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Task-specific experience and task-specific talent: Decomposing the productivity of high school teachers

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ABSTRACT

We use administrative panel data to decompose worker performance into components relating to general talent, task-specific talent, general experience, and task-specific experience. We consider the context of high school teachers, in which tasks consist of teaching particular subjects in particular tracks. Using the timing of changes in the subjects and difficulty levels to which teachers are assigned to provide identifying variation, we show that a substantial part of the productivity gains to teacher experience are actually subject-specific. Similarly, while three-quarters of the variance in the permanent component of productivity among teachers is portable across subjects and levels, there exist non-trivial subject-specific and level-specific components. Counterfactual simulations suggest that maximizing the test-score contribution of task-specific experience and task-specific talent can increase student performance by as much as .04 test score standard deviations relative to random assignment of teachers to classrooms.

1. Introduction

How should principals allocate teachers to courses so as to maximize the teachers' contribution to student achievement?

The optimal course assignment depends on teachers' existing comparative advantages in different courses or classroom environments, as well as the extent to which current assignments will increase teachers' future productivity (or the principal's information about such productivity). However, the large literature on teacher value-added and the returns to teaching experience (discussed below) has focused primarily on estimating variation in teacher productivity that is assumed (or restricted) to be common to all course or grade assignments. If this assumption is true, then any allocation of existing teachers with fixed course loads will feature the same distribution of value-added contributions to achievement. However, if this assumption is false, then improving the mechanism by which teachers are assigned to courses may yield significant gains at potentially low cost (Jacob and Rockoff, 2011).

To see this, suppose first that teachers have pre-determined comparative advantages for particular subjects or difficulty levels. Then course swaps among teachers could produce efficiency gains if both teachers move toward their relatively more effective courses. Furthermore, if principals cannot ascertain teachers' relative strengths at the time of hire, then the optimal assignment strategy might involve rotating teachers across several different classroom contexts early in their careers so as to produce information about the courses the teachers will be particularly effective at teaching. Permanent subject-specific skill might exist, for example, if a teacher's choice of undergraduate major leads to a deeper understanding of the content in a particular subject (e.g. Physics rather than Biology). Permanent level-specific skill might exist, for example, if a teacher's natural charisma or sense of humor leads to strong classroom control skills that are comparatively more important in the remedial or basic level courses where students may tend to be less engaged.

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Now suppose instead that task-specific skill is primarily learned through experience rather than predetermined prior to the time of hire. Then rotating the classroom environments to which teachers are assigned will waste a component of each teacher's skill, and slow each teacher's progress toward his/her full potential. Subject-specific experience might be important, for example, if a teacher's knowledge of the subject content deepens with each opportunity to teach it. Track- or level-specific experience might also be significant if the appropriate pace at which to deliver content depends on student skill and is slowly calibrated with practice. In addition, experience teaching a certain subject–level combination (e.g. honors biology) might be particularly valuable if it allows teachers to hone particular lectures over time that would be inappropriate for either a different level or a different subject.

More generally, knowledge of the importance of task-specific talent and task-specific experience is essential for any employer wishing to maximize the productivity of his/her workforce. For tasks with larger potential experience gains and smaller variance in task-specific innate talent, the key to a productive workforce is employee retention: the optimal strategy is to keep employees of all talent levels at their originally assigned tasks to benefit from experience. Conversely, for tasks featuring smaller experience gains and a larger variance in task-specific talent, the optimal strategy is to lay off or reassign low performing workers in an attempt to either improve general worker skill or identify superior worker–task matches.

Thus, in this paper we introduce a method for decomposing worker productivity into components relating to general talent, task-specific talent, general experience, and task-specific experience. Our decomposition requires data featuring (1) signals (possibly noisy) of individual workers' task-specific output, (2) histories of worker task assignments, and (3) frequent rotation of workers across tasks. We implement our method using the context of high school teachers, in which tasks consist of teaching particular subjects in particular tracks (difficulty levels).[1]

Specifically, we use administrative panel data from the North Carolina Education Research Data Center (NCERDC) to decompose teacher effectiveness at improving student achievement into (1) a set of permanent components capturing general talent, subject-specific talent, level-specific talent, and subject–level specific talent, and (2) a set of functions capturing returns from general experience, subject-specific experience, level-specific experience, and subject–level-specific experience. The data track teachers and students in the universe of public high schools in North Carolina from 1997–2009. Critically, the data feature over 24,000 within-teacher changes in subject assignments and over 18,000 changes in academic-level assignments. Such rich data permit estimation of an education production function that features general, subject-specific, level-specific, and subject–level-specific experience profiles as well as a full set of school–teacher–subject–level fixed effects. The flexibility of our model allows us to control for many potential biases that might otherwise accompany endogenous course assignment decisions. We then use our results to project the potential student achievement gains that could be reaped by better utilizing knowledge about course-specific experience and skill relative to the course assignment patterns observed in the data.

Myriad papers have estimated education production functions featuring both teacher fixed effects and a common experience profile. The bulk of the evidence suggests that the standard deviation of permanent teacher quality is between .1 and .2 test score standard deviations at both the primary or secondary school levels.[2] Similarly, the existing literature suggests that while teachers tend to improve with experience by around .05 test score standard deviations in their first year, another .03 to .05 over the next couple of years, and another .03 to .05 over the next several years, with the profile for mid-career teachers flattening out at between .1 and .2 standard deviations better than a novice teacher.[3] More recent studies relax the functional form assumptions imposed in these early studies and find somewhat larger returns to high levels of teaching experience.[4]

However, this literature has generally ignored the possibility that the baseline effectiveness of a teacher and/or the gains to teaching experience might be specific to a particular classroom environment. In such a context, models that impose homogeneity of productivity across different classroom environments will return a weighted average of teacher productivity across the environments each teacher actually faced (weighted by the fraction of time spent in each environment). To the extent that teachers face different classroom contexts over their careers, models that impose homogeneity of returns to experience across different classroom environments may underestimate the gains to context-specific experience. Similarly, to the extent that teachers' classroom environments remain somewhat stable during their careers, such models may overestimate the returns to general experience.

A few papers, though, have addressed various aspects of the context-specificity of teacher productivity, mostly using elementary or middle school data. Jackson (2013) shows that a substantial portion of the variation in teacher contributions to student achievement is specific to the school in which a teacher has taught. Lockwood and McCaffrey (2009) and Aucejo (2011) examine the degree to which teachers have comparative advantages at teaching relatively high versus low ability students, and find evidence that a small component of teaching productivity is specific to student ability level. Perhaps more closely related to our paper is work by Ost (2014) showing that teachers who always repeat elementary grade assignments improve 35% faster than teachers who never repeat grade assignments. Similarly, Master et al. (2012) show that the efficacy of a teacher teaching English-language learners (ELL) depends on his/her experience teaching the ELL population. The paper most closely related to ours is Condie et al. (2014), who also consider subjects as tasks. They demonstrate the existence of meaningful comparative advantages of elementary teachers at teaching English vs. math. These papers, however, focus either on context-specific experience or context-specific skill, rather than providing a unified treatment of both factors.

Given the applicability of our methodology to the broader worker-to-task assignment problem, our paper also contributes to a growing literature on task-specific human capital, brought to the forefront by Gibbons and Waldman (2004), which considers the possibility that a considerable portion of a worker's human capital might be specific to the particular tasks the worker has performed at the jobs the worker has held.[5] Part of the literature on task-specific human capital either has assumed that only the experience component of human capital is task-specific (e.g. Clement et al., 2007, DeAngelo and Owens, 2012,

[1] Throughout the paper below, we use the term "task" to refer to a subject–level combination, while we use the term "context" more generally to refer to particular characteristics or features of the classroom environment, which include but are not limited to the subject and level.

[2] For primary school estimates, see, for example, Rockoff (2004), Hanushek et al. (2005), Clotfelter et al. (2006), Sass et al. (2014), Boyd et al. (2008), Jackson and Bruegmann (2009), Harris (2009), Harris and Sass (2011), and Jackson (2013). For secondary school estimates, see, for example, Aaronson et al. (2007), Jackson (2014), and Mansfield, 2015. Harris (2009), by contrast, finds little evidence of returns to experience using high school data from Florida.

[3] E.g. Rivkin et al. (2005), andClotfelter et al. (2007).

[4] Wiswall (2013) and Papay and Kraft (2015).

[5] See, for example, Yamaguchi (2012), Clement et al. (2007), Polataev and Robinson (2008), Gathmann and Schoenberg (2010), and DeAngelo and Owens (2012).