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Revisiting Dynamic Complementarity in the Production of Cognitive Skill and its Implications for a Cognitive Achievement Gap Decomposition

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Abstract

The literature shows evidence of dynamic complementarity in the production of cognitive skill. This means that skill attained at earlier stages increases the productivity of inputs occurring later in the life of children. For educational inputs, however, the relation between their productivity and prior cognitive achievement might not always be positive. If the input has a low cognitive demand, more advantaged students will not necessarily benefit from it, but it can be productive among less advantaged children. This is the first study to explore this possibility. I find evidence of heterogeneity in the relation between preschool cognitive achievement and the effect of primary school inputs in Peru. I find dynamic complementarity but only in the upper quintile of the school quality distribution. In the lower 20% of this distribution, a raise in preschool skill reduces the productivity of school inputs. I also propose a decomposition strategy that accounts for complementarity between preschool skill and school inputs. I use it to measure the contribution of school influences to the cognitive skill gap observed between urban and rural children in Peru. I obtain an estimate for this contribution (37%) larger than that found in previous studies that relied on a linear production function. An important implication of this is that one does not need to wait until urban and rural children share similar levels of preschool skill to exploit the equalizing potential of school influences. It is not "too late" for rural children currently at school, despite their preschool skill deficits.

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JEL codes: I24, O15, C18
Keywords: cognitive skill, dynamic complementarity, cognitive skill gap decomposition, Peru.

1. Introduction and motivation

Differences in developmental outcomes between children of dissimilar socioeconomic backgrounds are especially significant in the developing world (Grantham-McGregor et al., 2007; Walker et al., 2007). These differences or gaps emerge early in the life of children and tend to persist throughout their school years (Heckman, 2006, 2007; Paxson and Schady, 2007; Schady et al., 2014).

Peru is no exception to the presence of these early forms of inequality. Table 1 presents longitudinal evidence for a large sample of Peruvian children at ages 5 and 8.[1] As documented in other recent studies,[2] Table 1 confirms that gaps in cognitive development emerge before children enter school and exhibit little variation as they grow older and progress into primary education. Differences in test scores between the first and fourth quartile of the wealth distribution in the Young Lives sample are around 1.5 standard deviations at both 5 and 8 years of age. Interestingly, Table 1 also reveals that the urban/rural gap is very significant (amounting to, at least, 1 standard deviation) and remains practically unchanged between ages 5 and 8.

Cognitive skill formation is a cumulative process and, therefore, achievement gaps such as the one documented above must be understood as the result of the effects of all relevant influences on cognitive development until the time at which outcomes are measured. In principle, differences in initial endowments, early environments and influences exerted later both at home and at school can all play a role in shaping these gaps.

The fact that preschool gaps have a similar size than those observed later during primary education apparently suggests that school influences play only a subsidiary role, while differences in early childhood environments are much more important. In addition, previous studies using Peruvian data report results that tend to favour the role of household characteristics over that of school or community-level influences when decomposing cognitive achievement gaps between indigenous and non-indigenous children (Hernandez-Zavala et al. (2006), Arteaga and Glewwe (2014)).

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[1] This is based on the information collected for the younger cohort of the Young Lives Study in Peru. Young Lives is an international study of childhood poverty, following 12,000 children in 4 countries (Ethiopia, India, Peru and Vietnam) over 15 years. The first round was collected in year 2002. In Peru, it follows two cohorts of children: the younger cohort (aged 1 in 2002) and the older cohort (aged 8 in 2002). The Peruvian sample has a slight pro-poor bias as it excludes households belonging to the richest 5% of districts. Therefore, socioeconomic gradients must be even steeper than those reported in Table 1. Because excluded rich districts are only urban, the sample can be regarded as representative of the rural domain.

[2] Recent work by Schady et al. (2014) has documented socioeconomic gradients for cognitive development in five Latin American countries including Peru. They found steep wealth gradients in a common measure of cognitive development in all five countries, and confirmed that these gaps are well established by age three and remain practically invariant once children enter school.

Table 1
Peru: standardized PPVT scores[(a)] at 5 and 8 years of age by wealth quartile[(b)] and geographical domain

	No. of obs.	Mean		Difference[(c)]	
		5 year-olds	*8 year-olds*	*5 year-olds*	*8 year-olds*
A: Household wealth					
Q1	430	-0.78	0.95		
Q2	433	-0.34	1.53	0.44***	0.58***
Q3	433	0.33	2.09	1.11***	1.14***
Q4	421	0.81	2.34	1.6***	1.39***
B: Geographical domain					
Urban	1,234	0.30	2.02		
Rural	483	-0.76	0.97	1.05***	1.05***
All	**1,717**	**0.00**	**1.73**		

Source: Second and third round of data from the younger cohort of the Young Lives Study. The information was collected in years 2006 and 2009, respectively.
(a) PPVT scores refer to the result obtained in the Peabody Picture Vocabulary Test. This is a test for receptive vocabulary that has a Spanish version adapted for Latin America (Dunn et al., 1986). It is a widely used measure of cognitive achievement as it has a strong positive correlation with several measures of intelligence (Cueto and Leon, 2012). Raw scores were standardized using the mean and standard deviation obtained in round 2.
(b) Based on a wealth index comprising dwelling characteristics, access to basic services and durable goods consumption (Escobal et al., 2003).
(c) For household wealth, differences were computed with respect to the first quartile. For the geographical domain, the difference is urban minus rural.
Significance levels: *** p<0.01, ** p<0.05, * p<0.1

In Castro and Rolleston (2015) the authors employed a rich longitudinal dataset including cognitive test scores and household, family and school characteristics to decompose the cognitive achievement gap observed, at age 8, between urban and rural children in Peru. They found that observable school influences occurring between ages 6 and 8, account for a significant share (around 35% and no less than 28%) of the difference in cognitive skill. The share attributable to differences in the early childhood environment is important but no larger than 50%.

Castro and Rolleston (2015) proposed a novel decomposition strategy less prone to biases than those employed in previous studies. In particular, they classified covariates as school or home influences considering that some of these covariates have a direct effect on skill (are skill inputs) while others belong to the demand function of omitted inputs and these omitted inputs can be either from the school or the home environment. Their decomposition strategy, however, relied on the assumption of linearity of the production function of skill. This assumption is rather strong as it implies that all the inputs of skill are perfect substitutes.

One way to relax this assumption is by postulating that past cognitive achievement can influence the productivity of later inputs. This has already been addressed in the literature under the concept of dynamic complementarity (Cunha and Heckman, 2008; Cunha et al., 2010). These authors postulated and found evidence that skills produced earlier in the life of children, increase the productivity of parental investments occurring later. They assume, however, that there is no heterogeneity in this relationship. In other words, a rise in past cognitive achievement will always have a positive effect on the productivity of later inputs, independently of the nature of these later inputs. This is also a rather strong assumption as some inputs of skill can be effective to promote learning among low-skill children but not among more advantaged students. This can be true, for example, for student-teacher interactions or learning materials that have a low cognitive demand (e.g. a textbook that is fairly easy to read). In this case, an increase in the level of skill produced earlier in the life of children would no longer raise the productivity of this input and could even reduce it.

This analysis seeks to contribute to the literature on childhood development and education in two ways. First, it will explore the existence of heterogeneity in the relation between past cognitive achievement and the effect of primary school inputs. In particular, I will test whether a raise in the level of cognitive skill attained before entering school always raises the productivity of school inputs or if the relation between past cognitive achievement and the effect of school inputs depends on the level of these inputs.

Second, I will reassess the importance of school influences for the emergence of cognitive achievement gaps between urban and rural children after relaxing the assumption of linearity in the production function of skill. In particular, I will explore the consequences for a cognitive achievement gap decomposition of postulating that past cognitive achievement can influence the productivity of later inputs and that this relationship, in turn, can be heterogeneous.

The existence of complementarity between prior skill attainment and later inputs has already been analysed in the literature. This is, however, the first study to consider the implications of such complementarity in a decomposition exercise. Also, this is the first study to explore if such complementarity depends on the level of inputs involved.

The rest of the paper is organized as follows. Section 2 presents the analytical framework. I elaborate on the concept of dynamic complementarity and explain why there can be heterogeneity in the relation between past cognitive achievement and the effect of school inputs. Section 3 presents the empirical strategy. It explains how this heterogeneity will be tested. It also explains the decomposition categories including the one accounting for the relation between past cognitive achievement and school inputs. The results are presented and discussed in Section 4. Section 5 closes with some concluding remarks.

2. Analytical framework

This analysis will be based on the production function proposed in Castro and Rolleston (2015). Accordingly, I will divide the relevant phase of child development into two time periods. The first begins when the child is born and finishes at age 5, that is, when the child is ready to start the basic education cycle and enrol in primary school. The second period corresponds to the time when the child remains within primary school age. Consistent with the notion that skill formation is a cumulative process, I will assume that skill exhibited by child i at the end of period 2 (A_{i2}) is a function of contemporaneous and past direct influences affecting the child. Formally:

$$A_{i2} = A(H_{i2}, H_{i1}, S_{i2}, h_{i2}, h_{i1}, f_i, \mu_{i0}) \quad (1)$$

where H_{i1} are educational inputs provided during early childhood (period 1); H_{i2} are educational inputs provided at home during period 2; S_{i2} are educational inputs provided at the school where the child is enrolled during period 2; h_{it} indicates the child's health status during period t; f_i captures predetermined direct influences; and μ_{i0} is the child's innate ability.

As stressed in Glewwe and Miguel (2008), all the variables in the production function should affect skill directly, and all the variables with a direct effect should be included in this function. These variables will reflect the environment surrounding the child (characterizing activities, materials and individuals), as well as child characteristics that influence directly the acquisition of skill.

I further classify these direct influences as inputs (if they are determined by families' choices during the period under analysis) or as predetermined (if they are outside the current choice set of families). The arguments in this production function are similar to those prosed in Glewwe and Miguel (2008) except for the presence of f_i. This formulation, thus, allows for predetermined child and parental characteristics (e.g. parental education) to have a direct influence on skill.

We can also express the production function given in (1) as:

$$A_{i2} = A'(A_{i1}, H_{i2}, S_{i2}, h_{i2}, f_i, \mu_{i0}) \quad (2)$$

In (2), the effect of inputs and other predetermined direct influences that occurred in period one is subsumed in period one (or preschool) skill(A_{i1}). Todd and Wolpin (2003) discuss the assumptions required for (2) to be valid expression of (1) in its linear version. If fact, the underlying assumption is that the effect of all influences must decay at the rate given by the parameter associated to A_{i1} in the empirical version of (2).

Castro and Rolleston (2015) assumed that the production function can be expressed as a linear combination of inputs and predetermined direct influences. One way of relaxing this linearity assumption is to postulate that past cognitive achievement can affect the productivity of contemporaneous inputs. This is consistent with the concept of "dynamic complementarity" discussed in Cunha and Heckman (2008). According to these authors, the production function of skill exhibits dynamic complementarity when skills produced at one stage of the life cycle raise the potential effect of influences that occur in later stages (i.e. they increase the productivity of later inputs). In terms of the production function given in (2), this will imply that: $\frac{\partial^2 A_{i2}}{\partial S_{i2} \partial A_{i1}} > 0$.

It is reasonable to postulate that the effect of school inputs $\left(\frac{\partial A_{i2}}{\partial S_{i2}}\right)$ can depend on the level of skill that the child brings to school (A_{i1}). For example, the same textbook can have a different effect on learning depending on whether the child is or not highly skilled. The concept of dynamic complementarity analysed thus far in the literature postulates that more preschool skill will increase the productivity of the school input, independently of the nature of this input. In other words, all school inputs will have larger effects on more advantaged children.

Here, I propose to revisit this result based on the notion that learning occurs when there is a match between the skill of the student and the cognitive demand of the process or interaction expected to produce learning. Consider, for example, the pedagogical approach known as “Teaching at the Right Level”. This approach requires adapting the activities and materials used in class to the competency level of students. Evidence shows it is successful in improving learning outcomes (Banerjee et al., 2016).

An important implication of this is that a process with low cognitive demand can have no effect on highly skilled students but can produce learning among students of the same age but with a lower level of skill. By the same token, an increase in the level of skill that students bring to school will not necessarily raise the productivity of school inputs. It can have this positive effect on inputs with a sufficiently large cognitive demand. The effect, however, can be negative for those inputs with a low cognitive demand.

The above implies that there can be heterogeneity in the relation between preschool skill and the effect of school inputs. This heterogeneity, in turn, can depend on the nature of the school input under analysis and, in particular, on the level of cognitive demand that is involved in the application of the input. In terms of the production function given in (2), this heterogeneity can be represented as follows. If we assume that the level of cognitive demand involved in the interaction with the student is a positive function of the level of school input itself and we let $\frac{\partial A_{i2}}{\partial S_{i2}} = A'_S$, then:

$$\frac{\partial A'_S}{\partial A_{i1}} = f(S_{i2}) \tag{3}$$

$$f(S_{i2}) \begin{cases} \geq 0 \; if \; S_{i2} \geq S^* \\ < 0 \; if \; S_{i2} < S^* \end{cases} \tag{4}$$

This means that the effect of preschool skill on the productivity of the school input depends on the level of this school input, and that this effect can be positive or negative depending on whether the level of school input is above a threshold (S^*) or not.

3. Empirical strategy

3.1 The marginal effect of school inputs

A common linear version of (2) is what the literature describes as the “value added model” (Andrabi et al., 2011; Todd and Wolpin, 2003). If we assume that skills are measured with random error through test scores T_{it} ($T_{it} = A_{it} + \varepsilon_{it}; E(\varepsilon_{it}) = 0, Cov(A_{it}, \varepsilon_{it}) = 0; t = 1,2$), we can express the value added model as follows:

$$T_{i2} = \rho T_{i1} + H'_{i2}\gamma + S_{i2}\phi + h_{i2}\varphi + f_i'\lambda + e_i \tag{5}$$

where $e_i = \mu_{i0}\beta + \varepsilon_{i2} - \rho\varepsilon_{i1}$. It is possible to extend this specification to include exogenous input determinants (z_i). Variables contained in vector z_i express family resources and preferences, and differences in prices and the availability of goods and services. The result can be classified as a "value added hybrid model". Formally:

$$T_{i2} = \rho T_{i1} + H_{i2}'\gamma + S_{i2}\phi + h_{i2}\varphi + f_i'\pi + z_i'\psi + e_i^H \tag{6}$$

As discussed by Castro and Rolleston (2015) and Castro (2015), exogenous input determinants such as family income or the number of siblings can have a role in the estimation of production function parameters insofar they are controlling for the presence of omitted inputs. In fact, if we assume that the demand function of omitted inputs can be expressed as a linear function of its determinants, the inclusion of these variables in (6) implies that one has replaced the omitted inputs by their corresponding demand functions.[3] This is a fairly common strategy in the literature to try to circumvent omitted variable biases. The implications of this strategy for a decomposition exercise, however, have been addressed only recently in Castro (2015) and will be briefly discussed in the next section.

The presence of innate ability in the error terms of (5) and (6) can complicate the identification of production function parameters, including the one capturing the effect of school inputs (ϕ). Even in a value added model such as (5), it is reasonable to assume that at least a fraction of the effect of innate ability persists and might correlate with observed inputs (Andrabi et al., 2011). The relevant question, thus, is how problematic is this for the estimation of production function parameters.

In this regard, empirical results presented in several recent studies corroborate that value added models can provide reliable estimates of the individual effects of skill inputs. These studies are reviewed in Singh (2015). They show that value added models such as the one presented in (5) outperform other empirical strategies when recovering teacher effects from simulated data (Guarino et al., 2012), and provide the same results as experimental and quasi-experimental methods used to identify school or teacher effects (Deming et al. (2014) Kane et al. (2013), among others). Moreover, value added estimates given in Singh (2015) for the effect of private school enrolment on the achievement of rural children were also found to be similar to the results provided by an experimental exercise carried out in the same region of India (Muralidharan and Sundararaman, 2013). Also, Andrabi et al. (2011) found that OLS estimates of the private-school skill premium in Pakistan provided by a valued added model turned out similar to those obtained after using item response theory and dynamic panel data methods to mitigate the effects of measurement error and observed innate ability, respectively. All these results indicate that lagged achievement is a sufficient statistic to control for assignment mechanisms that correlate with innate ability.

In what follows, I will use the two value added specifications given in (5) and (6) and check the robustness of results to the inclusion of exogenous input determinants. Importantly, to relax the linearity assumption, I will introduce three additional variables: (i) the square of school inputs (S_{i2}^2); (ii) an interaction term between preschool skill scores and school inputs $(S_{i2}T_{i1})$; and (iii) and interaction term between preschool skill scores and the square of school inputs $(S_{i2}^2 T_{i1})$. Formally:

[3] Notice that the parameters accompanying predetermined direct influences (f_i) are different in (8) than in (7). This is because the demand function of omitted inputs also includes these predetermined influences. See Glewwe and Miguel (2008) for a comprehensive discussion about input demand functions.

$$T_{i2} = \rho T_{i1} + H_{i2}'\gamma + \phi_1 S_{i2} + \phi_2 S_{i2}^2 + \phi_3 S_{i2} T_{i1} + \phi_4 S_{i2}^2 T_{i1} + h_{i2}\varphi + f_i{}'\lambda + e_i \quad (7)$$

And for the value added hybrid model:

$$T_{i2} = \rho T_{i1} + H_{i2}'\gamma + \phi_1 S_{i2} + \phi_2 S_{i2}^2 + \phi_3 S_{i2} T_{i1} + \phi_4 S_{i2}^2 T_{i1} + h_{i2}\varphi + f_i{}'\pi + z_i'\psi + e_i^H \quad (8)$$

Notice that a single interaction term between preschool skill and school inputs would suffice to test for dynamic complementarity. There would be evidence of dynamic complementarity if the parameter associated to this interaction turns out to be positive. The formulation proposed above includes two additional terms that involve S_{i2}^2. This allows for the effect of school inputs to depend on their level (i.e. it allows for increasing or decreasing returns in school inputs). Importantly, this also allows for the effect of preschool skill on the productivity of school inputs to depend on the level of school inputs. The latter is what I described in Section 2 as heterogeneity in the relation between preschool skill and the effect of school inputs.

To see this, notice that the effect of school inputs in (7) and (8) is given by: $\frac{\partial T_{i2}}{\partial S_{i2}} = \phi_1 + 2\phi_2 S_{i2} + \phi_3 T_{i1} + 2\phi_4 T_{i1} S_{i2}$. In this formulation, we can talk about dynamic complementarity if $\frac{\partial^2 T_{i2}}{\partial S_{i2} \partial T_{i1}} = \phi_3 + 2\phi_4 S_{i2} > 0$. If $\phi_4 \neq 0$, we can further say that this complementarity is heterogeneous and depends on the level of school inputs. Also notice that if $\phi_3 < 0$ and $\phi_4 > 0$, there can be a sufficiently low value of S_{i2} for which $\frac{\partial^2 T_{i2}}{\partial S_{i2} \partial T_{i1}} < 0$ and a sufficiently large value of S_{i2} for which $\frac{\partial^2 T_{i2}}{\partial S_{i2} \partial T_{i1}} > 0$. This type of result is consistent with the discussion presented in Section 2 regarding the sources of heterogeneity in the relationship between the productivity of school inputs and the level of preschool skill. In particular, that school inputs with low cognitive demand can be less productive among highly skilled children (or more productive among children with less skill) whereas school inputs that involve a large cognitive demand can be more productive among highly skilled children.

Finally, it is also worth noticing that the returns to school inputs are not constant if $\frac{\partial^2 T_{i2}}{\partial S_{i2}^2} = 2\phi_2 + 2\phi_4 T_{i1} \neq 0$.

3.2 The decomposition exercise

The objective of the decomposition exercise is to measure the importance of influences that occurred at school for the cognitive achievement gap observed, at age 8, between urban and rural children in Peru.

Consistent with this objective and the type of inputs considered in the production function given in (2) above, the categories involved in the decomposition should measure the contribution of past influences captured in the measure of preschool skill (T_{i1}), period 2 home inputs (H_{i2}), school inputs (S_{i2}), period 2 health inputs (h_{i2}) and predetermined direct influences (f_i).

Two additional elements are present in this analysis besides the categories listed above. First, the empirical version of the value added model can also include exogenous input determinants to control for omitted inputs (as in (6) above). Second, the complete empirical specifications given in (7) and (8) include three interaction terms that involve variables that belong to the “school inputs” and “past influences” categories.

Castro and Rolleston (2015) and Castro (2015) have already explored the implications of controlling for input determinants in a decomposition exercise. The main implication is that one should be careful when assigning the contribution of exogenous input determinants to a particular family or category on inputs, as these variables can be controlling for omitted inputs that belong to more than one category.

For example, family income can be a valid argument in the demand function of inputs provided both at home and at school. Therefore, if one seeks to measure the relative importance of influences occurring at home and school, family income should not be assigned to either of these categories unless one is willing to make strong assumption about the nature of omitted inputs. Castro and Rolleston (2015) propose to group these input determinants into a special decomposition category hosting omitted inputs to avoid making these strong assumptions. In the analysis that follows, I will use this strategy and group all exogenous input determinants into a special category hosting omitted inputs.

The idea behind the decomposition is that each category should reflect the contribution of a particular type of input to the urban-rural gap in cognitive skill. Table 2 presents the different categories associated to each empirical specification. The expression given in row (1), for example, reflects the contribution of period 2 home inputs to the urban-rural gap. This is given by the difference in mean values of home inputs between the urban and rural domain (upper bars denote sample means) weighted by the coefficients of these inputs in the production function.

Interactions between school quality and past skill, however, contain variables that belong to two different categories: “school inputs” and “past influences”. Urban-rural differences in these interactions, therefore, belong to both categories. In Table 2, I propose a way of isolating the contribution of these two categories from the marginal contribution caused by introducing changes in both of them simultaneously. Row (3) captures de contribution of differences in school inputs only. Row (6) captures the contribution of differences in past influences only.

These contributions can be understood as the fraction of the urban-rural gap that would be closed if rural school inputs or rural past influences were equated to the school inputs or past influences present in the urban domain, respectively. The fraction of the gap that would be closed if school inputs *and* past influences were equalized between the rural and urban domain is given by the sum of rows (3), (6) and (7). Therefore, the category labelled “Interactions” (row 7) captures the marginal or additional gain obtained due to the complementarity between school inputs and past influences.

Table 2
Categories related to each empirical specification and their contribution to the urban-rural gap in cognitive skill

Category	Value added	Value added hybrid
(1) Period 2 home inputs	$(\bar{H}_U - \bar{H}_R)'\hat{\gamma}$	$(\bar{H}_U - \bar{H}_R)'\hat{\gamma}$
(2) Period 2 health inputs	$(\bar{h}_U - \bar{h}_R)'\hat{\gamma}$	$(\bar{h}_U - \bar{h}_R)'\hat{\gamma}$
(3) School inputs only	$(\bar{S}_U - \bar{S}_R)\hat{\phi}_1 + (\overline{S_U^2} - \overline{S_R^2})\hat{\phi}_2 + (\bar{S}_U\bar{T}_R - \bar{S}_R\bar{T}_R)\hat{\phi}_3$ $+ (\overline{S_U^2}\bar{T}_R - \overline{S_R^2}\bar{T}_R)\hat{\phi}_4$ $= (\bar{S}_U - \bar{S}_R)(\hat{\phi}_1 + \bar{T}_R\hat{\phi}_3)$ $+ (\overline{S_U^2} - \overline{S_R^2})(\hat{\phi}_2 + \bar{T}_R\hat{\phi}_4)$	$(\bar{S}_U - \bar{S}_R)\hat{\phi}_1 + (\overline{S_U^2} - \overline{S_R^2})\hat{\phi}_2 + (\bar{S}_U\bar{T}_R - \bar{S}_R\bar{T}_R)\hat{\phi}_3$ $+ (\overline{S_U^2}\bar{T}_R - \overline{S_R^2}\bar{T}_R)\hat{\phi}_4$ $= (\bar{S}_U - \bar{S}_R)(\hat{\phi}_1 + \bar{T}_R\hat{\phi}_3)$ $+ (\overline{S_U^2} - \overline{S_R^2})(\hat{\phi}_2 + \bar{T}_R\hat{\phi}_4)$
(4) Predetermined direct influences	$(\bar{f}_U - \bar{f}_R)'\hat{\lambda}$	--
(5) Predetermined direct influences and omitted inputs	--	$(\bar{f}_U - \bar{f}_R)'\hat{\pi} + (\bar{z}_U - \bar{z}_R)'\hat{\psi}$
(6) Past influences only	$(\bar{T}_U - \bar{T}_R)\hat{\rho} + (\bar{S}_R\bar{T}_U - \bar{S}_R\bar{T}_R)\hat{\phi}_3 + (\overline{S_R^2}\bar{T}_U - \overline{S_R^2}\bar{T}_R)\hat{\phi}_4$ $= (\bar{T}_U - \bar{T}_R)(\hat{\rho} + \bar{S}_R\hat{\phi}_3 + \overline{S_R^2}\hat{\phi}_4)$	$(\bar{T}_U - \bar{T}_R)\hat{\rho} + (\bar{S}_R\bar{T}_U - \bar{S}_R\bar{T}_R)\hat{\phi}_3 + (\overline{S_R^2}\bar{T}_U - \overline{S_R^2}\bar{T}_R)\hat{\phi}_4$ $= (\bar{T}_U - \bar{T}_R)(\hat{\rho} + \bar{S}_R\hat{\phi}_3 + \overline{S_R^2}\hat{\phi}_4)$
(7) Interactions	$(\overline{ST}_U - \overline{ST}_R)\hat{\phi}_3 + (\overline{S^2T}_U - \overline{S^2T}_R)\hat{\phi}_4$ $-(\bar{S}_U\bar{T}_R - \bar{S}_R\bar{T}_R)\hat{\phi}_3 - (\overline{S_U^2}\bar{T}_R - \overline{S_R^2}\bar{T}_R)\hat{\phi}_4$ $-(\bar{S}_R\bar{T}_U - \bar{S}_R\bar{T}_R)\hat{\phi}_3 - (\overline{S_R^2}\bar{T}_U - \overline{S_R^2}\bar{T}_R)\hat{\phi}_4$	$(\overline{ST}_U - \overline{ST}_R)\hat{\phi}_3 + (\overline{S^2T}_U - \overline{S^2T}_R)\hat{\phi}_4$ $-(\bar{S}_U\bar{T}_R - \bar{S}_R\bar{T}_R)\hat{\phi}_3 - (\overline{S_U^2}\bar{T}_R - \overline{S_R^2}\bar{T}_R)\hat{\phi}_4$ $-(\bar{S}_R\bar{T}_U - \bar{S}_R\bar{T}_R)\hat{\phi}_3 - (\overline{S_R^2}\bar{T}_U - \overline{S_R^2}\bar{T}_R)\hat{\phi}_4$

3.3 Data sources and variables

This analysis uses the Peruvian dataset of the Young Lives Study. Young Lives is an international study of childhood poverty, following 12,000 children in 4 countries (Ethiopia, India, Peru and Vietnam) over 15 years. The analysis considers the first three rounds of the child and household surveys, as well as the school survey, focusing on the Younger Cohort. Table 3 summarizes the basic structure of these data.

Table 3
Time-structure and sample sizes of the relevant Young Lives databases

	Child and household survey			*School Survey 2011*
	Round 1 2002	*Round 2 2006*	*Round 3 2009*	
Younger cohort's age (years)	1 (0.5-1.5)	5 (4.5-5.5)	8 (7.5-8.5)	10 (9.5-10.5)
Sample size (children)	2,052	1,963	1,943	572 (132 schools)
Educational attainment	--	Preschool	Grade 2	Grade 5

Source: Young Lives Study (Peru).

All the information was merged into a single dataset at the child level. Children included in the sample used for this analysis as those that report cognitive skill scores for rounds 2 and 3 and were attending one of the schools school included in the school survey.[4] This produced a sample of 454 children.

Consistent with the analytical framework described above, period 1 variables will correspond to influences relevant from birth up to age 5, and period 2 variables will correspond to influences relevant between the ages of 5 and 8. Accordingly, period 1 variables will be provided by rounds 1 and 2, while period 2 variables will be provided by round 3. School inputs captured in the school survey will be assumed to be the same as those present in period 2. As is Castro and Rolleston (2015), I am assuming that school characteristics have not changed significantly between 2009 and 2011, and that the child has remained in the same school since her enrolment in Grade 1 (at age 6) until the school survey was conducted (when she was 10 years old).[5]

The cognitive skill measures used in this analysis are the scores obtained in the Peabody Picture Vocabulary Test (PPVT). This is a widely used test of receptive vocabulary that has a strong positive correlation with several measures of intelligence (Cueto and Leon, 2012) and has a Spanish version adapted for Latin America (Dunn et al., 1986).

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[4] The risk of selection bias due to this second condition is very small. Primary school attendance in Peru is close to 100% (only 0.7% of Young Lives younger cohort children were not attending school in Round 3). In addition, schools participating in the school survey were randomly selected within the four strata considered by the designers of the survey (urban-private, urban-public, rural-public, rural-bilingual-public; see Guerrero et al. (2012)).

[5] According to administrative data collected from the schools included in the survey, school switching is not significant. On average, only 2% of students enrolled in primary education changed school each year between 2009 and 2010.

The specific variables considered to reflect home inputs, health inputs, predetermined direct influences and input determinants are the same as those used in Castro and Rolleston (2015). The reader can refer to these authors for a detailed description. Table 4 presents the variables considered within each category, their source and their basic descriptive statistics including the urban/rural gap present in the sample relevant for this analysis.

Different from Castro and Rolleston (2015), here I use a single variable to reflect the school inputs captured in the school survey. Having a single measure is important because I am interested in testing if the return to school inputs, in general, depends on preschool skill and if this, in turn, depends on the level of school inputs. This single variable corresponds to the first principal component of a set of 29 indicators reflecting school: (i) size, organization and timetable; (ii) infrastructure; (iii) climate; (iv) activities and materials; and (v) teacher characteristics. Appendix 1 presents the list of variables considered within each dimension of school quality. See Guerrero et al. (2012) for a detailed discussion of these dimensions.

Table 4
Description of the variables used in the empirical specifications

Variable type	Variable used in empirical specifications	Source	Mean	SD	Urban	Rural	Diff.
Period 1 measured cognitive skill (T_{i1})	Standardized raw PPVT score	Round 2	1.780	0.951	2.095	1.028	1.067*** (0.14)
Period 2 measured cognitive skill (T_{i2})	Standardized raw PPVT score[a]	Round 3	0.024	0.968	0.355	-0.766	1.121*** (0.13)
Period 2 educational home inputs (H_{i2})	Real expenditure on child (learning materials and entertainment; x1,000 soles; 2006 prices in urban Lima)	Round 3	0.432	0.572	0.517	0.230	0.287*** (0.063)
	Household had books and child was encouraged to read (yes = 1)	Round 3	0.450	0.498	0.478	0.382	0.096 (0.06)
	Household had a computer (yes = 1)	Round 3	0.140	0.347	0.195	0.007	0.188*** (0.039)
	Child received help from parents when doing homework (yes = 1)	Round 3	0.665	0.472	0.758	0.444	0.314*** (0.029)
	Hours in a typical day the child spent playing [b]	Round 3	4.346	1.517	4.488	4.005	0.483** (0.218)
	Hours in a typical day the child spent sleeping	Round 3	9.931	0.978	9.988	9.796	0.192 (0.114)
	Hours in a typical day the child spent studying	Round 3	1.945	0.834	2.120	1.526	0.594*** (0.078)
Period 2 health input (h_{i2})	Child was stunted (yes = 1) [c]	Round 3	0.189	0.392	0.120	0.354	-0.235*** (0.041)
School environment	Years of schooling	Round 3	2.374	0.544	2.429	2.243	0.186** (0.085)
	Hours in a typical day the child spent at school	Round 3	6.171	0.720	6.131	6.269	-0.138 (0.108)
	School inputs [d] (S_{i2})	School survey	0.000	2.656	1.008	-2.472	3.480*** (0. 218)

Variable type	Variable used in empirical specifications	Source	Mean	SD	Urban	Rural	Diff.
Predetermined direct influences (f_i)	Child's caregiver has higher education (yes = 1)	Round 3	0.179	0.383	0.245	0.021	0.224*** (0.037)
	Caregiver's age	Round 3	34.569	6.843	34.172	35.514	-1.342 (0.804)
	Child is male (yes = 1)	Round 3	0.478	0.500	0.490	0.451	0.038 (0.048)
	Child's mother tongue is Spanish (yes = 1)	Round 3	0.893	0.309	0.985	0.674	0.312** (0.104)
	Child's age in months	Round 3	96.510	3.708	96.500	96.537	-0.037 (0.507)
Exogenous input determinants (z_i)	Child lived in urban area (yes = 1)	Round 3	0.704	0.457	1.000	0.000	1.000
	Average household total income (x10,000 soles; 2006 prices in urban Lima)	Rounds 2 and 3	1.512	1.116	1.711	1.037	0.674*** (0.111)
	Average household size	Rounds 1, 2 and 3	5.538	1.849	5.270	6.176	-0.906** (0.306)
	Proportion of male siblings	Rounds 1, 2 and 3	0.495	0.333	0.490	0.506	-0.016 (0.026)
	Child birth order	Rounds 1, 2 and 3	2.475	1.584	2.194	3.144	-0.949*** (0.198)
	Caregiver aspiration for child's educational attainment was university education (yes=1)	Rounds 2 and 3	0.655	0.476	0.743	0.444	0.299*** (0.065)

(a) Round 3 and round 2 raw PPVT scores were standardized using the round 2 mean and standard deviation.
(b) The effects of children's time use categories are measured with respect to time spent working (the omitted time use category).
(c) A child is considered stunted if she exhibits a height for age z score below -2.
(d) First principal component of a set of 29 indicators reflecting school: (i) size, organization and timetable; (ii) infrastructure; (iii) climate; (iv) activities and materials; (v) teacher characteristics; and (vi) responsiveness.
The number of observations is 454 for all variables.
Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

4. Results

Table 5 shows OLS estimates of the value added and value added hybrid models given in (7) and (8). Coefficient values for the parameters of interest (i.e. those related to the variables reflecting school inputs and preschool skill) are fairly robust between specifications. This can be interpreted as evidence that there are no omitted inputs in the valued added model and is consistent with the empirical evidence surveyed above and showing that a value added specification can provide a fairly reliable estimate of production function parameters.

Table 5
Regression results

VARIABLES	**(1) Value added**	**(2) Value added hybrid**
Preschool skill (R2 standardized raw PPVT score)	**0.306*** (0.031)**	**0.274*** (0.038)**
Household has books and child is encouraged to read (R3)	0.244*** (0.072)	0.241*** (0.072)
Household has computer (R3)	0.082 (0.054)	0.058 (0.063)
Real expenditure on child (education, entertainment) (R3)	0.064 (0.057)	0.054 (0.052)
Child received help from parents when doing homework (R3)	0.047 (0.108)	-0.026 (0.107)
Hours in a typical day the child spent playing (R3)	-0.007 (0.023)	-0.014 (0.021)
Hours in a typical day the child spent sleeping (R3)	-0.038 (0.034)	-0.053 (0.035)
Hours in a typical day the child spent studying (R3)	0.064 (0.046)	0.035 (0.051)
Child stunted (R3)	-0.181** (0.079)	-0.174* (0.084)
Hours in a typical day spent at school (R3)	-0.063 (0.041)	-0.071 (0.044)
Years of schooling (R3)	0.259*** (0.068)	0.261*** (0.074)
School inputs	**0.042* (0.022)**	**0.033 (0.026)**
School inputs squared	**-0.008 (0.007)**	**-0.007 (0.007)**
Interaction: preschool skill and school inputs	**-0.022 (0.018)**	**-0.021 (0.020)**
Interaction: preschool skill and school inputs squared	**0.015*** (0.004)**	**0.018*** (0.005)**
Child's caregiver has higher education	0.086 (0.064)	0.032 (0.070)
Caregiver's age	-0.000 (0.005)	0.011* (0.006)

VARIABLES	(1) Value added	(2) Value added hybrid
Child is male	-0.049	0.038
	(0.046)	(0.089)
Child's mother tongue is Spanish	0.213	0.271
	(0.167)	(0.161)
Child age in months	0.004	0.004
	(0.010)	(0.009)
Child lived in urban area (R3)		0.076
		(0.083)
Average total income (Lima 2006 prices)		0.016
		(0.027)
Average household size		0.014
		(0.025)
Proportion of male siblings		-0.168
		(0.159)
Child birth order		-0.096**
		(0.037)
Caregiver aspiration for child is university education		-0.027
		(0.060)
Constant	1.265	1.328
	(1.148)	(1.066)
Observations	454	453
R-squared	0.583	0.599

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notice that the estimate of the parameter accompanying the interaction between preschool skill and the square of school inputs (ϕ_4) is positive and significant in both specifications. As discussed above, this is evidence of heterogeneity in the relation between the effect of school inputs and preschool skill. In particular, the level of school inputs has a positive effect on the degree of complementarity between preschool skill and school inputs. To measure the marginal effect of school inputs and preschool skill scores we can evaluate the mean value of the corresponding partial derivatives. These are presented in Table 6.

Table 6
Marginal effects at the mean value of preschool skill and school inputs

	VA			VA hybrid		
	Point estimate	**Confidence interval**		**Point estimate**	**Confidence interval**	
Average effect of school inputs $\left\|\frac{\partial T_{i2}}{\partial S_{i2}}\right\|_{S_{i2}=\bar{S}_2, T_{i1}=\bar{T}_1}$	0.04*	0.00	0.08	0.03	-0.02	0.08
Average effect of preschool skill $\left\|\frac{\partial T_{i2}}{\partial T_{i1}}\right\|_{S_{i2}=\bar{S}_2}$	0.31***	0.24	0.37	0.27***	0.20	0.35
Effect of preschool skill on the effect of school inputs (dynamic complementarity) $\left\|\frac{\partial^2 T_{i2}}{\partial S_{i2}\partial T_{i1}}\right\|_{S_{i2}=\bar{S}_2}$	-0.02	-0.05	0.01	-0.02	-0.06	0.02
Effect of school inputs on the effect of school inputs $\left\|\frac{\partial^2 T_{i2}}{\partial S_{i2}^2}\right\|_{T_{i1}=\bar{T}_1}$	-0.01	-0.04	0.02	-0.01	-0.04	0.02
Effect of school inputs on the relationship between preschool skill and the effect of school inputs $\left\|\frac{\partial^2 T_{i2}}{\partial S_{i2}^2 \partial T_{i1}}\right\|$	0.03***	0.01	0.05	0.04***	0.02	0.06

Three important results are worth highlighting from Table 6. First, the effect of an increase in school inputs in the average school on the cognitive skill of the average child is marginally significant and around 0.04 standard deviations. Second, there is no evidence of dynamic complementarity in the average school. Third, as already noted, school inputs appear to have a positive effect on the degree of complementarity between preschool skill and school inputs.

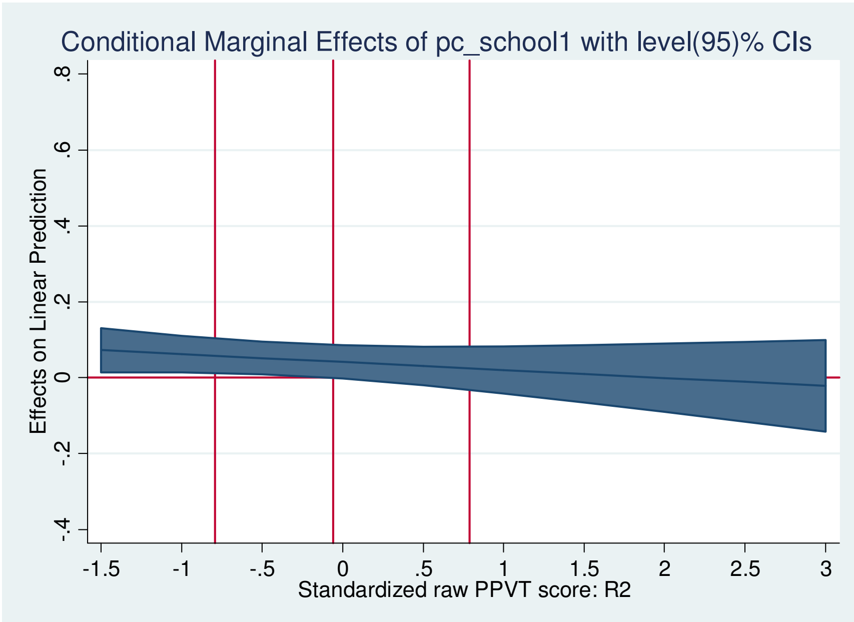
I further explore the relationship between school inputs and dynamic complementarity by plotting the relation between the effect of school inputs and preschool skill for different levels of school inputs. This corresponds to evaluating dynamic complementarity $\left(\frac{\partial^2 T_{i2}}{\partial S_{i2}\partial T_{i1}}\right)$ at different levels of school inputs. I use the results of the value added hybrid model. Table 6 shows there is no dynamic complementarity in the average school. Because the estimate of parameter ϕ_4 is positive, however, one should expect more school quality to increase the degree of complementarity.

Figure 1 plots the relation between the effect of school inputs and preschool skill scores for the average level of school inputs. Figures 2 and 3 plot the same relation but in the first and fifth quintile of the school inputs distribution, respectively. The slopes of the functions depicted in these figures reflect the sign and degree of complementarity between preschool skill and school inputs. Consistent with the results presented in Table 6, the slope in Figure 1 is practically zero, denoting no evidence of complementarity. Interestingly, figures 2 and 3 not only exhibit significant slopes but also relations with opposite signs. In the first quintile of the school inputs distribution (see Figure 2), an increase of one standard deviation in preschool skill reduces the effect of school inputs in 0.1 standard deviations. Figure 2 also reveals that in a low quality school, an increase in school inputs will only have a positive effect among children in the bottom half of the preschool skill distribution.

Results are quite different in the upper quintile of the school inputs distribution. According to the results shown in Figure 3, there is complementarity between preschool skill and school inputs in a high quality school. An increase of one standard deviation in preschool skill will raise the effect of school inputs in 0.13 standard deviations. Contrary to what happens in a low quality school, in the upper quintile of the school inputs distribution, a raise in school inputs will only benefit children in the upper 25% of the preschool skill distribution.

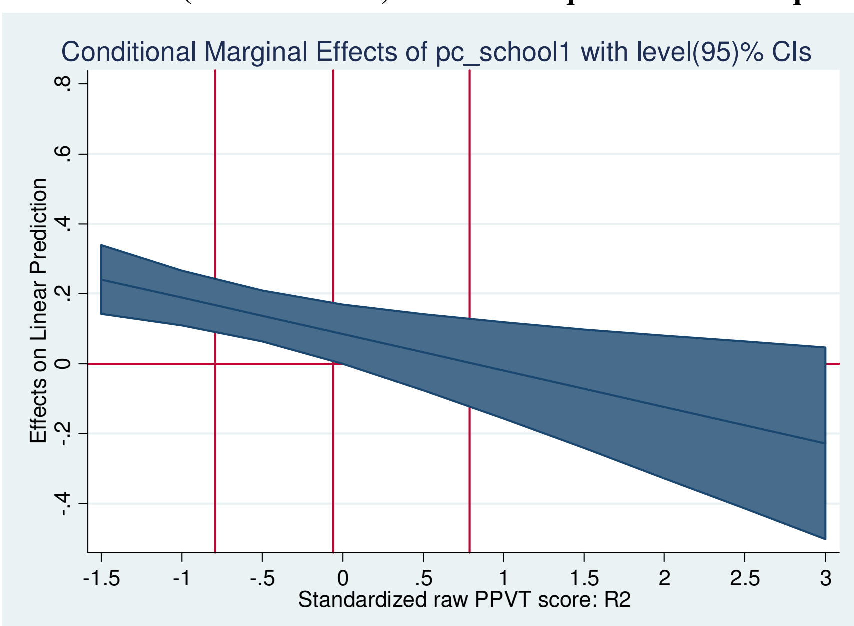
These results confirm the existence of heterogeneity in the relation between preschool skill and the effect of school inputs. In addition, this heterogeneity appears driven by the level of school inputs in a way that is consistent with the hypothesis presented in Section 2. In particular, that increases in school inputs in low quality schools carry a low cognitive demand so they will only benefit less advantaged children and an increase in preschool skill will lower their effect. On the contrary, in high quality schools, increases in school inputs carry a large cognitive demand. Therefore, they will only benefit highly skilled children and increases in preschool skill will raise their effect.

Figure 1
Relation between the effect of school inputs on cognitive skill (vertical axis) and preschool skill (horizontal axis) at the average level of school quality



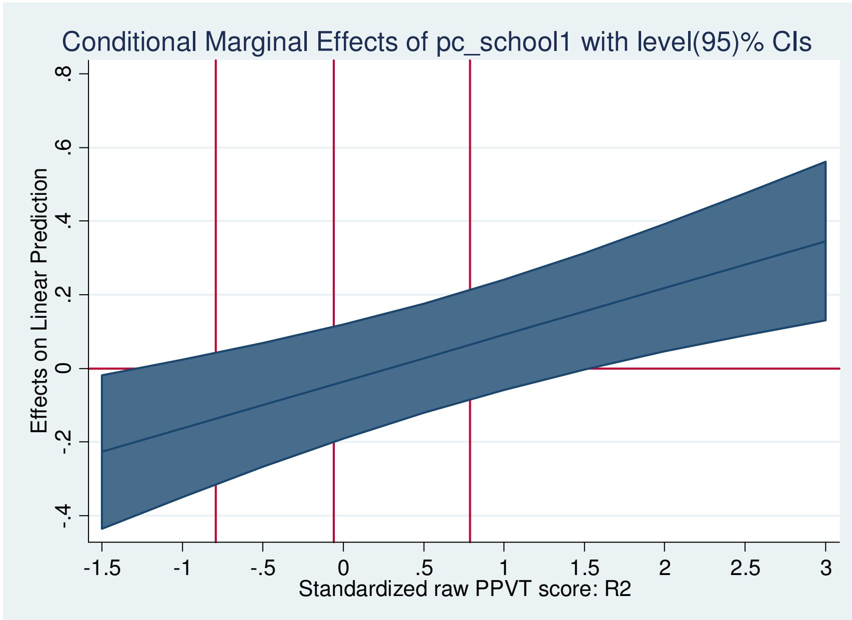
Estimated $\frac{\partial^2 T_{i2}}{\partial S_{i2} \partial T_{i1}} = \hat{\phi}_3 + 2\hat{\phi}_4 \bar{S}_2 = -0.02$.
Note: vertical lines denote quartiles in the preschool skill distribution.

Figure 2
Relation between the effect of school inputs on cognitive skill (vertical axis) and preschool skill (horizontal axis) in the lower quintile of school quality



Estimated $\frac{\partial^2 T_{i2}}{\partial S_{i2} \partial T_{i1}} = \hat{\phi}_3 + 2\hat{\phi}_4 \bar{S}_{2Q1} = -0.10^{***}$.
Note: vertical lines denote quartiles in the preschool skill distribution.

Figure 3
Relation between the effect of school inputs on cognitive skill (vertical axis) and preschool skill (horizontal axis) in the upper quintile of school quality



Estimated $\frac{\partial^2 T_{i2}}{\partial s_{i2}\partial T_{i1}} = \hat{\phi}_3 + 2\hat{\phi}_4\overline{S}_{2Q5} = 0.13^{***}$.

Note: vertical lines denote quartiles in the preschool skill distribution.

Table 7 and Figure 4 present the results of the decomposition exercise proposed in Section 3 using the results of the value added hybrid model.

It is interesting to assess the implications of considering the possibility that preschool skill and school inputs are complementary to each other when measuring the relative importance of these two influences for the urban-rural cognitive skill gap. In a previous study, Castro and Rolleston (2015) found that differences in school inputs play an important role and explain around a third of the urban-rural gap in cognitive skill in Peru. An important implication of this result is that closing differences in school influences can help reduce disparities in cognitive skill development during childhood.

This implication, however, is based on the assumption that the effect of school influences is independent of the level of skill development attained before entering school. One can predict that a strong complementarity between preschool skill and school inputs might lower the equalizing power of school influences. In fact, improving school inputs in rural areas might have only a small effect on the cognitive skill gap with respect to the urban domain if their effect depends on the level preschool skill and this remains low.

This prediction is consistent with the notion of dynamic complementarity considered thus far in the literature. Notice, however, that the previous analysis has revealed that there can be heterogeneity in the relation between preschool skill and the effect of school inputs, to the point that this relation can be negative. Increasing preschool skill will not necessarily enhance the productivity of school inputs. By the same token, a low level of preschool skill will not necessarily reduce the equalizing potential of an improvement in school inputs.

Results summarized in Table 7 and Figure 4 confirm this. In particular, there are two results worth highlighting. First, ignoring the possibility that preschool skill affects the effect of school inputs (i.e. assuming a linear production function as in Castro and Rolleston (2015)) yields a decomposition where school inputs explain 24% of the urban-rural cognitive skill gap observed in Peru by age 8. This is somewhat smaller than the contribution estimated by Castro and Rolleston (2015) and is likely due to the fact that they used a large set of school inputs instead of the single variable approach used here. Second, the contribution of school inputs increases to 37% after considering the interactions between preschool skill and school inputs. Consistent with this, the interaction component is negative and marginally significant (at 10% significance).

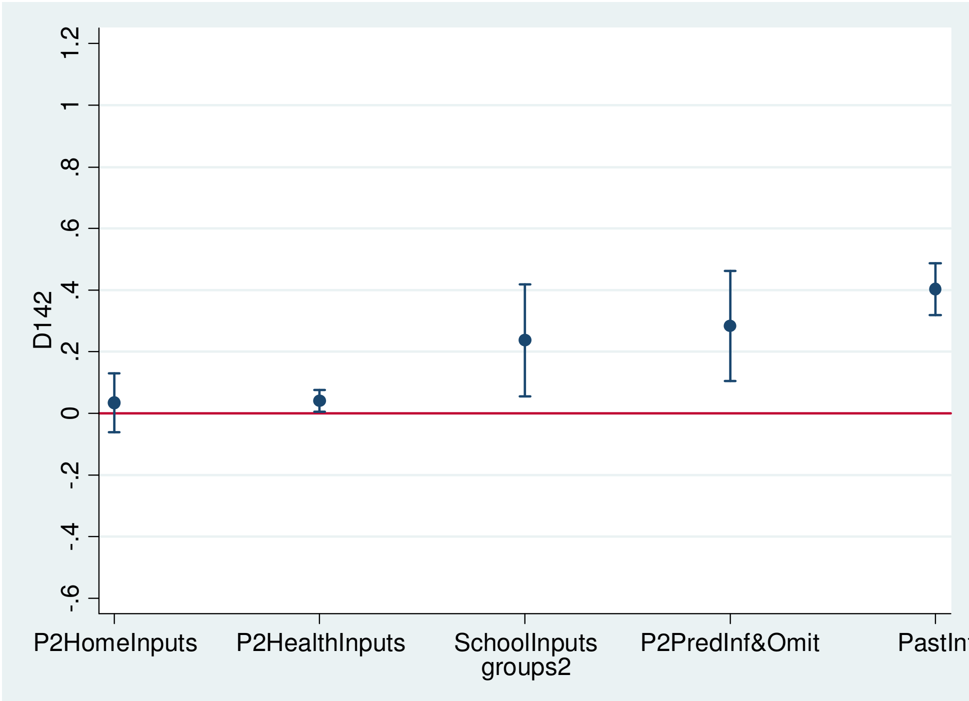
According to the interpretation given above, this means that there will be no additional gain of closing the preschool skill and school inputs gaps together. Moreover, the combined contribution of closing both at the same time is less than the sum of the individual contributions. This is consistent with preschool skill lowering the effect of school inputs and is explained by the fact that rural schools are low quality schools. In fact, the average level of school inputs in the rural area corresponds to the 23rd percentile in the school inputs distribution.

Table 7
Normalized contributions to the urban/rural gap in cognitive skill

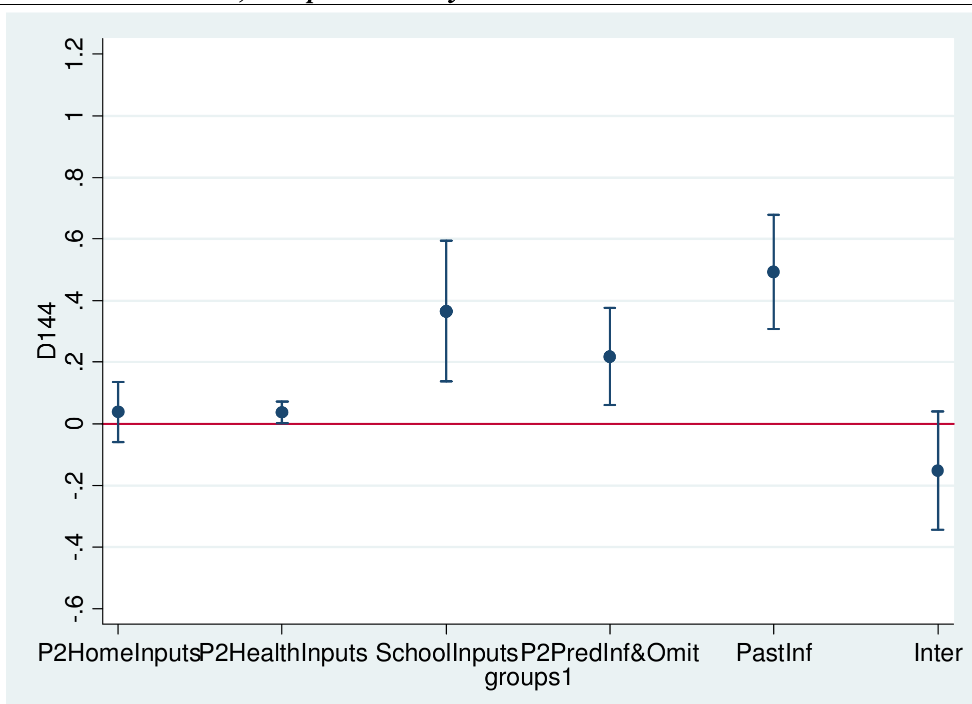
Category	VA model Linear version	VA model Complementarity
(1) Period 2 home inputs	0.034 (0.049)	0.037 (0.049)
(2) Period 2 health inputs	0.040** (0.018)	0.036** (0.017)
(3) School inputs only	0.237** (0.092)	0.365*** (0.116)
(4) Predetermined direct influences and omitted inputs	0.284*** (0.091)	0.218*** (0.080)
(5) Past influences only	0.403*** (0.042)	0.493*** (0.094)
(6) Interactions	--	-0.152* (0.098)

Figure 4
Normalized contributions to the urban/rural gap in cognitive skill
(point estimates and 95% confidence intervals)

A: Value added model; linear version



B: Value added model; complementarity



5. Concluding remarks

This analysis aimed at exploring the existence of heterogeneity in the relation between preschool cognitive attainment and the effect of primary school inputs. It is reasonable to postulate that past cognitive attainment can raise the productivity of later inputs (i.e. dynamic complementarity; Cunha and Heckman (2008)). It is also reasonable, however, to argue that the relation might not be always positive and that this can depend on the nature of the input under analysis.

This analysis also sought to revisit the importance of school influences for the urban/rural cognitive skill gap in Peru, after postulating that preschool skill can affect the productivity of school inputs. If preschool skill always rises the productivity of school inputs, ignoring such complementarity can lead to biased results when decomposing a cognitive achievement gap. In particular, it can lead to an overestimation of the contribution of school influences. The bias might be small (or even negative), however, if the relation between preschool skill and the effect of school inputs is not homogeneous.

I tested for and found evidence of heterogeneity in the relation between preschool skill and the effect of school inputs. In particular, a raise in preschool skill will lead to an increase in the productivity of school inputs but only in the upper part of the distribution of these inputs. In the lower 20% of the school quality distribution, a raise in preschool skill will lower the productivity of school inputs. This result is consistent with school inputs having effect on learning if they carry a degree of cognitive demand that matches the skill of students. An increase in school inputs with a low cognitive demand (in the lower part of the school quality distribution) will only benefit less advantaged children and an increase in preschool skill will lower their effect.

I also measured the contribution of school influences to the cognitive achievement gap observed between urban and rural eight-year old children in Peru. The decomposition strategy considered a special category to host the marginal gain that can emerge from closing preschool skill and school differences at the same time. I found that this category has a negative contribution. This means that the combined contribution of closing both differences at the same time is less than the sum of the individual contributions. This is consistent with rural schools being in the lower part of the school inputs distribution, so an increase in preschool skill will mitigate the productivity of their school inputs. Consistent with this result, the contribution of school inputs to the urban/rural cognitive achievement gap resulted even larger (37%) than that found in previous studies that assumed a linear production function.

These results should not be interpreted to mean that closing the preschool skill gap is a bad idea. In fact, closing the preschool skill and school input gaps together promises a larger equalizing effect than just closing one of them (the combined contribution is around 71%). The main message is than one should not worry about rural children not having sufficient preschool skill to enjoy the benefits of an improvement in their school environment. One does not need to wait until urban and rural children share similar levels of preschool skill to exploit the equalizing potential of school influences. It is not "too late" for rural children currently at school, despite their preschool skill deficits.

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Appendix 1
Variables considered within each dimension of school quality

Size, organization and timetable
1. Headmaster's managerial competence (score 14-56)
2. Headmaster's experience as headmaster
3. School has a librarian among the staff
4. School has a nurse among the staff
5. School has a psychologist among the staff
6. School is multigrade
7. Total number of students in primary education
8. Students per teacher in primary education
9. Teacher absenteeism (school average)
Infrastructure
10. Primary education students use playground at least once per week
11. Primary education students use sports ground at least once per week
12. Primary education students use technology resource centre at least once per week
13. School has electricity
14. School has toilets connected to a public water network
15. School has internet service
16. Primary education students use coliseum or gymnasium at least once per week
17. Primary education students use dining hall at least once per week
18. Primary education students use laboratory at least once per week
19. Primary education students use art or music room at least once per week
Climate
20. Quality of relationship between students (average school score 3-12)
21. Quality of relationship between students and teachers (average school score 2-8)
22. Absence of problems in class (average school score 12-48)
23. Absence of situations that impair teaching (average school score 6-24)
Activities and materials
24. Proportion of teachers that use books or workbooks
25. Proportion of teachers use three or more additional materials
26. Curriculum coverage in depth (% school average - language)
27. Curriculum coverage in depth (% school average - maths)
Teacher characteristics
28. Proportion of teachers that have a university degree
29. Teachers experience in the school (school average)