Paper 4

Title: Examining Teacher, School, and Program Moderators in the Context of Teacher Professional Development Studies

Authors and Affiliations:

Geoffrey Phelps: Educational Testing Service, gphelps@ets.org
Nathan Jones: Boston University, ndjones@bu.edu
Shuangshuang Liu: Educational Testing Service, sliu002@ets.org
Zahid Kisa: University of Pittsburg, zahidkisa@gmail.com

Background / Context:
A variety of factors have converged in the last decade to focus attention on the need for more rigorous designs of professional development. Mounting evidence indicates that teachers differ substantially in their effectiveness (e.g., Aaronson, Barrow, & Sander, 2007; Rivkin, Hanushek, & Kain, 2005; Rockoff, 2004). And teacher development is increasingly viewed as one of the primary levers for improving teaching quality and ultimately student achievement (Correnti, 2007; Desimone, 2009). This twin interest in teacher quality and teacher development has led major funding agencies to devote substantial resources to measuring and improving teacher quality and effectiveness. For instance, through many different programs and topics, the Institute of Education Sciences (IES) has funded over 60 projects that targeted the professional development of teachers and has recently established an entire program devoted to research on effective strategies for improving teacher quality through professional development (IES Education Research Grants, 2012).

However, the scientific basis for improving development has been hampered by two major limitations. One is a lack of suitable instruments that provide valid, reliable and relevant measures of PD outcomes. Student measures are arguably too distal because many factors intervene between effective PD and what students learn (Yoon, Duncan, Lee, Scarloss, and Shapley, 2007). Conventional assessments of teacher content knowledge typically consist of straight subject matter tests and do not focus on the specialized types of content knowledge emphasized in PD and used in teaching (Ball, Thames & Phelps, 2010). Proxies such as teachers' self-reports of their knowledge or learning do not assess what teachers actually know or learn (Garet, Porter, Desimone, Birman, & Yoon, 2001; Desimone, Porter, Garet, Yoon, & Birman, 2002).

A more direct and proximal outcome of PD is the content knowledge that is typically the focus of PD and that teachers actually use in enacting effective teaching. Recent research has linked PD with changes in teachers' knowledge and teaching quality (Correnti, 2007; Garet et al., 2001). More recent literature has also established links among teacher knowledge and student learning in multiple subjects (Baumert, Kunter, Blum, 2010; Hill, Rowan, Ball, 2005; Kersting, Givvin, Thompson, et. al, 2012). Further, federal policy has acknowledged the importance of teachers' knowledge and its role in teachers' PD (Yoon et al., 2007), and IES has repeatedly identified teachers' knowledge as a valued outcome (e.g., IES Education Research Grants, 2012, p. 19).

Until recently, there have been few instruments suitable for measures the types of teacher knowledge supported by the literature. However, new models of assessment are emerging that provide a direct measure of the content knowledge needed to address the content problems that arise in teaching. One prominent example are the Learning Mathematics for Teaching (LMT) measures developed by Ball, Hill, and colleagues (Hill, Schilling & Ball, 2004). There is strong evidence that the LMT assessments measure knowledge that is different from conventional tests of mathematics, specialized to teaching, sensitive to PD treatments, and associated with instructional quality and student outcomes (Hill et al., 2008; Rockoff, Jacob, Kane, Staiger, 2011; Hill, Rowan & Ball, 2004; Hill, Schilling & Ball, 2004).

A second limitation in the scientific basis or improving PD stems from the relative lack of relevant empirical estimates based new outcome assessments of teacher content knowledge.

Research focused on student learning outcomes has generated empirical estimates that can be used to appropriately estimate the power required for conducting group randomized trials (Hedges & Hedberg, 2007) as well as associated information on average effect sizes (Bloom, 2005; Jacob, Zhu, Bloom, 2010; Bloom, Zhu, Jacob, Raudenbush, Martineze & Lin, 2008). Research of this kind has just begun to estimate empirical parameters useful in designing appropriately powered group randomized trials that use teacher knowledge outcomes (Kelcey & Phelps, 2013a; Kelcey & Phelps, 2013b). However, there is limited information available on the average growth that researchers might expect to observe for teachers participating in PD.

In this session, we present data from Teacher Knowledge Assessment System (TKAS), which is designed to administer the LMT measures. TKAS is being widely adopted in the evaluation of PD programs with over 500 separate program administrations and 16,000 teachers representing every major region in the country. TKAS provides a first of its kind database that can be used to assess the suitability of teacher knowledge assessments as tools for studying teacher development across a wide range of contexts, teachers and program designs.

Purpose / Objective / Research Question / Focus of Study:

Researchers interested in using teacher knowledge assessments as outcomes in the study of PD need relevant information about what kind of growth they might expect. Without a general sense of how teacher knowledge changes and how this growth varies by design relevant characteristics of teachers, teaching context, and features of PD itself, researchers are largely guessing at what might constitute expected and meaningful change in teacher knowledge.

We will use the pre- to post-test gains in knowledge made by teachers over the course of their respective professional development programs to estimate empirical benchmarks for average teacher change across all PD program for each of the five teacher knowledge outcomes administered in TKAS. As a second step, we will select characteristics of teachers (degree training in mathematics, teaching experience), teaching environment (school SES, urbanicity and region), and basic design features of PD programs (the time of year that PD is conducted) that could act to moderate the average change in teacher knowledge pre- to post-test.

Setting and Data Collection:

The TKAS database includes 5 different elementary and middle school outcomes: (1) Elementary number and operations (ELNCOP); (2) Elementary patterns, functions and algebra (ELPFA); (3) grade 4-8 geometry (GEO); (4) Middle school number and operations (MSNCOP); (5) Middle school patterns, functions and algebra (MSPFA). Data comes from 41 states and the District of Columbia. While not nationally representative (or representative of states), these data comprise one of the largest samples of teacher PD programs to date. They also, given that the LMT assessments and TKAS are one of the only instruments available to use in pre- to post- test evaluations, are a viable sample for representing math PD that is involved in evaluation.

TKAS is used by a variety of users (e.g., teacher educators, district personnel) for a variety of purposes. To ensure that our analytic sample only included teachers enrolled in professional development programs, we limited our sample by first dropping preservice teachers and preservice programs from the sample and by excluding PD programs that had not yet administered a post-test to participating teachers.

Our final sample for each assessment is shown in Table 1. As indicated in Table 1, a large number of teachers did not complete post assessments. For the preliminary analyses reported on below, we have included only teachers who had pre- and post- test data available by employing list wise deletion. We will conduct final analyses using appropriate multiple imputation accounting for the cross-classified and nested structure of our data.

Research Design:
Our research goals are to first generate estimates of average change in teacher knowledge across all programs and next to examine the effects of design-relevant moderator variables on this average change. Our data structure has teachers cross-classified within schools and programs (i.e., in some cases, teachers from more than one school appears in a given program and in other cases, teachers from a single school appear in more than one program). To appropriately account for this cross-nested structure, we ran cross-classified models as specified above. In a second stage of the analysis we run a series of separate random intercept models with each moderator variable entered one at a time, the goal of which was to estimate the effects of the moderator variables in the average pre- to post-test estimates.

Statistical, Measurement, or Econometric Model:
To estimate the average pre- to post-test change for teachers attending math PDs, we use a cross-classified model which takes into account the non-hierarchical structure that teachers in one PD could come from different schools and teacher in one school could go to different PDs. Then, we add moderators into the unconditional model to examine the extent to which this change from pre- to post- test score are affected by teacher characteristics, PD and school features. This procedure is repeated across each of the five study outcomes. The unconditional model is specified by equation 1 and 2 below

$$Postscore_{ijk} = \beta_0 + \beta_1 \Pr escore_{ijk} + \varepsilon_{ijk} \quad (1)$$

$$\beta_0 = g_{00} + r_{1j} + r_{2k} + u_{ijk} \quad (2)$$

Or

$$\beta_0 = g_{00} + g_{01}W + r_{1j} + r_{2k} + u_{ijk} \quad (3)$$

Where g00 is the average change from pre- to post- test score PD, r_{1j} is the random effect for programs and r_{2k} is the random effect for schools. Equation 3 specifies the second level of the model when moderators are included, but the main level still remains the same. *W* in Equation 3 could be a teacher, PD or school variable. The model is repeated for each variable of interest with only one added at a time.

Significance / Novelty of study:
The empirical benchmarks of average change in teacher knowledge serves two purposes. First, these benchmarks provide a context for interpreting the magnitude of effect sizes drawn from future empirical studies. In this sense, our results provide a more relevant point of reference than two other commonly-employed benchmarks—Cohen's guidelines for small, medium, and large effect sizes, and empirical benchmarks that have been derived from studies using student outcomes. If studies include teacher knowledge as an outcome, the magnitude of their effects should be interpreted relative to other studies of teacher knowledge that use similar outcomes

and are conducted in similar contexts with similar teachers. Second, the results will provide guidance in the design of future studies of the effectiveness of PD interventions. As Desimone (2009) and others have argued, teacher knowledge is an important outcome in PD interventions, and it may provide a more proximal measure of a program's effectiveness than student achievement.

Findings / Results:

The pre- to post-test changes for each assessment are summarized in Table 2 along with the variance components attributable to school, PD program and to teachers. The average change varies from 0.17 for EL PFA to 0.30 for 4-8 GEO. The variance between PD programs is larger than schools, however the majority of variance remains at the teacher level. The variance at each level is similar across the five outcomes. Figure 1 presents a helpful visual representation of the distribution of how change in outcome measures varies across programs and illustrates the relatively small proportion of programs where teachers are showing substantial gains of 0.50 SD or more.

Tables 3-7 present the results for the moderator analysis for each outcome. One of the main outcomes of the work are the empirical estimates. Clearly, one limitation of these preliminary analysis is a limited sample size for a number of moderators, an issue that will be addressed in part when post scores are imputed for the roughly 50% of teachers missing at post test. However, across the tests there is sufficient sample size to note that a number of moderators are related to quite substantial differences in change. For example, having a math degree is constantly related to change that is 0.02 SD or more than teachers without a math degree. On the other hand, years of experience has different effects across different assessments, suggesting that this teacher characteristic is dependent on the outcome measure.

Conclusions:

These findings provide potential guidance for the design of studies using teacher knowledge as an outcome measure. In general, the estimates drawn from studies using teacher outcomes are smaller than those found in studies using student achievement as an outcome; they are also "small" based on the benchmarks put forward by Cohen. These findings suggest that studies using teacher knowledge as an outcome should be considered differently than those using measure of student achievement where larger effects might be expected. Most notable about our findings is the variation across outcomes, suggesting that researchers should consider the specific math outcome that is most relevant for their intervention. It is also noteworthy that design-relevant moderators have different effects on pre- to post-test change both within and across tests. While we anticipate that the coefficients will change after we complete analysis with appropriate imputation, we expect that the stronger trends noted above will be similar to what is shown in the preliminary analysis. These results provide context relevant guidelines (e.g., test outcome, characteristics of teachers, school or program) that researchers may use individually or in combination to design studies and/or assess the practical impact of teacher PD interventions.

Appendix A. References

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Appendix B. Tables and Figures

Table 1

TKAS Sample for Each Outcome Measure

	Teacher Pre-Test	Teacher Post-Test	Program (Pre)	School (Pre)
EL NCOP	4,313	2,129	112	994
EL PFA	2,574	1,253	55	612
MS NCOP	1,363	831	49	503
MS PFA	1,785	2,901	83	1,093
4-8 GEO	973	652	44	349

Table 2

Unconditional Estimates of Pre- to Post Test Change for Teacher Knowledge Outcomes

	Average Change	R_j^2	R_k^2	R_i^2	J	K	N
EL NCOP	0.24	0.04	0.01	0.44	71	505	1,432
EL PFA	0.17	0.08	0.02	0.55	36	299	818
MS NCOP	0.24	0.04	0.03	0.51	33	298	549
MS PFA	0.20	0.05	0.01	0.42	58	644	1,173
4-8 GEO	0.30	0.08	0.00	0.35	31	201	390

Note. R_j^2 and R_k^2 refer to the variance between PDs and schools, respectively. R_i^2 refers to the residual variance not due to additive effects of PDs and Schools.

Table 3
Moderator Estimates of Pre- to Post Test Change for Elementary Number Concepts and Operations

	Average Change	R_j^2	R_k^2	R_i^2	J	K	N
Unconditional Model	0.24	0.04	0.01	0.44	71	505	1,432
Math degree							
Yes	0.40	0.04	0.02	0.44	37	84	106
No	0.23	0.04	0.02	0.44	71	476	1,326
Years of Experience							
0-3	0.23	0.04	0.01	0.44	58	154	235
4-15	0.25	0.04	0.01	0.44	69	371	778
>15	0.23	0.04	0.01	0.44	62	221	419
Program type							
Summer Institute	0.29	0.04	0.01	0.45	15	119	327
School year program	0.20	0.04	0.01	0.45	25	167	580
Both	0.24	0.04	0.01	0.45	31	234	525
% of free/reduced lunch							
0-0.25	0.21	0.04	0.01	0.45	32	77	190
0.26-0.50	0.26	0.04	0.01	0.45	52	165	513
0.51-0.75	0.25	0.04	0.01	0.45	51	153	473
0.76-1	0.21	0.04	0.01	0.45	40	106	237
Region							
NE	0.45	0.04	0.02	0.44	3	21	31
S	0.20	0.04	0.02	0.44	19	171	510
MW	0.26	0.04	0.02	0.44	24	125	455
W	0.23	0.04	0.02	0.44	30	188	436
Urban							
City	0.29	0.04	0.01	0.44	36	129	330
Suburb	0.23	0.04	0.01	0.44	42	149	406
Town	0.19	0.04	0.01	0.44	33	69	170
Rural	0.23	0.04	0.01	0.44	55	158	526

Note. R_j^2 and R_k^2 refer to the variance between PDs and schools, respectively. R_i^2 refers to the residual variance not due to additive effects of PDs and Schools.

Table 4

Moderator Estimates of Pre- to Post Test Change for Elementary Patterns Functions and Algebra

	Average Change	R_j^2	R_k^2	R_i^2	J	K	N
Unconditional Model	0.17	0.08	0.02	0.55	36	299	818
Math degree							
Yes	0.44	0.08	0.02	0.54	20	57	75
No	0.14	0.08	0.02	0.54	36	274	743
Years of Experience							
0-3	0.20	0.08	0.02	0.55	24	86	124
4-15	0.19	0.08	0.02	0.55	34	220	478
>15	0.12	0.08	0.02	0.55	32	135	216
Program type							
Summer Institute	-0.04	0.07	0.02	0.55	3	26	123
School year program	0.11	0.07	0.02	0.55	8	97	300
Both	0.23	0.07	0.02	0.55	25	176	395
% of free/reduced lunch							
0-0.25	0.06	0.08	0.02	0.55	13	23	79
0.26-0.50	0.16	0.08	0.02	0.55	28	87	252
0.51-0.75	0.22	0.08	0.02	0.55	27	118	329
0.76-1	0.17	0.08	0.02	0.55	25	69	154
Region							
NE	-	-	-	-	0	0	0
S	0.09	0.07	0.02	0.55	21	166	495
MW	0.28	0.07	0.02	0.55	6	64	155
W	0.26	0.07	0.02	0.55	9	69	168
Urban							
City	0.18	0.08	0.02	0.55	22	63	158
Suburb	0.08	0.08	0.02	0.55	19	62	212
Town	0.23	0.08	0.02	0.55	21	58	129
Rural	0.18	0.08	0.02	0.55	26	116	319

Note. R_j^2 and R_k^2 refer to the variance between PDs and schools, respectively. R_i^2 refers to the residual variance not due to additive effects of PDs and Schools.

Table 5

Moderator Estimates of Pre- to Post Test Change for Middle School Number Concepts and Operations

	Average Change	R_j^2	R_k^2	R_i^2	J	K	N
Unconditional Model	0.24	0.04	0.03	0.51	33	298	549
Math degree							
Yes	0.39	0.04	0.03	0.49	32	147	224
No	0.16	0.04	0.03	0.49	32	212	325
Years of Experience							
0-3	0.16	0.04	0.03	0.51	25	99	134
4-15	0.26	0.04	0.03	0.51	31	205	291
>15	0.29	0.04	0.03	0.51	25	98	124
Program type							
Summer Institute	0.17	0.04	0.03	0.51	2	20	27
School year program	0.27	0.04	0.03	0.51	9	116	263
Both	0.24	0.04	0.03	0.51	22	164	259
% of free/reduced lunch							
0-0.25	0.43	0.03	0.03	0.50	13	28	41
0.26-0.50	0.30	0.03	0.03	0.50	25	101	161
0.51-0.75	0.25	0.03	0.03	0.50	27	109	240
0.76-1	0.04	0.03	0.03	0.50	19	58	105
Region							
NE	-	-	-	-	0	0	0
S	0.32	0.04	0.02	0.51	17	186	374
MW	0.22	0.04	0.02	0.51	4	29	45
W	0.12	0.04	0.02	0.51	13	83	129
Urban							
City	0.38	0.05	0.01	0.51	19	85	183
Suburb	0.10	0.05	0.01	0.51	15	48	75
Town	0.24	0.05	0.01	0.51	15	43	83
Rural	0.23	0.05	0.01	0.51	28	122	208

Note. R_j^2 and R_k^2 refer to the variance between PDs and schools, respectively. R_i^2 refers to the residual variance not due to additive effects of PDs and Schools.

Table 6

Moderator Estimates of Pre- to Post Test Change for Middle School Patterns Functions and Algebra

	Average Change	R_j^2	R_k^2	R_i^2	J	K	N
Unconditional Model	0.20	0.05	0.01	0.42	58	644	1173
Math degree							
Yes	0.33	0.05	0.00	0.42	54	330	489
No	0.12	0.05	0.00	0.42	57	434	684
Years of Experience							
0-3	0.09	0.05	0.01	0.42	52	206	290
4-15	0.23	0.05	0.01	0.42	55	444	648
>15	0.23	0.05	0.01	0.42	49	194	235
Program type							
Summer Institute	0.36	0.05	0.01	0.42	5	54	72
School year program	0.17	0.05	0.01	0.42	15	280	605
Both	0.19	0.05	0.01	0.42	38	321	496
% of free/reduced lunch							
0-0.25	0.22	0.05	0.01	0.42	23	66	95
0.26-0.50	0.23	0.05	0.01	0.42	46	170	269
0.51-0.75	0.19	0.05	0.01	0.42	48	244	494
0.76-1	0.17	0.05	0.01	0.42	36	152	302
Region							
NE	0.42	0.05	0.01	0.42	1	10	10
S	0.21	0.05	0.01	0.42	40	489	925
MW	0.10	0.05	0.01	0.42	5	34	54
W	0.20	0.05	0.01	0.42	15	111	183
Urban							
City	0.20	0.05	0.01	0.42	43	218	488
Suburb	0.15	0.05	0.01	0.42	22	90	133
Town	0.21	0.05	0.01	0.42	36	105	184
Rural	0.21	0.05	0.01	0.42	49	229	366

Note. R_j^2 and R_k^2 refer to the variance between PDs and schools, respectively. R_i^2 refers to the residual variance not due to additive effects of PDs and Schools.

Table 7
Moderator Estimates of Pre- to Post Test Change for 4-8 Geometry

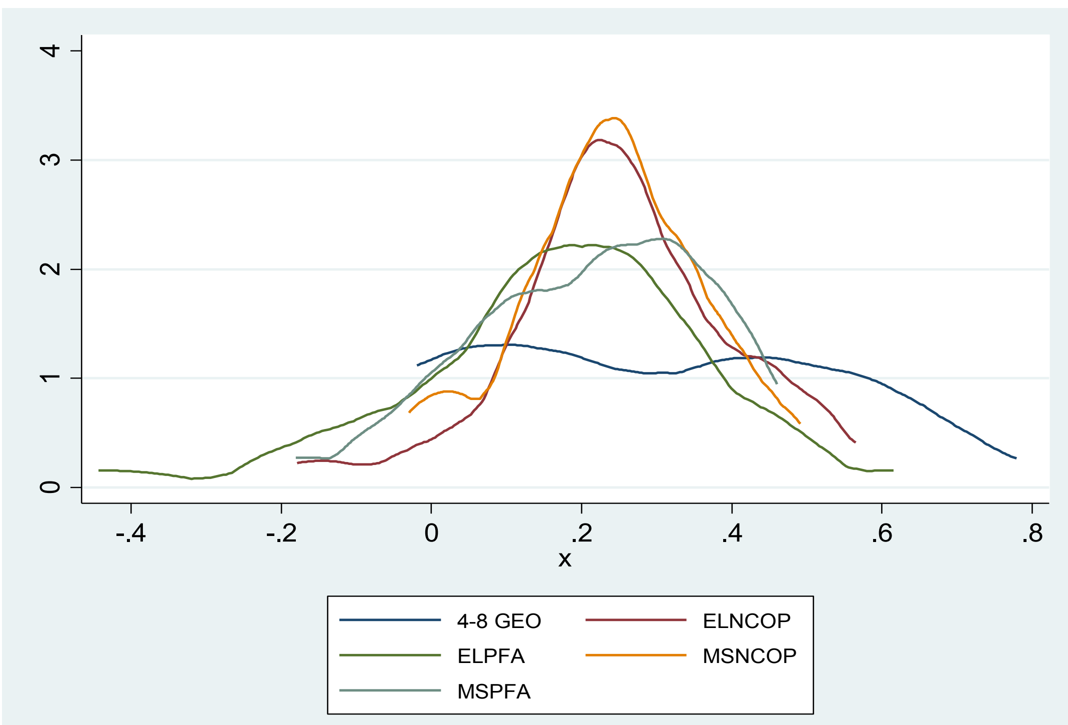
	Average Change	R_j^2	R_k^2	R_i^2	J	K	N
Unconditional Model	0.30	0.08	0.00	0.35	31	201	390
Math degree							
Yes	0.40	0.06	0.00	0.35	24	64	93
No	0.26	0.06	0.00	0.35	30	162	297
Years of Experience							
0-3	0.40	0.07	0.00	0.34	23	50	65
4-15	0.33	0.07	0.00	0.34	28	141	225
>15	0.16	0.07	0.00	0.34	27	77	100
Program type							
Summer Institute	-	-	-	-	0	0	0
School year program	0.41	0.07	0.00	0.35	9	78	107
Both	0.25	0.07	0.00	0.35	22	137	283
% of free/reduced lunch							
0-0.25	0.43	0.06	0.00	0.35	12	25	28
0.26-0.50	0.32	0.06	0.00	0.35	27	74	137
0.51-0.75	0.23	0.06	0.00	0.35	22	71	175
0.76-1	0.34	0.06	0.00	0.35	12	29	47
Region							
NE	-	-	-	-	0	0	0
S	0.30	0.07	0.00	0.35	21	145	286
MW	0.23	0.07	0.00	0.35	2	31	50
W	0.33	0.07	0.00	0.35	8	25	54
Urban							

City	0.42	0.07	0.00	0.34	19	43	89
Suburb	0.33	0.07	0.00	0.34	14	30	55
Town	0.12	0.07	0.00	0.34	14	40	69
Rural	0.29	0.07	0.00	0.34	24	88	177

Note. R_j^2 and R_k^2 refer to the variance between PDs and schools, respectively. R_i^2 refers to the residual variance not due to additive effects of PDs and Schools.

Figure 1

Distribution of Pre- to Post Test Professional Development Averages for Teacher Knowledge Outcomes



Note: The Y axis is reported as a probability density.