WITH UNMET NEED: EXPERIENCE AND RECOMMENDATIONS
13	RECOMMENDATIONS
13 14	RECOMMENDATIONS DR. FRIEDLAND: Good morning, everyone. And
13 14 15	RECOMMENDATIONS DR. FRIEDLAND: Good morning, everyone. And I'd really like to start off by thanking the FDA for
13 14 15 16	RECOMMENDATIONS DR. FRIEDLAND: Good morning, everyone. And I'd really like to start off by thanking the FDA for inviting us here to come and share our experiences
13 14 15 16 17	RECOMMENDATIONS DR. FRIEDLAND: Good morning, everyone. And I'd really like to start off by thanking the FDA for inviting us here to come and share our experiences enrolling an unmet need-type study. So I'm going to
13 14 15 16 17 18	RECOMMENDATIONS DR. FRIEDLAND: Good morning, everyone. And I'd really like to start off by thanking the FDA for inviting us here to come and share our experiences enrolling an unmet need-type study. So I'm going to go through some of these positions and give you the
13 14 15 16 17 18 19	RECOMMENDATIONS DR. FRIEDLAND: Good morning, everyone. And I'd really like to start off by thanking the FDA for inviting us here to come and share our experiences enrolling an unmet need-type study. So I'm going to go through some of these positions and give you the basis for the positions in my talk. I'm going to talk

1	And nonetheless, despite the difficulties of enrolling
2	these types of trials, the data that one can obtain
3	are critical and provide really important data to
4	clinicians. These smaller data sets can be highly
5	descriptive and they can support exposure-response
6	analyses. But it is imperative that data in this
7	unmet need population, including outcomes, is
8	integrated in some shape or form in the product label.
9	So why even conduct these unmet need
10	studies? We can just do a standard UTI II indication,
11	get the drug approved. And this slide highlights the
12	big differences between the standard population, say
13	for cUTI, complicated urinary tract infection, acute
14	pyelonephritis, versus a typical unmet need study, the
15	one that I'll be describing today, which is blood
16	stream infection and hospital-acquired/ventilator-
17	associated pneumonia due to carbapenem-resistant
18	Enterobacteriaceae. The standard UTI study does not
19	directly address an unmet need, where clearly if you
20	focus on unmet need, that's going to address that
21	particular population. In UTI, patients have few
22	comorbidities. There's low mortality rates, whereas

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in the unmet need population, there are significant
comorbidities, high mortality rates, multi-organ
failure, very, very different patient population.
Duration of therapy could be different.
Doses could be different. The pathogens are clearly
different. John Rex referred to UDR. So it's a
standard UTI trial has usual drug resistance. This
could include something like 15 to 20 percent extended
spectrum ß-lactamases. It's very unlikely you're
going to see carbapenem-resistant enteric.
Polymicrobial infections are usually excluded, whereas
in the unmet need study, they're all, by definition,
multidrug-resistant. We do see extremely drug-
resistant and even pan-drug-resistant strains. And
polymicrobial infections are common. PK is very
different in the two populations. UTI looks a lot
similar to Phase I-type populations, whereas in the
unmet need population, the PK is much less
predictable. There's much less variation.
Significant changes in volume of distribution. And in
our particular instance, we're studying our drug as a
single agent for UTI, but in combination in the unmet

need population. So one gets very different
 information.

So plazomicin is a new aminoglycoside that 3 4 Achaogen is developing and this drug has broad activity against Enterobacteriaceae, including strains 5 resistant to other classes like carbapenems. And you 6 can see there on the top line, the activity, the 7 8 minimum inhibitory concentration, 50 and 90 of plazomicin showing potent activity against this 9 10 collection of CRE isolates, in contrast with a group of other commonly used antibiotics. All the values in 11 12 red are resistant, with only a few that have some 13 activity, shown in blue.

So this is the basis of our Phase III 14 program. We have two Phase III trials. Our cUTI 15 trial, called EPIC, is the basis for registration. 16 That's the trial that we believe will give us approval 17 18 through the FDA and EMA. The CARE study, which is our 19 study in carbapenem-resistant Enterobacteriaceae, is providing additional support of data. It's a smaller 20 21 randomized trial. Originally we started with just the 22 CARE study. But later, as that study went on, it

became clearer that enrollment was going to be
 challenging. We introduced the UTI study as an easier
 path to approval. Both studies are expected to
 conclude later this year and support a filing in the
 second half of 2017.

So let's go back to the beginning and look 6 at our original CARE study design. And this was 7 8 originally designed as a randomized, open-label superiority trial in patients with bloodstream 9 10 infections and ventilated pneumonia due to CRE. This 11 was -- this is a comparative trial versus colistin. 12 The treatment arm is plazomicin in combination with 13 either meropenem or tigecycline, so a combination Comparator arm is the same combination, but 14 regimen. 15 using colistin this time.

Primary endpoint, 28-day all-cause mortality and we were planning on demonstrating superiority over the colistin regimen. And this was based on a metaanalysis at the time showing a 35 percent mortality in patients treated with colistin. And with a 12 percent absolute reduction in mortality, we would have 78 percent power with the sample size we calculated. We

1	did get a concession from FDA to do the one-sided
2	alpha of 0.05. The total sample size calculated
3	assuming an 80 percent evaluability was 360 patients.
4	So this was the original feasibility done by
5	our CRO. They did a very detailed exploration at many
б	sites around the world looking at incidence of CRE.
7	And this is the summary they came up with. In nine
8	countries, using 68 sites, in these nine countries,
9	they projected we could enroll 115 patients per year,
10	which would mean the study would take 360 would
11	take three, three-and-a-half years to conduct. As it
12	turned out, the only country which approached the
13	original prediction was Greece, and we can maybe talk
14	a little bit later about why Greece managed and why
15	the rest of the world struggled with this kind of
16	trial.
17	Early on in the study, we when the study
18	was going slowly, we looked at some of our metrics and

19 we looked at the number of patients that we
20 prescreened and by prescreened here, I mean patients
21 haven't signed consent yet. And you can see of the
22 almost 700 patients who were originally screened, only

1	14 patients were eligible for enrollment in the trial.
2	And here are some of the reasons why patients were not
3	eligible. Science could not prove that it was a CRE
4	and, very importantly, patients exceeded the 72 hours
5	of prior antibody therapy that we allowed in the
6	study. Other important exclusions are things like low
7	APACHE scores, polymicrobial infections and, very
8	importantly, emerging colistin resistance that
9	occurred during the conduct of this trial.
10	If we look at this on a more granular level,
11	this is the experience from one of our good sites in
12	Greece, showing that they definitely did see
13	carbapenem-resistant Klebsiella in their hospital.
14	And this is a detailed analysis, 17 patients that they
15	looked at with carbapenem-resistant Klebsiella.
16	Importantly, none were in ICU and this is important
17	because most of our investigators are intensivists.
18	But out of the 17 patients they looked at, only two
19	could be enrolled and there are the reasons why
20	patients were excluded low APACHE scores,
21	resistance to colistin. So you can see that even
22	though these infections are fairly common, these kinds

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1	of exclusions are very difficult to predict up front.
2	Because of the slow enrollment, we
3	implemented two major amendments to the study. The
4	first one, we tried to loosen or broaden the entry
5	criteria for the randomized cohort. So we allowed all
6	hospital-associated pneumonias to be enrolled. We
7	clarified some of the definitions of pneumonia. And
8	we also added slightly different endpoint. Instead of
9	just doing mortality, we did so-called mortality-plus,
10	which is mortality plus other significant disease-
11	related complications which are more closely related
12	to the primary infection. Despite these changes, we
13	saw minimal impact of this amendment.
14	So we then introduced a second amendment and
15	the second amendment actually introduced a totally new
16	cohort and this was a single arm, plazomicin treatment
17	arm in which all the patients who were not eligible
18	for the randomized cohort could come into that cohort
19	and still get treated with plazomicin. And this
20	included now patients with urinary tract infection who
21	were excluded from the randomized cohort, lower APACHE
22	scores and importantly are things like colistin

1	resistance, which was not allowed in the randomized
2	cohort because colistin was the comparator.

And this is a snapshot of enrollment. 3 This 4 graph is not necessarily to scale. But you can see the original projection of 360 patients and our actual 5 enrollment is tracking far short of that prediction. 6 You can see where we introduced cohort two, which was 7 8 the single-arm plazomicin treatment arm that did result in a bump up of enrollment. Unfortunately, the 9 10 randomized cohort still tracks quite a lot below that.

11 So what have we learned from our experience 12 in the CARE study? The site surveys that CROs perform 13 -- I think a lot of us do know this -- grossly overestimated patient enrollment. Of all our sites, 14 only a small subset, maybe 15, 20 percent, actually 15 enrolled more than one patient. Superiority studies 16 like this would only be feasible if many sites in 17 18 countries have a CRE incidence similar to Greece. And 19 those of you who know what the situation in Greece is, their carbapenem-resistance rate in Klebsiella runs 20 about 80, 85 percent in ICUs. And clearly we don't 21 2.2 want that situation to emerge in the rest of the world

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1	before we can conduct these kinds of trials.
2	There are the barriers to enrollment
3	actually evolved during the trial. For example,
4	resistance to colistin became more and more of a
5	problem as the study went on. Site engagement is
6	critical. These are difficult trials. The VSCAs [ph]
7	get easily discouraged. We spend a lot of time
8	talking to our sites, doing site engagement
9	activities. The studies are expensive. And in this
10	instance, BARDA's support for this trial was essential
11	for a small company like us to conduct a trial like
12	this.
13	But if we are going to undertake these
14	studies, and we do believe one can get extremely
15	useful and important information, it is critical that
16	somehow this information does get included in the
17	label to ensure that the information is available to
18	prescribers. And here I'm talking about even efficacy
19	data in this unmet need population. This is in the
20	context of we do actually have proven efficacy in the
21	usual population. It will be a smaller data set. It
22	will have uncertainty. But I think the nature of the

data set, the uncertainty can be highlighted in the
label. The PK is very different in these populations.
The microbiology can be very different. I think it's
a given that we would include safety information in a
different population like this. And this may be the
only source of information on combination therapy.

7 So this is just highlighting how different 8 the populations are in terms of PK. And the basis for this is largely differences in renal function. 9 This 10 is a renally excreted drug. And you can see a very 11 broad range of renal function that we see in our CARE 12 study in comparison to our EPIC study, our cUTI study, 13 and what we'd estimated from population PK modeling, which is based on Phase I and Phase II. And you can 14 15 see on the Phase I/Phase II, our UTI study, we get mostly normal, mild and moderate renal dysfunction. 16 17 But in CARE, now we start seeing substantial numbers 18 of patients with hyperclearance, which we know it's 19 this population in particular that has caused problems in the past. We also get a substantial number of 20 21 patients with severe renal failures, including those 22 who are on continuous renal replacement treatment. So

1	a very different experience. It's very difficult to
2	design Phase I or Phase II or UTI studies that can
3	capture this kind of variability. Also interestingly,
4	because of this extreme variability, we do get a whole
5	range of exposures, which does make this data set very
6	rich for doing exposure-response analyses.

7 The microbiology is also unique in the unmet 8 need population. Yes, in our UTI study, it is focused on Enterobacteriaceae. Yes, we do see multi-drug-9 10 resistant enterics like ESBLs. We do see 11 aminoqlycoside enterics. But the CARE study is where 12 we get carbapenem-resistant strains, colistin-13 resistant carbapenem strains, tigecycline-resistant. So kinds of resistance mechanisms and patients with 14 these infections that you can't get in other kinds of 15 16 trials. Also, we do get patients with higher MICs and this collection of these organisms with high MICs will 17 18 help provide a more robust breakpoint assessment. And 19 we also see bacterial species, maybe a little less 20 important. But usual UTI is E. coli and this is 21 focused on CRE. So it's mostly Klebsiella.

In conclusion, it's infeasible to conduct

2.2

rigorous inferential trials in these kinds of unmet 1 2 need populations. And here, I'm referring to carbapenem-resistant enterics, resistant Pseudomonas 3 4 populations, Acinetobacter-type studies. But these studies do provide really important and interesting 5 information that's critical for clinicians to make 6 7 treatment decisions. It is imperative, though, that 8 these data do get included in the product label. And I think we would all agree that if the regulatory path 9 10 was really clear, the studies in the unmet need 11 population would be more likely to be undertaken and 12 funded.

13 This is a last word, if I can get the slide Thank you. My thoughts based on our 14 to move. 15 experience in what are considerations one needs to 16 take into account in thinking about viable study designs in this unmet need population. We do need to 17 18 think what we can do with small studies, try and make 19 them more efficient. So let's first start with rather than start with theoretical study design, let's start 20 21 with what's feasible and look at this is possibly the 22 population we can enroll and what can we do with this

1 number.

So these kinds of studies, to me what's 2 feasible is somewhere between 40 and 80 patients, 3 4 definitely less than a hundred. And the question is if you've got that number of patients, what can you do 5 with that? We can definitely look at different 6 7 endpoints, and I think we are working with CTTI and 8 FNIH on more sensitive endpoints for things like HABP/VABP. Because of the small number of patients, I 9 10 believe we should aim to get all or nearly all the 11 patients on your study drug, which would then mean 12 that we need to get control data somewhere else. So 13 either external controls, shared controls and here is where I actually think a trial network could be very 14 15 useful helping us get control data in this unmet need 16 population.

17 Clearly designs that allow early institution 18 of study therapy are very important. Our CARE study 19 requires the confirmation of a carbapenem-resistant 20 Enterobacteriaceae. That can take three or four days. 21 To me, that misses the whole opportunity for drugs to 22 be started early, to show their true potential. So if

1	we can't come up with study designs where you can use
2	study therapy early, or at least as early as possible,
3	I think we've missed the opportunity to really test
4	the true drug effect. And obviously here rapid
5	diagnostics can help. I do think we are going to have
6	to think of pathways that incorporate combination
7	therapy as a sort of definite simplifier, trial
8	designs that will allow us to treat polymicrobial
9	infections, which are common, that will allow us to
10	start therapy earlier. And lastly, I do fully
11	appreciate and definitely want to encourage the
12	harmonization between FDA and EMA because clearly it
13	is a barrier to sponsors when the two agencies have
14	slightly different approaches. And thank you for your
15	attention.
16	[Applause.]
17	DR. COX: Thanks, Ian. We appreciate you
18	sharing your experiences and your insight. I think
19	it's helpful to the field in general, and your
20	willingness to present to the group on that is greatly

22 to the podium. Mike is the senior vice president and

appreciated. So now, I'd like to welcome Mike Dudley

21

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1	head of R&D at The Medicines Company. And he'll be
2	talking with us about planning and executing a
3	carbapenem/ß-lactamase inhibitor program focused on
4	treatment of KPC-producing CREs. Thanks for joining
5	us, Mike.
6	PLANNING AND EXECUTING A CARBAPENEM/ß-
7	LACTAMASE INHIBITOR PROGRAM FOCUSED ON
8	TREATMENT OF KPC-PRODUCING CRE
9	DR. DUDLEY: Yeah. Thanks, Ed. And thanks
10	to you and your colleagues for putting this program
11	on. I think that all of us in industry are
12	appreciative of what the regulatory bodies have done
13	to really advance this field forward. My disclosures
14	are here. And what I'm going to talk about is really
15	starting from the beginning of what our thinking was
16	as we designed this program from really the chemist
17	bench and then moving all the way through design of a
18	Phase III program. And it was around actually in the
19	2008-2009 timeframe when many of us were sitting
20	listening to the spread of KPC-producing CRE in New
21	York City that we regarded this as even before CDC
22	as an emergent urgent threat that was going to be

1 facing healthcare institutions. It truly was a 2 tipping point when one was now seeing resistance in 3 Enterobacteriaceae, the most common infections in the 4 hospital, to a very effective class of drugs known as 5 the carbapenems.

So in terms of doing that, we went to the 6 7 laboratory and designed then a program that was going 8 to culminate in a new class of ß-lactamase inhibitor 9 based upon a Pharmacophore [ph] which microbiologists 10 knew about in terms of boronic acids of inhibiting 11 serine carbapenemase -- serine &-lactamases and 12 optimized it then to be used for inhibiting the KPC 13 enzyme. Secondly, we really wanted to work very carefully on optimizing its properties to work in 14 15 combination with the carbapenem antibiotic. And this 16 program advanced from literally the chemist benchtop 17 to completion of enrollment in a pivotal Phase III 18 trial in only six years. And largely a lot of that 19 was because of the support of BARDA and many other 20 partnerships that we've had throughout the year of 21 being able to move this program forward.

22

Now, we optimized it for a carbapenem

1	because we recognized then that we could make use of
2	the potency of a carbapenem antibiotic against
3	Enterobacteriaceae and in contrast to cephalosporin
4	combinations, which would then be subject to so-called
5	usual drug resistance of ESBLs, we really focused then
6	on a program that was going to optimize the molecule
7	for inhibiting serine carbapenemases. And you see
8	that evidenced here when you look at a very multi-
9	drug-resistant or XDR-resistant panel, as shown on the
10	bottom of the slide there, by double-digit MIC90s.
11	Within this panel, 70 percent of these strains are
12	inhibited by less than or equal to 0.6 μ g/mL of
13	meropenem in the presence of 4 μ g/mL of vaborbactam.
14	The second piece that we did too though, and
15	being mindful of the other part of this, is the
16	pharmacokinetics. And we wanted to ensure a couple of
17	things. One was is that we could match the
18	pharmacokinetics of the partner ß-lactam here,
19	meropenem with the ß-lactamase inhibitor
20	vaborbactam, both within plasma as well as within
21	epithelial lining fluid. And we accomplished that.
22	We saw evidence of that in nonclinical models and then

1	this work done by Keith Rodvold published last year
2	shows that in fact the penetration into ELF is very,
3	very high, of course known for meropenem, when given
4	by a three-hour infusion, but also comparably for
5	vaborbactam as well. So well-matched microbiology,
6	well-matched pharmacology to move forward.

7 It was then what do you do then in terms of 8 designing a Phase III program to go forward with this. And Ian has covered many of the things -- and others 9 10 have covered many of the considerations that we had 11 here as well because we felt with a program that had 12 been very mindful from the beginning of focusing on 13 the pathogen and the infections where the pathogen was going to be found, we wanted to make sure then that we 14 would have a Phase III program that would really 15 16 reflect and translate a lot of that thinking that had 17 taken place within the nonclinical and the early 18 clinical development.

So I would just add also not only
understanding exposure-response relationships within
patients, understanding pharmacokinetics in special
patient populations and safety as well. One other

1	issue which I would refer you to is the nice work from
2	ICPD that actually with tigecycline that also
3	uncovered also effect modifiers, both with respect to
4	the patient's protein status as measured by albumin
5	and how it modulated the exposure-response
6	relationship in both HAP as well as VAP patients as
7	well.

8 But also, I think, as we've talked about, it's important to inform clinicians about the results 9 10 -- all the results that occur in Phase III programs in 11 these patient populations. And I would draw your 12 attention to even though we were thinking about this, 13 a very fine viewpoint that Brad Spellberg and colleagues published earlier this year, that where 14 they pointed out that for most drugs that are 15 16 developed, the appropriate use in the clinic does in 17 fact mirror the way that the drug was proven to be 18 effective and safe in clinical trials. And so, a 19 trial that also is involving these types of patients 20 that Ian and I are talking about is also going to 21 empower stewardship going forward because we want to 2.2 provide information for clinicians in terms of

defining those indications and uses in that treatment
 population of patients.

So indeed, it's a novel idea. How about 3 4 studying a drug designed for CRE in patients with CRE infection? And that's what we did. We came up with 5 It's the TANGO program, TANGO I and II. 6 two trials. TANGO I was indeed a guidance-directed both with EMA 7 8 as well as FDA study looking at complicated urinary tract infections in acute pyelonephritis where CRE are 9 10 indeed frequently found. So we rejected the idea of going, for example, to intra-abdominal infections 11 12 because you don't see CRE infections generally in the 13 usual population of complicated intra-abdominal infections. Our comparator was piperacillin and 14 15 We recently announced the completion and tazobactam. 16 the results of that trial where non-inferiority was indeed shown in the primary analysis population with 17 18 indeed superiority also shown within that primary 19 analysis population and in the primary endpoint.

Now, TANGO II is a pathogen-focused study, as you've heard about there. It was a study then that was designed to go into those patient populations,

1	nowtigularly the complicated unineque twent infections
T	particularly the complicated urinary tract infections,
2	HABP and VABP and also bloodstream infections where
3	patients had known or expected CRE. We designed it to
4	be a 2:1 randomization so that we to get more
5	exposures again in these patient populations with CRE,
6	with meropenem and vaborbactam and that study is
7	ongoing. And here's where kind of we more detail
8	in terms of how we ended up with this. These patients
9	are randomized, as I mentioned, 2:1 to receive
10	meropenem-vaborbactam or best available therapy for 7
11	to 14 days. These are patients with either known or
12	suspected CRE, as shown on the slide here, with a
13	diagnosis of infection sites that I mentioned earlier.
14	It is an open-label design, as you might expect, with
15	the best available therapy arm, although we've done
16	quite a bit here to try to reduce bias by having
17	blinded investigators and adjudication committees,
18	where needed, that we added as an amended protocol.
19	And we used pre-specified outcomes I think much like
20	what Ian was getting at here in terms of cure rates
21	within these patients with meropenem and vaborbactam.
22	Now, I want to move though in terms of what

1	we sort of in planning this trial, what did we have
2	to begin to think about. Well, one is what is best
3	available therapy for CRE infections. And these are a
4	number of retrospective studies that appeared in the
5	literature here, with some of the learnings from those
6	studies as well. It's certainly that, I think to Ed's
7	point earlier, that carbapenems appear to have some
8	treatment effect, even in this setting of resistance
9	as well. But there are a variety of other factors
10	that were identified retrospectively in these studies.
11	So what we did do though is in planning this
12	trial and ultimately executing it was that we actually
13	went forward to the sites that were actually many
14	of the sites that were going to actually participate
15	in the TANGO II trial to generate retrospective data
16	from those institutions about outcomes and best
17	available therapy, so somewhat of an external control
18	approach, but more importantly, to really to teach
19	us about what these patients actually had, how were
20	they treated and how could we design the protocol then
21	to optimize their enrollment within the study as well.
22	And so, Elizabeth Alexander and Jeff Loutit and other

1	colleagues in our group that led this analysis did
2	this study in these 22 major medical centers, both in
3	the U.S. and Italy, again in Europe many of which,
4	of course, would be sites in the TANGO II study.
5	And here's what we found. And we found,
6	perhaps not surprisingly, what we know now is that
7	many of these patients have comorbidities that would
8	usually result in an exclusion from the typical
9	registration trial. So as you scan down this list
10	here, you can see that many of these patients were
11	immunocompromised, about a quarter of them. Many of
12	them had prior transplantation as part of it, chronic
13	renal insufficiency, septic shock and APACHE scores
14	with the means somewhere in the 20s.
15	So again, these are very, very sick
16	patients, oftentimes not the ones that are going to be
17	currently enrolled in typical registration trials.
18	These are the primary endpoint which we were
19	collecting, of course, which included mortality as
20	well as other factors as well. Overall mortality,
21	around 28 percent in all these. But note that 18
22	percent mortality even in patients who had UTIs and

acute pyelonephritis. Again, not typical of the types 1 of patients that you're going to be enrolling with a 2 UTI or acute pyelonephritis study and the typical 3 4 registration trial as well. Many of these patients spent many, many days related to their CRE infection 5 in the intensive care unit. As well, many of these 6 7 patients being hospitalized certainly related to their 8 index CRE infection for weeks at a time.

Now, what about best available therapy? 9 10 What did we learn about that? Well, not surprisingly, the percentage here of non-susceptibility among 11 12 existing antibiotics was pretty high. Quinolone's up 13 to 90 percent. Even colistin/polymyxin B, up to 25 percent of them were non-susceptible based upon in 14 15 vitro susceptibility testing. Now, probably one of 16 the -- I was trying to figure out how do I summarize all this in terms of the therapies that we saw. 17 And 18 we saw everything from one-drug to four-drug therapies 19 with about two-thirds of patients either getting mono therapy or three-drug therapy. But there was actually 20 21 69 different directed therapy antimicrobial regimens, 22 okay? Sixty-nine different regimens involving one to

1	four drugs as part of that. I'd say that's not much
2	of a consensus in terms of what you have and what
3	you're going to get in these trials because of
4	differential susceptibilities is lots of variability
5	in what the control regimens are going to be.

6 So how did this help us then design the 7 trial that ended up as being TANGO II? And the team 8 worked then to really expect the enrollment. Our experience was not unlike that which Ian recounted for 9 10 you is that a lot of these patients were getting 11 knocked out based upon the usual types of exclusion 12 So allowing immunocompromised patients, criteria. 13 including those with prior organ -- solid organ transplants, those patients even on hemodialysis as 14 15 well as have severe renal disease and also liver 16 And then, as shown there kind of in the fine disease. print, which is always the dreaded language that 17 18 knocks out a lot of patients with life threatening 19 diseases with all sorts of medical complications, we 20 changed that to simply be those patients broadly 21 defined as having life threatening diseases with the 2.2 subject needs to be surviving more than 72 hours from

1 randomization.

2	Well, finally, let me make a it's like
3	one of those things, Joe, if you've ever asked for
4	comments, be careful what you wish for. So let me
5	make a few comments about a couple of things in terms
б	of clinical trial networks and so forth as we sort of
7	reflect upon this experience. We believe that the
8	clinical trial network discussion is a really helpful
9	one right now. But we believe that those are mostly
10	going to be useful studying patients with resistant
11	pathogens like CRE. We don't think that that's going
12	to be very helpful with doing networks of registration
13	trials such as in complicated urinary tract infections
14	and intra-abdominal infections. We already know how
15	to do those trials.

16 I'm not convinced that there's going to be 17 much cost savings by being able to cycle through 18 those. I think that the clinical trial networks and 19 public funding for that should be used to help us 20 solve the tough problems, not just saving cost should 21 be the driver here. But it needs to be helping us to 22 solve the problems. And one of the problems that we

1	had of course for us was trying to could we use
2	rapid diagnostics, susceptibilities, resistance
3	testing programs within the context of a trial. That
4	would be very helpful to have within a trial network.
5	Help us identify which of those 69 regimens might be
6	the best available therapy regimen to carry forward
7	that would be helpful for that. Then that would serve
8	as a basis for evaluation of these new agents.
9	And of course strategies for managing these
10	patients as well. And I think Ian would probably join
11	me in saying we're kind of battle-worn going through
12	this. And again, if this were part of a our
13	experience was part of a network, it would have been
14	nice to have this experience preserved in some way
15	such that we can be able to get the kind of
16	information that I think we all would like to see as
17	part of our as part of our experience carrying
18	forward in these patients.
19	Lastly, I'll add our voice as well to the

19 Lastly, I'll add our voice as well to the 20 idea that communicating the experience in these 21 patient populations and pathogens is of interest, from 22 a modeling standpoint as well as from descriptive

1	information, with the modeling approaches that we've
2	touched on and heard about earlier as well. And I
3	recognize that there are differences between Europe
4	and the U.S. with respect to this. I know the Code of
5	Federal Regulations is very specific about this. And
б	I would just simply say if we need the CFR changed,
7	let's change it so that we can be able to communicate
8	this information to clinicians as well.
9	So just in summary, what I think we would
10	all add here is that, very similar to the points made
11	earlier, is that don't expect these clinical trials in
12	these patients with pathogens of interest is to really
13	yield the same information as guidance-directed
14	registration trials. Absolutely agree that these non-
15	inferiority trial approaches are really good ones for
16	us to really get the pivotal information. But you
17	need to get information I think in the target patient
18	population. That really helps us to really understand
19	these drugs. You don't do these for inferential
20	testing. I think others have made that point very
21	well this morning as well.

22

We can use these studies and the

1	information, particularly using PK/PD bridges to get
2	us there. So information from larger clinical trials
3	can of course be informative for interpreting these
4	trials as well. And we would say that these studies
5	are difficult. There's no question. But they're
6	important. They're enrollable. And I think that we
7	need to look at ways that we can basically be able to
8	make these trials happen here and figure out ways to
9	have these in the product labeling.
10	And finally, I'd like to thank my
11	colleagues, particularly Jeff Loutit, Elizabeth
12	Alexander and others that participated in the TANGO II
13	and the 506 natural history study investigations.
14	These are hard things. And I'd also like to thank
15	BARDA for their ongoing support. Thank you.
16	[Applause.]
17	CLARIFYING QUESTIONS (PANELISTS AND
18	AUDIENCE)
19	DR. COX: Thank you, Mike. Now, we'll move
20	over to a brief clarifying questions for the
21	panelists. And Joe, I might just ask one clarifying
22	question from you. Thinking back, just help me

1	remember what you were thinking in terms of the
2	clinical trial network and the focus. Was it on the
3	non-inferiority trial designs or was it for the drug-
4	resistant or was it for both?
5	DR. LARSEN: It was for non-inferiority
6	standard clinical trials. And it was more about
7	streamlining the fact that we have to pay to establish
8	the infrastructure to do these trials each time we do
9	it.
10	DR. BOUCHER: So I wanted to just ask a
11	question or follow-up about the clinical trial network
12	because I thought there was some that part of the
13	reason that we didn't have more U.S. participation in
14	a lot of these trials had to do with the fact that a
15	lot of academic centers aren't sort of up to speed
16	with doing high quality registration-type trials in a
17	reproducibly high quality and efficient way and that
18	part of the rationale for this network was to do that
19	because we know we have the patients.
20	But many of us in academia aren't
21	participants in industry trial and I think it's
22	because it's not necessarily because we don't want

	5
1	to be. It's because we don't necessarily meet the
2	criteria. We don't perform well enough and as an
3	academic I can sort of say that. So one idea of
4	having a trial like Joe is outlining is that people
5	would be up to speed. They'd have an infrastructure
6	to be enrolling patients with whichever indication,
7	whether it's intra-abdominal, UTI I mean, they're
8	slightly different actually.
9	But if we had that kind of infrastructure
10	going, if we had down to the study coordinators - we
11	weren't always renting one for each study that that
12	would make it more efficient and I think certainly a
13	global desire would be to include more of those
14	patients. So I just would love to hear from Ian and
15	Mike a little bit more about thoughts.
16	DR. MARKS: So maybe we'll go from John to
17	Dennis and then we'll come back and see if Ian and
18	Mike have additional comments.
19	DR. REX: So to pick up on the theme about
20	the trial network and then segue a little bit, the
21	you know, Mike, you're right. We do know how to do
22	complicated UTI studies. But at the same time, every

1	time we do one, even though I know how to do it,
2	there's always the six-month ramp-up. You always have
3	to go out and train all the sites. It takes time to
4	get going. And that time lag is just a function of
5	how fast you can roll it out. One of the fundamental
6	ideas behind the UDR-focused network was that the
7	network would be on constantly. The sites and at
8	your site, every time you see an intra-ab, you think,
9	trial network. And maybe they're only going to get
10	randomized to meropenem because that's the only active
11	drug. But you're actually paying for a clinical trial
12	coordinator. The system is up and running and you
13	bring a new drug in and it's instantly on at a hundred
14	sites that are already enrolling. And so, the notion
15	is it's almost an instant-on and instant-off of the
16	drug that gets dropped into the system.
17	There's a paper that's going to come out in
18	Clinical Infectious Diseases in a couple of weeks.
19	Anthony McDonald, the first author, is an economist
20	with whom I worked and we actually model it average
21	40 percent cost and time savings, if you actually get
22	one of these networks up and running. So it's not

1	that we don't know how to do it. It's that we
2	there's an inherent inefficiency every company has
3	to build a one-off trial network to do its program.
4	and that just takes time to turn on and turn off. So
5	that's the trick.

6 So but a question for the agencies. 7 Listening to these comments about the harder one, 8 particularly Ian's slide about how different the EPIC -- different the two groups were in terms of renal 9 10 function, it made me think this is the same problem we 11 have in pediatrics where what we have is the 12 difficulty with it's an unusual patient group, if you 13 will. They're relatively harder to get at. And yet, we would very much like to be enabled to use the drug 14 15 in that setting.

And the evolution of our thinking in infectives is moving from I'd like to have an efficacy study in two-month-olds with your new drug, which people would say, I'll do that, and then five years later you couldn't do it, to just give me the PK data to tell me how do I dose it in a neonate, how do I dose it in a four-month-old. Could it be that we need

1 to take a page out of the idea of the evolution of the 2 thinking about pediatrics and say maybe that's kind of 3 what we're trying to do here, is tell me how to dose 4 it in, you know, fill in the name of, you know, a 5 goofy subset.

No, a good point is the --6 DR. COX: Yeah. 7 you know, as the talks have been going on and we've 8 been looking at the PK results and seeing some of the differences in the two groups, you know, it does seem 9 10 like a very valuable piece of information that can be qathered from these different patient populations. 11 Ι 12 kind of hinted at this just briefly in my talk to the 13 issue of generalizability if we are doing, you know, NI studies because they are feasible and that's where 14 you can study, you know, the safety and the efficacy 15 of a drug in a population where you can enroll a fair 16 number of patients. 17

18 If the trial and patients with more highly 19 resistant organisms is one where it's just simply hard 20 to find the patients. It's hard to enroll. Then it 21 does seem like, you know, gathering PK data from that 22 patient population could be particularly informative

1	and could help to, you know, understand better how to
2	use that drug in that patient population. And if
3	it's, you know, a more abbreviated program focused on
4	unmet need, it seems like that's an important piece of
5	information in essence to bridge over to that
6	population, if you will.
7	The other thing to think about too is that
8	is there a way within the NI trials because I don't
9	think it's the resistance phenotype per se that's
10	driving, you know, the question about generalizability
11	here. I think it's more, you know, who are these
12	patients with regards to their comorbidities and all
13	the other factors. So to the extent that you can
14	understand that, whether that be in the patients that
15	are enrolled in the NI trial because you seek out
16	patients that are sicker or have greater numbers of
17	comorbidities, that may also help to bridge the gap to
18	some extent too.
19	DR. MARKS: So before we go to Dennis, just
20	quick from Marco. Then we'll go to Dennis and then
21	back to Mike.
22	DR. CAVALERI: Yeah. Just to add to what Ed

1	was saying, I think, yeah, indeed this is an important
2	aspect. And I would like also to come back to what
3	Paul was saying this morning. We are asking
4	developers to consider straightaway if the new
5	antibiotic is for unmet need and we'll be using the
6	ICU to generate PK data in those patient populations
7	because we know that there is an increased renal
8	clearance. And we want to see the data and the target
9	attainment there.
10	So it's pretty clear that we are demanding
11	this data and it will be very important and would
12	bring up, you know, important information from the
13	standpoint of what could be the activity in this
14	patient population. And pediatrics, as you may know,
15	we started working on an addendum of our guidance.
16	And indeed, one of the options that we were looking to
17	is how much we can use PK data in order to support
18	extrapolation to the various pediatric age groups.
19	DR. COX: Yeah, and one more quick point
20	too. I think it may have been in Ian's talk. He
21	talked about how, you know, the exclusion criteria
22	essentially you know, that the patients wouldn't

1	get into the NI trial. I mean, that gives good reason
2	I think for us to look back at the exclusion criteria
3	for the NI trial because we probably shouldn't be
4	excluding those patients. We should be getting them
5	into the trial because, you know, we need to know how
6	the drug works in that group of patients too.
7	DR. MARKS: So, Dennis?
8	DR. DIXON: Just to speak to Helen's point
9	about the being up to speed or not in the United
10	States, and I'll limit my comments to a very special
11	subset of trials, not the usual registrational trial
12	and network but rather the public health questions of
13	resistant pathogens, be there Enterobacteriaceae or
14	non-Enterobacteriaceae for carbapenem resistance. And
15	with our experience on one large PK study,
16	observational, and one large so large in that case
17	was 150 large in the randomized control trial with
18	colistin alone versus colistin plus the carbapenem
19	would be over 400.
20	The primary factor was the density of
21	infections at the site. And so, quality was not an
22	issue in the preponderance of the United States sites.

We enrolled zero to one subjects per year at most of 1 Closed those sites, added international sites 2 them. and now we have a subset that are enrolling three to 3 4 five subjects per month. And we have come up with this concept of alignment of networks rather than 5 building one we can't afford in the beginning. 6 And 7 the alignment is our contract-based trial on 8 carbapenem alone -- colistin alone versus carbapenem, we're aligning with COMBACT. And we have the hope of 9 10 adding up to 10 sites in the next two years that could 11 enroll in that range.

12 And on paper, if we find those sites, we 13 will complete the study. How many times do things work out exactly -- within three years or so. 14 But we 15 know that time could tell otherwise on that. So it 16 wasn't the quality, but it was the absolute incidence 17 of infection, going to places like Greece and other 18 places in Europe to find those places through census 19 and site assessment and retrospective analysis of the subjects relative to the exclusion criteria look like 20 21 they would work. So that's what we're hoping to do. 22 And we also had an all carbapenem study to -- in our

1	colistin study to expand the definition of pneumonia
2	because the subjects were not meeting the pre-
3	specified criteria. We've modified that to be more
4	liberal to improve our numbers.
5	DR. MARKS: So we'll go to Mike. We'll give
6	Ian an opportunity. And if you have questions in the
7	audience, if you'd just make your way to the
8	microphones, we'll get to you next as we head towards
9	lunch.
10	DR. DUDLEY: Yeah. Let me just kind of
11	elaborate on a couple of things that John and Helen
12	have mentioned as well. And I'm sensitive to the idea
13	of the time lag that it may take. I think there's a
14	couple of responses to that. One is we're actually
15	quite aware right now, since we've stopped enrollment
16	at our UTI trials, that another company has been able
17	to come in and make very, very good use of that
18	infrastructure through a CRO. So I guess I would say
19	that a healthy clinical trials environment, which is
20	what CROs were designed to do in the first place, was
21	to basically set up networks where you could do trials
22	like these is probably what you need.

1	We've gone through somewhat of a nuclear
2	winter over the last decade with not a lot of
3	development. So a lot of the stuff has had to be put
4	together from scratch. But at least we're more than
5	one program where they haven't experienced much of a
6	time lag at all and been able to sort of tack on top
7	of that.
_	

8 Secondly, I don't think clinical trial network is going to solve some of the fundamental 9 10 problems that we have in that. And Helen, to your 11 point, it's not so much a quality issue. It's an 12 issue now that oftentimes, for example, the Stop 13 Sepsis campaigns that say you've got to have antibiotics in within 24 hours really work against 14 15 Most of the clinical trials that are done now that. 16 in urinary tract and intra-abdominal infections, 17 particularly in urinary tract infections, are done ex-18 Infectious disease clinicians aren't interested U.S. 19 in doing urinary tract infection studies in a normally 20 healthy population of patients that are in that; same thing with intra-abdominal infections. 21

22

So you know, we're talking about usually

1	different people who want to do those trials. Most of
2	the trials our experience was the same as others',
3	that most of the urinary tract infection patients are
4	enrolled ex-U.S. And I don't think a clinical trial
5	network is going to solve all that as well. I think
6	that what we what we if we're going to put some
7	resource against that, I would say that let's try to
8	get infectious disease clinicians that are struggling
9	with CRE and other multi-drug or XDR-resistant
10	infections engaged by a trial network that's going to
11	be talking about getting information in those patient
12	populations. And I think let's help the CRO industry
13	do what they're good at doing and setting up trials
14	and having a vibrant pipeline that will make use of
15	that.
16	DR. MARKS: So thanks, Mike. So we'll go to
17	Helen quickly. We'll finish with Ian, unless Dan had
18	something so Ian and Dan. Then we'll take lunch.
19	How about that?
20	DR. BOUCHER: Yeah. So just really quickly,
21	I hear you on all fronts. And certainly no one's more
22	enthusiastic about studying CRE than I am. But we've

1	heard from a lot of IDSA members and people in LLG and
2	other groups that people in America infectious
3	disease physicians in America aren't interested in
4	studying in a Phase III way these infections, but find
5	it incredibly difficult with the academic sort of
6	structure, when you don't have infrastructure to be
7	running a trial and you can't have a coordinator all
8	the time because you don't have a budget. And this up
9	and down is just not tenable for folks.
10	But you know, there is an interest and I
11	think for our patients, it really matters. But from
12	the IDSA perspective, you know, it's worth figuring
13	this out. And I think to Joe's earlier point, you
14	know, if this network was functioning, we could learn
15	a lot of other things about natural history of this
16	disease, about diagnostics, about, you know, even
17	other drugs that might not be being developed by a
18	sponsor, but that might be useful to take off the
19	shelf. And we haven't even touched that subject. But
20	I think again just to sort of make sure we don't kill
21	this too quickly, I think that there are some other
22	potential benefits. And at some level, it still

1 troubles me as a doc to think that I'm going to be 2 giving my patients drugs that are developed 80 percent 3 ex-U.S. when we have patients here who have these 4 infections.

DR. MARKS: So, Ian?

5

So I'm going to echo a lot 6 DR. FRIEDLAND: 7 of what Mike was saying. I definitely do take what 8 John is saying in that having a little bit more efficient, shorter start times is valuable to 9 10 sponsors. But we can actually run UTI II trials, yes. 11 Money would be -- having funding would be good and if 12 you give us the funding, we can run those trials. We 13 can't run them that well in the U.S. Helen's exactly right. And it's for other reasons -- they may be the 14 15 ones that you think of. For example, UTI -- U.S. 16 investigators will not treat on an IV drug for seven 17 days. So we actually can't enroll those patients in 18 the U.S. But in other countries, that's their 19 standard of care.

20 So I think there are lots of reasons why the 21 U.S. goes -- it's not just lack of experience of the 22 U.S. investigators. But where we do struggle is

1	exactly where Mike Dudley referred to, is if we're
2	setting up these unmet need populations, different
3	kind of populations, we don't know enough about them
4	to really design efficient trials upfront. And then,
5	we learn as we're conducting the trial of all the
6	errors we made. It makes much more sense that we
7	first do the research up front, learn about the
8	population, learn about the inclusions/exclusions and
9	then we can design the trials more efficiently. And
10	that's where I think something like a network could be
11	very useful, gathering that kind of information for us
12	before actually conduct the trials.
13	DR. MARKS: Thanks, Ian. Dan, and then
14	we'll come back.
15	DR. RUBIN: So, first I want to thank the
16	two groups for conducting trials in this very
17	difficult area, in the patients with greatest need. I
18	just have two clarifying questions for Dr. Friedland.
19	First, could you talk a little about what, if any,
20	difficulties the availability of ceftazidime-avibactam
21	during your trial had on your ability to randomize to
22	a colistin-based comparator and whether that was any

1	factor in the enrollment challenges? And then
2	secondly, you mentioned the issues with emerging
3	colistin resistance and the fact that those patients
4	had to be excluded due to the colistin-based
5	comparator regimen. I was wondering wouldn't that
6	emergence of colistin resistance actually make it
7	easier to show a difference or superiority, if not
8	using if using a best available-type therapy
9	regimen in your analysis for the future. Thanks.
10	DR. MARKS: So maybe we do it this way,
11	because we have an hour right after lunch and this
12	discussion ponder that over a sandwich or whatever.
13	But I did want to get a quick comment from Sam, and
14	then we'll come back. And Dan, if you'll remind us of
15	that right at the very beginning, then we'll get to
16	you. Is that okay? Thank you. Sam?
17	DR. BOZZETTE: I want to quickly pick up on
18	what Helen and Mike were saying and point out that
19	there are additional benefits to having clinical
20	trials networks that are, you know, external
21	externalities, if you will external to the conduct
22	of the trial itself. You often increase quality of

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1	care and you develop a cadre of clinical trialists and
2	experts in the field. I think that's what happened
3	with the AIDS clinical trials groups, for example.
4	That's worked very well and essentially the whole
5	notion of the HIV physician came out of that effort.
6	DR. MARKS: Thank you. Okay. No questions
7	from the audience. So why don't we adjourn? We'll
8	come back since I got the time wrong last time, let
9	me look
10	DR. COX: At 1 o'clock?
11	DR. MARKS: At 1 o'clock. Thanks very much.
12	[WHEREUPON, the foregoing went off the
13	record at 12:21 p.m., and went back on the record
14	at 1:09 p.m.]
15	PANEL DISCUSSION 2
16	DR. COX: we'll start in about one
17	minute. I'll make a trip outside in just a sec just
18	to bring folks in if we don't all sort of manage to
19	get in here.
20	DR. MARKS: All right. Let's go ahead and
21	get started for the panel discussion. I think where
22	we left off was Dan was going to restate is question,

and then we were going to hear from Ian and Mike, at
 least. Dan?

Thanks. So the two questions 3 DR. RUBIN: 4 that were addressed to Dr. Friedland, but anyone else can chime in, were on the availability of ceftazidime-5 avibactam and how that impacted whether it was 6 7 possible to enroll in the colistin-compared superiority trial and then secondly you mentioned the 8 emergence of colistin resistance and comments on the 9 10 rationale for excluding these patients rather than 11 randomizing them to a treatment regimen or best 12 available therapy regimen since that may be the one 13 group where it is possible to evaluate a treatment effect. 14

15 DR. FRIEDLAND: So first on this 16 ceftazidime-avibactam, when we started the trial, 17 ceftazidime-avibactam was not approved, was not 18 available and in fact even now most of our patients 19 are being enrolled in Europe, where ceftazidimeavibactam is not yet available. But it does speak to 20 the fact that these kinds of trials do have a limited 21 22 lifespan because as new therapies do become available,

1	it does become almost impossible to run a trial now
2	versus colistin, in which we have more effective
3	treatments. So I think this is also part of the
4	problem of these trials, is that you can only run them
5	for so many years before new therapies become
6	available and the comparator you chose is no longer
7	now, you know, a valid comparator.
8	What happened with colistin is when we
9	started the trials, colistin resistance wasn't as much
10	of a problem as it has become. So clearly
11	investigators were keen to engage in that study with
12	colistin as a comparator. It was one of the few
13	available options. But it sort of became apparent
14	that colistin resistance was a problem and in fact we
15	picked up colistin resistance from our central lab,
16	that the local sites didn't even know about. And we
17	actually pointed out to them that they actually had
18	colistin resistance and then when they started testing
19	more accurately, they realized that they did have a
20	problem.

They do have alternatives, because it is a it is a required comparator. It's not a best

1	available treatment. It's colistin and they do
2	theoretically have other drugs available like
3	tigecycline. So in that situation where they think
4	they have other therapies rather than colistin, they
5	will they'd be very reluctant to enroll someone in
6	a trial where they know there's a strong likelihood
7	you can be resistant to the comparator. So in that
8	situation, they'd rather not enroll them in the trial.
9	They'd rather wait to get the colistin susceptibility
10	result. And then, if it's susceptible, they'll run
11	the trial. But if it's resistant, then they're going
12	to look for alternative treatment and not put them in
13	the trial. So I think that's sort of the situation
14	we're in now.
15	DR. DUDLEY: Yeah. The only thing I'll add
16	to that was actually I think we've chatted with Dr.
17	Alexander, who's running our TANGO II trial. And she
18	actually thinks that it's actually helped, although we
19	don't again, Avycaz is not available in Europe yet.
20	But in the United States, it actually has helped the
21	awareness a bit and that patients don't have to
22	necessarily be randomized to colistin. So Avycaz is

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1	fair game in the best available therapy arm.
2	DR. MARKS: Go ahead, John.
3	DR. REX: Well, if you listen to the theme
4	there, you know, Avycaz should be increasingly
5	available towards the end of this year. And then,
6	you're going to be filing you think you're going to
7	file your NDA when, for
8	DR. DUDLEY: Publicly we've said second half
9	first half of next year. Okay, so 2017 our
10	utility date
11	DR. REX: Yeah.
12	DR. DUDLEY: So 2017. So, and then,
13	plazomicin will come along. So sometime in fast-
14	forward two years from now. There could be two or
15	three choices that, you know, are each one of them
16	has its quirks. But you know, net of it is it will be
17	really hard to explain to somebody why they should be
18	randomized to colistin. The echo over here was thank
19	God.
20	DR. MARKS: Sam?
21	DR. BOZZETTE: Is a general comment in
22	order? Okay. This morning okay, never mind. In

1	general, this morning's discussions didn't hit the
2	role of diagnostics much. And I thought that I should
3	say a couple of words on that. First of all,
4	diagnostics should be able to provide substantial
5	efficiencies in the conduct of these trials by helping
6	to identify who actually has a bacterial infection as
7	opposed to some other condition that put them in the
8	ICU and made them toxic and septic-looking. In terms
9	of rapid identification, and particularly
10	antimicrobial sensitivity testing, probably through
11	genotypes, but they have their issues, the whole
12	genotype/phenotype issue and I think the industry is
13	working hard to get to rapid phenotypic sensitivity.
14	And I suppose in the case of genotypes I should say
15	resistance testing rather than that.
16	And the other thing I guess I would say is
17	that and the thing that really hits me from this
18	morning is the possibility of a virtuous cycle with
19	drug development and diagnostics, the idea that
20	diagnostics could help the conduct of trials,
21	particularly through patient selection up front, by
22	allowing people to discontinue or dis-enroll patients

1	when it becomes clear that they don't have the
2	organism infection of interest. But at the same time,
3	these trials particularly the trials networks are
4	perfect sources for development of diagnostics. One
5	of our big problems is that we don't have a lot of
6	money. And just accumulating the specimen banks is
7	pretty much shoots our development budget for a lot of
8	potential diagnostics.

9 So the idea that we could draw from both the 10 control and the various active arms in a master protocol context I think is something that would be 11 12 tremendously helpful for us. And then, the 13 diagnostics that are developed through that mechanism could feed back into the trials, even during the 14 15 course of the trials. If a trial's ongoing and we 16 develop a better way of determining the patients of 17 interest, that could be incorporated into the trials as it goes along. So I think this idea of a virtuous 18 19 cycle is something that the group should look at, you 20 know, very seriously. We're going to have some conversations about how to do that and I hope other 21 2.2 people who are interested in diagnostics and other

1	diagnostic companies could participate as well.
2	DR. MARKS: Any follow-up on that piece? I
3	mean, I think from most everybody I've ever talked to,
4	diagnostics are critical in this as part of the
5	solution. Every report I see that comes out also
6	calls for that as well. John?
7	DR. REX: Just to extend on that, I really
8	do think that the diagnostics could make trials more
9	efficient. But there's something that Ed has it's
10	taken me a while to fully articulate this. The
11	diagnostics enable you to find the patient. But it
12	doesn't make the patient with the rare bacteria more
13	common. So it enables you to find them. It doesn't
14	create them. And so, if the target organism is
15	only occurs, you know, 2 percent of the time, it only
16	occurs 2 percent of the time. And the test would
17	enable would mean you might miss fewer of them.
18	You'd be able to find a few more. You'd be able to
19	find them a little and maybe the patients you enroll
20	in the trial would be once you actually enroll,
21	would be much more likely to have the target organism,
22	the ones you actually enroll. But you still have to

1 screen the other 98 who didn't have it in order to 2 find the two.

There's no substitute for running the test 3 4 in a hundred people to get those two. And that's actually one of the things about the trial network 5 concept focused on the UDR setting where everybody 6 with intra-ab gets enrolled is that you could actually 7 8 inside that be looking for the oddball pathogens 9 because you're actually going to -- you've got 10 something to do for everybody in a UDR-focused study. 11 Everybody with intra-ab in a UDR network gets enrolled 12 and you can run your diagnostic on them and pick out 13 the unusual ones and spin them into something else.

I would agree with you that 14 DR. BOZZETTE: 15 the main utility would be the ability to screen out 16 individuals. You're not going to make more individuals with disease. But if you have -- if 17 18 you're talking about a condition in which there is an 19 imperative to treat, the difference between only having to do that with a single dose or two doses 20 21 versus following the person for two or three days 22 should be substantial, I would think.

1	DR. REX: Right. And the big cost is
2	it's the enrolled patient that's the most expensive
3	part.

4 DR. BOZZETTE: Oh, absolutely. Absolutely. 5 DR. REX: I say that -- I should really say that -- I don't know the precise percentage. But a 6 7 big part of our budget isn't just the cost of the 8 patient. It's the running cost of the site. So I've got to have the IDP and the pharmacy. I've got to, 9 10 you know, go back and audit. I've got to, you know, do all that stuff just to keep the site up and 11 12 running. And so, that's why the patient cost a 13 hundred thousand dollars. It's not because I spend a 14 hundred thousand dollars on that patient.

DR. MARKS: So why don't we bounce to Nick? Then we'll do Kert and then our colleagues in the audience.

DR. KARTSONIS: I just want to make an additional comment about that and then maybe ask a question to Ian and Mike about their experiences, because we're doing a resistant infection study right now for imipenem-relebactam. And one of the things

1	that we've done from a diagnostic standpoint is we've
2	two years' ahead of time, we actually developed the
3	panels that actually had imipenem, as well as
4	colistin, as well as imipenem-relebactam and literally
5	gave them to all of our sites to use as screening
6	tools, susceptibility panels. That obviously cost
7	time and money to do that. It's not a simple endeavor
8	and I can tell you it cost millions of dollars to
9	implement that.
10	What it has shown us, and it's probably a
11	poor man's diagnostic, is that, as John has alluded
12	to, we're picking up 1 to 2 percent of all and
13	we're obviously in geographically enriched regions
14	that have the resistant infections. But we're still
15	only picking up 1 to 2 percent of all of the KPCs
16	and/or resistant Pseudomonas you know, carbapenem-
17	resistant Pseudomonas pathogens and what have you. So
18	I guess a question I have for Mike and Ian is have you
19	used any enrichment tools? Have you used any
20	diagnostics that might help you expand on TANGO II
21	that you're willing to share or from the CARE study?
22	DR. FRIEDLAND: So we allow our sites to use

1	whatever rapid diagnostics they have available. And a
2	lot of our sites, like in Greece, do have rapid
3	diagnostics. We don't have one specific diagnostic
4	that we you know, that we demand. But a lot of our
5	sites do use their local and that has been very
6	helpful. They can enroll patients sooner with that.
7	DR. DUDLEY: Yeah. My colleague, Jeff
8	Loutit, is actually at the microphone and we have
9	actually discussed this. So maybe, Jeff, if you want
10	to comment on how we have been thinking about
11	enrichment with the diagnostics and so forth?
12	DR. LOUTIT: Yeah. Thanks, Mike. And this
13	speaks to the comments from John and Sam as well. So
14	as part of so I work with Mike as part of The
15	Medicines Company and work with Elizabeth in running
16	the TANGO II trial. We're part of the consortium to
17	develop a cartridge through Cepheid to look at
18	identification of CRE directly from specimens so
19	urinary tract or respiratory tract specimens, et
20	cetera.
21	What was very and we then went out and
22	found that pretty much every site that we were going

1	to, had the GeneXpert system. So we knew they could
2	do it. And then, we said, okay, how about actually
3	screening all these patients who have suspected CRE.
4	And you saw the numbers that Ian put up there,
5	essentially screening close to 600 patients to get to
6	14. And the microlabs just looked at us and said,
7	you're out of your mind. So we cannot we could not
8	get at least the microlabs to want to take on that
9	work to screen patients into the study. So we have
10	the test. We have the patients. We have the machine
11	to run the test. We just don't have the ability for
12	the microlabs to do that.
13	DR. MARKS: Thanks. Kert?
14	DR. VIELE: I was going to mention that the
15	notion of trial networks in this context with
16	diagnostics, having a network and having multiple
17	drugs, a lot of the newer platform trials that are
18	being run in, say, oncology, they partition a patient
19	stream on the basis of biomarkers, if you have a HER-
20	2-positive breast cancer, you're eligible for certain
21	drugs in the study and not others. Having a network
22	and a central way to do that kind of screening you

1	know, if you imagine that you're running a trial and
2	he's running a trial and you can't enroll the exact
3	same patients, when you encounter a patient that you
4	can't enroll but he can, having a way to take that
5	full patient stream and just efficiently getting it to
6	the drugs that are still in the running for that
7	patient population would be valuable.
8	DR. DUDLEY: Yeah. I would agree. I think
9	the interesting question here for Sam I'll get
10	there in a second. But the elephant in the room right
11	now though is that what we're hearing is that
12	developing these tests for clinical trials from a
13	diagnostic industry standpoint, okay, maybe. But a
14	diagnostic test for use in clinical use for doing
15	exactly what Jeff just described in clinical practice,
16	not enough of a market there. So maybe you could help
17	us understand if that's you know, is that something
18	the way that you see the universe or because I think,
19	yes, having a diagnostic to help us get a clinical
20	trial done is great. But I think what clinicians'
21	expectations are is that they'd really love these
22	direct specimen tests to be able to make those

decisions at the bedside, to be able to put patients
 on the appropriate drug.

3 DR. BOZZETTE: Okay. Let me -- let me one 4 quick comment on the microlabs. One of the barriers 5 to rapid diagnostics is the tradition of microbiology. 6 There are expert systems that will release 7 identifications from automatic machines automatically. 8 They are essentially always right. And at least 9 they're as right as a human would be.

10 But people are reluctant to turn them on 11 because microbiologists are used to looking at the 12 results and releasing the ones that they think are 13 most appropriate. In addition, microlabs tend to run only during the day or at least into the evening. 14 So 15 if you have a diagnostic that takes two or three 16 hours, you run the test at 8 o'clock at night, no 17 one's going to know anyway. And so, we face this when 18 you shorten, say, times to positivity in blood 19 cultures. You know, if a result falls in the forest at 3:00 in the morning and there's no one there, does 20 21 it make a sound? And the answer is no, it doesn't. 2.2 So I think part of the clinical trials

1	infrastructure should involve buffing up laboratories
2	and increasing laboratory capability. Now, in respect
3	to developing tests, we have two problems. One is
4	that we face commodity pricing. We don't have value-
5	based pricing. When a test comes on, they'll look at
6	the cost of a similar test and say, okay, that's what
7	you get. So we get I don't know, we'll get \$80 to
8	do to run a companion diagnostic test on an
9	oncology drug that's costing \$60,000, \$80,000 a year.
10	So we face commodity pricing.
11	And the second thing is cost of development.

11 12 And so, when you look at the NPV for narrowly focused 13 tests, it's just not there. So why are we willing to develop specific tests for specific trials and 14 15 specific drugs? Frankly, because you guys are paying for it. And so, it lowers the development cost and 16 17 our marginal costs, you know, our marginal cost to 18 production will be hopefully not that high and we'll 19 make some money back. So what's the answer? I think 20 what we've heard in terms of decoupling for pharmaceuticals needs to be developed for diagnostics 21 22 as well. So fixed amount of pharmaceuticals, paid for

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1	in an upfront payment of some sort, market entry fee,
2	whatever. And something similar needs to happen to
3	the diagnostics that would go along with that
4	indication.
5	Now, in microbiology, the diagnostics are
6	not going to be true companion diagnostics for a lot
7	of the reasons that John has pointed out in terms of
8	the variety of alternatives and stuff. But when you
9	get into tomorrow I'm sorry I won't be here you
10	may get to the point where we're talking about
11	something that really is a true companion diagnostic.
12	And in that case, we're going to have to tweak the
13	model because the oncology model frankly isn't working
14	for us.
15	DR. MARKS: We have a colleague over at the
16	microphone over there. Just your name and your
17	affiliation, please.
18	DR. CONNELLY: Yeah, Lynn Connelly, with
19	Achaogen. So I work with Ian on the CARE study. In
20	addition to rapid diagnostics, we can look at patient
21	characteristics or epidemiological factors that place
22	them at high risk for infection by the target

1	pathogen. We found that very useful in the context of
2	our study to allow patients to enroll on the basis of
3	being known colonized with CRE or because they reside
4	in an ICU where the rate is so high of CRE. So we can
5	look at things that are less technologically
6	challenging in order to help in all these studies.
7	DR. MARKS: David, your name and your
8	leisurely retirement affiliation?
9	DR. SHLAES: Yeah, David Shlaes, retired.
10	So after hearing today's presentations, it kind of
11	brought me around to thinking about tomorrow. And I
12	had a few thoughts and questions I'd like to share.
13	One question is, Ian and Mike, and we just talked
14	about this, but if you had a drug for which there
15	wasn't the non-inferiority possibility so pathogen-
16	specific given your experience with your CRE
17	development programs and the kinds of patients you
18	have to study, would you as a company be willing to
19	take the risk to do it? And you know, I think that
20	one of the jobs that we'll have to undertake in terms
21	of thinking about feasibility for pathogen-specific
22	drugs, which again I guess we'll talk about tomorrow,

1	is how do we de-risk these sorts of trials. And I
2	think it'll be as we talked about earlier, it'll be
3	important to think about external controls.

4 The other comment I'd like to make is given the importance of pharmacokinetics and PK/PD in the 5 way we're going to be -- we're thinking about the 6 7 drugs that we're talking about today and even more the 8 ones we're going to be talking about tomorrow, from kind of a commercial perspective, when you think about 9 10 how you're going to deal with this with physicians and 11 hospitals treating patients, especially in the United 12 States where 70 percent of hospitals are under a 13 hundred beds or under 200 beds, this is going to require a huge -- I believe a huge educational effort 14 15 to make people understand that PK/PD can actually 16 contribute to their decision-making process for 17 individual patients. So I think those kind of two 18 things, along with external controls, they all kind of make a set of issues that we still have to grapple 19 20 But I'd be interested in comments, especially with. 21 from Mike and Ian, on that.

22

DR. FRIEDLAND: I'll go first on part one.

1	
1	You know, this is the reason why we're having this
2	workshop and why there's the whole discussion tomorrow
3	is because I think we all recognize that there are
4	therapies in development that are pathogen-specific.
5	And I think without figuring out what are the pathways
6	to get these developed is a major disincentive to
7	continuing those programs. I am hopeful that we will
8	come up with something because pathogens like
9	Acinetobacter is far too much of a problem without us
10	coming up with some sort of solution on how to treat
11	these. But I think you are right in that we do have
12	to have some assurance that there is a pathway before
13	one will actually sort of undertake these clinical
14	trials. We may develop them up to the point we get to
15	Phase I and PK/PD. But without knowing the clinical
16	pathway, it's not going to go much further than that.
17	DR. DUDLEY: Yeah. I'll just add a couple -
18	- I may keep our powder dry until tomorrow on the
19	single pathogen. But what I will tell you is that,
20	you know, we have intravenous minocycline, which we
21	recently had approved with a new formulation in the
22	United States. And we'll be looking at a program for

1	Europe where Acinetobacter, as you well know, is, if
2	anything, a bigger problem for multi-drug-resistant
3	Acinetobacter. So that'll we'll talk a little bit
4	more about what our thoughts are about that tomorrow
5	and how that might how one might go through that,
6	where clearly a non-inferiority trial is probably not
7	going to be very feasible there.

8 What I would say about the PK/PD question, I 9 think that a lot of us that have been working in this 10 area have recognized that the educational component 11 needs to come with better software and better ways of 12 communicating what the PK/PD is telling us.

13 So I will -- and Paul may want to comment on this, and I -- because it's his program -- but I think 14 that PK-PD Compass program, which is an iPhone/iPad-15 16 based program which I think really takes all of that 17 information and sort of demystifies a lot of the 18 mathematics and a lot of -- uses real-time information 19 either from an individual hospital or from 20 surveillance data, epidemiologic data and using the best available information that we have about clinical 21 22 pharmacology of these drugs is going to help us I

1	think make better decisions as it relates to thinking
2	about things as not sensitive or resistant, but
3	thinking about I think, as one of our panelists
4	stated here, is that it's a distribution of exposures
5	and a distribution of MICs that will help us make
б	better decisions at the bedside. And I don't know if
7	you want to add anything more, Paul, to that, but
8	thank you.
9	DR. MARKS: Well, we might be interested in
10	Helen's perspective on these in the clinical utility
11	realm of this type of approach.
12	DR. BOUCHER: You know, I agree a hundred
13	percent and I think that we see stewardship programs
14	
14	as a major vehicle for helping to do this. I mean, we
15	as a major vehicle for helping to do this. I mean, we have thankfully a few new drugs and all of those are
15	have thankfully a few new drugs and all of those are
15 16	have thankfully a few new drugs and all of those are being used in stewardship programs where they exist an
15 16 17	have thankfully a few new drugs and all of those are being used in stewardship programs where they exist an we're really happy that CMS has its proposed rule to
15 16 17 18	have thankfully a few new drugs and all of those are being used in stewardship programs where they exist an we're really happy that CMS has its proposed rule to make stewardship a condition of participation in
15 16 17 18 19	have thankfully a few new drugs and all of those are being used in stewardship programs where they exist an we're really happy that CMS has its proposed rule to make stewardship a condition of participation in hospitals in the U.S. I think the form that
15 16 17 18 19 20	have thankfully a few new drugs and all of those are being used in stewardship programs where they exist an we're really happy that CMS has its proposed rule to make stewardship a condition of participation in hospitals in the U.S. I think the form that stewardship takes is going to be different. You know,

program in that setting is like one that one of my former fellows is running now in North Carolina where she sits in Charlotte, but is in charge of stewardship for academic hospitals, community hospitals and indeed physician practices where the largest amount of antibiotic overuse takes place.

7 So you know, stewardship is not always going 8 to be what we have at Tufts. You know, it's going to be different things. But thankfully, I think the era 9 10 is coming where we'll have more and where tools like Dr. Ambrose's tool can be used. I would still 11 12 advocate you need the experts who use it and interpret 13 it and the doctors who we serve largely when we see their patients want what drug at what dose and for how 14 15 long do I give it.

DR. MARKS: So we'll go to John, and then thanks for being patient, and then we'll come to the audience. Thank you.

DR. REX: So picking up on this PK question and unusual populations and sort of thinking about what I said earlier about, you know, pediatrics, you're often thinking about extrapolating based on

1	just getting the PK right in the neonate. One of the
2	changes that has occurred for FDA labeling in the
3	recent years has been that the information around
4	pharmacology has been more and more limited to just
5	the approved indications, and for reasons having to do
6	with the way the Code of Federal Regulations talks
7	about what you can put in the label. And I'm not
8	quite sure for EMA where that is.
9	But I'd like to I guess ask our regulatory
10	colleagues to think out loud about the question of
11	providing the pharmacology data for other scenarios.
12	And in the case of pediatrics, it's little people.
13	And in the case of the rest you know, everybody,
14	it's oddball body types or odd physiologic conditions,
15	that sort of thing. So it's this notion in a

16 sense, it's analogous to the second group of organisms 17 in the microbiology section where the first group, we 18 talk about the ones that actually have clinical data. 19 The second group, we talk about ones where, well, 20 we've never actually studied it, but it looks like it

21 might be susceptible.

22

And so, I'm thinking about those themes and

1	wondering if that's something because we've heard a
2	couple of calls for information in the label from
3	these difficult trials. And it feels like sort of the
4	minimum thing you could get at would be in the spirit
5	of the way we did pediatrics and dosing, could we do
6	that here.

7 DR. COX: All right. So let's see, maybe 8 I'll start out -- I mean, you are right, John. Ι think it was -- I don't know if we used to do it. 9 But 10 I know -- I mean, even 15 years ago, we -- you know, the attention to the information provided with regards 11 12 to drug levels, you know, in various different tissues 13 is, you know, one where the labeling would include information for sites that were relevant, you know, to 14 15 the approved indication.

16 So if you had a skin indication and you had a blister fluid study, the information would be in 17 18 If you also had, you know, information about there. 19 ELF levels, but it didn't have any sort of pneumonia 20 indication, then that indication would not go in the So I think this stems from sort of a balancing 21 label. 22 of providing information, you know, that's consistent

1 with the approved indications and then some concern 2 about providing information that might in essence sort 3 of enable off-label use in the setting of not having 4 an indication that was relevant to the particular 5 tissue fluid level.

You know, this is something that we've been 6 7 looking at a little bit more over, you know, the last, 8 oh, couple of years, I'd say, you know, because it's coming, you know, more apparent that there are 9 10 situations where such information, you know, could be 11 helpful to folks. It is information too that is, you 12 know, essentially straight factual, if you will. Ιt 13 doesn't tell you that the drug is going to work. Ιt does provide you some information about the level in a 14 15 particular tissue fluid. So I would say, you know, 16 this is something that we're still looking at and trying to figure out, you know, how do we balance, you 17 18 know, providing this information. What's the 19 implications for the approved indications, for indications that are essentially not approved or, 20 21 quote, unquote, "off-label"?

22

And then, the other thing too that we always

1	have to be mindful of is that we generally try and
2	take approaches that, you know, are the same. And so,
3	you know, we think about these things a lot of times
4	from the standpoint of the particular therapeutic
5	areas that we look at in, you know, our groups. But
6	there's also implications too for other areas. So
7	there's you know, a fair degree of, you know, trying
8	to navigate through all of the implications of doing
9	something about including information about tissue
10	sites that might be, you know, related to indications
11	that are not approved. So but yeah, no, I understand.
12	And this is something we've talked about it at
13	meetings before over time. This has come up, so
14	DR. MARKS: Marco?
15	MR. CAVALERI: Yeah, I think we are
16	completely in line with what Ed just said about sort
17	of being careful, not promoting off-label use. But of
18	course in the context of the potential of granting an
19	indication per pathogen, it may come up the issue on
20	how to provide information to the prescriber about
21	different set of infections that we did not study,
22	which could be don't do that because the PK is not

1 supporting you. But it might be that the PK is good 2 enough. So you may consider that. So I think here, 3 in that context only, it would be important to try to 4 reflect about how best we could include this kind of 5 information in the SmPC.

DR. MARKS: Thank you, Marco. So we'll 6 7 bounce to our audience. Name and affiliation, please? 8 DR. KINDRICK: Sure. Amy Kindrick, from Genentech Roche. I'd like to go back to something 9 10 that was touched on briefly earlier today and that is 11 the issue of excluding patients with prior antibiotic 12 exposure. The interval I think is 72 hours within 13 which only one dose could have been given. And I think Mike Dudley or Ian Friedland -- I can't remember 14 15 which -- pointed out that it's one of the major 16 reasons for screen failures. And it's a bit of a 17 conundrum because one of the things we know for sure 18 is that prior antibiotic exposure is one of the 19 biggest predictors of antibiotic-resistant infections. So it's really an effort to try to balance scientific 20 21 rigor with the reality, which is that, at least in our 22 experience, large numbers of ICU patients violate that

1	prior antibiotic exposure. So does the panel have any
2	thoughts about ways that potentially we could address
3	that when we're looking at drug-resistant infections?
4	DR. COX: So maybe just a few comments on
5	the issue. So and Dan and Sumathi are going to
6	correct me if I stray here. But essentially, if
7	you're doing a superiority trial, you can have prior
8	therapy. It doesn't really I mean, it decreases
9	your it may decrease your chance of showing
10	superiority if it's effective therapy. But in the
11	setting of a superiority trial, you could use prior
12	therapy. Another situation but if you use too much
13	of it, you may treat the infection and then the
14	ability to show superiority may essentially evaporate.
15	There are situations too where patients get
16	prior therapy and essentially they're failures.
17	They're not responding to therapy and you continue to
18	have positive cultures. So in that situation, the
19	presumption is that you're really not affecting the
20	course of treatment. So that patient could still be
21	enrolled. You know, and we describe that in our
22	guidance documents that talk about non-inferiority

trial designs and, you know, I've already said for
 superiority, you could give antibiotics. So you could
 obviously do it there too.

4 Now, the issue becomes if you're actually treating the infection. You know, and we've heard 5 about the importance of those early doses and, you 6 7 know, the literature bears that out too. The early 8 doses in serious infections are so important and, you know, getting effective therapy on board within hours 9 10 or less, you know, in order to be able to reduce 11 mortality. You know, and if you've actually had a 12 significant impact on the infection, it can be 13 difficult to, you know, do a good test of the antibacterial drug. And no one wants an antibacterial 14 15 drug out there that we really don't know if it works 16 when it's being used for patients with serious infections. 17

So you know, so now, to get to what do we do about this, so the CTTI folks are tackling at least one approach to this. And the way Vance Fowler describes this is that, you know, if there's only so far that we can go with prior therapy on this end of

1	the equation because we'll be treating the infection,
2	what can we do over here. So the CTTI folks are
3	working on a study in HAP/VAP with the first
4	observational phase to understand, you know, who are
5	the patients who are developing HAP/VAP. Can we
6	identify risk factors? Can we pre-consent patients?
7	You know, are there other mechanistic things that can
8	be put in place to minimize, you know, the need for,
9	the pressure for, you know, longer courses of therapy
10	before getting into a trial.
11	And I think, you know, those sorts of
12	efforts I'm very optimistic about this I'm
1 0	hoping it will help. I'm hoping that it will allow
13	noping it will neip. I a noping that it will allow
14	for patients to be, you know, more routinely enrolled
14	for patients to be, you know, more routinely enrolled
14 15	for patients to be, you know, more routinely enrolled into the trial with shorter durations of prior
14 15 16	for patients to be, you know, more routinely enrolled into the trial with shorter durations of prior antibacterial therapy. And if you look at our
14 15 16 17	for patients to be, you know, more routinely enrolled into the trial with shorter durations of prior antibacterial therapy. And if you look at our guidance documents, we do allow some prior
14 15 16 17 18	for patients to be, you know, more routinely enrolled into the trial with shorter durations of prior antibacterial therapy. And if you look at our guidance documents, we do allow some prior antibacterial therapy just because if we didn't, it
14 15 16 17 18 19	for patients to be, you know, more routinely enrolled into the trial with shorter durations of prior antibacterial therapy. And if you look at our guidance documents, we do allow some prior antibacterial therapy just because if we didn't, it would be probably impossible to run a trial.
14 15 16 17 18 19 20	for patients to be, you know, more routinely enrolled into the trial with shorter durations of prior antibacterial therapy. And if you look at our guidance documents, we do allow some prior antibacterial therapy just because if we didn't, it would be probably impossible to run a trial. And in particular, we think it would be

1	situation. I think this underscores really, you know,
2	one of the very difficult challenges in studying an
3	antibacterial drug the urgent need to start
4	therapy, you know. This can happy anywhere at any
5	point in time to any one patient. You know, and you
6	don't really know exactly what you're treating when
7	you start this first course of therapy out.
8	So I think there are efforts being made.
9	But it is a tough problem. And you know, it's not
10	just prior therapy too. But we'll be talking more
11	about this too tomorrow. But it's concomitant therapy
12	also. And you know, to get drugs that don't overlap
13	with the spectrum of your investigational drug,
14	particularly at the point in time when you're
15	initiating empiric therapy, can be really difficult.
16	But at the same time too, you know, if the
17	concomitant therapy is all you really need, then, you
18	know, the quality of the test for assessing the test
19	drug is, you know, really pretty limited. So yeah, so
20	maybe my final comment on this is that I think we all
21	you know, we're all trying to do some things to try
22	and make this better. But it is a it is a

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1 difficult problem, so --
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DR. MARKS: But you certainly don't want to delay starting therapy while you're trying to get informed consent for an investigational agent. So that ability to at least start something makes a big difference. Marco, any other add-ons?

7 No. I think I fully agree DR. CAVALERI: 8 with Ed. This is a very difficult topic. We are 9 putting efforts in trying to allow as much as 10 possible. But we have to be careful in not 11 contaminating the data. So we are open to discuss 12 evidence that is emerging and whether we can allow 13 more. But at this stage, it's difficult to go beyond what we are recommending. 14

DR. MARKS: Thanks. And over to the microphone again? Name and affiliation, please? And then we'll come back to you, Aaron.

DR. HILLAN: Ken Hillan, Achaogen. At the recent ASM, I had an opportunity to talk to someone presenting data on Avycaz and I was asking about susceptibility testing and what they had seen. And they said they didn't know because they actually

1	didn't have susceptibility testing available in the
2	U.S. at their institution. I also went to a seminar
3	at ASM and had an opportunity to learn that it can
4	take three to four years sometime to have broad
5	availability of antimicrobial susceptibility testing.
6	And it seems for these new drugs, we've made amazing
7	progress in getting rapid regulatory pathways to
8	approval.
9	But some relatively basic things, like broad
10	availability of automated susceptibility testing takes
11	so long. And it seemed, at least if you were trying
12	to organize this a priori, you would want the
13	availability of the testing to be available exactly
14	the same time as the availability of the drug. And I
15	wondered could people comment on what we should be
16	striving for moving forwards and what we can do to
17	streamline the process to make both the drug and the
18	susceptibility testing available at the same time.
19	DR. COX: Go ahead. You do it.
20	DR. NAMBIAR: Yeah. So thanks for that
21	comment. I think we're acutely aware of the issue and
22	we've heard it from many different stakeholders, be it

1 sponsors, drug companies like you or clinicians who 2 are trying to use the drug because I think the point 3 you make is very valid. Having that drug approved 4 just doesn't make it, you know, easy for the clinician 5 to use it and use it appropriately. It was very 6 important that these products be used appropriately in 7 the right patient.

So having said that, we know it's a problem. 8 We've heard this in other fora and we are in close 9 10 conversations with our colleagues at CDRH and 11 hopefully in the coming few months we plan to have a 12 public discussion. So I think that would be very 13 good, where we can facilitate the process and the interaction between the various stakeholders to be 14 able to find the solution forward. So I think we 15 16 recognize that this is important and need to address 17 it. Thank you.

Oh, yeah, and Ed reminded me, I think there's also work ongoing -- I don't know if anyone from CDRH is here or not. But there is ongoing work on a draft guidance being published on co-development of diagnostics and that touches upon AST devices as

Page 228 well with drugs. So that's forthcoming. I don't have 1 an exact timeline. But I think your comment is very 2 timely and we are aware of it and we should hopefully 3 4 start the conversation soon. DR. MARKS: Aaron? Oh, David? 5 DR. SHLAES: I was just going to add --6 7 DR. MARKS: You've got a follow-up? 8 DR. SHLAES: A lot of this is not really a regulatory problem. It's a diagnostic company issue. 9 10 So what we used to do in the old days is we would give laboratories discs because the disc criteria are 11 12 available immediately on approval. And they would use 13 the discs and get an idea of what the susceptibilities were in their hospitals and that was a reasonable 14 15 interim step. These days it's harder because 16 microlabs are more constrained. But I think it's an 17 important problem. But there may be ways to deal with 18 it. 19 DR. MARKS: Thanks, David. Aaron? 20 It's kind of a question for MR. DANE: Yes. 21 Mike actually. But, so Mike, you were talking about 22 the idea of like a CRE network rather than a broader

1	network. And I just wondered how that would work, you
2	know, because if you had a much narrower population
3	you were going after, is how you would set up the
4	network in terms of where you go and also getting more
5	cross-sponsor commitment to do that when not
6	everybody's going to be going off to CRE, for example.
7	So I didn't know how you saw that. That maybe
8	DR. DUDLEY: Yeah. Can I have my first
9	slide no. That's a tall that's a tall order.
10	What I what I guess I would say is that what I
11	believe I've heard here is that there is somewhat of a
12	I won't say consensus, but I think a recognition
13	that this type of information is important. And I
14	think that we want to I think take a balanced approach
15	towards looking at this and saying, well, look, there
16	are a number of sponsors that are interested in
17	conducting these types of trials. There are a number
18	of sites and investigators that are interested in
19	developing these trials. We heard from Helen that a
20	lot of them would like to participate, but not having
21	some sort of base support to build infrastructure
22	within their institutions would be helpful.

So this to me sort of sounds like we're 1 asking the right questions when we're asking -- when 2 we're trying to establish trial networks. I think 3 4 that we would just say that it may be useful for us to think about it in the context, and at least from our 5 perspective, that need is more to try to create the 6 7 infrastructure to get these sicker patients into the 8 trials and to get the proper GCP training and base 9 support in those laboratories. Look, we're not going 10 to solve -- what we want is a network of engaged 11 clinical investigators that are in infectious 12 diseases.

And that isn't necessarily what happens in a CUTI network. Those are urologists and people are treating patients in the outpatient. So I think if we want to, you know, address this problem head-on with the best minds, I think I would advocate that let's try to figure out how to crack this problem of getting the sicker patients with CRE into a network.

20 MR. DANE: Yeah, and maybe that's what I was 21 thinking, is you could do both at the same time in 22 some sense.

1	DR. DUDLEY: Yeah.
2	MR. DANE: So if we have a network that
3	isn't too narrow, we can we'll get some resistant
4	pathogen data. I mean, we talked about the
5	operational efficiencies. The other factor that's
6	incredibly important is it can be a much more
7	efficient use of data and patient data because we can
8	share control on. So we could do all of that and try
9	to address some of these resistant pathogen questions
10	at the same time I think.
11	DR. DUDLEY: Yeah. I think clinicians would
12	like to know, out of those 69 regimens that we
13	identified in our natural history, which of the few of
14	those look pretty good. And so, I think strategy
15	trials and, you know, Sam mentioned ACTG and I'm from
16	that era as well where the clinical trial networks
17	with AIDS clinical trials was instrumental. And not
18	so much in actually developing new drugs. It did do
19	that, but it actually was understanding strategies of
20	how to use them. Do I start with two drugs or do I
21	start with three drugs? When do I add the third drug?
22	What patient populations benefit by that?

1	Those were enormously important questions
2	that served as the basis for HIV treatment guidelines
3	for decades and they were based on those. So yes,
4	let's go ahead and create a network now and answer the
5	question what is the best available therapy. So, and
6	then set that framework so that we can start rotating
7	these new therapies in, much like what others have
8	proposed.

9 I think the other aspect to that MR. DANE: 10 -- we were talking about over lunch, which is if you got to a point where that network and the data were 11 12 broad enough, you might even be able to have a new 13 product coming through and you can somehow try and match the patients to the appropriate ones that you've 14 15 got. And that might give you a more meaningful 16 comparison than what we try to do at the moment.

DR. COX: Yeah, maybe just to follow up, and Aaron, you may have been hinting at this, if you've already said it. But I'm trying to figure out -- so if, you know, resistant phenotype is not really a determining factor per se, but it's more patient comorbidities and patient factors, I mean, surely

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1	there must be other patients out there with similar
2	comorbidities, similar factors who don't necessarily
3	have the resistant phenotype. I think that may be
4	what you were getting at.
5	MR. DANE: Yeah, last point, that's exactly
6	it. Yeah, so it might be that you can try and match
7	people up a bit more and you'll have a richer data set
8	to do that with.
9	DR. COX: If the particular resistant
10	phenotype is really so rare that it's hard to
11	constitute the trial. But if there's a lot of other
12	similar people with regards to other patient factors
13	but, you know, they may have the organism, they may

have -- you know, they may not have the particular 14 15 resistant phenotype. It seems like that may be the 16 sort of information that could be helpful and then you 17 wouldn't necessarily be so restricted by the 18 prevalence of a phenotype -- resistant phenotype 19 that's exceedingly difficult to identify.

20 MR. DANE: Yeah, and you're more likely to get that in a network than just your single narrow 21 22 trial where you may get a couple of patients like

1 that.

2 DR. MARKS: Sam? DR. BOZZETTE: Can I say something about why 3 4 development diagnostics is low --DR. LOUIS: Just one more quick promotion of 5 networks and that is for patients who may not be 6 available for any of these trials and are in what 7 8 would hope to be an observational database, you'd still want to have it be observational and not passive 9 10 with standardized data collection. And that really won't happen I think without some kind of a network 11 12 wrapper on the whole thing. 13 DR. BOZZETTE: I think that to accelerate the development of automated diagnostics, what's going 14 15 to have to happen is to have -- for these purposes is 16 to have sort of a stable pipeline of customers, meaning pharmaceutical companies. And we need to 17 18 start collaborating much earlier than we do now. Ιt 19 is not so easy -- it's not the same thing as developing a disc or an e-test where you can just say 20 21 one drug because there are only a limited number of 22 slots in these cards. And every time we change one,

1	we have to make an essentially new application because
2	it's a new card. So it's complicated, but doable.
3	And I think that, as I said, what we really need is to
4	upstream the collaboration so that this just works
5	better for everybody.

6 DR. COX: I might ask -- I mean, we're 7 almost at 2 o'clock. But before we, you know, leave 8 this little section -- and we can come back to it later if there's a whole bunch more thoughts -- but a 9 10 difficult problem. You know, we've heard some about, 11 you know, the patients that we might see in a non-12 inferiority trial. We've seen data about who actually 13 gets in to, quote, unquote, the "resistant", you know, pathogen studies that have been out there. 14 Some of 15 the PK differences. We've heard some of the ideas 16 about how we might approach, you know, the PK being 17 one of the things we can measure. You know, Aaron was 18 mentioning the idea of, you know, maybe you can enroll 19 patients with similar comorbidities who didn't necessarily have the resistance phenotype of interest. 20 21 I'm wondering are there any more thoughts on 22 potential ways to address, you know, the issue of, you

1	know, the differences in the patient populations to
2	get at, you know, how you could generalize information
3	beyond these two ideas, both of which are good ideas,
4	because it seems like this is an important issue.
5	Other thoughts or other ways we might tackle that?
6	And if there's nothing, maybe you know, we can
7	always come back to it later on if people come up with
8	good solutions because it's a difficult problem. And
9	that's why I'm asking the question. I think, you
10	know, we've got two good ideas about things that could
11	be done. I'm just wondering if folks have any other
12	thoughts.
13	MR. DANE: Well, I guess if you were
14	confident enough about the characteristics you had or
15	are there other external sources of information you
16	could draw upon. I mean, I can't think of any
17	straightaway. But that might be another potential as
18	a way of providing some context for what you see in
1 0	

19 some of these smaller studies, particularly in areas 20 where we anticipate the responses to be pretty low. 21 So then you can say, well, if we have got a relatively 22 small number and the responses are much better, that Γ

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1	gives us a lot of confidence about what we're doing.
2	DR. MARKS: One final question before we go
3	back to the presentation. Name and affiliation,
4	please?
5	MR. MOORE: Sure. John Moore, unemployed.
6	I have a I have a regarding the automated
7	susceptibility testing, I understand that by adding
8	one drug, you've got to take another drug off. Has
9	there been discussions around trying to develop a
10	panel, whether it be Vitek or MicroScan, of drugs in
11	which are used for unmet medical need. For
12	example, when you run your primary panel, if you get a
13	certain resistant phenotype, a resistance to this,
14	this and this, then run your secondary panel that has
15	all the other drugs on it. That way, you don't have
16	to worry about taking a drug off and adding another
17	one on. Has that been discussed at any length
18	somewhere?
19	DR. BOZZETTE: Sure.
20	MR. MOORE: Yes, it has? And is there any -
21	- is there opposition to something
22	DR. BOZZETTE: Well, you

MR. MOORE: I can see how a company would not want their drug to be on a secondary panel. But reality is that's how they're utilized.

4 DR. BOZZETTE: The real issue is the one at a time thing. You know, so do you make a card that 5 has two drugs, three drugs, you know, when in fact 6 7 we're looking at, you know, 64 and soon to be a 8 hundred well cards. So you know, the trouble is that the economics of the N + 1 drug is not good. But I 9 10 agree with you that, you know, secondary cards -- and 11 we do do that actually, secondary cards or cards for 12 specific markets, like Japan where they have a 13 different profile of drugs that are used and that sort of thing is something that we do, and we could do more 14 15 of, I suppose.

16 SESSION 3: STATISTICAL CONSIDERATIONS

DR. COX: All right. Well, thanks. We're at the 2 o'clock hour. So I thought we'd move on to our next section to talk about statistical considerations for studying drugs that are being developed for treating patients with unmet medical need. And our first speaker of the session is Dan

1	Rubin. Dan's a statistician with us here at FDA. And
2	he's worked with us on a number of different
3	antibacterial drug applications and also with some
4	antiviral drugs. And we appreciate Dan's willingness
5	to give the talk with us here today. He's always a
6	source of very interesting ideas, as he not only tries
7	to understand the statistical issues but some of the
8	other practical and, you know, clinical issues faced
9	with studying these drugs. So Dan, the podium is
10	yours.
11	EVALUATING ANTIBACTERIAL DRUGS IN UNMET NEED
<u> </u>	
12	SETTINGS
	SETTINGS DR. RUBIN: Well, thank you very much for
12	
12 13	DR. RUBIN: Well, thank you very much for
12 13 14	DR. RUBIN: Well, thank you very much for the opportunity to present today. I'll first discuss
12 13 14 15	DR. RUBIN: Well, thank you very much for the opportunity to present today. I'll first discuss randomized trials in the resistant pathogen setting,
12 13 14 15 16	DR. RUBIN: Well, thank you very much for the opportunity to present today. I'll first discuss randomized trials in the resistant pathogen setting, focusing on several examples, the potential for
12 13 14 15 16 17	DR. RUBIN: Well, thank you very much for the opportunity to present today. I'll first discuss randomized trials in the resistant pathogen setting, focusing on several examples, the potential for platform trials and trials that combine subjects with
12 13 14 15 16 17 18	DR. RUBIN: Well, thank you very much for the opportunity to present today. I'll first discuss randomized trials in the resistant pathogen setting, focusing on several examples, the potential for platform trials and trials that combine subjects with infections at different body sites. I'll then discuss
12 13 14 15 16 17 18 19	DR. RUBIN: Well, thank you very much for the opportunity to present today. I'll first discuss randomized trials in the resistant pathogen setting, focusing on several examples, the potential for platform trials and trials that combine subjects with infections at different body sites. I'll then discuss challenges and options when it's very difficult to

1	Bayesian and frequentist statistics.
2	The table on this slide is showing four
3	recently published randomized clinical trials that
4	compared colistin monotherapy to colistin combination
5	therapy with either rifampicin, fosfomycin or
6	meropenem for treating life-threatening carbapenem
7	Acinetobacter baumannii infections. The fourth trial
8	is still ongoing and Acinetobacter is the dominant,
9	but not exclusive pathogens. And you can see that the
10	trials together have enrolled about 600 total
11	subjects. And they're addressing an important
12	question, because if combination therapy is improving
13	survival, then that's a major benefit. If it's not
14	improving survival, then the benefit-to-risk profile
15	would be unfavorable because rifampicin, for instance,
16	would lead to a lot of drug-drug interactions.
17	The table on this slide is showing the
18	mortality results in the three completed trials. You
19	can see from the pooled results that we don't actually
20	have an answer yet for whether combination therapy
21	should be given to these patients. There was
22	approximately 50 percent mortality in both subjects

1	randomized to colistin monotherapy or combination
2	therapy. But the confidence interval for the
3	treatment difference can't rule out a mortality
4	benefit from combination therapy of as high as 15
5	percent.

6 Now, fully powered randomized trials would 7 provide the most statistically reliable answers to the most important questions, such as this question with 8 combination therapy. For complicated patients with 9 10 many comorbidities, randomization ensures that 11 treatment effect estimation is not confounded by 12 baseline differences between treatment and control 13 groups.

The most natural questions in this setting 14 15 are superiority questions because patients with 16 effective therapeutic options could be folded into 17 more traditional non-inferiority trials. However, as 18 shown in the previous example, to obtain definitive 19 answers, it must be possible to enroll a relatively 20 large number of subjects with infections due to multi-21 drug-resistant pathogens. So discussion topics for 2.2 today have been what other strategies are there to

1 increase enrollment and then what can be done if it 2 simply is not possible to enroll large numbers of 3 subjects.

4 One method to make trials in this setting more achievable, as we've discussed today, are 5 platform trials and a platform trial using a common 6 master protocol could potentially allow for a study of 7 8 multiple antibacterial drugs, studies of multiple indications or a study using a shared control group. 9 10 Just from sharing a control group, the potential gains 11 are if two sponsors run separate trials of drug A 12 versus control and drug B versus control with 100 13 subjects per arm, the sponsors together must enroll a total of 400 subjects and compete for study sites. 14 15 But if instead there's a three-arm trial with drug A, 16 drug B and control with 100 subjects per arm, the trial only enrolls a total of 300 subjects rather than 17 18 400 subjects. And separate statistical comparisons could be made for drug A versus control and drug B 19 versus control. 20

In a straightforward platform trial design,
drugs would enter/exit the study in a staggered

1	manner. The study would attempt to answer multiple
2	questions of interest. There would be advantages in
3	shared clinical trial infrastructure, study sites and
4	IRBs. The study would be able to prospectively plan
5	for how comparisons would change if the standard of
6	care regimen had to be updated due to ongoing trial
7	results. And the comparisons of interest would be
8	between subjects concurrently randomized to tested
9	control drugs.

10 The slide here is showing the abstract from a prostate cancer MAMS trial, standing for multi-11 12 arm/multi-stage trial, which along these lines was a 13 seamless Phase II/III design that uses shared 14 continuously updated control group to evaluate 15 multiple interventions for prostate cancer. It's 16 important to note that many statistical design 17 features could potentially be part of a platform 18 trial, but are separate issues that would need to be 19 considered independently of whether to evaluate antibacterial drugs using a common protocol. Such 20 21 issues include response-adaptive randomization, 22 Bayesian adaptations for efficacy and futility,

stopping criteria or use of statistical modeling with non-randomized comparisons such as comparisons between subjects in the trial assigned to drug A or drug B who are not concurrently randomized.

Now, beyond platform trials, another method 5 that may make studies in this setting more achievable 6 would be to combine subjects with infections at 7 different body sites. To illustrate the potential 8 utility, the CDC says about carbapenem-resistant 9 10 Enterobacteriaceae that patients whose care requires 11 devices like ventilators, urinary catheters or 12 intravenous catheters and patients who are taking long 13 courses of certain antibiotics are most at risk for CRE infections. And some CRE bacteria have become 14 15 resistant to most available antibiotics.

So then, the question becomes should one conduct a single trial, combining subjects with, say, nosocomial pneumonia, bloodstream infections and complicated urinary tract infections, despite possible differences in endpoints, comparators, durations and patient characteristics and recent examples of Antibacterials that may have had discordant efficacy

1	results	across	body	sites.
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In principle, we can use body site-specific 2 endpoints or responder indices, comparators and 3 treatment durations. And statistical methods can use 4 smoothing or shrinkage to form more accurate body 5 site-specific estimates of treatment effects by 6 7 borrowing information across subgroups. However, 8 whether to do this is not only a statistical heterogeneity issue, but also a clinical heterogeneity 9 10 issue regarding whether patients with infections at different body sites constitute a reasonable combined 11 12 target population because we may have very low 13 statistical power to detect differences in treatment effects between different body sites. And with small 14 15 sample sizes, statistical methods also can't quarantee 16 accurate estimation for every body site subgroup in terms of having both low bias and low variance. 17 18 The table on this slide is showing the 19 percentages of subjects with different body site

20 infections from the three completed Acinetobacter 21 trials that I mentioned earlier. You can see from the 22 first column that pneumonia was the predominant

1	infection. In one of the trials, about a fifth of the
2	subjects had bacteremia and there was a scattering of
3	other types of infections, like intra-abdominal
4	infections and urinary tract infections. So these
5	were in some cases multiple body site trials.

6 For the remainder of the presentation, I'll 7 discuss statistical considerations when it's simply 8 very difficult or not possible to enroll a large number of subjects with resistant pathogens in a 9 10 clinical trial. The sample size table in this slide 11 is showing that to statistically demonstrate 12 superiority with a reasonable number of subjects or 13 even with a few hundred subjects per arm with the resistance marker, the new antibacterial drug would 14 15 need to provide relatively large benefits compared to 16 current standards of care.

Now, given the sample size calculations from
the previous slide, a natural question is whether it's
possible to move from studies that use inferential
statistics to studies that use descriptive statistics.
FDA has traditionally interpreted trials that use
inferential statistics and formal tested hypotheses as

1	providing reliable evidence. Descriptive analysis of
2	a clinical trial would present success rates for drug
3	A and drug B, but would not necessarily formally test
4	a hypothesis. And descriptive analysis is useful for
5	assessing patterns and examples of descriptive
6	statistical analyses of antibacterial drugs include
7	many Phase II studies, pediatric studies and safety
8	studies, including the Phase II studies factoring into
9	the FDA approval of ceftazidime-avibactam in 2015 and
10	also FDA approvals of antibacterial drugs in earlier
11	decades in clinical data used to set susceptibility
12	breakpoints.
13	So then, a really important question becomes
14	can trials pre-specify decision criteria somewhere
15	between P less than 05 at each body site and post hoc
16	descriptive analysis that would give reasonable
17	operating characteristics in the unmet need setting.
18	I'll next discuss differences between
19	frequentist inferential statistics and Bayesian
20	inferential statistics. Frequentist methods such as P

22

21

values and confidence intervals have been the default

paradigm for clinical trials. By a type 1 error rate

1	control, the usual statistical significance level, we
2	mean that approximately only one out of every 40
3	clinical trials have ineffective treatments, will
4	falsely conclude efficacy. And we have the coverage
5	guarantee that in approximately 95 out of every 100
6	clinical trials, the confidence interval for the
7	treatment effect will contain the true effect. The
8	nice thing about these methods is that statistical
9	theory provides type 1 error rate control and coverage
10	guarantees under essentially minimal conditions
11	without need for a lot of modeling assumptions or data
12	external to the clinical trial of interest.
13	Now, Bayesian methods are a different class
14	of statistical methods from frequentist methods and I
15	won't be able in this talk to go through the machinery
16	of how the Bayesian analysis would work or some of the

17 more conceptual differences, other than to say that in 18 practice, this isn't necessarily how the difference 19 between the two types of methods are defined, but in 20 practice, the main difference between using Bayesian 21 methods and using frequentist methods is in how the 22 Bayesian methods attempt to integrate the data from

the trial itself with data or evidence from other
 sources.

For antibacterial drugs, the prior evidence 3 4 may come from previous randomized or observational studies of the new drug, comparator or related drugs, 5 previous studies at different body sites of infection, 6 PK/PD data, animal data, in vitro data or expert 7 8 elicitation. And an advantage of Bayesian methods is 9 that they can attempt to incorporate more of this 10 information into the analysis and formalize for 11 different sources of uncertainty. A disadvantage is 12 that this can lead to erroneous answers if the prior 13 beliefs are incorrect and are debatable or too strongly held. And I'll give examples of Bayesian and 14 15 frequentist methods in the next few slides.

16 So we saw earlier in the Acinetobacter 17 studies that in the pooled randomized trials, there 18 were mortality rates of 51 percent for subjects 19 treated with colistin monotherapy and 47 percent for 20 subjects treated with combination therapy. If you 21 pool the studies -- and this is just illustrative, not 22 necessarily to endorse raw pooling as the way that

these studies should be meta-analyzed -- but if you 1 pool the studies, you would estimate a difference in 2 mortality rates to be 4 percent, with a confidence 3 4 interval from -6 percent to 15 percent. And because the lower confidence limit does not exceed zero and 5 because the upper confidence limit can't rule out a 6 mortality benefit of as high as 15 percent, the usual 7 8 interpretation is that this confidence interval is too wide to tell us whether combination therapy improves 9 10 survival.

11 With the same data, the Bayesian analysis 12 can actually depend on prior information. If we use a 13 so-called uninformative prior that attempts to handle the treatment and control as neutrally as possible, 14 15 which would imply that before the trial we thought 16 that there was a 50/50 chance that monotherapy or combination therapy had better survival, then the 17 18 frequentist and Bayesian decisions would tend to be 19 very similar after the trial results came in. however, if we used an informative prior, say that 20 before the trials we model from the available evidence 21 2.2 that there's an 80 percent chance that the mortality

1 rate for subjects treated with colistin monotherapy is 2 between 0.6 and 0.7, then after the trials, we would 3 find from a beta binomial model that there's a 99 4 percent chance that colistin combination therapy 5 actually improves survival.

So the next few slides illustrate this. 6 The 7 top histogram in this slide is showing the 8 uninformative prior for the chance of death with colistin monotherapy before the trial results. And 9 10 you can see that it's essentially placing any 11 mortality rate between zero and one for the 12 monotherapy group on equal footing. If you use this 13 uninformative prior, then after the trial results, you'll get the histogram on the bottom of this slide, 14 15 which is called a posterior distribution. And you can 16 see that the chance of death with colistin monotherapy 17 is centered around the 50 percent rate that was 18 actually observed in the trial.

19 Conversely, the top histogram in this slide 20 is showing a very informative prior for the chance of 21 death with colistin monotherapy, and which we have 22 modeled based on whatever evidence is available before

1 the trial results that the chance of death with 2 colistin monotherapy is fairly concentrated at around about 65 percent. In this case, because the Bayesian 3 4 analysis would depend both on the trial results where we saw a 50 percent mortality rate for this group and 5 the prior evidence, the result of the analysis would 6 be to say after the trial results that there's still a 7 8 fairly high chance that subjects treated with colistin monotherapy would have a death rate exceeding 50 9 10 percent.

11 In summary, there are opportunities for 12 conducting randomized trials in the resistant pathogen 13 setting using platform trials. A trial combining subjects with different body site infections can be 14 15 statistically analyzed. But then, the important 16 question becomes how should heterogeneity be addressed. Conducting powered superiority trials in 17 18 the unmet need setting requires either a large 19 treatment effect or a large sample size. So the important question here is what pre-specified decision 20 21 criteria are reasonable beyond descriptive analysis. 22 And Bayesian and frequentist methods are both valid

	5
1	statistical tools. But in the anti-infective setting,
2	the most important consideration is how much weight to
3	give modeling of nonrandomized evidence. And here are
4	my references. So, I thank you.
5	[Applause.]
6	DR. MARKS: Thank you, Dan. And building on
7	this construct in terms of innovative trial designs,
8	Kert Viele, director and senior statistical scientist
9	at Berry Consultants, is going to share his thoughts
10	as well. Thank you, Kert.
11	INNOVATIVE TRIAL DESIGNS
12	DR. VIELE: There we go. So thank you for
13	having me. The work presented here is funded by ARLG.
13 14	having me. The work presented here is funded by ARLG. It's a project directed by Roger Lewis and Brad
14	It's a project directed by Roger Lewis and Brad
14 15	It's a project directed by Roger Lewis and Brad Spellberg. This discussion has involved a lot of
14 15 16	It's a project directed by Roger Lewis and Brad Spellberg. This discussion has involved a lot of academics, pharmaceutical companies, the FDA, BARDA
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14 15 16 17 18 19	It's a project directed by Roger Lewis and Brad Spellberg. This discussion has involved a lot of academics, pharmaceutical companies, the FDA, BARDA have been involved in this. One of my goals is really to talk about several different innovations that have all been talked about today, but provide a few more

1	to focus on the resistant pathogens. But this is
2	particularly relevant to a network that might enroll
3	UDR and resistant pathogens within the context of the
4	trial. Of course, lots has been said today. It's
5	hard to do inferences on resistant pathogens. So I'm
6	going to be talking a lot on how far can you get in
7	order to bridge this divide between the sample sizes
8	are too small versus we'd really like formal kinds of
9	statistical methods.
10	Standard trials, we see a lot of trials that
11	focus on one drug versus one control at one body site.
12	And this gets repeated. Lots of trials happen. We've
13	enrolled the control arm in multiple studies. We've
14	got UTI in this study. We've got intra-abdominal in
15	that study. What do we do? So I'm going to talk

16 about three innovations: platform trials -- and all 17 of this is building off of what Dan talked about --18 early stopping and sharing information across the body 19 sites. Each of these has the potential to decrease 20 the required sample sizes for trials.

I'll start with platforms. This has been
mentioned a lot. It's been mentioned in the sense of

1	trial networks. But this could also be used simply
2	for three companies getting together and putting their
3	drugs all in one trial at the same time. So this is a
4	scalable enterprise. Some examples, platform trials
5	are being used in lots of areas. One of the oldest
6	running platform trials is something called I-SPY 2,
7	which is a breast cancer study.

8 Nice things about I-SPY, you can see lots of articles -- not the most recent, but a recent New 9 10 England Journal of Medicine had four articles on I-SPY I-SPY 2 is interesting from the standpoint of it 11 2. 12 tries to match drugs to particular patient 13 populations, which may be relevant for resistant versus UDR kinds of mechanisms. There's different 14 15 types of allocation for HER2-positive breast cancer. Drugs can graduate with certain signatures. We think 16 17 this drug works in people with triple-negative breast 18 That's one of the outcomes of that study cancer. 19 which may be relevant for antibiotics.

20 Other examples, so again, just trying to 21 emphasize this isn't new and radical. This is 22 happening in a lot of places. The IMI EPAD initiative

1	is an Alzheimer's study that's intended to test
2	combinations. If you have a trial network, you have a
3	patient stream that's big enough that you can start
4	thinking about combining drugs in different ways.
5	There's a PREPARE initiative in Europe which is
6	intended to be ready for epidemics. The influenza
7	study of that I think is what Mike Dudley was talking
8	about in terms of a learning health system.
9	We know lots of things that we think will
10	work. But physicians differ. They make decisions on
11	what they've seen before. The notion of using this
12	health system and having all the data come in.
13	Patients are randomized and in real-time having access
14	to these are the things that are working and these are
15	the things that aren't that's the kind of thing
16	that you can do within a trial network and it is an
17	example of a platform trial. GBM AGILE, this is
18	getting a lot of press. If you want to see some
19	really slick videos on YouTube, whoever their PR
20	person is, they're really good. There's also an Ebola
21	trial which, as an example of trying to put together a
22	platform trial that works incredibly quickly of

getting drugs in combinations to patients as quickly
 as possible. So this is something that we're getting
 a lot of experience about in the broader realm.

4 The sharing of control information is the key place that we gain efficiency in these kind of 5 I've talked about 40 drugs here, the notion 6 trials. of doing this for 10, 12 years. But the efficiency 7 8 gains on the order of 25, 30 percent, even three or four companies getting together, just the mere fact 9 10 that you've saved a control arm is worth that kind of 11 advantages. So you could really do some good things 12 here.

13 There are some synergies in a platform. Ι haven't even talked about early stopping yet. But if 14 15 you have a platform trial where drugs can go in and 16 out and stop, when one drug stops, another one can come in. Being able to do that, it doesn't work quite 17 18 like compound interest. You know, you don't double every month or whatever. But this notion of investing 19 savings forward certainly does exist and it's very 20 21 valuable to combine early stopping with a platform 2.2 kind of idea.

1	Platforms in general, if you can run lots of
2	drugs at the same time, savings can be 35 percent.
3	This is a paper that the clinical trials paper
4	that's coming out. It may be in print now, but it
5	will be shortly if not. This shows savings up to 50
б	percent just from the ability of sharing a control arm
7	and being able to stop drugs. I think this paper has
8	response-adaptive randomization in addition to try to
9	tailor drugs to particular patient groups. Early
10	stopping of body sites. We're talking about a trial
11	that enrolls in multiple body sites.
12	If you have a drug like daptomycin and
13	you're able to see this is failing in HAP/VAP, you can
14	stop that and enroll the HAP/VAP patients in other
15	
10	things. I'm not going to spend a lot of time on this.
16	things. I'm not going to spend a lot of time on this. This early stopping I think is more well understood.
16 17	
	This early stopping I think is more well understood.
17	This early stopping I think is more well understood. But the sample size savings there can often be 15 to
17 18	This early stopping I think is more well understood. But the sample size savings there can often be 15 to 20 percent compared to running a standard trial. One
17 18 19	This early stopping I think is more well understood. But the sample size savings there can often be 15 to 20 percent compared to running a standard trial. One thing to keep in mind, when we talk about formal

50 percent power is aimed at if I get exactly what I'm
 expecting.

To get 80 or 90 percent power, you're saying 3 4 even if I get unlucky and I get less than what I'm expecting, I still want to get conclusive evidence. 5 If you're talking about a platform and you're going to 6 7 have 30 or 40 drugs, you're not going to get unlucky 8 all the time. If you're one company, you don't want your one product to die on the vine or one of your key 9 10 products to die on the vine. But if we're running, you know, 20, 30, 40 drugs over the course of many 11 12 years, we're lucky half the time. We're unlucky have 13 the time. We may as well make sure we get the savings. We don't need to protect ourselves against -14 15 - we don't need to buy an insurance policy for every single drug and early stopping lets us do that. 16

As I said, early stopping has synergies with platform trials. If you're talking about getting 40 drugs over the course of a decade or more, saving 20 percent, you can evaluate 48 drugs. So again, this notion of paying forward. And I've tried to save time for this one thing that hasn't been talked about much

1	today which is sharing information across body sites.
2	In a lot of cases, trials are run in, say, UTI or run
3	in intra-abdominal and maybe you're not you don't
4	want to run a trial in HAP/VAP because of the expense.
5	The ability to run potentially smaller trials across
6	multiple body sites and sharing the information across
7	those body sites excuse me has a lot of value in
8	terms of you can get more statistical efficiency and
9	of course it also allows us to see exactly how a drug
10	does perform in those settings rather than having to
11	rely on extrapolation.

12 I'm not going to get into the details of the 13 modeling here, for the same reasons Dan didn't. It's 14 difficult within the time allotment. But a notion of 15 the kind of fear that you have in running small trials 16 in several body sites. Suppose we ran a trial and we 17 had HAP/VAP, UTI and intra-abdominal together in the 18 trial. And I'm focused on just these are the 19 resistance that come out of this.

20 So you can imagine a larger trial. I may 21 have several hundred usually. I'm trying to answer 22 the question what about the resistant populations

1	here. So in HAP/VAP, my control data I got 5 out
2	of 12 successes, 42 percent. In the treatment, I'm
3	doing great, 10 out of 13, huge advantage. The
4	problem is if I'm looking for a P value of 0.025, I am
5	a Bayesian, but so I've termed this in terms of
6	posterior probabilities and 97.2 percent chance of the
7	treatment is better. That corresponds to about a
8	0.028. I just missed. Yuck. Now, I'm going to have
9	to go in and ask for, well, was I close enough.
10	But I didn't just run the HAP/VAP study.
11	I've got the UTI data next to it. I've got 9 out of
12	25, 36 percent on control, 23 out of 25, 92 percent on
13	treatment. This is fantastic results. This is a slam
14	dunk win. No one's going to question the UTI results
15	here. And then, in intra-abdominal, remember one
16	thing that happens in intra-abdominal, a lot of times
17	you get successes on the basis of surgery. So the
18	control rates are often higher. So I got 14 out of
19	22, 64 percent for the control and 87 out of the
20	treatment. That's a Bayesian probability of 94.5
21	percent. It's a P value of 0.055. I missed again.

When we talk about the notion of I can't achieve statistical, formal inferential statistics in small trials, I'm not saying I can't get trends. I'm saying I can't get 80 or 90 percent power. And this is the type of setting that you're in. This is where you're missing, lots of trials that give you indications, but they're not conclusive.

8 A key point here though is that none of these data -- while only the UTI is convincing in and 9 10 of itself, the context here is very important. I just 11 missed in HAP/VAP and I have a promising trend in 12 intra-abdominal. I may not be willing to say for 13 intra-abdominal this is conclusive evidence. But doesn't it matter that it's paired with the other 14 15 things that are going on? Seeing the intra-abdominal 16 results in a vacuum, this is my only study is one thing. Seeing the intra-abdominal results combined 17 18 with the fact this is a slam dunk win in UTI, combined 19 with the fact that the HAP/VAP data is strong, this is more evidence in favor. 20

21 What the more -- the methods that Dan was 22 talking about for borrowing information across sites,

1	what they aim to do is essentially partition the
2	variation that you're seeing in the data. They're
3	partitioning it into what kind what's the true
4	differences between the sites and what's just result
5	of noise, sampling variability. Here, what we're
6	seeing is general effects. So the differences that we
7	see among these drugs, it's more likely to be sampling
8	variability. These are small trials. We just
9	couldn't recruit enough patients. But the overall
10	trend is consistent. We attribute the variation here
11	to sampling variability and that the true differences
12	are small.
13	When we fit these models, generally what

happens is the effective sample size is increased 14 15 through this analysis. And good models do this 16 dynamically. So this isn't a situation -- I'm not 17 pooling the data together. Pooling's a very dangerous 18 thing. There's been -- Sumathi was talking about the 19 dangers inherent in this. You never want to put 20 together unlike things. Good models do this dynamically these days whereas if they see common 21 22 trends, they borrow information between the groups.

But if they see very disparate trends, they borrow a
 lot less. And that's a protection against the kind of
 dangers that you'd see when you pool data together.

4 Back to our sample data set, if you see the bottom numbers in red, what's happened is because 5 these data don't appear in a vacuum, we see each of 6 them combined with strong results. The HAP/VAP data 7 8 that just missed at 97.2 goes up to 99.7. The UTI is still a slam dunk. The intra-abdominal also went up. 9 10 The consistent picture has allowed us to increase the 11 effective sample size in each group. And I think this 12 is intuitively what clinicians would do. I know this 13 drug works in UTI. I've got data that says it works reasonably well in others. 14

15 What are you going to do? If you can't enroll the big study, you're going to basically do the 16 intuitive conclusion here, which is this probably 17 18 works. That's what this is trying to formalize and 19 trying to put some statistical teeth on it and statistical teeth in a way that allows us to test the 20 21 operating characteristics. We can go to the FDA and 22 say here is our design in advance. Here are the error

1	rates attached to it. This isn't ad hoc, oh, we know
2	we missed, but can't you just give us the benefit of
3	the doubt. This is a way where we know what the error
4	rates are for this procedure.

5 Here is another data set. This is a situation where intra-abdominal appears to have a 6 7 significant problem. You can see again HAP/VAP, the 8 treatment is doing better than the control data. UTI, again, the treatment's doing much better than the 9 10 control better. We actually seem to be doing harm to 11 the intra-abdominal subjects. So they're going the 12 wrong way and I picked this to be an extreme example 13 for a number of reasons. One reason I picked this is to illustrate the dangers of pooling. If you said in 14 15 advance, I was going to pool the data, what in effect 16 you would do is the good HAP/VAP and UTI sites and the very bad intra-abdominal, you'd pool those together 17 18 and you'd end up saying my essential conclusion is 19 that nothing is going on, which isn't what the data 20 seem to be telling you at all. It tells you something 21 horrible is going on in intra-abdominal.

22

This is also intended to be a data set that

1	shows you the dynamic part of these kind of models.
2	The probability the treatment is better, you can see
3	if I analyze the intra-abdominal separately, that
4	probability is 1.4 percent. That's very low. So
5	again, separate analyses recognize there's a problem.
6	If you do if you did pooling, you would pull that
7	up dramatically. You would say, well, I'm just going
8	to average out the HAP/VAP and UTI and you'd say,
9	well, maybe it works in intra-abdominal.
10	Here, what happens is the model recognizes
11	that the difference between HAP/VAP and UTI, it's more
12	than can be accounted for by sampling and variability
13	and it doesn't pull up the intra-abdominal. So I
14	think there's a lot of hope here to be able to get
15	data in multiple body sites and be able to still make
16	inferences potentially with smaller sample sizes than
17	doing one body site and having a big study and
18	effectively having zero in other sites.
19	Sharing information, this can save sample
20	sizes 30 to 45 percent. It's substantial. So to give
21	a notion about this is more aimed at a trial network
22	kind of arrangement, but a standard design say

1	you're doing a UTI trial, non-inferiority. You're
2	going to add these features, potentially look at
3	resistant pathogens. A standard design may require
4	400 to 425 per arm. If you borrow and that's
5	across sites, 400, 425 across all three sites.

6 Borrowing alone can reduce those sample 7 sizes to 300 per arm. If you add early stopping to 8 that, you can get to 230, 275 per arm. There are assumptions attached on this. I haven't gone through 9 10 all of them. So these are scalable kinds of savings. 11 And then, finally, putting those kinds of drugs in a 12 platform and sharing the control information, it 13 becomes more relevant to talk about this as a per drug kind of issue because you'll have a shared control 14 15 But that gets down to something like 325 per arm. 16 drug, which is not arms. So these are substantial 17 kinds of savings. And it depends on the assumptions 18 and the treatment effects. But there's a lot of 19 potential here that we can start making more efficient 20 designs and trying to expedite this process. 21 So in summary, I talked about platform

22

trials, early stopping sharing of information. Main

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1	thing I want to emphasize is there's just a lot of
2	synergies here, the ability to put drugs together.
3	You can start playing with a lot of interesting levers
4	to try to make things work more efficiently. And
5	certainly I again want to emphasize these aren't novel
6	or crazy ideas. These are things that are being done
7	in a variety of areas and hope we can do them in
8	antibiotics. Thank you.
9	[Applause.]
10	CLARIFYING QUESTIONS (PANELISTS AND
11	AUDIENCE)
12	DR. COX: Thanks to both Kert and Dan for
13	your excellent presentations. I just sort of wanted
14	to open it up now for questions about the
15	presentations. Aaron?
16	MR. DANE: Yeah. I suppose my first comment
17	would be, you know, with Bayesian methods, all the
18	information borrowing, the critical element is the
19	assumptions and an explicit discussion of the
20	assumptions going in. So these are approaches that
21	are quite reasonable. But you need to be able to
22	assume, for example, that the responses are going to

1	perform similarly across body sites because although
2	it does deal with that to some degree, as Kert showed,
3	you know, you do increase your chance of making the
4	wrong decision, if that's not true. But it feels that
5	should be just a discussion we have up front and
6	decide whether it's a reasonable thing to do and not a
7	reason not to do it. So it's just to state that
8	really, that that's one of the key things here.
9	There's probably additional assumptions that we make
10	when we do this that we just have to be mindful of.
11	DR. COX: Ian?
12	DR. FRIEDLAND: I have a comment and then I
13	have a question. So the examples that were given of
14	the platform-type protocols, there are actually
15	well, I know at least one example in the antibacterial
16	space. Sivextro and Cubist got together and with the
17	FDA came up with a joint protocol for osteomyelitis in
18	pediatrics. They had a common protocol with a shared
19	control group. Unfortunately, that study wasn't
20	conducted for reasons other than the study itself. It
21	was a financial disagreement.

1	examples. I think pediatrics definitely lends itself
2	to that kind of opportunity. And one would imagine in
3	even in the unmet need space, if two drug developers
4	had drugs for the same target, that there could be a
5	potential for coming up with a common protocol with a
6	shared control group. I just think we don't always
7	think about this in industry that much. That was the
8	comment.
9	And the question I had is and as I said,
10	the statisticians on the panel what they think
11	about the DOOR and RADAR analyses that Scott Evans
12	described because those kind of analyses do send to
13	lend themselves to smaller studies.
14	DR. RUBIN: Yes. I can comment on that
15	since I was a co-author on one of the RADAR papers.
16	So the idea behind here is to use sort of an ordinal
17	outcome, meaning that instead of someone being a
18	success/failure, you have to be able to rank patients.
19	So if you have two patients, you have to say which one
20	of them had the better outcome in terms of maybe, you
21	know, efficacy, safety or some combination. They're
22	actually used in stewardship trials, where if there's

1	a tie, the patient who's on antibiotics for the least
2	length of time is the winner. And then, what you do
3	is average all of the subjects and try to determine
4	whether subjects randomized to one arm or the other
5	would, on average, have the higher ranking or be the
6	winner. It's been used in some stewardship trials.
7	So I think it is an innovation that has some
8	utility. It's mainly for superiority analyses. So
9	you'd have to have some type of benefit over what
10	you're trying to compare against. It may not
11	necessarily have to be in terms of an efficacy
12	benefit. It could be a safety benefit that RADAR
13	would also try to take into account.
14	Now, it's not a there's no free lunch
15	here. There are disadvantages of it that have to be
16	worked through. Like any composite, it can be driven
17	by its weakest link, in that a major a negative
18	treatment effect on one component of the composite can
19	be outweighed by a positive effect on less components
20	in the stewardship trials if there's a danger that you
21	could approve a less effective drug using this method
22	if it just simply leads to the intervention leads

1 to less antibiotic use. So that has to be taken into 2 account, that it is a different method of given some 3 kind of introduction to it that could potentially be 4 applied in some of these settings.

Yeah, and I would -- so it's 5 MR. DANE: clearly helpful in that compared to our traditional 6 7 response yes and no, it gives you more granularity 8 than that. So it can give you a bit more information. I guess the challenge often in designing the studies, 9 10 that you get into some guite complicated assumptions you have to make around if you have five different 11 12 groupings, for example, you know, if you're moving 13 from efficacy with no toxicity, efficacy with toxicity and then you often end up with five categories. 14

15 You've got to make assumptions on how many patients are in each of those different groups to be 16 17 able to figure out how many patents you need to 18 demonstrate superiority. So that can be a challenge 19 in terms of investing in that study and knowing how likely you are to succeed. And I guess something else 20 21 Dan just touched on is that the way that works is 22 you're assuming each of those different categories has

equal weight as well. So you're assuming it's equally
 as important as you go through each of those. So I
 can see some use.

4 But at the moment, it feels like it would be a useful tool as a sensitivity or additional 5 information rather than the method you would use to 6 interpret a study because the other thing that I 7 8 forgot to mention was that you end up with a figure and some evidence of effect. But you don't know quite 9 10 how to interpret it because it's a number you don't 11 really know what it means. So you'd still have to use 12 it with some of your more traditional methods I think 13 and it just may give you a view of the evidence. 14 DR. COX: John? 15 DR. REX: First, thanks for those two really

16 good presentations. And I'd like to ask Dan a 17 question to test my understanding and then that may 18 lead to a comment. So are Dan's slides something that 19 can be brought back up? Because my question will make 20 more sense. Can you go to slide 18? All right. So 21 in this slide, there was a slide before -- actually, 22 back up one, slide 17.

1	So you analyzed the same data twice, right?
2	And so, the first time you look at it, you say, okay,
3	51 percent versus 47 percent. So a difference of 4
4	percent, broad confidence interval. Those look like
5	they could be about the same, or can't tell. It's
6	kind of wide, wide? Next slide. Now, you look at it
7	again and the first time you look at it, you say, I
8	don't know the 0.5, the prior 0.5 means I have no
9	opinion. That's the way I should put that into
10	English, is I have no opinion. And so, when I get
11	those data back, I don't know. I'm not much smarter
12	one way or another.
13	The second time, you say, I have an opinion

and I believe that the combination is better. 14 Ι 15 believe that pretty strongly. So now, when you do the 16 math, would it be correct to say that you've concluded 17 that the combination is better, largely because you 18 believed it before you went in, and the only thing 19 that would have turned you back would have been really 20 a grossly negative result. So as long as it was sort of consistent with your belief, you're happy and you 21 22 declare victory. Am I saying it correctly in English?

1	DR. RUBIN: I think you are saying it
2	correctly, that with a Bayesian analysis, if you have
3	an extremely strong prior for what's going to happen,
4	you're going to stay with that opinion unless there's
5	really a lot of evidence to move you in the other
6	direction. This is meant to be illustrative of that.
7	It's probably a stronger prior than anyone would use
8	in a practical analysis with this type of data.
9	DR. REX: Because I've always wanted to be a
10	Bayesian and yet you've made me not so happy with what
11	that did there because it actually sort of twisted
12	that.
13	MR. DANE: But John, slide 19, the next
14	slide is actually quite useful for your question.
15	DR. REX: Well, okay. But I wanted to ask
16	why is this but so now my question then spins off
17	of Kert's presentation where, in effect, he showed us
18	data in here little experiments intra-ab, UTI and
19	nosocomial pneumonia and said, look, you know,
20	they're all kind of the same, you know. Actually,
21	both all three of them look like something better
22	than a sharp stick in the eye was happening. So why

1	shouldn't we buy into that? And he did that without
2	showing us any more math than that other than, you
3	know, these three numbers are all pointing in the same
4	direction. And I'm just it feels to me like
5	something about writing these numbers down made me
6	less happy with it, yet I looked at his three examples
7	and I thought, well, that looks not too bad if I just
8	eyeball it. That's not much of a question. I'm
9	sorry. I'm just kind of bothered by what's going on.
10	DR. RUBIN: That's okay. Well, there were a
11	lot of intricacies in exactly what to model, what the
12	prior is and how the different sources of evidence are
13	combined. And I think that the two examples from mine
14	and Kert are illustrating that, you know, those
15	assumptions and the specific statistical analyses can
16	really change the results. But there are a few other
17	people more familiar with Bayesian methods than me in
18	the room. So
19	DR. COX: So why don't we go we'll go to
20	Kert, if you're set, Dan. Okay. We'll go to Kert.
21	Then we'll go to Thomas. And then, we'll come over to
22	Mike. Sure. Tom, you willing to take him up on that?

1	DR. LOUIS: I'll start by saying I'm known
2	as a Bayesian, but what I really am is a statistician
3	who uses the Bayesian strategy for most things, as a
4	kind of guide to navigation. And I think Dan's
5	example I'm just going to respond to one or two
б	things and leave the rest for later in the afternoon.
7	But I think whether you're a frequentist or a
8	Bayesian, the only place that beliefs have a role
9	and they really have a role in whether you're a
10	frequentist or a Bayesian is, for example, in what
11	data are relevant to the current study, whether it be
12	for designing or analyzing.
13	In Dan's example, if he had used the word

that investigators had the belief that the following 14 15 five studies were relevant to the current study and 16 used those to develop a prior and it was the prior 17 that he put down, there's still belief floating 18 But really, the prior subject to at least around. 19 which studies are relevant is an empirically based thing. And I think in the realm of public policy, 20 21 clinical policy, put whatever word you want with 22 policy as the last word, that has to be what's going

1	on in the Bayesian formulism and that we have to
2	always understand the objective properties. And Berry
3	Associates learned a lot of CPU, a lot of this CPU and
4	a lot of that CPU understanding the objective
5	properties of a protocol-driven analysis that is
6	embedded in Bayesian formulism.
7	And so, I want to push for there being a
8	little less separation of maybe 40 years ago when I
9	would sit around and say, you know, frequentists are
10	idiots I no longer say that. I'm sort of a
11	frequentist. The world has gone beyond that, at least
12	for most people, and that we're trying to design and
13	analyze studies doing a good job and that the Bayesian
14	stuff, now with computing available, is not a panacea.
15	In fact, the obligations are greater. But there's no
16	free lunch. But there are a lot of reduced price
17	lunches and we should be going for them. I'll save
18	other comments until later.

19DR. COX: Kert, do you want to add?20DR. VIELE: I was hoping you'd say that and21figured you'd say it better than me. So I let you go22ahead and go. So to piggyback off of that, when we

1	design trials, one thing that we spend a lot of time
2	on is going through individual data sets and the
3	conclusions that would be drawn from them. This
4	particular example I think is a good one. I think Dan
5	was saying it's a fairly extreme assumption. And it's
6	interesting to see this data set. I think this is
7	almost a treasure trove example. We're making an
8	assumption, 80 percent chance that the mortality rate
9	for colistin monotherapy is between 60 and 70 percent.
10	That's a strong assumption in there. If
11	it's true, this is the right conclusion to draw from
12	this and that's what the Bayesian machinery is doing.
13	If you're uncomfortable with this and I sense that
14	you are I think what you're aiming at is not the
15	methodology itself, but that you don't buy the 80
16	percent chance is between 0.6 and 0.7. And when we
17	design trials, I think that's one thing we like to
18	show to people. Here are the conclusions that it
19	would draw if this data set doesn't make you
20	uncomfortable and basically tease out what are the
21	comfortable assumptions. And the assumption that you
22	may be willing to make here is that not this one, so I

1 don't want to draw that	1	don't	want	to	draw	that
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2	Related to this I'm going to talk for a
3	little while, I guess. I might be more inclined in
4	this example. If you look at the you've got 88 out
5	of 174 for colistin. There are multiple ways to
б	incorporate the prior. A lot of methods these days
7	include what I'm going to call an off-ramp. It
8	essentially says we've got control data in my current
9	study and I've got this control data from the past
10	that was the basis of this 80 percent belief. A lot
11	of methods these days and I think Dan did a
12	simplified example to illustrate things, so not
13	picking on your example at all.
14	Having that kind of off-ramp I think would
1 -	

15 do a better analysis here because it would let you see 16 the 88 out of 174. The data that you have in front of 17 you isn't consistent with the assumption. So maybe I 18 should borrow from it less and that would weaken this 19 conclusion that you have now. So this notion of continually having models that check their own 20 assumptions I think are viable and that's what this 21 22 notion of dynamic borrowing, being able to decide

based on data is it valuable or not is big. And as a
 final point to this, I think it shows a dichotomy
 here.

4 We've talked about historical controls in the past. There's two notions of historical or 5 external controls. There's fully external controls, 6 where there's no controls in the study whatsoever and 7 8 then there is running a 3:1, 2:1, 4:1 study where you enroll some controls in. And those are night and day. 9 10 They tend to be lumped under historical controls when 11 we talk about them. But the ability to see control 12 data here is so valuable in testing those assumptions 13 that having some in, I'd always recommend that we have some control data in any of the especially later phase 14 15 studies that we do.

16 DR. COX: Thanks, Kert. And Mike still? 17 Yeah?

DR. DUDLEY: Yeah. I think so. Thank you to both of you actually for both the presentations. So let me try this because I think, Dan, you brought this out about the Bayesian priors can come from a variety of different sources. So if we think about

1 earlier this morning, Dr. Ambrose's presentation 2 taught us that a lot of things that we call failure 3 are just simply because we're too low on the dose-4 response curve and we've become pretty good about 5 modeling and attaining high probabilities of getting 6 what we consider to be therapeutic exposures.

7 How would you use that type of information 8 then to come up with a prior that would help you then to sort of become more confident in your small trial 9 10 observation? So in other words, if we carried into 11 that trial a prior belief that a dosage regimen is 12 going to provide a certain level of exposure that's 13 going to be attaining a pre-specified target, would we be able to use that to sort of strengthen our 14 15 conclusion, sort of, to use Kert's term, borrow from that to help us understand? 16

DR. RUBIN: Right. That's a great question. And at this point, you've kind of put me on the spot. But I don't think FDA can necessarily endorse or not endorse that type of analysis. In the past, that type of data has been more hypothesis generating data, used for dose selection and used to set up candidate drugs

1	to see if they'll work really in the full standalone
2	test of a Phase III trial. In terms of using an
3	analysis that formalizes the borrowing PK/PD data and
4	integrates that with the trial data, I mean, it's
5	something that we'd have to think about in terms of
б	what the details would be. I guess the concern would
7	be, you know, how well do we how strongly do we
8	believe that these data can predict how the results
9	will translate to clinical to treatment effects on
10	clinical outcomes and how suspect are we of the
11	modeling assumptions. Those would really be the
12	issues to address.
13	DR. DUDLEY: And just to follow up, if I
14	can. So I suspect that that's all in sort of the
15	secret sauce of the weighting exercise here about how
16	much do you weight. Is that correct? You can sort of
17	control I think, Kert, you said you can control how
1.0	

18 much you're going to borrow I think from these things.

19 Is that what will happen, is that we'll sort of

20 throttle that a little bit by deciding how much we

21 want to borrow from that?

22

DR. RUBIN: Exactly. That was the last

point in my last slide, was that it's not so much Bayesian versus frequentist. It's how much weight do you want to give when making a decision to modeling of data other than the randomized --

5 DR. DUDLEY: So let me try this one more, just if I can -- and I'm not looking for any -- you 6 7 know, I'm just -- this is just sort of idea sharing. 8 So one might say then that based upon an a priori -when we're designing a small trial, we might be able 9 10 to come to an agreement and say here's my PK -- here's my nonclinical PK/PD data or here's what I've learned 11 12 from Phase I and nonclinical.

13 I'm going to propose that I borrow some of this information for my prospective, smallish trial 14 15 that we're going to do and we might come to an agreement prospectively that says how much weight or 16 17 how much borrowing we're going to be able to do, sort 18 of in a prospective way so everybody kind of gets 19 comfortable that we're not going to put our thumb on the scale at the end of something like that. Is that 20 21 one possible way of doing this or --

22

DR. RUBIN: Pre-specification is always good

Page 285 1 and would be needed for this type of analysis. I just 2 can't give you an answer yet on --DR. DUDLEY: But that might be some way of 3 4 kind of thinking through how you can pre-specify. 5 Maybe --6 DR. COX: Okay. Either Aaron, are you on 7 the same topic, because Tom, I'm guessing yours is a 8 follow-up. 9 MR. DANE: You go first, yeah. 10 DR. COX: Go ahead, yeah. 11 DR. LOUIS: I just want to make sure -- I 12 don't think we should be pre-specifying the weight. Ι 13 think we need to -- and Kert emphasized this. We should be pre-specifying a model that includes a 14 15 between study or a between body site or a between 16 whatever it might be variance component that the data help estimate and not automatically, but with pre-17 18 specification of the structure, allow the data to say 19 should it be given a lot of weight or not much weight. I think pre-specifying the actual weight is a 20 21 dangerous idea. Pre-specifying a model that will 22 adapt the weights is the right idea.

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DR. RUBIN: Sorry. I misspoke. I concur,
pre-specify the model.
DR. VIELE: Can I one to quickly add to
this we've designed studies where we have specified
in advance if the data matched up your prior
expectation exactly, we'll weight your prior
expectation 25 percent. But if they don't, then they
weight at zero and it's dynamically you know, once
you've programmed the airplane, it goes on autopilot
and it decides the weight based on the results. So
you've pre-specified exactly how you're going to
determine the weight. But the weight is not fixed.
DR. COX: Okay. So I've got Aaron, Paul and
John. Is it a direct follow-up or
MR. DANE: Yeah. So mine was to that
question
DR. COX: Okay. Aaron, you've been patient.
So, please.
MR. DANE: It was something that I've looked
at before about can we use the PK/PD as a prior. And
I guess to this point that it should be data-driven in
some way, and although it's data, it's not the same

1 endpoint. It's not even patients necessarily. So
2 it's more challenging. So does that say you ignore
3 it? Maybe not. But it's probably the strength of it
4 that you actually alter in some way.

And then, that does get to this idea of 5 rather than pre-specifying the weight, but what you 6 7 probably want to do is say, well, okay, we have an 8 approach we're going to take and then we look at various scenarios under simulation or something where 9 10 we say, well, what would it look like at the end so that we could all be comfortable that it makes sense. 11 12 But I guess in summary it just felt like it was more 13 challenging here because you've got to make that leap from the PK/PD data to the clinical data to construct 14 15 a trial that just makes it more challenging generally. 16 DR. COX: And then, Paul? DR. LOUIS: I'll let the speakers -- yeah, 17 it's challenging and yet I think the benefits, in at 18 19 least most cases, are worth it. But there may be situations where it's so complex at the moment, 20 without understanding of the science, the biology and 21

22 so on, that it's not ready for that, but maybe it's

not yet ready for any other analysis either. It's not
 clear.

MR. DANE: But one thing you could do is -you could -- yeah, even if it's not -- yeah, this concern here that this probably is too strong, you could even limit the less feasible type responses from the PK/PD which gives you a bit more information, even if it doesn't take you to somewhere like this. So it at least makes it more feasible than it is otherwise.

DR. COX: We'll go to Paul, and if there are folks in the audience that have questions, please start working your way up to the microphone. Paul?

13 DR. AMBROSE: Hi. Maybe it'd be easier to work the preclinical data in if we think of it in 14 15 terms of exposure-response in the animal system and an exposure-response analysis of the human data. 16 Oftentimes we can drive dose really low in the animals 17 18 and get tons of failure of course and very high --19 higher than we would in people and we can begin to see a plateau of relationship. 20

21 But I think if we were able to take a 22 clinical data set, maybe one from a program or two

1	that had a problem, and get a good Bayesian exposure-
2	response analysis incorporating the animal data and it
3	gives you a y-intercept so it tells you something
4	about the no treatment effect, right, as drug exposure
5	goes to zero and the plateau of that effect and
6	magnitude of factor and some confidence bounds around
7	that, it'll give you that. That'll help you decide
8	how power or how many patients should be enrolled
9	in the study.
10	And also, for a given regimen or for a given
11	drug regimen, it will tell you how much efficacy is
12	being left on the table, right? The dose worked or it
13	barely worked or it kind of didn't work. But how much
14	how much room do I have to bring it up and get more
15	effect out of that regimen. So I think maybe
16	incorporating into all into an exposure-response
17	type analysis might be something to think about.
18	DR. COX: And John?
19	DR. REX: So I want to be sure I heard
20	something clearly because Mike asked a question that I
21	think caused Tom and Kert to talk about different
22	ideas. So Mike's question was before I do my Phase

1	III trial, I have some PK/PD or other information that
2	tells me that I believe that I think that this
3	exposure is going to work. And Mike said could we
4	agree how we're going to weight that. And then, the
5	debate that went back and forth here was is that Kert
6	said, well, yes, you could. Tom said I wouldn't pre-
7	specify the weights. But I think you may have been
8	thinking about if I did three different body sites and
9	I don't want to pre-specify the weight across those.
10	Go back to the case of I'm going to do
11	it's like this one right here. I'm only going to do
12	one site. Ignore the fact there isn't a site here.
13	But I'm only going to study nosocomial pneumonia.
14	It's the only one indication. I get one result.
15	So the only thing I have before I do that is my prior
16	belief from PK/PD and anything I've generated at Phase
17	I and Phase II that there's exposure, everything that
18	I can figure out that tells me I think I could work in
19	the long and then, I get one clinical trial result.
20	So would we agree so because I think
21	we're talking about two different things and I
22	because there's something potentially very valuable in

1	here in using some of this weighting in advance if we
2	could really agree to do that because it's actually
3	potentially a way to buffer against heterogeneity in
4	small populations. And I'm sorry that's a complicated
5	question. So I can either draw it out. But that
6	were you guys talking about different things? Does
7	this make sense, that you were talking about weights
8	across individuals
9	DR. LOUIS: Let me start first by saying I'm
10	still suffering a little bit from jet ears plugged.
11	So I don't think I clearly didn't hear his question
12	accurately because I think for the PK/PD, importing
13	whatever you know for the current study
14	DR. REX: Once.
15	DR. LOUIS: I would probably give it, if
16	not 100 percent weight, unless there's some competitor
17	that I could use, I would give it 100 percent weight.
18	I was answering a question about in the outcome
19	endpoint side of things, priors for the treatment
20	effect or whatever it might be. And so, I think I
21	answered correctly, but the wrong question.
22	DR. REX: Okay.

DR. LOUIS: But take my point as being a
point that's valid but not necessarily for the
question that he asked.

4 DR. REX: Well, so one of the things that 5 comes up in tomorrow's discussion is the problem in smaller data sets when movement of a single patient 6 7 from one category to another causes you to go crazy 8 because all of a sudden you've drifted over some magic margin or confidence interval limit. And it could be 9 10 that a Bayesian prior would allow you a little more 11 buffer in a really small program. The problem in 12 small programs, how do you get enough buffer against 13 the stuff happens problem.

MR. DANE: So I think it's probably 14 15 important that Ed suggests -- you know, there are 16 different ways we can apply this. So one is the way 17 Kert was talking where you're borrowing information 18 across body sites, all in patients, all at the same 19 time and that might be quite different from what we do when we're using preclinical PK/PD information and 20 21 have to make this leap to a different endpoint.

22

But I guess the common principle is this

1 idea of dynamic borrowing means that to some degree 2 it's driven by the amount of similarity you have in 3 the historical data or the prior data and what you 4 have. But what you can do is then try and understand 5 how that's going to look. So you can -- to some 6 degree, you can limit how strong that prior is going 7 to be, you know, by the uncertainty you impose on it.

8 But also, then that's when you can start to look at different scenarios at the design stage and 9 10 then make sure you're happy with what you end up with. 11 You know, since it's to ensure that the prior doesn't 12 overrule the data or something like that. So a lot of 13 this is possible. It's just being clear when you're setting it up that you have to know how it's going to 14 15 look and then it's not going to undermine all the 16 conclusions at the end.

DR. VIELE: At the risk of perhaps saying something different again, you're talking about tiny, tiny, tiny sample sizes with your last question. So I think that becomes a qualitatively different problem. If you're talking an example like Dan was giving, there's a lot of control data that can bring to bear

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1	on your
2	DR. REX: [Inaudible, off mic.]
3	DR. VIELE: Right, yeah. So we're talking
4	if you're smaller than that, the nice thing about any
5	kind of dynamic borrowing is the ability of the model
6	to make an assessment over are the assumptions valid
7	and adjust to that. When you get down into the sample
8	sizes as small as you're talking about, you know,
9	three, four, six patients, there's not enough data to
10	assess that.
11	And I think I'll let you weigh in as well
12	I think at some point if you're going to weight
13	prior information at all, you have to come up with
14	some weight in advance. And you need to understand
15	your study well enough to understand the risks. But I
16	don't think you have enough information to dynamically
17	assess that during your study. And then, it's a
18	question of the Bayesian methodology that's intended
19	to bring in all the information. But if you've made
20	an assumption that's wrong, it's going to lead you in
21	the wrong direction.
22	DR. COX: And then, over to the microphone,

Γ

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1	if we can. Thomas, did you want to follow up
2	immediately or
3	AUDIENCE MEMBER: Yes, I
4	DR. COX: Okay. To the microphone?
5	AUDIENCE MEMBER: Flick Gabray [ph]
6	transcript. I have a question in that really what we
7	seem to be doing here is we are going from a
8	homogenous group into a heterogeneous group
9	potentially even when we're looking at very small
10	sample sizes. And I would like to go back to what
11	Aaron said earlier on about matching and case controls
12	because a lot of the data we have from PK/PD and from
13	our early data is from very homogenous patient sets
14	and our biggest challenge, even with the modeling,
15	when we come to Phase III data is however much we
16	drill down in our multiple logistic regression, we
17	often end up with very small numbers of patients.
18	And we did a study back in the '90s in
19	SmithKline looking at the impact of some of those
20	confounding variables on the outcome of infection.
21	And it was much greater than the impact of the
22	antibiotic. And Helen will identify with this,

1	relating to the endocarditis study, and we go back to
2	Ed's issue right at the beginning around how in
3	serious bacterial infections the confounding variables
4	become more of a challenge and the much more difficult
5	to identify into putting them into our prior analyses.

6 So I wonder whether you have in small data 7 sets a way of dealing with this. I work a lot in drug 8 safety and in very large data sets we have means of dealing with it. But in these kind of small data 9 10 sets, how do we deal with these very big confounding 11 variables like patients who have COPD in HAP compared 12 to those who are relatively -- have relatively fit 13 lungs?

Any takers on that one? 14 DR. COX: Aaron? 15 Only to say my suggestion of MR. DANE: 16 matching relies on there being a data set to match to, 17 which we haven't got at the moment. So that's 18 probably a much longer term aim that would have to 19 come from a network in many years' time because at the 20 moment we are struggling to find external data to try 21 and put what we're finding into context.

2.2

AUDIENCE MEMBER: Well, with the -- just to

1	come back to that, with there are programs in HAP
2	and so on that we've already entered many patients
3	into who have HAP. We could go back and look at those
4	data sets. The agencies could go back and look at
5	those data sets and we could understand the impact
6	much better. And I think we haven't been good at
7	looking in those data sets to understand the impact of
8	comorbidities which might help us to be able to
9	analyze much smaller data sets more effectively.
10	DR. COX: Thomas, did you want to follow up?
11	DR. LOUIS: Just a partial answer and that
12	is that you have for all of these, I think we have
13	to think of it in the context of as compared to what.
14	And what I mean by that is the Bayesian approach isn't
15	going to be magically solving these problems. But the
16	non-Bayesian approach or set aside Bayes isn't going
17	to solve them either if you have lots of complications
18	of heterogeneity of patient attributes but essentially
19	no data, then you have to do something.
20	And at least for me, a strategy of having a
21	discussion about if there are any data that are
22	relevant, build a model with those and build in it the

1	opportunity for people to be individualized as data or
2	as a group of people to be individualized as
3	information builds up so that early on and what I
4	mean by that is early on either in a set of studies
5	for one individual or as data accrue for individuals -
6	- you'll be using as your curve or whatever it might
7	be the whatever your best guess was a priori.
8	But you will then, as time goes on, be
9	giving more weight to the direct evidence as the
10	direct evidence needs less help. And this is part of
11	that dynamic weighting where the model gives the
12	opportunity for the direct evidence as it becomes more
13	stable to be given more weight. And I'm not saying in
14	this case you described this is going to be magical
15	because if there's no information, there's no
16	information. But it's no worse than having no
17	Bayesian formulation and it may be a little better if
18	you can even just have expert opinion give you a good
19	start if that's all you've got.
20	DR. COX: Okay. I was going to go to John.
21	DR. TOMAYKO: Yeah. Thanks, Ed.
22	DR. COX: Yeah.

1	DR. TOMAYKO: John Tomayko, Spero
2	Therapeutics. I have two comments, kind of related.
3	First, as a former sepsis researcher, I just sort of -
4	- I like this idea of matching that Aaron brings up.
5	But I think about what happened in the last 10 or so
6	years with sepsis, which is pretty amazing actually.
7	You know, Xigris comes on the market for a short
8	period of time and they start surviving sepsis with
9	this mandate of reducing mortality in severe sepsis by
10	25 percent over five years. And I was sitting there
11	when that first came out thinking, wow, that's a
12	pretty tall order. I guess they really think this
13	Xigris stuff is going to be great.
14	But it wasn't necessarily the Xigris because
15	it came off the market and they achieved it just by
16	getting us to pay quicker attention and more diligence
17	to starting antibiotics and doing source control,
18	managing the ventilator appropriately even though
19	that's been somewhat controversial and a number of
20	other kind of standard of care-type approaches. So
21	that's a pretty hard endpoint and a really important
22	to me lesson of how much we could really predict, how

1 much heterogeneity is out there and how much could we 2 really control.

But then, the other thing I wanted to maybe 3 4 ask because I agree, Dan and Kert's talks were really great, what's the kind of -- how do we judge -- you 5 know, what's the measure that we're going to judge on 6 or agree that this is the right prior weighting we 7 8 should give. I mean, there has to be some sort of 9 formula, and I'm going to stick my neck out and say, 10 you know, we're always concerned about type one error. 11 But I don't understand how you're going to handle it, 12 what does the context of one type of error mean, means 13 change somehow when you weight things differently or what's -- so could somebody help me understand that 14 15 point?

DR. VIELE: I'll definitely take that one. So I think that's an incredibly important question and a key thing that happens when we design trials in this way, we don't want to change the definition of what makes a good trial. The goal -- I mean, so issues like type one error, power, to the extent that they were valuable yesterday, if you switched the design,

you can evaluate it. I certainly didn't show them.
But we have we have type one error rates
for this design. You can see situations where it
reduces type one error and situations where it raises
it. And you can weigh how often that happens. But we
would assess these kinds of trials the same way we
would assess any others, which is given a certain
treatment effect, what is the probability that you
make the right decision. We may, as we go forward,
want to adopt an approach where we are maybe a little
more utility patient-centered, you know, what
proportion of the population do we treat well. That
may be possible.
But we could assess a frequentist trial or a
But we could assess a frequentist trial or a Bayesian trial by that same way. So in effect, we
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Bayesian trial by that same way. So in effect, we
Bayesian trial by that same way. So in effect, we perform the same calculations. And so, I mean, one
Bayesian trial by that same way. So in effect, we perform the same calculations. And so, I mean, one I didn't show it, but largely this sample size savings
Bayesian trial by that same way. So in effect, we perform the same calculations. And so, I mean, one I didn't show it, but largely this sample size savings comes about by being able to get the equivalent type
Bayesian trial by that same way. So in effect, we perform the same calculations. And so, I mean, one I didn't show it, but largely this sample size savings comes about by being able to get the equivalent type one error and getting more power out of the design and

1	DR. COX: Okay. Well, why don't we do this?
2	I know there's one person over here at the microphone
3	and there was another person there and if your
4	questions have been answered, that's fine. But let's
5	go ahead and take a break. We're at 3:16. We were
6	supposed to go 3:10 to 3:30. So why don't we go
7	until 3:35 and then we'll come back and the person at
8	the microphone over here, we'll start with you at the
9	next session. You'll help kick us off with the next
10	portion of the program. Thank you very much. See you
11	at 3:35.
12	[WHEREUPON, the foregoing went off the
12 13	[WHEREUPON, the foregoing went off the record at 3:17 p.m., and went back on the record
13	record at 3:17 p.m., and went back on the record
13 14	record at 3:17 p.m., and went back on the record at 3:43 p.m.]
13 14 15	record at 3:17 p.m., and went back on the record at 3:43 p.m.] DR. COX: All right. I'll ask that folks
13 14 15 16	record at 3:17 p.m., and went back on the record at 3:43 p.m.] DR. COX: All right. I'll ask that folks move towards your seats. We'll get going here in just
13 14 15 16 17	record at 3:17 p.m., and went back on the record at 3:43 p.m.] DR. COX: All right. I'll ask that folks move towards your seats. We'll get going here in just a minute. And maybe while folks are moving towards
13 14 15 16 17 18	record at 3:17 p.m., and went back on the record at 3:43 p.m.] DR. COX: All right. I'll ask that folks move towards your seats. We'll get going here in just a minute. And maybe while folks are moving towards your seats, out at the registration table, you'll find
13 14 15 16 17 18 19	record at 3:17 p.m., and went back on the record at 3:43 p.m.] DR. COX: All right. I'll ask that folks move towards your seats. We'll get going here in just a minute. And maybe while folks are moving towards your seats, out at the registration table, you'll find a copy of a case that we'll discuss tomorrow as part

	i dge 505
1	that contributed to putting that together. It's meant
2	to be a challenging example to help illustrate some of
3	the issues that need to be worked through if you have
4	a drug that targets a single species and that species
5	occurs relatively infrequently.
6	And just so folks know too, the slides from
7	today and I believe the case that we'll talk about
8	tomorrow are posted on the Web and on the back of
9	your agenda, you'll see the Web address if you want to
10	find those materials. I'm not sure if things I
11	don't think things are up for tomorrow yet. But
12	DR. NAMBIAR: For tomorrow they are.
13	DR. COX: For the slides?
14	DR. NAMBIAR: The slides are
15	DR. COX: Okay.
16	DR. MARKS: A fair bit of tomorrow's stuff -
17	_
18	DR. COX: Well, I think everybody's slides
19	except my own are up for tomorrow.
20	DR. MARKS: The intro material is up.
21	DR. COX: But you'll also find slides there
22	at that same website and after I get mine, I'm sure

1 they'll be up there too. And I think that's it for
2 the announcements. And folks are back, so that's
3 good. And I think at the microphone over here just
4 before we broke, I think Todd Black, from Merck, had a
5 question for the group. So, Todd, go ahead.

DR. BLACK: Yeah, so earlier today we were 6 7 talking about how best available therapy can evolve 8 very rapidly. So I'm just trying to understand in the context of a platform-type study, if we're going to be 9 10 doing this, you know, longitudinally over time, how do we account for then those potential differences in the 11 12 control group, and I think also in the context of what 13 we just talked about in the colistin example, it was really about trying to modify our understanding of the 14 15 control response rather than the treatment response in that case. So you know, how do we bring a Bayesian 16 component into that when it really could be truly due 17 18 to an evolution in the population in the control set? 19 DR. COX: Does anyone want to try and grab hold of that one? 20 Kert? 21 I'll start. It's a little bit DR. VIELE:

22 traumatic to a trial when the control arm changes.

This certainly has happened to I-SPY recently with I 1 think pertuzumab, which it's going through that kind 2 If you're talking about a trial network, 3 of change. 4 there are some advantages, especially if the new drug -- if your network is large enough that the reason 5 you're changing control arms is because of a drug that 6 was in your network, you have the particularly nice 7 8 setup where you already have data on that drug within 9 your network.

10 So you can do it a little more seamlessly. But there's absolutely going to be challenges. 11 I′m 12 not sure they're any more challenging than starting 13 new trials with that. But certainly you'd have to make adjustments and you'd have to update -- you know, 14 15 update forms and everything else that goes with it. It's an uprooting experience, but it can be -- it can 16 be accomplished. 17

DR. RUBIN: I would say that -- oh, sorry -that the ability of a platform trial to anticipate and plan ahead from when one of the arms may become the standard of care and change the control group is actually a big advantage of studying drugs in a master

1	protocol and being able to prospectively plan for
2	those whereas if separate sponsors are conducting
3	individual trials and not knowing when a different
4	sponsor may win or when the standard of care may
5	change, that that would be something that would be
6	harder to implement.
7	DR. COX: Okay. And Aaron?
8	MR. DANE: Yeah, and I would just add the
9	Bayesian component to that is probably less of the
10	issue because this is true whatever analysis you're
11	doing. If that happens, you've still got to handle

13 certain comparisons. But as Kert said, you know, you 14 can handle that with the data you're generating as an 15 externality in that study. 16 DR. COX: Okay. And then, over here at the

that same problem that, you know, halfway through

12

microphone -- and just so folks are aware, at 3:30, we're supposed to have public comments. So after this question at the microphone, if there's anybody who wants to make public comments, we have a little session then and then we'll go back to the discussion after we've completed that. So please introduce

1	yourself at the microphone on my right.
2	MR. WEBBER: Yeah. My name is Frank Webber.
3	I'm an independent consultant from Europe. I want to
4	come back to Dan's wonderful case. What I saw on the
5	chart is a mortality rate of 50 percent what I saw
6	on the chart was a 50 percent mortality rate in that
7	infection. And given the statistics he gave us, to
8	bring it down to 40 percent, you would need 385
9	patients for a superiority trial. And I think
10	everybody admits that 385 patients in such an
11	infection, to show that mortality is a no-go because
12	it's not recruitable. It's an 800-patient study. And
13	everybody I think would admit that going to 40 percent
14	mortality in that infection would be an advancement of
15	care. And the question then is how much more are this
16	panel or the FDA willing to accommodate Bayesian
17	borrowing to the control group to allow an
18	augmentation treatment to get down to 40 percent and
19	have an approval of being an effective augmentation of
20	colistin or whatever.
21	So in other words, colistin, having 50
22	percent, the erratic add-ons not being much better,

1	but a new drug would give you 40 percent. How would
2	you try to develop that drug and what type of
3	statistics would you allow being borrowed from
4	historical control groups, matched control groups and
5	perhaps from the active arm through a Bayesian
6	approach.

7 You want to do that one Aaron? DR. COX: Well, I won't speak -- I mean, 8 MR. DANE: Kert's done a lot more on this than me. 9 But this 10 comes down to this question of whether you can use 11 external controls, I think, could help to some degree. 12 So if you're in a situation where you've got some 13 recent trials that are conducted in a similar way, then you could borrow some of that information and, I 14 15 mean, I know Kert's done some work on augmenting 16 control designs which do borrow that information in 17 some way and reduce the burden of the study. I don't 18 think that's going to help us when we're talking about 19 40 or 50 patients. But it may do when we're talking 20 in the 100 or 200 patients.

21 DR. RUBIN: Yes. An intervention that 22 reduces the mortality rate from 50 percent to 40

1	percent is kind of an interesting example because, on
2	the one hand, it would be a very major benefit in
3	terms of saving the life of 1 out of every 10 subjects
4	in terms of number needed to treat. But on the other
5	hand, the sample size tables show that the randomized
6	trial would become very difficult, but also the
7	treatment effect of 50 to 40 isn't so large that in a
8	nonrandomized comparison you wouldn't be worried about
9	confounding and whether selection effects outweigh
10	treatment effects. So I think that's kind of why
11	we're talking about this today.
12	DR. COX: And John Rex?
13	DR. REX: So the generalized question, as I
14	heard it, was if the mortality for your best therapy
15	is 50, 60, 70 sorry, excuse me, if the survival
16	if the mortality is 50, 40 or 30 and you want to show
17	a reduction by from 40 to 30 or from 40 to 20, right -
18	- so that's the question by adding something on.
19	And your question was not about a different therapy
20	but about an add-on. Is that correct? It was about a
21	
22	MR. WEBBER: [Off mic] replace what you

Page 310 have with colistin, you have already to go to this --1 [off mic] -- leave out colistin, take my new drug and 2 3 the --4 DR. REX: Okay. MR. WEBBER: [Off mic] -- it doesn't address 5 unmet medical need. If the patient is dying -- how 6 7 about when the patients are dying and I think the 8 unmet medical need is getting down. 9 DR. REX: Right, so --10 MR. WEBBER: [Off mic] -- you do it in heart 11 failure. You do it in oncology. You do it -- I know 12 you augment as long as it's tolerable and then you'll 13 have incremental benefits, whether you're --Right. So it's really important 14 DR. REX: 15 to separate the case of augmentation, as you're saying, standard of care versus standard of care-plus 16 17 as opposed to new drug versus old drug. So the case of standard versus standard-plus, you phrased it as if 18 19 the question was what will the FDA accept. I'm going to argue that that question is incorrect and that it's 20 21 not -- you know, what the FDA accepts or not is, in a 22 sense, irrelevant. If you can't -- if FDA approves

1 it, if it's available on the market, you still have to 2 go to a payer and say, all right, you should pay me 3 \$10,000 for this and they're going to say why, show me 4 why.

5 And if your answer is sort of a collection 6 of sort of stray bits of data that you assemble into 7 an argument, you're not going to get your \$10,000. 8 You're going to have to show on something that's 9 really, really clear why you should pay on top of. 10 It's different from instead of, A versus B. It's 11 different from A added onto B.

12 And I think it's really important to be 13 aware of that. You know, we're doing pricing and payer arguments around the world right now and I can 14 15 just tell you flat out that you're not going to get 16 anybody to reimburse for an add-on unless you have 17 some very strong data to say why you need to do the 18 add-on. And in cardiology, they do that. You know, 19 you generate large data sets. So you know, I'm just telling you the reality as I have faced it in, you 20 21 know, recent days, weeks and months.

22

DR. COX: Yeah, and maybe just to follow up

1	on it, I think, you know, people, patients, everybody
2	in general would be interested in a drug therapy that
3	can reduce mortality by, you know, 10 percent. I
4	mean, there's no question about that. And I think
5	really what this workshop is about is how do you work
6	through some of the challenges that are faced in
7	demonstrating such a finding.

8 And you know, we talked some about this at the break. You know, this point in time where 9 10 colistin might be best available therapy for some patients we hope is time-limited. And you heard, you 11 12 know, some experiences with trying to show 13 superiority. It's not easy. So I think that's why we're talking about some of the options which you 14 15 might utilize here, whether it be, you know, trying to 16 study the drug in non-inferiority setting where you 17 can understand its safety and efficacy, the trial's 18 feasible. You can gather some PK data. Maybe you can 19 enrich for some sicker patients and that might be a 20 pathway to study for a drug. When you've also heard 21 some of the discussions about, you know, Bayesian 22 approaches, how you might use them.

1	So I don't know that we can specifically
2	answer your question. But I think that's what we're
3	trying to get at here today, which is, you know, what
4	are some of the feasible approaches. How can you
5	actually, you know, develop this drug, study it in a
б	way so that it can be available to patients.
7	Other questions, thoughts on this particular
8	issue? And then, we'll open it up for the public
9	comment period. And maybe I'll just move towards
10	that. Is there anyone who does want to make a
11	specific public comment at today's workshop? If you
12	do, I will pause for a minute as you start making your
13	way towards the microphones. Everybody can just take
14	a deep breath for a moment.
15	PANEL DISCUSSION 3 (COVERING ALL TOPICS)
16	DR. COX: Seeing no takers, I guess we will
17	move on. Any questions that folks want to pose,
18	either on the panel, topics for discussion? Lynn,
19	you've got a question. But I at the nope,
20	you're just working your way towards the seat or did
21	you have a question at the microphone?
22	MS. KEANE: No, I was ambivalent about

Page	314
Page	314

1	whether	Ι	wanted	to	ask	it	or	not.	Anne	Keane	from
2	Achaoger	ı -									

3 DR. COX: Just please get a little closer to4 the microphone so we can all hear you.

5 MS. KEANE: Okay. Anne Keane, from Dr. Cox, in the beginning of June, you were 6 Achaogen. at BIO and you had made a comment that if the LPAD 7 8 legislation passed, the division would feel that that would give you greater flexibility to approve drugs 9 10 for rare, very serious pathogen studies, that it would 11 give you more flexibility because you'd be able to 12 take into consideration the risk-benefit of the drug. 13 And unfortunately, as of today, from what I've heard, the LPAD legislation is stuck, made it all the way 14 15 through the House, made it all the way through the 16 Senate subcommittee and now it's attached to an 17 innovations bill that Patty Murray is holding up 18 unless she gets a guarantee of \$8 billion a year for 19 So it may go nowhere. NIH.

20 So what I'm wondering is given everything 21 that we've heard today and kind of acknowledgement I 22 think from most people that there is an unmet need,

1	that these patients have a very high mortality rate
2	and there are lots of creative ideas about things that
3	we can do moving forward, but those ideas are all
4	going to take years probably to come to fruition, and
5	there is subpart E regulations which talks about using
6	the broadest regulatory flexibility when you're
7	reviewing NDAs for drugs, for patients with severe,
8	life-threatening infections, instructs FDA to consider
9	risk-benefit to allow greater uncertainty and also
10	gives or suggests at least that FDA work with sponsors
11	to agree on post-marketing commitments that could
12	collect additional data to increase the knowledge
13	about the drug and the risk-benefit.
14	I'm wondering if in the absence of a
15	functional Congress if FDA can rely on the existing
16	regulations that give you that flexibility and in
17	particular in settings where you have a pathogen-
18	focused study in the setting of a separate randomized
19	control study in another indication.
20	MS. BORIO: [Off mic.]
21	[Laughter.]
22	DR. COX: All right. So maybe I'll just

1	tell you a story. So yeah, so without, you know,
2	commenting on any particular, you know, pending
3	legislation and that sort of stuff in any sort of
4	direct way, so the question that Anne asked me when I
5	was out at Bio was, you know, if LPAD doesn't change
6	the standard, then what does it do for you. And you
7	know, we talked about some of the tools that LPAD has
8	within it where, you know, there'd be premarket review
9	of promotional materials, a designation of, you know,
10	a product as an LPAD product so that people would
11	understand there was a greater degree of risk or, you
12	know, greater degree of uncertainty and/or risk
13	associated with a product and that that, you know,
14	probably would impact upon, you know, how folks
15	utilize the product out there.
16	So it gives us maybe a little more it
17	gives us some tools to give us some of the potential
18	risks and/or uncertainty associated with a product.
19	So I think now you're asking me, you know, how do we
20	deal with this, you know, situation where, you know,
21	we're dealing with unmet medical needs and, you know,
22	there may be products out there where there may be

1	greater degrees of risk and uncertainty. And I think,
2	you know, what you're seeing and hearing today is
3	we're really trying to work the best we can within the
4	tools and situations that we have, you know, to be
5	able to gather the evidence to understand how these
6	products worked, how these products work as best as
7	possible, you know, will I think you've heard some
8	ideas here.
9	And you know, clearly when we think about
10	product development and you'll hear this also
11	tomorrow too, and that is that there really do need to
12	be, you know, achievable pathways so that the drugs
13	that are out there can be developed. You know,
14	patients, you know, need new options now. We know
15	they'll need new options in the future. And you know,
16	we'll continue to try and take, you know, a science-
17	based approach and do the best that we can with the
18	tools that we have available to us. So maybe I'll
19	stop there and hope that that's given you some
20	insights into your question. David?
21	DR. SHLAES: Yeah. I actually want to go
22	back to the discussion, if I can, and leave LPAD,

1	between with Mike and pharmacometrics a little bit,
2	just to try and expand on this and maybe, Paul, you
3	can help with this. But this is something we actually
4	talked about I think back in 2012 or so, where the
5	idea was, for example, with meropenem, to take a
6	practical example, you have a target attainment of 90
7	percent or something in most patients. Is there if
8	you could then reduce that to what happens in patients
9	with Pseudomonas infections, in patients with VAP and
10	you could look at what happens with a Pseudomonas MIC
11	goes up to eight, you would get then a predicted
12	control response level which would which and the
13	question is how robust could one make that in terms of
14	using it to establish or contribute to a dataset of
15	external controls for the kinds of things we're going
16	to be talking about tomorrow. So I guess that's
17	DR. AMBROSE: Sure. Most of the clinical
18	data sets, since many of the drugs don't are not
19	frank disasters, right, there's not lots of exposures
20	that approach zero our confidence bounds on those
21	relationships get quite wide as we go from the upper
22	asymptote down, the exposure-response function. And

1	that's the that's the main problem with those
2	relationships. And that's why we've, you know, done
3	things like bring in the preclinical data to help
4	inform that slope. But that's been the problem with
5	them.
6	DR. SHLAES: Yeah. Okay, so the answer is

7 that the existing data, including the PK -- sparse PK 8 from the Phase III trials does not provide enough -- a 9 robust enough dataset to really use that way. Is that 10 right?

DR. AMBROSE: At least in individual trial.
I don't know. Maybe you could do something by looking
at a bunch of different trials.

DR. SHLAES: Multiple trials. Yeah, that's -- so something I've asked the Agency. I mean, have you guys ever tried to look back at those data in the -- because, I mean, you have access to all the data.

DR. COX: Yeah, so we have. I don't know if any of our clin pharm folks are here. But they have looked back. I mean, it's come up in the area of pediatrics in particular, where, you know, we've tried to go back and look at the data. And I think that

	5
1	sometimes the data that we have is not what people
2	think we have. And it hasn't been quite as rich a
3	resource as we might have hoped that it would have
4	been. But we have tried to do that, particularly in
5	the area of biothreat agents. So you know, we may not
6	have quite as much as you think we have. So, but we
7	have tried. We have tried to do it in some areas.
8	DR. MARKS: I think John wanted to go next.
9	DR. REX: So that question made me ask
10	made we wonder about the question of is there a
11	generalized framework under which you approach the
12	question of constructing a Bayesian prior. And you
13	know, like in benefit-risk, there's these semi-
14	quantitative benefit-risk analysis tools that are
15	supposed to help you at least document your reasoning
16	as to how you get to, you know, conclusion X. And it
17	feels to me like one of the issues with the Bayesian
18	thing, or Bayesian prior is that at some point it
19	involved making a choice. You know, is the number 65?
20	Is it 62? Is it you know, what's the shape of the
21	prior.
22	And I'm just is there a general approach

22

And I'm just -- is there a general approach

to that that has ever been developed? You know, how is it done such that everybody, you know, understands the tradeoffs that went into it and the documentation of same and sort of does it the same way the next time for a case that's got some of the same features? How do you do it?

7 DR. LOUIS: Good question. The answer, I 8 think, is both yes and no. The yes part is that there's a fairly developed literature on eliciting 9 10 prior opinions, not necessarily based on empirical 11 evidence; possibly so, but a process to have a group -12 - either an individual or a group or individuals come 13 up with their individual priors and then decide whether you're going to simply do a mixture of those 14 or take each of them on their own and do a sensitivity 15 16 analysis. But the process for doing that is pretty 17 well developed, not that there isn't work that can be 18 done.

For empirically based priors where the information -- excuse me, the opinion part may be mostly on what data are relevant, Dan and Kert may have something different to say. I don't think it's

1	very well formalized, any more formalized than our
2	using those same data sources to decide on the design
3	of a study in terms of baseline rates, this, that and
4	the other thing. So there may be some general
5	principles. But I don't know of anything that could
6	be approximating an algorithmic approach. But I'll
7	turn it over to the other side there.

8 DR. VIELE: I think the answer for us is largely no. What we tend to do in practice when we 9 10 design trials is we may elicit. But more than likely, we look at the available stuff and we do custom priors 11 12 for each individual project. So I know of no piece of 13 software that -- I mean, there are pieces of software that will elicit priors, but will not design a 14 15 clinical trial for you. What we tend to do is to try 16 to stress test our designs in a lot of detail. And 17 essentially we go back to operating characteristics. 18 If we use this prior, here is how well it works under 19 a variety of assumptions.

20 So if your prior belief accurately reflects 21 the world, here's the advantage that you get from 22 using the prior because it's giving you good

1	information. If your prior doesn't match the world,
2	here is the risk that you are taking by incorporating
3	that prior if in fact it is wrong and it becomes a
4	risk-benefit to the sponsor of I know under what
5	situations I'm going to get a benefit from using this
6	prior and I know under what situations I'm going to
7	take a risk. And then, it's a question of how much do
8	you believe it.
9	DR. REX: Are they using expert elicitation
10	in any of the I-SPY, lung map, any of these platforms?
11	Do they put that in place up front or is that a
12	strength or a weakness of platform trials to be able
13	to do that?
14	DR. VIELE: I-SPY I should be careful. I
15	don't know every detail of I-SPY. But by in large, I-
16	SPY uses non-informative priors. And it is Bayesian
17	from the standpoint that the accumulating data within
18	the trial is used to update those priors. But there's
19	not expert opinion going in up front. It's the fact
20	that after you've enrolled a couple hundred patients,
21	that data is used to update.
22	DR. LOUIS: If I could, I'd like to use that

1	to segue to another benefit of the Bayesian formalism,
2	setting aside the issue of priors and in fact sticking
3	with let's say uninformative priors. For both basic
4	and complicated settings, you get to use the laws of
5	probability to make your inferences, and especially
6	for a nonlinear model and so on. You're no longer
7	doing Taylor series and plugging things in. You're
8	letting the full uncertainty percolate its way through
9	the system and frequently ending up with more
10	uncertainty than you would as a frequentist. It's not
11	always an uncertainty win. It's always, or almost
12	always a validity win. And it also is very effective
13	at addressing nonstandard goals. And I'll just
14	mention one.
15	If you're ranking things, whether it be

15 If you're ranking things, whether it be 16 drugs or small area disease rates, it actually isn't 17 best to simply take your point estimates however you 18 produce them and rank those. One of the nice things 19 about the Bayesian structuring is you say if I only 20 knew those underlying parameters, if I had them in my 21 hand, how would I rank them? Well, I'd put them in a 22 line, small to largest. I don't get to see them, but

1	what I do get to see is the posterior distribution of
2	them. And I can do what is a nonstandard computation
3	to get the best ranks and the associated
4	uncertainties. It's just one example where it's very
5	hard to even know how to think about that without the
6	Bayesian formalism, not necessarily the Bayesian
7	philosophy, if you'd like, you know.
8	DR. COX: Yeah, Kert?
9	DR. VIELE: Yeah, very quick follow-up. In
10	terms of when we say Bayesian methods, we design, you
11	know, a hundred trials a year. By in large, almost
12	all of ours are non-informative priors. We use
13	Bayesian in terms of how to use the data that's coming
14	into the trial as it accumulates more than in the
15	sense of incorporating these extra pieces of
16	information prior to the trial. So there's just
17	another way to use Bayesian methods.
18	DR. REX: Because I think that in this
19	particular area, what we're faced with if you look
20	at the handout for tomorrow, you're going to see
21	there's this hypothetical drug that we've, you know
22	it's actually pretty close to some real cases. But

Page 326 the sense you have going into Phase III is that it 1 does what all other antibiotics do. It seems to kill 2 bacteria and it works in a variety of models in 3 4 animals and even in a little version of a human being, 5 or sorry, version of a human illness. And so, you have this belief going into 6 7 Phase III that, you know, it probably will do 8 something. And so, I guess what you're saying is that there's not a standard way of taking that, the 9 10 observation that you'll see in the handout and turning it into some sort of an informative prior as opposed 11 12 to an uninformative prior. 13 DR. VIELE: I think that in general would be very hard. 14 15 DR. REX: Yeah. I think this gets back to what 16 DR. VIELE: Ed was saying. You know, if there was a long history 17 of here is the data that I had prior to a number of 18 19 trials and here is how this evidence translated into my clinical endpoint, you could do a lot with that. 20 21 But I'm not sure -- I'm not sure we're there. 2.2 DR. REX: Well, but in fact, those data do

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1	exist because that's the domain of Paul Ambrose. You
2	know, all of that still like the little picture you
3	showed just this morning, Paul, of the likelihood of
4	Phase III efficacy success based on where you were in
5	your preclinical PK where your actual pharmacology
6	came out on the doses on the exposure-response curve.
7	So in effect, that exists. One of the maybe one of
8	the stepping stones.
9	DR. COX: I think Aaron?
10	MR. DANE: Yeah. I mean, that starts to
11	inform I guess what we would have to look at is the
12	uncertainty around that and what the prior
13	distribution would look like because the numbers are
14	small, just because there haven't been that many
15	development programs. And it gives some comfort, but
16	I'm not sure how much it would help in terms of an
17	informative prior.
18	DR. MARKS: Sam?
19	DR. BOZZETTE: Well, I think it is an
20	informative prior because I think that's what
21	Ambrose's presentation showed us. I mean, it showed
22	us we have some failed programs and when we went back

1	and looked, there was an informative prior that either
2	people chose to ignore or that we discovered
3	afterwards. So I do think that there are informative
4	priors. I don't think we have a lot of examples
5	and we can come to those of clinical trials that
6	failed because of sunspots or some unexplained
7	phenomenon in the universe.

8 I think that's been the lesson over the last 9 few decades is that we've had -- we've learned a lot 10 about doses and we've learned a lot about exposure-11 response relationships that a lot of these sort of 12 failed trials are rooted in that area where I believe 13 those priors are going to be extremely important in 14 terms of structuring our priors for clinical trials.

15 MR. DANE: I think the point is, Mike, that it depends whether you want your prior to be elicited 16 or data-driven or empirical because if you elicit it, 17 you can make that comment. But if it's more data-18 19 driven or you're using the numbers you've got, that's 20 where there's a lot more uncertainty, because the 21 numbers are small. You know, we haven't got many. 2.2 We've only got -- I can't remember the numbers now,

Page 329 but a relatively small number of approvals or failed 1 studies. So yeah, normally we'd ideally want the 2 prior to be driven by the data rather than 3 4 elicitation, if we can. And there's still uncertainty there just because there's not a lot of data there to 5 do that with in terms of drugs that have been approved 6 7 or haven't. 8 DR. MARKS: Sam, we'll bounce back to you, 9 then --10 DR. LOUIS: I think the very act of going 11 into Phase III means somebody thinks something good 12 has a reasonable chance of happening. Otherwise, I 13 can't imagine going into Phase III. And it might be the prior. But it might also be the industries' or 14 15 the government's or somebody's utility that even with a relatively broad uninformative prior, the win would 16 17 be so big if we got it that it's worth doing. So I 18 think we need to -- can't unlink priors from utilities 19 basically. And some combination of those makes it a 20 good bet I guess is the way to put it. 21 One more time, Sam. DR. MARK: 22 DR. BOZZETTE: My prior is that there's a

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1	lot of information about priors out there. And even
2	in even in failed trials, you know, there's
3	information in the control arm and especially in the
4	context of a platform trial looking at, you know,
5	informing estimates of the effect in the control arm.
6	It seems to me that there are a lot of studies out
7	there that could be used to do that. So I don't think
8	I mean, it's certainly PK but I think clinical data
9	is there.
10	It's just going to take a specific effort to
11	pull that stuff together. And I don't know if you do
12	that through agency, you do that through well, it
13	was mentioned at lunch a big data effort from clinical
14	databases, you know, the large clinical databases or
15	of it's done by a consortium of companies looking at
16	their own trials. But there's an awful lot of
17	information out there on what happens in standard
18	therapy.
19	MR. DANE: I don't think that needs to be
20	Bayesian. I think we should just do that anyway,
21	irrespective of the analysis approach you're going to
22	take. You know, there's an element of this, well, we

should try and pull together the information we have.
 And then, we'd get into discussions of what's the most
 appropriate analysis. But all of that's going to
 inform whatever we do and however we do it, I would
 say.

DR. MARKS: John?

6

7 AUDIENCE MEMBER: Yeah, I thought that was a 8 nice comment that Sam made, that there's a lot of prior out there. But I also think there's a lot of 9 10 heterogeneity out there that I worry about. And you 11 know, maybe my memory doesn't serve me correctly. But 12 I think when doripenem came to an ad com, the first 13 time around, it was like a 500 mg three time a day dose and they did what I thought was the first study 14 15 in VAP patients, theDORI-10 study. And if I recall, 16 they met the endpoint. But there were some issues and 17 we were changing endpoints. It was a clinical cure 18 endpoint. But there were some issues.

And then, they went out and, probably for good reason that wasn't disclosed that I know, doubled that dose and failed to even complete a study because it stopped for futility. So I mean, I don't know. I

1	know that getting the dose right is important. But
2	Paul talked about augmented renal clearance and I
3	heard about that. You know, that's a hard thing to
4	study ahead of time. Yeah, you could go to an ICU
5	population and maybe do some BALs and whatever. But
6	there's just a lot of variability in exposure that
7	you're going to see in your patients. It's hard to
8	DR. BOZZETTE: Yeah, but there are millions
9	let me just say there are millions of cases out
10	there, not only I mean, if one wants to you can
11	look beyond the clinical trials even and look at the
12	large EMR datasets to get some sense of what happens
13	with these patients. And they have things like
14	creatinine clearance and some other things. It's
15	certainly not PK data. But it's things that you can
16	make inferences from, you know, and comorbidity
17	information, labs, et cetera, et cetera. So I think
18	both within clinical trials and in large, you know,
19	EMRs, that there might be some potential. Sorry to
20	interrupt.
0.1	

DR. AMBROSE: So even with the doripenemhigher dose study, right, it was a gram every eight

Page 333 hours and it was over a four-hour infusion. 1 So the 2 steady-state drug concentration for a four-hour infusion on average for doripenem would be 16 µg/mL. 3 4 It penetrates about 25 percent of the epithelial lining fluids, so let's just make the math. Should we 5 drop it to $\mu q/mL$? And then you throw on 60, 70 6 7 percent variability on clearance and volume. You end 8 up with people approaching drug exposures of zero again. I don't -- you know, the dose wasn't high 9 10 enough. It's just -- it's the variability. It's what 11 gets you. 12 AUDIENCE MEMBER: But the first time the 13 dose did not -- [off mic]. DR. AMBROSE: No, it wasn't good enough. 14 Ιt 15 didn't get approved. 16 AUDIENCE MEMBER: It didn't get approved --[off mic]. 17 18 DR. AMBROSE: No, it had more mortality. I 19 believe it was with seven deaths in the doripenem arm and one versus the control or some number like that. 20 21 But --22 DR. MARKS: We'll go to the microphone.

1	DR. BLACK: Yeah, Todd Black, with Merck.
2	So I think just to point out, all the new drugs we're
3	talking about today are ß-lactams, ß-lactamase
4	inhibitors, aminoglycosides. Having done drug
5	discovery now for many, many years, you know, what we
6	would really want, that new agent, new mechanism is
7	really, really hard to come by. It's not for lack of
8	trying. So our only solution in the future may be
9	this adjunctive therapy. So to John's point, that may
10	be where these priors and understanding or how you're
11	modeling I guess the add-on on top of an effective
12	therapy. Does it open up a door for us there to help
13	us do these developments with an adjunctive therapy as
14	a primary, as we, you know, get around all these
15	concerns and questions about combination therapies.
16	DR. MARKS: And I was going to ask a
17	question about sort of the borrowing piece, to go back
18	a little bit, borrowing across body sites, how
19	comfortable we are with, let's say, if we have good
20	success in intra-abdominal infections, does that help
21	with HAP/VAP? You might say not very much. But if
22	you had success with HAP/VAP, would you weight that

1	more heavily in terms of trying to support an intra-
2	abdominal infection and how people feel about the
3	different body sites influencing the data more or
4	less.

5 DR. AMBROSE: I'll take a whack at it. Yeah, I'd feel more comfortable going backwards from 6 7 HAP/VAP. Why would that be? I think when we've 8 looked at, from a PK/PD perspective, clinical trial datasets, an intra-abdominal infection requires 9 10 something like net bacterial stasis in the animals. 11 It's a relatively low, low threshold and, generally 12 speaking, those studies are done at relatively modest 13 bacterially dense inoculums, right? The pneumonia studies are done at high bacterial inoculums and, 14 15 generally speaking, require more drug.

So I do feel that generally speaking, if you can treat a pneumonia, you probably are going to be okay in an intra-abdominal infection, assuming, you know, you're not inactivated in a more acidic environment or something like that. I'd feel more comfortable in that direction than the other.

2.2

DR. MARKS: And how about UTI when it comes

1	to intra-abdominal infections? Because intra-
2	abdominal infections, I don't know, one-and-a-half,
3	maybe two times slower to enroll, a little bit less
4	influence in the antibiotic, more related to the
5	surgical intervention. If you had a lot more urinary
6	tract infections, would you be more comfortable
7	propping up the difficult intra-abdominal infections?
8	DR. AMBROSE: I think a urinary tract
9	infection, relative to pneumonia, again, is a little
10	bit easier to deal with, most of them anyways than a
11	pneumonia. But are you asking me to rank it versus
12	intra-abdominal infection? You know, we don't have
13	many exposure-response analyses at all in the urinary
14	tract infections. It hasn't been a place that we've
15	done those analyses. My gut instinct is that some
16	you know, generally speaking, it's not as high a
17	threshold as ventilator-associated pneumonia.
18	DR. REX: I'll just add an observation that
19	we had out of the Avycaz program, which was that if
20	you take nosocomial pneumonia, intra-ab and UTI and

22

21

look at actual physiologic derangements, which one of

the three is the hardest on average in that population

1	to hit the exposure you want, and it turned out that,
2	at least for that combination, intra-ab was actually
3	the hardest. You know, and nosocomial pneumonia was a
4	close second. But intra-ab was really tough.
5	And I think the logic, the best we could
6	tease it out, was you've got people going to surgery,
7	you've got deranged volumes of distribution in the
8	belly. So all kinds of whacky things are happening
9	with your blood volume. So you know, I guess to
10	answer your question, I think one of the things I got
11	out of that was that intra-ab is surgery is a
12	confounding variable. But on the other hand,
13	pharmacokinetically, it's a very demanding setting. I
14	just thought that was an interesting observation.
15	That will be in some one of our papers somewhere, that
16	that fact was observed.
17	DR. MARKS: Helen, any thoughts?
18	DR. BOUCHER: Yeah, I would just add that
19	clinically it sort of comes back to something we
20	talked about this morning. I think the inclusion of
21	any group of patients certainly with pneumonia, but
22	also with bloodstream infection, is incredibly

1	meaningful to the clinician. And that's also in this
2	group where there's a predictable high mortality.
3	So if we see that the new drug works, that's
4	incredibly useful, especially if the main study is a
5	UTI study, where I know we get the bacteria. We have
6	the potential for statistical testing. But
7	clinically, we're not always comfortable with just UTI
8	data to take it into that much sicker population.
9	And so, if there's any way to learn that
10	information in a high quality type of study, like a
11	registration type of study, even if it's not the whole
12	study, that's a lot better than relying on a random
13	publication. And I think in the real world, we're
14	often that's what we get and we get it two years
15	later, you know, after the approval is publication of
16	cases and again, don't get me wrong. That's my
17	business. But the high quality data, the patients
18	enrolled and monitored and studied for safety as well
19	as efficacy in this kind of setting really does have
20	power that's important.
21	DR. MARKS: Well, let me draw on that a
22	little bit more because some sponsors are going with

1 the complicated urinary tract infection studies and 2 then jumping to a multi-body site, more drug resistant 3 population. But what's missing in that equation for 4 you and what -- how could they supplement that package 5 to get you more interested?

DR. BOUCHER: I think that, you know, in 6 7 doing that kind of a thing, really important is going 8 to be the enabling work that enables them to go into those other body sites and, coming back to Paul's work 9 10 and others, to make sure the dose is correct or is as 11 good as we can estimate. And again, you know, in a 12 perfect world, we'd have the perfect. But this is not 13 the kind of thing that's going to lend itself to perfect. So really good enabling data, really good 14 15 ability to describe the patients that are treated in 16 terms of diagnosis and in terms of outcome, really, 17 really important. And we didn't get into this today. 18 But again, from Nick and my earlier life with 19 aspergillosis, you know, drugs have been approved on historical controls and that's all about the ability 20 21 to describe the population in each individual patient 22 to ascertain that they really had the infection, to

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the best of our knowledge, that they had a good
 treatment effect.

DR. MARKS: So on Sumathi's slide earlier 3 4 this morning, she had cUTI, stroke, cIAI or whatever acronym you used on that slide, as sort of 5 interchangeable, one or the other. Would you prefer 6 7 one or the other in terms of a sponsor coming to you 8 for running clinical trials? You'd rather have an intra-abdominal infection program rather than a UTI? 9 10 You want both? You want --

11 DR. BOUCHER: I mean, again, I think in a 12 perfect world, we'd want it all, right? And so, 13 treating the kind of patients that I treat, I would always prefer to see some experience in the more ill 14 15 patients. But I could see very reasonable approaches 16 using either. And I think a lot of the pros and cons 17 have been articulated. You know, UTI, you get the 18 It's a more homogenous population. bugs.

19 So that's a good thing in some ways. And on 20 the other hand, in the complicated intra-abdominal 21 infection, it's a little harder to treat. The 22 patients are more ill. There's more probably sepsis

1 in that study and things that might, you know, make us 2 feel more comfortable in a population. But that could 3 be addressed in other ways if you did the small 4 pathogen -- the small group study. So I think both 5 could work.

DR. MARKS: So it would be a review point,just to use the FDA language. Sorry. Ian?

8 DR. FRIEDLAND: So I have a question. Ι'd be interested in what Helen has to say and what the 9 10 regulatory folks have to say. And this is also again about prior knowledge. So if you're dealing with a 11 12 known class, let's say ß-lactams, we know a lot about 13 ß-lactams. We know a lot about the PK/PD, versus a completely new class that has a new PK/PD. Would you 14 15 be more comfortable with uncertainty when there's like a known class of drug, even if it's a new drug versus 16 17 like it's a completely new class or are you totally 18 agnostic of the drug class?

DR. COX: So if you think about it, I mean, the question is at least two-dimensional. And so, you're asking suppose somebody else comes in with, you know, another member of the same class. So the level

of innovation there may not be huge. It may offer
something that existing drugs don't offer. But it
probably, on the benefit side, is not going to be sort
of something completely different. So I mean, we
would take that level of benefit into consideration.
Is it addressing some unmet medical need? What do we
know about the safety? And weigh those two things.

8 Now, the thing that you are contrasting that is a wholly new class, something that operates via a 9 10 completely different mechanism. I can make good arguments to accept a fair degree of uncertainty 11 12 around that drug because I'm presuming that it may be 13 able -- you know, it operates via a wholly new class. So it ma, you know, provide benefit in certain patient 14 15 populations that, you know, may go beyond what you 16 could do with a class modification. So you know, those benefits may be for a particular subset of the 17 18 population, not for the population at large. But I 19 mean, you can argue these situations both ways.

20 So I don't know that there's an answer one 21 way or another, specifically what's easier, you know, 22 this way or that way. I think there's -- you know,

1	each of those two molecules and these are
2	hypotheticals, so we don't know exactly what they do -
3	- you know, has the potential to bring, you know,
4	either, you know, different levels of benefit, you
5	know, based on the type of molecule. And then, you
6	know, the other question is what do we know about
7	risk. Sometimes you come into your clinical program
8	with, you know, completely clean animal studies and it
9	doesn't look like it's provoking much of anything.
10	And you know, then it looks clean even in the limited
11	safety database. That doesn't give you guarantees,
12	but it sure, you know, looks like it's not a big
13	problem.
14	The flipside is suppose that preclinical
15	data you know, you're starting to see significant
16	toxicities already and you've seen some of that being
17	reflected in the patients that you see. So it's very
18	hard to answer those hypotheticals. But I've outlined
19	at least some of the things that you might think about
20	as you're looking at these two different types of
21	prototypical agents, something from a new class and
22	something from a wholly new or something from a new

class versus a class modification. So hopefully that
 makes sense.

DR. KARTSONIS: So to kind of seque a little 3 4 bit more to the safety question, we talked a lot obviously today about efficacy. But -- and I know the 5 original streamline guidance spoke to a sort of 6 specific safety database of at least 300. Has any of 7 that thinking changed or is it still the assumption 8 that it's 300 and is there a modification on that at 9 10 this point? Just curious on that.

Yeah. So the derivation of the 11 DR. COX: 12 300 number. So if you do 300 patients and you don't 13 see anything terrible within the 300, the upper bound of the 95 percent confidence interval I think is 1 14 15 percent for that zero number. So that's where the 300 16 comes from. And, you know, I mean, at some point, it's just trying to figure out, you know, how much do 17 18 you want to know about a drug before it's out there on 19 the market. You know, the 300 number is one that, you know, we've sort of turned to and, you know, I don't 20 21 know that there's anything magical about it. But it 22 gets you to a certain level of certainty with regards

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1	to bounding risk, you know, before a drug gets out on
2	the market. Are you suggesting we go higher or are
3	you suggesting we go lower?
4	DR. KARTSONIS: I was just wondering if
5	there's been because we didn't touch on it today
6	I just
7	DR. COX: Yeah.
8	DR. KARTSONIS: I mean, I particularly think
9	it's going to be relevant as we speak tomorrow about,
10	you know, single pathogen because you may be in
11	situations where you may not be able to get to 300
12	without
13	DR. COX: Right. So you're right. We will
14	talk about it some more tomorrow too. And you know,
15	while it may be difficult to get that number of
16	patients with a particular target pathogen of
17	interest, in the course of, you know, doing what
18	you're doing in your trial, unless you have a really,
19	really good diagnostic, you may be able to gather some
20	safety data from other patients that don't necessarily
21	have the target pathogen of interest. Their course of
22	therapy may not be as long, unless you find out they

1	have something else, you might stop the therapy. But
2	you may be able to gather some additional safety data.
3	So you know, it may you know, it may be a
4	number that still is achievable within the development
5	program. And you know, if you think about it, you'll
6	have some, you know, multiple dose studies and, you
7	know, studies in patients. So you know, I think it
8	probably is still achievable, even though even
9	though, you know, because you're going to be getting
10	data beyond just the patient population with the
11	single species of interest. That's my impression.
12	I'd welcome thoughts from other people on that too,
13	from the experiences you may have.
14	DR. LOUIS: So I need to do a methodological
15	moment. If you see N events in trials, as long as N $$
16	is greater than about 15, the upper 95 percent limit
17	is three over N, no matter what N is. Pretty cool.
18	DR. COX: So did I get the math right?
19	DR. LOUIS: Absolutely.
20	DR. COX: Okay. That's good.
21	DR. LOUIS: N was greater than 15 and three
22	was [off mic].

1	DR. MARKS: Just going back and reflecting
2	on I think John mentioned it earlier in terms of
3	trying to work through all the pricing and
4	reimbursement, which I know we don't directly deal
5	with here, but when you think of statistics and how to
6	have these kinds of conversations with payers and we
7	start adding in things like we're borrowing from here,
8	there and yon, I was on a call recently with some
9	other pharmaceutical companies talking to a European
10	pricing reimbursement group, which said essentially
11	you're telling me that this drug is essentially the
12	same as what's already approved. How am I supposed to
13	pay you a premium for that? Now, we're going to have
14	another complicated situation of trying to describe,
15	well, we borrowed from here, we borrowed from there.
16	So I think that'll be interesting times.
17	MR. DANE: Although some of those payer
18	groups have been doing the Bayesian analysis more than
19	we have in the regulatory setting. So I'm not sure
20	there's still to be worked through the assumptions and
21	everything like that. But I'm not sure it necessarily
22	is a huge problem in that some of that's brought in

1 for some of the indirect comparisons that happen and 2 all sort of other things that tend to happen in that 3 reimbursement setting.

4 DR. REX: So it wasn't a huge news release. 5 But about 10 days ago, Sweden announced that it was going to engage in a two-year pilot program to test a 6 novel way of buying antibiotics. And the Swedish 7 8 model is one of simply paying an access fee on an annual basis to ensure that the drug is available. 9 10 And then, there's -- and they estimate that they will 11 use a tiny number of courses of the drug. But they 12 simply want to know that it's available and that it 13 will be available to them. And there are a couple of drugs that look like they would be appropriate 14 15 candidates for that pilot. And they've said they're going to figure out how to do that this fall. 16

And I'm close enough to that to know that, you know, really part of what tips it over there is that the agents have a very clear-cut -- each one of them has a very clear-cut thing that it offers and so, you can articulate it. It's a very clear sciencebased story. It's an organism that is otherwise

1	difficult or treats a form of resistance that is
2	otherwise difficult and the data are really reasonably
3	good. And that's why I come around to Mike there's
4	another conversation going on in the U.K. about a
5	model that has a somewhat different structure. It's
6	an annual fee that includes a number of courses of
7	therapy. But it's essentially the same thing. It's a
8	market entry reward. And the same things are tipping
9	the balance there is that you've got to be very clear
10	about what you're buying for your money.
11	And it was it's been those conversations
12	that led me to the fire extinguisher analogy to saying
13	that there's just not going to be a lot of interest in
14	the same old fire extinguisher. And that's just a way
15	to articulate what you need to get reimbursed. And
16	so, you know, it's just kind of part of what you've
17	got to deal with. It isn't because it's inherent
18	in all of this.
19	You don't buy a new iPod or a new iPad or a
20	new I-anything unless there's some feature you want
21	that's not in the one you've got, right? And so, I
22	just I think it's important to keep that in mind.

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1	And you know, it's also that bit about statistics,
2	only show you what you can already kind of see. You
3	know, that's the you know, stats, if you can't
4	already sort of see it with your eye, you're probably
5	not going to believe the stats. So I think that's
6	something else to remember in all of this. We can
7	buff it up a little bit with statistical calculations.
8	But fundamentally, it better be something that you can
9	sort of see in the dataset.
10	DR. BOZZETTE: I guess I would just say that
11	I'm not sure how diagnostics would fit into the
12	schemes that John has discussed. But we have to
13	figure that out or there won't be the kind of
14	supportive diagnostics that are needed.
15	DR. REX: I a hundred percent agree and I
16	mention the DRIVE A/B project going on in Europe right
17	now about the value of antibiotics. There is a DRIVE
18	D/X that is just now forming up that is meant to
19	tackle the same problem because I think the
20	reimbursement issue for diagnostics is at least an
21	order of magnitude harder than it is for
22	antimicrobials. And yet, we desperately need you to

Page 351 1 make good tests. 2 DR. MARKS: And the other thing I've figured out is my next career, I'm going to offer a non-3 4 informative priors as an expertise. So I learned 5 that. [Laughter.] 6 7 DR. REX: So -- so before we close, could I 8 say something about tomorrow, just real quick? 9 DR. MARKS: Please do. 10 DR. REX: There is -- if you didn't get one 11 already, there's a handout on the table outside. And 12 if you didn't -- if you don't want that, you can also download it. If you'll go to the webpage for the 13 meeting, you'll find it with FDA unmet need workshop 14 15 2016. That's how I'm finding it on my browser. 16 There's a hypothetical case of a drug called X1 that 17 is a narrow spectrum anti-pseudomonal and a number of 18 us have collaborated on pulling together a story. 19 What you'll be able to download is the preclinical database and a little bit of Phase I and Phase II data 20 21 and your homework for tonight while you're having your 22 glass of wine with dinner is how would you develop

1	this. And there's some useful tables provided.
2	What's the frequency of Pseudomonas? But you've got
3	to design a real program. And my target upper limit
4	suggestion for you is within 1,000 patients get this
5	study do the Phase III program because that's, you
6	know, somewhere between \$60 and \$100 million,
7	depending on how you do it, and you might be able to
8	get that much money together to do this. So that's
9	I just want to say that that challenge is there. And
10	a fair number of people at the table right now have
11	been involved in kind of turning that into what we
12	hope is a very realistic story. So don't miss your
13	homework. So tomorrow will be more interesting to you
14	if you've done that.
15	DR. COX: All right. Well, it seems like
16	we've arrived for today. So I want to thank everybody
17	for joining us here today and participating in the
18	discussions. And I think it was, you know at least
19	from my standpoint, it was an excellent day with lots
20	of important information imparted and a good chance to
21	talk through a number of issues. Tomorrow, we'll
22	start at 8:30. So get some rest. John's giving you -

Γ

	Page 353
1	- has given you your homework. And believe me, it is
2	quite an assignment and we'll spend some time
3	discussing that tomorrow. So we look forward to
4	seeing you tomorrow. Have a good night.
5	
6	
7	[WHEREUPON, the foregoing adjourned at 4:41
8	p.m.]
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