Early Predictors of Student Academic Performance

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It is important for academics to examine the ways in which non-congitive factors affect student performance. In an exploratory study in conducted in a school in Uruguay, Gabriel Inchausti concluded that there may be a relation between absenteeism during primary school (up to 111years old)) and student performance in the third year of middle school (up to 15 years old). Regression analysis succeeded in bringing statistically significant estimations that explain 10% of the variation of grades in secondary school. Early absenteeism may be a "proxy" measurement of how important a family considers school for their children and the linear regression may be capturing the effects of the "academic mindset" of a family on their children grades. Using standardized absenteeism as a proxy of the academic mindset of homes and a simple questionnaire for assessing non-cognitive skills, it is possible to demonstrate the important influences in the academic performance of a single student.

1.0 INTRODUCTION

What explains academic success at school? John Hattie groups influences student academic performance in six categories: the child, the home, the school, the curriculum, the teacher, and the teaching approach (Hattie, 2008). In his giant meta-study that is regularly updated with new findings, Hattie gathers evidence on the relative weight of each of these factors. Although most educators will not have many problems in agreeing with Hattie on what factors influence student academic performance; nevertheless, each individual will hold their own views, based on their own personal experience about the relative impact in a particular teaching environment.

The purpose of the note is to review some tools that allow the measurement of the relative importance of different determinants of academic performance in school with focus on non-cognitive factors.
Such tools can bring more information to educators and improve their strategies when facing a student in the class, or when discussing a new program to be applied in the school. In the following paragraphs I will briefly discuss a framework on skill formation and then present my experience in looking for ways to measure determinants of academic performance at the student level in a South American school environment.

2.0 BACKGROUND

The development of capabilities inherent to any education process is the result of a wide set of determinants that include cognitive and non-cognitive factors. During their life, children develop skills that help them to interact positively with the world. These skills allow them to not only understand how things work, but also develop the ability to interact productively within it. As adults, we usually face situations where "how we deal with them" ends being more important than "what we do with them". The "how" can be related to the way we interact with things (aspects closer to the non-cognitive skills space) while the "what" is more related to our knowledge of the specifics of the situation we face.

In examining the role of non-cognitive skills and the ability of individuals in compensating cognitive shortcomings with them, Cunha and Heckman model the formation of skills as the result of the accumulation of both cognitive and non-cognitive skills (Cunha & Heckman, 2007). Moreover, the authors go further and propose that the inventory of these same skills in their parents impact on students' academic trajectories.

Cunha and Heckman provide a rich discussion on parental investment decisions on skill formation of their children and relate them (among other factors) to their inventory of cognitive and non-cognitive skills. Therefore, two of the factors identified by Hattie (the child and the home), are present in Cunha and Heckman model with additional emphasis placed on the process of formation of non-cognitive skills.

The role of non-cognitive skills in school performance of young students has captured the attention of academia. For example, the University of Chicago Consortium produced a report that successfully systematizes a framework to analyze them (Farrington et al., 2012). The report identifies five categories of non-cognitive factors related to academic performance: **academic behaviors** (those behaviors commonly associated with being a "good student", as arriving ready to work or paying attention in class), **academic perseverance** (the ability to overcome distractions or obstacles to complete school assignments), **academic mindset** (the beliefs of a student about oneself in relation to academic work), **learning strategies** (the processes and tactics students employ to aid their cognitive work), and **social skills** (that refer to the ability of engaging in behaviors that improve positive social interactions). The report argues that test scores are useful to measure content knowledge and academic skills, while educators use grades to add their evaluation in some of the non-cognitive factors. Therefore, the absence of a specific instrument to assess the so called "soft-skills" is evidence of how methods to assess cognitive and non-cognitive skills are at a different stage of development.

While teachers and professors have plenty of well-developed and structured devices to assess the evolution of hard skills traditionally associated with learning, tools for evaluation of non-cognitive aspects are less generalized. The application of specific instruments to measure and give visibility to those non-cognitive skills present an opportunity to better assess student trajectory and the efficacy of teaching strategies. In education, as in any other field, good decisions depend on good measurement.

3.0 MEASURING NON-COGNITIVE SKILLS

Educators mainly run diagnosis tests to evaluate the development of skills in students. Running standardized tests is a very powerful way to understand where students stand. Nevertheless, studies point to the fact that motivation plays a significant role in its results. These studies pose some concerns about the efficacy of standardized tests as individual assessment tools as results can be heavily influenced by the wider social context (Gneezy et al., 2017).

The assessment of non-cognitive skills not only informs educators about the progress of the student, but in combination with traditional evaluation tools, can also help to identify the potential academic performance of any single student.   Measuring the inventory of skills at a certain point in time allows an "instant estimative" of future student performance. This prediction can be used as a reference point to evaluate how students performed during the year against their individual set of capabilities. This evaluation is not a strange thing for a professor to do because almost every student performance is seen in the context of their capabilities. However, improving the quality of the inputs of such evaluation can make the process more robust.

4.0 FINDING EXPLORATORY POWER

Inspired by the models that relate cognitive and non-cognitive factors with academic performance, I conducted some exploratory tests to find their predictive power in the early years of secondary school. Every professor holds their own set of beliefs about how students can and will develop their abilities in the year to come. It is possible that many of them agree with Cunha and Heckman and argue that both cognitive and non-cognitive skills inventory and family influence play a major role in student performance. It is possible to relate family influence with what Farrington et al define as academic mindset. The work of a student in school ends reflecting the value his family sees in education.

An exploratory study I performed in a school in a low socioeconomic status neighborhood in Uruguay suggested a relation between absenteeism during primary school (up to 11 years old) and student performance in the third year of middle school (15 years old). Although more research is needed to understand to what extent early absenteeism is a robust predictor of future grades, a linear regression succeeded in bringing statistically significant estimations that explain 10% of the variation of grades in secondary school. Although variation of grades are caused by many factors, the method shows that each day skipped in primary school has a direct negative relation with grades (absenteeism explains 10% of the total variation in grades while 90% is attributable to other factors). It is important to highlight that this relation does not prove causation, it is not possible to affirm that the absenteeism in primary school caused lower grades in middle school. The finding is consistent with the idea of "academic mindset" in a family, in a given community families that are more committed to school and let their children skip fewer classes, probably hold a stronger "academic mindset". In a way, early absenteeism may be a "proxy" measurement of how important a family considers school for their children and the linear regression may be capturing the effects of the "academic mindset" of a family on their children grades. As said, more research[1] is needed at this point.

A second exploratory study with another school in the same region succeeded in showing a relation between cognitive and non-cognitive tests when entering secondary school (age 12) and the performance in first year. In this case, I was able to explain average grades in regular tests using a linear regression which utilised the average of the answers of the MESH questionnaire developed by TransformingEd, and the results of a mathematics literacy test and a reading comprehension test administered at the beginning of the year. The regression demonstrated significant coefficients and was able to explain one third of the variation of grades during the year. Moreover, the MESH variable alone was able to explain almost half of that variation. Although the MESH test was not developed as an individual assessment tool in SEL, it proved to have an interesting predictive power.

A particularly interesting dynamics took place when discussing these findings with the academic staff of the school . The outliers (those students that performed significantly better than colleagues with same MESH results, or those that performed significantly worse of similar colleagues) inspired a discussion about the specifics of those cases, which brought new insights about their performance evaluation and how the staff adapted them.

[1] I used average absenteeism between fourth and sixth grade of primary school to explain grades in third year of middle and high school.

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Bringing visibility to dimensions that are usually hard to measure allow educators to operationalize some evaluation that, although are present in their assessment of performance, are hard to properly weigh in front of figures coming from hard cognitive tests.

5.0 CONCLUDING REMARKS

This note argues about the possibility of implementing ways to measure non-cognitive factors that both educators and academics find relevant and propose simple tools to conduct studies.

Using standardized absenteeism as a proxy of the academic mindset of homes and a simple questionnaire for assessing non-cognitive skills, it is possible to demonstrate the important influences in the academic performance of a single student.

The proper measurement of these factors helps inform areas of opportunity in the development of a child and can be of use as a tool to assess actual versus potential academic performance at an individual level.

6.0 ABOUT THE AUTHOR

Gabriel Inchausti graduated in Economics from the University of the Republic (Uruguay). Gabriel has professional specialization in corporate finance and strategy and received his Masters Degree in Behavioural Sciences from the London School of Economics. He is a professor and lecturer in topics related to Behavioral Economics in Uruguay and Brazil, and is an active researcher in the field. His research focus is in the area of education and time preferences. Moreover, Gabriel served as the Executive Officer for a major South American beef group and the General Manager in an important media group in Uruguay. Currently, he is chairman of the board of a South American software company.

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