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Explaining Student Achievement: The Influence of Teachers' Pedagogical Content Knowledge in Statistics

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Abstract:	<p>Statistics is an increasingly important component of the mathematics curriculum. StatSmart was a project intended to influence middle-years students' learning outcomes in statistics through the provision of appropriate professional learning opportunities and technology to teachers. Participating students in Grade 5/6 to Grade 9 undertook three tests, a pre-test, a post-test and a longitudinal retention test over a period of two years. Their teachers completed a survey that included items measuring pedagogical content knowledge (PCK) for teaching statistics. Despite the development of valid instruments to measure both student and teacher content knowledge and teachers' PCK, linking teachers' knowledge directly to students' learning outcomes has proved elusive. Multi-level modeling of results from 789 students for whom there were three completed tests and measures from their teachers indicated that students' outcomes were influenced positively by their initial teacher's PCK. Extended participation of teachers in the project also appeared to reduce negative effects of changing teachers.</p>
Response to Reviewers:	<p>A rationale for the use of Shulman's definition of PCK has been added and an explanation of why more fine-grained measures were not used is included (Reviewer 1).</p> <p>Both reviewers commented on the lack of clarity of the analysis. The analysis has been completely reworked. Students who changed schools were removed from the data set and a linear model was fitted to the data. This change made very little difference to the findings but removed some complications. The steps in the analysis, and the underlying assumptions, have been more clearly explained, together with the justification for inclusion, or otherwise, of variables. Correlations among variables are provided in the text.</p> <p>A justification has been provided for the decision not to nest in classes (Reviewer 2). A section has been added to better explain the Rasch analysis and fit and reliability statistics provided for all tests, and this is included before the HLM analysis. (Reviewer 2)</p> <p>A justification for using the first teacher's PCK measure has been added with a new</p>

reference (Dochy et al., 1999) (Reviewer 2).
A new Table 2 has been added to summarise the characteristics of the teachers involved (Reviewer 1).
ICMI has been changed to Commission (from Congress) (Reviewer 1).
The discussion has been substantially rewritten. It now takes better account of the two major findings of an association with teachers' measured PCK and their students' outcomes, and the effects of changing teachers. Additional links have been made to the literature (Reviewer 1) and the limitations of the study have been considered (Reviewer 1 and 2).
In the rewrite some reorganisation occurred that we believe aids the flow of the paper. The authors would like to thank the reviewers for their detailed and helpful comments that have aided the reworking of this report.

Explaining Student Achievement: The Influence of Teachers' Pedagogical Content Knowledge in Statistics

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Explaining Student Achievement: The Influence of Teachers' Pedagogical Content Knowledge in Statistics

Statistics is an increasingly important component of the mathematics curriculum. *StatSmart* was a project intended to influence middle-years students' learning outcomes in statistics through the provision of appropriate professional learning opportunities and technology to teachers. Participating students in Grade 5/6 to Grade 9 undertook three tests, a pre-test, a post-test and a longitudinal retention test over a period of two years. Their teachers completed a survey that included items measuring pedagogical content knowledge (PCK) for teaching statistics. Despite the development of valid instruments to measure both student and teacher content knowledge and teachers' PCK, linking teachers' knowledge directly to students' learning outcomes has proved elusive. Multi-level modeling of results from 789 students for whom there were three completed tests and measures from their teachers indicated that students' outcomes were influenced positively by their initial teacher's PCK. Extended participation of teachers in the project also appeared to reduce negative effects of changing teachers.

Keywords: pedagogical content knowledge, student achievement, statistics, middle years

Introduction

Since the last decade of the 20th century, statistics has had a defined place within the school mathematics curricula of many countries, including the United States (National Council of Teachers of Mathematics [NCTM], 1989), Australia (Australian Education Council [AEC], 1991), and New Zealand (Ministry of Education [MENZ], 1992). Although there have been some revisions to the suggested content over the years (e.g., Australian Curriculum, Assessment and Reporting Agency [ACARA], 2011; Franklin et al., 2007; MENZ, 2007; NCTM, 2000), the place of statistics has been consolidated and a research field of statistics education established. The progress of this field has been summarized in the reviews of Konold and Higgins (2003) and Shaughnessy (2007). As progress was made on documenting

students' developing understanding, the scope widened to include teachers' understanding of statistics and their needs to facilitate successful implementation of the statistics component of the mathematics curriculum in the classroom. The many issues surrounding the complexities of translating the curriculum to successful learning outcomes for students via teachers in classrooms are explored in detail by Batanero, Burrill, and Reading (2011) following an intensive International Commission on Mathematical Instruction (ICMI) and International Association for Statistics Education (IASE) joint study in 2008. Acknowledging that many teachers had not studied statistics in their own education and training, many of the studies looked at the pre-service and in-service learning of teachers and the measurement of their improvement in understanding content and pedagogy (e.g., Author1 & Author3, 2011; Makar & Fielding-Wells, 2011; Pierce& Chick, 2011).

Of concern in this paper is the complicated relationship between teachers' pedagogical content knowledge (PCK) for teaching statistics and students' learning outcomes as they develop understanding of statistical concepts. As part of a complex three-year study that took place between 2007 and 2010 associated with a professional learning program for teachers in statistics, instruments were developed and/or adapted to measure various aspects of teachers' knowledge for teaching statistics and of students' understanding of the concepts (Author 1 & Author 3, 2007). This paper reports on teachers' initial levels of PCK for teaching statistics and the change in student understanding as measured at three points in time: before exposure to a unit on statistics, after the unit, and one year later.

Measuring Teachers Knowledge

Interest in measuring teachers' knowledge for teaching mathematics has developed since Shulman's (1987) general categorization of seven types of teachers' knowledge required for successful teaching: curriculum knowledge, general pedagogical knowledge, content

knowledge, pedagogical content knowledge, knowledge of learners and their characteristics, knowledge of education contexts, and knowledge of education ends, purposes, and values.

Since Shulman published his seminal work, many approaches have been taken, and attempts have been made to describe, characterise, and measure teachers' mathematics knowledge. Ma (1999) described elementary teachers' deep connected mathematics knowledge as Profound Understanding of Fundamental Mathematics (PUFM). Even and Tirosh (2002) went beyond mathematics knowledge to consider teachers' knowledge of students' mathematical learning.

Other researchers have worked with or adapted Shulman's framework for the teaching of mathematics or statistics. For example, Author3 (2001) developed a profile instrument to measure teachers' knowledge on each of Shulman's dimensions in relation to the teaching of data and chance. This instrument was later broadened for the teaching of middle school mathematics more generally (Beswick, Author1, & Author3, 2011; Author3 et al, 2011).

A major contribution to the field was that of Hill, Ball and colleagues (e.g., Ball, Thames, & Phelps, 2008; Hill, Schilling, & Ball, 2004; Hill, Sleep, Lewis, & Ball, 2007). They adapted Shulman's work, originally focussing on the mathematics knowledge required but later expanding their work to acknowledge other necessary aspects: common content knowledge, specialized content knowledge, knowledge at the mathematical horizon, knowledge of content and students, knowledge of content and teaching, and knowledge of curriculum. These components encompass what others have continued to recognize as pedagogical content knowledge including an implicit appreciation of students as learners (Author 1 & Author3, 2011) and the recognition of the particular affordances of tasks chosen by teachers for use in the classroom (Chick, 2007). More specifically in relation to teaching statistics, Groth (2007) synthesized the work of Ball and her colleagues into four categories for the statistics classroom: common knowledge, specialized knowledge, mathematical

knowledge, and non-mathematical knowledge, implicitly recognising the importance of context in statistics (Author1, Author3 et al., 2012).

In the *StatSmart* project, pedagogical content knowledge was framed within Shulman's (1987) original definition:

the blending of content and pedagogy into an understanding of how topics, problems, or issues are organized, represented, and adapted to the diverse interests and abilities of learners, and presented for instruction. Pedagogical content knowledge is the category most likely to distinguish the understanding of the content specialist from that of the pedagogue. (1987, p. 8)

This definition was chosen because it was closely aligned to the aims of the study, which were focussed on the improvement of statistics teaching rather than the nature of teachers' statistical PCK. Nevertheless, with the increasing pressure for accountability in schooling and the scale of the project, there was also interest in providing solid quantitative data about both teachers' knowledge and students' learning outcomes in statistics.

Instruments were developed to measure teachers' statistical PCK that considered (i) their prediction of students' likely answers to statistical problems; (ii) teachers' responses to students' actual answers taken from student surveys; and (iii) teachers' intervention strategies in relation to students' current knowledge (see Author1 & Author3, 2011 for further details). As such, these instruments addressed many of the aspects of Ball et al's (2008) conceptualisation of teachers' knowledge, and Groth's (2007) framework for considering teachers' statistical knowledge. For example, items relating to prediction of correct and incorrect responses drew on both teachers' own statistical understanding, without which they could not predict high level responses, and their specialised knowledge of statistics in the classroom, which they needed to identify students' common misconceptions. Time constraints on teachers prevented the administration of more nuanced instruments because these would have required a longer survey with more items to address clearly the

different domains. Hence a “thick” construct of teachers’ statistical PCK was the target variable used in the *StatSmart* study.

Measuring Student Understanding

In contrast to the measurement of teacher knowledge, measuring student knowledge has a longer history. The measurement of student understanding of statistical concepts dates back to ideas associated with “average,” usually interpreted as the arithmetic mean, as well as concepts in probability. Both of these topics were typically found in earlier curriculum documents associated with procedures for calculating means and probabilities. In the 1980s Pollatsek, Lima and Well (1981) and Mevarech (1983) demonstrated student difficulty with weighted averages, as did Strauss and Bichler (1988) with the general properties of the mean. Mokros and Russell (1995) identified the dilemma of representativeness for averages and Cai (1995, 1998) revealed difficulties with the notion of mean due to students’ failure to work the algorithm backward. Similarly Green (1983, 1986, 1991) produced the first large scale longitudinal research in the related area of probability.

With the advent of the statistics component of national curricula, interest in measuring student understanding over a broader range of statistical ideas grew, for example including sampling (Author3 & Moritz, 2000) and beginning inference (Author3 & Moritz, 1999). The work of Author3 and colleagues was consolidated in a scale of statistical literacy (Author3 & Author1, 2003) based on student surveys, and in a scale of statistical understanding reflecting adoption of the concepts of variation and expectation (Author3 et al., 2007) based on in depth student interviews. Many of the items used in these studies drew on the earlier work of other researchers, such as Batanero and her colleagues (e.g., Batanero, Estepa, Godino & Green, 1996).

The *StatSmart* study drew on this body of work to develop instruments to measure students' statistical understanding. Items included many that had been used in prior studies (e.g., Author3 & Author1, 2003) together with a small number of new items to expand the item pool and provide additional information about specific statistical ideas.

Relationship between Teacher Knowledge and Students' Outcomes

Despite the activity on developing instruments and identifying key aspects of teacher knowledge, it has been surprisingly difficult to link teacher knowledge directly to students' learning outcomes. It has long been recognised that using proxy measures of teachers' mathematical knowledge, such as qualifications or training experience, shows no relationship to students' learning outcomes in mathematics (e.g., Mewborn, 2001).

A major contribution to the field was made by Hill and colleagues (Hill, Schilling & Ball, 2004; Hill, Rowan & Ball, 2005) who unpacked ideas about teachers' specialised mathematical knowledge and developed an instrument to measure elementary teachers' mathematical knowledge for teaching. This measure included actions such as providing examples, explaining concepts, correcting work and using a range of representations of mathematical ideas. They found that teachers' "knowledge of mathematics for teaching" predicted gain scores in two lower elementary grades.

More recently, a German study of a representative sample of Year 10 classrooms over 1-year identified that teachers' pedagogical content knowledge had a large positive impact on their own students' learning gains (Baumert et al., 2010). They identified that 39% of the variance between classrooms was due to the variable they identified as PCK. Further they indicated that the relationship was linear and that PCK was more important than content knowledge.

These findings suggest that classroom teachers understand mathematical ideas in specialised ways, and that this specialised knowledge has a positive impact on students' learning gains. In the study reported here, the context was statistics, rather than pure mathematics, and students' learning trajectories were considered using at least three data points. Rowan, Correnti and Miller (2002) have suggested that this approach avoids some of the difficulties associated with using learning gains. In addition, similar to the Hill et al. (2005) and the Baumert et al. (2010) studies, a direct measure of teachers' knowledge was used, rather than proxy measures such as mathematical qualifications.

There were a number of differences between the *StatSmart* study and those of Hill et al. (2005), and Baumert et al. (2010). These two studies identified a link between teachers' PCK and their current students' learning outcomes. *StatSmart*, in contrast, was a 3-year longitudinal study in which the context of the project meant that there was no control by researchers over which grades and classes teachers taught, at what point in the school year statistics was taught, or any changes to teachers and classes during the study. During the project students changed classes and teachers, sometimes into classes taught by teachers not participating in StatSmart, some teachers left their schools, and others taught different grades from year to year. In this naturalistic situation, untangling the influence of a particular current teacher proved impossible because of the number of uncontrolled variables. A decision was made to consider only the initial teacher's PCK on a particular student's outcomes. It is known that students' prior achievement is a predictor of future learning outcomes (Dochy, Segers, & Buehl, 1999). Hence it is not unreasonable to suppose that the influence of an initial teacher's PCK might continue to impact on students' future learning outcomes.

Methodology

The context

The context of the research reported here was a 3-year research project, *StatSmart*, in conjunction with the Australian Bureau of Statistics (ABS), the US manufacturer of the software Fathom (Finzer, 2002) and TinkerPlots (Konold & Miller, 2005), and an independent expert in professional learning for teachers of mathematics. Initially 42 teachers were chosen from 18 schools in three Australian states. A commitment was made by the teachers and schools to implement statistics units within the middle school years (grades 5 to 9) and their state's mathematics curriculum, based on the research findings on the development of student understanding (Author3, 2006) and employing one or both of the software packages that were provided to every school. To assist further, each year a 2-day workshop with all expenses paid, was held in the ABS offices in Melbourne, including the software developers from the US. Teachers were expected to complete a teacher profile, including items developed to measure PCK. Examples of items used in the profile are found in Author3 et al. (2008) based on proportional reasoning and in Author1 and Author3 (2011) based on odds.

Participants

Students

Students in the middle years of schooling (ages 10 to 15 years) together with their teachers were the target groups. These students and teachers were located in three Australian states that had similar but not identical curricula (see Author1, 2010, for details). Over the course of the project each student undertook three surveys of statistical literacy. The first two were taken at the start and end of the first year in which they entered the study, and the third survey was a follow up taken about 12 months after the second survey. Over the 3-year study there

were two phases of students who completed all three surveys and one phase that completed only the first two surveys (see Author1 & Author3, 2007 for details of the research design). A small number of students completed a fourth survey because they happened to be in a class taught by a project teacher at the time the survey was completed.

The sample used in the analysis reported here consisted of 789 students for whom there were three or four data points over three years and who did not change schools. All of these students were part of Phase 1 and Phase 2 of the study. More specifically 70 students had four observations and the remaining 719 had three observations. All of the students did an initial survey and a follow up survey after about six months while they were still in the same year groups at school. After 12 months, most of them ($n = 765$) completed a longitudinal survey. A small number had different participation patterns (see Table 1 for details). All of these students were taught by teachers who had completed the initial teacher survey, and for whom there were PCK measures available.

Table 1.

Test participation patterns for 789 students with teacher PCK data

Rd1 ¹	Rd2	Rd3	Rd4	Rd5	Rd6	Total
✓	✓		✓		✓	70
✓	✓		✓			352
✓	✓				✓	24
		✓	✓		✓	343
Total						789

¹ Note: Rd 1, Rd 2, etc refer to the *StatSmart* test rounds.

There was an approximately even split of male and female students (48.7% male) and just over 10% of the students came from backgrounds where they did not speak English at home (Non-English Speaking Background (NESB) = 10.6%). When they commenced the study, students' ages ranged from 10.1 yrs to 15.8 yrs ($M=12.9$, $SD=1.0$), and most (72%) of them

were attending a secondary school.

Teachers

At their first test, these students were taught by 36 different teachers located in 15 schools. Of these teachers just over half (56%) were male. Teachers also completed three surveys, one in each year of the project. Particular care was taken to ensure that teachers could be associated with particular groups of students in order to associate teachers' measured knowledge directly with students' outcomes. The teachers had varied backgrounds in both the level of mathematics studied and teaching experience, summarised in Table 2.

Table 2.

Characteristics of StatSmart teachers

Mathematics background	n		Mathematics teaching experience	n	
No maths	3	91%	<2 years	0	
1 semester tertiary	8	23%	2-5 years	5	14%
1 year tertiary	10	28%	6-10 years	0	
Undergraduate major	14	40%	11-15 years	10	29%
			16-25 years	7	20%
			>25 years	13	37%

Instruments and analysis

Surveys

Teachers completed a profile instrument that included a set of 12 items designed to measure PCK in statistics, rather than general mathematics. Figure 1 contains an example of an item that had been used in student surveys and was intended to measure teachers' content knowledge, knowledge of students as learners, and pedagogical content knowledge for intervention in the classroom. Contextually, it refers to shops common in Australia and had been used in several previous studies of students providing a pool of examples of students'

thinking (e.g., Author3 & Author1, 2003) against which teachers' responses could be compared and coded.

<INSERT FIGURE 1 ABOUT HERE>

Figure 1. Typical teacher PCK item addressing knowledge of students and knowledge of pedagogy.

A second item type asked teachers' to respond to students' actual answers to survey questions (see Figure 2 for an example). These items addressed teachers' capacity to provide student-centred ideas for intervention. Scoring rubrics were developed for teachers' responses to both types of survey question based on increasing complexity and mathematisation. The rubrics for questions 5.3 and 5.4, are also shown in Figure 2.

<INSERT FIGURE 2 ABOUT HERE>

Figure 2. An example of student answer items, together with the scoring rubric, used in the teacher survey.

Students undertook one of three test forms, all linked by a core of 10 common items (Author1 & Author3, 2007). Each test had between 22 and 24 items addressing different aspects of statistical literacy, hereafter termed statistical literacy knowledge (SLK).

Both student and teacher responses to the surveys were analysed using Rasch measurement using the software Winsteps 3.75.0 (Linacre, 2012). Rasch analysis (Bond & Fox, 2007; Rasch, 1960) uses the interactions between items and test takers (persons) to place all items and persons on the same interval scale. The approach is based on a probabilistic model underpinned by three key assumptions: (i) the items address a single unidimensional construct; (ii) the probability of a correct or higher level response increases monotonically with an increase in a person's ability or understanding; and (iii) all items are independent of

each other. Where these assumptions are violated, the fit to the model falls outside acceptable parameters. Hence fit to the model becomes of prime importance in determining the validity of the construct and the suitability of the measures obtained for the intended purpose. The specific model used was the Partial Credit Model (PCM) (Masters, 1982) where the scoring rubrics, for both students and teachers, were used to provide partial scores.

Model fit is reported by Rasch modelling programs as four statistics: the Infit is a weighted least squares measure and the Outfit is the unweighted measure. Both have an ideal value of 1.0, and values suitable for measurement purposes lie between 0.5 and 1.5. (Linacre, 2002). In addition a standardised z score is provided for each with acceptable values lying between ± 2 . Rasch reliability statistics are the Item and Person Separation Indices. These provide a measure of the consistency with which persons or items are located on the scale produced. In general Person Separation is considered satisfactory if the index is >0.8 and Item Separation is satisfactory if the index is >0.9 (Linacre, 2013). Both indices are uninfluenced by model fit. The fit to the model, and reliability indices for the tests used in the analysis reported here for both students' SLK and teachers' PCK are summarised in Table 3. Item separation indices are not available for tests that are anchored to a previous administration. All fit and reliability statistics for the tests used in the analysis were generally acceptable.

Table 3

Summary statistics for Item (I) and Person (P) measures for student SLK tests and teacher

PCK assessment

Test	Rasch item separation index	Rasch person separation index	Infit (I)	Infitz(I)	Outfit (I)	Outfit z (I)	Infit (P)	Infitz (P)	Outfit (P)	Outfit z (P)
SLK 1	0.99	0.86	0.99	-0.2	0.98	-0.3	1.06	0.1	0.98	0.0
SLK 2	anchored	0.85	1.06	0.7	1.08	0.7	1.13	0.4	1.13	0.5
SLK 3	anchored	0.84	1.10	1.2	1.11	1.2	1.17	0.6	1.18	0.7
Teacher PCK	0.93	0.77	1.0	0.1	0.99	0.0	1.03	0.0	0.99	0.0

Rasch person measures in logits, the logarithm of the odds of success used as the unit of Rasch measurement, were estimated for each of the three student tests. These estimates were anchored to the first test to ensure that all were directly comparable on the same measurement scale (Bond & Fox, 2010). A range of demographic variables was also included. For the purpose of the analysis reported here only the PCK measure applicable to the students' first test was used, usually the teacher's initial measure. These measures were then used as input variables to create hierarchical models.

Analysis

Simple descriptive techniques were initially used to explore the impact of teacher factors on measures of students' statistical understanding. Multilevel regression models were then used to control for the effects of demographic variables. These models were used to capture the longitudinal nature of the outcome variable and dependence between students attending given schools. It was not possible to model the dependence of students within classes, because nearly two-thirds of the students (63%) changed teachers after the second test, often to teachers who were not part of the project, and from whom there were no PCK measures available. In addition, only students who had undertaken Test 1 or Test 2 were tracked, so that classes taught by a non-*StatSmart* teacher did not provide intact class data. Model estimates were obtained using the software package R (R Development Core Team, 2011) and in particular the Multilevel package (Bliese, 2012) as described in Faraway (2006).

Results

Descriptive analysis

Initial results considered the changes in the overall SLK scores across time. SLK scores in Tests 1 and 2 were correlated ($r = 0.67$), as were scores between Tests 2 and 3 ($r = 0.67$). On average students obtained relatively low SLK scores in their first test ($M = -0.53$,

$SD = 0.71$) and these improved in their second test ($M = -0.25$, $SD = 0.64$), with this increase statistically significant ($\Delta M = 0.28$, $t = 8.4$). The scores, however, appeared to decline slightly for the third test ($M = -0.27$, $SD = 0.65$), though this was not statistically significant ($\Delta M = 0.03$, $t = 1.4$)¹. This pattern is not unexpected in studies of this type, where the pre- and post-tests occur within a relatively short period, and the longitudinal test is some considerable time after the post-test (Cohen, Manion & Morrison, 2011). The growth pattern also appeared to be influenced by grade level with differences occurring between Test 2 and Test 3. As shown in Figure 4, the 124 students in Grades 5 and 6 showed a slight increase between these tests, whereas the scores of the 285 students in Grades 8 and 9 fell slightly. Similar patterns have been shown in other studies across the middle years of schooling (e.g., Hill, Rowe, Holmes-Smith, & Russell, 1996).

<INSERT FIGURE 3 ABOUT HERE>

Figure 3. Distribution of SLK scores across three tests for younger and older students.

Next, the impact of the teacher on students' SLK scores was explored. PCK scores for the initial teacher, the one teaching the students for the period including Tests 1 and 2, ranged from -1.61 to 2.47 logits ($M = 0.25$, $SD = 0.78$). These were weakly correlated with the students SLK scores in Tests 1 ($r = 0.17$) and 2 ($r = 0.08$), but not in Test 3 ($r = 0$), suggesting a waning effect.

Given the large number of students who changed teacher between Tests 2 and 3, the effect due to this change was also considered. In particular, the results of students who did not change teachers were compared with those who changed to a teacher in the *StatSmart* project and with those who changed to a teacher not in the *StatSmart* project (see Table 4). As

¹ The 70 students who did four tests reported a non-significant increase of 0.05 logits on their last test.

is seen in the table, the students who changed to a non-*StatSmart* teacher tended to have a fall in results between Tests 2 and 3. Students who did not change teachers and those who changed to *StatSmart* teachers tended to experience gains. Those who did not change teacher started from a much lower mean result in their first test than the other two groups. This particular group tended to be younger ($M = 12.6$ yrs) than the other students ($M = 12.9$ yrs) and, as is seen in Figure 3, younger students tended to score lower in these tests than their older peers. They were also more likely to be in a primary school setting, where teachers may follow a class of students over more than one year. Continuing to be taught by a teacher who was involved with the project, however, appeared to have a positive influence on students' outcomes, and this finding is further considered in the Discussion.

Table 4.

Influence of changing teachers on students' SLK scores

Status	Mean/SD	Mean/SD	Mean/SD	N
	Test 1	Test 2	Test 3	
Changed to non-StatSmart teacher	-0.44/0.64	-0.18/0.56	-0.24/0.64	498
Changed to StatSmart teacher	-0.91/0.89	-0.54/0.75	-0.47/0.67	125
Did not change teacher	-0.52/0.66	-0.23/0.70	-0.20/0.62	166

Other teacher factors were also considered. Students taught by female teachers, for example, on average scored lower than students taught by male teachers in Test 1 ($\Delta M = 0.29$, $t = 6.3$), Test 2 ($\Delta M = 0.25$, $t = 5.8$), and Test 3 ($\Delta M = 0.22$, $t = 5.0$). Further, those students taught by teachers with tertiary level mathematics background performed better than those taught by less qualified teachers in each of Test 1 ($F = 20.6$, $p = 0.0$), Test 2 ($F = 18.0$, $p = 0.0$), and Test 3 ($F = 6.6$, $p = 0.0$). In both cases, however, the lower performing groups were likely to be younger students in primary settings.

One school level factor was also considered. The Indicator of Community Socio-Educational Advantage (ICSEA) measure (ACARA, 2012) was used to assess the impact of school level socio-economic status on students' SLK scores. The mean for ICSEA is set at 1000, and the schools in the study had ICSEA scores ranging from 912 to 1168. Correlations between this index and students' SLK scores were positively associated in each of Test 1 ($r = 0.27$), Test 2 ($r = 0.27$), and Test 3 ($r = 0.33$).

Multivariate analysis

Initially, an analysis of variance was conducted on the SLK results for each of the three tests against class and school groups. For Test1, results suggested that 15% of the variance could be attributed to between school effects, 28% to between class effects, and the remainder to between student effects. Similar results were obtained for the other tests, suggesting that grouping by classes and schools was desirable. As reported earlier, however, grouping by classes was not possible because most students changed teacher after Test 2, a situation common in the Australian context. Instead the change of teachers was modelled using a change teacher variable. Given the risk that standard errors may be overestimated, the a more stringent critical value of 1% was adopted, as recommended by Thomas (2001).

A random intercept model was applied to these data. The model assumes that at the individual student level, growth in statistical understanding is linear and expressed as:

$$Y_{tij} = \beta_{0ij} + \beta_1 t + \epsilon_{tij} \text{ ----- (1)}$$

where the errors (ϵ_{tij}) are assumed to be independent, distributed normally and with a common variance. Y_{tij} is the mathematics achievement of student i , from school j , at time t ($t = 0, 0.4, 1.4$, and for some 2.4 yrs). The initial status of student i from school j is denoted β_{0ij} and the model assumes that growth during the period of the study is the same² for each

²A random slopes model that allows different growth trajectories was also tested, but failed to converge.

student β_1 . The parameter β_{0ij} , however, is assumed to vary randomly across students within schools, in that

$$\beta_{0ij} = \gamma_{00j} + u_{0ij} \text{-----}(2)$$

where: γ_{00j} is the estimated initial mean score for all students attending school j , and u_{0ij} is the discrepancy between this and the initial score of student i in school j . The parameter γ_{00j} is assumed to vary randomly across schools, in that

$$\gamma_{00j} = \tau_{000} + u_j \text{-----}(3)$$

where: τ_{000} is the grand mean initial score for all students across all schools, and u_j the discrepancy between this grand mean and the mean for school j .

Equations (1), (2) and (3) above represent the unconditional model reported as Model 1 in Table 5. In line with recommendations from Dedrick et al. (2009) underlying assumptions of the model, including the absence of an autoregressive structure, were assessed and found to be satisfactory. As is seen in Table 3, the null model predicted that students' participation in the study for one year was associated with an increase in SLK of 0.14 logits.

In developing the final model, several factors were introduced in order to explain each of the variance components in the null model: the residual or within student variance, $var(\epsilon_{tij})$; the between student variance, $var(u_{0ij})$; and, the between school variance, $var(u_j)$. Changing teacher, for example, was found to be a significant predictor of SLK scores that reduced within student variance from 0.134 to 0.128 (5% reduction). Student level factors, including their standardised age when they completed Test 1 (*agez*), whether they spoke a language other than English (*NESB* = 1) and the standardised PCK score of their initial teacher (*PCKZ*) were significant predictors of SLK that reduced between student variance from 0.185 to 0.178 (6% reduction). Other teacher factors such as sex and

mathematical background did not predict SLK in the model. Finally the standardised ICSEA index (*ICSEAZ*) was found to be a significant predictor of SLK that reduced between school variance from 0.089 to 0.028 (69% reduction).

Given the results of the descriptive analysis, two interactions were then introduced into the model. The first was an interaction between PCK and time, in that the earlier analysis suggested a waning effect. The second was an interaction between commencement age in the project and time, in that results displayed in Figure 3 suggest that older students typically had greater initial scores than their younger peers but less steep growth trajectories. Both of these interactions were found to be significant predictors of SLK that improved model fit (based on a comparison of deviance test). The final model is shown as Model 2 in Table 5.

As is seen in Model 2 of Table 5, changing teacher to a *StatSmart* teacher (*chgtss* = 1) was not significantly different to not changing teachers at all. Changing teacher to a non-*StatSmart* teacher (*chgtms* = 1), however, was associated with a significant reduction in SLK scores ($\gamma = -0.14$). Student level factors, including their standardised age when they completed Test 1 (*agez*), whether they spoke a language other than English (*NESB* = 1), and the standardised PCK score of their initial teacher (*PCKZ*) were significant predictors of SLK that reduced between-student variance. Students with non-English speaking backgrounds, for example, were predicted to score 0.17 logits lower than their peers throughout the study. The model also suggests that teachers' initial PCK was associated with higher SLK scores ($\gamma = 0.07$), but that this association fell by 0.03 logits with each year that the student was in the study. The ICSEA index was found to be a significant predictor of SLK that reduced between school variance, in that students from schools with an ICSEA value one standard deviation higher than the mean were predicted to scores on average 0.23 logits higher than their peers.

Table 3.

Results of multilevel models

Variable	Model 1		Model 2	
	Estimate	SE	Estimate	SE
<i>Fixed effects</i>				
Initial mean SLK (γ_{00})	-0.44 ¹	0.08	-0.42	0.05
Time	0.14	0.01	0.20	0.02
chgtss			-0.06	0.04 ²
chgtns			-0.14	0.03
agez			0.16	0.02
NESB			-0.17	0.06
PCKZ			0.07	0.02
ICSEAZ			0.23	0.04
PCKZ * Time			-0.03	0.01
agez * Time			-0.05	0.01
<i>Random effects</i>				
Within student $var(\epsilon_{ti})$	0.134		0.128	
Between student $var(u_{0i})$	0.185		0.173	
Between school $var(u_{1i})$	0.089		0.028	
Model deviance	3354		3205	
Number of parameters	5		13	

¹ All effects are in logits.² This effect is not statistically significant. All others are significant at the 1% level.**Discussion**

In the final model a substantial part of the between-school variance was explained by socio-

economic factors represented by the school variable ICSEA. Age of the student at the first test and whether the student spoke a language other than English at home contributed substantially to between-student variance explained. These results are not surprising, and echo those from other studies (Hattie, 2008). Of particular interest, however, is the effect of the first teacher's measured pedagogical content knowledge (PCK). This variable had a significant effect on students' achievement, in line with other studies undertaken with elementary teachers (Hill et al., 2005), or with students nearing the end of high school (Baumert et al., 2010). The *StatSmart* study addressed the middle years of schooling, hence establishing that PCK is a key variable for considering teachers' impacts on their students' learning across the years of schooling. The PCK/time interaction term, however, was negative, suggesting a waning effect, in that the influence of good, or bad, teachers wanes as students progress through school. Intuitively, this finding seems sensible. It is the current teacher who is likely to have immediate impact but because of the nature of the study, modelling this effect proved impossible. The teacher's mathematical background, gender, and years of teaching experience had no significant impact on students' measured achievement, in line with other studies (e.g., Mewborn, 2001). Although this study was undertaken in the context of statistics education there is no reason to suppose that it would not apply in the mathematics domain more generally, given that statistics is taught within the mathematics curriculum.

StatSmart was able to track both students and their teachers across time. It proved difficult to find similar studies in which both student and teacher achievement data were available and linked together, other than the two referred to earlier (Hill et al., 2005; Baumert et al., 2010). Sustainability across time appears to be imperative at the teacher level. Effective schools are known to provide consistency for students as they move up the grade levels (Hill et al., 1996; Hill & Rowe, 1998). The finding that change to a non-*StatSmart* teacher, had a

negative effect on students' measured achievement is important. Much is made in the research literature of key transitions, such as the move from primary to secondary school, but there is little to identify other transitions.

The *StatSmart* study appears to indicate that moving from one teacher to another teacher having similar professional learning experiences, reduced any negative effects of transition. Rowan et al. (2002) argued that using students' individual growth trajectories tracked across at least three time points, as was done in this study, is preferable to using single achievement scores or gain scores. They also showed that when elementary students moved from class to class across years, the effect of changing teachers was inconsistent, with some students making gains and others not. The difficulties of establishing teacher effects across more than one class are well documented (e.g., Hill & Rowe, 1998), especially in systems where schools attempt to create classes each year that take account of individual student's needs, as is common in Australia. The finding reported here has potential implications for systems and schools. Although the identified teacher effects were small, they are educationally important. Teacher quality is likely to be more amenable to policy intervention than are the large effect variables of socio-economic status (ICSEA) and non-English speaking background (NESB) (Hattie, 2008).

Time in the program also had relatively large effect on students' SLK scores. Partly this is explained by increasing age and experience. The finding, however, has potential implications for both policy makers and schools when taken together with the changing teacher effects. Having a sustained focus by teachers who participated in professional learning for an extended period had a positive effect on their students' achievement in this study. Many professional learning programs are undertaken by schools or systems for short periods, in line with funding availability. The *StatSmart* project was a three-year program, and retained a majority of the original teachers for the whole period. These teachers were, by

their continued presence in the project, highly committed and during the three years made changes to their practice, and reported back on these at annual conferences. In addition, there was ongoing contact with the research team. Only rarely do projects such as *StatSmart* hold teachers over time, especially where the schools are “conscripted” into professional learning studies by the funding bodies (e.g., Author3, Brown, Beswick, & Wright, 2011). The implication is that education systems and schools need to make a long-term commitment to a particular program or approach to teaching, rather than commonly occurring situations where one-off professional learning is delivered by an expert through workshops disconnected from teachers’ classrooms.

The findings from this study must be considered in the light of the limitations imposed by the naturalistic setting. There are myriad uncontrolled variables that impact on students, in classes, in schools. These create considerable “noise” and unexplained variance in the data collected, and this is acknowledged. Nevertheless, the findings are similar to those of other studies conducted in more controlled conditions.

Conclusion

This study has indicated that teachers’ pedagogical content knowledge in statistics was associated with their students’ learning outcomes in different educational contexts to those reported in previous studies. In addition, the findings indicated that negative effects due to transitions to new teachers can be mitigated if the new teacher has similar professional learning experiences. With these two findings, the *StatSmart* study has added to the growing body of evidence that knowing the subject matter alone is not sufficient for positive teaching outcomes. It is the specialised way in which teachers understand their subject: that complex blend of subject matter knowledge, understanding of student learning, and school context, known as pedagogical content knowledge, that makes a difference, together with a sustained

focus on, in this instance, specific professional learning.

One next step is to consider whether particular groups of students, such as low achievers, benefit more than others. Another is to consider how the nature of PCK changes with levels of schooling, and the effects of different approaches to developing teachers' PCK. There is still much to be researched in the area of teacher knowledge and its influence on student outcomes.

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Figure 1

<h1>Coles Myer accelerates retail purge</h1>	<h2>Nationwide retail grocery market shares</h2> <table border="1"><thead><tr><th>Company</th><th>Market Share</th></tr></thead><tbody><tr><td>Other</td><td>61.2%</td></tr><tr><td>Woolworths*</td><td>28.5%</td></tr><tr><td>Coles</td><td>21.1%</td></tr><tr><td>Davids</td><td>13.3%</td></tr><tr><td>IHL</td><td>4.4%</td></tr></tbody></table> <p>Source: McLennan Magasanik Associates *(includes Safeways in Victoria)</p>	Company	Market Share	Other	61.2%	Woolworths*	28.5%	Coles	21.1%	Davids	13.3%	IHL	4.4%
Company	Market Share												
Other	61.2%												
Woolworths*	28.5%												
Coles	21.1%												
Davids	13.3%												
IHL	4.4%												
<p>What is the newspaper trying to tell its readers in this pie chart?</p> <p>Is there anything unusual about it?</p>													
<p>4.2a What responses would you expect from your students? Write down some appropriate and inappropriate responses (use * to show appropriate responses).</p> <p>4.2b How would/could you use this item in the classroom? For example, how would you intervene to address the inappropriate responses?</p>													

Figure 2

Consider the following problem that students were asked in a survey about chance and data:

The average number of children in 10 families in the neighbourhood is 2.3.
 One family with 5 children leaves the neighbourhood. What is the average number of children per family now?
 Show your work here.

Consider each of the following answers and explanations given by students in response to the problem.
Explain how you would respond to each answer.

5.3
 $2.3 \times 10 = 23 - 5 = 18 \div 10 = 1.8$

Code	Description
1	General response not involving the mathematics of the problem: “get student to explain thinking.”
2	Comment on number of families or equation structure (problem content only).
3	Questioning of student in relation to one of the issues: number of families <u>or</u> equation structure.
4	Sequencing of task with questions for student to complete.

5.4
 I don't know how many children in each family so how do you work it out?

Code	Description
0	Unsure how to proceed/no mathematics in response.
1	Single isolated question or suggested approach, e.g., discuss average and how to work out.
2	Extended explanation related to formulas involved.
3	Suggestions that go beyond the formula to model the problem.

Figure 3

