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1	STATE OF FLORIDA DEPARTMENT OF EDUCATION
2	AMERICAN INSTITUTES FOR RESEARCH
3	
4	FLORIDA'S RACE TO THE TOP
5	STUDENT GROWTH IMPLEMENTATION
6	COMMITTEE MEETING
7	
8	University of Central Florida
9	Teaching Academy Building
10	Orlando, Florida
11	
	T I I V 10 0011
12	Thursday, May 19, 2011
13	Volume 1
14	
15	
16	DEPARTMENT OF EDUCATION:
17	KATHY HEBDA, Deputy Chancellor for Educator Quality JUAN COPA, Director, Research & Analysis
18	AIR MEMBERS PRESENT:
19	JON COHEN, Ph.D., Executive Vice-President HAROLD DORAN, Ed.D., AIR, Principal Research Scientist CHRISTY HOVANETZ
20	MARY ANN LEMKE
21	
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25	
	American Court Reporting 850.421.0058

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1	(Whereupon, the meeting was called to order	1	directors for Florida PTA, and I'm here
2	by Kathy Hebda, after which the following	2	representing parents.
3	occurred:)	3	MS. WESTPHAL: Lori Westphal. I'm a
4	, * * * * * *	4	teacher for hard of hearing at (inaudible) Early
5	MS. HEBDA: Good morning, everyone, and	5	Learning Literacy Center, Lake County.
6	welcome to the next meeting of the Student	6	MR. CAMPUTARO: Joseph Camputaro,
	-	-	
7	Growth Implementation Committee under Race to	7	kindergarten teacher, Lee County schools.
8	the Top. I'm Kathy Hebda, I'm the Deputy	8	MS. NOYA: Cristina Noya, St. Lucie County
9	Chancellor for Educator Quality with the	9	assistant principal.
10	Department of Education. I'd like to not only	10	MS. FRAKES: Stacey Frakes. I'm an
11	welcome our committee members this morning but	11	instructional coach Madison County.
12	welcome our audience that might be watching over	12	MR. FOERSTER: Sam Foerster, associate
13	the web, and anybody present in the room. If	13	superintendent in Putnam County.
14	there are audience members present in the room,	14	MS. FEILD: Gisela Feild, administrative
15	we are very, very pleased that you're here.	15	director, Miami-Dade County.
16	We'll have hard copies of the power point for	16	MS. TOVINE: Gina Tovine, assistant
17	you at the lunch break, and we also would remind	17	superintendent Levy County.
18	you that this is a webcast and is always open to	18	MS. STEWART: Pam Stewart, deputy
19	the public. We are very pleased that folks are	19	superintendent, St. Johns County.
20	interested in this meeting. This is a working	20	MS. BROWN: Anna Brown, director for
20	group. The committee members, the ones that	20	assessment of performance management,
			Hillsborough County Public Schools.
22	will be speaking during this time and doing the	22	2 7
23	work of the committee, and we appreciate your	23	MS. WOODHOUSE-YOUNG: Tamar
24	participation.	24	Woodhouse-Young. I'm a math teacher in Duval
25	Members, I'm going to let you begin by	25	County.
	American Court Reporting		American Court Reporting
	850.421.0058		850.421.0058
	3		5
			-
1	introducing yourselves one more time. Most of	1	MR. TOMEI: Lance Tomei. I'm the director
1 2	introducing yourselves one more time. Most of you were here in person at the last meeting, but	1 2	MR. TOMEI: Lance Tomei. I'm the director for assessment accreditation in data management
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2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24	 you were here in person at the last meeting, but if you were participating from afar or not quite in the room, I'm going to let you do that. If you would just say your name and your position and who you represent, and we'll start with Ronda. MS. BOURN: I'm Ronda Bourn. I'm supervisor of special projects at the Northeast Florida Educational Consortium. MS. EDGECOMB: Doretha Edgecomb, school board member, Hillsborough County Schools. MS. KRISHNAIYER: Latha Krishnaiyer, Broward County. MR. MOREHOUSE: Lawrence Morehouse, president of Florida Education Department and professor of USF. MR. LeTELLIER: John LeTellier, music teacher, Stanton Weirsdale Elementary School, Marion County. MS. ACOSTA: Sandi Acosta. I'm a middle school science teacher at Kenwood KA Center in Miami. MS. KEARSCHNER: I'm Linda Kearschner, I'm a business owner and I'm on the board of 	2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24	for assessment accreditation in data management in the College of Education here at UCF. MS. MARSALA: Nicole Marsala, 8th grade U.S. history teacher in Broward County. MR. MURPHY: Jeff Murphy, director of student services Florida Virtual School. MS. HALL: Stephanie Hall, Brevard County. MS. HEBDA: Thank you very much, committee members. I appreciate that. Just for housekeeping purposes, was the sound okay? Could you hear everyone. MR. ROBERTS: You need to be a little bit louder. MS. HEBDA: Okay. Members, just for the folks that may be watching online, we do have the microphones placed around the table so if you could just direct your voice towards those microphones, it should pick it up fine. I want to go through with you you have in your packet a power point that we will use just like we did last time when you were here that will kind of keep us framing your discussion and the process that you'll use throughout the next two days.

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	6		8
1	The first couple of things on that just to	1	So I know this work you're doing today is very
2	get everything set up before I turn it over to	2	important, and on behalf of the Commissioner,
3	our experts, you have two sides that cover the	3	Chancellor, and the Department of Ed and State
4	meeting agenda for today and tomorrow. We begin	4	Board of Ed, I really want to say how much we
5	at 8:30 each day and will adjourn at 5:00 today	5	appreciate your time and attention and your
6	and at least by 5:00 tomorrow, no later than	6	devotion to this task and the expertise that you
7	5:00 tomorrow.	7	bring with you, and just keeping in mind,
8	One of the things that I would say about	8	though, that it is the beginning.
		9	
9	the agenda, you can I won't read every line	-	So here you are. You may remember these
10	to you; you can see that on your own. Our	10	slides from last time. This is the process for
11	contractors, the American Institutes for	11	sort of the year one of the grant with
12	Research that worked with you the last time at	12	relationship to student growth. You already
13	the last meeting, what we've asked them to do	13	identified the initial models that you wanted
14	this time for your benefit since your big goal	14	and selected models for comparison. That's what
15	this time is to work towards recommendations to	15	you did at your last meeting and determining
16	the commission for a value added model to be	16	you had a discussion of the variables and
17	used with FCAT data, is to provide you not just	17	business rules. One of the things we'll do
18	the results of all the data requests that you	18	after I finish these introductory slides is
19	made of them at the last meeting but also a	19	we're actually going to spend a couple of
20	method for you to make and work towards that	20	minutes reminding you of what those decisions
21	decision. And they developed a process that	21	were. In case you don't have your notes with
22	will help you do that and track the information	22	you or any of those sorts of things, we'll lay
23	that you receive from that data analysis and	23	out very succinctly where you've come so far.
24	from the results of those data runs, and that	24	That will help remind you where you are and what
25	will help you as work towards making your	25	you're going to do next, and of course, anybody
23	American Court Reporting	23	American Court Reporting
	850.421.0058		850.421.0058
			9
	7		9
			-
1	decisions over the next two days. So I think	1	who's watching the proceedings, we'll also help
2	that's something that you can look forward to	2	who's watching the proceedings, we'll also help them know exactly what's happened if they miss
	that's something that you can look forward to and feel comfortable about because I know that	2 3	who's watching the proceedings, we'll also help them know exactly what's happened if they miss the first meeting.
2	that's something that you can look forward to and feel comfortable about because I know that you may be thinking, well, you asked for a lot	2	who's watching the proceedings, we'll also help them know exactly what's happened if they miss the first meeting. So you finished all that at the last
2 3	that's something that you can look forward to and feel comfortable about because I know that you may be thinking, well, you asked for a lot of information last time and how are you going	2 3	who's watching the proceedings, we'll also help them know exactly what's happened if they miss the first meeting. So you finished all that at the last meeting. What's in the loop here is what you're
2 3 4	that's something that you can look forward to and feel comfortable about because I know that you may be thinking, well, you asked for a lot	2 3 4	who's watching the proceedings, we'll also help them know exactly what's happened if they miss the first meeting. So you finished all that at the last
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	10		12
1	decisions about performance next year. That's	1	gifted, age, class size, homogeneity of class,
2	the process they'll be going through this summer	2	mobility, and school effects that will all
3	after that data is provided to them.	3	appear in the models as well.
4	So that's where you are in your timeline.	4	Just to reiterate some of the milestones,
5	Again, this is the goal of the meeting.	5	when initially presented we looked at eight
6	It's a simple goal; it's an important goal.	6	different models. We selected three and at AIR
7	Just reminding you again that your goal is to	7	we went ahead and evaluated those three models
8	make recommendation. The Commissioner does have	8	and some variants of those models. So you'll
		9	-
9	the responsibility to make the final selection.	-	actually be seeing more results than for just
10	Then, of course, as that model is implemented	10	three models today. I believe there are results
11	next year and the following year and the year	11	for seven different models that we'll be looking
12	after that, every year there's a process built	12	at today. We provided guidance and direction.
13	into the grant to make sure we analyze how	13	We'll show you how we incorporated the business
14	effective the model was and ways to make	14	rules that we made decisions on from last time.
15	improvements in the model as we go.	15	We'll talk specifically about how we identified
16	One other reminder before I turn it over to	16	and defined each one of the variables from the
17	our AIR partners is their role throughout this	17	last meeting, and so today we'll be looking at
18	process, just like you saw in the very first	18	all of these results making some initial
19	face-to-face meeting you had, their rule is not	19	recommendations to have it finalized by June
20	to make a recommendation. That's your role.	20	1st.
21	Their role is to fulfill your request for data,	21	So I'd like to call Dr. Harold Doran up to
22	provide information, answer your questions, lend	22	start discussing through some of our initial
23	expertise to the process, but the decision are,	23	results and findings.
			_
24	in fact, yours. I want to make sure that	24	DR. DORAN: Good morning, everybody. Thank
25	everybody is very, very clear about that.	25	you for having us back. So last time that I was
	American Court Reporting		American Court Reporting
	850.421.0058		850.421.0058
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		1	
	14		16
1	from the last time we were together, any	1	really saturates and we understand what we're
2	particular concerns or issues, or if we're just	2	estimating.
3	ready to move on.	3	The green line is the line that would be
4	Hearing none, why don't we start? All	4	fit through a covariate adjustment model, and
5	right.	5	essentially, one of the things that we see here
6	One of the commitments that we have in	6	in this red line is the simple differences
7	terms of implementing the value added models and	7	model. It essentially has a slope of one within
8	coming back to this group is we want to be clear	8	each of the performance categories, whereas the
9	about what we call an estimand. What are the	9	other model has a slope of whatever it is. It's
10	different value added models actually estimating	10	not necessarily one; it doesn't have to be
11	in clear terms, because these are statistical	11	constrained to be one. But it's not the same
12	models that are doing something that has to be	12	within a performance category where you see the
13	understood in terms of their transparency, in	13	red line expects lower growth for students at
14	terms of what they are estimating.	14	the lower end of the score distribution relative
15	Essentially, there are two types of models	15	to the covariate adjustment model. The
16	that we're going to present today. We reviewed	16	important point that we want this group to
17	three genres of models last two genres of	17	recognize is that the models differ in terms of
18	models, what we called the layered and	18	their expectations for growth for students
19	persistence model or the learning path models	19	within a particular performance model. My team
20	and the covariate models. So now let's talk	20	want to add anything?
21	about what are the models actually estimating,	21	DR. COHEN: Yes, I want to add a little
22	the differences model is we say this, expect	22	bit. This is we've boiled it down to just
23	students who score the same in the pattern here	23	two classes of models earlier.
24	to score the same and to continue to score the	24	DR. DORAN: The web books have the web
25	same, and assumes the same amount of growth for	25	books have these, is that correct.
	American Court Reporting		American Court Reporting
	850.421.0058		850.421.0058
	15		17
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1	each student in each achievement model. So	1	MS. HEBDA: Is that correct.
1 2	each student in each achievement model. So students within performance level one are	1 2	MS. HEBDA: Is that correct. DR. COHEN: Just to make sure that everyone
	each student in each achievement model. So students within performance level one are expected to have the same level of growth that		MS. HEBDA: Is that correct. DR. COHEN: Just to make sure that everyone followed, the X axis is the kids' score last
2	each student in each achievement model. So students within performance level one are expected to have the same level of growth that all other students in that performance level.	2	MS. HEBDA: Is that correct. DR. COHEN: Just to make sure that everyone followed, the X axis is the kids' score last year; the Y axis is the kids' score this year.
2 3	each student in each achievement model. So students within performance level one are expected to have the same level of growth that all other students in that performance level. Students in the third performance level have a	2 3	MS. HEBDA: Is that correct. DR. COHEN: Just to make sure that everyone followed, the X axis is the kids' score last year; the Y axis is the kids' score this year. The little blue dots okay. We've plotted all
2 3 4	each student in each achievement model. So students within performance level one are expected to have the same level of growth that all other students in that performance level.	2 3 4	MS. HEBDA: Is that correct. DR. COHEN: Just to make sure that everyone followed, the X axis is the kids' score last year; the Y axis is the kids' score this year. The little blue dots okay. We've plotted all the kids in grade seven, these are their math
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	40		00
	18		20
1	to look at your score and subtract out the	1	we have two years of prior achievement data.
2	average growth from within that group. We'll	2	What I mean by that is in this regression we
3	just look at the average growth for kids who	3	have what's called a dependent variable
4	started at the same achievement level; and	4	that's the current year's score and then we
5	instead of having a best fitting slope, it has a	5	use two prior years of achievement data. We
6	slope of one. You look, it's hard for you to	6	call those lags. So one lag means in the
7	see in some places where these lines differ.	7	regression model, one of our independent
8	But you do see that they cross a number of	8	variables is a prior test score. If we had two
9	times. Where the red line is above the green	9	lags then we're using two prior test scores.
10	line, that means that you're predicting higher	10	The rationale for that and whether or not that
11	performance among the kids than is typically	11	matters is going to become clear as we look at
12	observed. The green line is what's typically	12	some of the results comparing Model 1 and Model
13	observed; it's also the line hit by the	13	1A.
14	covariate adjustment model.	14	Model 2. It's the same as Model 1 but
15	So down here the difference in models	15	estimated with fixed effects. Let me say
16	predicting less growth than is typically	16	something now and we'll talk more about this
17	observed. That would tend to say that teachers	17	throughout the day if we need to. We estimated
18	teaching these students would typically exceed	18	the model with fixed effects just as we said we
19	that more readily. At the other end you see	19	would. We're not presenting them today although
	this is where it goes if you follow this, at the	20	we can fully talk about them. Let me explain
20		20	
21	end of this group, teachers teaching these kids		why.
22	would have a harder time exceeding that because	22	Algebraically, mathematically, we know that
23	you're expecting more growth than is typically	23	the random effects and the fixed effects are
24	observed. Does that make sense? That's the	24	guaranteed to be the same as the number of kids
25	difference between the covariate adjustment	25	in a class gets larger. That's the constraint
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1	model and simple differences model. So we're	1	that has to be in place. They can be the same
1	model and simple differences model. So we're clear? Questions? Okay, back to Harold.	1 2	that has to be in place. They can be the same and they estimate the same quantity. Early on
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2 3 4	model and simple differences model. So we're clear? Questions? Okay, back to Harold. DR. DORAN: All right. Let's go to the next slide. So let's talk about a summary of	2 3 4	that has to be in place. They can be the same and they estimate the same quantity. Early on in the analysis we saw that the models with fixed effects were yielding unstable results.
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		-	
	22		24
1	close to it. It would almost have the exact	1	three-level model.
2	same number of kids but they might be off by one	2	Model 3A has no additional variance.
3	kid or two. That causes for a problem in the	3	That's it. The description that we see.
4	mathematical estimation of the model. What was	4	Then we have Model 3A1. Model 3A1 is Model
5	happening was that those teacher effects were	5	3A but it differs only in terms of the number of
6	causing those teachers in the data, without	6	prior achievement test scores. It has one lag,
_	conditions it appears to be true were causing	7	not two.
7		-	
8	for the results to be unstable. In fact, if we	8	Model 3B. This is the description, but it
9	remove some of those issues and we estimate the	9	includes ELL, SWD, and attendance. We use two
10	model with fixed effects and we correlate it	10	prior test scores oh, there's a note there.
11	with the random effects, they are correlated	11	It always uses two prior test scores.
12	better than 0.9. A correlation ranges from -1	12	Model 3c, ELL, SWD, attendance, and the
13	to 1; a correlation of 1 means there is a	13	following additional variable class size,
14	perfect relationship between the two, a 1 to 1	14	homogeneity of class composition. Let me
15	correspondence. A correlation of zero means	15	explain that variable. That is a variable that
16	there is no correspondence between the two	16	describes how similar students are within a
17	estimates. The closer you get to 1, the greater	17	class, all right. So we construct a variable,
18	that correspondence between those two is. A	18	call it the homogeneity variable, and it's
19	correlation better than 0.9 tells us what we	19	essentially I think we've got another slide
20	hypothesize about this. When we were here last	20	that describes it, but I'm going to mention this
21	time six weeks ago that the models were	21	now. I have to find the easel to talk about
22	estimating the same thing and that turns out to	22	things multiple times. It is the difference
23	be true in the data.	23	between the students at the 75th percentile
24	The issue here is and the reason we're not	24	within a class and the 25th percentile within a
25	presenting it is because there is a business	25	class. So if students within a class are very
23	American Court Reporting	23	American Court Reporting
	850.421.0058		850.421.0058
			25
	23		
1	rule that prevents these models from being	1	similar in terms of their prior test scores,
1 2	rule that prevents these models from being estimated and presented in a reasonable way to	2	similar in terms of their prior test scores, that difference will be small.
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2 3	rule that prevents these models from being estimated and presented in a reasonable way to this group, but we do know that we could rely on the fact that both algebraically and in the real world the results are highly correlated when we	2 3	similar in terms of their prior test scores, that difference will be small. If students within a class, if a teacher has a class that is very different in terms of their ability, that number will be very big.
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2 3 4 5 6 7	rule that prevents these models from being estimated and presented in a reasonable way to this group, but we do know that we could rely on the fact that both algebraically and in the real world the results are highly correlated when we remove that particular issue and when we don't take it into consideration.	2 3 4 5 6 7	similar in terms of their prior test scores, that difference will be small. If students within a class, if a teacher has a class that is very different in terms of their ability, that number will be very big. It's a spread. It's essentially a spread between kids within class. How different are
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	26	1	28
	the models and all of our slides use labels like	4	conversation with Sam is not random.
1		1	
2	1, 1A, 3A, 3A1, and so forth, and we don't want	2	Have you forgotten anything? You've
3	you to get lost in the details of the models.	3	evaluated the models based on empirical
4	So what we've created is this little scorecard;	4	criteria. There's going to be a ton of
5	and essentially what you see is Model 1 and its	5	discussion and other things that you care about
6	key characteristics. So, for example, Model 1	6	perhaps beyond this, but the goal here is we
7	has one lag and had teacher effects only. No	7	have to have a process by which we evaluate the
8	school effects. The covariates that are	8	models that's better than our opinions on what
9	included are SWD, ELL, attendance, and the	9	we think the world should look like. So we made
10	effects, the teacher effects are random, and	10	an attempt not only to estimate a large number
11	school effects if they are included. There's no	11	of models with multiple areas, but to also come
12	school effects in Model 1.	12	up with what we believe are reasonable
13	All right. Now I'm calling this a	13	indicators that you can use as the lens by which
14	scorecard because one of the things that we're	14	you can evaluate the model, then this decision
15	hoping we will do is by the end of the day we	15	is yours. It's not us standing here telling you
16	have to make a recommendation, and Sam is going	16	this model needs to compute, it's statistically
17	to facilitate a conversation. What we have over	17	very nice. It looks good, the plot looks good,
18		18	and we remove hopefully all of it. Keep this by
	here in terms of notes, these are the primary		
19	evaluation criteria by which we'll be looking at	19	your side throughout the day.
20	these models today. We have data that show you how these models stack up against each other	20	Jon, go ahead.
21		21	DR. COHEN: I just want to help with a
22	based on those criteria.	22	little bit of organization here. It's not
23	One of the things we're hoping this	23	entirely clear from the chart I mean, it's
24	scorecard will be used for is as we talk about	24	there but it doesn't just pop out at you
25	precision, for example, and the precision of the	25	Model 1 doesn't include school effects. It's
	American Court Reporting		American Court Reporting
	850.421.0058		850.421.0058
	27		29
1	different models, you will come up with your own	1	only teacher effects. Model 3 includes teacher
2	ranking system and maybe you'll use a 1 to 10	2	only teacher effects. Model 3 includes teacher and school effects. We've tried to have at
2 3	ranking system and maybe you'll use a 1 to 10 scale. Maybe you'll use a 1 to 50 scale. Maybe	2 3	only teacher effects. Model 3 includes teacher and school effects. We've tried to have at least pairs of models so you can evaluate
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	30		32
1	ranges from none to a few to the kitchen sink.	1	order?
2	MR. TOMEI: Quick question. I'm looking at	2	DR. HOVANETZ: We would use the prior
3	the chart and it appears that the lags for 3A	3	years.
4	and 3A1 may be inverted, based on what's on the	4	DR. DORAN: Any scores.
5	slide; is that correct?	5	MS. FEILD: Regardless of the grade level.
6	DR. COHEN: Right, 3A and 3A1 are inverted,	6	DR. DORAN: I don't remember that
7	yes, thank you for that. So 3A should have a	7	(inaudible) if we use any prior school
8	checkmark under two lags; 3A1 should have a	8	DR. HOVANETZ: With the exception of 3rd
9	checkmark under one lag. Thank you for that.	9	graders, we do not use any 3rd graders.
10	That's a good catch.	10	MS. FEILD: What about retained 3rd
11	DR. DORAN: Let's all make that change to	11	graders? No?
12	make sure we're all on the same page.	12	DR. DORAN: No. Remember, we cannot
	MS. FEILD: Shouldn't 3B have the covariate		-
13		13	estimate teacher effects in 3rd grade because
14	ELL, SWD, and attendance based on that?	14	there's no prior achievement data. So the only
15	DR. DORAN: Yes. Thank you.	15	you have students who have two 3rd grade
16	DR. COHEN: Excellent. Thank you.	16	scores because they were retained for some
17	COMMITTEE MEMBER: Would you say that	17	reason, you'd get biased effects because of
18	again, please?	18	that.
19	DR. DORAN: Yeah, SWD under row 3B under	19	MS. BROWN: On the chart 3C in the
20	covariates, in 3B under covariates, write SWD,	20	covariate, it lists gifted but I don't see
21	ELL, and attendance. Under Model 3A in that	21	gifted on the slide as a covariate.
22	row, remove the checkmark under one lag and	22	DR. DORAN: Gifted is in the model. It
23	instead put the checkmark under two lags. In	23	should be on the slide.
24	the row below it, Model 3A1, put a checkmark in	24	DR. COHEN: It's actually in every model
25	the column for one lag and remove the column for	25	that includes SWD, it also includes gifted.
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	31		33
	51		55
1	two lags. Thank you for that catch; I'm sorry	1	DR. DORAN: Let's add that. Any place you
1 2	-	1 2	
	two lags. Thank you for that catch; I'm sorry		DR. DORAN: Let's add that. Any place you
2	two lags. Thank you for that catch; I'm sorry for the error.	2	DR. DORAN: Let's add that. Any place you see SWD, also add gifted.
2 3	two lags. Thank you for that catch; I'm sorry for the error. DR. COHEN: Okay, so there are four	2 3	DR. DORAN: Let's add that. Any place you see SWD, also add gifted. DR. COHEN: It should say exceptional
2 3 4	two lags. Thank you for that catch; I'm sorry for the error. DR. COHEN: Okay, so there are four dimensions to the models. Differences versus	2 3 4	DR. DORAN: Let's add that. Any place you see SWD, also add gifted. DR. COHEN: It should say exceptional students.
2 3 4 5	two lags. Thank you for that catch; I'm sorry for the error. DR. COHEN: Okay, so there are four dimensions to the models. Differences versus covariate, four versus everybody else. Only	2 3 4 5	DR. DORAN: Let's add that. Any place you see SWD, also add gifted. DR. COHEN: It should say exceptional students. DR. DORAN: I was so certain I had this
2 3 4 5 6	two lags. Thank you for that catch; I'm sorry for the error. DR. COHEN: Okay, so there are four dimensions to the models. Differences versus covariate, four versus everybody else. Only teacher effects and school effects, Model 1	2 3 4 5 6	DR. DORAN: Let's add that. Any place you see SWD, also add gifted. DR. COHEN: It should say exceptional students. DR. DORAN: I was so certain I had this right.
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	34		36
1	with data, so there's no virtually no	1	statistic? Then there's a why. Why do you care
2	subjectivity in that regard. Whether or not the	2	about this? So each of these criteria will be
3	models are precise is an empirical question.	3	structured around those four things: What's the
4	Whether or not they are school effects, we show	4	question? What's the statistic that answers
5	you the consequences of school effects or not,	5	that question? What's the evidence what are
6	and there's data. Same thing with parsimony,	6	we looking for in that statistic? And then why
7	classification, accuracy, and lags. There are	7	do you care about this?
8	data that we will present associated with each	8	Yes.
9	of these criteria and you can make a judgment on	9	MR. TOMEI: Kind of related to the question
10	whether Model 1 is better than Model 2 based on	10	on gifted, within SWD how many different
11	the results of what we show you.	11	categories did you look at independently?
12	Christy?	12	DR. DORAN: We looked at Christy, remind
13	DR. HOVANETZ: Just for clarification, this	13	me.
14	is just an advance organizer for you all to take	14	DR. HOVANETZ: We going to talk about this
15	into we're not necessarily going to ask you	15	in two slides.
16	to keep track of points or numbers, but just for	16	DR. DORAN: Yeah, right, we're just about
17	you to be able to reflect in an organized way	17	to transition over
18	and that we're all doing it the same way. So	18	MR. TOMEI: We know from research in other
19	when we're talking about Model 3A, you can look	19	areas, we know there are differences among the
20	at 3A and see the notes that you've taken for	20	different
21	that specific model to help refresh your memory	21	DR. DORAN: Yes.
22	because there are seven different models that	22	DR. HOVANETZ: There are
23	have not very fancy names.	23	DR. DORAN: I'll get to this and then I'll
24	DR. DORAN: Yes, ma'am?	24	pass it over to Christy for the actual operation
25	MS. BROWN: I just want to clarify the	25	lies where the variables are.
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1	gifted SWD. Was gifted included as a separate	1	I'm going to actually get a glance this
2	gifted SWD. Was gifted included as a separate covariate in each of these situations, in	2	I'm going to actually get a glance this is a slide we talked about last time. I already
2 3	gifted SWD. Was gifted included as a separate covariate in each of these situations, in addition to SWD, or included as SWD?	2 3	I'm going to actually get a glance this is a slide we talked about last time. I already mentioned this when I was talking about the
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		r –	
	38		40
1	are near colineal, the models are essentially	1	control, whether or not it was already being
2	doing what we hypothesized; they're estimating	2	measured by another variable that we were
3	the same thing. There is essentially no	3	looking at, and also whether or not it could be
4	difference in what is being estimated.	4	explained by pre-test data. That was the
5	And when I talk about what, I'm talking	5	framework that we were operating under to put
6	about this thing called a teacher effect,	6	variables into the model for evaluation.
7	value-added effect.	7	We evaluated a lot of variables where we
8	Christy, why don't I toss this over to you	8	thought let's just see what this looks like and
9	to do what's next?	9	we'll base our judgments on the results, but we
10	DR. HOVANETZ: We'll update the scorecard	10	will be using the same framework as we're
11	or note taking device and make copies of it so	11	considering the results of these variables, not
12	you'll have a new one.	12	just whether or not they're significant but
13	Since we already had started talking about	13	whether or not it does make a difference in the
14	the variable discussion, just to be very clear	14	precision of the model and whether or not
15	why we are talking about including variables in	15	policy-wise it's the right variable to be
16	the models to begin with; and just to refresh	16	included. So just keep those same conversations
	our memory as to the discussions that we had on	17	in mind that we had before.
17	-		
18	April 4th and 5th and again on the 14th at our	18	Okay. This is the list of variables that
19	webinar, the reason we are looking at adding	19	have been evaluated within the models. Students
20	controlled variables is to reduce the variances'	20	with disabilities status was done with a
21	unequal distribution of students that	21	dichotomous variable for each of the individual
22	(inaudible) in teachers' courses. There's	22	disabilities. So we can either play a game
23	limited debate. We had this conversation back	23	where you guess which variables are D, E, Z, or
24	on the 4th and 5th and we did on the 14th about	24	I can just tell you. We did not include the
25	whether or not adding a lot of controlled	25	exceptionality codes listed here based on the
	American Court Reporting		American Court Reporting
	850.421.0058		850.421.0058
	39		41
1	variables is going to make a difference in the	1	recommendations of this group last time. So as
1	variables is going to make a difference in the model, whether or not it's going to make it more	1 2	recommendations of this group last time. So as a reminder, occupational and physical therapy
2	model, whether or not it's going to make it more	2	a reminder, occupational and physical therapy
2 3	model, whether or not it's going to make it more precise and whether or not it's going to	2 3	a reminder, occupational and physical therapy were not included as variables. Z is a not
2 3 4	model, whether or not it's going to make it more precise and whether or not it's going to actually level the playing field for teachers.	2 3 4	a reminder, occupational and physical therapy were not included as variables. Z is a not applicable variable; U is a established
2 3 4 5	model, whether or not it's going to make it more precise and whether or not it's going to actually level the playing field for teachers. Some of the rationales for including	2 3 4 5	a reminder, occupational and physical therapy were not included as variables. Z is a not applicable variable; U is a established conditions; T is developmentally delayed; M is hospital or homebound; C is orthopedically
2 3 4 5 6	model, whether or not it's going to make it more precise and whether or not it's going to actually level the playing field for teachers. Some of the rationales for including student characteristics is to eliminate that bias, but the policy implications of it is	2 3 4 5 6	a reminder, occupational and physical therapy were not included as variables. Z is a not applicable variable; U is a established conditions; T is developmentally delayed; M is
2 3 4 5 6 7	model, whether or not it's going to make it more precise and whether or not it's going to actually level the playing field for teachers. Some of the rationales for including student characteristics is to eliminate that bias, but the policy implications of it is student who want to set it for differing	2 3 4 5 6 7	a reminder, occupational and physical therapy were not included as variables. Z is a not applicable variable; U is a established conditions; T is developmentally delayed; M is hospital or homebound; C is orthopedically impaired; F is speech impaired; and L is gifted.
2 3 4 5 6 7 8	model, whether or not it's going to make it more precise and whether or not it's going to actually level the playing field for teachers. Some of the rationales for including student characteristics is to eliminate that bias, but the policy implications of it is student who want to set it for differing expectations for different students. So just a	2 3 4 5 6 7 8	a reminder, occupational and physical therapy were not included as variables. Z is a not applicable variable; U is a established conditions; T is developmentally delayed; M is hospital or homebound; C is orthopedically impaired; F is speech impaired; and L is gifted. Those are not considered disability categories that we evaluated within these models.
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2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24	model, whether or not it's going to make it more precise and whether or not it's going to actually level the playing field for teachers. Some of the rationales for including student characteristics is to eliminate that bias, but the policy implications of it is student who want to set it for differing expectations for different students. So just a little reminder or refresher about the conversation that we were having on these variables before. Reminder on the framework that we operated under when we were talking about which variables to include. First of all, we went through and we looked at the variables that were in Senate Bill 736, the SWD, the ELL, and the attendance, and then we had the brainstorming session where you all listed out 20 or so variables that we had conversations about initially on the 4th and 5th and then went through each of them in detail on the 14th and made judgments about them then. When we talked about including variables in the evaluation, we talked about whether or not it was a variable that was within the teacher's American Court Reporting	2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24	a reminder, occupational and physical therapy were not included as variables. Z is a not applicable variable; U is a established conditions; T is developmentally delayed; M is hospital or homebound; C is orthopedically impaired; F is speech impaired; and L is gifted. Those are not considered disability categories that we evaluated within these models. We had 14 different SWD exceptionalities that we did evaluate within the model. Four of these exceptionality codes have been collapsed and so we will only be presenting on ten of these exceptionalities. What happened is there were three codes that were collapsed into the W code, which is intellectual disability, back in 2007-08; so you won't see as many disabilities or exceptionality codes as we talked about because they don't exist in the data anymore. So that's where you'll see a difference in what we talked about versus what's being presented. Gifted status was done as it's own independence variable. Dichotomous variable. The student was listed as gifted or not listed as gifted. With the students with disabilities American Court Reporting
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	42		44
1	codes, we had talked about looking at primary	1	class, a larger difference is a less homogenous
2	and other exceptionalities. This is only	2	class and this was done on a continuous
3	looking at primary student disability. We did	3	variable.
4	not look at secondary or other exceptionalities.	4	The mobility calculation, also a continuous
5	It's only primary.	5	variable, we looked at the number of transitions
6	For English language learner status, this	6	a student made from school to school. If we
7	is also a dichotomous variable. Students have	7	have only one record for the student, the
8	to be coded as LY or currently receiving ESL	8	student had zero transitions. If we have two
9	services, and they can only be coded as LY for	9	records for the students in different schools,
10	two or fewer years. So if a student is in his	10	that's considered one transition. So each time
11	third year of receiving services, they are not	11	a student changed schools during the school
12	considered an ELL student for our purposes.	12	year, it's counted as a transition. We did
13	Yes.	13	encounter some students that had two records
14	MS. ACOSTA: Just to clarify, the LY	14	with two entry dates into the same school. If
15	classification has really no bearing on their	15	there was a 21-day period between the exit date
16	ESOL level, so in other words they could have	16	of the school and the following entry date into
17	been receiving for two years and have reached	17	that same school, they were considered to have
18	ESOL level four or still be in ESOL one, and they'll be treated equally?	18	made a transition. If they spent time somewhere
19	DR. HOVANETZ: Yes.	19 20	else, it may not have been in Florida, but we're not at that school that actually made
20 21	For attendance, we treated attendance as a	20	transitions.
21	continuous variable the number of days the	21	Age is also a continuous variable. We
22	student was in attendance at the school. So if	22	looked at and calculated the modal age for the
23	a student was in multiple schools, we added the	23	grade as of September 1st and took the
24	number of days in attendance in all of those	25	difference between the modal age and the
25	American Court Reporting	25	American Court Reporting
	850.421.0058		850.421.0058
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	43		45
1	-	1	
1	43 schools to get the total number of days the student was in attendance. It's a continuous	1	45 student's actual age to come up with the age difference.
	schools to get the total number of days the		student's actual age to come up with the age
2	schools to get the total number of days the student was in attendance. It's a continuous	2	student's actual age to come up with the age difference.
2 3	schools to get the total number of days the student was in attendance. It's a continuous variable, just the number of days present. Just	2 3	student's actual age to come up with the age difference. And I will turn it back to Dr. Doran.
2 3 4	schools to get the total number of days the student was in attendance. It's a continuous variable, just the number of days present. Just as a reminder for this particular variable, this	2 3 4	student's actual age to come up with the age difference. And I will turn it back to Dr. Doran. DR. DORAN: All right.
2 3 4 5	schools to get the total number of days the student was in attendance. It's a continuous variable, just the number of days present. Just as a reminder for this particular variable, this is information that comes in during survey five	2 3 4 5	student's actual age to come up with the age difference. And I will turn it back to Dr. Doran. DR. DORAN: All right. DR. HOVANETZ: Well, first, do you have any
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	46		48
1	DR. HOVANETZ: We are only looking at	1	DR. HOVANETZ: I have an entire course code
2	survey two data and survey three data, so it's	2	directory that I can show you there are 166
3	that second week in October and that second week	3	courses that were polled for reading and 90
4	in February, and it's whichever students are	4	courses that were polled for math, and it's
5	enrolled during those two specific weeks in that	5	based on the Department's determination in the
6	particular course in that school, in that	6	course code directory of what is a math course
7	district with that period number. That's	7	and what is listed as a reading or English
8	considered the number or the count of enrollment	8	language arts course. And in your packet it
9	for class size.	9	shows specifically there's a course code
10	MR. TOMEI: I'd like to ask the P-12 reps	10	directory on how those determinations were made
-	•	-	•
11	on the committee. Do you see that as a fairly	11	by the Department. It's a separate handout that
12	stable statistic or is that one where there	12	was behind your Power Point on the right-hand
13	could be variance in the statistic itself that's	13	side and the reading courses are courses that
14	not going to be captured in the reported data	14	are identified as requiring a reading
15	that will be used in the model?	15	certification to teach them or a course that is
16	MS. FEILD: Why not it was sort of a	16	mandated by the State Board of Education as a
17	combination question. First, what was the self	17	remedial course, a remedial reading course.
18	count within the class period teacher that was	18	Math courses are identified by the prefix,
19	used to either aggregate the data or not?	19	those are a little bit more simplistic to
20	Secondly, how are we handling semester courses	20	identify. English language arts was determined
21	in the high schools? Generally, the kids are	21	by a committee and then also by the course code
22	FTE's, did we account for that?	22	prefix. So I have a list of all the courses
23	DR. HOVANETZ: Yes and no. So	23	that were included for the particular analysis.
24	unfortunately we don't have a minimum class size	24	MS. YOUNG: I remember the discussion about
25	to a discussion that we can have, but based on	25	attendance, but I didn't remember the outcome.
	American Court Reporting		American Court Reporting
	850.421.0058		850.421.0058
	47		49
1	the estimations that we did for these particular	1	For students that are in multiple courses during
1 2		1 2	For students that are in multiple courses during the day and they have a tendency to leave after
	the estimations that we did for these particular		
2	the estimations that we did for these particular models, we did not limit the number of students	2	the day and they have a tendency to leave after
2 3	the estimations that we did for these particular models, we did not limit the number of students that had to be in a course in order for a teacher to generate a value-added score.	2 3	the day and they have a tendency to leave after lunch, did we do we have data for that or just the whole day or they're marked present for
2 3 4	the estimations that we did for these particular models, we did not limit the number of students that had to be in a course in order for a teacher to generate a value-added score. With respect to semester versus full year	2 3 4	the day and they have a tendency to leave after lunch, did we do we have data for that or just the whole day or they're marked present for the whole day, that's it?
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	50		50
	50		52
1	offering it as a semester so students can	1	how data is currently being collected and
2	request So we'll have to take that into	2	putting in new data collection procedures. All
3	account.	3	the information we're reporting here is
4	DR. HOVANETZ: And that's okay, though,	4	information that has been collected for decades.
5	because we will still have the district, the	5	So they have a system in place to capture this
6	school, and the course number for that	6	data information that we talked specifically
7	particular student. So we do have that	7	about here. I think those need to be refined.
8	information right now and in the evaluation.	8	The department will be working on that to assist
9	Other questions? Ask as many questions as	9	districts and process these in order to be sure
10	you want today. Today is all about just getting	10	that is all reflected accurately.
11	you information, making sure that you're	11	MS. FEILD: So let me make sure I
12	comfortable with the results based on the models	12	understand the premise of the analysis, so an
13	we've selected or you selected, and we want to	13	elementary teacher who is sitting in a classroom
14	get all the information because we'll start	14	with 25 kids; at the end of the year you'll look
15	making decisions tomorrow, or you'll all be	15	at the data for the 25 kids. You'll see whether
16	starting to make decisions tomorrow about which	16	those kids were there for both FTE's. If only
17	ones we're leaning towards.	17	20 of them were there for both FTE's, those 20
	MS. EDGECOMB: In one of the earlier slides		will comprise her data analysis, correct? Is
18	when you began talking this morning, you talked	18 19	that correct?
19			
20	about the importance of data availability and	20	DR. HOVANETZ: If the student was enrolled
21	accuracy. Is the assumption that all districts	21	in survey two or three, they're included in the
22	have in place the capacity to provide those two	22	analysis right now.
23	characteristics about data and input?	23	MS. FEILD: "Or" did you say or "and"?
24	DR. HOVANETZ: That's a great question. I	24	DR. HOVANETZ: Right now, it's "or". So
25	think a lot of the data that we are using is	25	the information that we have is for
	American Court Reporting		American Court Reporting
	850.421.0058		850.421.0058
	E1		
	51		53
1	accurate because it's been used for other	1	MS. FEILD: I thought you said "and" at the
1 2	accurate because it's been used for other purposes. There are some pieces of information	1 2	MS. FEILD: I thought you said "and" at the beginning.
	accurate because it's been used for other purposes. There are some pieces of information that will hopefully get more accurate as we		MS. FEILD: I thought you said "and" at the beginning. DR. HOVANETZ: Or. We have survey two
2	accurate because it's been used for other purposes. There are some pieces of information	2	MS. FEILD: I thought you said "and" at the beginning.
2 3	accurate because it's been used for other purposes. There are some pieces of information that will hopefully get more accurate as we	2 3	MS. FEILD: I thought you said "and" at the beginning. DR. HOVANETZ: Or. We have survey two
2 3 4	accurate because it's been used for other purposes. There are some pieces of information that will hopefully get more accurate as we continue to use them, but this is the best available information and as we select which variables to be included and highlight that with	2 3 4	MS. FEILD: I thought you said "and" at the beginning. DR. HOVANETZ: Or. We have survey two information and survey three information. The
2 3 4 5	accurate because it's been used for other purposes. There are some pieces of information that will hopefully get more accurate as we continue to use them, but this is the best available information and as we select which	2 3 4 5	MS. FEILD: I thought you said "and" at the beginning. DR. HOVANETZ: Or. We have survey two information and survey three information. The data set that we have has students that were
2 3 4 5 6	accurate because it's been used for other purposes. There are some pieces of information that will hopefully get more accurate as we continue to use them, but this is the best available information and as we select which variables to be included and highlight that with	2 3 4 5 6	MS. FEILD: I thought you said "and" at the beginning. DR. HOVANETZ: Or. We have survey two information and survey three information. The data set that we have has students that were enrolled in survey two and enrolled in survey
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	E 4	1	50
	54		56
1	course not the teacher, correct? We were	1	constraints of what we have currently collected
2	talking here about reading endorsement, but if a	2	for this modeling purpose, but just so everyone
3	teacher is a social studies teacher in a high	3	is aware as well, both the law requires a roster
4	school who happens to have a reading endorsement	4	verification process to be in place for this
5	and is teaching two periods of intensive reading	5	when this is operational, the Department with
6	and she has 25 kids, which we have now a lot	6	partner districts. Hillsborough is one, NEFEC
7	right, 25 kids in each course, tenth grade for	7	is another one, and also Osceola County of
		-	
8	periods of European history, two periods of	8	developing a teacher-student data link roster
9	intensive reading, she will have data for those	9	verification system through a grant process with
10	50 kids and those two intensive reading courses?	10	SELT, which is I don't know what I can't
11	DR. HOVANETZ: Yes, this is based on the	11	think of what the acronym is right now, but they
12	courses the student are holding.	12	have a grant through the Gates Foundation. So
13	MS. FEILD: I could go on. I could ask	13	we're working with them over the next year and
14	another question. Elementary school,	14	coming months and we'll be putting forth a
15	self-contained teachers who are teaching both	15	process in place working with our district
-	-	16	partners and open to the entire state on a
16	reading and math would have two value-added	-	
17	scores, a reading score and a math score?	17	roster verification system to improve that data
18	DR. HOVANETZ: Correct.	18	that will be so fundamental to this purpose so
19	MS. FEILD: Assuming the school coded that	19	that we can deal with those issues such as the
20	as a self-contained?	20	variability in how schools or districts may
21	DR. HOVANETZ: Correct.	21	report this course information, since it hasn't
22	MS. FEILD: So if in fact the school is	22	been used for this high stakes accountability
23	departmentalizing it but they did not code the	23	purpose in the past.
24	teacher as departmentalized, which we know they	24	MR. LE TELLIER: Going on with what you
25	do, then the teacher will be attributed math	25	were saying with the count two and three if the
20	American Court Reporting	20	American Court Reporting
	850.421.0058		850.421.0058
	55		57
	and the second second in Constants and the		and the state of t
1	scores in essence and in fact that teacher	1	student moves from one school to another, is the
1 2	didn't really have math scores.	1 2	teacher that had them for the second count or
	didn't really have math scores. DR. HOVANETZ: Correct.		teacher that had them for the second count or the October would that affect their
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	50	1	00
	58		60
1	found the expectations of students in two or	1	school and I'm in a class and it's all kids who
2	more reading courses higher than a student	2	are struggling with algebra just like I am, it
3	enrolled in just a reading course, but the	3	would have very little homogeneity. I have both
4	difference between a student enrolled in 2 and 3	4	those variables in the model. So that's a class
5	reading courses was not significant. So the	5	level as opposed to a course level model.
6	expectation of growth for a student is based on	6	I want to remind you all, you guys are the
7	the number of courses they're enrolled in.	7	working group and the committee, so the
8	The attribution of that growth is given to	8	attribution that Christy is talking about is
9	each teacher that student had. So if the	9	what was understood to come out of the committee
-		-	
10	student's growth expectation is based on one	10	before. There's nothing that stops you from
11	course and they've had one teacher, that teacher	11	revisiting that. We're here to implement your
12	is fully accountable for that student's growth.	12	affectations. So mathematically let's think
13	If a student is enrolled in two or more courses,	13	about the easiest case. You're a teacher who's
14	that growth expectation is a little bit higher	14	teaching just a team taught course and there are
15	and that teacher both of those teachers that	15	two teachers in the classroom with the same
16	that student had whether it's the same	16	kids, and that's the only class you teach.
17	teacher or different teachers, both of those	17	Let's say you're an elementary teacher; it's the
18	teachers are accountable for that higher growth	18	only class you teach. It doesn't matter whether
19	expectation.	19	it's a hundred percent or fifty percent
20	So if Gisela and I both had reading courses	20	attributable to you because all of it is like a
21	she was teaching one reading course and I was	21	weighted average, right? So the average
	teaching another and Stephanie was in our class,		
22		22	multiplying everything by fifty percent, each
23	she has a higher growth expectation because she	23	kid by fifty percent, it's the same as the
24	is taking two courses. I'm fully accountable	24	average is going to be if you multiplied each
25	for what you do in meeting that higher growth	25	kid by one. Does that make sense?
	American Court Reporting		American Court Reporting
	850.421.0058		850.421.0058
	59		61
			-
1	expectation and Gisela is fully accountable for	1	The only time it makes a difference is when
1 2		1 2	The only time it makes a difference is when you're teaching kids with a differential number
	expectation and Gisela is fully accountable for		
2	expectation and Gisela is fully accountable for you meeting that higher growth expectation. So we're both accountable for that higher	2	you're teaching kids with a differential number of courses. So I have some of my kids who I'm
2 3	expectation and Gisela is fully accountable for you meeting that higher growth expectation. So we're both accountable for that higher expectation.	2 3	you're teaching kids with a differential number of courses. So I have some of my kids who I'm their only teacher for, they count one; I have
2 3 4 5	expectation and Gisela is fully accountable for you meeting that higher growth expectation. So we're both accountable for that higher expectation. MS. FEILD: So how would the homogeneity of	2 3 4 5	you're teaching kids with a differential number of courses. So I have some of my kids who I'm their only teacher for, they count one; I have some kids who are in my class and in another
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	62		64
1	there a delineation	1	course in that school. So those are the kinds
2	DR. COHEN: There's no way to capture that	2	of recommendations we can make to the this
3	because you don't capture the kid's achievement	3	group can make to the Department. You all have
4	at a different point in time; you only have at	4	the ability to say we'd like to see it done this
5	the end of the year.	5	way, but right now this is the best available
6	So if a couple of your kids let's say	6	information. Nicole?
7	I'm not a great teacher and there's a great	7	MS. MARSALA: Does it have to be the same?
8	teacher over there, and a bunch of my kids	8	I mean, do we have to say I mean, maybe for
9	transfer into that great teacher's class, I'm	9	middle school and elementary where we don't have
10	going to get the benefit from that. That's just	10	the block scheduling; can it be two and three
11	the case because you don't have a measurement of	11	where they have the block scheduling it could be
12	a year. I think it's maybe not all that likely	12	two or three, or does it have to be the same
13	when kids transfer or leave your class they're	13	everywhere?
14	all going to go to teachers with particularly	14	DR. HOVANETZ: Again, that's a decision
15	high or particularly low	15	that the committee is going to be able to make.
16	MR. LeTELLIER: That's what	16	You all can decide how that's done. If you want
17	DR. COHEN: It's an excellent question;	17	it to be that that student has to be with that
18	it's a good insight.	18	particular teacher for the entire year during
19	MS. TOVINE: For evaluation purposes,	19	elementary school, again it's a decision
20	though, it seems fair for teachers if students	20	entirely up to the committee.
20	included for their score could be ones that were	20	MR. LeTELLIER: Is this something that can
22	there for the majority of the year, similar to	22	be made at some point as a business rule of some
22	the way you do student grading, and they have to	22	sort? In talking with the Department, you know,
		23 24	whether or not this could be something
24	be there for both counts. I mean, it doesn't seem reasonable that a student would come in in		-
25		25	implemented that we can look at because you were
	American Court Reporting 850.421.0058		American Court Reporting 850.421.0058
	63		
	03		65
			talking shout attendance and how we would de
1	January or February or whatever time period, and	1	talking about attendance and how we would do
2	January or February or whatever time period, and that child is now going to count in the	2	that, where we could just come up with some
2 3	January or February or whatever time period, and that child is now going to count in the calculation	2 3	that, where we could just come up with some simple rules that would articulate what we would
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2 3 4 5	January or February or whatever time period, and that child is now going to count in the calculation DR. COHEN: That is a policy decision and I'm going to hand that over to Christy. I don't	2 3 4 5	that, where we could just come up with some simple rules that would articulate what we would expect to be used? DR. HOVANETZ: Yes, as soon as we have the
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	66	T	68
4	that because I've heard a lot of feedback from	1	in multiple courses.
1	teachers who have watched the webinar and	2	-
2			MS. FEILD: Okay, so I teach her for
3	language arts is taught quite differently when	3	English.
4	you're focusing on writing.	4	And you, who is my reading teacher, will
5	DR. HOVANETZ: It's a fantastic point you	5	have different growth for each of us.
6	make. Tomorrow afternoon we have a conversation	6	DR. HOVANETZ: Well, she's not in my class,
7	about the course code directory that we don't	7	so I'm not but, yes, your higher expectation
8	want to overwhelm you with now, as we're trying	8	I will be accountable for, as well as your
9	to facilitate the process of having you all make	9	teacher that you're in the class with for Gina.
10	recommendations to the commissioner. But for	10	And again, this is a decision the committee
11	the process of this evaluation, we use the	11	made last time about setting expectations and
12	information the Department had for course	12	setting attribution. If we want to change how
13	code directly. The Department recognizes that	13	that's done, it's again something we should be
14	this needs to be revised or evaluated at least	14	talking about here and now on what that
15	to determine are these appropriate courses to	15	expectation should be. I would like to have
16	have for the evaluation of teachers on their	16	some results presented first so you can
17	reading FCAT and on the math FCAT. And we have	17	understand what the expectations will take and
18	a list, the master directory of all the courses	18	how it's actually attributed. Jon?
19	that were included. Like, I believe there are	19	DR. COHEN: One thing that folks are
20	166 for reading and 90 for mathematics that were	20	discussing that maybe they shouldn't get lost is
21	included for purposes of this evaluation.	21	we kind of covered two topics. One is how do
22	This summer, this committee's	22	you attribute stuff and we can figure that out.
23	responsibility when we get together next will be	23	Christy says we'll look at some data and figure
24	to talk about which courses should be the ones	24	that out. The other thing is the data
25	included or required for the FCAT statewide	25	collection. Right now with the data we collect
	American Court Reporting		American Court Reporting
	850.421.0058		850.421.0058
	67		69
1	evaluation. So they're bringing up fantastic	1	we can't tell whether a course is intended as a
2	points. The Department has fully recognized	2	one-term course or a year long course. People
3	that's for tomorrow.	3	are concerned, well, the kid's only in my class
4	Gisela?	4	for half the course, how can that be attributed
5	MS. FEILD: Let me make sure I understand	5	to me? We don't know if it's half the course
6	the growth. Gina and I are sitting in the same	6	unless we know whether it's a full year or a
7	English 1 9th grade class, we both happen to	7	half-year course, right? Gathering this data
8	have the same 8th grade FCAT reading score	8	and - and the committee, I would recommend that
9	whatever that happens to be; we're both not ELL,	9	the committee think for a couple of minutes
10	we're no SWD, we're not gifted, we're twins. I	10	about that issue and which data you need to
11	happen to have had some issues for some	11	support the kinds of analysis, the kinds of
12	reason I'm also sitting in an intensive reading	12	attribution you want because right now that's
13	class or maybe Gina had parents who said I'm not	13	not in the state data system. Particularly it's
14	putting her in intensive reading, right?	14	not
15	MS. TOVINE: She's qualified but she's not	15	PANEL MEMBERS: (Over-speaking.)
16	enrolled.	16	DR. COHEN: So we could have.
17	MS. FEILD: She's not enrolled. We both	17	DR. HOVANETZ: The only thing we don't know
18	have scores that qualify. So we're both in	18	with the identified data set is there is not a
19	English 1 with the same teacher, and I have an	19	term that says that this is a full year course
20	extra reading class with you. So when we build	20	or if this is a semester course. So if a
21	my expected growth, my expected growth will be	21	student is repeating a high school course, it
22	higher than Gina's because I'm sitting in two.	22	will look to us as if it's a full year course
23	DR. HOVANETZ: Based on the recommendations	23	rather than repeating a semester course, but
24	of this committee last meeting, yes, there will	24	that's an infrequent occurrence.
25	be additional expectations if they're enrolled	25	DR. COHEN: We know how long kids were
1	American Court Reporting	1	American Court Reporting
	850.421.0058		850.421.0058

-	70	-	72
1	enrolled.	1	just because we're actually converting our term
2	DR. HOVANETZ: Correct.	2	3 courses into term 1 and 2 even in elementary
3	DR. COHEN: So we don't know about block	3	because it's possible for a student to transfer
4	schedules. We don't have that.	4	between two fourth grade teachers and have one
5	DR. HOVANETZ: We don't technically have	5	term 1 and another term 2, we can see fifty
6	that information. We have what district and	6	percent partial attribution even though they
7	school and course number and period number and	7	were enrolled in the same course for the entire
8	we have which survey the student was enrolled in	8	year.
9	it; and if they're enrolled in the same one	9	MS. ACOSTA: I have a question actually,
10	identical information for two in survey 2 and	10	maybe some of you can address this as well. I
11	survey 3, the assumption is it's a whole year	11	think you partly answered it, Anna. I was
12	course. If they're only enrolled it in one	12	curious how many kids are actually impacted by
13	semester in survey 2 or survey 3, the assumption	13	having semester courses for FCAT, for things to
14	can be it's a semester long course, but there's	14	get tested on the FCAT because at our school it
15	no actual data that says semester or full year.	15	would be a rare student who would be enrolled in
16	MS. BROWN: I'm confused and this will ask	16	a year-long course that had an FCAT test. Do
17	everybody else. At least in our scheduling	17	you see what I'm saying?
18	system that we report, there's a cell for term	18	How many students are we talking about? Is
19	term 1, term 2, or term 3. Term 1 is for	19	this very common that you only have a semester
20	semester, term 2 is second semester, term 3 is a	20	course that's going to be tested on the FCAT?
21	year long course. So I don't understand why	21	MS. FEILD: I think part of the case in
22	that data element isn't available to you.	22	Miami-Dade is, of course, recovery. They're
23	DR. HOVANETZ: We'll get that data	23	even talking now in terms of algebra making it a
24	MS. BROWN: I think part of the problem is	24	semester course for course recovery, taking the
25	sometimes schools semester-ize courses for GPA,	25	DOC in December. So it's really sometimes
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	71		73
			15
1	for kids in graduation, and if that happens	1	kids pass the first semester but fail the second
1	for kids in graduation; and if that happens after the collection period it's possible there	1	kids pass the first semester but fail the second
2	after the collection period it's possible there	2	semester, so they're course recovery-ing at the
2 3	after the collection period it's possible there could be some error in that, but you're right.	2 3	semester, so they're course recovery-ing at the beginning of the next year just the second
2 3 4	after the collection period it's possible there could be some error in that, but you're right. MS. FEILD: But in general you should be	2 3 4	semester, so they're course recovery-ing at the beginning of the next year just the second semester or vice versa. So there's thousands in
2 3 4 5	after the collection period it's possible there could be some error in that, but you're right. MS. FEILD: But in general you should be able to know. You should clearly be able to see	2 3 4 5	semester, so they're course recovery-ing at the beginning of the next year just the second semester or vice versa. So there's thousands in Miami-Dade, thousands who fall in that criteria.
2 3 4 5 6	after the collection period it's possible there could be some error in that, but you're right. MS. FEILD: But in general you should be able to know. You should clearly be able to see how that student is scheduled in that reading	2 3 4	semester, so they're course recovery-ing at the beginning of the next year just the second semester or vice versa. So there's thousands in Miami-Dade, thousands who fall in that criteria. MS. BROWN: And what we see is that is
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	74		76
1	multiple purposes. It will be used to evaluate	1	everything to business models. You know,
2	teacher effectiveness; it will be used to	2	accountability is kind of something we haven't
3	evaluate school and possibly district level	3	talked about too much, but all this stems out of
4	effectiveness; and it will be used to evaluate	4	a business model of being accountable for what
5	teacher preparation program efficacy. What may	5	your job is and making sure that you're reaching
6	work at some levels and I will go back to the	6	those goals or exceeding them. Well, if we're
7	class size the question I asked about class	7	truly going to do that, it would have to be
8	size and how stable that is between the	8	something that that teacher is able to reach.
9	measures. When you get a large enough end, if	9	So I just wanted to piggyback off of that.
		-	
10	you're using data to evaluate a teacher	10	MR. TOMEI: I think part of that overall
11	preparation program that puts out a thousand	11	goal has to be that we need to do everything we
12	students a year, it's probably not an issue.	12	can within the legal limits that we have in
13	But for one individual teacher it could be a	13	terms of what variables we can put in the model
14	really big deal if that statistic is unstable.	14	to mitigate to the greatest extent possible the
15	So we've got to keep in mind to protect the	15	unintended consequences of discouraging the best
16	transparency and the integrity of the model for	16	teachers from going into the locations that are
17	individual teacher accountability. I think	17	in most need.
18	that's the lowest common denominator and I think	18	MR. LeTELLIER: Absolutely, and I just
19	that has to be an important outcome of this	19	thought of this about an hour ago, is we had
20	committee.	20	talked about unintended consequences. I can't
21	So these conversations and comments like	21	remember what you what's the word you used
22	things are infrequent, well, if you're that one	22	last time?
23	teacher that experienced that infrequent event,	23	PANEL MEMBER: (Inaudible.)
24	that doesn't mean a lot to you. We need to	24	MR. LeTELLIER: And I've been dying to say
	protect that teacher as well.	24 25	
25		25	this and I haven't said this publicly, but I
	American Court Reporting		American Court Reporting
	850.421.0058		850.421.0058
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1	So again, I just want to emphasize that I	1	think we should: Every profession is going to
1 2	So again, I just want to emphasize that I think this is an extremely important	1 2	think we should: Every profession is going to have people that try to play the game, that are
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		1	
	78		80
1	majority of teachers care, we love what we do.	1	technical assistance with MIS directors and
2	We want to help kids and the last thing on our	2	others who are reporting on that information up
3	minds is how do we game the system. So I think	3	to the state to be sure that they are following
4	that's very important, something that I just	4	what's in the data element dictionaries.
5	want to share.	5	MS. BROWN: If I can just piggyback on that
6	MS. EDGECOMB: In this discussion and maybe	6	because uniformity is so important to the
7	I'm not hearing it correctly and maybe I	7	validity of the entire process, and in my
8	shouldn't get bent out of shape about it. I'm	8	experience what I can see the writing on the
9	worried about uniformity I'm hearing. Is that	9	wall where we're going to need to go is how we
10	something because I hear how people are	10	clearly define those business rules for
11	capturing and coding and talking about courses	11	eligibility because in some cases we may not
12	and when they end, how they end, and what they	12	have uniformity in say, for example, course
13	are and what they are not. If we're using the	13	assignment. But we can create uniformity by
14	motto that's supposed to be fair and formalized	14	creating the right business rule that looks at
15	instruction to capture and save information,	15	those in an either/or situation, but then also
16	isn't there some importance and value in some	16	the process itself starts to find the anomaly
17	uniformity here?	17	and when we start to find the thing that stands
18	DR. HOVANETZ: There is. I absolutely	18	out as different then there's just that
19	agree. The Department has a directory that	19	oversight that starts to correct everything
20	defines each of the particular variables that we	20	towards uniformity.
21	are using, so I think they are well defined.	21	We've discovered that in our own district
22	It's assuring and again they have been reporting	22	when we're looking across large numbers of
23	these variables to the Department for in many	23	schools and how individuals are scheduled, et
24	cases decades. In the same way with actual data	24	cetera, and we would do that major oversight and
25	elements, definitions, and particulars on how	25	you think that you have every one common, and
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	79		81
1	they're supposed to report it and when they're	1	then when you start to look at the data set you
2	supposed to report it, each one of them is very	2	go, what the heck is this? And then that is
3	defined.	3	where you go to that situation and say you've
4	It's assuring that they're following those	4	got to fix it. And so through the process we'll
5	proper procedures, which I'm assuming the	5	get there, but I can so respect and I would like
6	majority of the districts are but continuing to	6	to piggyback on that, that that uniformity has
7	reiterate as soon as we do determine which are	7	got to be part of the goal in order for there to
8	the control variables or the covariates we're	8	be any kind of validity for the comparisons that
9	going to be including in these models to	9	are going to be made.
10	highlight those when they do that and I ask	10	DR. HOVANETZ: And you make a fantastic
11	for when they're at the consortium meetings	11	point, and when this committee makes a decision
12	to be able to highlight and say these are the	12	about which model is actually going to be used
13	particular covariates that are included in the	13	and the commissioner approves it, the first AIR
14	models, these are the data definitions that you	14	responsibility is to generate those value-added
15	need to be paying attention to, and then also	15	scores for teachers in Florida and have those
16	through the review process to pay particular	16	posted this summer. That would be our first
17	attention to these covariates, but I agree,	17	opportunity to start looking for any type of
18	uniformity is going to be paramount for insuring	18	data anomaly for districts and schools to
19	the accuracy of these calculations. I think	19	review, to start looking at what the data and
20	that there are already a lot of processes that	20	information looks like in order to identify the
21	the Department has in place to insure that and	21	anomaly where we see something happening in one
22	continue to use this data and information that's	22	of the districts but not the other 66 and be
23	going to improve the quality of it, too. But I	23	able to start identifying where we need to
1		1	
24	absolutely hear that that is a concern and I	24	provide additional technical assistance.
24 25	absolutely hear that that is a concern and I think it's going to just take additional PD and	24 25	provide additional technical assistance. MS. NOYA: Also, if you leave up to the
	absolutely hear that that is a concern and I		•

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	82	1	84
1	interpretation of every district then we start	1	model that we use so that people can just look
2	doing everything differently, and that's been	2	and say, okay, here's where we're at. We tweak
3	one of the problems across the state for years.	3	it from there, nobody's jobs on the line because
		-	
4	So transparency, teachers are asking when in	4	of the data coming out in the summer. I think
5	the summer? Are you going to do this late	5	that's what people are kind of
6	summer so when they come back and they're in a	6	MR. COPA: Absolutely, yeah. This is for
7	rush, they won't even see the transparency?	7	information purposes.
8	DR. HOVANETZ: Juan is panicking because of	8	DR. DORAN: That's a good point. This
9	what I said, but there's	9	gives us the basis by which we can look at some
		-	
10	MR. COPA: I just heard an audible groan	10	of the data, changing some of those business
11	with the word "posted", but this is very	11	rules wouldn't switch, for example, which
12	districts have been very interested, of course,	12	value-added model necessarily look different,
13	as we're developing part of Race to the Top	13	but it would change some of the things about
14	their evaluation systems, information needed to	14	attribution. So it's still us; we're still on
15	inform those decisions regarding their	15	safe ground on how we discuss what we intend to,
16	evaluation systems, and we are committed to	16	even when the business rules perhaps don't
	· · ·		
17	providing districts with data on the model that	17	change.
18	is eventually selected to help them form	18	MS. FEILD: Which FCAT scores are you
19	decisions. So it's really a provision of data	19	using? The old scale, the ten year scale?
20	to districts in a useable form to help folks	20	PANEL MEMBERS: Over speaking.
21	start to understand what it means, make informed	21	DR. COPA: Correct, for the purposes of
22	decisions about how to apply an evaluation	22	this summer you're well aware it's equated
23	system. So that's the key point we'll	23	exactly to the old scale, but it's part of their
24	accomplish this summer.	24	work as well. It's no secret we're moving to
25	MS. TOVINE: Once those results are	25	new standards beginning this fall. It will be
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	83		85
1	actually run and they go back, some of them are	1	applied starting with the spring 2012
1	actually run and they go back, some of them are	1	applied starting with the spring 2012 assessment, so any change in the assessment will
2	selected, will this committee come back	2	assessment, so any change in the assessment will
2 3	selected, will this committee come back together, say, in the fall or whatever time	2 3	assessment, so any change in the assessment will likely result in further refinement of the
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	86		88
1	MR. COPA: These are all empirical	1	MS. EDGECOMB: Oh, is that what that means?
2	questions. The commissioner must make a	2	How many other people knew what that meant?
3	selection by June 1st. When that becomes part	3	Okay.
4	of State Board rules, I mean, that is something	4	DR. DORAN: Doretha, it's not a stupid
5	that would happen in the future going forward	5	question. It's exactly a right on question. Is
6	after we've had the work of this committee to	6	there value in adding additional covariates over
7	look at years of performance, refinements, and	7	time?
8	models; and even when it becomes part of the	8	Well, given the covariates that we have we
9	State Board rule you could further refine that	9	can evaluate is it good to have some or more,
		_	
10	going forward, as well. So that's a key thing	10	and we can provide you data that suggests
11	to keep in mind. It's not something that we	11	whether or not it's good to have some, only a
12	will be etched in stone that cannot be changed.	12	few, or whether it's good to have more and we're
13	The anticipation here, of course, is this will	13	going to look at exactly that question when we
14	be an evolving product.	14	go through the parsimony issue today.
15	MR. MOREHOUSE: I'm just curious. Is it	15	MR. LeTELLIER: Can you define 'parsimony'?
16	possible to develop a description, a course	16	DR. DORAN: Remember, when you go down the
17	description? There seem to be so many	17	criteria, if you have a question, we'll define
18	variations in terms of how a course is	18	everything, we'll talk about what we're looking
19	delivered, some courses will be graded one	19	for and why you should care about each one of
20	semester, some are year long courses, some are	20	those things.
		20	-
21	team taught, some are not taught; is it possible		DR. COHEN: Other things being equal,
22	to have a description of those options for the	22	simpler is better.
23	committee so that any rules that we have to make	23	MS. EDGECOMB: Absolutely.
24	in my mind, it's hard to depend upon how those	24	MS. HEBDA: Okay. To keep things simple,
25	courses are delivered and how they're graded and	25	we'll take a 15 minute break. We'll regroup at
	American Court Reporting		American Court Reporting
	850.421.0058		850.421.0058
	87		89
1	when they're delivered.	1	20 minutes till.
1 2	when they're delivered. DR. HOVANETZ: Yes, and I think we can fold	1 2	
	-		(Whereupon, a short recess was had.)
2 3	DR. HOVANETZ: Yes, and I think we can fold this into our course code discussion that we'll	2 3	(Whereupon, a short recess was had.) DR. DORAN: The part of the conversation
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	90		92
1	There's no reason you have to hang your hat on	1	predicted score and we have a prior score, if
2	the things that were cited, as far as I know, in	2	you just subtract the prior score from that
3	terms of going forward when this becomes	2	predicted score for each kid you get an expected
		-	
4	operational.	4	growth. And that's a statistic that we formed
5	But we're going to look now at some of the	5	some summary statistics on and we will show you
6	data, and we will evaluate some of the models	6	later on in the presentation.
7	based on the different categories that we've	7	Christy already went over those.
8	laid out for you. So let's talk about a couple	8	Let me talk briefly about this. The
9	of things and a couple of terms.	9	expected scores change in terms of their
10	One, let's talk about this thing called a	10	definition depending on which model we look at.
11	deviation from an expectation. Given prior	11	Now, for each model we form an expectation, and
12	scores and other characteristics of kids,	12	I'm going to put an extra word in there. We
13	whether or not they're ELL, special ed, gifted,	13	form what is called a conditional expectation.
14	so on and so forth, enrolled in two courses, we	14	It's conditional on what your prior score was.
15	have what is the average score of similar	15	Kids with two different prior scores have
16	students. That's what's called an expectation.	16	different expectations, but kids who have the
17	If you recall back to that scatter plot where we	17	same prior score have the same expectation.
18	had those regression lines, the expectation is	18	It's also conditional on whether or not you were
19	that line. Remember that line changes according	19	SWD, special ed or gifted or so forth. So, for
20	to students. So with students you have all	20	example, I think Gisela was asking this question
21	things being equal similar prior scores would	21	earlier, two kids who are exactly identical on
22	have the same expectation. Students who score	22	all of their characteristics prior score and
23	above that or below that have a deviation from	23	categorization in gifted, special ed, and so
24	that expectation. In statistical terms that's	24	forth they're the same on all of those. They
25	referred to a residual. It's the deviation from	25	have the exact same predicted score, everything
	American Court Reporting		American Court Reporting
	850.421.0058		850.421.0058
	91		93
1	91 that expectation.	1	93 being equal, but you change one of those things.
1 2		1	
	that expectation.		being equal, but you change one of those things.
2	that expectation. What score did the student actually get in	2	being equal, but you change one of those things. So suppose students are exactly the same in
2 3	that expectation. What score did the student actually get in testing that's sometimes called an observed	2 3	being equal, but you change one of those things. So suppose students are exactly the same in terms of their gifted coding and SWD coding and
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	24		22
	94		96
1	lot of models and many different variables. We	1	extensive testing to make sure that the models
2	have eight different models, seven grades in two	2	behave in the way they're supposed to behave.
3	subjects. There are more than 100 models that	3	We look at the standard errors which we'll
4	were estimated, and we have 18 different	4	define in just a little bit. We want to make
5	criteria by which we evaluate the models. If we	5	sure that the models and the software behave in
6	wanted to spend time looking at each model for	6	the right way.
7	each grade for each subject against each	7	There's an extensive amount of testing that
8	criteria, we would need to be here for four	8	we do on simulated data. Simulated data means
		-	
9	years. This wouldn't be a four year contract;	9	we make up data according to some assumptions
10	we'd be here for a very long time. It's not	10	and we test out our models and we make sure the
11	viable. Just simply cannot do it.	11	models give us back answers that we know they're
12	Now we're going to try and consolidate this	12	supposed to give us back. Jon's going to expand
13	information based on some things that seemed	13	on that as soon as I give him the microphone
14	reasonable to do; I'm going to show you how we	14	because we did an extensive number of
15	try to narrow some how we're facilitating	15	simulations to make sure that things were
16	this conversation today. The point here is that	16	working as expected. You want to talk about
17	there is a lot to look at there are many	17	that?
18	different variants that were estimated from many	18	DR. COHEN: Yeah, I'll talk briefly about
19	different grades and subjects. But as we're	19	it. There will be a technical report that has
20	going to show you, the key results are	20	all this in here, but we're going to when you
21	consistence across all grades. If we saw that	21	estimate a model you want to make sure that the
22	models behaved differently across grades and	22	model is unbiased, right? We want to have
	, -		
23	across subjects, we would need to have pulled	23	unbiased estimates of teacher effects and we
24	those models out and examined them. Why does	24	want to make sure that the way we're doing
25	grade seven Model 1 look so different than Model	25	things statistically isn't introducing a bias.
	American Court Reporting		American Court Reporting
	850.421.0058		850.421.0058
	95		97
			-
1	1 in grade four in math? We don't see the	1	What is a bias? If there's a true value then
1 2	1 in grade four in math? We don't see the behavior of the models that would have required	1 2	-
	1 in grade four in math? We don't see the		What is a bias? If there's a true value then
2	1 in grade four in math? We don't see the behavior of the models that would have required	2	What is a bias? If there's a true value then any deviation from that true value is a bias,
2 3	1 in grade four in math? We don't see the behavior of the models that would have required that. I'm going to show you in a moment.	2 3	What is a bias? If there's a true value then any deviation from that true value is a bias, right?
2 3 4	1 in grade four in math? We don't see the behavior of the models that would have required that. I'm going to show you in a moment. Essentially, what we're going to do is	2 3 4	What is a bias? If there's a true value then any deviation from that true value is a bias, right? So in the real world we don't know how much
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2 3 4 5 6	1 in grade four in math? We don't see the behavior of the models that would have required that. I'm going to show you in a moment. Essentially, what we're going to do is we're going to choose a particular grade, grade seven, we chose grade seven because it's in the middle and because it's like the other models	2 3 4 5 6	What is a bias? If there's a true value then any deviation from that true value is a bias, right? So in the real world we don't know how much value each teacher has. You can't know that about teachers. The teacher fairy can't land on your shoulder and whisper in your ear "Miss
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		T	
	98		100
1	value-added, we'll just give it a little Greek	1	would fall outside that range of the true value.
2	symbol there for the value-added just to have	2	So it's important, it's technical. There
3	something to put up there.	3	will be a technical report on it for anyone who
4	All right. So let's say a teacher's score	4	wants to read that. A couple of people here
5	is right in the center. So your value-added	5	indicated they would like to see that. We can
6	score is I don't know what the number is,	6	show you results if you want to see them. They
7	maybe you're adding 20 points. That 20 points	7	look like numbers. We expect 10%, 10.1%, we
8	is a point estimate, but it's not really a point	8	expect 5%, we're looking at 4.89%. So we're
		-	
9	estimate because we don't know. All we have is	9	getting lots of data back for lots of different
10	we a probability distribution and they tend to	10	models on lots of different situations. No one
11	come out to be normal probability distributions	11	ever tells me they can't hear me.
12	 there are proofs that statisticians like to 	12	So I think that's it. The models are also
13	think about. So here's your point estimate.	13	unbiased. We got on average the right estimates
14	Each point estimate comes with a standard error,	14	back and consistent, that means as the sample
15	right? So you know that the teacher is very	15	size gets bigger the estimates get more precise
16	likely to be at this point, a little less likely	16	and all the models we're working with have that
17	to be at this point, way less likely to be down	17	characteristic as well. So as we move forward,
18	there, really unlikely to be up here. But it's	18	rest assured standard error we're talking about
19	a probability distribution; it's possible.	19	are accurate standard errors when the data
20	So we estimate these standard errors. When	-	
		20	corresponds.
21	we talk about precision, we're going to be	21	DR. DORAN: All right.
22	leaning on these standard errors. If the	22	MS. BROWN: Before you leave, when you
23	standard error is smaller, the model is more	23	talked about precision, could you kind of define
24	precise. I have less uncertainty. If I had a	24	for me precision as accuracy?
25	curve like this, I would know with some	25	DR. DORAN: Would you mind if we hold
	American Court Reporting		American Court Reporting
	850.421.0058		850.421.0058
	99		101
	99		101
1		1	DR. COHEN: It's easy. This standard error
	certainty that this teacher was in at least in	1	DR. COHEN: It's easy. This standard error
1 2 3	certainty that this teacher was in at least in this range and did not fall out here. Is that		DR. COHEN: It's easy. This standard error curve is more narrow, it's more precise. This
2 3	certainty that this teacher was in at least in this range and did not fall out here. Is that clear?	2 3	DR. COHEN: It's easy. This standard error curve is more narrow, it's more precise. This means the estimate is more precise. If it's
2 3 4	certainty that this teacher was in at least in this range and did not fall out here. Is that clear? So more precise is better. It sounds	2 3 4	DR. COHEN: It's easy. This standard error curve is more narrow, it's more precise. This means the estimate is more precise. If it's wider, it's less precise.
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		1	
	102		104
1	grades in both subjects, and this is going to be	1	we're going to introduce this now but we're
2	the first thing that we're going to show you is	2	going to look at this in a very detailed way in
3	a line graph that shows the magnitude of the	3	just a little bit is what happens when we add
4	effects. Let me actually just show you what	4	the school effects back into the teacher
5	we've got here. We're going to start with	5	effects. In part, we're not ready to evaluate
6	reading. This is all models, all grades. This	6	this criteria yet because we really haven't
7	slide and the next slide are the only time today	7	defined why you should care about school and/or
8	that we will show you a statistic on all models	8	teacher effects just yet. This is a high level
9	for all grades as we go forward and as I'll	9	overview.
10	explain in this particular slide here, this	10	What happens if you add those school
11	slide provides the justification for why we only	11	effects back in; essentially what we see is that
12	look at one particular grade but all models. We	12	the models behave similarly again. So adding
13	always look at all models, but only for a given	13	school effects back in as opposed to having only
14	grade. In this particular slide, we look at all	14	teacher effects in some of the models causes for
	-		
15	models for all grades, okay. This is the last	15	the behavior of the models to be similar. Let
16	time we'll do this, the only time we'll do it.	16	me go to the next slide because we see something
17	All right. Here on the X access we have	17	similar in math, and I'm going to revisit the
18	each grade and on the Y access we have what	18	key point that we're looking for here. The key
19	we're calling the size of the effects. Now this	19	point, the key take away in the slide that I
20	here, the model, remember looking at your sheet	20	showed you before, in the slide that I'm showing
21	differ in terms of a few characteristics. Some	21	you now is that the behavior of the models
22	of them only have teacher effects and some of	22	across grades for both reading and math is
23	them have both the teacher and school effects.	23	comparable. They're similar. So we're using
-			
24	We'll actually define what that means to have	24	this as a justification for why later we're only
25	both teacher and school effects in just a little	25	going to look at a single grade all models.
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1	bit.	1	You're not ready yet to evaluate any of the
1 2		1 2	
	bit. But what we see here is that these are the		You're not ready yet to evaluate any of the models based on the criteria, the precision, the
2 3	bit. But what we see here is that these are the covariate adjustment models and they behave very	2	You're not ready yet to evaluate any of the models based on the criteria, the precision, the accuracy, and so forth just yet. This is just
2 3 4	bit. But what we see here is that these are the covariate adjustment models and they behave very similarly. The effects are comparable across	2 3 4	You're not ready yet to evaluate any of the models based on the criteria, the precision, the accuracy, and so forth just yet. This is just the high level overview.
2 3 4 5	bit. But what we see here is that these are the covariate adjustment models and they behave very similarly. The effects are comparable across all grades. We don't see the lines	2 3 4 5	You're not ready yet to evaluate any of the models based on the criteria, the precision, the accuracy, and so forth just yet. This is just the high level overview. We see the same thing in math. We don't
2 3 4 5 6	bit. But what we see here is that these are the covariate adjustment models and they behave very similarly. The effects are comparable across all grades. We don't see the lines criss-crossing in very unpredictable strange	2 3 4 5 6	You're not ready yet to evaluate any of the models based on the criteria, the precision, the accuracy, and so forth just yet. This is just the high level overview. We see the same thing in math. We don't see the model here and here and
2 3 4 5 6 7	bit. But what we see here is that these are the covariate adjustment models and they behave very similarly. The effects are comparable across all grades. We don't see the lines criss-crossing in very unpredictable strange ways. We don't see something that looks	2 3 4 5 6 7	You're not ready yet to evaluate any of the models based on the criteria, the precision, the accuracy, and so forth just yet. This is just the high level overview. We see the same thing in math. We don't see the model here and here and criss-crossing lines which would suggest that
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1	MR. LeTELLIER: And the second thing is	1	affect a teacher in a certain way and we're
2	when we're looking at the effects of the	2	going to take that into account. Now obviously
3	variables when deciding this, I know now we're	3	if it only affects one teacher across the state,
4	looking at sort of a macrocosm sort of dealing	4	is that the norm? No. But what we're saying is
5	with the big picture; are we going to look at	5	if all teachers that would have a kid that
6	how those variables may affect an individual	6	missed 60 days, let's say, whatever teacher that
7	class?	7	was, is that an effect? Are we looking at that
8	DR. DORAN: Yes. Not a particular teacher,	8	in that way?
9	but on average across many teachers, yes. We	9	DR. DORAN: Yes. Before we go into the
10	see exactly that.	10	different effects including attendance has on
11	MR. LeTELLIER: Versus just plugging in to	11	the predictions of the
12	the whole state is what I'm saying because if	12	MR. LeTELLIER: Attendance was just an
13	you in other words, you may have with the	13	example
14	attendance issue of a kid that missed 60 days	14	DR. DORAN: Of the different covariates.
15	out of the 180 days, that certainly hopefully is	15	MR. LeTELLIER: Okay. Thank you.
16	not the norm, but that may have great weight for	16	DR. COHEN: I think it's math per grade
17	that teacher in that class. So if we only plug	17	says a kid who missed 60 days, everything else
18	that into those 10,000 teachers, it's going to	18	being equal, would have an expected scale score
19	be a blip on the screen and won't show up.	19	of seven points less. So you would have one kid
20	That's my question.	20	who has an expectation of seven points less
21	DR. DORAN: All right. We don't look at	21	among your whole class. So it may matter and
22	any one teacher where there's any particular	22	attendance is something that you want to think
23	impact, so does adding that variable in change	23	about. You can't learn if you're not in school,
24	your ranking from high or low. But one of the	24	right?
25	things that we do look at is how correlated,	25	DR. DORAN: One thing that I didn't tell
	American Court Reporting		American Court Reporting
	850.421.0058		850.421.0058
	107		109
1	what's the relationship of the teacher effects	1	you at the beginning of the day is for grade
2	what's the relationship of the teacher effects across the different models. That tells us	2	you at the beginning of the day is for grade seven. We brought data with us, some data
2 3	what's the relationship of the teacher effects across the different models. That tells us whether there's a flip-flop of teachers being	2 3	you at the beginning of the day is for grade seven. We brought data with us, some data files, so if there are things that you're
2 3 4	what's the relationship of the teacher effects across the different models. That tells us whether there's a flip-flop of teachers being highly classified and under one model then maybe	2 3 4	you at the beginning of the day is for grade seven. We brought data with us, some data files, so if there are things that you're curious about that we don't present or there are
2 3 4 5	what's the relationship of the teacher effects across the different models. That tells us whether there's a flip-flop of teachers being highly classified and under one model then maybe being classified differently under another	2 3 4 5	you at the beginning of the day is for grade seven. We brought data with us, some data files, so if there are things that you're curious about that we don't present or there are some questions that we can look at, if I'm
2 3 4 5 6	what's the relationship of the teacher effects across the different models. That tells us whether there's a flip-flop of teachers being highly classified and under one model then maybe being classified differently under another model. We do look at that. I can tell you now	2 3 4 5 6	you at the beginning of the day is for grade seven. We brought data with us, some data files, so if there are things that you're curious about that we don't present or there are some questions that we can look at, if I'm talking Jon will crank through and maybe data
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	110		112
1	MS. WESTPHAL: Well, no, the consistency of	1	MS. BROWN: I have a question about and
2	the models seven, eight, nine, ten versus four,	2	we may get there and it's okay if you tell me
3	five, and six.	3	we're going to get there. But when we're
4	DR. COHEN: No, I think the important thing	4	looking at this, it's obvious we're going to
5	to take away from this is that the model even	5	have different patterns subject-wise, but
6	though it's developmental scales, the scales are	6	ultimately we have to pick one model. So are we
7	kind of different between grades, and so you	7	going to have some analysis about how one model
8	don't necessarily expect the same numbers in	8	reacts in subject one and subject two? In other
9	each grade. What's important is the relative	9	words, will it have the highest effects in both
10	ranking of the models. Model 1 always sees the	10	subjects or high here, low here? We need to
11	biggest teacher effect, Model 2 always sees the	11	make that decision.
12	next biggest effect, so the lines are parallel.	12	DR. DORAN: Yes, essentially what we're
13	That's what you're looking for in this. There	13	going to do is we're going to look at all the
14	are differences in the estimated effect size	14	models in one grade and you're going to evaluate
15	across grades and there's a difference in the	15	that in reading, see how it behaves in reading
16	pattern between math and reading. But that	16	and how it behaves in math. I'll tell you now
17	confounded with the differences in the	17	that the models behave similarly across the
18	measurement itself. We have run everything and	18	different subjects.
19	we've looked at all the data and the big	19	DR. COHEN: In most regards.
20	findings stay the same. We just didn't want to	20	DR. DORAN: Pardon?
20	try and present, you know, two subjects times	20	DR. COHEN: In most regards.
		21	DR. DORAN: In most regards, yes. So
22 23	seven grades for this many models. You'd never be able to look at the data.	22	you'll see, I think I don't know, but part of
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24	MS. WESTPHAL: Well, let's say we're	24	where you're going is you're wondering might I
25	looking at grade six. Two of the models or	25	choose Model 1 for reading and Model 3 for math
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1	however many lines, it's hard to tell	1	or something like that?
2	however many lines, it's hard to tell color-wise, but there seems to be a bigger gap	2	or something like that? MS. BROWN: Or if we are forced to make one
2 3	however many lines, it's hard to tell color-wise, but there seems to be a bigger gap between those two models than there does once	2 3	or something like that? MS. BROWN: Or if we are forced to make one choice, we have to make a decision; so that's
2 3 4	however many lines, it's hard to tell color-wise, but there seems to be a bigger gap between those two models than there does once you get to 7th, 8th, 9th, and 10th.	2 3 4	or something like that? MS. BROWN: Or if we are forced to make one choice, we have to make a decision; so that's important.
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	114		116
1	Precision in terms of its questions, what	1	Essentially, what you're saying is here's the
2	characteristics of value-added models lead to	2	teacher effects, the teacher has high value
	more precise estimates of the teacher effects?	_	added. How certain are you? Not so certain at
3	-	3	
4	The statistic that we're going to look at is	4	all. That would be bad.
5	called the standard error. We're going to look	5	Instead, we want the inference to be,
6	at the standard error of the teacher effects.	6	here's the teacher effect, the teacher has high
7	Let me talk about what a standard error is.	7	value added. How certain are you? Pretty
8	It's actually something that's very	8	certain. Standard error is relatively small.
9	familiar in polling, so for example if you look	9	That's our goal, that's what we're looking for
10	at the president's popularity rating and the	10	in the next couple of slides.
11	president's popularity rating is 50% plus or	11	What I'm showing you here are what are
12	minus 3 percentage points. That's typically	12	called box and whisker plots of the teacher's
13	what we see, right? That means, you know, it	13	standard errors. We've got them ranked by the
14	could be it's a little bit more than this but	14	different models, model 1, 1A, 3A, 3A1, 3B, 3C,
15	it's somewhere between 47% or somewhere between	15	and Model 4. Refer to your little cheat sheets
16	53%. We're pretty sure it's within a small	16	so you can remember which is which.
		17	Now this black dot in the center is the
17	range. That's standard error.		
18	Now supposed the president's popularity is	18	median standard error, okay, the median standard
19	50% plus or minus 20 points. Well, is the	19	error. We see in all of these covariate
20	popularity when I say 20 points, 30, or 70?	20	adjustment models, Models 1 through 3, that they
21	That's a big range. It's a big range of	21	are on the same scale. I'm going from about 3
22	uncertainty. The standard error tells you I've	22	to a little bit about 30. We're on the same
23	got a statistic, the president's popularity is	23	scale. So those can be compared very easily and
24	'X' 50%, but how certain am I that it's within	24	we can see the black dot is pretty close to
25	that range. It's a certainty statistic. Well,	25	being about the same, but you can see small
	American Court Reporting		American Court Reporting
	850.421.0058		850.421.0058
	115		117
1	if the standard error is big, we don't know. If	1	differences. Model 1A has smaller standard
2	there's a big range, it could be anywhere in	2	errors than Model 1 on average. That's what the
3	there or is there a small range? I actually	3	black dot represents. You can look and you can
4	know it's in here. There are some statistics	4	see the standard errors are smaller under a
5	that we use, this is called the standard error.	5	couple of models, Model 3 has slightly smaller
6	A small standard of error is more desirable	6	standard errors than almost all the others,
7	than a large standard error. Let me apply that	7	right?
8	to a teacher effect. We're going to get a	8	Now Model 4 is on a different scale. You
9	number; that number is a teacher effect or a	9	can see it ranges from 0 and this goes up to
10	point estimate. That number and then we get	10	800. There are some outlines up there. Now
11	the standard error that tells us, well, how	11	it's hard to compare Model 4 to the other ones
12	certain are we that this is where the teacher's	12	because it's on a different scale. So one of
13	ranking really is? A small standard error tells	13	the things I'm going to tell you is the average
14	us, the variability is pretty small. A big	14	standard error of the simple differences model
15	standard error means we've got a lot of	15	is much, much larger than the average standard
16	uncertainty. It's not very precise. So what	16	error of some of the other models. Now that's
17	are we looking for? We're looking for a model	17	what this little black dot is.
18	that yields with other things being equal	17	What we also see is a distribution. This
19	smaller standard errors. This is what we want	10	is the standard error of the 25th percentile and
	to see. These are data that we're about to show	20	this is the standard error of the 75th
20		-	
21	you.	21	percentile, and then this shows the standard
22	Why do you care? Well, a standard error	22	error of the 5th percentile and the standard
23	tells us that the estimated teacher effect is	23	error of the 95th percentile. So what are we
• •			
24	more precise. You don't want to estimate	24	looking for in these box and whisker plots?
24 25	teacher effects with a lot of uncertainty.	24 25	What would be desirable? Well, we want to see
	•	_	

	110		100
	118		120
1	that the black dot would be over to here to the	1	these are empirical data. We're looking at
2	left indicating that on average it has a smaller	2	criterion, standard errors. That is an
3	standard error by the way, this is math,	3	important statistical criterion. We're not
4	grade seven math. Two of the black dots over	4	bringing to you any opinions about which model
5	here to the left indicating that the model has a	5	we think works differently here. We're showing
6	smaller standard of error relative to the	6	you the results of the empirical evaluation and
7	standard error of other models, these are	7	we can tell you now that these models behave
8	standard errors of the teacher effects.	8	similarly across grade attendance to the similar
9	Then we want to see smaller spread. We	9	trends we see about these models in the
10	don't want this box to be big. That's not	10	different grades, but notice what you see here.
11	desirable. That means on average of small	11	I was asking the question the behaviors of the
12	standard error but there's a lot of variability.	12	models across the different subjects. We see
13	What we want is the black dot to be on the left	13	some relative consistency on this particular
14	and that box to be smaller. That would be	14	criterion. It's an important criterion,
			•
15	desirable. So what do you observe? Any reactions to the teacher effects standard	15	precision is important but it's not the only
16		16	thing. There are other things that we're going
17	errors?	17	to look at today.
18	MR. LeTELLIER: Model 3C, 3B, and 3A all	18	Let's do something real quickly here. We
19	are about the same, the spread and they all have	19	can just tell you an observation that you've
20	similar low error range. That's what I would	20	already made. Suppose we were to do the
21	quickly say.	21	ranking, which one took the smallest standard
22	DR. DORAN: That's a good observation. I	22	errors on average, and if we rank them what are
23	want to go to another person, but I want you	23	the characteristics of those particular models?
24	I'm giving you an assignment. I want you to go	24	Here's a chart that summarizes this for you. So
25	to your cheat sheet and I want you to find any	25	Model 3C has on average in both subjects a
	American Court Reporting		American Court Reporting
	850.421.0058		850.421.0058
	110		404
	119		121
1	characteristics of those models that they have	1	smaller standard error. There are small
1 2	-	1 2	
	characteristics of those models that they have		smaller standard error. There are small
2	characteristics of those models that they have in common.	2	smaller standard error. There are small differences between the different models. You
2 3	characteristics of those models that they have in common. Any other observations about box spots?	2 3	smaller standard error. There are small differences between the different models. You see 3C and 3B are consistent in the first two
2 3 4	characteristics of those models that they have in common. Any other observations about box spots? MR. TOMEI: They all have two lags, they	2 3 4	smaller standard error. There are small differences between the different models. You see 3C and 3B are consistent in the first two rows and both subjects, but there's a little bit
2 3 4 5	characteristics of those models that they have in common. Any other observations about box spots? MR. TOMEI: They all have two lags, they all have school effect and teacher effect.	2 3 4 5	smaller standard error. There are small differences between the different models. You see 3C and 3B are consistent in the first two rows and both subjects, but there's a little bit of a difference. But you don't see that that 1A
2 3 4 5 6	characteristics of those models that they have in common. Any other observations about box spots? MR. TOMEI: They all have two lags, they all have school effect and teacher effect. DR. DORAN: An interesting observation.	2 3 4 5 6	smaller standard error. There are small differences between the different models. You see 3C and 3B are consistent in the first two rows and both subjects, but there's a little bit of a difference. But you don't see that that 1A is over here and here and it's minor
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		1	
	122		124
1	mentioned about if we're bound to use the same	1	generate for a teacher we would only generate
2	model for both and Juan said no; maybe we should	2	data for the kids who have two lags?
3	put a slash here so that we can look at both.	3	DR. DORAN: No, no. We can make a decision
4	DR. DORAN: Yeah, put a little line through	4	so that when students have two prior test
5	it.	5	scores, there can be a decision, a policy
6	MR. LeTELLIER: This way we're evaluating	6	decision. When students have the two available
-		-	
7	for reading and math, and at the end of the day	7	test scores, you use them and if a student has
8	it's the same, great, but it'll be easier to	8	perhaps only one of the two, then what we would
9	remember, I think.	9	do is we could put in what's called just a code
10	DR. DORAN: Yeah, I wish I had given you	10	that would indicate that one of those two scores
11	two sheets.	11	is missing and only use one of the scores. Of
12	MS. FEILD: Can I ask when you ran them	12	course, if the student doesn't have anything,
13	going back to the models with the two year lag	13	then you can't use them at all. But I don't
14	ones that seemed to have better precision, did	14	think we can use them but you can make a
15	that include every 7th grader in the state	15	decision.
16	regardless of whether they had two data points	16	Use two where available and when it's not
17	or three data points, or was it only	17	available use one of the two, or maybe you just
18	DR. COHEN: No, this only included the ones	18	use the most recent of the two.
19	that had both data points.	19	MS. FEILD: So if we were to use that
20	DR. DORAN: Let's say something about this.	20	combination meaning however many it's one set.
21	You only put a student for two data points	21	If you have two, three years with current, you
22		22	use three. Do we know how that affects the
23	MS. FEILD: No, no, we have these models	23	precision of the model?
24	the top models all yielded two lags. That	24	DR. COHEN: Not there's a standard error
25	means they would have had three data points.	25	for each individual teacher, each teacher's
	American Court Reporting		American Court Reporting
	850.421.0058		850.421.0058
	123		125
	23		120
1	-	1	-
1	DR. DORAN: Correct. The correct score for	1	estimate. So if a teacher had a lot of students
2	DR. DORAN: Correct. The correct score for the	2	estimate. So if a teacher had a lot of students with only one year of prior data, the standard
2 3	DR. DORAN: Correct. The correct score for the MS. FEILD: In other words, your fourth	2 3	estimate. So if a teacher had a lot of students with only one year of prior data, the standard error around their estimate would be a little
2 3 4	DR. DORAN: Correct. The correct score for the MS. FEILD: In other words, your fourth grade model for that component would never have	2 3 4	estimate. So if a teacher had a lot of students with only one year of prior data, the standard error around their estimate would be a little bit larger.
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	100	1	100
	126		128
1	developmental scale score points or less; 25% of	1	I'd have more teachers with smaller standard
2	your teachers have, I don't know, let's call	2	errors. I want more teachers so really, what
3	that 18 developmental scale score points or	3	you want is you don't want any - you don't want
4	more. So there's some variation in that.	4	a lot of teachers falling in high ranges; you
5	MS. FEILD: Right. I understand that. But	5	don't mind a lot of teachers falling in low
6	let's say that was the model we picked and let's	6	ranges. So you look at Model 3, the 3A one, and
7	say that we're telling teachers this is your	7	Model 1, they're both pretty variable, but the
8	standard error, but really if you happen to have	8	75% of the teachers in the Model 3A one have a
9	some kids happier kids don't happen to be	9	standard error of less than 24 points, whereas
10	missing one data point; your standard of error	10	with Model 1 you wind up with is it 1 or 1A
11	could be bigger.	11	in Model 1 you wind up with, I don't know,
12	DR. COHEN: And it would be reported as	12	the 75th percentile and about 27 points. Right?
13	larger. You would know that it was larger; we	13	So you want more teachers down at that end of
14	would capture that in the model and you would	14	the scale which is the reason we display it that
15	know that they had a larger stay there, just	15	way so you can see where you have a lot of
16	like you know that this teacher has a standard	16	outliers up here.
17	error and the ones down here have the smaller	17	DR. DORAN: Pretty much what you see in
18	standard error; you might have	18	Model 3B.
19	MS. FEILD: Right, I understand.	19	DR. COHEN: Yeah, you've got a long left
20	DR. COHEN: more up there, yeah.	20	tail. You've got lots of guys down here and
21	MS. FEILD: And we know that the more years	21	that's okay. We know about some teachers with
22	of data you have the more precise you get, but	22	more precision.
23	teachers have to understand that if their	23	MS. FEILD: I think that from a policy
23	children do not have the multiple years there	23	perspective, right, we have to think about it
24	will be more error in terms of that child's	24 25	from the committee's perspective. If we choose
25	American Court Reporting	25	American Court Reporting
	850.421.0058		850.421.0058
	127		129
4		4	-
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	400		100
-	130	_	132
1	top, you see the standard error is there. I'm	1	discussion on precision? Yes, Stacey?
2	eyeballing this. The standard error is around	2	MS. FRAKES: Model 4, the distances model,
3	40 or 50 points. If you'll recall from this	3	is that correct?
4	model, the estimated effects were also larger.	4	DR. DORAN: Yes.
5	The typical effects were estimated to have	5	MS. FRAKES: And the others are the
6	larger magnitude, either negative or positive,	6	covariates?
7	but larger magnitude. So fifty points relative	7	DR. DORAN: That's correct. So Model 4 is
8	to the size of the effect being estimated is not	8	the simple differences model and all of these
9	as bad. I want to make sure that we don't	9	are the covariate adjustment models, and Models
10	ignore this model unless the committee wants us	10	1 and 1A are the ones that have the teacher
11	to ignore the model.	11	effects and anything with a 3 here's an easy
12	I think the you can see why let me	12	way to remember it anything with a 3 is a
13	back up a bunch of slides and show you this	13	3-level model. It has students, teachers, and
14	model is finding bigger typical effects. It's	14	schools.
15	because we're estimating something different.	15	MS. FRAKES: Thank you.
16	It's estimating deviations from a different	16	DR. DORAN: Jon, is that why they were
17	line. Let me go back there and show you that	17	called Model 3?
18	again.	18	DR. COHEN: I'll exclaim yes but I might
19	Remember the red line here, this is a	19	not be telling the truth.
20	simple differences model, and this is the one	20	DR. DORAN: I actually just thought of that
21	that shows you what is typical, what is	21	now and I thought, wow. Just because the way we
22	currently typical. The magnitude of the effect,	22	write them and the analysis specifications.
22	a typical student a teacher teaching only	22	DR. HOVANETZ: I will have to say, though,
	typical students with typical growth right here	23 24	we did revise them to have simple differences,
24			• •
25	will appear to have a big effect. I don't know	25	that's the reason why a two tiered model is 2A
	American Court Reporting		American Court Reporting
	850.421.0058		850.421.0058
	131		133
		1	and a three tiered model is 30
1	how big that is on the scale. That's probably		and a three tiered model is 3A.
2	200 points on the scale down here just for	2	DR. DORAN: Well, it works out to be a
	200 points on the scale down here just for teaching typical students, so there's that big		DR. DORAN: Well, it works out to be a beautiful heuristic device. If you have a 3
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	· • ·	1	100
	134		136
1	at one, okay. The covariate adjustment model	1	at a 500 versus 2500, and if you go in that
2	takes all of those idiosyncrasies across and	2	range all kids are going to fall along that line
3	finds the line, the slope of that line, that	3	and that may not be precise at some point.
4	best fits the data given some of those wobbles	4	Like, maybe the kids that are at 750, you
5	because you do expect some wobbles. Now you can	5	actually would go up a little bit.
6	do other things statistically to account for	6	DR. COHEN: You can see the scatter plot
7	some of the curves and the data and you can fit	7	here. That's why we have the scatter in the
8	a whole bunch of different things, but that line	8	background; you see it's pretty evenly
9	finds the best fit of that line through that	9	distributed there, right? You see a little bit
10	cloud of data.	10	more variability down at the lower end than you
11	MR. LeTELLIER: Okay. I guess I was having	11	do at the top end and a little bit less
12	a hard time with that because it just seemed	12	variability, but it cuts through the center of
13	like we're making that slope and now we're just	13	that cloud. So often what you'll see if the
14	 all kids are following this where you may 	14	model doesn't fit if you have that kind of
15	have one area of growth that may be higher or	15	problem is this cloud won't really be centered.
16	lower, and so we can't really account for that	16	It will look more like a curve or a curve the
17	precision.	17	other way and we don't see that.
18	DR. COHEN: Well, we do in fact, and the	18	MR. LeTELLIER: If we expected kids to be
19	other model where we could let's go back to	19	a kid's that at a thousand this year, we
20	that. We don't have a graph on this, but with	20	expect that he will be at a thousand next year
21	the help of a graph we do have a bit of	21	in his next grade or wherever this line falls?
22	imagination as an interpretive dance. All	22	DR. COHEN: Whatever, yeah.
23	right. Ignore the red line, ignore the man	23	MR. LeTELLIER: Right. So I guess what I'm
24	behind the counter, ignore the red line. We'll	24	saying is that 'cause last time when we had
25	go to the green line, it's just a straight line.	25	discussed this, we were going to look at where
	American Court Reporting		American Court Reporting
	850.421.0058		850.421.0058
	405		
	135		137
1	Now let's suppose we include this covariate a	1	students were in that range, so similar students
1 2		1 2	
	Now let's suppose we include this covariate a		students were in that range, so similar students
2	Now let's suppose we include this covariate a little flag which we did, a flag that says this	2	students were in that range, so similar students at a thousand where they would be expected to
2 3	Now let's suppose we include this covariate a little flag which we did, a flag that says this is an ELL student, a student who is in one of his first two years of ELL. There will be a	2 3	students were in that range, so similar students at a thousand where they would be expected to be. Couldn't there be a see, I guess maybe mathematically I am not going with your
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	100	1	440
	138		140
1	mistaken attributes of teacher effect.	1	MS. BROWN: He's also asking for multiple
2	You saw prediction errors that weren't	2	regression lines or regression line per
3	constant across the range. So we tried and we	3	DR. COHEN: It wouldn't be a regression
4	didn't see that, I guess is the answer. I mean,	4	line. They're asking for each scale score
5	there are literally an infinite number of curves	5	point, right?
6	we might try fitting. You know, we tried some.	6	MR. LeTELLIER: So it would look like this?
7	MR. LeTELLIER: Why does it have to be I	7	You have a point at 1,000 and 1,100 and
8	don't know if I'm stating it why does it have	8	DR. COHEN: You could do that when we
9	to be a line? Why can't it just be whatever the	9	estimate a model like that. What we do is we
10	students in that area	10	just have a separate point for each scale score
11	DR. COHEN: Well, that's exactly what this	11	point. What you give up there is you give up
12	is. This says within the and the areas are	12	precision, the precision of the expected value
13	defined by achievement level. It says, okay,	13	and therefore the precision of the teacher
14	kids in achievement level one we're expecting	14	effects would be much, much, much more variable.
15	I don't know what the number is a hundred	15	You've got 70 or 80 different scale score
16	point spread. Kids in achievement level two	16	points, so you'd be dividing your sample into
17	we're expecting 50 points. That's the simple	17	many smaller units. So you would give up
18	difference; that's what the red line is doing.	18	precision, so you might see that this scale
19	MS. BOURN: Can I take a stab at what I	19	scores where the average is about there and this
20	think you're asking? I think he's asking why	20	scale score point is here, but they might not
21	can't you look at each score point along the	21	even be any different. We can try something
22	axis and take the average of what the Y-axis	22	like that. That hadn't come up in the prior
23	would be for the score point and that's the	23	meetings as something to try.
24	expectation, instead of just using a line to	24	MS. GINN: Why would that be important if
25	describe the entire set of data.	25	it was used?
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	850.421.0058		850.421.0058
	139		141
1	MR. LeTELLIER: Yes, that was much more	1	MR. LeTELLIER: Well, because and I think
2	eloquent.	2	it's a matter of looking at statistics versus
3	DR. COHEN: I suppose we could certainly do	3	mathematics, and if I'm the only one here that's
4	that.	4	fine; I don't want to beat a dead horse. But
5	MR. LeTELLIER: It doesn't make sense	5	I'm thinking that more people are on this line
6	because what we were discussing last time, and	6	than not just in real life a kid that scores
7	I'm just throwing this out here, because what we	7	1,000 that next year scores 1,100, and we say
8	were looking at, and I remember clearly	8	most of the children in that category that were
9	conversations because I remember the number 140	9	1,000 last year are now 1,100; that's the
10	offhand, and we were talking about students next	10	expected growth. That's real life versus this
11	year, we were going from a baseline, those	11	line which is not going to take that into
12	students would be the teacher would be	12	account, I don't think, as fully from what
13	assessed according to where the general kids at	13	PANEL MEMBERS: (Over-speaking.)
14	140 were the next year. And with a straight	14	MR. COHEN: Let me show you another fairly
15	line with that big of a spread, there's no way	15	simply graph that we have that we just created.
16	to do that, and in the center of the line	16	DR. DORAN: While he's creating that, I
17	obviously as you moved the slope there's less	17	think that there may be just a little
18	movement and the outer parts move more.	18	misunderstanding. Either it's me or we're just
19	DR. DORAN: Can I ask for a clarification?	19	talking past each other. What you just said now
20	Are you asking what would happen if we took a	20	was in the real world there are kids who have
21	particular range of the X axis here of those	21	1,000; and there should be some prediction
22	kids that were in that range what the expected	22	that's similar for those kids who had a score of
23	score on the Y axis? Is that what you're	23	1,000 the prior year, right?
24	asking?	24	MR. LeTELLIER: No, what I'm saying is real
25	MR. LeTELLIER: Yes.	25	life scenario, this year they're at 1,000; next
1	American Court Reporting	1	American Court Reporting
	850.421.0058		850.421.0058

	142		144
1	year we'll see they're at 1,100. We're going to	1	that were right here on average actually score
2	see those two numbers. So when we're looking at	2	here; that would make it here. The kids here on
3	outcome and we're saying where a teacher should	2	average score here and the kids here on average
	have their students, we can visibly see that the	-	-
4		4	score here. When you connect those points these
5	general student that was at that level should be	5	are still average. Again, that's not what I'm
6	at such and such level.	6	saying.
7	MR. DORAN: That's what this is doing,	7	DR. COHEN: Let me show you what you would
8	that's what this is doing. This is showing for	8	see. If this were the case you would see that
9	any given for any kid who had the same prior	9	on that graph.
10	test score, what are they expected to do in the	10	MS. BROWN: You would see a plot line.
11	subsequent year? That's exactly what this line	11	DR. COHEN: Let me draw you what you would
12	does.	12	see. If we try to defend it around this line,
13	DR. COHEN: There is a linear assumption	13	you would see a scatter plot that looks
14	here that that data goes in a line. He's saying	14	something like this.
15	couldn't we do something non-parametric where	15	MS. BROWN: So the scatter plot would have
16	the line and plots go wherever it wants to.	16	to be shaped
17	MR. LeTELLIER: Yeah, I understand this	17	DR. DORAN: You see that plot in the
18	plot. I see where the kids were the first year	18	residual and you don't see that, you don't see
19	or the second year, but life is not linear.	19	that here.
20	DR. COHEN: It's often more linear than you	20	DR. COHEN: Let me see if I can I have
21	think, but let me I have a question over	21	some data
22	here.	22	PANEL MEMBERS: (Over-speaking.)
23	MS. BROWN: Well, I just want to see if	23	MS. BROWN: Can I just say that in like
24	this is where you're trying to go because it	24	common terms?
25	isn't linear when you look at each case in	25	DR. COHEN: Yes.
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1	143	1	
1	point, and that's absolutely true. The purpose	1	MS. BROWN: Because now you're both saying
2	point, and that's absolutely true. The purpose of this is to look at a large set so that we see	2	MS. BROWN: Because now you're both saying the same thing and the point is if, in fact, the
2 3	point, and that's absolutely true. The purpose of this is to look at a large set so that we see on average because those if I'm understanding	2 3	MS. BROWN: Because now you're both saying the same thing and the point is if, in fact, the actual performance of the average group of
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2 3 4 5	point, and that's absolutely true. The purpose of this is to look at a large set so that we see on average because those if I'm understanding this correctly, all the points are actual performance, and that line is not a forced line.	2 3 4 5	MS. BROWN: Because now you're both saying the same thing and the point is if, in fact, the actual performance of the average group of students was the line like this, the scatter plot of points behind the line would also be a
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1	would see the scatter plot like that, okay? Now	1	all models are wrong, some models are useful.
2	we compute what's called the residual. The	2	We can't fit a model that fits, you know, into
3	residual was the difference between the kids'	3	every single one of these points. That would be
4	observed score and their expected score.	4	what's called a saturated model and it's not a
5	We did many, many analyses to look on those	5	reduction of the real world. So we have to
6	residuals to look at whether they fit particular	6	investigate which model is the best reduction of
-	<i>,</i> ,	-	-
7	patterns. They normally distribute it, how did	7	the real world data that we can apply and get
8	those fitted values plot the fitted values	8	reasonable inferences from. So that's what
9	plot against some of the residuals? Those	9	we're trying to do here. That's why we're
10	strange trends would have shown up in our	10	looking at other fixed effects, other covariates
11	analysis of the residuals, and we would have	11	and control variates. Adding those terms when
12	thought we need to go back and fit cubic trends,	12	they fit the data and then when they're
13	quadratic trends, do some local smoothing, you	13	excluded.
14	know, use different polynomial terms to account	14	All right. Christy gave me the flag of
15	for the bends in the data. We actually did do	15	five more minutes. Why don't I start on
16	something like that back at the lab to see if	16	something and we'll finish it after
17	those models fit the data better than these	17	We're going to start with spool effects
18	straight line models and they didn't. Not only	18	now. We're going to define why we care and what
19	did they not, but in all of our analysis of the	19	we're looking for. So again, using the same
20	residuals that we do that we're not presenting	20	questions that we looked at before, let's look
20	here, but if you want to see we can show you	20 21	at the question.
			Should value-added models account for
22	some of these things, we don't see those strange	22	
23	patterns of the curvature that we would get to.	23	systematic differences between schools? The
24	Perfectly reasonable what you're asking to	24	question is a straightforward question but it's
25	look at whether that's true or not because if we	25	a hard one to answer. Remember, some of the
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	850.421.0058		850.421.0058
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1	do see that the role is not as linear as these	1	value-added models include school effects, some
1 2	do see that the role is not as linear as these models have turned out to be, because it's just	1 2	value-added models include school effects, some of them include only teacher effects. Let me
	do see that the role is not as linear as these models have turned out to be, because it's just a line, a straight line okay, perhaps the		value-added models include school effects, some of them include only teacher effects. Let me talk about why that's important and what
2	do see that the role is not as linear as these models have turned out to be, because it's just	2	value-added models include school effects, some of them include only teacher effects. Let me
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	150		152
			These are the teacher effects on a standard
1	ignore school effects and let's say there are	1	
2	good things happening in the school and let's	2	deviation scale, all right? Essentially, what
3	suppose those school effects are real and big,	3	this means is this is Model 1, looking at your
4	what happens is they get pushed into the teacher	4	sheet you'll see that Model 1 is one that
5	effects and those teacher effects may appear to	5	includes only teacher effects. What we see here
6	have higher added value rankings than they truly	6	is that the teacher effects appear to be really
7	deserve because they're getting some credit that	7	big, okay. The number 30 is not necessarily
8	the school is doing.	8	meaningful saying ten points higher than this
9	I look really good because things that the	9	model over here is irrelevant. What's important
10	school does that I didn't initiate got pushed	10	here is that you see the magnitude of what's
11	into my effect or vice versa. Things that the	11	happening here. So when you have teacher
12	school is doing are dragging down a particular	12	effects, teacher effects appear to be really big
13	teacher's effect. All right? So that's part of	13	under this model and this model.
14	the reason that we're interested in looking at	14	Now here in Model 3 we include teacher
15	this. Are there things at the school level,	15	effects and school effects. Note what happens
16	initiatives or programs that are also partly	16	here. Teacher effects get smaller almost
17	because of changes in student growth that we	17	always, always relative to this, teacher effects
18	want to account for? When you do that then what	18	get smaller and the school variability the
19	you do is you partition the variability and	19	school effects are relatively big. What is
20	growth. We get teacher effects and we get some	20	this graphic suggesting? This graphic is
21	of the variability and growth that's due to the	21	suggesting that if you ignore teacher effects in
22	school. Those are estimated.	22	reading, if you ignore school effects in
23	So what do we look at? That's the	23	reading, teacher effects appear to be very big.
24	question. Should school effects be included?	24	When you then account for school effects and
25	What statistic do we look at? We're going to	25	teacher effects, that is, those systematic
	American Court Reporting		American Court Reporting
	850.421.0058		850.421.0058
	151		153
1	look at the variation in student growth between	1	things that schools also do that may be outside
1	look at the variation in student growth between schools.	1 2	things that schools also do that may be outside the control of a particular classroom, but also
	look at the variation in student growth between		things that schools also do that may be outside
2	look at the variation in student growth between schools.	2	things that schools also do that may be outside the control of a particular classroom, but also are the cause for a relationship with an improvement in student achievement or changes in
2 3	look at the variation in student growth between schools. Evidence in favor of a desirable model. If	2 3	things that schools also do that may be outside the control of a particular classroom, but also are the cause for a relationship with an
2 3 4	look at the variation in student growth between schools. Evidence in favor of a desirable model. If the model suggests that there are systematic	2 3 4	things that schools also do that may be outside the control of a particular classroom, but also are the cause for a relationship with an improvement in student achievement or changes in
2 3 4 5	look at the variation in student growth between schools. Evidence in favor of a desirable model. If the model suggests that there are systematic school effects then the policy must decide how	2 3 4 5	things that schools also do that may be outside the control of a particular classroom, but also are the cause for a relationship with an improvement in student achievement or changes in student achievement. Schools have an effect. They seem to matter. So essentially what you're doing is now
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1	Let's pretend for just a moment that we	1	all have, let's assume, very high positive
2	included school effects but suppose this part of	2	deviations from the typical expectation. What's
3	the school effect was really small and this was	3	the expectation? Remember that regression line?
4	really big, okay? And this was small and this	4	That's the expectation. Every kid in your
5	was small and that was small. That would	5	class, Sam, had positive deviations from that
6	suggest that even after accounting for school	6	typical expectation. So now we've got what we
7	effects, teacher effects are still really big.	7	call a residual. It's a little bit more than
8	If that were the case, we might say school	8	just taking the average, but let's just work
9	effects are not necessarily needed. Now I can't	9	with this.
10	tell you how big the effect of the school should	10	So now I've got for all the kids in your
11	be before you make a decision, a policy decision	11	class, I take the average of those residuals.
12	on whether or not you include it. This is data,	12	They're all positive, which means every single
13	these are data that suggest that school effects	13	kid in your class for the sake of argument meets
14	seem to account for a large proportion of the	14	the typical expectation. Let's just say they
15	differences in student achievement. Maybe	15	beat that expectation by a lot. Your teacher
16	schools matter.	16	effect would essentially be about the average of
17	When we come back from lunch, Kathy, I'll	17	those residuals. They're all positive, you look
18	let you close this out soon, we'll explore the	18	really good relative to the typical teacher in
19	observations that we're making about the	19	the state.
20	differences between models and whether or not	20	Now I've got another teacher and so suppose
21	you think school effects should be included or	21	now I have a group of students and I didn't do
22	only teacher effects, and we'll talk about any	22	as well with those kids as would be expected.
23	questions you might have.	23	Suppose each of the students in my class fell
24	MS. HEBDA: Thanks, Harold. A lot to chew	24	below that typical expectation. Now I've got
25	on during lunch. We're going to stop the	25	all those negative residuals and we take the
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1	recording and break for lunch now.	1	average of those in a sense, and now I look very
2	recording and break for lunch now. (Whereupon, a lunch recess was had.)	2	average of those in a sense, and now I look very low relative to the typical teacher. What's
2 3	recording and break for lunch now. (Whereupon, a lunch recess was had.) DR. DORAN: Before we went to lunch, we	2 3	average of those in a sense, and now I look very low relative to the typical teacher. What's interesting is the teacher effect, you have
2 3 4	recording and break for lunch now. (Whereupon, a lunch recess was had.) DR. DORAN: Before we went to lunch, we started with the question of whether school	2 3 4	average of those in a sense, and now I look very low relative to the typical teacher. What's interesting is the teacher effect, you have those residuals the difference between how they
2 3 4 5	recording and break for lunch now. (Whereupon, a lunch recess was had.) DR. DORAN: Before we went to lunch, we started with the question of whether school effects should be included in the value-added	2 3 4 5	average of those in a sense, and now I look very low relative to the typical teacher. What's interesting is the teacher effect, you have those residuals the difference between how they perform and how they were expected to perform,
2 3 4 5 6	recording and break for lunch now. (Whereupon, a lunch recess was had.) DR. DORAN: Before we went to lunch, we started with the question of whether school effects should be included in the value-added model, in addition to teacher effects, or only	2 3 4 5 6	average of those in a sense, and now I look very low relative to the typical teacher. What's interesting is the teacher effect, you have those residuals the difference between how they perform and how they were expected to perform, and you average them in a class to get that for
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	158	1	160
1	have negative deviation for all of my kids.	1	It's the deviation. Then the teacher effect is
2	Now the world is not that straightforward.	2	the deviation from that school effect. Yes?
	Your class maybe some of them have positive	2	MS. ACOSTA: I have a question about the
3		-	·
4	deviations, some of them did not, so there's a	4	average that we get from including everybody.
5	little bit more than that. Again, you still	5	That includes students within that teacher's
6	take all of those residuals and we do a little	6	class so those kids are counted within the
7	math with those and we come up with, well, for	7	average and then separately? Do you see what
8	the most part your kids did pretty well and for	8	I'm saying? As well as for all the things we're
9	the most part my kids did not do as well. So	9	looking at. When we say we're going to get
10	the teacher effect is the deviation from that	10	their regression line for everyone, that
11	expectation.	11	includes for example students with disabilities.
12	The same concept applies to the school	12	So we make another line with just the students
13	effect. So essentially what we've got is a	13	with disabilities; so they're in the initial
14	group of kids who are within a school, from many	14	line as well?
15	schools, and essentially what we're looking at	15	DR. DORAN: That's right. So let's just
16	is those kids, how did they fare relative to the	16	play it out a little bit. We've got
17	expectation? All of the kids in the school?	17	expectations for kids with disabilities and some
18	Then kind of in this now when we actually do	18	of those kids are in your class, so we've got
19	the math, mathematically now what we do now	19	observed scores, and we say did they beat those
20	I've got this effect. See, all of the kids in	20	predictions? And they did and there are other
21	this school on average perform lower than was	21	kids who don't have disabilities who got a
22	typically expected. Now I look at, well, the	22	separate expectation for them when that variable
23	kids in Lance's class, they're in that school;	23	is included in the model and did they beat that
24	how did they perform relative to the school	24	expectation? They did. So no matter who you
25	average? So now I've got kids in your class,	25	taught, all the kids in the class beat their
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			161
	159		161
1	they performed higher on average relative to	1	expectations. Now we've got those residuals and
2	they performed higher on average relative to other kids in that school. Me, kids in my	2	expectations. Now we've got those residuals and we'll average those together, say, and they did
2 3	they performed higher on average relative to other kids in that school. Me, kids in my class, did poorly relative to other kids in the	2 3	expectations. Now we've got those residuals and we'll average those together, say, and they did better than expected.
2 3 4	they performed higher on average relative to other kids in that school. Me, kids in my class, did poorly relative to other kids in the same school. So now I've got two deviations for	2 3 4	expectations. Now we've got those residuals and we'll average those together, say, and they did better than expected. So where we were going with this is to
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	162		164
1	schools are not included teachers appear to be	1	whether to attribute it all to teachers, whether
2	very different, but when schools are included	2	to attribute none of it to teachers, or whether
2	they seem to account for some total proportion	2	to attribute part of it to teachers.
_		-	-
4	of the variance. It's not tiny, it's some	4	MS. GINN: Question. Then really does it
5	portion. And teacher effects are smaller than	5	show that without putting the school in teacher
6	when you only have teacher effects.	6	impact has allowed fluff?
7	John, you had a question?	7	DR. COHEN: That might be a technical term
8	MR. LeTELLIER: Yeah, the counter would be	8	there, right?
9	true as well if you had a negative school	9	MS. GINN: You know what I'm saying.
10	effect, then that would change the teacher	10	DR. COHEN: I can't make the decision for
11	effect as well?	11	you. This is not a statistical decision.
12	DR. DORAN: It could.	12	MS. GINN: I'm just asking you, based on
13	MR. LeTELLIER: Okay. I'm not saying	13	what you have there because of the school
14	that's going to happen, but that could happen?	14	impact, we'll keep the difference, okay.
15	DR. DORAN: It could happen.	15	DR. COHEN: All I'm
16	DR. COHEN: Yes, it does happen. Some	16	MS. GINN: We don't want to touch that,
17	schools are better than others not better.	17	fine. Here's my second question.
18	Some schools show a higher student effect, some	18	We keep using the school effect positively,
19	schools show lower student effects. Can I say	19	but the school effect can also be negative.
20	something else?	20	DR. COHEN: By definition the models are
21	DR. DORAN: Yeah, go ahead.	21	estimated, half the schools are better than
22	DR. COHEN: This is pure policy decision.	22	average, half the schools are worse than
23	We're presenting the statistical data and the	23	average. So it's positive or negative. It
24	data tell you go from policy decision to make.	24	really has to do with what you believe affects
25	This line here shows you that student	25	if you believe that any common influence in a
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	163		165
1	growth varies somewhat by school, not as much as	1	school is 100% student teachers and you're ready
2	it doop by topchor, but it yorion by school	2	
2	it does by teacher, but it varies by school.	2	to stand by that, choose one of these models or
3	Meaning that if you take it out of the model,	3	to stand by that, choose one of these models or use one of these models that has the school
3 4	Meaning that if you take it out of the model, any gross that's common within the school will	3 4	to stand by that, choose one of these models or use one of these models that has the school effect back into the teacher effect.
3 4 5	Meaning that if you take it out of the model, any gross that's common within the school will be attributed 100% to the teachers, and that's	3 4 5	to stand by that, choose one of these models or use one of these models that has the school effect back into the teacher effect. MS. HALL: How are the schools being rated?
3 4 5 6	Meaning that if you take it out of the model, any gross that's common within the school will be attributed 100% to the teachers, and that's fine if that's the policy decision you want to	3 4 5 6	to stand by that, choose one of these models or use one of these models that has the school effect back into the teacher effect. MS. HALL: How are the schools being rated? Is it the same thing as the teacher or is school
3 4 5 6 7	Meaning that if you take it out of the model, any gross that's common within the school will be attributed 100% to the teachers, and that's fine if that's the policy decision you want to make. Model 1A and Model 1 make that it's a	3 4 5 6 7	to stand by that, choose one of these models or use one of these models that has the school effect back into the teacher effect. MS. HALL: How are the schools being rated? Is it the same thing as the teacher or is school grades or how are we determining how are you
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	166		168
1	tell you, it's not sure, Harold or I would be	1	That's a classification rule and now how those
2	happy to tell you what the right answer is, but	2	effects relate to the other grades, I have no
3	not statisticians and not giving you an answer.	3	idea and I don't want to speculate on it.
4	This really has to do with what you believe	4	Whether it's plausible that they could look good
4 5	matters in an education system and how you think	5	under one model and not look good under another
		_	_
6	accountability ought to be distributed between	6	maybe, but there's no basis for me to make that
7	leadership and the teachers.	7	decision. That's pure speculation.
8	DR. DORAN: This decision would be really	8	But the issue about classification is
9	easy. Jon's exactly right; this is a policy	9	something we'll talk about later today; and that
10	decision. Remember, we looked at precision	10	is do we have to use the average? No, you can
11	before. Everything is policy decision, slash,	11	use above the average to create more stringency
12	statistical decision. But here if we did this	12	and go up by five, one, you know, you can be one
13	and we said that schools didn't account for	13	standard error above that, you can be two
14	anything at all, your decision would be	14	standard errors, one-and-a-half standard errors.
15	relatively easy. There's no need to account for	15	We can come up with different classification
16	the school effects because they don't account	16	rules and we're going to show you the
17	for any other variance and scores. But here we	17	consequences of what happens when you choose the
18	don't see that to be the case. We see that	18	classification rules at the end of the day.
19	schools seem to have differences between them	19	MS. FEILD: I think you misinterpret
20	and that that seems to affect the differences in	20	DR. DORAN: But how we score grades,
21	the teacher effects, right? So there is	21	there's no way to
22	something that matters systematically between	22	MS. FEILD: I understand. I think the
23	schools.	23	misinterpretation is when we talk about a school
24	Yes?	24	effect, at least in the original conversation
25	MS. FEILD: Let me make sure I understand.	25	before lunch, I was thinking we were looking at
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1	The school effects here is really the same as	1	other variables that had to do with schools
2	The school effects here is really the same as the teacher, but it's kind of aggregated for the	2	other variables that had to do with schools separate from value-added, school grades,
2 3	The school effects here is really the same as the teacher, but it's kind of aggregated for the school?	2 3	other variables that had to do with schools separate from value-added, school grades, accountability, but in
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	170		172
1	determined statistically. We've just shown you	1	good teacher to have a good value-added model
2	the graphs and just based on the visual displays	2	score because those kids are already performing
2	it seems to be a large proportion of the total	2	so high, the school is performing so high, the
4	variance of scores. Teachers are less different	4	teacher goes in and the kids are doing well.
5	from each other when including school effects.	5	DR. DORAN: In some respects, yes. In some
6	What does that mean?	6	respects that is almost what you would expect.
7	When we don't include the school effect, we	7	If those kids are doing well because of things
8	have this much variability between teachers.	8	the school is doing then you want to
9	There's a lot of variability. Teachers are very	9	differentiate that from the teacher effects,
10	different from each other, but when you include	10	right? But if you ignore the school effects in
11	the school effects part of what made that	11	that particular case then everything that's
12	teacher look really, really good before gets	12	happening systematically in that school gets
13	soaked up by the school effect; or part of what	13	pushed into the teacher effect, and those
14	made that teacher look really, really, really	14	teachers may appear to be high value-added, not
15	low value-added before gets soaked up by the	15	necessarily because of what they're doing but
16	school effect. The teachers appear to be less	16	because of other initiatives in that school.
17	different from each other under that model.	17	But now you account for the other things
18	Yes?	18	happening in that school, and the teacher
19	MS. FRAKES: So when the school effect is	19	effects could in fact, they will be smaller
20	smaller, the teacher effect could be greater.	20	as we see here. The teacher now has to
21	So when you're talking about	21	demonstrate that they're doing things above and
22	DR. DORAN: It would be greater by	22	beyond what's normally happening in that school
23	definition, so as this gets smaller this will	23	to have a higher value-added effect relative to
24	get bigger.	24	other teachers in that same school.
25	MS. FRAKES: So when you're talking about	25	MS. BROWN: I think what is discomfort and
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1	moving your best teachers into your lowest	1	where some people are settled is how then when
1 2		1 2	
	moving your best teachers into your lowest		where some people are settled is how then when
2	moving your best teachers into your lowest performing schools, I mean, when you're taking	2	where some people are settled is how then when you look at the full distribution is there still
2 3	moving your best teachers into your lowest performing schools, I mean, when you're taking into account as a school this is the school	2 3	where some people are settled is how then when you look at the full distribution is there still equal opportunity to achieve a, quote, if 50 is
2 3 4	moving your best teachers into your lowest performing schools, I mean, when you're taking into account as a school this is the school effect that the students are not performing, and	2 3 4	where some people are settled is how then when you look at the full distribution is there still equal opportunity to achieve a, quote, if 50 is high just pick a number, doesn't matter
2 3 4 5	moving your best teachers into your lowest performing schools, I mean, when you're taking into account as a school this is the school effect that the students are not performing, and then that teacher goes there and she does what she does so well; that's really going to show as opposed to that school effect, correct?	2 3 4 5	where some people are settled is how then when you look at the full distribution is there still equal opportunity to achieve a, quote, if 50 is high just pick a number, doesn't matter can you do you have equal opportunity to
2 3 4 5 6	moving your best teachers into your lowest performing schools, I mean, when you're taking into account as a school this is the school effect that the students are not performing, and then that teacher goes there and she does what she does so well; that's really going to show as opposed to that school effect, correct? DR. DORAN: That's correct. The teacher	2 3 4 5 6	where some people are settled is how then when you look at the full distribution is there still equal opportunity to achieve a, quote, if 50 is high just pick a number, doesn't matter can you do you have equal opportunity to achieve a value-added score of 50 at a school
2 3 4 5 6 7	moving your best teachers into your lowest performing schools, I mean, when you're taking into account as a school this is the school effect that the students are not performing, and then that teacher goes there and she does what she does so well; that's really going to show as opposed to that school effect, correct? DR. DORAN: That's correct. The teacher would appear to be very high performing within	2 3 4 5 6 7	where some people are settled is how then when you look at the full distribution is there still equal opportunity to achieve a, quote, if 50 is high just pick a number, doesn't matter can you do you have equal opportunity to achieve a value-added score of 50 at a school with a more positive school effect as you would at a school with a more negative school effect because if you are the same teacher in both
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	174		176
1	as they're doing those things, they have equal	1	teachers potentially within the district or
2	opportunity.	2	within wherever have lower scores when compared
3	DR. COHEN: Can I break in here?	3	to each other?
4	DR. DORAN: Yes.	4	DR. COHEN: You're unwinding it. You're
5	DR. COHEN: It's a little more complicated	5	making an assumption about what you're going to
6	than an extra decision that you have to make.	6	do with the school effect. If you ignore the
7	I'll put a little example up here. Let's say	7	school effect, you wind up with this. If you
8	we're going to talk about one school. That	8	have Model 1 or 1A, you wind up attributing
9	school has four teachers, and the math is not	9	anything that might be the school effect to
10	exactly this math does not come out exactly	10	this.
11	the same, but it comes out really close in this	11	MS. BROWN: I understand that.
12	illustration.	12	DR. COHEN: Right, and that's the situation
13	So the school effect, estimated according	13	in which if there really is an independent
14	to let's say Model 3A school effect is 10,	14	effect of the school that is not due to the
15	teacher effect is 20 minus 20, 10 and minus 10;	15	teachers, then the schools happening to be in
16	so they're equal. They have an average of zero	16	the better schools will be advantaged and the
17	around the school mean. If we were to ignore	17	teachers who happen to be in the worst schools
18	the school effect and just estimate it for the	18	will be disadvantaged.
19	teachers and say everything is attributable to	19	MS. BROWN: Correct.
20	the teacher, those scores under Model 1A would	20	DR. COHEN: One might argue, and I'm not
21	be 30 minus 10, 20, and 0, right. So this is	21	making this argument necessarily, but just to
22	attributing all effects to the teacher, so we	22	point out, somebody might say, yeah, the
23	just assume that any school effects are just the	23	principal matters but he does all of his work
24	result of an aggregate teacher effect.	24	he matters through the teachers who are
25	If we take 20 minus 20, 10 and minus 10,	25	interacting with the kids day to day. So the
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	850.421.0058		850.421.0058
	175		177
	110		
1	that's attributing 100% of the school effect, of	1	principal's influence is through teachers.
1 2	-	1 2	
	that's attributing 100% of the school effect, of		principal's influence is through teachers.
2	that's attributing 100% of the school effect, of whatever is common in the school to the school.	2	principal's influence is through teachers. Therefore, it really is a teacher effect.
2 3	that's attributing 100% of the school effect, of whatever is common in the school to the school. So great principal or a bad principal, it's all	2 3	principal's influence is through teachers. Therefore, it really is a teacher effect. Someone could argue that this is average teacher
2 3 4	that's attributing 100% of the school effect, of whatever is common in the school to the school. So great principal or a bad principal, it's all on the principals. But what we did down here is we say, well, we decide we're going to split	2 3 4	principal's influence is through teachers. Therefore, it really is a teacher effect. Someone could argue that this is average teacher effect and that's how you should do it. The point being that there is a policy
2 3 4 5	that's attributing 100% of the school effect, of whatever is common in the school to the school. So great principal or a bad principal, it's all on the principals. But what we did down here is	2 3 4 5	principal's influence is through teachers. Therefore, it really is a teacher effect. Someone could argue that this is average teacher effect and that's how you should do it. The point being that there is a policy decision to be made. The data won't give you
2 3 4 5 6	that's attributing 100% of the school effect, of whatever is common in the school to the school. So great principal or a bad principal, it's all on the principals. But what we did down here is we say, well, we decide we're going to split this half and half. We're going to say half of it is due to the fact of the school and half of	2 3 4 5 6	principal's influence is through teachers. Therefore, it really is a teacher effect. Someone could argue that this is average teacher effect and that's how you should do it. The point being that there is a policy decision to be made. The data won't give you any information to help you make this policy
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	178	1	180
1	this is part of what you're getting at. Suppose	1	the kids there.
2	I had two schools or two teachers and suppose	2	MR. MOREHOUSE: What happens to the
2	some teacher had a suppose at the school A	2	students who perform below the average?
		-	DR. DORAN: Again, a teacher has a group of
4	it's typical for the students to score 20 points	4	
5	above the state average. Let's just use that	5	kids who perform below the average of the
6	term, it's typical for kids in school A to score	6	school?
7	20 points above the average. Now suppose that	7	MR. MOREHOUSE: Yes.
8	that teacher, a teacher within that school has	8	DR. DORAN: They would not appear to be
9	kids who only score 20 points above the average.	9	high value-added relative to that school. They
10	That teacher didn't do anything above and beyond	10	don't do that's what we regard as a low
11	what's typical for students in that school,	11	value-added effect because
12	right?	12	MS. BROWN: But don't confuse that with a
13	Now let's take another situation, another	13	teacher that has a group of level 1 students.
14	teacher, who's in a different school. In that	14	Those are two different things.
15	school, let's just say it's typical for teachers	15	DR. DORAN: That's exactly right.
16	to score 10 points below the average. That's	16	MS. BROWN: Because you can have all
17	typical for that school. But that teacher, a	17	students that score at level 4 and they all
18	teacher in that school scores 20 points above	18	don't gain, and you would be considered
19	the average, the same as the other teacher,	19	(inaudible). But just because you have maybe
20	okay, in the different school. That teacher	20	lower performing students coming in, that
21	would appear to have a higher value added	21	wouldn't necessarily be the case.
22	because that teacher is doing something that's	22	DR. DORAN: Right, right, because of
23	very different than what's typical in that	23	intake. The kids you intake are not to be
24	school. Do you see? So while two teachers did	24	confused with the potential for a value-added
25	the same thing, this teacher over here is doing	25	effect to be higher.
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	850.421.0058		850.421.0058
	179		181
1	what's typically expected or typically observed	1	MS KEADSCHNED, I want to go back to
			MS. KEARSCHNER: I want to go back to
2	for kids in that school. There's nothing	2	something Jon said earlier about a high
2 3	for kids in that school. There's nothing exceptional happening there, whereas this other	2 3	something Jon said earlier about a high achieving or IB school, for example, where if
2 3 4	for kids in that school. There's nothing exceptional happening there, whereas this other teacher went away above and beyond what's	2	something Jon said earlier about a high achieving or IB school, for example, where if the school effect this is a high performing
2 3 4 5	for kids in that school. There's nothing exceptional happening there, whereas this other teacher went away above and beyond what's typically observed for kids in that class.	2 3	something Jon said earlier about a high achieving or IB school, for example, where if the school effect this is a high performing school and you have all level 5 students. How
2 3 4 5 6	for kids in that school. There's nothing exceptional happening there, whereas this other teacher went away above and beyond what's typically observed for kids in that class. Now while two teachers have the same	2 3 4	something Jon said earlier about a high achieving or IB school, for example, where if the school effect this is a high performing school and you have all level 5 students. How are you going to show gains, student growth in
2 3 4 5 6 7	for kids in that school. There's nothing exceptional happening there, whereas this other teacher went away above and beyond what's typically observed for kids in that class. Now while two teachers have the same both have kids that performed at the same level	2 3 4 5 6 7	something Jon said earlier about a high achieving or IB school, for example, where if the school effect this is a high performing school and you have all level 5 students. How are you going to show gains, student growth in those situations?
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		1	
	182		184
1	But in those situations does that school effect	1	effect.
2	narrow? I'm trying to understand when you get	2	MS. KEARSCHNER: That's my question really.
3	to that end are you bumping up against something	3	That's what I think I was trying to get at. Is
4	where it has less effect?	4	there could there be any correlation with the
5	DR. COHEN: Point of diminishing returns.	5	school effect in those kinds of populations?
6	But that's my point; you get to a ceiling.	6	DR. DORAN: Let's take an example and
7	MS. KEARSCHNER: A ceiling.	7	answer the question. Could there be? Suppose
8	MR. MURPHY: There might be a smaller range	8	we have a very high performing school and
9	of difference between a group of teachers, but	9	suppose we have a school where there are a lot
10	the percentages we would use would still point	10	of students who come in with very high scores in
11	out the teachers that were high performers or	11	the intake, right? Let's just say all of the
12	the ones with the bigger value add. The range	12	kids are clustered in this particular area.
13	is going to be smaller is what you're saying,	13	Now, can that school still show a positive
14	right, because of the school	14	effect? Well, one of the things that we saw was
15	DR. DORAN: I see where you're going. There are some potential ceiling effects. One	15	there is pretty significant scatter around that expectation line even at the high end of the
16		16	
17 18	of the graphs that Jon was showing earlier there is the highest obtainable scale score and	17 18	score distribution, right? It resulted that there was virtually no scatter around that
10	there's the lowest obtainable scale score and	19	point, we would observe that students for
20	There are some kids who score so high that their	20	whatever reason weren't deviating much from the
21	score gets truncated to the top; they just can't	20	conditional expectations of the high or low end
22	score any higher. How large are the ceiling	22	of the distribution. It's plausible that being
23	effects when we went through this; do you	23	at the end of the extremes, very low end of the
24	remember?	24	distribution, could limit your ability to be
25	DR. COHEN: I don't remember and the	25	classified as low value-added, or being at the
	American Court Reporting		American Court Reporting
	850.421.0058		850.421.0058
	183		185
1	ceiling effects could actually be more subtle	1	very high end of the distribution if you have a
1 2	because your measurement error gets bigger at	1 2	cluster of kids who could be there, it's
	because your measurement error gets bigger at the ends of the scale. So there are ceiling		cluster of kids who could be there, it's plausible. The degree to which it happens, I
2	because your measurement error gets bigger at the ends of the scale. So there are ceiling effects. There is a small negative correlation	2	cluster of kids who could be there, it's plausible. The degree to which it happens, I just don't know because we don't subset the
2 3 4 5	because your measurement error gets bigger at the ends of the scale. So there are ceiling effects. There is a small negative correlation we'll show you this later between the	2 3 4 5	cluster of kids who could be there, it's plausible. The degree to which it happens, I just don't know because we don't subset the schools when that happens and see if there is a
2 3 4 5 6	because your measurement error gets bigger at the ends of the scale. So there are ceiling effects. There is a small negative correlation we'll show you this later between the expected scores and yeah, we did it by but	2 3 4 5 6	cluster of kids who could be there, it's plausible. The degree to which it happens, I just don't know because we don't subset the schools when that happens and see if there is a particular consequence. But to the degree that
2 3 4 5 6 7	because your measurement error gets bigger at the ends of the scale. So there are ceiling effects. There is a small negative correlation we'll show you this later between the expected scores and yeah, we did it by but a small negative correlation between the	2 3 4 5 6 7	cluster of kids who could be there, it's plausible. The degree to which it happens, I just don't know because we don't subset the schools when that happens and see if there is a particular consequence. But to the degree that would play out in the real world, I'm not sure
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				relationship between teachers under every single
		, -		one of the models, and what you see is virtually
23say 90% of the kids are being double-dipped23a perfect correlation between teacher effects				•
				and models 1 and any of the models 3. What that
	25	-	25	suggests is that however teachers are classified
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		1			
	190		192		
1	under this particular model, the teacher only	1	stakeholder committee involved in this process		
2	model, they remain similarly classified under	2	because what Harold is expressing now is		
3	this one.	3	opinion. He believes this to be he believes		
4	If they have high value-added effects under	4			
5	one model, they would also have high value-added	5	committee here because it's your beliefs about		
6	effects under the other model. We could	6	whether those things are affecting the teacher		
7	recreate that and show that to you so you could	7	effect. It's your beliefs about those things		
8	see there's virtually a very strong linear	8	8 that should be driving the day and driving the		
9	relationship between the two.	9			
10	One of the things that might have been a	10			
11	concern is what if the correlation was zero or	11			
12	even negative? Would it contain the teacher	12	then the average teacher effect within each		
13	effect under this model and look at its	13	-		
-					
14	relationship to the teacher effects under this	14	5		
15	model, and suppose the correlation became	15	, , , , , , , , , , , , , , , , , , , ,		
16	negative or zero, meaning they flip-flopped or	16			
17	there's no relationship? That doesn't happen.	17	represent the folks who are going to be affected		
18	We know and we can show you that the correlation	18	by this, whose children are going to be affected		
19	between the teacher effects under all of these	19	by this, whose staff are going to be affected by		
20	models is very close to one.	20	this. You need to figure out what you believe		
21	Yes?	21	affects student learning in the school.		
22	MS. BROWN: I just want to throw something	22	MS. FEILD: But speaking from the political		
23	out for thought, politically correct or not.	23	perspective, if you're selling this model to		
24	But sometimes you know, we started our last	24	teachers and you're saying to teachers that it's		
25	discussion when we were here face to face	25	not just the math or reading teacher that		
	American Court Reporting		American Court Reporting		
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	191		193		
1	talking about wishing we could incorporate	1	counts, but everything else that everybody else		
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	talking about wishing we could incorporate		counts, but everything else that everybody else		
2	talking about wishing we could incorporate things that we don't measure, like parent	2	counts, but everything else that everybody else is doing is contributing to the achievement of		
2 3	talking about wishing we could incorporate things that we don't measure, like parent involvement, homework completion, things like	2 3	counts, but everything else that everybody else is doing is contributing to the achievement of the student, then I think you have a better		
2 3 4	talking about wishing we could incorporate things that we don't measure, like parent involvement, homework completion, things like that that we have no data for. When we look at	2 3 4	counts, but everything else that everybody else is doing is contributing to the achievement of the student, then I think you have a better chance of having a school-wide attempt to work		
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		1	100			
	194		196			
1	No.	1	dealing, I assume, or is that dealing with			
2	DR. COHEN: I don't know enough about all	2	DR. DORAN: Real world data.			
3	the things that are going on.	3	MR. TOMEI: Okay. Here's my question.			
4	MS. KEARSCHNER: It's actually required by	4	There's been a fair amount of research done			
5	law that there's pieces from parents, from	5	historically looking at different types of			
6	students. There's all these other things that	6	student growth models, including value-added			
7	have to go into the evaluation. That might be	7	models. The work that was done previously in			
8	the other 50%, but it could certainly be	8	Florida among the things that were done was they			
9	incorporated as part of this school effect. I	9	looked at how those models categorized teachers			
10	mean, that's another	10	into quartiles, which is interesting because			
11	MS. FEILD: I was thinking when we add	11				
12	staying to the achievement side we eventually	12	,			
13	should be looking at models for, let's say,	13				
14	advance placement scores or international	14				
15	baccalaureate, so if those get tied into an	15	would logically expect to occur. At any point			
	· · · ·					
16	overall school effect then again you're sort of	16	in time, are we going to know how these models			
17	tying in all of the achievement results.	17	evaluate real teachers from year to year over time and the consistency there because I think			
18	MS. BROWN: Technically, if you tie all	18	•			
19	those different assessments together at a school	19	that's another important attribute that we need			
20	level then it's all going to play into the	20	to consider.			
21	school effects.	21	DR. DORAN: I think Jon and I were the			
22	MS. FEILD: The teacher may be teaching	22	first people to write a paper on this about			
23	English in 10th grade, AP English in 10th grade,	23	eight or seven years ago on the volatility of			
24	and that student is taking the FCAT 10th grade	24	teacher effects that we observe over the time,			
25	reading test and the AP English test, right?	25	and the paper we called it From Saint to Sinner			
	American Court Reporting		American Court Reporting			
	850.421.0058		850.421.0058			
	195		197			
		4				
1	And in theory at some point I would assume at	1	Pattern, we saw teachers that were sort of			
1	And in theory at some point I would assume at some point that teacher may be measured on both	2	<i>Pattern</i> , we saw teachers that were sort of bouncing around. That's a well known effect			
		-	•			
2	some point that teacher may be measured on both	2	bouncing around. That's a well known effect			
2 3	some point that teacher may be measured on both those assessments, both the FCAT and the	2 3	bouncing around. That's a well known effect observed in value-added models. When you			
2 3 4	some point that teacher may be measured on both those assessments, both the FCAT and the advanced placement, and eventually there will be	2 3 4	bouncing around. That's a well known effect observed in value-added models. When you estimate teacher effects on a limited subset of			
2 3 4 5	some point that teacher may be measured on both those assessments, both the FCAT and the advanced placement, and eventually there will be more than that.	2 3 4 5	bouncing around. That's a well known effect observed in value-added models. When you estimate teacher effects on a limited subset of data, you're going to get an estimate and if you			
2 3 4 5 6	some point that teacher may be measured on both those assessments, both the FCAT and the advanced placement, and eventually there will be more than that. DR. DORAN: I think this is an interesting	2 3 4 5 6	bouncing around. That's a well known effect observed in value-added models. When you estimate teacher effects on a limited subset of data, you're going to get an estimate and if you estimate it again the following year you're			
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1	collect more data. We would expect more stable					
2	estimates as you use more data.					
3	* * * * *					
4	(Whereupon, this concludes Day 1, Volume 1.					
5	Volume 2 continues without interruption.)					
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