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Essays on Labour skills and educational quality

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Introduction

Investment in human capital has been identified in literature as one of the key sources of long-term economic growth (see, for instance, Hanushek and Kimko 2000, Barro 2001, Krueger and Lindahl 2001, Hanushek and Woessmann 2012 and Castello-Climent and Hidalgo-Cabrillana 2012). By investment in human capital, we refer to improvements in the skills of the labour force necessary for production so that human capital is a multidimensional concept and refers to the skill set that makes workers more productive. Knowledge is the most important of these, but other factors like habits, social and personality attributes and health also matter (Goldin 2016).

But the skills required for production have not always been the same throughout history. The technological advances embodied in the successive industrial revolutions identified in literature have been modifying the complementarity between human and physical capital and, therefore, the relevant skills for production.[1]

Several works have highlighted the potential impacts of the recent process of technological change on the labour market (Brynjolfsson and McAfee 2014; Autor et. al. 2003; Spitz-Oener, 2006; Acemoglu and Autor 2011; Frey and Osborne 2013; OECD 2016). The literature emphasises that technological progress, in particular the advance in digital technologies, communication and robotics can create jobs and increase benefits for many workers. But at the same time, it means that certain activities run a high risk of becoming obsolete, since some of them, such as routine tasks, or those which can be replaced by code, can be easily automated, leading to what is commonly known as technological unemployment. A first branch of papers specifically

[1] See Gordon 2016 for a review of the process of technological change since 1750.

analyse the impact of technological change on the displacement of a large part of existing occupations (Brynjolfsson and 2014, Frey and Osborne 2013, OECD 2016).

On the other hand, other studies focus on the type of tasks that are most likely to suffer this displacement as well as the types of tasks which could be increasingly demanded by the new technologies (Autor, et. al, 2003; Spitz-Oener, 2006; Acemoglu and Autor, 2011). This last approximation to the effect of technological change on labour markets is usually called the task content approach. In general, this literature concludes that jobs intensive in cognitive tasks, particularly in the case of non-routine cognitive tasks, such as abstract thought, creativity, the ability to solve problems and communications skills which are normally performed by highly-skilled workers, would be stimulated by this process. Therefore, labour placement, as well as labour productivity, will be increasingly linked to the ability of workers to develop these kinds of cognitive tasks.

Clearly, this phenomenon puts pressure on the educational systems which should be able to move in line with the technological trends, providing an increasingly intensive training in cognitive skills required for current jobs. In this sense, an exhaustive analysis of the educational systems and of the most important inputs to improve the cognitive skills of students becomes extremely important.

In the last decades, in the field of education, developed countries have accumulated a large amount of empirical data on the performance of students in the school period, not only across-countries (for example, through the Program for the International Evaluation of OECD students, PISA) but also within the country. Thanks to this greater availability of data, the empirical literature on education has grown exponentially.[2]

From the previous literature an extensive consensus has been generated, both on the part of policy makers and researchers, that teacher quality is a key input in the process of student learning (Hanushek, 2003; Hanushek and Rivkin 2007; Hanushek, 2010; Hanushek and Rivkin 2010; among others). Indeed, several papers state that teacher quality represents the single school

[2]See, Hanushek 2003 for a comprehensive review of the empirical literature on Education.

input with the highest incidence in the educational results (Hanushek, 2003, Klein et al., 2010; Gates, 2011; and Hiatt, 2009.). For instance, Hanushek (2010) demonstrates that the difference between a good and a bad teacher is equivalent to advancing knowledge in an academic year. On the other hand, Chetty et al. (2011) states that having good teachers improves not only the standardized test scores but also generates long-term effects, both economic and social.

However, there is much less agreement on what aspects determine the quality of teachers, as well as reduced theoretical literature that analyses the process of teacher selection. The main limitation in the study of teacher quality stems from the fact that teacher quality is unobservable.[3] Moreover, previous evidence suggests that observable characteristics of teachers do not present a clear correlation with the achievements reached by the students (Rockoff, 2004; Jepsen, 2005; Hanushek and Rivkin, 2007; Hanushek 2010 among others). In this sense, there is still a lot of scope to investigate the importance of teacher quality as an educational input and, fundamentally, how to influence teacher quality in order to improve educational results.

The aim of this dissertation is precisely to shed light on these issues. On one hand, the objective of this paper is to identify the kind of task which is most in demand in the current labour market. On the other hand, we study how the educational system provides these skills by focusing on the analysis of the quality of teachers. The dissertation consists of three chapters, each of them written in the style of an academic paper.

The first chapter analyses the employment profile trends in Latin American and Caribbean countries according to the task content performed by the workers in their jobs for the last twenty years. The main motivation for this chapter stems from the fact that most of the literature regarding the potential impact of technological change on labour markets is based on developed countries. However, evidence for emerging countries and particularly evidence for Latin America and the Caribbean is much more limited. Indeed, as far as I know, the study in this dissertation is the first that makes this analysis for a representative set of Latin American and Caribbean countries.

[3]The assumption of the non-observability of the teacher skill is suggested in previous studies. See for instance Hanushek (2010) and Rothstein et al.(2014).

Latin American and Caribbean countries show very different characteristics to developed countries which could potentially lead to different trends in technological advance and task profile of the labour markets. Indeed, the economic structure and, consequently, specialization is different between developed and emerging countries. Latin American and Caribbean countries are also characterised by lower wages and therefore lower incentives for automation with respect to developed countries. Finally, Latin American countries usually show lower performance in comparative test of cognitive skills which could imply constraints from the labour supply to move toward a task profile more intensive in cognitive tasks.[4]

Therefore, focusing on the evidence for Latin America and the Caribbean, the main research question of the chapter is if the technological change has also provoked a growing demand of cognitive skills for workers in emerging countries, or if on the contrary, this growing demand for cognitive skills is not yet registered in these countries.

To do that, the chapter aims to produce an approximation of the impact of technological change on the labour market. Specifically, I build an indicator that captures the relative importance of four types of tasks, cognitive versus manual tasks and routine versus non-routine tasks, based on the information provided by Occupational Information Network (O*NET) and household surveys. The empirical approach follows the task content methodology proposed in the seminal paper of Acemoglu and Autor (2011).

The analysis finds that in the last two decades the relative importance of non-routine cognitive tasks in the workplace has increased in line with the reduction of manual tasks. These conclusions are in line with the stylised findings highlighted in the literature for developed countries, on which the empirical analysis had focused. That is, our first chapter shows us that the growing demand for non-routine cognitive occupations in the labour market is a trend that is occurring in all countries, regardless of their level of development.

We also study whether the increased demand for new tasks in the labour market affects the risk of polarisation of the labour market by looking at

[4]See, for example, the gaps in cognitive skills between emerging and developing countries in the PISA test (OECD, 2015) and the PIAAC survey (OECD, 2013).

labour income. We show that wages reflect a higher relative remuneration for cognitive tasks. Therefore, occupations intensive in cognitive abilities represent a growing demand and higher remuneration compared to occupations intensive in manual tasks. In this context, since cognitive abilities have a better insertion in the labour market, the educational system needs to take this into account by providing and developing more of these.

Particularly, the second chapter analyses, why do some countries obtain better educational results than others? This chapter analyses this relevant question, focusing on the role of teacher quality. In this chapter, I propose and calibrate a micro-founded theoretical model of teacher selection of heterogeneous agents, that differ in the general skill and the teacher skill, for a set of 22 OECD countries.

As mentioned above, there is a scarcity of theoretical literature that analyses the process of teacher selection. The proposed model helps us to understand the mechanisms through which individuals decide to become teachers and how educational institutions select them. Clearly, understanding this selection process in depth is the first step to understanding the variables that characterise the quality of teachers in a country, and therefore, to designing educational policies to improve school performance. Note that, improving the performance of students matters since they not only gain individual benefits through better working placements and returns from investment on education (see for example Cameron and Heckman 1993, 1998) but also aggregate benefits through greater economic growth in the country (see, among others, Hanushek and Kimko, 2000; Hanushek and Woessmann, 2012).

Based on the model, I build time series of teacher quality (TQ) for each country, analyse its main drivers and study the importance of TQ in explaining differences in student achievements. My proxy of TQ measured in different years helps me to analyse whether teacher quality trends can explain the evolution of student achievements at a country level. To my knowledge, no previous studies include this analysis because time series of country measures of teacher quality were not available. Having time series of teacher quality for a set of countries is important because the reasons behind the cross-country dispersion in student outcomes could potentially be the learning culture or the educational institutions. With my time series of TQ, I am controlling for these unobservable country fixed effects.

The theoretical model shows that in equilibrium, the relationship between teacher salaries and TQ is non-linear and even non-monotonic which helps us to understand the ambiguous findings in the empirical literature between teacher salaries and student achievements. The evidence suggests that salaries are not a reliable proxy of teacher quality, since most studies do not find a statistically significant effect between salaries and student outcomes.[5] However, the reason for this could be that different countries could be in different parts of the equilibrium curve. This is so because on one hand, previous empirical analysis based on cross-section data within a given country probably captures a small segment of the equilibrium curve since teacher wage dispersion is usually small within the country. On the other hand, the parameters controlling the teacher selection process differ across countries and, as I explain later on, the equilibrium curve is quite sensitive to these parameters.

My proposed measure of TQ is strongly positively correlated with cross-country dispersion in student outcomes, even controlling for student and school characteristics, family background, macroeconomic context and unobservable country and timing fixed effects. In the chapter, I perform several counter-factual exercises in order to discuss the importance of TQ in explaining cross-country differences in student outcomes, as well as to understand the main factors behind the TQ differences across countries.

The first counter-factual exercise shows us that cross-country differences in TQ explain approximately 22% of the observed cross-country variance in student outcomes. The importance of TQ is quite similar to the family background effect and clearly higher than the relevance of other school inputs.

The second counter-factual exercise helps to understand the main variables affecting the quality of teachers. Previous literature teaches us that teacher quality matters, but little is known regarding its main determinants. Counter-factual exercises based on the model allow me not only to identify, but also to quantify the main drivers of cross-country differences in TQ. This exercise shows that initial distributions of population skills are crucial in explaining current differences in TQ across countries, while teacher salaries and labour market conditions are of lesser importance.

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[5] Hanushek (2003) provides an extensive review on this issue.

Notice that the theoretical model used in this dissertation is like a small laboratory that allows us to understand the behaviour of the different agents in the educational system, as well as the interactions between them. Consequently, the model provides us with a conceptual framework that enables us to evaluate quantitatively several educational policies. This is precisely what I do in the third chapter.

The third chapter analyses the trade-off between teacher quality and teacher quantity by studying the efficient allocation of the educational wage bill -where the wage bill takes into account the interaction between teacher wages and the number of teachers. To do that, I use a modified version of the model developed in chapter 2 -since now teacher wages and class size are both endogenous. And as in the previous chapter, since the theoretical model includes supply and demand of teachers, the analysis is a general equilibrium framework which takes into account how supply and demand interact.

The main motivation of this chapter stems from the fact that educational literature has been generally oriented towards the study of the effectiveness of various educational policies considered individually. This type of analysis has been stimulated in turn by the increasing use of random controlled experiments for the evaluation of policies. However, papers which compare various alternatives for the use of a single resource are much less frequent. This chapter specifically analyses the efficient allocation of the educational wage bill in order to improve student achievement. This analysis is of special relevance given that, due to the scarcity of resources, it is necessary to improve the efficiency of the public sector by directing efforts towards those factors that have a greater impact on school performance.

Focusing the attention on the wage bill is important for at least two reasons. First, the wage bill represents, on average, approximately 65% of total educational expenditure in OECD countries (see OECD, 2017). Second, teachers represent the educational input with the greatest impact on students' academic performance (Hanushek, 2003, Klein et al., 2010; Gates, 2011; Hiatt, 2009), and salaries area good tool to attract the best teachers. Therefore, the efficiency of the education sector may well be closely related to decisions on salary compensation.

The discussion regarding the allocation of the educational wage bill is characterised by a clear trade-off between teacher quality and teacher quantity. On one hand, higher salaries could act as an incentive to attract and retain the best teachers to the education sector (Dolton and and Marcenaro Gutierrez, 2011; Loeb and Page, 2000).[6] On the other hand, a rise in the number of teachers allows a reduction of class size which is usually linked to a better study environment, and therefore, to better student outcomes (Card and Krueger, 1992; Hoxby, 2000; Woessman, 2005). When faced with a lack of resources, policy makers need to choose between both alternatives.

In this chapter, we calibrate the theoretical model of teacher selection for 22 OECD countries between 2006 and 2015. Then, based on these calibrations and the estimated educational production function, we compute the optimal allocation of the educational wage bill in each country. Additionally, based on the predicted student outcomes imposing the observed and the optimal allocation for the wage bill, we build an index that measure the inefficiency in the allocation of quantity and qualities of teacher -and thus, that measure the inefficient wage bill of each country in our sample. The results state that the average inefficiency in the allocation of the wage bill for the group of countries considered is 16%. That is, resources currently allocated to the educational wage bill could have a significantly greater impact on educational outcomes by improving their allocation between wages and teaching hours. Moreover, in most countries, the inefficiency gap is generated by a bias to prioritise the quantity more than the quality of teachers.

Finally, at the end of the dissertation, I present general conclusions of the whole research.

References

Acemoglu, D. and D. Autor, (2011). Skills, Tasks and Technologies: Implications for Employment and Earnings". Handbook of Labor Economics, Volume 4b.

Autor, D., F. Levy and R. Murnane (2003). The Skill Content of Recent Technological Change: An Empirical Exploration. Quarterly Journal of Economics 118(4): 12791333

[6]The results of chapter 2 also support this idea.

Barro, R.J. (2001). Human capital and growth. American Economic Review Pap. Proc 2001; 91:1217.

Brynjolfsson, E. and A. McAfee (2014). The second machine age: work, progress, and prosperity in a time of brilliant technologies. First edition. New York: W.W. Norton & Company.

Cameron S. and J. Heckman (1993). "The nonequivalence of high school equivalents". Journal of Labor Economics ll(1):l-47.

Cameron S. and J. Heckman (1998). "Life Cycle Schooling and Educational Selectivity: Models and Choice" Journal of Political Economy, April, 1998.

Castello-Climent A. and A. Hidalgo-Cabrillana (2012). The role of education quality and quantity in the process of economic development. Economic Educational Review 2012;31:391409.

Card, D. and A. Krueger (1992), "Does school quality matter? Returns to education and the characteristics of public schools in the United States", Journal of Political Economy, 100(1),1?40.

Chetty, R., J.N. Friedman, and J.E. Rockoff, (2011). The Long-Term Impacts of Teachers: Teacher Value-Added and Student Outcomes in Adulthood, NBER Working Paper No. 17699.

Dolton, P. and O. Marcenaro-Gutierrez (2011). "If you pay peanuts do you get monkeys? A cross-country analysis of teacher pay and pupil performance." Economic Policy 26 (65): 5-55.

Frey, C. and M. Osborne (2013). The Future of Employment: How Susceptible Are Jobs to Computerisation?, Working paper, Oxford University, Oxford, U.K.

Gates, B. (2011). How Teacher Development Could Revolutionize Our Schools, The Washington Post

Goldin C. (2016) Human Capital. In: Handbook of Cliometrics. Heidelberg, Germany: Springer Verlag; 2016.

Gordon, R. J. (2016). "The rise and fall of American growth: the U.S.

standard of living since the Civil War". Princeton University Press, 2016

Hanushek, E. (2003). "Teacher Quality". In Lance T. Izumi and Williamson Evens (eds), Teacher Quality.

Hanushek, E. (2010). "The economic value of higher teacher quality". CALDER Working Paper N 56, December, Urban Institute.

Hanushek, E and D. Kimko (2000). "Schooling, labor force quality, and the growth of nations," American Economic Review, 90, 1184-1208.

Hanushek, E, and S. Rivkin (2007). "Teacher Quality," In Handbook of the Economics of Education, ed. E. A. Hanushek and F. Welch, 1051-78. Amsterdam: North Holland.

Hanushek, E. and S. Rivkin (2010). "Generalizations about Using Value-Added Measures of Teacher Quality." American Economic Review 100(2):267–71.

Hanushek, E. A. and L. Woessmann (2012). "Do better schools lead to more growth? Cognitive skills, economic outcomes, and causation, "Journal of Economic Growth, 17, 267- 321.

Hiatt, F. (2009). How Bill Gates Would Repair Our Schools, The Washington Post, March 30 2009.

Hoxby, C. (2000). "The effects of class size on student achievement: new evidence from population variation", Quarterly Journal of Economics, 115(4), 1239?85.

Jepsen, C. (2005). Teacher Characteristics and Student Achievement: Evidence from Teacher Surveys, Journal of Urban Economics, 57, 302-319.

Klein, J., M. Rhee, P. C. Gorman, R. Huberman, C. R. Johnson, A. Alonso, T. Boasberg, A. Ackerman, W. Hite Jr., JC. Brizard, J. Torres, J. Covington, T. Grier, P. Vallas, E. White, and L. Sheffield (2010). How to Fix Our Schools: A Manifesto by Joel Klein, Michelle Rhee and Other Education Leaders, The Washington Post, October 10 2010.

Krueger, AB. and Lindahl M. (2001). Education for growth: why and for whom. Journal of Economic Literature 2001; 39 : 110136.

Loeb, S. and M. Page (2000). ‘Examining the link between teacher wages and student outcomes: The importance of alternative labor market opportunities and non-pecuniary variation’, Review of Economics and Statistics, 82(3), 393–408.

OECD. (2013). OECD skills outlook 2013: First results from the survey of adult skills. Paris: Organisation for Economic Co-operation and Development.

OECD. (2015). PISA 2015 Results (Volume I). Excellence and Equity in Education. Paris: Organisation for Economic Co-operation and Development.

OECD (2016). Automation and Independent Work in a Digital Economy. Policy Brief on the Future of Work. Paris: OECD Publishing

OECD (2017). "Education at a Glance (2017): OECD Indicators", OECD Publishing, Paris.

Rockoff, J. (2004). The Impact of Individual Teachers on Student Achievement: Evidence from Panel Data, American Economic Review Papers and Proceedings, 94, 247-252.

Rothstein, J. (2015). "Teacher quality policy when supply matters". American Economic Review, Vol, 105, No 1, January, pp 100-130.

SpitzOener, A. (2006). Technical Change, Job Tasks, and Rising Educational Demands: Looking Outside the Wage Structure. Journal of Labor Economics 24 (2): 235270

Woessman, L. (2005). "Educational production in Europe", Economic Policy, 20 (Issue 43), 445-504.

Introducción (Spanish)

La inversión en capital humano se ha identificado en la literatura como una de las principales fuentes de crecimiento económico a largo plazo (véanse, por ejemplo, Hanushek y Kimko 2000, Barro 2001, Krueger y Lindahl 2001, Hanushek y Woessmann 2012 y Castello-Climent y Hidalgo-Cabrillana 2012). Por inversión en capital humano, nos referimos a las mejoras en las habilidades de la fuerza de trabajo necesarias para la producción, de modo que el capital humano es un concepto multidimensional y definidas como el conjunto de habilidades que hacen a los individuos productivos. El conocimiento es la más importante de estas dimensiones, pero otros factores, como los hbitos, los atributos sociales y de personalidad así como la salud también importan (Goldin 2016).

Pero las habilidades requeridas para la producción no siempre han sido las mismas a lo largo de la historia. El avance tecnológico encarnado en las sucesivas revoluciones industriales identificadas en la literatura ha modificado la complementariedad entre el capital humano y el físico y, por lo tanto, las habilidades relevantes para la producción. [7]

Varios trabajos han destacado los posibles impactos del reciente proceso de cambio tecnológico en el mercado laboral (Brynjolfsson y McAfee 2014; Autor et al., 2003; Spitz-Oener, 2006; Acemoglu y Autor 2011; Frey y Osborne 2013, OCDE 2016). La literatura enfatiza que el progreso tecnológico, en particular el avance en las tecnologas digitales, la comunicación y la robótica, puede crear empleos y aumentar los beneficios para muchos trabajadores. Pero, al mismo tiempo, significa que ciertas actividades corren un alto riesgo de quedar obsoletas, ya que algunas de ellas, como las tareas

[7] Ver Gordon 2016 para una revisin del proceso de cambio tecnolgico desde 1750.

rutinarias o las que pueden ser reemplazadas por códigos, se pueden automatizar fácilmente, dando lugar a lo que comúnmente se conoce como desempleo tecnológico Una primera rama de documentos analiza específicamente el impacto del cambio tecnológico en el desplazamiento de una gran parte de las ocupaciones existentes (Brynjolfsson y 2014, Frey y Osborne 2013, OCDE 2016).

Por otro lado, otros estudios se centran en el tipo de tareas que resulta más probable que sufran este desplazamiento, así como en los tipos de tareas que podrían ser cada vez más demandadas por las nuevas tecnologías (Autor, et al., 2003; Spitz-Oener, 2006; Acemoglu y Autor, 2011). Esta última aproximación al efecto del cambio tecnológico en los mercados laborales generalmente se denomina enfoque del contenido de tareas. En general, esta literatura concluye que los trabajos intensivos en tareas cognitivas, particularmente en el caso de tareas cognitivas no rutinarias, como el pensamiento abstracto, la creatividad, la capacidad de resolver problemas y las habilidades de comunicación que normalmente desempean los trabajadores altamente calificados, estarían siendo estimulados por este proceso. Por lo tanto, la inserción laboral, así como la productividad laboral, estarán cada vez más unidas a la capacidad de los trabajadores para desarrollar este tipo de tareas cognitivas.

Claramente, este fenómeno ejerce presión sobre los sistemas educativos que deberían ser capaces de moverse en línea con las tendencias tecnológicas, proporcionando y desarrollando las habilidades cognitivas requeridas para los trabajos actuales. En este sentido, un análisis exhaustivo de los sistemas educativos y de los inputs más importantes para mejorar las habilidades cognitivas de los estudiantes se vuelve extremadamente importante.

En las últimas décadas, en el campo de la educación, se ha acumulado una gran cantidad de datos empíricos sobre el desempeo de los estudiantes enel período escolar, no solo en datos comparables entre países (por ejemplo, a través del Programa de Evaluación Internacional de Estudiantes de la OCDE, PISA) pero también dentro de los países. Gracias a esta mayor disponibilidad de datos, la literatura empírica sobre educación ha crecido exponencialmente. [8]

[8] Véase, Hanushek 2003 para una revisión exhaustiva de la literatura empírica sobre educación.

De la literatura anterior se ha generado un amplio consenso, tanto por parte de los responsables políticos como de los investigadores, de que la calidad docente es un input clave en el proceso de aprendizaje de los estudiantes (Hanushek, 2003; Hanushek y Rivkin 2007; Hanushek, 2010; Hanushek y Rivkin 2010, entre otros). De hecho, varios artículos indican que la calidad del docente representa el insumo escolar con mayor incidencia en los resultados educativos (Hanushek, 2003, Klein et al., 2010, Gates, 2011 y Hiatt, 2009.). Por ejemplo, Hanushek (2010) demuestra que la diferencia entre un buen y un mal profesor es equivalente a avanzar el conocimiento en un ao académico. Por otro lado, Chetty et al. (2011) afirma que tener profesores de calidad mejora no solo los resultados de los exámenes estandarizados, sino que también genera efectos a largo plazo, tanto económicos como sociales.

Sin embargo, hay mucho menos acuerdo sobre qu aspectos determinan la calidad de los docentes, así como una literatura teórica reducida que analiza el proceso de selección docente. La principal limitación en el estudio de la calidad docente se deriva del hecho de que la calidad del docente es inobservable.[9] De hecho, la evidencia anterior sugiere que las características observables de los docentes no presentan una correlación clara con los logros alcanzados por los estudiantes (Rockoff, 2004; Jepsen, 2005; Hanushek y Rivkin , 2007, Hanushek, 2010 entre otros). En este sentido, todavía hay mucho margen para aprender sobre la importancia de la calidad del docente como insumo educativo y, fundamentalmente, cómo influir en la calidad docente con objeto mejorar los resultados educativos.

El objetivo de esta tesis es precisamente arrojar luz sobre estos temas. Por un lado, el objetivo de este documento es identificar el tipo de tarea que tiene mayor demanda en el mercado laboral actual. Por otro lado, estudiamos cómo el sistema educativo proporciona estas habilidades centrándonos en el análisis de la calidad de los docentes. Con ese fin, esta tesis consta de tres capítulos, cada uno de ellos escrito con el estilo de un documento académico.

El primer capítulo analiza las tendencias del perfil de empleo en los países de América Latina y el Caribe de acuerdo con el contenido de la tarea realizada por los trabajadores en sus trabajos en los últimos veinte años. La principal motivación para este capítulo proviene del hecho de que la mayoría

[9] El supuesto de no observabilidad de la habilidad docente se sugiere en estudios previos. Ver, por ejemplo, Hanushek (2010) y Rothstein et al. (2014).

de la literatura sobre el impacto potencial del cambio tecnolgico en los mercados laborales se basa en los países desarrollados. Sin embargo, la evidencia para países emergentes y particularmente para América Latina y el Caribe es mucho más limitada. De hecho, según mi conocimiento, este trabajo es el primero que hace este análisis para un conjunto representativo de países de América Latina y el Caribe.

Los países de América Latina y el Caribe muestran características muy diferentes respecto a los países desarrollados que podrían conducir a diferentes tendencias en el avance tecnológico y en el perfil de tareas de los mercados laborales. De hecho, la estructura económica y, en consecuencia, la especialización sectorial es diferente entre países desarrollados y emergentes. Los países de América Latina y el Caribe también se caracterizan por salarios más bajos y, por lo tanto, menores incentivos para la automatización con respecto a los países desarrollados. Finalmente, los países de América Latina suelen mostrar un menor rendimiento en las pruebas que miden las habilidades cognitivas de la población, lo que podría implicar restricciones de la oferta de trabajo para avanzar hacia un perfil de empleo más intensivo en tareas cognitivas.[10]

Por lo tanto, utilizando la evidencia de América Latina y el Caribe, la principal pregunta de este primer capótulo es si el cambio tecnológico también ha provocado una demanda creciente de habilidades cognitivas en los países emergentes o, por el contrario, esta demanda creciente de las habilidades cognitivas aún no se ha producido en estos países.

Para ello, el captulo tiene como objetivo producir una aproximación del impacto del cambio tecnológico en el mercado laboral. Especficamente, se construye un indicador que capta la importancia relativa de cuatro tipos de tareas, tareas cognitivas versus tareas manuales y rutinarias versus no rutinarias, basadas en la informacin provista por Occupational Information Network (O*NET) y la encuestas de hogares. El enfoque empírico sigue la metodologa del contenido de tareas propuesta en el trabajo de Acemoglu y Autor (2011).

El análisis encuentra que en las últimas dos décadas la importancia rela-

[10]Nota, ver por ejemplo, las brechas en las habilidades cognitivas entre y países en desarrollo en pruebas PISA (OCDE, 2015) y la encuesta PIAAC (OCDE, 2013).

tiva de las tareas cognitivas no rutinarias en el lugar de trabajo ha aumentado en línea con la reducción de las tareas manuales. Estas conclusiones están en concordancia con la evidencia existente en la literatura para los países desarrollados. Es decir, nuestro primer capítulo nos muestra que la creciente demanda de ocupaciones cognitivas no rutinarias en el mercado laboral es una tendencia que está a nivel global, independientemente del nivel de desarrollo de los países.

También estudiamos si el nuevo perfil en la demanda de tareas en el mercado laboral afecta el riesgo de polarización del mercado laboral mediante el estudio del ingreso laboral. Mostramos que los salarios reflejan una remuneración relativa más alta para las tareas cognitivas. Por lo tanto, las ocupaciones intensivas en habilidades cognitivas representan una demanda creciente y una mayor remuneración, en comparación con las ocupaciones intensivas en tareas manuales. En este contexto, dado que las habilidades cognitivas tienen una mejor inserción en el mercado laboral, el sistema educativo debe tener esto en cuenta al proporcionar y desarrollar más de este tipo de habilidades.

El segundo y tercer captulos se concentran en el sistema educativo. Particularmente, el segundo capítulo analiza, ¿por qué algunos países obtienen mejores resultados educativos que otros –donde los resultados educativos se miden utilizando datos de habilidades cognitivas? Este capítulo analiza esta relevante pregunta centrándose en el papel de la calidad del docente. En este segundo capítulo, propongo y calibro un modelo teórico micro-fundado de selección de profesores con agentes heterogéneos, que difieren en la habilidad general y la habilidad de ser (un buen) profesor, para un conjunto de 22 pases de la OCDE.

Como se mencionó anteriormente, hay una escasez de literatura teórica que estudie el proceso de selección de docentes. El modelo propuesto nos ayuda a comprender los mecanismos a través de los cuales las personas deciden convertirse en docentes y cómo las instituciones educativas los seleccionan. Claramente, entender este proceso de selección en profundidad es el primer paso para comprender las variables que caracterizan la calidad de los docentes en un país, y por lo tanto, para disear polticas educativas para mejorar el rendimiento escolar. Es necesario tener en cuenta que mejorar el rendimiento de los estudiantes importa ya que no solo se generan beneficios individuales a través de mejores puestos laborales y mejores rendimientos laborales (ver por ejemplo Cameron y Heckman 1993, 1998) sino también beneficios agregados a través de un mayor crecimiento económico en el país (ver, entre otros, Hanushek y Kimko, 2000; Hanushek y Woessmann, 2012).

A partir del modelo, se construyeron series temporales de la calidad docente (TQ) agregada para cada país, y se analizaron sus principales determinantes al tiempo que se estudió la importancia de la TQ para explicar las diferencias en los logros de educativos los estudiantes. Mi aproximación de la TQ medida para diferentes países en diferentes aos me ayuda a entender si las tendencias de la calidad del docente pueden explicar la evolución de los logros de los estudiantes a nivel nacional, medidos con los datos de PISA. Hasta donde tengo conocimiento, no hay estudios previos que incluyan este análisis debido a que no existen series temporales previas de medidas de calidad docente a nivel del país. Tener series temporales de calidad de docentes para un conjunto de países es importante porque las razones detrás de la dispersión entre países en los resultados de los estudiantes podran ser potencialmente elementos inobservables como la cultura de aprendizaje o las instituciones educativas. Contar con series temporales de TQ, nos permite controlar las estimaciones realizadas por estos efectos fijos inobservables a nivel de país.

El modelo teórico muestra que en equilibrio general, la relación entre salarios docentes y calidad docente (TQ) es no lineal e incluso podría ser no monótona. Este resultado teórico nos ayuda a comprender por qué la literatura empírica que analiza los salarios de los docentes y los logros educativos no es concluyente. La evidencia sugiere que los salarios no son un indicador fiable de la calidad del docente, ya que la mayoría de los estudios no encuentran un efecto estadísticamente significativo entre los salarios y los resultados de los estudiantes.[11] Sin embargo, una razón que podría explicar esta divergencia en resultados sería que distintos países están en diferentes partes de la curva de equilibrio. Esto es así porque, por un lado, el análisis emprico previo basado en datos transversales dentro de un país determinado probablemente captura un pequeo segmento de la curva de equilibrio ya que la dispersión salarial del docente suele ser pequea dentro de los países. Por otro lado, los parámetros que controlan el proceso de selección de docentes difieren entre países, lo que determina que la curva de equilibrio salario do-

[11] Hanushek (2003) proporciona una revisión extensa sobre este tema.

cente y calidad docente sea diferente entre los países debido a que la misma es bastante sensible a cambios en los parámetros exógenos.

La medida propuesta de TQ tiene una correlación fuerte y positiva con la dispersión entre países en los resultados de los estudiantes, incluso controlando por las características de los estudiantes y las escuelas, los antecedentes familiares, el contexto macroeconómico y los efectos fijos no observables del país. En el capítulo, realizo varios ejercicios contrafactuales para discutir la importancia de TQ para explicar las diferencias entre países en los resultados de los estudiantes, así como para comprender los principales factores detrás de las diferencias de TQ entre los países. El primer ejercicio contrafactual nos muestra que las diferencias entre países en TQ explican aproximadamente el 22% del total de la varianza observada entre países en los resultados de los estudiantes. La importancia de TQ resulta similar al efecto de contexto familiar y claramente más alta que la relevancia de otros insumos escolares.

El segundo ejercicio contrafactual ayuda a comprender las principales variables que afectan la calidad de los docentes. La literatura previa nos ensea que la calidad docente importa, pero se sabe poco sobre sus principales determinantes. Los ejercicios contra-fáctuales nos permiten cuantificar los principales determinantes de las diferencias entre pases en TQ y demuestran que las distribuciones iniciales de las habilidades de la población son cruciales para explicar las diferencias actuales en la TQ entre los pases, mientras que salarios docentes y condiciones del mercado laboral tienen una importancia menor.

El modelo teórico utilizado es como un pequeo laboratorio que nos permite comprender el comportamiento de los diferentes agentes en el sistema educativo, así como las interacciones entre ellos. En consecuencia, el modelo nos proporciona un marco conceptual que nos ayuda evaluar cuantitativamente varias políticas educativas. Esto es precisamente lo que hago en el tercer capítulo.

El tercer capítulo analiza la relación entre la calidad y cantidad docente mediante el estudio de la asignación eficiente de la masa salarial educativa, y donde la masa salarial tiene en cuenta la interacción entre los salarios docentes y el número de docentes. Para ello, utilizo una versión modificada del modelo desarrollado en el captulo 2, ya que ahora los salarios de los docentes y el tamaño de las clase son ambos endógenos. Y como en el capítulo anterior, dado que el modelo teórico incluye la oferta y la demanda de docentes, el análisis es un marco de equilibrio general que tiene en cuenta cómo interactúan la oferta y la demanda.

La principal motivación de este capítulo radica en el hecho de que la literatura educativa se ha orientado generalmente hacia el estudio de la efectividad de diversas polticas educativas consideradas individualmente. Este tipo de análisis ha sido estimulado a su vez por el uso creciente de experimentos controlados aleatoriamente para la evaluación de políticas. Sin embargo, los documentos que comparan varias alternativas para el uso de un único recurso son mucho menos frecuentes. Este capítulo analiza específicamente la asignación eficiente de la masa salarial educativa para mejorar el rendimiento estudiantil. Este análisis es de especial relevancia dado que, debido a la escasez de recursos, mejorar la eficiencia del sector público implica dirigir los esfuerzos hacia aquellos factores que tienen un mayor impacto en el desempeño escolar.

Centrar la atención en la masa salarial es importante por al menos dos razones. En primer lugar, la masa salarial representa, en promedio, aproximadamente el 65% del gasto total en educación en los países de la OCDE (ver OCDE, 2017). En segundo lugar, los docentes representan el imput educativo con mayor impacto en el rendimiento académico de los estudiantes (Hanushek, 2003, Klein et al., 2010; Gates, 2011; Hiatt, 2009), y los salarios son una buena herramienta para atraer y retener a los mejores docentes. Por lo tanto, la eficiencia del sector educativo puede estar estrechamente relacionada con las decisiones sobre la compensaciones salariales.

La discusión sobre la asignación de la masa salarial educativa se caracteriza por una clara disyuntiva entre la calidad y la cantidad de docentes. Por un lado, los salarios más altos podrían actuar como un incentivo para atraer y retener a los mejores docentes al sector educativo (Doltonand y Marcenaro Gutirrez, 2011; Loeb y Page, 2000).[12] Por otro lado, un aumento en el número de docentes permite una reducción del tamaño de clase que generalmente está asociada a un mejor ambiente de estudio y, por lo tanto, a mejores resultados de los estudiantes (Card y Krueger, 1992; Hoxby, 2000; Woessman, 2005).

[12] Los resultados del Capítulo 2 también respaldan esta idea.

En este capítulo, calibro el modelo teórico de selección de docentes para 22 pases de la OCDE entre 2006 y 2015. Luego, con base en estas calibraciones y la función de producción educativa estimada, calculamos la asignación óptima de la masa salarial educativa en cada país. Además, comparando los resultados estudiantiles medidos con PISA utilizando la cantidad y calidad de profesores teórica así como los observados en los datos, construimos un índice que mide la ineficiencia en la asignación de cantidad y cualidades del docente y, por lo tanto, mide la ineficiencia salarial de cada país de nuestra muestra. Los resultados indican que la ineficiencia promedio en la asignación de la masa salarial para el grupo de países considerado es del 16%. Es decir, los recursos actualmente asignados a la masa salarial educativa podrían tener un impacto significativamente mayor en los resultados educativos al mejorar su asignacin entre salarios y horas lectivas. Además, en la mayora de los países, la brecha de ineficiencia se genera por un sesgo al priorizar la cantidad respecto a la calidad de los docentes.

Finalmente, al final de la tesis, se presentan las conclusiones generales de toda la investigación.

References

Acemoglu, D. and D. Autor, (2011). Skills, Tasks and Technologies: Implications for Employment and Earnings". Handbook of Labor Economics, Volume 4b.

Autor, D., F. Levy and R. Murnane (2003). The Skill Content of Recent Technological Change: An Empirical Exploration. Quarterly Journal of Economics 118(4): 12791333

Barro, R.J. (2001). Human capital and growth. American Economic Review Pap. Proc 2001; 91:1217.

Brynjolfsson, E. and A. McAfee (2014). The second machine age: work, progress, and prosperity in a time of brilliant technologies. First edition. New York: W.W. Norton & Company.

Cameron S. and J. Heckman (1993). "The nonequivalence of high school equivalents". Journal of Labor Economics ll(1):l-47.

Cameron S. and J. Heckman (1998). "Life Cycle Schooling and Educational Selectivity: Models and Choice" Journal of Political Economy, April, 1998.

Castello-Climent A. and A. Hidalgo-Cabrillana (2012). The role of education quality and quantity in the process of economic development. Economic Educational Review 2012;31:391409.

Card, D. and A. Krueger (1992), "Does school quality matter? Returns to education and the characteristics of public schools in the United States", Journal of Political Economy, 100(1),1?40.

Chetty, R., J.N. Friedman, and J.E. Rockoff, (2011). The Long-Term Impacts of Teachers: Teacher Value-Added and Student Outcomes in Adulthood, NBER Working Paper No. 17699.

Dolton, P. and O. Marcenaro-Gutierrez (2011). "If you pay peanuts do you get monkeys? A cross-country analysis of teacher pay and pupil performance." Economic Policy 26 (65): 5-55.

Frey, C. and M. Osborne (2013). The Future of Employment: How Susceptible Are Jobs to Computerisation?, Working paper, Oxford University, Oxford, U.K.

Gates, B. (2011). How Teacher Development Could Revolutionize Our Schools, The Washington Post

Goldin C. (2016) Human Capital. In: Handbook of Cliometrics. Heidelberg, Germany: Springer Verlag; 2016.

Gordon, R. J. (2016). "The rise and fall of American growth: the U.S. standard of living since the Civil War". Princeton University Press, 2016

Hanushek, E. (2003). "Teacher Quality". In Lance T. Izumi and Williamson Evens (eds), Teacher Quality.

Hanushek, E. (2010). "The economic value of higher teacher quality". CALDER Working Paper N 56, December, Urban Institute.

Hanushek, E and D. Kimko (2000). "Schooling, labor force quality, and the growth of nations," American Economic Review, 90, 1184-1208.

Hanushek, E, and S. Rivkin (2007). "Teacher Quality," In Handbook of the Economics of Education, ed. E. A. Hanushek and F. Welch, 1051-78. Amsterdam: North Holland.

Hanushek, E. and S. Rivkin (2010). "Generalizations about Using Value-Added Measures of Teacher Quality." American Economic Review 100(2):267–71.

Hanushek, E. A. and L. Woessmann (2012). "Do better schools lead to more growth? Cognitive skills, economic outcomes, and causation, "Journal of Economic Growth, 17, 267- 321.

Hiatt, F. (2009). How Bill Gates Would Repair Our Schools, The Washington Post, March 30 2009.

Hoxby, C. (2000). "The effects of class size on student achievement: new evidence from population variation", Quarterly Journal of Economics, 115(4), 1239?85.

Jepsen, C. (2005). Teacher Characteristics and Student Achievement: Evidence from Teacher Surveys, Journal of Urban Economics, 57, 302-319.

Klein, J., M. Rhee, P. C. Gorman, R. Huberman, C. R. Johnson, A. Alonso, T. Boasberg, A. Ackerman, W. Hite Jr., JC. Brizard, J. Torres, J. Covington, T. Grier, P. Vallas, E. White, and L. Sheffield (2010). How to Fix Our Schools: A Manifesto by Joel Klein, Michelle Rhee and Other Education Leaders, The Washington Post, October 10 2010.

Krueger, AB. and Lindahl M. (2001). Education for growth: why and for whom. Journal of Economic Literature 2001; 39 : 110136.

Loeb, S. and M. Page (2000). 'Examining the link between teacher wages and student outcomes: The importance of alternative labor market opportunities and non-pecuniary variation', Review of Economics and Statistics, 82(3), 393–408.

OECD. (2013). OECD skills outlook 2013: First results from the survey of adult skills. Paris: Organisation for Economic Co-operation and Development.

OECD. (2015). PISA 2015 Results (Volume I). Excellence and Equity in Education. Paris: Organisation for Economic Co-operation and Development.

OECD (2016). Automation and Independent Work in a Digital Economy. Policy Brief on the Future of Work. Paris: OECD Publishing

OECD (2017). "Education at a Glance (2017): OECD Indicators", OECD Publishing, Paris.

Rockoff, J. (2004). The Impact of Individual Teachers on Student Achievement: Evidence from Panel Data, American Economic Review Papers and Proceedings, 94, 247-252.

Rothstein, J. (2015). "Teacher quality policy when supply matters". American Economic Review, Vol, 105, No 1, January, pp 100-130.

SpitzOener, A. (2006). Technical Change, Job Tasks, and Rising Educational Demands: Looking Outside the Wage Structure. Journal of Labor Economics 24 (2): 235270

Woessman, L. (2005). "Educational production in Europe", Economic Policy, 20 (Issue 43), 445-504.

Chapter 1

Technological change and Labour market trends in Latin America and the Caribbean: A task content approach

1.1 Introduction

Technological change, such as the advance in digital technologies, communication, and robotics, can lead to an improvement in the general well-being of the population and reduce poverty, thanks to the increase in global productivity of the economy.

The potential benefits of technological advance are important for both, workers and for consumers. Digital technologies, for example, can create jobs and increase benefits for small and medium-sized producers through the expansion of access to information and communication mechanisms, especially in those sectors which could be, or already are users of that technology. An example of this could be the creation of commercial platforms connected via the internet through which buyers and sellers can be brought together with

[0]This is a joint work with Ignacio Apella (World Bank)

minimum transaction costs.

From the point of view of consumers, the benefit coming from technological change is associated with the potential reduction in the price of products downstream - as a consequence of the profits gained from greater efficiencies and the increase in the range of goods and services available, thus generating a positive variation in consumer surplus. The majority of these consumer gains come from reduced marginal costs of production and distribution when the productive sector incorporates technological innovation and automates productive processes taking advantage of the economies of scale which are generated.[1]

However, if this process is not accompanied by complementary investments, that is, institutional reforms and public policies aimed at capitalizing on the advantages that this process permits, then, the technological advance could also deepen a situation of inequality. Indeed, technological advance, together with the reduction of access cost to new forms of production, generates a potential displacement of a part of the traditional labour force through machines administered from computerized systems, while at the same time paving the way for the creation of new types of jobs.

Technical progress, in particular, the advance of robotics, means that certain activities run a high risk of becoming obsolete, since some of them, such as routine tasks, or those which can be replaced by a code, can be easily automated, leading to what is commonly known as technological unemployment. Depending on whether the machines are capable of replacing only unskilled work, skilled work, or all work, the consequences will be distributed differently.

In this sense, this new setting poses some challenges or new complementary investments for the labour force in order that the benefits offered by the technological change are realized. In other words, it demands an increment in the productivity of workers through an increase in their human capital in order to ensure their adaptation to and compliance with the new forms of production. In effect, the benefit generated by the use of the new production technologies is not automatic. Not only does access to information

[1]However, the transfer of a technological improvement to final prices assumes a certain grade of competition in each market. In a market with a high concentration, profits from efficiency will be transferred to the profit margins of the companies.

services and digital communication need to be improved, but also new basic skills need to be incorporated through the updating of education systems and continuous training.

Several recent works have called attention to the potential impacts of the recent process of technological change on the labour market (Brynjolfsson and McAfee 2014; Autor et. al. 2003; Spitz-Oener, 2006; Acemoglu and Autor 2011; Frey and Osborne 2013; OECD, 2016). Particularly, these works highlight not only the possibility that technological change could displace a big part of the current occupations (Frey and Osborne 2013, Brynjolfsson and McAfee 2014, OECD, 2016) but also delve into the type of tasks that are most likely to suffer this displacement and, on the contrary, the types of tasks which could be increasingly demanded by the new technologies (Autor, et. al. 2003; Spitz-Oener, 2006; Acemoglu and Autor, 2011). The last approximation to the effect of technological change on labour markets is usually called as the task content approach.

Previous literature based on the task content approach states that jobs intensive in cognitive tasks, particularly in the case of non-routine cognitive tasks not only that they would suffer to a lesser extent the phenomenon of technological displacement but, on the contrary, they would be stimulated by this process (Autor et al., 2003, and Spitz-Oener, 2006, Acemoglu and Autor, 2011, Keister and Lewandowski, 2016). Therefore, labour placement, as well as the labour productivity, will be increasingly linked to the ability of workers to develop cognitive tasks.

However, most of the literature regarding the potential impact of technological change on labour markets is based on developed countries. Evidence for emerging countries and particularly for Latin American and the Caribbean is much more limited. Emerging countries show different characteristics than developed countries which could potentially leads to different trends of technological advance and task profile of the labour markets. Indeed, the economic structure/specialization is different between developed and emerging countries. Emerging countries are characterized by lower wages and therefore lower incentives for automation compared with developed countries. Finally, emerging countries usually show lower performance in comparative test of cognitive skills which could imply constraints from the labour supply to move toward a task profile more intensive in cognitive tasks.[2]

Therefore, the stylized facts for developed countries are not necessarily true for emerging countries. Then, the following question arise: Do technological change also have determined a growing demand of cognitive skills for workers in emerging countries? This chapter aims to provide elements to answer this question based on the evidence for Latin America and Caribbean in the last two decades.

In this line, the objective of this chapter is to study past tendencies in the level of employment according to the types of tasks that the workers did in their jobs, in order to approximately assess the possible impact of technological change on labour demand and to prompt a discussion on the possible responses to this challenge in public policies. To do that, we apply the task content methodology proposed to Acemoglu and Author (2011) to a set of 9 Latin American and the Caribbean countries (Argentina, Bolivia, Brazil, Chile, El Salvador, Mexico, Peru, Dominican Republic and Uruguay) which we understand represent quite well the different characteristics of the whole region.

This chapter provides new evidence which suggest that labour markets of the Latin American and the Caribbean countries are not exempt from this process. During the last 20 years, the labour force in the region has moved from developing more in the area of intensive manual tasks to instead that of performing cognitive tasks. This allows us to states that, on average across the whole market, jobs are changing and with that the type of skills, and workers, required. This phenomenon is a characteristic of the change processes in the production functions of economies, in particular, of the adoption of new technologies such as robotics, which permit manual labour to be substituted in certain tasks.

The chapter proceeds as follows. The next section discusses the theoretical framework of analysis related to the relationship between technological change and the rhythm of substitution of productive factors. The third section presents the methodology and information used. The fourth section analyses the main results obtained for a set of nine Latin American and the

[2]See, for example, the gaps in cognitive skills between emerging and developing countries in the PISA test (OECD, 2015) and the PIAAC survey (OECD, 2013).

Caribbean Countries. The fifth section discusses the challenges that these tendencies imply for public policies. Finally, some final reflections are made.

1.2 Theoretical framework

The impact of technological advance on the performance of the labour market is discussed at length in the literature (Autor et al., 2003 and 2013; Frey and Osborne, 2013; among others) in which it is suggested that there is a reduction in the level of employment in occupations high in routine tasks, that is, occupations which consist principally in tasks which follow well-defined procedures that can easily be performed by some sort of algorithm. This shows that not only technological advance, but also the reduction in cost of accessing these new production technologies, generates a potential displacement of a part of the labour force through machines administered by a computerized system. Therefore, technological change, in particular the advance of robotics, could give rise to an increase in technological unemployment.

Frey and Osborne (2013) distinguish between occupations at high, medium and low risk of being automated, and argue that close to 47% of the total work of the United States can be placed within the high-risk category. For its part, the World Bank (2016) estimates that an average of 50% of the current work in Latin America might not continue being performed by people in the future.

However, not all jobs are susceptible to being automated. The analysis of this phenomenon requires jobs to be differentiated, not by their levels of qualifications or skills, as may be suggested, but by the combination of tasks which are performed. This analysis framework, known as "task content", is the proposal of Autor et al. (2003) and Acemoglu and Autor (2011), among others. According to these authors, the tasks are not strictly the skills with which the worker is equipped, but those which are closely related with them.

Specifically, a task is defined as an activity which enables the creation of a product (Acemoglu and Autor, 2011). However, the workers need a series of skills to be able to carry out these tasks. As an example, an architect needs great numerical and mathematical skills to perform cognitive tasks which are generally non-routine, such as the design and development of plans. The skills may be seen as the ability of the workers to perform particular tasks.

Tasks can be classified in two large categories: routine or non-routine. A task is routine if its performance implies a clear and repetitive set of invariable actions. Many tasks, such as the temperature control of a steel production line or the transfer of a car part to its place in an assembly line, among others, have this characteristic. Since these tasks require the methodical repetition of a constant procedure, they can be clearly specified in a computer program and performed by a machine.

On the other hand, a non-routine task is that whose performance requires various actions to vary in time, and requires the ability to adapt to the context, using language, visual recognition and social interaction, among others. Following Polanyi (1966), this skill that says that a driver cannot be completely replaced; the knowledge that a person has about their own body differs completely from their knowledge of physiology; and the rules of rhyme and prose do not explain in themselves what a poem conveys. In this sense, the passage of a car through the traffic of a city, or the writing of a poem, fall into the category of non-routine tasks. The reason being that those tasks require the abilities of visual, socio-emotional and motor processing that cannot be described in terms of a set of programmable rules.

At the same time, the tasks in each of these two categories may be of a manual or cognitive nature, that is, that they are related to either physical work or to knowledge. From this, it is possible to establish four main categories of tasks:

1. Routine manual tasks: normally performed by low- or medium-skilled workers. Such tasks are highly codifiable and replaceable by automation, such as assembly line workers and manual factory workers.

2. Non-routine manual tasks: commonly performed by poorly-qualified workers. The performance of these tasks requires the ability to adapt to the situation, the language, visual recognition or social interaction. Drivers, mining workers and construction are examples of occupations which perform these types of tasks intensively. These workers have a low or zero probability of being computerized although Frey and Osborne (2013) suggested that some of these tasks, such as transport and logistics and administrative support, are at risk of being automated.

3. Routine cognitive tasks: are carried out by medium-skilled workers. In some occupations more than others, computers may be a substitution factor since they demand explicit and repeated sets of activities which could be coded in a computer program. The tasks performed by secretaries, salespeople, administrative staff and bank cashiers, among others, fall within this group.

4. Non-routine cognitive tasks: normally performed by highly-skilled workers. These tasks, which are often divided into two large subcategories, such as those of analysis and of personal relations, require abstract thought, creativity, the ability to solve problems and communication skills. Computers may complement the performance of these tasks, increasing the productivity of the skilled workers. These tasks are commonly performed by professionals such as managers, designers, engineers or information technology specialists, teachers, and researchers, among others.

All occupations, with differing levels of intensity, involve one or a combination of the tasks described. The intensity of the tasks may appear very heterogeneous between occupations. As an example, a car driver performs non-routine manual tasks the majority of the time but also performs personal non-routine cognitive tasks and routine cognitive tasks. In contrast a scientist dedicates the majority of their time to the performance of non-routine cognitive tasks but also preforms routine tasks with a lower frequency (cognitive and/or manual).

Owing to the decline in costs of access to new technologies, computer-controlled machinery could replace those workers that perform largely routine tasks, especially manual ones. This phenomenon is not new. This substitution has been seen since the first industrial revolution, but the technological revolution has developed in such a way that machines can perform cognitive tasks that decades ago were only performed by people. Following Bresnahan (1999), during the last three decades computers have replaced tasks associated with calculation, coordination of activities and communication, bank cashiers, telephone operators and other operators of repetitive information-processing tasks.

On the other hand, the ability of computers to replace workers employed in the performance of cognitive tasks is limited. The combination of tasks which demand flexibility, creativity, problem-solving and communication skills (non-routine cognitive tasks) are less susceptible to being automated. The need to establish a series of explicitly-programmed instructions constitutes a restriction.

Because computer technology is more adept at replacing workers who routinely perform routine tasks than non-routine tasks, it becomes a complementary factor for the development of non-routine tasks, and is even capable of increasing marginal productivity. To give an example, the ability to use a bibliographic search program through a networked computer increases the efficiency and quality of researchers that use such references as inputs.

Not all tasks are susceptible to being replaced by machines. The decision of the productive sector related to the optimum combination of production factors is found to be associated not only with the flexibility of the substitution between factors but also with the relative price of them. The simple model proposed by Autor et al. (2003) and also by Frey and Osborne (2013) allows these decisions to be formalized.

Assuming a Cobb-Douglas production function for work and capital in the following manner:

$$Q = (L_r + k)^{1-\beta} L_n^{\beta} \tag{1.1}$$

Where L_r and k are the work intended to be performed by the tasks susceptible to automation and the capital that these tasks can realize, respectively. Both factors are perfect substitutes. L_n represents the value of the work required so that the tasks are not susceptible to automation. Assuming that the price of the product is the numeraire and that w_r, ρ, and w_n are the salary of the work that can be automated, the price of the capital and the salary of the complementary work, respectively, of the first order conditions we can find the following expression.

$$PMg_{Lr} = PMg_k = (1-\beta)\frac{(L_r + k)^{-\beta}}{L_n^{-\beta}} = w_r = \rho \tag{1.2}$$

Where $\theta = \frac{(L_r+k)}{L_n}$ is the relationship between tasks susceptible and not susceptible to being automated within the production function. The optimal condition demands equality between the quotient of the marginal productivities of the factors and the relative prices:

$$\frac{PMg_{Lr}}{PMg_k} = 1 = \frac{w_r}{\rho} \tag{1.3}$$

Assuming a reduction of the price of capital, ρ, that implies that the technical substitution relationship is less than the relative prices, encouraging the company to seek a reallocation of productive factors in order to achieve economic efficiency. To do so, the company replaces labour with capital.[3] Simultaneously, a modification of the relative prices is generated, generating an increment of the redistribution L_r in relation to L_n. Of the first order conditions, we also have that:

$$(1-\beta)\theta^{-\beta} = \rho \tag{1.4}$$

Taking the natural logarithm of both sides and differentiating completely we have that:

$$\frac{dln\theta}{dln\rho} = -\frac{1}{\beta} \tag{1.5}$$

Thus, a substitution effect is generated in favour of tasks susceptible to automation, and within these, in favour of those made by capital.

This change of relative prices, in addition to the effect generated by the substitution, would generate incentives around the type of job. Following Goos and Manning (2007), for the case of Great Britain, it is possible to see a tendency in the polarization in the work market, with growth in high-income cognitive work and low-income manual occupations, accompanied by a reduction in routine tasks with medium incomes. In this sense, given a reduction in the prices of computing equipment, problem-solving skills are

[3] In the case of additive production functions, the only effect in the face of an exogenous price shock is the substitution effect.

becoming relatively more productive, which explains the growth in occupations which require the performance of cognitive tasks by a qualified labour force (Katz and Murphy, 1992 and Acemoglu, 2002).

1.3 Methodology and sources of information

To carry out this analysis, the information available in the O*NET (Occupational Information Network) database was used in conjunction with the Households surveys. This database provides information referring to the content of tasks of the occupations. Since 2003, O*NET data have been collected in the United States for approximately 1000 occupations based on the Standard Occupational Classification (SOC), and it has been updated periodically.[4]

Following the work of Acemoglu and Author (2011) four sets of O*NET data are used: skills, work activities, work context and skills. Each of them contains descriptors that try to measure the importance, level or scope of the activity from a scale. For this, data from O*NET 2003 and 2015 are used in order to capture the content change of the tasks within each occupation over time.

In order to estimate the content of the tasks in the occupations, the elements of the tasks provided by O*NET are mapped to the corresponding occupations of four digits in the International Standard Classification of Occupations (ISCO). This is combined with individual labour force data from household surveys. In general, each country has a specific version of the ISCO or, at least, in cases where a national classification is used, an ISCO equivalence is applied. On the other hand, O*NET follows a modified version of the Standard Occupational Classification (ONET-SOC). In order to be able to combine the appropriate occupational attributes to the household survey data, an equivalence table between these two classifications is used.

In many cases the correspondence tables do not determine a one-to-one

[4] O*NET is the successor of DOT (Dictionary of occupational titles) which is no longer updated. O*NET was launched in 1998 on the basis of the BLS Occupational Employment Statistics codes. In 2003, it was changed to SOC which implies that the consistent measures of task content are calculated from 2003.

correspondence between the occupation categories of O*NET and the household surveys. In these cases, the strategy used by Hardy et al. (2015) was followed. Four situations can be identified.

In the first case, there are situations where an occupational code of a specific classification corresponds to only one occupational code of the classification we want to map to. In this case the characteristics are attributed directly to the first code of the second classification.

In the second case, a specific code of a classification corresponds to more than one code of the classification we wish to map to. In this case, the characteristics of the same original code are attributed to all the occupations of the second classification.

In third case, various occupations from the original code correspond to the same code in the classification we are mapping to. In this case, the average value of the characteristics associated to the codes of the original classification are attributed to this last code.

The final case is where various codes in the original classification correspond to various codes in the mapped classification. In this situation, again an average value of the characteristics associated to the corresponding codes of the original classification is attributed to each code in the mapped classification.

Once the mapping has been done, following Acemoglu and Autor (2011) and Hardy et al. (2015), five measures of content or intensity of main tasks are constructed: cognitive non-routine analytical and interpersonal, routine cognitive and manual and non-routine manuals. These are building based on the attributes of the activities that the occupation requires. In this sense, some attributes (elements) that are representative of each task were selected. They are presented in Table 1.1.

After assigning each attribute to each task, and these to the information from the surveys, the values of each element t are normalized in order to enable information to be comparable across time, using the following formula:

$$\forall j \in J \quad t_{i,j}^{std} = \frac{t_i - \mu_j}{\delta_i} \tag{1.6}$$

Table 1.1: Construction of the measurement of the content of tasks

Tasks	O*NET information (*t*)
Non-routine cognitive (analitycal)	Analyzing data/information Thinking creatively Interpreting information for others
Non-routinecognitive (interpersonal)	Establishing and maintaining personal relationships Guiding, directing and motivating subordinates Coaching/developing others
Routine Cognitive	Importance of repeating the same tasks Importance of being exact or accurate Structured v. Unstructured work (reverse)
Non-routine manual	Operating vehicles, mechanized devices, or equipment Spend time using hands to handle, control or feel objects, tools or controls Manual dexterity Spatial orientation
Routine Manual	Pace determined by speed of equipment Controlling machines and processes Spend time making repetitive motions

Source: Own elaboration based on Acemoglu and Author (2011) where J is the combination of the 16 tasks listed in Table 1.1 for the occupation i and μ_j and δ_j represent, respectively, the weighted average and the standard deviation of the task j in the total of the period 1995-2015 computed as follows:

$$\forall j \in J \quad \mu_j = \frac{\sum_i^N t_{i,j} w_i}{\sum_i^N w_i} \tag{1.7}$$

$$\forall j \in J \quad \delta_j = \left(\frac{\sum_i^N w_i (t_{i,j} - \mu_j)}{\sum_i^N w_i} \right)^{1/2} \tag{1.8}$$

where w_i is the relative weighting attributed to the occupation i.

To construct the measures of intensity of each task each one of the elements of the same group of tasks is added up and each one of the five measures of intensity is standardized.

1.4 Empirical results

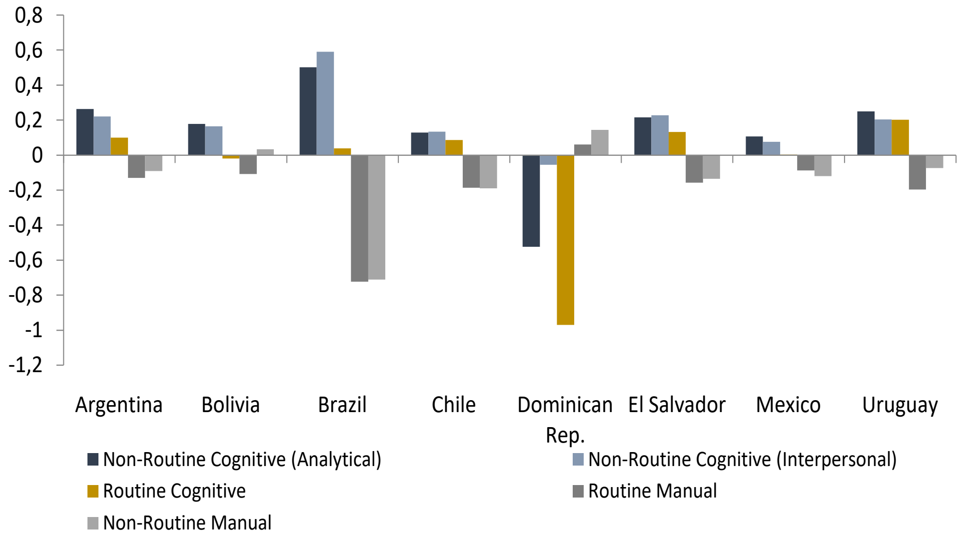
1.4.1 Relative importance of each task in the job

In this section, we present the empirical results related to the change in the tasks performed by the average employment of the selected countries between the middle 90s and 2015. The aim is not only to identify the changes but also the factors that promoted these changes and the effects on the wage distribution.

Figure 1.1 shows for each country, the variation of the content of each type of task in the average employment between the middle 90s and the year 2015.

Observing the variation between the extreme years in each country, a clear common tendency of change in the profile of the average employment of the region is appreciated, although with some differences that need to be highlighted.

Figure 1.1: Change of the content of the tasks carried out in employment by country. Mid-'90 - 2015.



Source: Own computations based on O*NET and Household surveys

In terms of the content of non-routine cognitive tasks, both analytical and interpersonal relations, all the countries analysed, with the only exception of the Dominican Republic, show an increase in the content of these tasks in average employment. This finding is in line with the process of changing tasks performed by workers in a context in which there is a risk of automation of many of them. As mentioned above, non-routine cognitive tasks are not susceptible to automation and therefore it is in this group of activities that space is generated for the work force.

In the case of manual tasks, both routine and non-routine, their relative importance within average employment decreased during the period of study in all countries, again with the exception of the Dominican Republic. For its part, Bolivia is a particular case, because although there is a drop in non-routine manual tasks, there is also a small increase in routine manual tasks.

On the other hand, the importance of routine cognitive tasks in average employment rises in five of the nine selected countries: Argentina, Brazil, Chile, El Salvador and Uruguay. On the contrary, in the case of Bolivia, Mexico, Peru and the Dominican Republic, the content of routine cognitive tasks in average employment decreased during the last twenty years.

The results found suggest that in Latin America and the Caribbean there was a change in the profile of employment, in terms of the intensity of the tasks that are carried by employees in their occupations, passing from jobs intensive in manual tasks to a greater intensity or content of cognitive tasks. The only exceptions to this common trend in our set of countries are the Dominican Republic, where the profile of employment changed in the opposite direction and Bolivia, where the content of routine manual tasks increased during the period under study.

In general, the region has shown a growth in the relative importance of non-routine cognitive tasks, both analytical and interpersonal, during the last twenty years. At the same time, the average intensity of manual tasks, both routine and non-routine, decreased. All these changes are in line with the findings reached in the most developed countries (Autor et al., 2003, and Spitz-Oener, 2006), and with the results of Keister and Lewandowski (2016) for the case of countries of Central Europe.

However, the evolution of the relative importance of routine cognitive tasks allows some space for a discrepancy in some countries of the region. Autor et al. (2003) show that the development of this type of tasks lost relevance in the US employment and Spitz-Oener (2006) obtained similar results for the case of Germany. However, a review and update by Acemoglu and Autor (2011) for the case of the United States found different trends during specific periods. In the same way, for several countries of Central and Eastern Europe, Keister and Lewandowski (2016) identify an increase in the intensity of routine cognitive tasks.

The importance of the increase in the content of routine cognitive tasks in the average employment in the countries of the region lies in the risk of automation that these types of task present. Indeed, the fact that the workforce carries out this type of task with greater intensity poses a risk in the medium term of displacement of a part of the workers due to automation. As mentioned previously, these type of tasks are carried out by workers at the intermediate level of education and who achieve an average labour income, which implies that, in the face of an automation and displacement process, a situation of distributive inequality would deepen.[5]

1.4.2 Factorial decomposition of the change in the content of tasks

The variations in the content of observed tasks raise some concerns related to the mechanisms that operate in changing the profile of average employment in each of the countries analysed. In this sense, it is possible to identify three major channels through which the changes in the importance of each task in average employment are generated.

The first one is associated with the movement that workers make between economic sectors, commonly called the between sector effect (BS). As an example, a migration of workers from an economic sector such as agriculture, traditionally intensive in manual tasks, to the service sector, which is more intensive in the development of cognitive tasks, leads to a change in the profile of tasks performed at the average employment of the countries.

Following Apella and Zunino (2017), this movement of workers between economic sectors can be motivated by different causes such as the change in the terms of trade that affect the sector as a whole and puts them at a disadvantage compared to international competition, changes in global trade centres and the emergence of other countries with greater comparative advantages in the sector, the urbanization processes that take place as people leave their jobs in rural areas and migrate to large cities to join the industrial sector, of services or commerce, among others. However, technological change does not play a minor role in this process. The incorporation of new production technology in sectors which traditionally are associated with the

[5] It could be suggested that it is the youngest generation of workers which has the greatest capacity to adapt to technological change, developing cognitive tasks more intensively which complement the new technologies. On the other hand, older generations could have greater difficulty in redefining tasks which are performed in their occupations, exposing themselves to greater risk of technological unemployment. In this context, a complementary approach is the analysis of the evolution of the content of tasks in the average occupation according to the cohort of birth of the workers.We advance in this line for the specific cases of Argentina and Uruguay in Appendix IV.

development of manual tasks forces workers to seek employment opportunities in other branches of activity.

The second factor is the movement of workers between occupations within the same branch of activity, called the between occupations effect (BO). As an example, one could mention the case of a worker who abandons his occupation as a bank teller, intensive occupation in routine cognitive tasks and begins to work as a taxi driver (non-routine manual). This example allows us to recognize the importance that technological change can have on the profile of average employment, encouraging movements of workers between occupations.

The third channel which drives into variations in the average content of the tasks performed by workers is the specific modifications within each occupation in time, usually called intra-occupations effect (WO). In other words, the incorporation of new production technology in each occupation forces workers to reassign their roles within the workplace. The adoption of assembly machinery which is automated and administered from a computer program requires those tasks previously performed by the labour force to be reassigned. For example, dedicating the majority of their time to tasks relating to sales and merchandising.

In order to examine in detail the importance these transmission channels have had in the changes observed on the content of the different types of tasks performed in the average workplace in our set of countries, there follows below a factorial decomposition exercise. In order to do this, we took as reference the total changes in the intensity of the tasks between the starting point of the analysis (middle 90s) and the ending point (middle 2010s) for our set of countries identifying the three possible separate effects, mentioned above and the interaction among them:

1. Structural change or effect between sectors (BS). The hypothesis behind this effect is that part of the change in the intensities of the tasks which the labour force performs is associated with a movement of the labour force between the sectors or branches of activity, being partly motivated by technological change, but also as mentioned by other exogenous factors.

2. Change between occupations or effect between occupations (BO). This

effect is related to the movements of workers between distinct occupations with different combinations of tasks.

3. Changes within each occupation (WO). In this case we try to capture the contribution of the changes which are produced within each occupation, in terms of the combination of tasks required for the performance of the same.

4. The interaction of all of the above (INT).

In the Appendix I the decomposition exercise methodology is described in detail while the results are presented in Figure 1.2.

Beginning with the between sectors effect, it is observed that the movements between branches of activity are an important factor to explain the increase in the content of routine cognitive tasks in Chile and the decrease in the relative importance of routine manual tasks in Uruguay and Mexico. Likewise, the same effect explains a significant share of the increase in the content of routine manual tasks in Bolivia.

Observing the changes in the share of employment among branches of activity in the last twenty years (see Appendix II for details), it can be seen that, both in Chile and in Mexico, there was a significant fall in employment in industry and in primary activities (sectors of intensive activity in manual tasks), increasing employment in the real estate sector and services (intensive sectors in routine cognitive tasks). Similarly, in Uruguay there is a significant movement of employment from the industrial sector to the services sector.

Contrary to the trend observed in the rest of the region, in Bolivia, the increase in the importance of routine manual tasks in average employment corresponds to a significant rise in employment in the primary sector, which showed an increase of 30% between the years 1995 and 2015.

Related to the between occupation effect, this turns out to be one of the main channels through which there is a change in the profile of employment in the region. Indeed, it is extremely important to explain the increase in the content of non-routine cognitive tasks and the drop in the content of manual tasks in Argentina, Bolivia, Brazil, Mexico, Peru, El Salvador and Uruguay.

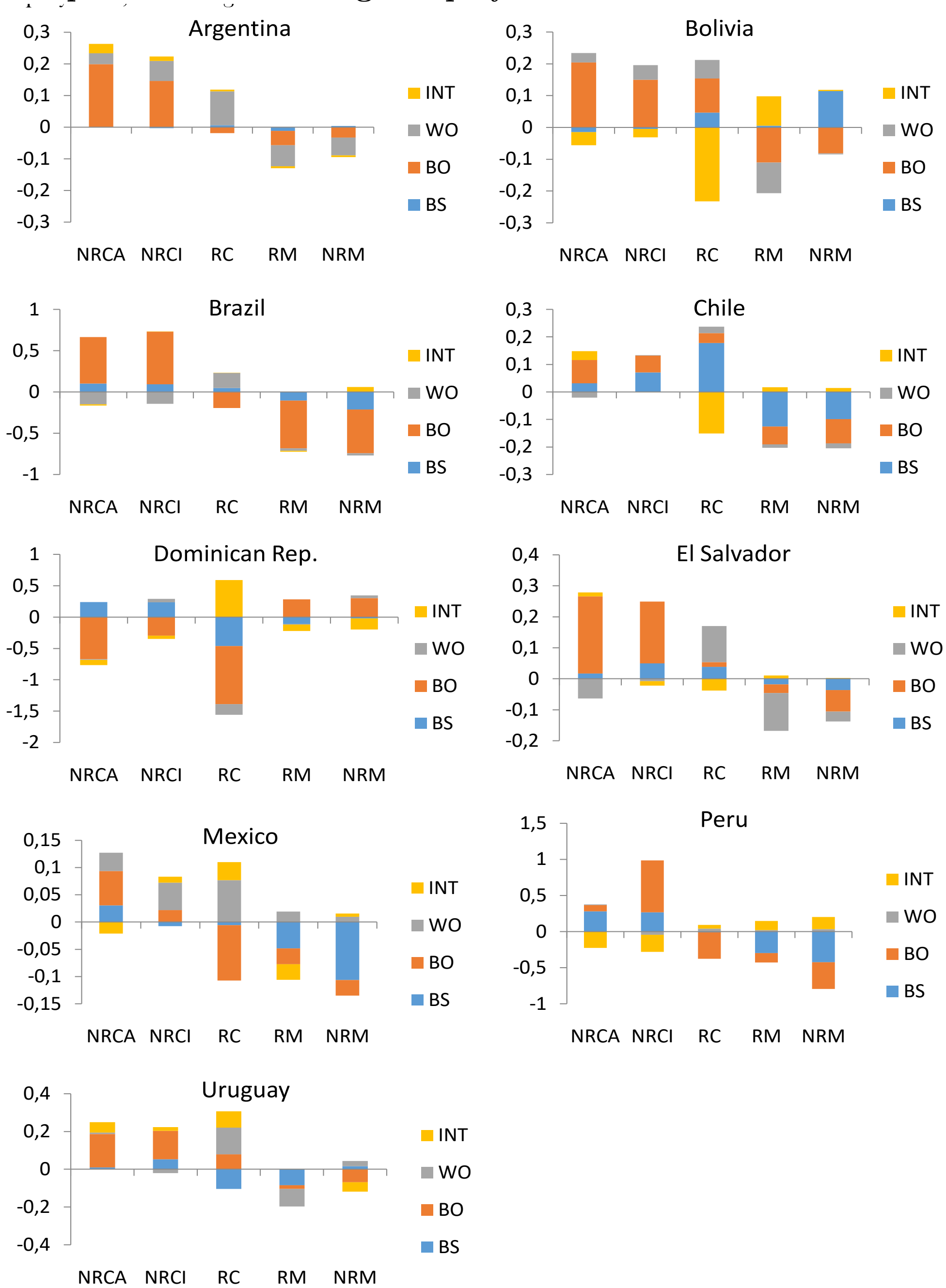
Finally, the change in the relative intensity of tasks resulting from specific changes to each occupation, that is to say, due to the intra-occupation effect, plays an important role in five countries: Argentina, Bolivia, Mexico, El Salvador and Uruguay. However, the tasks on which this effect has importance varies substantially in each country. In Argentina, changes in the combination of tasks that occur within each occupation explain the increase in the content of cognitive tasks, both routine and non-routine, and the drop in the importance of manual tasks. A similar picture, but to a lesser extent, occurs in Uruguay and El Salvador, where this effect explains the increase in the content of routine cognitive tasks in average employment and the reduction of routine manual tasks. In Mexico, this effect explains the increases in the relative importance of non-routine cognitive tasks, particularly those related to interpersonal relationships, and routine cognitive tasks. Lastly, in Bolivia, the intra-occupation effect is important to explain the increase in the content of routine cognitive tasks.

In a context of change in the importance that some types of tasks have in the average employment and therefore in need of readaptation by the labour force, there is a risk of polarization of the labour market. In this sense, the automation of certain tasks, especially the routine ones, could modify the structure of the labour market, being at the extreme represented by two large groups of workers. On the one hand, individuals of high qualification who work in occupations intensive in non-routine cognitive tasks, high productivity, and high income. On the other hand, a group of low-skilled workers, relegated to occupations intensive in non-routine manual tasks, and therefore low productivity and low incomes. This would happen while the workers of qualification and levels of average income generally devoted to the development of routine tasks (manual and cognitive) face the risk of a lower demand for employment or lower income.

Figure 1.3 presents, for the average of Latin America and the Caribbean, the task content for each decile of income per working hour according to the four large task groups previously defined for two different moments: middle 90s and 2015 (the same figure for each specific country is included in the Appendix III).

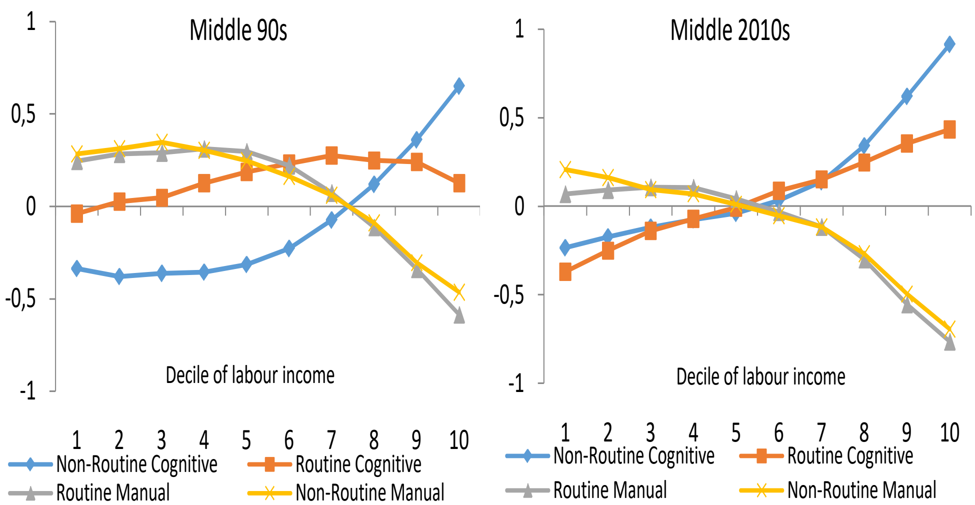
In line with the patterns observed in other countries, it can be appreciated that in the countries of the region most of the workers in the upper deciles

Figure 1.2: Factor decomposition of the change in the content of tasks performed in average employment. Middle 90s - 2015



Source: Own computations based on O*NET and Household surveys

Figure 1.3: Latin America and the Caribbean: Content of tasks according to decile of labour income. Middle 90s - 2015



Source: Own computations based on O*NET and Household surveys.
Note: simple average of Argentina, Bolivia, Brazil, Chile, El Salvador, Mexico, Peru, Dominican Republic and Uruguay.

performed non-routine cognitive tasks, while workers in the lower part of the distribution carried out manual tasks. As can be seen from the figure, the content of routine manual tasks in occupations has decreased for workers in all deciles of labour income. This result is in line with the previously discussed and the replacement of these tasks by automatic production mechanisms.[6]

On the other hand, the importance of non-routine cognitive tasks has grown in all income deciles. In this process, two important facts are observed. On the one hand, while in the mid-1990s only the workers of the last two deciles intensively developed this type of task, in 2015 deciles 7 and 8 were incorporated. On the other hand, the gap between non-routine cognitive tasks and the manual ones widened, suggesting that among the deciles of higher incomes the transition from manual tasks to cognitive tasks, especially non-routine ones, was particularly intense.

Observing the left tail of the distribution, it is appreciated that although the gap between the content of non-routine cognitive tasks and the rest was reduced, these tasks remain the least developed among the workers of the lowest income deciles. This phenomenon suggests that workers with lower labour incomes are engaged in occupations intensive in manual tasks. Indeed, non-routine manual tasks are the most important among workers in the lowest income deciles. While the content of this type of tasks was reduced in almost all the distribution, it remained almost unchanged among the workers belonging to the first two deciles, giving some indication of a concentration of this type of tasks in the lowest deciles.

Considering the last twenty years, it is possible to observe a transition towards a content structure of tasks in which non-routine cognitive tasks are developed mainly by the four highest income deciles (and increasingly remote from the average) and tasks Non-routine manuals concentrate on the lowest income deciles.

[6] In Appendix V, we depth into the analysis of a possible polarization of the labour market for the cases of Argentina and Uruguay. Particularly, in order to provide an approximation of the effect that the changes in intensity of the tasks performed by the labour force have on the well-being of the workers, we have estimated the significance of the relative importance of each task on the explanation of two key variables of workers‘ well-being: probability of becoming unemployed and level of income. The estimations and its analysis are included in the Appendix.

Even though labour markets are not yet polarized, in the future this phenomenon will clearly depend on the degree of progress of automation on routine cognitive tasks. Occupations intensive in this type of tasks, such as credit analysts, office assistants, cashiers, sellers, editors, including translators, are those through which workers with average qualification levels and incomes are located. In fact, in most of the developed economies, intensive occupations in routine cognitive tasks tend to have remunerations that are located in the mean of the distribution (Acemoglu and Autor, 2011, Goos et al., 2014).

Our findings for the region are different from what has been described in developed countries. Both in the 90s and in 2015, routine cognitive tasks have a significant relative importance between the deciles of labour income of the center and higher distribution (from the fifth decile). Indeed, while in the mid-90s the content of this type of tasks was important in all deciles from the fourth, after twenty years these tasks lost importance in the occupations performed by workers in the income lowest deciles.

For this reason, given the increase in the content of routine cognitive tasks in the average employment in the region, the risk of future polarization of the labour market will depend on the degree of automation of these.

1.5 Implications for public policy

The process of technological change that is going through not only the region but also the world is a potential source of productivity increases. However, this poses some challenges from the point of view of the labour market that conditions its use. The process of technological change could generate a reduction in the employment demand for those on middle incomes (in general associated with routine manual tasks), establishing a polarization of the labour market, creating two large groups of employment: one of poorly-paid activities, related to the performance of non-routine manual tasks, and the other of higher incomes related to non-routine cognitive tasks.

In this technological race, there is a clear challenge laid out for public policy associated with the need of low-skilled workers to reassign their tasks towards others not susceptible to automation, that is, towards those that require an intensive use of creative or social intelligence.

In the last 20 years the labour markets of the Latin American and the Caribbean region have experienced a substantial change, moving from manual work to cognitive work, which can largely be attributed to changes in the share of occupations in the total employment, the modernization within the occupations themselves and, in some cases, to a movement of workers between sectors. As in the United States, Germany, and the countries of Central and Eastern Europe, the importance of non-routine cognitive tasks in the average workplace has shown signs of considerable increase in Latin American Countries. Two effects of technological change and its reduced access cost can be seen: one more short term and one of medium or long term but which requires immediate action.

The first is associated with a lower requirement for routine manual tasks and therefore, an increase in technological unemployment in some segments of the labour force. The second is related to the challenge of preparing the younger generations, in their process of acquiring human capital, for the performance of occupations which do not exist yet but will certainly incorporate a major component of non-routine cognitive tasks.

In relation to technological unemployment, the policies aimed at confronting the negative effects of the movement of employment from intensive production in routine manual work towards intensive production in technological capital and cognitive work are of crucial importance. The transition may be confronted from two different perspectives, one from the point of view of labour demand and the other from supply.

From the perspective of labour demand, that is to say the actual productive sector which chooses the combination of factors which maximizes its benefits, the transition could be attenuated through regulations which limit the substitution of labour force by capital. These regulations could be enhanced by the political economy itself in each economy. As an example, unions play an important role in the political economy with the ability to apply pressure on the productive sector and the state in order to prevent changes in production functions. An example of that is the frustrated attempt of the Central Bank of Argentina in 2016 that the commercial banks gradually substitute printed summaries of accounts with those in digital format. This constituted a risk of reduced labour demand for the postal and delivery workers. Confronted with such a risk, the truck drivers union opposed, and managed to block the implementation of the initiative proposed by the monetary authority. In another similar case, in 2008 in Uruguay, an attempt was made to replace the bus conductors with automatic ticket dispensing machines, but the transition was never completed in order to avoid the effect that it would have on the level of employment in that occupation.

Alternatively, the authorities could design fiscal incentive mechanisms, such as subsidiary schemes for sectors or occupations which require tasks of a routine nature. In this way, the state would indirectly modify the relative prices of the production factors, discouraging the replacement of labour force by capital.

However, whichever initiative is adopted from this perspective, it must take into account the social costs and benefits which are generated. In this sense, it is essential to analyse the costs of these decisions (for example, in terms of increased production cost and reduced well-being of the consumers who pay higher market prices) and the benefits (maintaining employment levels in certain occupations). In the same way, it is important to stress that technological change is a continuous phenomenon and therefore the access cost will continue to decrease. That implies that the trend towards automation is growing over time, which implies that the costs of its deterrence shall too. In other words, to maintain its effect, this type of intervention will need to increase over time as the process of technological change advances, accepting ever greater costs of intervention.

Alternatively, public policy could focus its efforts on labour supply. In this sense, the consistent challenge in the strengthening of the spaces or instruments of re-adaptation of the labour supply, that is, redesigning continuous training systems taking into account the new labour demands. That should consider the promotion of public-private cooperation, not only in terms of financing, but also in terms of defining the training strategy and taking advantage of economies of scale on training tasks. For that, it is necessary to clearly identify the factors which put the success of this type of initiative at risk, above all, between older workers.

The medium-term challenge, but which in reality needs to be addressed immediately, is the preparation of the young generations, in their process of accumulation of human capital, for the performance of roles which still "do not exist". Beyond the potential creative destruction of employment, and its consequential technological unemployment, this process could be a step towards an increase in global productivity of the economy and to the generation of new occupations which are currently unknown.[7]

Economic growth takes place as jobs become more productive, but also as more productive jobs are created and those less productive disappear. In the latter instance, these benefits may be as a consequence of new products, new methods of production and transport and new markets, but they appear through a constant restructuring and redistribution of resources, including the labour force. Since economies grow as high productivity jobs are created and low productivity jobs disappear, the relationship between increases in productivity and the creation of jobs is not mechanical. Even if in the short term the innovations may imply increases or reductions in levels of employment, in the medium term the increase in employment will tend towards being closely aligned with economic growth.

In a context where many of the jobs that shall be performed by the children of today still do not exist, it is not possible to plan specific training for such occupations. The challenge, however, consists of preparing their cognitive skills in such a way as to generate their capacity to create and adapt to whatever situation presents itself.

To achieve this, it is essential to rethink the educational system at all levels, achieving rapid adaptability of subjects to labour demand as it arises. In this sense, we suggest that it is necessary to switch focus from one which bases educational systems on the paradigm of acquiring knowledge (memorizing) to one which prioritizing the development of cognitive and socio-emotional skills, through problem-solving, as a foundation to gain technical skills in a continuous form.

The challenge consists in recognizing the importance and generating the paths for the development of a mechanism of study associated with the development of critical thought (argue, think, analyse), that is, the generation of transferable/adaptable skills which are useful in different activities, that is, with a great capacity for fast adaptation.

[7]It is possible to expect a deepening of these trends, in favour of non-routine cognitive tasks to the detriment of routine manual tasks, as technological change advances and it may be appropriate and adapted by the productive sector of developing countries.

It is crucial that all students of the educational system develop and learn their basic cognitive skills, above all the numeric skills and problem-solving, since cognitive deficiencies developed at an early age are extremely difficult to overcome later in life. This must be accompanied by a constant update process, not only of the tools but also of the vocabulary itself. As an example, Internet access has a minimum requirement of a new kind of literacy (cognitive and digital).

1.6 Conclusions

Technological innovation, such as the advance of the digital technologies, communications and robotics, may imply an improvement in the general well-being of the population and reduce poverty by increasing the overall productivity of the economy. However, if this process is not accompanied by complementary investments, that is to say institutional reforms and public policies directed at making the most of its advantages, the technological advance could also deepen a situation of inequality.

From a study of the employment profile trend in the last 20 years in Latin American and the Caribbean countries it is possible to see a significant increase in the relative importance of cognitive tasks in the workplace to the detriment of manual tasks. In effect, these changes are generated through changes produced within the occupations in terms of the combinations of types of tasks which are performed to produce a good or service; the movement of workers between occupations, within the same branch of activity; and structural changes, that is, movements of workers between branches of activities. We find that the movement of workers between occupations within the same branch of activity is extremely important to explain the increase in the content of non-routine cognitive tasks and the drop in the content of manual tasks in most of the countries analysed.

Moreover, in line with the patterns observed in other countries, we find that in the countries of the region most of the workers in the upper deciles performed non-routine cognitive tasks, while workers in the lower part of the distribution carried out manual tasks. Considering the last twenty years, the gap between non-routine cognitive tasks and the manual ones widened, suggesting that among the deciles of higher incomes the transition from manual tasks to cognitive tasks, especially non-routine ones, was particularly intense.

It is possible to expect a deepening of these trends, in favour of non-routine cognitive tasks to the detriment of routine manual tasks, as technological change advances and it may be appropriate and adapted by the productive sector of developing countries. Clearly, this will imply a reduction in specialized labour demand in routine manual tasks, generating technological unemployment in the short term. However, any technological change which replaces workers with machines will have effects on all the product and factor markets. An increase in production efficiency which allows the costs of production methods to be reduced could generate an increased demand in other goods and services.

Therefore, technological progress has two effects on the level of employment. In the first place, a destructive effect, as technological change replaces the labour force; and in second place, an effect of creating new jobs, as the number of production units that internalize new technologies increases and productivity increases, complementary employment in these sectors expands and other occupations are generated that meet new demands for goods and services. In this context, it is key to define two different strategies, one short term and one long term but which requires immediate action.

With respect to the potential situation of technological unemployment it is important to orchestrate mechanisms which permit a strengthening of the continuous training system in a way that allows the re-adaptation of the labour supply. In other words, it is important to redesign the systems of continuous training considering the new labour demands. This should take into account the promotion of public-private cooperation not only in terms of financing but also the definition of a training strategy and the use of economies of scale in training.

The long-term challenge, but which in reality needs to be addressed immediately, is the preparation of the young generations, in their process of accumulation of human capital, for the performance of roles which still "do not exist". Growing cognitive skills are required to satisfy the rise in the demand for non-routine cognitive tasks. In this sense, Latin American and the Caribbean countries need to improve the quality of education systems and reduce the educational gap between different sectors of the population, because increasingly, the educational level will be key variable to have a good job placement. The next two chapters of this dissertation concentrate on the challenge for education systems of increasing the cognitive skills of students.

1.7 References

Acemoglu, D., (2002). Technical Change, Inequality, and the Labor Market. Journal of Economic Literature 40(1): 7-72.

Acemoglu, D. and D. Autor, (2011). Skills, Task and Technologies: Implications for Employment and Earning. Handbook of Labor Economics. Elsevier, pp: 1043-1171

Aedo, C., J. Hentschel, J. Luque and M. Moreno, (2013). From Occupations to Embedded Skills. A Cross-Country Comparison. Policy Research Working Paper 6560, Banco Mundial, Washington, D.C.

Apella, I. and Zunino, G., (2017). Technological Change and the Labor Market in Argentina and Uruguay: A Task Content Analysis. World Bank Policy Research Working Paper No. 8215.

Autor, D., (2015). Why Are There Still So Many Jobs? The History and Future of Workplace Automation. Journal of Economic Perspectives 29(3), 330.

Autor, D., F. Levy and R. Murnane, (2003). The Skill Content of Recent Technological Change: An Empirical Exploration. The Quarterly Journal of Economics 118(4): 1279-1333.

Bresnahan, T., (1999). Computerisation and Wage Dispersion: An Analytical Reinterpretation. Economic Journal, 109(456): 390-415.

Frey, C. and M. Osborne, (2013). The Future of Employment: How Susceptible are Jobs to Computerization? Oxford University Paper, United Kingdom.

Brynjolfsson, E., and A. McAfee (2014). The second machine age: work, progress, and prosperity in a time of brilliant technologies. First edition.

New York: W.W. Norton & Company.

Goos, M. and A. Manning, (2007). Lousy and Lovely Jobs: The Rising Polarization of Work in Britain. Review of Economics and Statistics 89:118-133.

Hardy, W., R. Keister and P. Lewandowski, (2015). Do Entrants Take It All? The Evolution of Task Content of Job in Poland. IBS Working Paper 10, Poland.

Katz, L. and K. Murphy, (1992). Changes in Relative Wages, 1963 1987: Supply and Demand Factors. The Quarterly Journal of Economics 107(1): 35-78.

Keister, R. and P. Lewandowski, (2016). A Routine Transition? Causes and Consequences of the Changing Content of Jobs in Central and Eastern Europe. IBS Policy Paper 5/2016, Intytut Badan Strukturalnych, Poland.

Mincer, J., (1974). Schooling, Experience, and Earnings. National Bureau of Economic Research, New York.

OECD. (2013). OECD skills outlook 2013: First results from the survey of adult skills. Paris: Organisation for Economic Co-operation and Development.

OECD. (2015). PISA 2015 Results (Volume I). Excellence and Equity in Education. Paris: Organisation for Economic Co-operation and Development.

OECD (2016). Automation and Independent Work in a Digital Economy. Policy Brief on the Future of Work. Paris: OECD Publishing

Polanyi, M., (1966). "The Tacit Dimension", New York, Doubleday.

SpitzOener, A., (2006). Technical Change, Job Tasks, and Rising Educational Demands: Looking Outside the Wage Structure. Journal of Labor Economics 24 (2): 235270

World Bank, (2016). Report on Global Development 2016: Digital Dividends. General Panorama booklet, World Bank, Washington, DC.

1.8 Appendix

1.8.1 Appendix I. Task Decomposition exercise

The decomposition is computed for each country according to the formula:

$$IT_{i\in T}(IT_i^{2015} - IT_i^{1995}) = \sum_{j\in S} t_{i,j,15}^{15} h_j^{15} - \sum_{j\in S} t_{i,j,15}^{95} h_j^{95}$$

$$IT_{i\in T}(IT_i^{2015} - IT_i^{1995}) = BS_i + BO_i + WO_i + INT_i$$

where

$$\forall_{i\in T} \quad BS_i = \sum_{j\in S} [t_{i,j,95}^{95}(h_j^{15} - h_j^{95})]$$

$$\forall_{i\in T} \quad BO_i = \sum_{j\in S} (t_{i,j,95}^{15} - t_{i,j,95}^{95}) h_j^{95}$$

$$\forall_{i\in T} \quad WO_i = \sum_{j\in S} (t_{i,j,15}^{15} - t_{i,j,95}^{15}) h_j^{95}$$

$$\forall_{i\in T} \quad INT_i = \sum_{j\in S} (t_{i,j,15}^{15} - t_{i,j,95}^{95})(h_j^{15} - h_j^{95})$$

where,

- $t_{i,j,15}^{15}$ and $t_{i,j,95}^{95}$ represent the average value of the intensity of task i for the workers in sector j, in the year y=[1995,2015], calculated from the use of O*NET 2015 and 1998, respectively

- h_j^{15} represents the share of workers in sector j in the total employment in year y.

- T is the set of the five tasks defined above.

- S is the set of 13 sectors, defined from SIC to one digit.

1.8.2 Appendix II. Employment by economic sector.

Employment variation between Middle 90s and 2015

Argentina

Descripción	Variación 2015-1998
Comercio	-2.9%
Industria	-2.5%
Act. Financieras	-0.4%
Act. Inmobiliarias	-0.3%
Actividad primaria	-0.2%
Minas y canteras	0.1%
Electricidad, gas y agua	0.4%
Org. extranjeros	0.5%
Transporte, almacenamiento y comunicaciones	0.6%
Hoteles y restaurantes	0.6%
Construcción	1.2%
Otros servicios	2.9%

Bolivia

Descripción	Variación 2015-1995
Comercio	-12.2%
Otros servicios	-8.5%
Industria	-8.3%
Minas y canteras	-1.0%
Transporte, almacenamiento y comunicaciones	-0.4%
Org. extranjeros	-0.2%
Act. Financieras	-0.1%
Act. Inmobiliarias	-0.1%
Electricidad, gas y agua	0.0%
Hoteles y restaurantes	0.3%
Construcción	0.7%
Actividad primaria	29.9%

Brasil

Descripción	Variación 2013-1996
Actividad primaria	-10.3%
Industria	-4.4%
Transporte, almacenamiento y comunicaciones	-2.1%
Electricidad, gas y agua	-0.5%
Org. extranjeros	0.0%
Minas y canteras	0.0%
Act. Financieras	0.4%
Hoteles y restaurantes	1.7%
Comercio	2.7%
Otros servicios	3.1%
Construcción	3.6%
Act. Inmobiliarias	5.8%

Chile

Descripción	Variación 2015-1996
Actividad primaria	-5.5%
Industria	-5.3%
Act. Financieras	-4.3%
Electricidad, gas y agua	0.0%
Org. extranjeros	0.0%
Transporte, almacenamiento y comunicaciones	0.4%
Construcción	0.5%
Minas y canteras	0.6%
Otros servicios	1.7%
Hoteles y restaurantes	2.2%
Comercio	2.9%
Act. Inmobiliarias	6.8%

El Salvador

Descripción	Variación 2014-1998
Industria	-3.8%
Actividad primaria	-2.7%
Construcción	-0.5%
Act. Financieras	-0.3%
Transporte, almacenamiento y comunicaciones	-0.2%
Org. extranjeros	0.0%
Minas y canteras	0.0%
Electricidad, gas y agua	0.2%
Comercio	0.9%
Otros servicios	1.0%
Act. Inmobiliarias	1.5%
Hoteles y restaurantes	3.8%

México

Descripción	Variación 2014-1996
Actividad primaria	-6.8%
Industria	-2.2%
Transporte y almacenamiento	-0.5%
Electricidad, gas y agua	-0.1%
Minas y canteras	-0.1%
Otros servicios	0.0%
Comunicaciones	0.3%
Construcción	0.7%
Comercio	1.9%
Act. Financieras	2.1%
Act. Inmobiliarias	2.1%
Hoteles y restaurantes	2.6%

Perú

Descripción	Variación 2013-1997
Actividad primaria	-3.8%
Comercio	-1.5%
Industria	-0.2%
Electricidad, gas y agua	-0.2%
Otros servicios	0.0%
Act. Financieras	0.0%
Org. extranjeros	0.0%
Minas y canteras	0.5%
Act. Inmobiliarias	0.6%
Construcción	1.1%
Transporte, almacenamiento y comunicaciones	1.3%
Hoteles y restaurantes	2.3%

República Dominicana

Descripción	Variación 2014-1996
Industria	-7.9%
Actividad primaria	-2.4%
Org. extranjeros	0.0%
Transporte, almacenamiento y comunicaciones	0.1%
Minas y canteras	0.2%
Electricidad, gas y agua	0.2%
Act. Financieras	0.7%
Construcción	1.2%
Act. Inmobiliarias	1.6%
Otros servicios	1.8%
Hoteles y restaurantes	2.3%
Comercio	2.3%

Uruguay

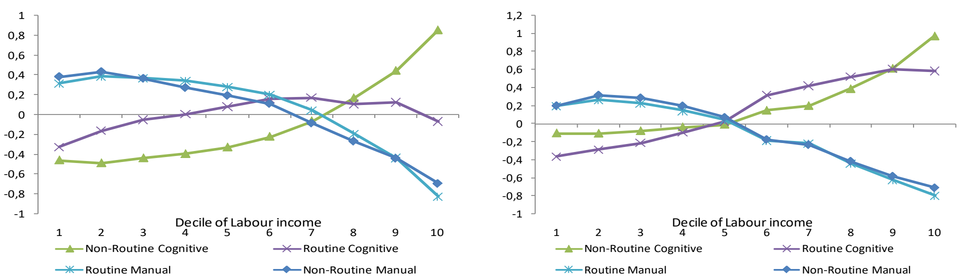
Descripción	Variación 2015-1995
Industria	-11.1%
Act. Inmobiliarias	-2.9%
Act. Financieras	-0.5%
Electricidad, gas y agua	-0.2%
Org. extranjeros	0.0%
Minas y canteras	0.0%
Hoteles y restaurantes	0.8%
Comercio	1.3%
Construcción	1.6%
Transporte, almacenamiento y comunicaciones	1.9%
Actividad primaria	2.1%
Otros servicios	7.0%

Source: Own elaboration based on Household surveys

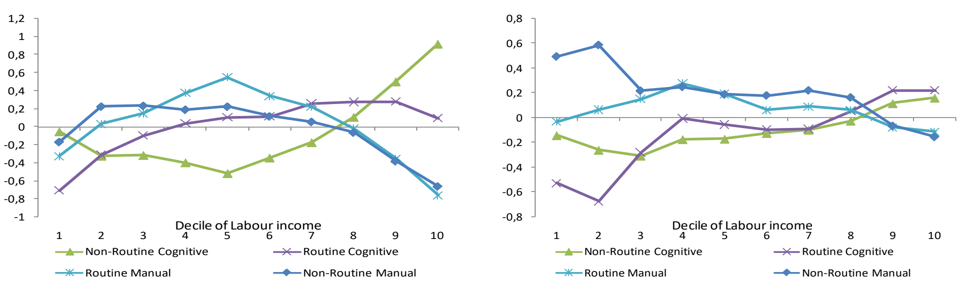
1.8.3 Appendix III. The content of tasks according to decile of labour income. Mid-'90 - 2015, by country.

Figure 1.4: Content of tasks according to decile of labour income. Middle 90s - 2015 (by countries)

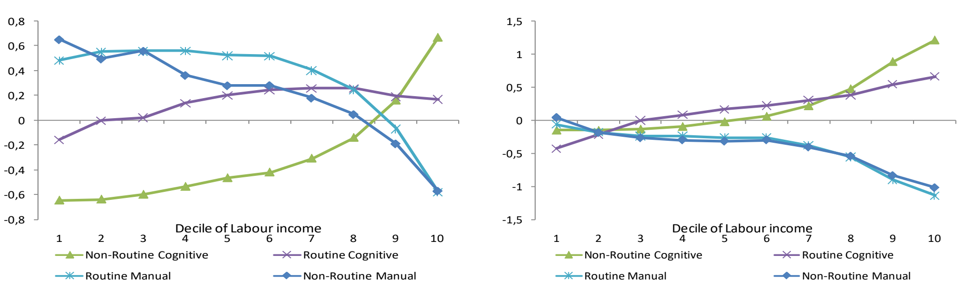
Argentina



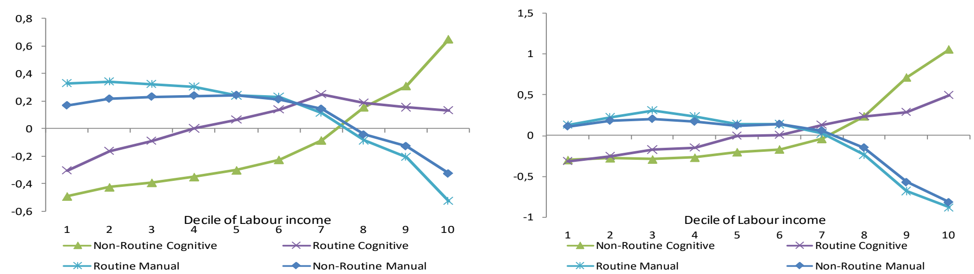
Bolivia



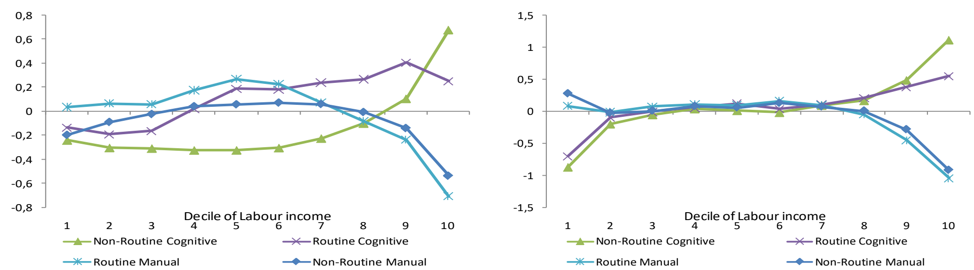
Brasil



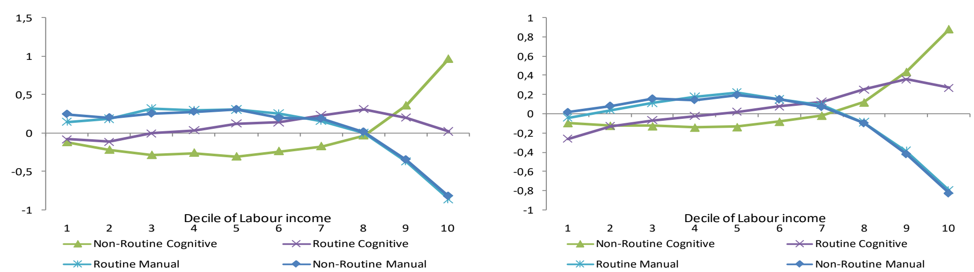
Chile



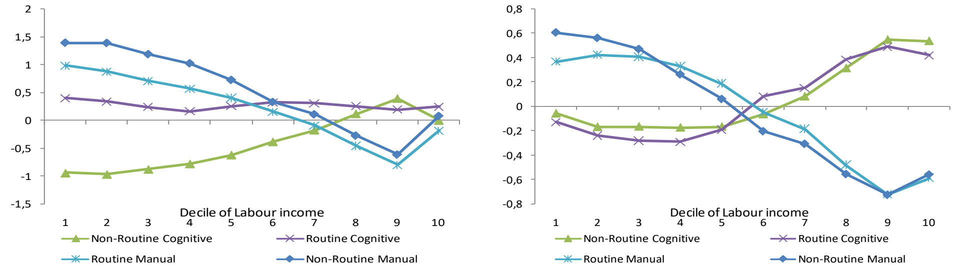
El Salvador



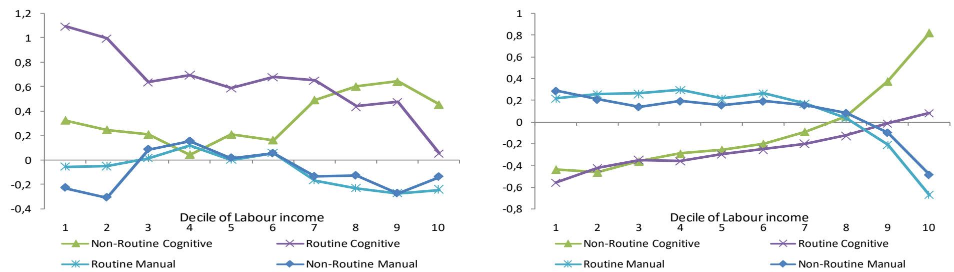
México



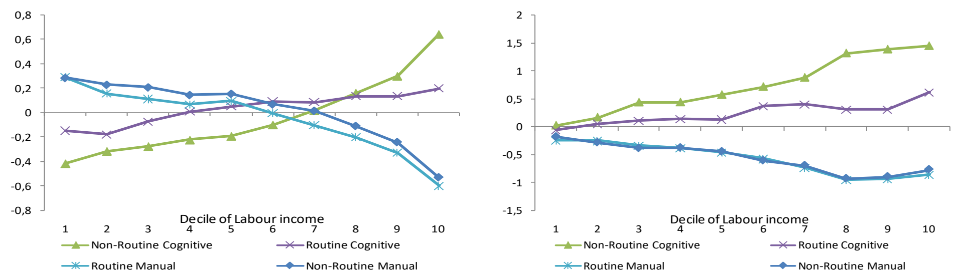
Perú



República Dominicana



Uruguay



Source: Own computations based on O*NET and Household surveys.

1.8.4 Appendix IV. Changes from an intergenerational perspective (The cases of Argentina and Uruguay)

It could be suggested that it is the youngest generation of workers which has the greatest capacity to adapt to technological change, developing cognitive tasks more intensively which complement the new technologies. On the other hand, older generations could have greater difficulty in redefining tasks which are performed in their occupations, exposing themselves to greater risk of technological unemployment. In this context, a complementary approach is the analysis of the evolution of the content of tasks in the average occupation according to the cohort of birth of the workers. For that, Figure 1.5 shows the evolution of the relative intensity of each type of task in the average job, according the birth cohort of the workers.

With respect to the intensity of the non-routine cognitive tasks in the job, both with the analytical and the interpersonal tasks, a clear stable trend can be seen for the cohorts before 1971. For its part, the relative importance of this type of task in occupations chosen by cohorts following this year shows a clearly positive trend. This suggests that older workers have greater difficulty in adopting and performing non-routine cognitive tasks than the young. For its part, the rapid growth in the importance of analytical cognitive tasks between the youngest generations could be attributed to two complementary factors: i) a greater capacity to adapt to change in the combination of tasks that are required, and ii) a composition effect, that is, the entrance of younger generations to the labour market is delayed since they spend more years in education and therefore their weighting in the average increases as they enter.

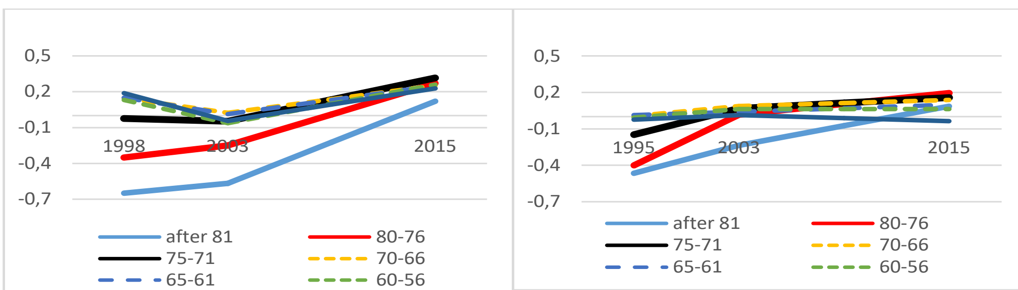
Conversely, in observing the variation in the relative importance of routine manual tasks in employment this suggests that although this shows a stable trend for all cohorts greater than 1971, the incline becomes negative for younger cohorts. Something similar, though of a lesser magnitude, is observed in the intensity of non-routine manual tasks.

In both cases, during the period under study a greater decline can be seen in the youngest cohorts, which suggests that on one hand, the young are directing their entrance into the labour market towards occupations which are less intensive in terms of non-routine manual tasks, and on the other hand, that as this group of workers has a greater capacity for adaptation they replace occupations intensive in these types of tasks with those more cognitively intense.

Figure 1.5: Intensity index of the tasks in the job (t_j)according to the cohort. Years 1995/98 2015

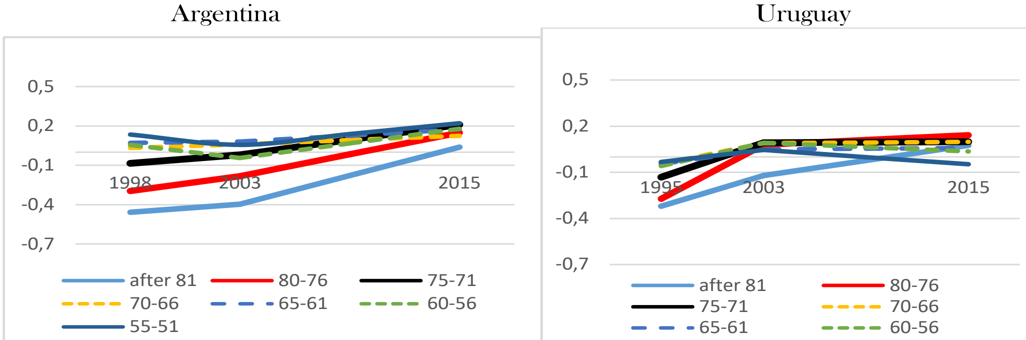
a) Non-routine cognitive tasks - analytical

Argentina Uruguay

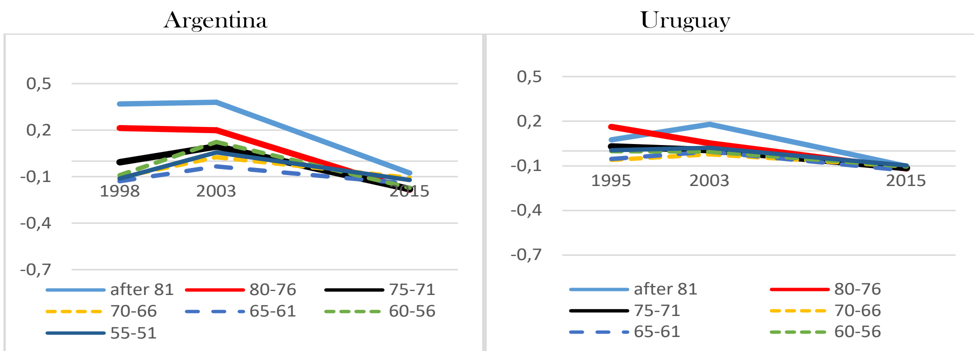


b) Routine cognitive tasks –interpersonal

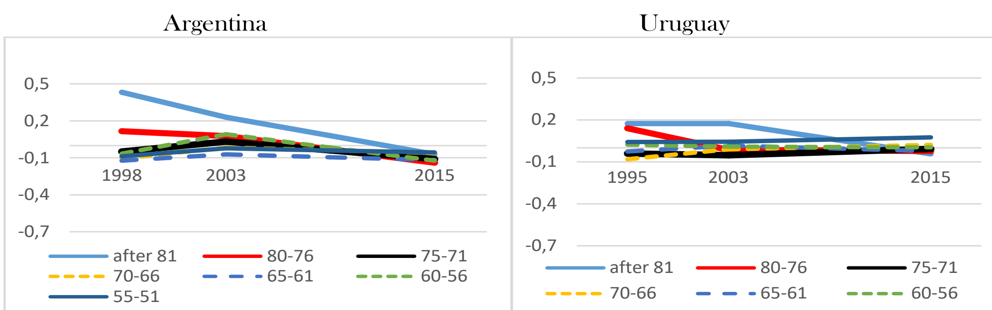
Argentina Uruguay



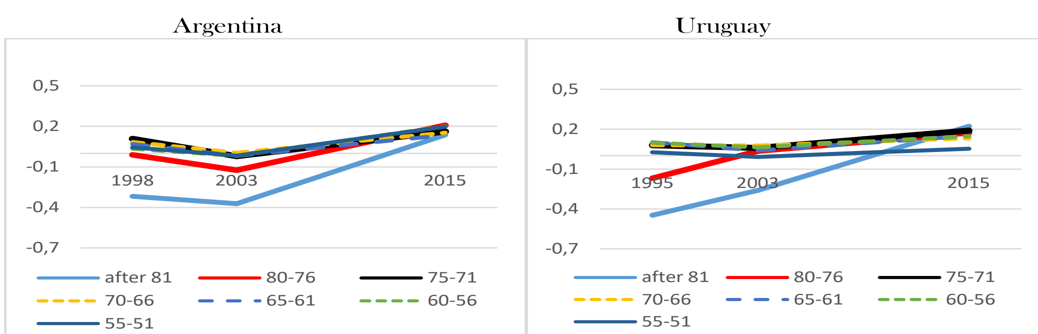
c) Routine manual tasks



d) Non-routine manual tasks



e) Routine cognitive tasks



Source: Our own estimation based on household surveys and O*NET

With respect to the relative importance of routine cognitive tasks, again the youngest cohort is that which defines the trend of the change, while the older generations remain relatively constant in the tasks which they perform in their occupations.

In summary, during the last two decades, the workplace in Argentina and Uruguay has experienced some changes in terms of the type of tasks which workers perform in their jobs. In this sense, we can detect an increase in the relative importance of non-routine cognitive tasks and a reduction in the intensity of manual tasks. In contrast with that seen in developed countries, work intensive in routine cognitive tasks has shown signs of growth. These variations correspond to various explanatory factors. On one hand, the process of technological change which incentives the modification of the optimum combination of tasks within an occupation. At the same time, and for the case of Uruguay, there is also still an effect of sectoral change, that is, the movement of work between branches of activity, moving from those which are more intensive in manual tasks to sectors with a greater emphasis of occupations intensive in cognitive tasks.

All changes are enhanced by the educational expansion that took place in the labour force, since as the workers increase their levels of qualification, they increase their chances of dedicating a larger proportion of their time to the performance of cognitive tasks. In any case, it is the young generations who dominate these trends, which suggests that they have a greater capacity for adaptation than the older generations.

1.8.5 Appendix V. Polarization of the labour market (The cases of Argentina and Uruguay)

The process of adopting new production technologies based on automation, robotics and digital communication would permit an increase in global productivity and therefore economic efficiency. However, that also implies a risk from the point of view of distribution. That being through the generation of a possible polarization of the labour market, since the transition from occupations which are intensive in manual tasks towards those more intensive in cognitive tasks demands a greater level of qualification from the labour force.

In this sense, this distribution risk is that the labour market remains represented by two large groups of workers. On one side, those who are highly-qualified, who perform tasks requiring an intensive use of non-routine cognitive tasks, of high productivity and high incomes. On the other side, a group of poorly-qualified workers, relegated to occupy those positions requiring intensive use of non-routine manual tasks, and therefore of low-productivity and low incomes. This will occur while workers with medium-level qualifications and incomes, face the risk of a reduced labour demand in the performance of routine tasks. This polarization may manifest itself through two complementary paths: employability (with increases in the extremities of the productivity distribution and falls in the center) and salary levels.

In order to provide an approximation of the effect that the changes in intensity of the tasks performed by the labour force have on the well-being of the workers, we have estimated here the significance of the relative importance of each task on the explanation of two key variables of workers' well-being: probability of becoming unemployed and level of income. The identification of the determinants of the probability of becoming unemployed is done by the estimation of the following probit model:

$$Pr(d_i) = f(t_{ij}; \Theta_j; u_i)$$

Where d_i takes the value of one if the individual finds themselves unemployed and zero if they are employed, t_{ij} represents the intensity of the task j which the individual i performs and Θ_i is a vector of individual control variables such as age, a dummy variable which takes the value of one if the person is a man and the number of years of study. The hypothesis states that those workers who perform routine tasks more intensively have a greater probability of finding themselves unemployed as a result of facing a greater risk of substitution, while those who perform more cognitive tasks have a lesser risk of finding themselves in that situation.The results of the estimation are presented in Table 1.2.

The results found confirm the trends observed and partially confirm the hypothesis suggested for developed countries. In this sense, the variable "Routine manual" has the positive sign expected and is significant to 1%. That suggests that the possibility of becoming unemployed increases as the relative importance of the routine manual tasks performed in that occupation grows. In other words, those workers in occupations that require a higher intensity of routine manual tasks face a greater risk of finding themselves unemployed, with this effect being greater in Argentina than in Uruguay. These results allow us to suggest that technological change, and therefore, the possibility of replacing tasks with automation, increment the probability of unemployment for those workers who spend the majority of their working hours performing routine manual tasks.

However, and in line with that discussed previously, no positive relationship is found between the probability of being unemployed and the intensity of routine cognitive tasks in the previous occupation. In effect, and in contrast to what has taken place in developed countries, in Argentina and Uruguay we have seen an increase in the relative importance of this type of task in the average workplace over the last 20 years.

With respect to the level of labour income, we propose the estimation of the Mincer equation (1974) in order to better understand the relationship between the relative importance of the tasks which workers perform in their jobs and their level of income per hour.

For this, the following equation is estimated:

$$log(w_i) = \beta_0 + \beta_1 t_{i,nrc} + \beta_2 t_{i,rc} + \beta_3 t_{i,rm} + \beta_4 t_{i,nrm} + \beta_j \Theta_j + u_i$$

where w_i is the salary per hour, $t_{i,j}$ is the index of intensity of each task j $Theta_i$ is a vector of individual control variables: work experience, work experience squared, a dummy variable which takes the value of one if the individual is a man, the years of education, and a dummy variable which takes the value of one if the worker has formal employment.

The results of the estimation through the Ordinary Minimal Squares (Table 1.3) are as expected. Workers in occupations which require a greater relative importance of cognitive tasks have an output, in terms of hourly salary, greater than those who perform a greater intensity of manual tasks.

Table 1.2: Estimation of the probability of being unemployed. Year 2015

Variables	Argentina	Uruguay
Non-routine cognitive	-0.0514244*	-0.0172726*
	´(0.029028)	(0.0010277)
Routine cognitive	-0.1406224***	-0.0769139***
	(0.018459)	(0.009799)
Routine manual	0.3346739***	0.0505115***
	(0.041706)	(0.013147)
Non-routine manual	-0.1563471***	-0.0074673
	(0.038226)	(0.015701)
Man	-0.1227095***	-0.2669335***
	(0.034698)	(0.020472)
Yearsof education	-0.0014153	-0.045073***
	(0.005044)	(0.003176)
Age	-0.0233769***	-0.0244753***
	(0.001292)	(0.000695)
Constant	-0.791312***	-0.0257861
	(0.104482)	(0.044926)
Nº of observations	24299	53740
LR Chi2	902.52	1989.95
Prob> Chi2	0.0000	0.0000
Pseudo R2	0.1024	0.0787
Log likelihood	-3954.6	-11648.1

Source: Our own estimation based on household surveys and O*NET

Note: Standard error is shown in parenthesis. *** significant to 1%, ** to 5% and * to 10%.

In both countries, non-routine cognitive tasks have a greater remuneration than routine ones.

The results found allow us to suggest that the changes observed in the workplace, in terms of the types of tasks that the labour force performs, and the changes to be expected in the future while the access costs to new technologies decrease and the capacity to adapt to them increase, could imply a greater risk of polarization of the labour market.

A greater insertion of new technologies of automated production has two direct effects on the market. On one hand, the increase in probability of unemployment (technological unemployment) among those workers in occupations intensive in routine manual tasks. On the other hand, a reduction in the level of income for those who work in occupations which are intensive in manual tasks, and an increase in income for those workers in occupations intensive in cognitive tasks, especially non-routine.

Table 1.3: Ordinary Least-Square Mincer's Equation. (Year 2015)

Variables	Argentina	Uruguay
Non-routine cognitive	0.138261***	0.0571613***
	(0.006626)	(0.003453)
Routine cognitive	0.0579983***	0.0297189***
	(0.004752)	(0.003486)
Routine manual	0.0430737***	-0.0182148***
	(0.012302)	(0.004679)
Non-routine manual	-0.0248547**	-0.0263061***
	(0.0105)	(0.005292)
Experience	0.012084***	0.0247491***
	(0.000921)	(0.000736)
Experiencia2	-0.000134***	-0.0002611***
	(0.000002)	(0.000001)
Man	0.0722601***	0.2277636***
	(0.009096)	(0.006925)
Years of education	0.0371603***	0.0808401***
	(0.001416)	(0.001138)
Formal	0.4958803***	0.3572354***
	(0.00881)	(0.008088)
Constant	2.571179***	3.188941***
	(0.02658)	(0.01651)
Nº of observations	21707	49256
Statistic F	1053.0	2143.1
Prob > F	0.0000	0.0000
R2	0.30	0.28
R2 adjusted	0.30	0.28

Source: Our own estimation based on household surveys and O*NET
Note: Standard error is shown in parenthesis. *** significant to 1%, ** to 5% and * to 10%.

Chapter 2

Teacher Quality and Cross Country Differences in Student Achievements

2.1 Introduction

Student outcomes show high variance across countries even among OECD developed countries. Why do some countries obtain better educational results than others? This chapter analyses this relevant question, focusing on the role of teacher quality.

From the previous educational literature an extensive consensus has been generated, both on the part of policy makers and researchers, that teacher quality is a key input the process of student learning (Hanushek, 2003; Hanushek and Rivkin 2007; Hanushek, 2010; Hanushek and Rivkin 2010). Indeed, several works suggest that having an effective teacher is probably the most important school factor for student achievements (Hanushek, 2003, Klein et al., 2010; Gates, 2011; and Hiatt, 2009). On the other hand, Chetty et al. (2011) state that having good teachers improves not only the standardized test scores but also generates long-term effects, both economic and social.

But the importance of teacher quality as an educational input is a necessary but not sufficient condition for it to be a relevant factor in explaining the gap across countries in educational outcomes. Indeed, to be a relevant factor in explaining the cross-country gap, significant differences in teacher quality between countries are needed. However, finding evidence regarding differences in teaching quality between countries is extremely difficult, since there are no international comparable measurements of teacher quality. Additionally, most of the empirical works state that teacher quality is not strongly correlated with observable characteristics of teachers (Rockoff, 2004; Jepsen, 2005; Hanushek and Rivkin, 2007; Hanushek; 2010 among others). Therefore, teacher quality cannot be approximated by observable variables for which there are international statistics.

Attending to the previous points, two relevant questions arise: What is the role of teacher quality to explain cross-country differences in student outcomes? and; Why is TQ different across-countries? This chapter tries to shed some light on these issues.

Specifically, in this chapter I construct a proxy for teacher quality (TQ for short). I also analyse the key variables determining teacher quality and discuss its importance as a source of cross-country differences in student achievements. To this end, I propose and calibrate a theoretical model of teacher selection for a set of 22 OECD countries.

From the theoretical point of view, the model proposed here is an extension of previous theoretical models. Previous literature basically focuses on the self-selection of workers between the teaching profession and other occupations (See for instance, Nagler et al. 2015, Rothstein 2014 and Tincani 2011). The model proposed in this chapter includes two stages in a general equilibrium framework instead. Like in the previous models, the first stage is a self-selection stage that determines the supply of teachers in the economy. Additionally, this model includes a second stage in which how the education system selects their teachers is discussed. This second stage analyses the demand for teachers.[1] The micro-founded model developed in this paper is a useful tool in several dimensions.

[1] My model simplifies the self-selection analyses compared to the models in previous papers because I do not work in a dynamic framework. However, I include the analysis of school decisions that is omitted in other models.

Firstly, it is useful to proxy TQ at the country level. Based on the calibration of nine parameters, I build a proxy of teacher quality for a large set of countries in different years. To my knowledge, the only comparable proxy is the one developed by Hanushek et al. (2014) who discuss the link between teaching skills and student outcomes across countries. They measure TQ with teaching skills in literacy and numeracy using the PIAAC survey of adult skills.[2] Although the work of Hanushek et al. (2014) is the first one in measuring TQ using the PIAAC survey, their proxy presents several limitations: i) it includes only the cognitive skill dimension, ii) it is built for only one year since PIAAC is a cross-section data set. My proxy measured in different years helps me to analyse whether teacher quality trends can explain the evolution of student achievements at a country level. To my knowledge, no previous studies include this analysis because time series of country measures of teacher quality were not available. Having time series of teacher quality for a set of countries is important because reasons behind the cross-country dispersion in student outcomes could potential be learning culture or educational institutions. With my time series of TQ, I am controlling for for these unobservable country fixed effects.

Secondly, the model is also useful to understand the ambiguous findings in the empirical literature regarding the relationship between teacher salaries and student achievements. The evidence suggests that salaries are not a reliable proxy of teacher quality, since most of the studies do not find a statistically significant effect between salaries and student outcomes.[3] On the contrary, the works of Loeb and Page (2000) and Dolton and Marcenaro Gutierrez (2011) find a positive relationship between teacher salaries and student achievements. In my model, the equilibrium relationship between teacher salaries and teacher quality is non-linear and may be non-monotonic. Therefore, different countries could be in different parts of the curve. This is so because on the one hand, previous empirical analysis based on cross-section data within a given country probably captures a small segment of the equilibrium curve since teacher wage dispersion is usually small within the country. On the other hand, the parameters controlling the teacher selection process differ across countries, and, as I explain later on, the equilibrium curve is quite sensitive to these parameters.

[2]They approximate the mean teacher skill in math (reading) with the mean cognitive skill in numeracy (literacy) of teachers measured in PIAAC.

[3]Hanushek (2003) provides an extensive review on this issue.

Thirdly, the model helps to understand the main variables affecting the quality of teachers. Previous literature teaches us that teacher quality matters, but little is known regarding its main determinants. Counter-factual exercises based on the model allow me not only to identify, but also to quantify the main drivers of cross-country differences in TQ. Notice that, since the theoretical model includes supply and demand of teachers, the analysis is a general equilibrium framework that takes into account how supply and demand interacts. To my knowledge, no previous papers study this issue. Clearly, this is a first important step if we want to design economic policies oriented to improve TQ, and thus student outcomes.

In this chapter, through the lens of my model, I build time series of teacher quality at the country level. Additionally, with the objective of assessing if my proposed measure is a good proxy of TQ, I include the TQ measure as well as student and school characteristics, family background and educational spending as inputs in the estimation of an empirical educational production function (EPF) using the micro-data of PISA over a panel of 22 OECD countries for the period 2000-2015. The model highlights the importance of teacher quality as an educational input because I find that my proxy of TQ is strongly correlated positively with cross-country dispersion in student outcomes, even while controlling for student and school characteristics, family background, macroeconomic variables and unobservable country fixed effects. Then, based on the theoretical model and on the proposed EPF, I carry out several counter-factual exercises with the dual objective of firstly determining the importance of teacher quality as a source of cross-country differences in student achievements, and secondly, discussing why teacher quality differs across countries.

I find that cross-country differences in TQ explains approximately 22% of the observed cross-country variance in observed student outcomes. Its importance is quite similar to the family background effect and clearly higher than the importance of other school inputs. This finding is in line with the previous literature that highlights the importance of teacher quality as educational input (Hanushek, 2003; Metzler and Woessmann 2012, Hanushek et al 2014 among others).

When I study the main determinants of cross-country dispersion in TQ, I find that the initial distributions of skills within the population are crucial in determining current dispersion in TQ across countries, since a larger mean in the skills of the population derives in a better teacher selection process. Moreover, teacher salaries and labour market conditions play a less important role in explaining dispersion in TQ. These results are relevant because suggest a hysteresis in the cross-country differences in student outcomes.

The rest of this chapter is organized as follows. The next section presents the theoretical model of teacher selection used to generate country measures of teacher quality. Section 2.3 includes the calibration of the model for a panel of 22 OECD countries. Section 2.4 presents different counter-factual exercises to analyse the importance of teacher quality as a source of cross-county differences in student achievements. Section 2.5 includes counter-factual exercises to discuss the determinants of cross-country differences in teacher quality. Finally, section 2.6 concludes.

2.2 The Model

This section presents the theoretical framework to study the process of teacher selection with the aim of estimating the average teacher quality for a panel of countries. My strategy relies on analysing the individuals' decision to become teachers as well as the schools' decision about hiring. This analysis enables to me to estimate the general equilibrium effects of different variables affecting teacher quality.

The economy considered is inhabited by a measure one of individuals characterized by the pair $(\widehat{\theta}, \widehat{t})$, where $\widehat{\theta}$ is an observable skill that determines individual productivity in the non-teaching sector and $\widehat{t}$ represents an unobservable teacher skill.[4]

For each individual, the pair of skills $\left(\widehat{\theta}, \widehat{t}\right)$ is assumed to be distributed log-normally.

[4] The assumption of the non-observability of the teacher skill is suggested in previous studies. See for instance Hanushek (2010) and Rothstein et al.(2014).

$$\ln \begin{pmatrix} \widehat{\theta} \\ \widehat{t} \end{pmatrix} \sim N \left(\begin{bmatrix} \mu_\theta \\ \mu_t \end{bmatrix}, \begin{bmatrix} \sigma_\theta^2 & \sigma_{\theta t} \\ \sigma_{\theta t} & \sigma_t^2 \end{bmatrix} \right). \tag{2.1}$$

Let $\rho_{\theta t} = \frac{\sigma_{\theta t}}{\sigma_t \sigma_\theta}$ to state the correlation coefficient between both skills for the total population of potential teachers. I assume that $\rho_{\theta t} \geq 0$, which seems consistent with recent empirical studies.[5]

I assume that the wage in the teaching sector, $\widehat{w}_0$, is the same for all teachers.[6] In contrast, the wage in the market sector, $\widehat{w}_\theta$, depends on the non-teaching skill $\widehat{\theta}$ (general skill in ahead) as follows:

$$\widehat{w}_\theta = \widehat{\theta}^\alpha, \tag{2.2}$$

where α, which is the wage elasticity with respect to the general skill, measures the market return to the general skill $\widehat{\theta}$.

The model has two stages of selection. The first one is the self-selection stage. This stage determines the supply of teachers in the economy. The second one is the school board stage and concentrates on the demand for teachers.

2.2.1 Self-selection stage

In the first stage every individual i makes his occupational choice to maximize his utility, u_i. This stage is based on a Roy model, which is the most used framework in the field of work self-selection.[7]

[5]A positive correlation between teaching and non-teaching skills is implicit in the following works. Hanushek et al. (2015) study the private returns to cognitive skills using the PIAAC survey, and find a positive effect of cognitive skills on salaries. On the other hand, Hanushek et al. (2014) study the effects of teacher cognitive skills, also measured based on the PIAAC survey, on student achievements. This work finds a positive effect of teacher skills on student outcomes. Therefore, the same skills present positive effects in both, the teaching and non-teaching sectors.

[6]This assumption captures the empirical fact that the variance between teacher salaries is very low compared to the variance of salaries across the whole economy.

[7]Roy models have been successfully used to study the selection process in labour markets in many contexts, for instance: immigration (Borjas, 1987), government employment

The individual utility function is given by:

$$u_i = \begin{cases} \ln(\widehat{w}_0) + \ln(\widehat{t^\tau}) \text{ if be a teacher} \\ \ln(\widehat{w}_\theta) \text{ otherwise,} \end{cases} \tag{2.3}$$

where $\ln(\widehat{t^\tau})$ captures the non-pecuniary utility of teaching. The parameter τ measures the elasticity of the non-pecuniary utility with respect to the individual teacher quality.

The utility obtained as a teacher depends not only on the wage but also on the individual teacher's ability. The idea behind this is that teaching skills must be positively correlated with the vocation of becoming a teacher. Thus, the more motivated the teacher, the larger the non-pecuniary utility of teaching is.[8] The Appendix I discusses the sensitivity of the model's equilibrium to changes in the parameter values. Particularly, the case where utility depends only on monetary compensation ($\tau = 0$) is analysed.[9]

Given the utility function of Equation (2.3), individuals choose to become teachers if:

$$\ln(\widehat{w}_0) + \tau \ln(\widehat{t}) > \alpha \ln(\widehat{\theta}). \tag{2.4}$$

Defining $\ln(\widehat{x}) = x$, using equation (2.4) and regrouping, the condition above can be written as:

$$\alpha\theta - \tau t < w_0, \tag{2.5}$$

(Borjas, 2002), manufacturing industries (Heckman, 1985) and entrepreneurs (Evans and Jovanovic, 1989).

[8]This interpretation could be replaced by assuming some wage dispersion within the teacher sector where the best teachers are better paid. That is, τ could be interpreted as the elasticity of teacher wages respect to the individual teacher skill without modifying any result of the model. If τ is lower than α the scenario is still compatible with the fact of lower wage variance within the teacher sector with respect to the whole economy.

[9]In the utility function, I do not consider the probability of not being selected for a teaching position because I assume that individuals who are not selected as teachers can apply for a job in the market sector under the same conditions as the rest of the population.

Additionally, define $v = \alpha\theta - \tau$ as the "self-selection function". Since v is a sum of two normal random variables, it is also distributed normally. Particularly, $v \sim N(\mu_v, \sigma_v^2)$, with mean $\mu_v = \alpha\mu_\theta - \tau\mu_t$ and variance $\sigma_v^2 = \alpha^2\sigma_\theta^2 + \tau^2\sigma_t^2 - 2\alpha\tau\sigma_{t\theta}$. This self-selection function will help us to identify the supply of teachers, the average quality of the teacher supply as well as the correlation of this self-selection function with the general skills.

Let define the following indicator function:

$$I = \begin{cases} 1 \text{ if the individual choose to be a teacher} \\ 0 \text{ otherwise.} \end{cases} \tag{2.6}$$

The probability that an individual chooses to work in the teaching sector, $P(I = 1)$ which is the teacher supply size, is given by:

$$\begin{aligned} P(I &= 1) = P(v < w_0) = P\left(\frac{v - \mu_v}{\sigma_v} < \frac{w_0 - \mu_v}{\sigma_v}\right), \\ &= \Phi\left(\frac{w_0 - \mu_v}{\sigma_v}\right) = \Phi(z), \end{aligned} \tag{2.7}$$

where Φ is the cumulative distribution function of the standard normal distribution, and $z = \frac{w_0 - \mu_v}{\sigma_v}$. Since, the cumulative distribution function of the standard normal is an increasing function in z, and z is an increasing function of the teacher salary (w_0), the teacher supply is also an increasing function of the teacher salary.

The average quality of the teacher supply, $E(t|I = 1)$, is computed as follows:[10]

$$E(t|I = 1) = E\left(t|\frac{v - \mu_v}{\sigma_v} < \frac{w_0 - \mu_v}{\sigma_v}\right)$$

[10] This expression corresponds to the mean of an incidentally truncated bivariate normal distribution. Just to simplify, I present the expected mean of t instead of $\widehat{t}$. Note that, since the logarithm is a strictly increasing function, any change in the mean of t implies a change of the same sign in the mean quality of teachers (i.e. mean of $\widehat{t}$).

$$= \mu_t + \rho_{vt}\sigma_t \left(\frac{-\phi(z)}{\Phi(z)} \right), \tag{2.8}$$

where μ_t is the mean teacher skill of the total population in the economy, $z = \frac{w_0 - \mu_v}{\sigma_v}$, ρ_{vt} is the correlation coefficient between the self-selection function and the teacher skill, and ϕ and Φ are the density function and cumulative distribution function of the standard normal distribution respectively. The expression $\sigma_t \left(\frac{-\phi(z)}{\Phi(z)} \right)$ in Equation (2.8) is always negative. Therefore, the average quality among the supply of teachers, $E(t|I = 1)$, is lower than the population mean (μ_v) when ρ_{vt} is positive. And thus, a negative selection bias in the teacher supply arises.[11] On the other hand, when ρ_{vt} is negative, the supply of teachers presents a positive selection bias.

The expression for ρ_{vt} is given by:

$$\rho_{vt} = \frac{\sigma_{vt}}{\sigma_t \sigma_v} \tag{2.9}$$

Since, σ_t and σ_v are always positive terms, the selection bias of the teacher supply will depend on the sign of σ_{vt}. Moreover, $\sigma_{vt} = cov(\alpha\theta - \tau t; t) = \alpha\sigma_{\theta t} - \tau\sigma_t^2$. Hence, a negative selection bias arises when $\sigma_{\theta t} > \tau\sigma_t^2/\alpha$ while a positive selection bias arises in the opposite case. Therefore, even discarding the less intuitive cases where $\sigma_{\theta t}$ is negative, a positive selection bias is possible. If the non-pecuniary utility of teaching is eliminated, $\tau = 0$, and $\rho_{\theta t} \geq 0$ holds, the model always predicts a negative selection bias in the teacher supply.

2.2.2 School selection stage

In the second stage of selection, I assume that the school board hires a fixed number of teachers, γ. Let Θ be an indicator function that states whether an individual from the teacher supply is selected for a teacher position.

[11] A negative selection bias implies that the average teacher skill within the teacher supply is lower than in the total population. In contrast, a positive selection bias appears when the average teacher skill within the teacher supply is higher than in the total population.

$$\Theta = \begin{cases} 1 \text{ if the individual is selected} \\ 0 \text{ otherwise.} \end{cases} \tag{2.10}$$

The probability of obtaining a teacher position is $P(\Theta = 1) = \gamma$.

I assume an educational production function in which student outcomes depend on family resources (F), school resources (R), school organization[12] (Sch) and student characteristics (St). Additionally, following the empirical literature of "teacher value added", I assume that student outcomes (y) depend positively on teacher ability ($TQ = E(t|\Theta = 1)$).

$$y = y(F, R, Sch, St, TQ), \tag{2.11}$$

the school board selects teachers to optimize student achievements (y), taking the teacher salary ($\widehat{w}_0$) as given.[13] Note that, the wage bill is exogenous in the model, since it depends on the teaching staff size (γ) and the teacher salary ($\widehat{w}_0$), both exogenous variables. The next chapter of this dissertation work with a version of the model where ($\widehat{w}_0$) and class-size are endogenous. The main mechanisms of the model hold under this more general framework.

Since the individual teaching skill is unobservable, and $\rho_{\theta t} \geq 0$ holds, the school selection strategy is simple. Indeed, the school board seeks to screen the true teaching ability of candidates based on its observable general skills θ and then select the fraction γ of individuals with a higher level of θ. The school strategy is based on the fact that individuals with a higher level of θ also have a higher expected teacher ability $E(t)$. The conditional expectation of interest is then the expected teaching skill of teachers, that is $TQ = E(t|\Theta = 1)$. Indeed, maximising TQ is equivalent to maximize student outputs, given the educational production function of equation (2.11).

Let us define θ^* as the minimum level of the general skill required to obtain a teacher position such that a fraction γ of individuals within the teacher

[12]The typical variables included in the educational production function related to school organization are the student-teacher ratio, levels of school autonomy and school size.

[13]I assume that school budget is enough to hire γ teachers at the exogenous teacher salary, $\widehat{w}_0$.

supply has a level of general skill higher than θ^*, that is $\int_{\theta^*}^{\infty} f(\theta/I = 1)\partial\theta = \gamma$ holds. The value of θ^* is endogenously determined by the teacher staff size (γ) and by the distribution of θ within the teacher supply. A rise on θ^* implies a rise on the expected general skill among teachers $E(\theta/\Theta = 1)$, and therefore, a rise in the expected ability of teachers, TQ.

Since the conditional expectation $TQ = E(t|\Theta = 1)$ does not have a closed expression, I will obtain them by simulation. Before doing this, the next section discusses under which circumstances the school strategy attracts effective teachers.

2.2.3 The effectiveness of the school strategy

The effectiveness of the school strategy depends crucially on the correlation between the teacher skill and the general skill *within the teacher supply* ($\widetilde{\rho}_{\theta t}$), which is endogenously determined in the model. This is so because schools use the general skill as a proxy for the unobservable teacher skill. Therefore, the larger the correlation between the two within the teacher supply, the more precise the proxy is, meaning a more effective school strategy. On the contrary, when this correlation is weak, the signal will be much less precise.

I denote this correlation as $\widetilde{\rho}_{\theta t} = E\left(\rho_{\theta t}|I = 1\right)$, which is given by the following expression:

$$\widetilde{\rho}_{\theta t} = \frac{\widetilde{\sigma}_{\theta t}}{\widetilde{\sigma}_t \widetilde{\sigma}_\theta}, \tag{2.12}$$

where $\widetilde{\sigma}_{\theta t}$ represents the covariance between the teacher skill and the general skill restricted to the teacher supply, and $\widetilde{\sigma}_t$ and $\widetilde{\sigma}_\theta$ are the restricted standard deviations of the teacher and general skills respectively.[14] In what follows, I study its quantitative value and how teacher wages, $\widehat{w}_0$ affect its magnitude.

[14]See Rao (1989) for details regarding the computation of the restricted variances and covariance.

The correlation between skills within the teacher supply could be higher than, lower than or equal to the correlation in the total population. This is so because firstly, the restricted standard deviations $\widetilde{\sigma}_t$, $\widetilde{\sigma}_\theta$ are always lower than the population ones (σ_t and σ_θ). Secondly, the restricted covariance $\widetilde{\sigma}_{\theta t}$ could be higher or lower than the population value ($\sigma_{\theta t}$).[15]

If $\rho_{\theta t}$ is relatively low, $\widetilde{\rho}_{\theta t} > \rho_{\theta t}$ holds for any teacher salary. On the other hand, if $\rho_{\theta t}$ is relatively high, the inequality $\rho_{\theta t} > \widetilde{\rho}_{\theta t}$ holds for any teacher salary. Additionally, when $\widetilde{\rho}_{\theta t} \neq \rho_{\theta t}$, the distance between the restricted and unrestricted correlation coefficients decreases with the supply of teachers, which in turn, depends positively on wages. Therefore, a rise in teacher wages determines the convergence between the restricted and the unrestricted correlation.[16]

Since the convergence between the restricted and the unrestricted correlation could be from above or from below, the sign of the relationship between teacher salary $\widehat{w}_0$ and the effectiveness of the proxy $\widetilde{\rho}_{\theta t}$ is not theoretically defined. Specifically, if $\widetilde{\rho}_{\theta t} < \rho_{\theta t}$ holds for any level of $\widehat{w}_0$, a positive relationship between the teacher salary and the quality of the proxy, ($\widetilde{\rho}_{\theta t}$) is obtained. In this case, when schools set a higher salary, the proxy to identify the best teachers becomes powerful. On the contrary, when $\widetilde{\rho}_{\theta t} < \rho_{\theta t}$ holds for any $\widehat{w}_0$, a negative relationship between $\widetilde{\rho}_{\theta t}$ and $\widehat{w}_0$ is obtained. In this case, when schools fix a higher salary, the proxy to identify the best teachers becomes weaker.

2.2.4 The equilibrium in the market for teachers

The equilibrium of the model is defined as a minimum level of general skill required to be selected for a teacher position and the associated distribution of the teacher skill among teachers ($\theta^*, f(t/\Theta = 1)$), such that:

- No individuals wishes to change occupation from the teacher sector to the market sector, given the market wages.

[15] Particularly, $\sigma_{\theta t} \leq \widetilde{\sigma}_{\theta t}$ if an only if $\rho_{\theta t} \leq \tau/\alpha$.

[16] In the extreme, when w_0 tends to infinite and thus, the teacher supply tends to the total population, i.e. $\widetilde{\rho}_{\theta t}$ tends to $\rho_{\theta t}$.

- The school board maximises student outcomes given the teacher salary.
- The school board hires the required number of teachers. That is, θ^* holds that: $\int_{\theta^*}^{\infty} f(\theta/\Theta = 1)\partial\theta = \gamma$

Note that some individuals that choose to apply for a teacher position in the self selection stage could not be hired, so that, an excess of supply in the teacher market could be observed in equilibrium.[17] Nevertheless, no agents have incentives to change their decisions.

2.2.5 Equilibrium representation

Even though the model generates the complete equilibrium distribution of the teacher ability among teachers, in this section, I concentrate only on the mean of the distribution of TQ.

For each level of teacher salary and each parameter, the model states a TQ in equilibrium. Since TQ is a key input for student outcomes, it is relevant to study its relationship with teacher wages.

The "Teacher Wage-Teacher Quality" curve (in advance TW-TQ curve) shows for each level of teacher salary, w_0, and a given vector for the rest of model parameters, the expected teacher ability of the teacher staff, $TQ = E(t/\Theta = 1)$, that holds the equilibrium conditions of the model. Figure 2.1 represents the TW-TQ curve for a baseline economy. Parameters in this baseline economy were chosen in order to: i) work with standard normal marginal distributions in both skills, $\mu_t = 0$, $\sigma_t = 1$, $\mu_\theta = 0$, $\sigma_\theta = 1$; ii) fix an elasticity of the individual utility respect to the general skill higher than the elasticity respect to the teacher skill, $\alpha = 1$, $\tau = 0.1$[18]; iii) Work with a positive, but not very strong, correlation between skills, $\rho_{\theta t} = 0.5$. Appendix I discuss in detail how the TW-TQ curve is modified when we change the parameter values of the model.

[17] Recall that, individuals who are not selected for a teacher position can apply for a job in the market sector like any other individual.

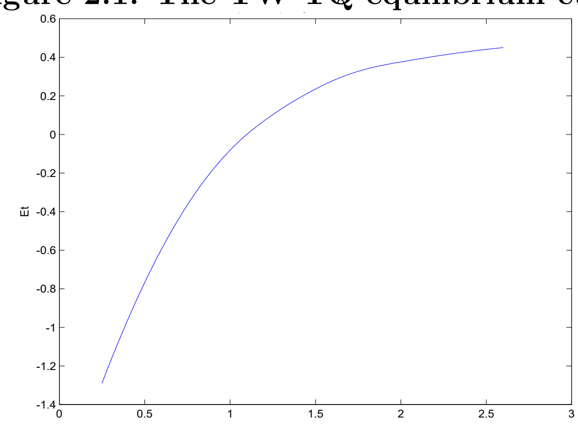
[18] This assumption states that wages are more relevant than motivation in the occupational choice.

Figure 2.1 shows an increasing and concave TW-TQ equilibrium curve. Teacher salaries increase TQ but at a decreasing rate. That is, when salaries are relatively low, an increase in salaries has a strong impact on the quality of the teaching staff. When salaries are relatively high instead (i.e. more than two times the median wage on the non-teaching sector), the effect of teacher wage on the TQ is smaller and becomes almost zero for higher levels of teacher wage. The shape of the curve is the consequence of the interaction of three different mechanisms of transmission which are discussed in detail in the next section.

Notice that the non-linear shape of the curve could help us to understand the inconclusive relationship of previous empirical works between teacher salaries and student outcomes. Hanushek (2003) provides an extensive review of several studies analysing the relationship between teacher salary and student performance. He shows that most of the studies do not find a statistically significant positive correlation. As exceptions, Loeb and Page (2000) and Dolton and Marcenaro Gutierrez (2011) find a positive relationship between teacher salaries and student achievements and provide elements to understand the previous failures in the finding of a statistically significant relationship which are in line with the shape of my TW-TQ curve.

One possible explanation for these ambiguous findings is that different countries could be in different parts of the curve. This is so because on the one hand, empirical analysis based on cross-sectional data within a country probably captures only a small segment of the equilibrium curve since teacher wage dispersion is usually small within country. Note that a linear regression over different segments of the TW-TQ curve of Figure 2.1 could generate very different results. In fact, an estimation over a sample of low teacher wages probably suggests a significant relationship between teacher salaries and student outcomes. However, with a sample of high teacher salaries it would be more difficult to find a significant relationship. On the other hand, the parameters controlling the teacher selection process differ across countries, and as it is explained in the Appendix I, the equilibrium curve is very sensitive to the value of these parameters.

Figure 2.1: The TW-TQ equilibrium curve



Note: Teacher wage is expressed in terms of the median wage in the non-teaching sector.

2.2.6 Teacher salary and teacher quality: Three channels of transmission

Teacher salaries impact the quality of teachers through three different channels: the quantity channel, the quality channel and the signal channel. Furthermore, the sign of the latter two channels depends on $\rho_{\theta t}$. I will also discuss how each channel operates for different values of $\rho_{\theta t}$.

The quantity channel affects the teacher supply size (γ). A rise in the teacher wages increases the incentive to become a teacher. Therefore, a higher teacher salary determines a larger teacher supply and more possibilities of selection for schools. Panel A of Figure 2.2 shows the relationship between teacher salaries and the teacher supply size for different values of $\rho_{\theta t}$. This channel is almost insensitive to different values of $\rho_{\theta t}$.

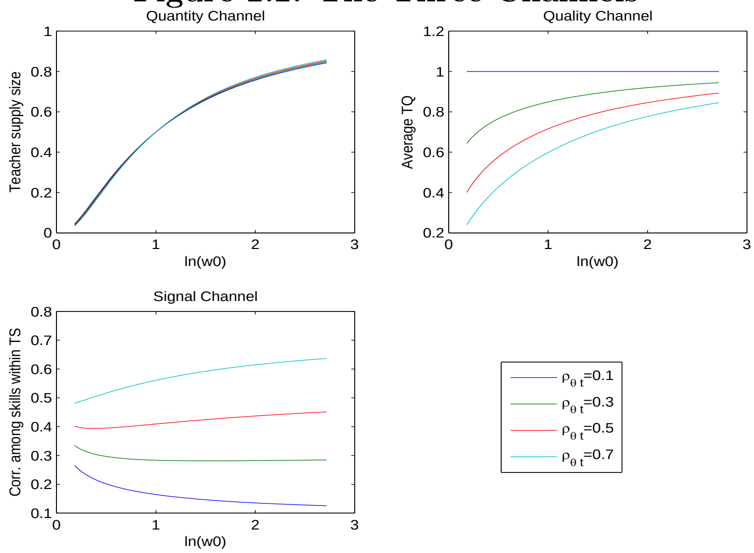
The quality channel affects the average teacher skill of individuals within the teacher supply, $E(t/I = 1)$. The sign of the quality channel effect depends on $\rho_{\theta t}$. With a high correlation between general and teacher skills, a rise in the teacher salary determines a rise in the average teacher ability within the teacher supply. Note that a higher quality of teacher supply improves the pool of selection for school. In contrast, the quality of the teacher supply is almost independent of the teacher wage in the case of a small correlation among skills in the population (see the case of $\rho_{\theta t} = 0.1$).[19]

Finally, panel C of Figure 2.2 shows the signal channel (i.e. $\widetilde{\rho}_{\theta t}$) for different values of $\rho_{\theta t}$. As was explained in Section 2.2.3, the larger the correlation is between the teaching and the general skill within the teacher supply ($\widetilde{\rho}_{\theta t}$) the more powerful is the signal, and thus, the more efficient is the selection strategy of schools.

The relationship between the teacher salary $\widehat{w}_0$ and $\widetilde{\rho}_{\theta t}$ depends on the correlation between both skills in the total population, $\rho_{\theta t}$. Indeed, as we can see from the graph, $\widetilde{\rho}_{\theta t}$ and $\widehat{w}_0$ are increasing (decreasing) in teacher wages when the correlation between skills in the total population is strong (weak). Therefore, when $\rho_{\theta t}$ is high, paying higher wages makes the signal in the selection process more accurate. On the contrary, when $\rho_{\theta t}$ is low, paying

[19] Indeed, assuming $\rho_{\theta t} < 0.1$ the sign of this channel becomes negative. Since, empirical evidence is in favour of $\rho_{\theta t} > 0$ we do not concentrate on this case.

Figure 2.2: The Three Channels



higher salaries determines a less accurate signal in the selection process.

In summary, in the case of a strong correlation between skills in the population, a rise in teacher salaries leads to a more efficient method of selecting teachers. This is so because higher wages imply that: i) the selection pool of teachers is larger, ii) these agents are of better quality and iii) the signal is powerful (the restricted correlation is larger). However, in the case of a weak correlation between skills (see for instance, the case of $\rho_{\theta t} = 0.1$), a rise in the teacher salary imply that i) the selection pool of teachers is larger but ii) the average quality of the teachers could not increase and iii) the proxy of the unobservable teaching skill is less accurate. As a consequence of these opposing effects, the marginal effect of teacher salary on TQ is weaker (or even negative) in this last case.[20]

Recall that the evidence suggests that observable characteristics of teachers are not a good proxy for teacher ability (Rockoff, 2004; Jepsen, 2005; Hanushek and Rivkin, 2007; Hanushek; 2010). Therefore, the parameter $\rho_{\theta t}$

[20]See Appendix II for a graphical analysis of the three channels for different values of $\rho_{\theta t}$.

of the model could be small which introduces uncertainty regarding the sign of the last channels.

2.3 Calibration

The sensitivity of the equilibrium TW-TQ curve to some parameter values (see Appendix I) introduces difficulties to use the model in order of computing the expected quality of the teaching staff for a given country. Therefore, using the model to generate measures of TQ at a country level requires an accurate process of calibration. The model will only be useful if the correct TW-TQ equilibrium curve is identified.

The model has nine parameters to determine. Five parameters are associated with the skill distribution among the population: the mean and variance of the marginal distribution of the unobservable teacher skills, μ_t and σ_t, mean and variance of the marginal distribution of the observable general skill, μ_θ and σ_θ and the correlation between both skills $\rho_{\theta t}$. Three parameters are related to the labour market conditions: $\widehat{w}_0$ measures the teacher salary relative to the median wage in the market sector; α states the elasticity of market wages to the observable general skill and γ indicates the share of teachers among the total labour force. Finally, parameter τ represents the elasticity of the non-pecuniary utility to the individual teacher skill.

I calibrate the model for a set of 22 OECD countries in the years 2000, 2003, 2006, 2009, 2012 and 2015.[21] I assume that all the parameters of the population distribution of skills and parameters τ and γ are time invariant [22] and parameters α and $\widehat{w}_0$ vary across years. Furthermore, I assume that parameters μ_t, σ_t, μ_θ, σ_θ, $\widehat{w}_0$, α and γ vary across countries, while parameters

[21] Years and countries were selected for reasons of data availability. The database includes the years in which the PISA test was available. The set of countries was restricted by the information required to the calibration of parameters.

[22] The assumption of a fixed distribution of skills in the adult population for a period of 12 years is not so strong. For instance, the PIAAC survey measures skills for populations whose ages are between 16 and 66 years (50 cohorts). Therefore, in a period of 12 years only a quarter of the cohorts changes. On the other hand, assuming a time invariant utility function for a shorter period seems quite reasonable.

$\rho_{\theta t}$ and τ are constant across countries.

Observable parameters are approximated with country data. Unobservable parameters are approximated indirectly. The following section describes the strategy applied in each case.

2.3.1 Observable Parameters

The individual general skill and the labour market condition are assumed as observable variables in the model. Thus, these variables are approximated from country statistics. Tables 2.1 presents the sources of information used to approximate the observable parameters.

Parameters corresponding to the moments of the country general skill distribution (μ_θ and σ_θ) are approximated with the corresponding moments of an average of skills included in the PIAAC survey for adult populations. The PIAAC survey for adult populations is used to obtain a comparable measure of skills across countries. This survey measures adults' skills in literacy, numeracy and problem solving in technology-rich environments - and gathers information and data on how adults use their skills at home, at work and in the wider community.[23]

Hanushek et al. (2015) studies the wage returns to the cognitive skills measured in the PIAAC survey. In line with the assumption of equation (2) regarding the general skill, the paper finds a positive effect on salaries from all three cognitive skills measured in the survey. Based on these result, the general skill of our model (θ) is approximated as an average of the test scores in the three skills measured in the PIAAC survey.[24] Test scores are standardised with a mean μ_θ zero and a standard deviation of one across countries σ_θ.

The wage return to the general skill (parameter α) is approximated by

[23]See more details about PIAAC survey in OECD(2013).

[24]The results Hanushek et al (2015) states that the wage returns to each skill included in the PIAAC survey are different. Then our general skill (θ) which capture the relevant skills for the market is constructed as a weighted average of the skills in PIAAC, where the weight of each skill follows from the wage returns estimated in the work of Hanushek et al (2015).

Table 2.1: Approximation for observable parameters

Parameter	Definition	Source
μ_θ	mean of the general skill distribution	PIAAC
σ_θ^2	variance of the general skill distribution	PIAAC
γ	share of teacher into the labour force	EG
α	elasticity of wages with respec to the general skill	EG
$\widehat{w}_0$	teacher salary relative to the median wage in the market sector	EG and IMF

the returns to tertiary education. Since the individual general skill θ was calibrated based on the cognitive skills of the PIAAC survey, the best option to approximate α would be the average returns to these skills. However, this option is available only for a single year (2012). Therefore, in order to consider the time dynamic of parameter α, it was approximated with the wage returns to tertiary education, available on Education at a Glance-OECD (EG, OECD) for all of the years included in the analysis.[25] In line with the model, the wage return to tertiary education captures a premium associated with an observable approximation of individual skills.

Parameter $\widehat{w}_0$, indicates the relative teacher salary with respect to the median wage in the market sector. It is approximated with the ratio of the teacher salary in lower secondary education (available at Education at Glance, OECD 2001) and the GDP per habitant (from IMF) both in PPP dollars.

Finally, parameter γ is approximated with the share of teachers in the total employment, measured by Education at a Glance, OECD, 2001.

[25] The wage returns to education present a high positive correlation of 0.78 across countries with the returns to the cognitive skills in the PIAAC estimated in Hanushek et al (2015).

2.3.2 Unobservable parameters

Teacher skills are unobservable, and thus parameters μ_t, σ_t, and $\rho_{\theta t}$ can not be approximated directly by country data. Similarly, since individual preferences are unobservable, there is no information for parameter τ. All these unobservable parameters are approximated indirectly.

I assume that the variance of the teacher skill distribution, σ_t, is equal to the variance of the general skill, σ_θ. In practice, this decision implies working with only eight, instead of nine parameters. The correlation between variances in observable skills is strong across countries.[26] In addition, I assume that countries with a high variance in some observable skill usually exhibit a large variance in unobservable skills too.

Meanwhile, parameters μ_t, $\rho_{\theta t}$ and τ are calibrated together through an iterative process explained in Figure 2.4.

I start approximating the average teacher quality $\mu_t/\Theta = 1$ for each country in 2015, based on the PISA results for that year.

According to equation (2.11) in the theoretical model, the following educational production function is assumed:

$$y_{is} = \beta_0 TQ_{cts} + \beta_1 S_i + \beta_2 F_i + \beta_3 SCH_i + \beta_4 M_{ct} + T_t + C_c + u_{is}, \quad (2.13)$$

where y_{is} states the average student outcome for individual i in subject s; TQ_{cts} is the simulated TQ for country c, in period t for subject s, S_i represents a set of individual characteristics; F_i states the family background for individual i; SCH_i states the school characteristics for individual i; M_{ct} represents a set of macroeconomic variables for country c in period t, , T_t is time dummy for period t, C_c is a fixed effect associated with country c, and u_{is} is the residual of the equation.

Taking expectations on equation 2.13, assuming $E(u_{is}) = 0$, and regrouping, the expected teacher quality for each country, subject and period can be

[26]Cross-country standard deviations in numeracy and literacy skills of the PIAAC survey show a correlation of 0.84. Moreover, cross-country correlation among the cognitive skills measured in the PISA test are of the order of 0.97.

computed.

$$E(TQ_{is}) = E(y_{is} - B_1S_i + B_2F_i + B_3SCH_i + B_4M_{ct} + T_t + C_c) \quad (2.14)$$

The result of equation (2.14) is used to obtain the average teacher quality, $\mu_t/\Theta = 1$, for each country and subject in 2015. Note that, this value is an endogenous result of the model and it differs from parameter μ_t which states the average teacher skill of the total population.

In order to operate with equation (2.14), first at all I need an approximation to each component of the right side of the equation. Student characteristics include gender, age, migration status, and dummies regarding repetition and difference between the language of the test and language at home. Family background is approximated with the index of economic social and cultural status of PISA (ESCS index). This index was created on the basis of the highest levels of education and occupational status of the student's parents; the number of books at home; and an index of other home resources.[27] School characteristics include an index of autonomy developed by PISA, school size and the student-teacher ratio.[28] Finally, I control by the educational expenditure in primary and secondary education as a percentage of the GDP, the GDP per capita in PPP dollars, and the growth rate.

Finally, the vectors of parameters B_i are estimated by running the OLS regression with the objective to obtain an empirical estimation of the TW-TQ curve. The empirical TW-TQ is estimated based on our sample of 22 OECD countries between 2000 and 2015. The estimation includes all of the controls of equation (2.13) with the exception of TQ, which is replaced by the relative teacher salaries. Concretely, the following regression is estimated:

[27] The index of other home resources was created on the basis of whether there is a quiet study space, internet access, TV, and stories and novels at home. For more details on the ESCS, see the Annex I of PISA (2015)- OECD.

[28] The index of school autonomy is calculated as the percentage of tasks included in the questionnaire of school for which the principal, teachers or the school governing board have considerable responsibility. See the Annex A1 of PISA (2015)- OECD Volume II for details of the index of school autonomy. The school size is measured as the total student enrolment. The student-teacher ratio is measured as at a school level as the ratio between the total number of teachers in the school and the total enrolment.

Table 2.2: Empirical TW-TQ curve

	student score
b_1	34.771**
b_2	-8.934**
Average R-Squared	0.2282
Observations	577909
Sample	2000-2015

Note: Teacher salaries are expressed as a percentage of the GDP per capita. Significance levels: *p<0.1, **p<0.05, ***p<0.001. Data source: PISA 2000-2015; OECD, IMF.

$$y_{is} = b_1\widehat{w}_{ct} + b_2\widehat{w}_{ct}^2 + B_1S_i + B_2F_i + B_3SCH_i + B_4M_{ct} + T_t + C_c + u_{is}, \quad (2.15)$$

where $\widehat{w}_{ct}$ indicates the ratio among the teacher salary and the GDP per capita (both in PPP dollars) for country i in period t. Consistent with our theoretical equilibrium curve TW-TQ, the empirical specification in Equation 2.16 needs to include a quadratic term to capture non-linear effects of salaries.

Table 2.2 reports the values for parameters b_1 and b_2 from the empirical estimation of the TW-TQ curve of equation (16).[29] The quadratic term is significant, so that the empirical TW-TQ curve is also concave.

Once I have an estimation of $\mu_t/\Theta = 1$ for each country in 2015, the second step of the process involves recuperating parameter μ_t, that is, the population mean of the teacher skill distribution. This step implies solving the model inversely. Solving the model in this way requires first, using the values for each exogenous parameter, including $\rho_{\theta t}$ and τ still in the process of calibration. Therefore, to run this step, I use initial values for those parameters. I call these values $\rho_{\theta t}^0$ and τ^0.

After this step, I obtain a preliminary calibration for μ_t conditional on the initial values $\rho_{\theta t}^0$ and τ^0. In the third step, parameters $\rho_{\theta t}$ and τ are calibrated in order to minimize the distance between the theoretical and

[29]For a complete estimation of the regression see the Appendix IV.

empirical TW-TQ curve. The empirical curve is building based on previous estimation. The theoretical TW-TQ is computed using the calibrated values for observable parameters and the initial values for the unobservable ones.

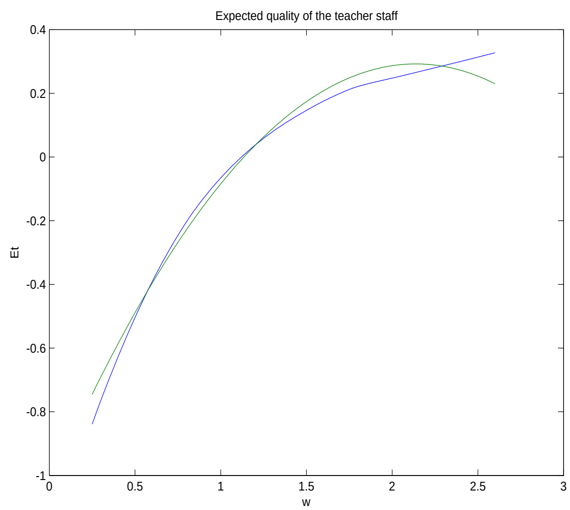
Finally, the fourth step consists of checking the distance between the initial values of $\rho_{\theta t}$ and τ and the values obtained in the previous step. Let us define $\epsilon = 0.001$ as a convergence criteria. Hence, this step implies checking if the following conditions are satisfied:

1. $|\rho^0_{\theta t} - \rho_{\theta t}| < \epsilon$
2. $|\tau^0 - \tau| < \epsilon$

If the convergence conditions are satisfied, the process of calibration concludes. If not, the iterative process reverts back to the second step taking the new values of $\rho_{\theta t}$ and τ as input instead of the initial values $\rho^0_{\theta t}$ and τ^0.

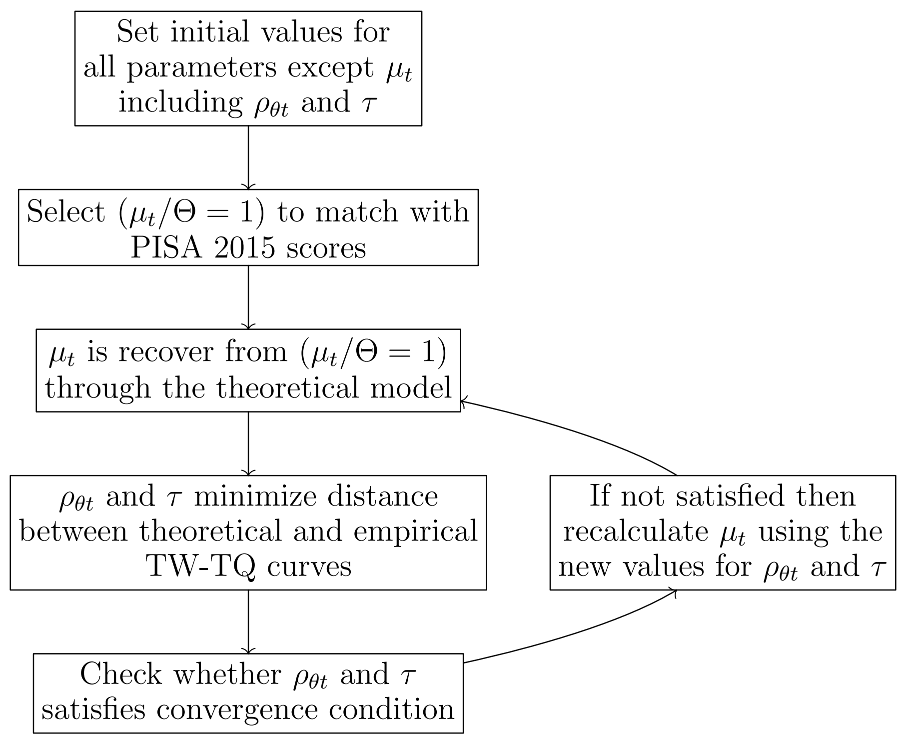
Figure 2.3 shows the theoretical (blue line) and empirical (green line) curves together after finish the calibration process. Figure 2.4 summarises the process of calibration for parameters μ_t, $\rho_{\theta t}$ and τ. The Appendix III presents details of the iteration process.

Figure 2.3: Theoretical vs Empirical TW-TQ curve



Note: Theoretical curve (green line) vs Empirical curve (blue line). Teacher salaries are expressed as a percentage of the GDP per capita.

Figure 2.4: The iterative process of calibration



2.3.3 Calibration Results

Tables 2.3, 2.4 and 2.5 summarise the parameters values for our set of 22 OECD countries. Table 2.3 presents the time-invariant parameters, while Tables 2.4 and 2.5 show the time-variant parameters between 2000 and 2015. By examining these tables three results of the calibration are particularly remarkable.

First, the variance across countries of the unobservable teacher skill is quite similar to the variance across countries of the observable general skill. Hence, even though the calibration determines significant differences in the mean of the distribution of teacher skills across-countries, those differences are in line with cross-country differences in other measured skills. Particularly, the variance across countries of the average teacher skill is similar to the cross-country variance in the average skills measured in the PIAAC survey.

Second, the calibrated correlation between the teacher and general skill ($\rho_{\theta,t}$) is positive but not very high (0.57). This correlation is clearly weaker than the individual-level correlation between the skills in the PIAAC survey (0.87 between numeracy and literacy and 0.73 between numeracy and problem solving) and in PISA results (0.85 between maths and reading and 0.9 between maths and science). This result support the idea that observable skills are not a very reliable proxy for teacher skills, as is shown by previous works (Rockoff 2004, Jepsen 2005, Hanushek and Rivkin, 2007 and Hanushek, 2010).

Finally, the elasticity of the non-pecuniary utility with respect to the individual teacher skill is relatively small (approximately a quarter) compared to the elasticity of wages with respect to the general skills. This result highlights that, even though, effective teachers obtain an average higher utility of teaching (so, the motivation factor matters), wages are the most relevant factor in the individual occupational choice.

Table 2.3: Time invariant parameters

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	μ_θ	σ_θ	γ	μ_{Math}	μ_{Read}	ρ	τ
Australia	0.4072	0.7666	2.30	0.2532	0.7661	0.57	0.24
Austria	0.1851	0.6919	2.60	0.6014	-0.1568	0.57	0.24
Belgium	0.6748	0.7033	3.60	1.3791	0.7642	0.57	0.24
Canada	-0.0821	0.6070	1.70	1.6046	2.1071	0.57	0.24
Czech. R	0.3980	0.7972	2.10	0.1179	-0.2052	0.57	0.24
Denmark	0.3640	0.6223	2.80	1.4871	0.6785	0.57	0.24
Estonia	0.2412	0.6216	2.50	1.8271	1.6212	0.57	0.24
Finland	1.3688	0.6338	2.40	1.4981	2.2881	0.57	0.24
France	-1.2216	0.5958	2.70	0.3782	0.7398	0.57	0.24
Germany	0.0266	0.7941	1.90	1.0954	1.1828	0.57	0.24
Ireland	-0.9330	0.8007	2.80	0.9893	1.9286	0.57	0.24
Italy	-2.1209	0.8795	2.90	-0.0108	-0.3119	0.57	0.24
Japan	2.0886	0.6747	1.50	2.7245	1.4741	0.57	0.24
Korea	-0.2139	0.6121	1.40	2.2649	1.6541	0.57	0.24
Netherlands	1.0773	0.6414	2.80	1.6097	0.9129	0.57	0.24
Norway	0.7556	0.6299	3.70	1.0570	1.6702	0.57	0.24
Poland	-0.7740	0.6926	2.50	1.0552	1.0372	0.57	0.24
Slovak, R.	0.1121	0.6451	2.50	-1.0269	-2.3060	0.57	0.24
Spain	-1.7549	0.6280	2.70	-0.0235	0.5819	0.57	0.24
Sweden	0.6816	0.6554	2.80	0.5233	0.8699	0.57	0.24
UK	-0.3772	0.8947	2.40	0.2708	0.6202	0.57	0.24
US	-0.9032	0.9051	2.20	-1.2038	0.5548	0.57	0.24

Note: Columns (1)-(3) are observable parameters while columns (4)-(7) states the unobservable ones. Sources: PIAAC, OECD and own calibration.

Table 2.4: Time-variant parameters

	α					
	2000	2003	2006	2009	2012	2015
Australia	0.9050	0.8928	0.89	0.92	0.91	0.92
Austria			1.06	1.05	1.16	1.02
Belgium	0.8640	0.8767	0.90	0.89	0.87	0.92
Canada	0.9146	0.9171	0.93	0.95	0.94	0.94
Czech. R	1.2105		1.24	1.27	1.19	1.30
Denmark	0.8378	0.8386	0.85	0.86	0.86	0.85
Estonia				0.93	0.91	0.87
Finland	1.0332	1.0172	1.01	0.99	1.00	0.91
France	1.0122	1.0151	1.01	0.99	1.04	0.95
Germany	0.9678	1.0379	1.11	1.06	1.18	1.07
Ireland	0.9591	1.0080	1.14	1.11	1.19	1.10
Italy	0.8577	1.0320	1.11	1.01	0.99	0.96
Japan				1.00	1.03	1.03
Korea	0.9143	0.9509	0.95	0.89	1.00	0.94
Netherlands	0.9537	1.0033	1.00	1.08	1.06	1.00
Norway	0.8982	0.9273	0.87	0.86	0.88	0.85
Poland			1.17	1.13	1.16	1.10
Slovak, R.				1.25	1.17	1.15
Spain	0.9747	0.8708	0.89	0.96	0.95	0.95
Sweden	0.8875	0.9127	0.86	0.85	0.87	0.83
UK	1.0739	1.0977	1.08	1.08	1.05	1.00
	1.1654	1.2357	1.19	1.21	1.18	1.14

Source: OECD.

Table 2.5: Time-variant parameters

	w0					
	2000	2003	2006	2009	2012	2015
Australia	1.33	1.30	1.16	1.19	1.18	1.20
Austria	0.93	1.07	1.04	1.11	1.07	1.00
Belgium	1.17	1.21	1.11	1.20	1.18	1.10
Canada					1.38	1.43
Czech. R	0.61	1.02	1.04	0.96	0.72	0.57
Denmark	1.02	1.08	0.99	1.36	1.21	1.13
Estonia			0.46	0.77	0.50	0.47
Finland	1.05	1.19	1.04	1.19	1.06	1.04
France	1.03	1.09	0.96	0.99	0.94	0.89
Germany	1.43	1.60	1.46	1.70	1.58	1.47
Ireland	1.10	1.06	1.06	1.40	1.21	0.89
Italy	1.00	1.06	0.95	1.15	1.06	1.00
Japan	1.68	1.66	1.55	1.55	1.34	1.22
Korea	2.66	2.35	2.14	1.90	1.54	1.30
Netherlands	1.06	1.23	1.13	1.37	1.47	1.34
Norway	0.58	0.71	0.60	0.73	0.61	0.65
Poland				0.91	0.92	0.93
Slovak, R.				0.62	0.51	0.56
Spain	1.33	1.48	1.41	1.70	1.44	1.35
Sweden	0.92	0.96	0.85	0.98	0.85	0.79
UK	1.43	1.48	1.29	1.34	1.17	1.12
US	1.10	1.11	0.92	0.95	0.91	1.10

Note Teacher salaries are expressed in terms of the GDP per capita (as proxy of the median wage in the non-teaching sector). Sources: OECD and IMF.

2.3.4 Model Results

This section discusses the model results. Our model is able to generate the complete distribution of teacher quality among teachers for each country. Nevertheless, in this work, I focus on the distribution's mean as a summary statistic.

Figure 2.5 shows the average teacher quality between 2000 and 2015 for each country of our panel. The model results predict that Korea, Canada and Japan have the highest teacher quality in the considered period in maths while Estonia, Finland and Canada have the highest teacher quality in reading. In the lower bound of the distribution the Slovakia and US shows the lower teacher quality of our sample in maths. In reading, again Slovakia presents the lower estimations of teacher quality followed by Italy and the Czech Republic. Even though we observe changes in the relative positions of countries among subjects, we have a strong cross-country correlation between teacher quality in both subjects.

Once I obtain the TQ results, a natural question arises: Are the model results a reliable proxy of a country's teacher quality? It is difficult to answer this question because there are no quantitative measures of teacher quality at a country level. The only consensus in previous literature states that teacher quality impacts student outcomes.[30] I evaluate my proposed measure of TQ based on its correlation with student outcomes.

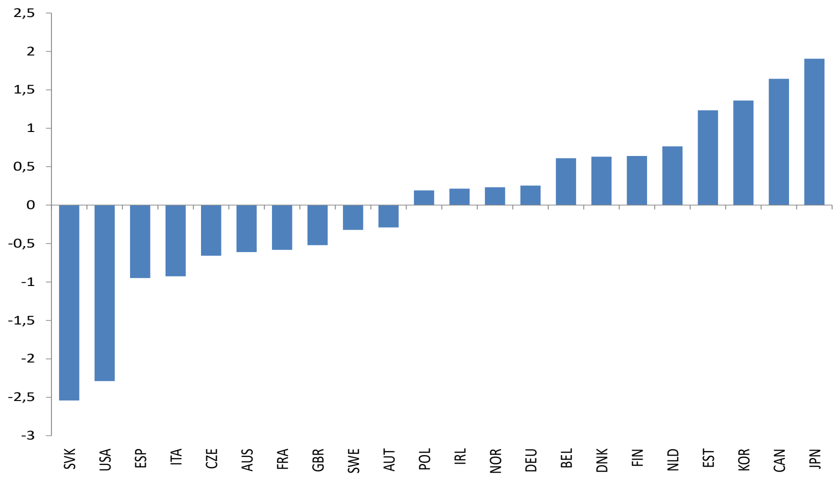
A first approximation is a simple correlation between the model measure of teacher quality and student outcomes. I use the PISA results as a comparable measure of student outcomes across countries. The correlation between TQ and student outcomes in maths and reading is 0.73 in our panel of 22 countries between 2000 and 2015. Figure 2.7 shows a scatter plot between the average TQ by countries and the average student achievement on the PISA test, both for the period 2000-2015 and for the two different subjects. The correlation between the measure of country TQ and country results on the PISA test is strong in both maths and reading.

A second more elaborate approximation is an estimation of an Educa-

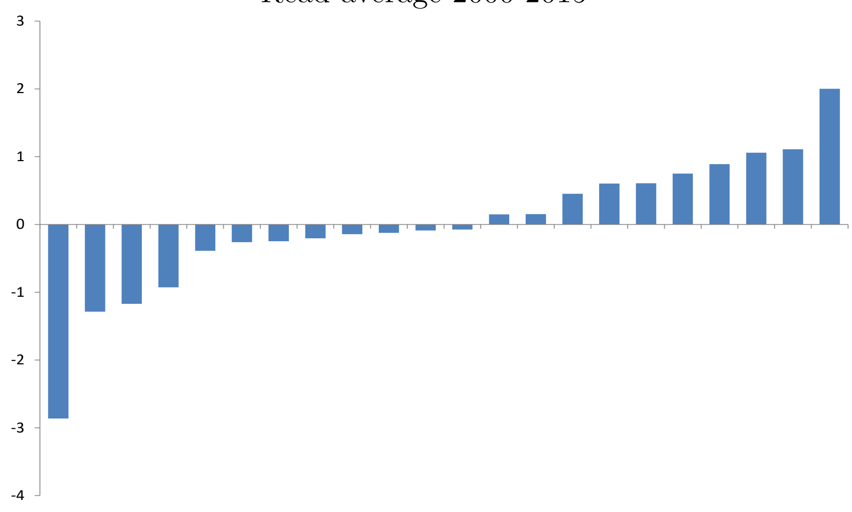
[30] See for instance Hanushek and Rivkin (2006), Hanushek (2010) and Hanushek and Rivkin (2010).

Figure 2.5: Teacher quality by countries.

Math average 2000-2015

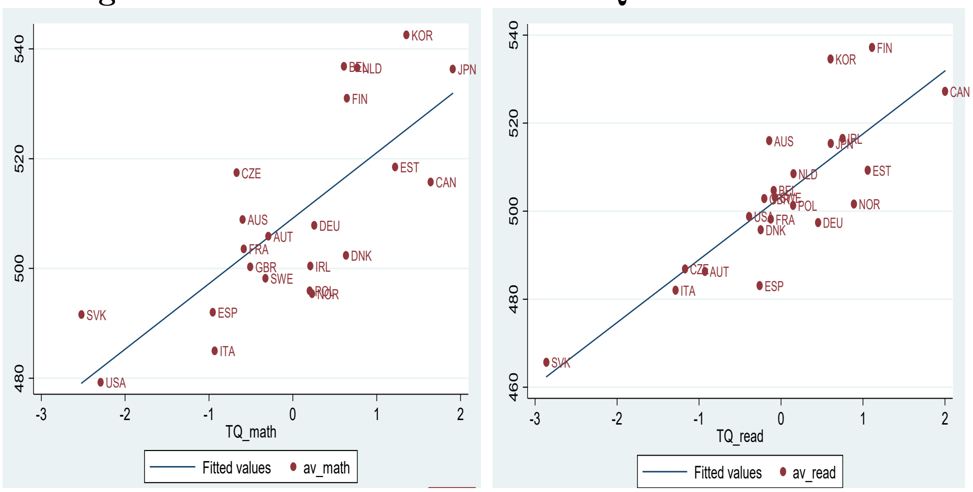


Read average 2000-2015



Sources: Own computations based on the theoretical model of teacher selection.

Figure 2.6: Model estimates of TQ and PISA results



Sources: Own computations and PISA, OECD (average 2000-2015).

tional Production Function (EPF) based on the PISA test scores that includes our model measure of TQ as an educational input together with other controls. In concrete, I use the model measurement of teacher quality to estimate the following specification of the educational production function, based on equation (2.13).

$$y_{is} = \beta_0 TQ_{cts} + \beta_1 S_i + \beta_2 F_i + \beta_3 SCH_i + \beta_4 M_{ct} + T_t + C_c + u_{is},$$

where y_{is} states the student score for individual i in subject s; TQ_{cts} is the simulated TQ for country c, in period t for subject s, S_i represents a vector of individual characteristics; F_i states the family background for individual i; SCH_i states a vector of school characteristics for individual i; M_{ct} represents a set of country variables for country c in period t, C_c is a fixed effect associated with country c, T_t is dummy for period t, and u_{is} is the residual of the equation.[31]

[31]Details regarding the estimation, including the set of individual, family and country variables considered in the specification are presented in the Appendix IV.

My econometric specification identifies the parameter of the model measurement of TQ based on the dispersion within students and between subjects[32]. Several concerns could arise from this estimation. First, the possibility of having unobserved omitted variables, for example, the educational attitude in a country. Societies that emphasize the importance of good education may have both, high-quality teachers and parents who strongly support their child's education. In this sense, teacher quality and student scores could be significantly correlated but there is not a causal effect. Second, if there is a subject-specific attitude in a country (a favourable attitude towards language or mathematics). Third, self-selection or sorting of students and teachers across schools (within countries) and within schools could also biased our coefficient of interest. And finally, country specific measurement of teacher quality are likely measured with error such that OLS estimates are biased toward zero.

I deal with these concern by including a country fixed effect such that we control for all the unobservable time-invariant omitted variables associated to countries. That is, having time series of teacher quality for a set of countries is important for the baseline specification. This is so because potential reasons behind the cross-country dispersion in student outcomes could be, as explained above, learning culture or educational institutions, which are set up at the country level. Using time series of TQ, we are controlling for for these unobservable country fixed effects. Unfortunately, the problem of subject attitude in a country could not be removed by the country fixed effect. The third concern is not an issue in my framework, because my object of interest is teacher quality at the country level. And finally the last concern does not seem to be a problem because, as explain in what follows the estimated coefficient of TQ is positively significant and far away form zero. Since, I can not deal with all concern explained above, I refuse to interpret the OLS estimate of β_0 as causal.

Table 2.6 summarises the estimations using the micro data of PISA. Column (1) presents the results of an OLS estimation without any control except time dummies and country fixed effects. Column (2) shows a regression between PISA results and the model TQ measure including controls by individual characteristics, family background, school resources and macro variables.

[32]Within-student across-subject variation has already been used in Dee 2005, Metzler and Woessmann 2012, and Hanushek et. al. 2014.

Finally, column (3) makes the same estimation of column (2) using a different sample.

The results show that the effect of the model measurement of TQ on student outcomes is strongly robust to introducing controls and changing the estimation sample. Moreover, in line with Hanushek (2003), I also find that TQ is the single school input with the highest impact on student outcomes. Indeed, the standardized effect of TQ on the student outcomes is greater than the estimated standardized impact for the rest of the school inputs considered in the EPF, including the student-teacher ratio, education spending and variables of school organization.[33]

The estimated EPF indicates that moving up one standard deviation in the average TQ of the country determines a rise of 0.121 standard deviations (almost 11.307 PISA points) in the score of the students of this country. This result is slightly higher than the teaching quality effect estimated in Rivkin et al. 2001 (0.11 sd) from an estimate based on teacher fixed effects but lower than the result of Hanushek et al. 2014 (0.2 sd) based on a similar strategy to that of this work. Indeed, Hanushek et al. 2014 also estimate and EPF based on micro data of the PISA test based on a within-student between subject strategy of identification. The main of our estimations respect to the work of Hanushek et al. 2014 are the measurement of teacher quality and the sample of the estimation.[34] Additionally, because I have time series of TQ, I include country fixed effects in the empirical model.

Attending to the correlation of the model measurement of TQ and student outcomes, in what follows, I assume that my model measurement is a reliable proxy of the average teacher quality at the country level. Once I have a comparable TQ measurement across countries, I can discuss the main question of the paper, that is: What is the role of teacher quality to explain cross-country differences in student outcomes?

Our educational production function states that cross-country dispersion in student outcomes could essentially arise from differences in: teacher

[33]Appendix IV reports the complete estimation.

[34]The work of Hanushek et al. 2014 approximates the average teacher quality in a country based directly on the average score in PIAAC of teachers. Therefore they have only one measurement of TQ by country without time variation. The last point limits their sample of estimation which includes the dataset of PISA in 2009 and 2012.

Table 2.6: Effect of TQ on student achievements

	student score in PISA		
	(1)	(2)	(3)
TQ	9.4332***	10.28***	11.307***
Student characteristics	no	yes	yes
Family background	no	yes	yes
School characteristics	no	yes	yes
Macroeconomic variables	no	yes	yes
Country fixed effects	yes	yes	yes
Time dummies	yes	yes	yes
R-Squared	0.0344	0.2473	0.2509
Sample	2000-2015	2000-2015	2006-2015
Observations	1580069	1135585	953240

Note: Appendix IV reports the complete estimation. Significance levels: *p<0.1, **p<0.05, ***p<0.001. Data source: PISA 2000-2015; OECD, IMF.

quality, student characteristics, family background, school organization (i.e. school autonomy, school size and the student-teacher ratio), educational expenditures, and unobservable country fixed effects.[35] To my knowledge, this is the first exercise that makes an integrated analysis of several inputs in the production function of student achievement to evaluate the relevance of each one as sources of cross-country dispersion in student outcomes. To this end, using my theoretical model and the estimated EPF, I study several counter-factual exercises.

Each exercise consists of removing the country differences in all sources of dispersion except to one, the selected input. I repeat this exercise for each one of the school inputs included in my educational production function. In this way, I identify the individual contribution of each source to cross-country differences in student outcomes. Then, I compute how much of the observed variance on test scores in the data could be explained by the variance of the

[35]This fixed effect captures, for instance, differences in the characteristics of the educational systems or the importance attached to education by the society.

Table 2.7: Effect of Educational Inputs on cross-country variance in student achievements

	% of the observed variance explained by each component
Teacher Quality	22%
School organization	5%
Student Teacher ratio	1%
Expenditure on education (% of GDP)	8%
Family Background	20%

specific source. Table 2.7 summarise the results.[36]

In line with the results in Hanushek (2014), I find that differences in teacher skills are a significant determinant of international differences in student performance. Indeed, the results of the counter factual exercise state that nearly a quarter of the cross-country variance in student achievements observed in test scores is obtained by considering only differences in TQ. In order to contextualise the importance of TQ to explain cross country difference in student achievements, note that the results indicate that the TQ effect is quite similar to the family background effect. Differences in family background have been identified in previous literature as one of the main determinants of cross-country differences in student outcomes (See, for instance, review of Björklund and Salvanes 2011 and Woessmann, et al. 2009).

The other school inputs have a weaker impact. Indeed, a scenario in which all country differences are removed except the variables related to school organization (school autonomy and school size) exhibits a cross-country variance in student achievements of approximately 5% of the observed variance in our panel of countries. Taking into account only differences in the student teacher ratio produces a variance on the PISA results of a 1% of the observed variance in the panel. Finally, differences in educational spending generate a cross-country dispersion of student outcomes equivalent to 8% of the total variance of the panel. That is, with the exception of TQ, differences in school inputs play a minor role in explaining cross-country differences in

[36]Individual contributions do not sum 100 because the sources covariate among them, and I include only variables related to the education system in the table.

student achievements.

2.4 Why is TQ different across-countries?

If TQ is so important in explaining cross-country differences in student outcomes, we need to go further into the analysis and ask why TQ differs across countries. The theoretical model of this paper helps us to shed light on the answer of this question.

The model allows me to study the importance of different sources of TQ dispersion across countries. In particular, I classify three different sources: i) country differences in teacher salaries, $\widehat{w}_0$; ii) country differences in labour market conditions (summarised with the parameters α and γ); and; iii) country differences in initial distributions of skills, (summarised with the parameters μ_θ, σ_θ, μ_t and σ_t). Of course, these different sources of variance covariate among them. Therefore, removing one source of TQ differences does not necessarily reduce the cross-country variance of TQ.

I use counter-factual exercises to evaluate the importance of each determinant. Each exercise consists of modifying one of the model parameters in order to obtain new estimations of TQ for each country and year. Table 2.8 summarised the results.

In the first exercise, to evaluate the role of teacher salaries, I compute a new vector of country measurements of TQ under the assumption that each country pays the same relative teacher wage, which I assume to be equal to the average wage $\widehat{w}_0$ across all countries of the panel and across years. In this new set up, without differences in teacher wages, the variance of TQ in the panel falls by 6.6%. The decrease in TQ dispersion is because the simulated TQ after the removal of differences in teacher wages and the observed vector of teacher salaries is positively correlated (i.e. 0.24). That is, between 2000 and 2015, countries with better estimations of TQ after removing differences in wages, also paid, on average, better salaries. Consequently, during this period teacher salaries amplify the TQ dispersion across countries. Nevertheless, the effect of removing differences in $\widehat{w}_0$ is relatively weak.

A second source of TQ differences across countries is the labour market conditions which are captured in the model by parameters α and γ. I simulate alternative scenarios removing differences in labour market parameters by imposing the mean of the panel on all countries.

In a second exercise, I remove differences in the wage returns to the observable skill (α). In this scenario, the variance of TQ remains almost constant (decreases by 0.2%). The almost null effect of α over TQ dispersion is because the observed values of (α) across countries, on average, covariate negatively with other sources of dispersion in our panel. Therefore, even though the exercise removes the variance of one element that impacts on the TQ variance, the overall variance of TQ remains almost constant. This result implies that current differences in the labour market returns do not play a key role in explaining differences in TQ across countries.

In the same line, I build a third scenario removing differences in the share of teachers in the labour force (γ). In this case, the variance of TQ falls by 3.5%. Thus, the share of the teacher staff is a relevant amplifier of TQ variance even though its effect is weak.

Finally, I evaluate the role of the general skills of the population. For that, I simulate a fourth scenario without differences in the population distribution of skills. In this case, I impose the same values (panel means) for parameters μ_θ, σ_θ, μ_t and σ_t on all countries. Under this assumption, cross-country differences in TQ are due entirely to the fact that teacher salaries and labour market conditions determine that the hired teachers belong to different percentiles of the skills distribution. In this scenario, the cross-country variance of TQ falls by 91%. This scenario highlights the importance of initial distributions of population skills to determine the quality of teachers.

To understand the implication of this result, we can think of a scenario in which teachers in all countries belongs to the same percentile of the population skill distribution. In this case, all the cross-country differences in TQ are explaining by the initial distribution of the population skills. Of course, countries with an initial distribution located at the right (higher mean) will hire teachers with higher skills. So, in order to converge in terms of TQ, countries where the initial distribution of skills is characterised by a smaller mean would need to hire their teachers from a higher percentile of the population distribution with respect to the average.

Table 2.8: Sources of TQ differences across countries

	Modified parameters	Imputed value	Variance in TQ
Ex. 1	$\widehat{w}_0$	panel mean	-6.6%
Ex. 2	α	panel mean	-0.2%
Ex. 3	γ	panel mean	-3.5%
Ex. 4	μ_t, μ_θ,σ_t, σ_θ	panel mean	-91%

In summary, previous counter-factual exercises suggest that the initial distribution of skills determines most of the current TQ differences. The teacher selection process leads to better results in countries with a high quality space of selection. In this sense, the history of educational results and its implications on current population skills plays a key role in explaining current dispersion in student achievements.

Additionally, observed differences in teacher salaries and labour market conditions act as amplifiers of initial differences in populations skills. For instance, countries with better initial conditions in terms of the teacher ability distribution also pay, on average, higher teacher salaries. Therefore, a different configuration of labour market conditions, and particularly of teacher salaries would be required to break down the hysteresis introduced by initial differences in population skills.

2.5 Conclusions

This paper evaluates to what extent teacher quality explains cross-country differences in student achievements. Additionally, using counter-factual exercises, the paper analyses the main drivers of teacher quality variation across countries.

To do this, I propose and calibrate a micro-founded model to study the teacher selection process. Based on the calibrated model, I build time series of teacher quality at a country level for 22 OECD countries and use them as input in the estimation of an education production function (EPF). To my knowledge, no previous studies provide time series of teacher quality. These time series allow me to analyse whether teacher quality trends can explain the evolution of student achievements at a country level. Finally, using the theoretical model and the estimated EPF, I carry out several counter-factual exercises to evaluate the contribution of different variables for explaining cross-country differences in student outcomes.

The chapter has three key results. First, the model measurement of teacher quality shows a significant positive correlation with student outcomes in PISA across countries, even when controlling for country fixed effects. This result suggests that our measurement of teacher quality at the country level seems a reasonable one. Second, TQ is the single educational input with the largest impact on cross-country variance in student achievements, explaining approximately 22% of it. Although, this result is in line with previous literature that highlights the importance of teacher quality as an educational input, I go further by comparing how important TQ is with respect to other inputs of the educational production function. I found that the impact of TQ is quite similar to the impact of family inputs and clearly higher than the effect of other school inputs. Third, initial distributions of population skills determine most of the current differences in TQ across countries. The effect of initial distribution results is significantly larger than the effects of teacher salaries and labour market conditions.

Changing labour market conditions, and particularly teacher salaries, are a key factor to breaking down the hysteresis introduced by initial differences in the skills of the population. This is a significant challenge for policy makers in countries with poor educational outcomes.

Finally, the micro-founded model proposed in this chapter could be a useful tool to analyse the effectiveness of different educational policies and to evaluate reallocations within the educational budget. We advance in this sense in the next chapter.

2.6 References

Borjas, G. (1987). "Self-Selection and the Earnings of Immigrants," American Economic Review, Vol. 77, No. 4, pp. 531-553.

Borjas, G. (2002). "The Wage Structure and the Sorting of Workers into the Public Sector," NBER Working Papers 9313, National Bureau of Economic Research, Inc.

Bjrklund, A. and K. G. Salvanes (2011). "Education and family background: Mechanisms and policies." In Handbook of the Economics of Education, Vol. 3, edited by Stephen Machin Eric A. Hanushek and Ludger Woessmann. Amsterdam: North Holland: 201-247.

Chetty, R., J.N. Friedman, y J.E. Rockoff, (2011), The Long-Term Impacts of Teachers: Teacher Value-Added and Student Outcomes in Adulthood, NBER Working Paper No. 17699.

Thomas S. (2005). "A teacher like me: Does race, ethnicity, or gender matter?" American Economic Review 95, no. 2: 158-165.

Dolton, P. and O. Marcenaro-Gutierrez. (2011). "If you pay peanuts do you get monkeys? A cross-country analysis of teacher pay and pupil performance." Economic Policy 26 (65): 5-55.

Evans and Jovanovic (1989). "An Estimated Model of Entrepreneurial Choice under Liquidity Constraints" Journal of Political Economy, Vol. 97, No. 4, pp. 808-827.

Gates, B. (2011). How Teacher Development Could Revolutionize Our Schools, The Washington Post

Hanushek, E. (2003). "The Failure of input-based schooling policies". The Economic Journal, 113, Febraury p.64-98.

Hanushek, E. (2010). "The economic value of higher teacher quality". CALDER Working Paper N 56, December, Urban Institute.

Hanushek, E.; Piopiunik, M. and S. Wiederhold (2014). The value of smarter teachers: International evidence on the teacher cognitive skills and student performance. Working Paper 20727, NBER.

Hanushek and Rivkin (2006). "Teacher Quality," In Handbook of the Economics of Education, ed. E. A. Hanushek and F. Welch, 1051-78. Amsterdam: North Holland.

Hanushek, E. Schwerdt,G. Wiederhold, S. and L. Woessmann (2015). "Returns to Skills around the World: Evidence from PIAAC". European Economic Review, Vol. 73, pp. 103-130.

Heckman, J. (1985). "Heterogeneity, Aggregation and Market Wage Functions: An Empirical Model of Self-Selection in the Labor Market". Journal of Political Economy, Vol 93, No 6, 1077-1125.

Hiatt, F. (2009). How Bill Gates Would Repair Our Schools, The Washington Post, March 30 2009.

Jepsen, C. 2005, Teacher Characteristics and Student Achievement: Evidence from Teacher Surveys, Journal of Urban Economics, 57, 302-319.

Klein, J., M. Rhee, P. C. Gorman, R. Huberman, C. R. Johnson, A. Alonso, T. Boasberg, A. Ackerman, W. Hite Jr., JC. Brizard, J. Torres, J. Covington, T. Grier, P. Vallas, E. White, and L. Sheffield, How to Fix Our Schools: A Manifesto by Joel Klein, Michelle Rhee and Other Education Leaders, The Washington Post, October 10 2010.

Loeb, S. and M. Page (2000). 'Examining the link between teacher wages and student outcomes: The importance of alternative labor market opportunities and non-pecuniary variation', Review of Economics and Statistics, 82(3), 393–408.

Nagler, M., M. Piopiunik and M. West (2015). "Weak Markets, Strong teachers: Recession at Career Start and Teacher Effectiveness". Working Paper 21393, NBER.

Metzler, J. and L. Woessmann (2012). "The impact of teacher subject knowledge on student achievement: Evidence from within-teacher within-student variation." Journal of Development Economics 99, no. 2 (November): 486-496.

OECD. 2015. PISA 2015 Results (Volume I). Excellence and Equity in

Education. Paris: Organisation for Economic Co-operation and Development.

OECD. 2013. OECD skills outlook 2013: First results from the survey of adult skills. Paris: Organisation for Economic Co-operation and Development.

Rao (1989). "A note on corrected correlation coefficients when observation on one variable is restricted". Biometrical Journal31. 6, 677-680.

Rivkin, S.G., E. Hanushek, and J.F. Kain (2001) "Teachers, schools, and academic achievement" Working paper No 6691, National Bureau of Economic Research.

Rockoff, J. 2004. The Impact of Individual Teachers on Student Achievement: Evidence from Panel Data, American Economic Review Papers and Proceedings, 94, 247-252.

Rothstein, J. (2015). "Teacher quality policy when supply matters". American Economic Review, Vol, 105, No 1, January, pp 100-130.

Tincani, M. (2011). "Teacher Labor Markets, School Vouchers and Student Cognitive Achievement: Evidence from Chile" (January 1, 2012). Dissertations available from ProQuest. Paper AAI3509495

Woessmann, L., E. Luedemann, G. Schuetz, and M. R. West. (2009). "School accountability, autonomy, and choice around the world." Cheltenham, UK: Edward Elgar.

2.7 Appendix

2.7.1 Appendix I. Equilibrium sensitivity

Figure 2.7 shows how sensitive the equilibrium TW-TQ curve is to changes in the exogenous parameters of the population skills.

Panels A and B of Figure 2.7 show the sensitivity of the equilibrium curve to changes on the mean (μ_t) and variance (σ_t^2) of the teacher skill distribution. A rise in the mean μ_t shifts the equilibrium curve up without significantly changing its shape. This result is quite intuitive. A population characterized by high levels of teaching skill results in better teachers. On the other hand, a rise in the variance of teachers skills σ_t^2 modifies the slope of the curve since it becomes steeper, specially when salaries are relatively low.

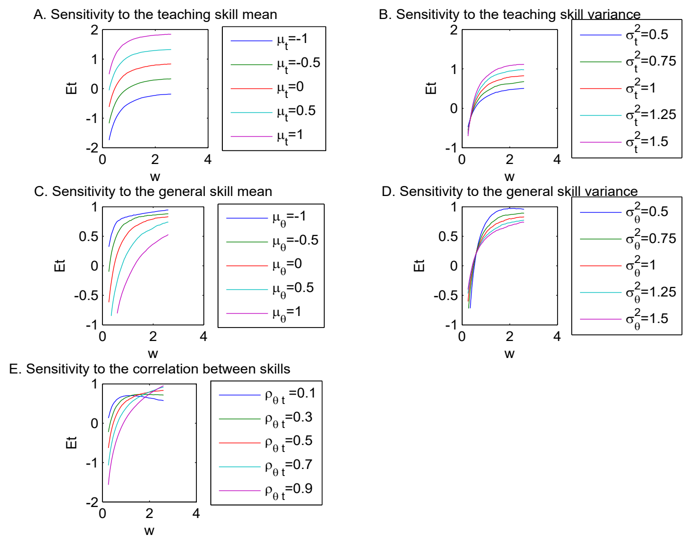
Panels C and D of Figure 2.7 show the sensitivity of the equilibrium curve to changes in the mean (μ_θ) and variance (σ_θ^2) of the general skill distribution. A higher mean of the general skill distribution μ_θ determines a fall on the average quality of teachers and a steeper curve.

Panel D shows that the larger the variance, the flatter the TW-TQ equilibrium curve is. If σ_θ^2 and salaries are low, the average TQ is low. However, if the variance is low, and salaries are high, the average TQ is high.

Finally, panel E shows the effects on the equilibrium results derived from changing the correlation between the two skills of the model ($\rho_{\theta t}$). Indeed, for a high correlation between both skills the curve TW-TQ is strictly increasing and nearly linear. In contrast, for smaller values of $\rho_{\theta t}$ it becomes more concave. In the extreme, i.e. $\rho_{\theta t} = 0.1$, the equilibrium relationship becomes decreasing at the end, and therefore, we obtain a non-monotonic equilibrium curve.

Figure 2.8 shows the sensitivity of the TW-TQ curve to changes in the rest of model parameters (α, τ and γ). Panel A shows that with a rise on the market return of the general skill (α) the TW-TQ curve becomes flatter. Panel B shows the sensitivity of the TW-TQ curve to changes in the non-pecuniary returns to the individual teacher skill (τ). Like other parameters, changes on τ have two different effects. First, a rise on τ moves up the TW-

Figure 2.7: Impact of changes in the skill distribution parameters on the TW-TQ equilibrium curve



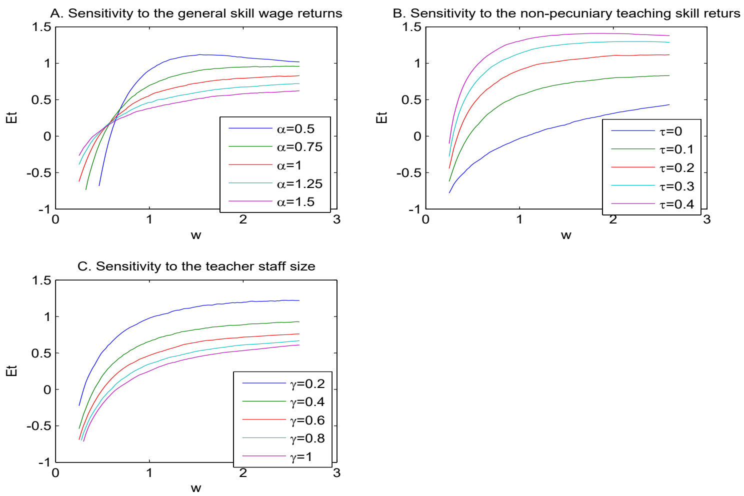
TQ curve and simultaneously, makes the TW-TQ equilibrium curve more concave. For the extreme case of zero non-pecuniary return (the blue line), the TW-TQ curve is nearly linear.

On the other hand, higher values of τ imply an increase in the slope when teacher salaries are low together with a marginal effect of almost zero when teacher salaries are larger than one time the median wage in the market sector (for instance, see the violet line corresponding with $\tau = 0.4$).

Finally, panel C shows the sensitivity of the equilibrium curve to changes in the share of teachers on the labour force (parameter γ). An increase in the number of teachers, i.e. on γ, moves down the TW-TQ equilibrium curve without significantly changing its shape.

Two key conclusions are derived from the previous analysis. First, the equilibrium relationship between teacher salary and the average quality of teachers could be non-linear and even non-monotonic. Therefore, the marginal effect of the teacher salary on the TQ is non-constant and depends on the

Figure 2.8: Impact of parameters α, τ and γ on the TW-TQ equilibrium curve



level of teacher salaries and the parameter values of the model.

Second, the model rationalises very different different shapes of the TW-TQ curve, which are derived from the interactions of three different channels operating in the model discussed in the previous section.

2.7.2 Appendix II. Transmission channels from teacher salaries to teacher quality

In this section, I explore graphically the three channels through which teacher salaries impact on the quality of teachers in two different scenarios. First assuming that correlation between the two skills are strong $-\rho_{\theta t} = 0.7$, and a second scenario under a weaker correlation of $\rho_{\theta t} = 0.1$.

Recall that three characteristics of the individuals that choose to apply for a teacher position (that is the supply of teachers), are relevant to study the school selection stage:

Firstly, supply size matters (i.e. the quantity channel). A higher number of individuals in the teacher supply increases the selection possibilities of schools. That is, schools are restricted to a larger subset when it solves its optimization problem. Just as example, if teacher supply is equal to the number of teacher required by the education system, the stage of selection developed by schools is not relevant. In fact, schools just hire all the individuals into the teacher supply. Therefore, supply size is the variable that determines the quantity channel.

Secondly, supply quality matters (i.e. the quality channel). Since schools select teachers from the teacher supply, the average teacher skill of this subgroup of the population is a key variable too. Independently of the selection strategy, the selection process will be very inefficient if all the individuals in the teacher supply are bad teachers. A higher average teacher skill within the teacher supply is a signal of a better quality in the selection space of schools. Therefore, the average teacher skill of the subset of individuals integrating the teacher supply illustrates our quality channel.

Finally, the correlation between teacher skills and general skills restricted to the teacher supply matters (the signal channel). Since schools use the general skill as signal to hire teachers (teacher skill is unobservable in the model), the correlation among both skills within the teacher supply determines the power of the signal used by schools.

Figure 2.9 shows a simulated population of 1.000.000 individuals for which skills follows a log-normal distribution (see equation 2.1). In the picture, each individual - characterized by a pair of skills (t, θ) - is identified as a point in the plane. The upper panel of the figure presents the total population while the lower panel focuses on the individuals who apply for a teacher position (i.e. the teacher supply).

The blue line of the upper panel is the indifference line for a different teacher salary.[37].) Individuals below the indifference line choose to apply for a job in the education sector. On the other hand, individuals above the indifference line choose to work in the market sector.

[37]Remember that each individual chooses the sector to work in order to maximize his utility (see equation 2.4. Indifference line has the following expression: $\theta = \frac{w_0+c+\tau t}{\alpha}$. The indifference curve is computed assuming that $\tau = 0.1$; and $c = 0$; and $w_0 = 0$ (or $\widehat{w}_0 = 1$)

The scatter plot in Figure 2.9 shows a strong correlation among the skills. As a consequence of this correlation, people with a high level of general skill, usually have a high level of teacher skill.

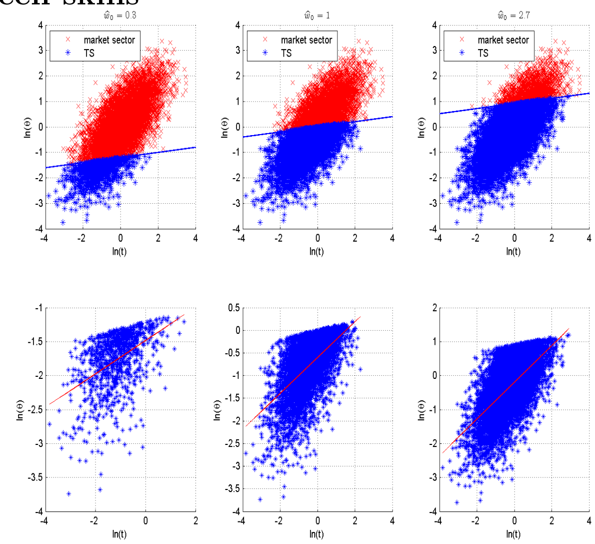
Note that the sub-population below the indifference curve has a different distribution of skills compared to the distribution of skill in the total population. Therefore, even though I assume a fixed mean, variances and correlation among skills for the total population, these moments are endogenous within the teacher supply. The lower panel of the Figure focusses on the individuals that choose to work in the teacher sector for the following relative teacher salaries (0.3; 1; 2.7).

A rise in the relative teacher salary moves up the indifference line. More individuals are located under the indifference line as a consequence of the rise in the teacher salary. That is, more individuals apply for a job in the teacher sector. A second effect of a rise in teacher salary is a higher quality of the teacher supply. A higher teacher salary induces to individuals with higher general skill (and therefore higher potential market wage) to choose the teacher sector. But, given the strong correlation between skills, these individuals, on average, also have a higher teacher skill. Finally, the figure shows that correlation between skills within the teacher supply, measured by the slope of the regression line -red line- in the lower panel, is stronger as higher is the teacher salary. Therefore, in this context a rise in the teacher salary increase the power of the signal used by schools in the second stage of selection.

In the second example, I simulate a population of 1.000.000 individuals for which the correlation between the two skills is very weak ($\rho_{\theta t} = 0.1$). Figure 2.10 presents the total population of individuals together with indifference curves for different levels of teacher salaries. Again, the upper panel of the figure presents the total population while the lower panel focuses on the individuals who apply for a teacher position (teacher supply).

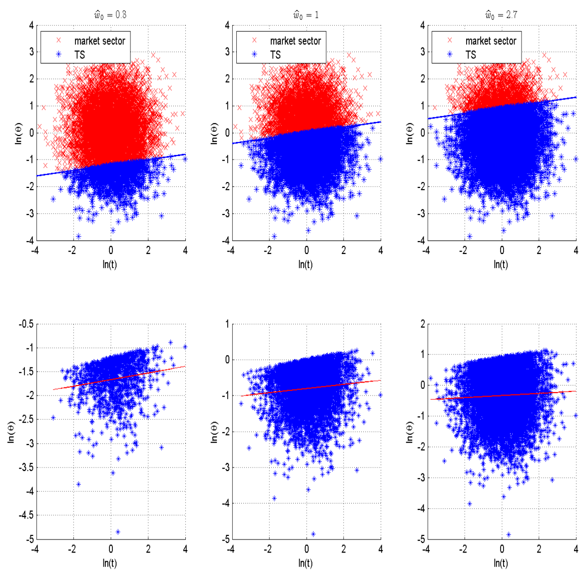
In this case, the points in the plane do not follow a clear pattern. Therefore, individuals with a high level of $\ln(\theta)$ show a high dispersion in terms of $\ln(t)$. As before, a higher teacher salary moves up the indifference line. Like in the strong correlation population, a higher teacher salary increase the number of individuals in the teacher supply. That is, a higher teacher salary enlarge the space of selection of schools (quantity channel). However, in

Figure 2.9: Teacher salary and teacher quality under a strong correlation between skills



this case the average quality of teacher supply does not change when teacher wage is higher. As before, a rise in the teacher supply induces to workers with higher general skill to choose the teacher sector, but in this case individuals with higher $\ln(\theta)$ do not necessarily has a higher $\ln(t)$. Therefore in this scenario, the quality channel does not operates or is very weak compared to the previous case. Finally, the picture show that in this case, as the small is the teacher supply and the higher is the correlation between skills, the higher is the power of the signal used by schools.

Figure 2.10: Teacher salary and teacher quality under a weak correlation between skills



2.7.3 Appendix III. The Iteration process of calibration

The process starts with the approximation of the average teacher quality ($\mu_t/\Theta = 1$) for each country in 2015, using PISA test scores for this year. The normalized values obtained operating with equation (2.15) are the following:

Table 2.9: Teacher quality by country 2015

	μt/Θ=1 *(math)*	μt /Θ=1 *(reading)*
Austria	0.1336	-0.687
Belgium	-1.4918	-1.707
Canada	0.3178	0.567
Czech. R	0.0203	-0.357
Denmark	-0.6905	-0.974
Estonia	0.9355	0.744
Finland	0.5268	0.782
France	-0.1939	0.417
Germany	0.5053	0.249
Ireland	-0.3211	0.544
Italy	-0.4066	-0.200
Japan	1.6963	1.829
Korea	2.2187	1.417
Netherlands	0.8025	0.404
Norway	-0.6062	0.104
Poland	1.1893	1.241
Slovak, R.	-1.0586	-2.118
Spain	-0.9770	-0.796
Sweden	-1.2453	-1.107
UK	-0.5750	-0.272
US	-0.7802	-0.081

The second step of the process involves to recuperate parameter μ_t. For that, I need to solve the model in an inverse sense.

Parameters to solve the model in the first iteration are included in table 2.10.

The third step implies to estimate parameters $\rho_{\theta t}$ and τ in order to minimize the distance between the theoretical and empirical TW-TQ. The process converge to $\rho_{\theta t} = 0.57$ and $\tau = 0.24$ starting from different initial values of $\rho_{\theta t}$ and τ.

Table 2.10: Parameter values.

Parameter	values
μ_θ	0
σ_t	1
σ_θ	1
α	1
γ	0.025
$\rho^0_{\theta t}$	0.5
τ^0	0.1

2.7.4 Apendix IV. Estimations

Table 2.11: Determinants of the student's score in PISA.

	TW-TQ curve	(1)	(2)	(3)
TQ		9.4332***	10.28***	11.307***
Teacher wage	34.771***			
Teacher wage (quadratic)	-8.934**			
female	7.313***		7.5879***	5.499***
F. Gen. Migrant	-13.6568***		-13.7194***	-12.689***
Diff. Language	-1.945		-1.4595***	-1.034
Age	15.504***		15.2119***	15.835***
Repetition	-50.122***		-50.7183***	-70.4472***
ESCS	32.674***		32.1402***	31.149***
Sch. Size	0.0094***		0.0094***	0.0078***
Sch Autonomy	0.5655		1.352	0.415
Student-teacher ratio	2.7597***		2.4607***	3.0096***
Student-teacher ratio (quadratic)	-0.0766***		-0.0698***	-0.0798***
% of private	8.248***		12.8591***	11.2779***
GDP growth	1.888***		1.0975***	1.2282***
GDP per capita	-0.0014***		-0.001***	-0.0016***
Expenditure on Educ (% of GDP)	-1.049*		0.0002	0.001
Country fixed effects	yes	yes	yes	yes
Time dummies	yes	yes	yes	yes
R-Squared	0.1976	0.0344	0.2473	0.2509
Sample	2000-2015	2000-2015	2000-2015	2006-2015
Observations	1183493	1580069	1135585	953240

Note: In the estimation of the TW-TQ curve, teacher salaries are expressed as a percentage of the GDP per capita. Significance levels: *p<0.1, **p<0.05, ***p<0.001. Data source: PISA 2000-2015; OECD, IMF.

Chapter 3

Teacher Quality or Quantity? An approach to the efficient allocation of the educational wage bill

3.1 Introduction

Educational literature has usually been oriented towards studying the effectiveness of different educational policies considered individually. This kind of analysis has been stimulated in turn by the increasing use of Random Control Experiments for the evaluation of policies.[1]

However, papers which compare various alternatives for the use of a single resource and discuss the efficient allocation of it are much less frequent. This chapter analyses the trade-off between teacher quality and teacher quantity by studying the efficient allocation of the educational wage bill between teachers' salaries and the number of teachers. This analysis is of special relevance given that, due to the scarcity of resources, it is necessary to improve

[0]This is a joint work with Ana Hidalgo-Cabrillana (UAM).

[1]See, Muralidharan (2016) for an extensive review of the random experiment literature in the field of education.

the efficiency of the public sector by directing efforts towards those factors that have a greater impact on school performance.

Focusing the attention on wage bill is important at least for two reasons. First, wage bill represents, on average, approximately 65% of total educational spending in OECD countries (see OECD, 2017). Second, the results of chapter 2 of this thesis and several previous studies show that teachers represent the educational input with the greatest impact on the academic results of the students (Hanushek, 2003, Klein et al., 2010; Gates, 2011; Hiatt, 2009). Therefore, the efficiency of the education sector could be closely related to decisions on salary compensation.

The discussion regarding the allocation of the educational wage bill is characterized by a clear trade-off between teacher quality and teacher quantity. On one hand, higher salaries could act as an incentive to attract and retain the best teachers to the education sector (Dolton and Marcenaro Gutierrez, 2011; Loeb and Page, 2000).[2] On the other hand, a rise in the number of teachers allows a reduction in class size which is usually linked to a better study environment, and therefore, to better student outcomes (Card and Krueger, 1992; Hoxby, 2000; Woessman, 2005).

As far as we know, the only work with a similarly aim to analyse the efficient allocation of the wage bill is the one carried out by Dolton and Marcenaro Gutierrez (2014). The estimation of efficiency developed by the authors is based on a stochastic frontier production function analysis.[3] This approach does not consider the indirect effects (general equilibrium effects) linked to changes in the number of teachers hired. That is, their analysis implicitly assumes that the educational system faces an infinitely elastic supply of homogeneous teachers. Then, hiring additional teachers impact only on the class size but not on the average quality of the teaching staff. Their assumption may be reasonable for analysing decisions in the margin, but it becomes unsatisfactory when we allow for significant variations in the number of teachers hired, which in turn are heterogeneous in quality. Indeed, the work of Rothstein (2014) shows how the evaluation of several education policies is substantially modified when considering restrictions or heterogeneities

[2]The results of chapter 2 support this idea.

[3]This econometric specification treats the educational system as if it were a company which attempts to obtain an output (student scores) by the transformation of a set of inputs (teacher wages and class size).

on the teacher supply.

Compared to Dolton and Marcenaro Gutierrez (2014), we not only developed an empirical approach but also propose a theoretical model which allows us to consider both direct and general equilibrium effects. Additionally, the theoretical model allows us to discuss the main factors affecting the optimal allocation of the wage bill. In this sense, a relevant contribution to this work with respect to the one in Dolton and Marcenaro Gutierrez (2014), is to introduce in the analysis a theoretical framework which allows us to consider general equilibrium effects and work with heterogeneous agents.

The proposed micro-founded model allows us to understand the process of teacher selection, and the determination of the average teacher quality of the education system in the case of an economy with two sectors and heterogeneous agents characterised by different skills. We use a modified version of the theoretical model proposed in chapter 2. Specifically, in this chapter, we work with a more general framework where teacher wages and class size (that implicitly measure the quantity of teachers) are both endogenous variables for the school board. Therefore, we can compute not only the expected TQ under the observed teacher wages and class size but also compute the average TQ under the optimal decision regarding both variables that results from the theoretical model. This comparison will be useful to compute the inefficiency of the wage bill.

Moreover, based on the model, we can capture the two different effects associated with changes in the number of teachers, that is, the direct effect on class size and the indirect effect on the average quality of teachers. That is, since the theoretical model includes supply and demand of teachers, the analysis is a general equilibrium framework that takes into account how supply and demand interacts. Specifically, our theoretical model shows us that if we increase the number of teachers hired, in order to reduce the class size, while maintaining constant teachers' wages, the average quality of the teaching staff will deteriorate. Therefore, an efficient distribution of the salary budget in the education system must necessarily consider the direct effects of teacher quality and quantity on student outcomes, as well as their interaction.

We then estimate an educational production function (EPF) using microdata of PISA to quantify how changes in our theoretical measure of teacher quality and class size both impact student achievements. This empirical production function in conjunction with the equilibrium TQ measurement and class size that emerges from our model allow us to compute the optimal allocation of the wage bill.

Then, comparing the optimal allocation for the wage bill with the observed data we build an index that measures the inefficiency in the allocation of quantity and qualities of teachers for 22 countries of the OECD. The results state that the average inefficiency in the allocation of the wage bill for the group of countries considered is 16%. That is, resources currently allocated to the educational wage bill could have a significantly greater impact on educational outcomes by improving their allocation between wages and teaching hours. Moreover, in most countries, the inefficiency gap is generated by a bias to prioritize the quantity more than the quality of teachers.

Finally, in order to evaluate the results of our model, we analyse the correlation between the proposed index of inefficient allocation with an empirical estimate of the overall inefficiency of the education system which is built independently of the model. Like the Solow residual in the literature of growth, our empirical estimate of the overall inefficiency of the education systems is constructed as the ratio between the educational score predicted by an estimated educational production function and the observed educational score. Notice that, given the importance i) of the wage bill within the educational costs and ii) of teaching quality within the overall school inputs, we will expect that inefficiency in the allocation of the salary budget explains a significant part of the overall inefficiency of the school system. This is already the case: our results show that including several control variables and using different econometric specifications, our estimations confirm a positive and significant correlation between the indicator of the allocative inefficiency of the salary budget obtained from our theoretical model and the empirical estimate of overall inefficiency of the educational system.

The rest of the chapter is organised as follows: the next section presents the theoretical model used in the analysis. The third section discusses the way in which the model is calibrated for a set of 22 OECD countries and the estimation of the efficient allocation for the education salary budget in each of them, based on the calibrated model. The fourth section presents an empirical approach to estimate the overall inefficiency of educational systems in the set of considered countries and discuss its correlation with our measure of inefficiency in the allocation of the salary budget derived from the theoretical model. Finally, the fifth section concludes.

3.2 The model of teacher selection

The theoretical model of teacher selection developed in this chapter is a modified version of the one carried out in chapter 2. As in chapter 2, the model comprises two stages. The first one is a self-selection stage in which agents decide if they apply for a teaching position or for a job in the non-teacher sector (market). In this first stage, the teacher supply of the economy is determined. This stage does not have changes respect to the model in chapter 2. In any case, with the aim that each chapter can be read as an independent research, we present again the self selection stage in this chapter.

In the second stage, the school board will decide how many teachers to hire and the level of the teacher wages according to their budget constraint. This stage represents an extension to previous models of teacher selection in the literature which focus on the self selection stage (see Nagler et al., 2015; Rothstein, 2014; and Tincani, 2011). Moreover, the school selection stage is substantially modified with respect to the model in chapter 2 in order to analyse issues related to efficiency. Indeed, in this model we consider both, teacher wages and the number of teachers hired as endogenous variables for the school board. Both variables are going to become crucial to study efficiency issues analysed in section 3.3.

The following sections analyse in detail both stages and the resulting equilibrium of the model.

3.2.1 Self selection stage

The economy considered is inhabited by a measure one of individuals characterized by the pair $(\widehat{\theta}, \widehat{t})$, where $\widehat{\theta}$ is an observable skill which determines individual productivity in the non-teaching sector (market sector) and $\widehat{t}$ represents the unobservable teacher skill.[4]

For each individual, the pair of skills $\left(\widehat{\theta}, \widehat{t}\right)$ is assumed to be distributed log-normally.

$$\ln \begin{pmatrix} \widehat{\theta} \\ \widehat{t} \end{pmatrix} \sim N\left(\begin{bmatrix} \mu_\theta \\ \mu_t \end{bmatrix}, \begin{bmatrix} \sigma_\theta^2 & \sigma_{\theta t} \\ \sigma_{\theta t} & \sigma_t^2 \end{bmatrix}\right). \tag{3.1}$$

Let $\rho_{\theta t} = \frac{\sigma_{\theta t}}{\sigma_t \sigma_\theta}$ to state the correlation coefficient between both skills for the total population of potential teachers. I assume that $\rho_{\theta t} \geq 0$, which seems consistent with recent empirical studies.[5]

I assume, that the salaries in the teaching sector, $\widehat{w}_0$, are the same for all teachers.[6] In contrast, wages in the market sector, $\widehat{w}_\theta$, depend on the non-teaching skill $\widehat{\theta}$ (general skill in ahead) as follows:

$$\widehat{w}_\theta = \widehat{\theta}^\alpha, \tag{3.2}$$

where α which is the wage elasticity with respect to the general skill, measures the market return to the general skill $\widehat{\theta}$.

In the first stage every individual i makes his occupational choice to maximize his utility, u_i. This stage is based on a Roy model which is the most extended framework in the field of work self-selection.[7]

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[4]The assumption of the non-observability of the teacher skill is suggested in previous studies. See for instance Hanushek (2010) and Rothstein, et al.(2014).

[5]A positive correlation between teaching and non-teaching skills is expected from the following works. On one hand, Hanushek et al. (2015) study the private returns to cognitive skills using the PIAAC survey and find a positive effect of cognitive skills on salaries. On the other hand, Hanushek et al. (2014) study the effects of teacher cognitive skills, also measured based on the PIAAC survey, on student achievements. This work finds a positive effect of teacher skills on student outcomes. Therefore, the same skills present positive effects in both teaching and non-teaching sectors, so they are implicitly positively correlated.

[6]This assumption captures the empirical fact that the variance between teacher salaries is very low compared to the variance of salaries in the whole economy.

[7]Roy models have been successfully used to study the selection process in labour markets in many contexts, for instance: immigration (Borjas, 1987), government employment

The individual utility function is given by:

$$u_i = \begin{cases} \ln(\widehat{w}_0) + \ln(\widehat{t}^{\tau}) \text{ if teacher} \\ \ln(\widehat{w}_\theta) \text{ otherwise,} \end{cases} \tag{3.3}$$

where $\ln(\widehat{t}^{\tau})$ captures the non-pecuniary utility of teaching. The parameter τ measures the elasticity of the non-pecuniary utility with respect to the individual teacher quality.

The utility obtained as a teacher depends not only on wages, but also on teacher's ability. The idea behind is that teacher skills must be positively correlated with the vocation of becoming a teacher. Thus, the more motivated is the teacher, the larger the non-pecuniary utility of teaching. Section 2.6 discuss the equilibrium of the model if the utility depends only on monetary compensation, $\tau = 0$. [8]

Given the utility function of Equation (3.3), individuals choose to become teachers if:

$$\ln(\widehat{w}_0) + \tau \ln(\widehat{t}) > \alpha \ln(\widehat{\theta}). \tag{3.4}$$

Defining $\ln(\widehat{x}) = x$ and regrouping, the condition above can be written as:

$$\alpha\theta - \tau t < w_0, \tag{3.5}$$

Additionally, define $v = \alpha\theta - \tau$ as the "self-selection function". Since v is a sum of two normal random variables, it is also distributed normally. Particularly, $v \sim N(\mu_v, \sigma_v^2)$, with mean $\mu_v = \alpha\mu_\theta - \tau\mu_t$ and variance $\sigma_v^2 = \alpha^2\sigma_\theta^2 + \tau^2\sigma_t^2 - 2\alpha\tau\sigma_{t\theta}$.

Let us define the following indicator function:

(Borjas, 2002), manufacturing industries (Heckman, 1985) and entrepreneurs (Evans and Jovanovic, 1989).

[8] In the utility function, I do not consider the probability of not being selected for a teaching position, because I assume that individuals who are not selected as teachers can apply for a job in the market sector under the same conditions as the rest of the population.

$$I = \begin{cases} 1 \text{ if the individual choose to be a teacher} \\ 0 \text{ otherwise.} \end{cases} \tag{3.6}$$

The probability that an individual chooses to work in the teaching sector is given by:

$$\begin{aligned} P(I &= 1) = P(v < w_0) = P\left(\frac{v-\mu_v}{\sigma_v} < \frac{w_0-\mu_v}{\sigma_v}\right), \\ &= \Phi\left(\frac{w_0-\mu_v}{\sigma_v}\right) = \Phi\left(z\right), \end{aligned} \tag{3.7}$$

where Φ is the cumulative distribution function of the standard normal distribution, and $z = \frac{w_0-\mu_v}{\sigma_v}$. $P(I = 1)$ is the teacher supply size. Since, the cumulative distribution function of the standard normal is an increasing function in z, the supply of teachers will rise as z rise. Particularly, since z is an increasing function of the teacher salary (w_0), the teacher supply is also an increasing function of the teacher salary.

The average quality of the teacher supply, $E(t|I = 1)$, is computed as follows:[9]

$$\begin{aligned} E(t|I = 1) = E\left(t|\frac{v-\mu_v}{\sigma_v} < \frac{w_0-\mu_v}{\sigma_v}\right) \\ = \mu_t + \rho_{vt}\sigma_t\left(\frac{-\phi(z)}{\Phi(z)}\right), \end{aligned} \tag{3.8}$$

where μ_t is the mean teacher skill of the total population in the economy, $z = \frac{w_0-\mu_v}{\sigma_v}$, ρ_{vt} is the correlation coefficient between the self-selection function and the teacher skill, and ϕ and Φ are the density function and cumulative distribution function of the standard normal distribution respectively.

[9]This expression corresponds to the mean of an incidentally truncated bivariate normal distribution. Just to simplify, I present the expected mean of t instead of $\widehat{t}$. Note that, since the logarithm is a strictly increasing function, any change in the mean of t implies a change of the same sign in the mean quality of teachers (i.e. mean of $\widehat{t}$).

3.2.2 School selection stage

The stage of school selection is substantially modified in this model compared with the framework presented in chapter 2. The modifications introduced to the model allow us to discuss the optimal allocation of the educational salary budget. Indeed, in chapter 2 we focused only on the strategy of teacher selection, taking as exogenous the teacher salaries and the number of teachers hired. Therefore, the theoretical framework of chapter 2 allows us to compute the expected quality of the teaching staff under the observed allocation of the educational salary budget, but not identify the optimal allocation.

In contrast, in this chapter, we propose a more general framework in which teacher salaries and the number of teachers are decisions made by the school board. Indeed, in this stage the school board will decide, acting as the only contracting party in the market, the number of teachers to hire and the level of wages to offer. Of course, the decision regarding the number of teachers to hire restricts the possibilities of salaries to offer because the budget is limited.

The school board will make their demand decision seeking to optimise the results obtained by their students, taking into account their budget constraints. We will assume that the school board knows how individuals make their occupational choice on the self-selection stage. Therefore, it knows the impact of changes in teacher wages on the quantity and quality of the teacher supply.

Additionally, we will assume that the student outcomes respond to the following educational production function:

$$y = y(I, F, TQ, STR, SCH), \tag{3.9}$$

where I represents a set of variables associated to the individual, F is a set de familiar inputs, TQ represents the average quality of teachers, STR represents the student teacher ratio, and SCH represents a set of characteristics linked to the school organization, like school autonomy, the school size and school ownership. In line with the previous literature, we assume that teacher quality positively affects student outcomes[10] while the student-teacher ratio has a negative impact, at least, after a certain threshold.[11]

Note that both individual characteristics and family inputs are exogenous variables for the school board ($I = I_0$ and $F = F_0$). Additionally, we will also consider the variables related to the school organization as exogenous because we will focus on the allocation of the wage bill. Therefore, we could express the educational production function as a function only on TQ and STR. Particularly, we will assume a baseline production function which contemplates the possibility of a non-linear impact of STR as follows:[12]

$$y = \beta_1 TQ + \beta_2 STR + \beta_3 STR^2 \tag{3.10}$$

where β_1, β_2 y β_3 represent the partial effects of changes in teacher quality and the student-teacher ratio on student outcomes.

Note that the teacher quality is an endogenous result of the model and therefore, it depends on all the parameters of the model. On the other hand, the student-teacher ratio depends on the number of students in the education system, which is exogenous, and the number of teachers hired, which is an endogenous result of the optimisation problem carried out by the school board.

The educational production function of equation (3.10) proposes that educational authorities could improve the student achievement either through a decrease in the student-teacher ratio or an improvement in the teacher quality. However, hiring a higher number of teachers or increasing the teacher wages in order to attract higher ability workers requires a higher budget for salary compensations (higher salary budget). Therefore, it becomes necessary to include in the analysis the budget constraint faced by the education system.

The budget constraint states that the educational salary budget must be less than or equal to an exogenously determined amount.

[10]Hanushek, 2003, Klein et al., 2010; Gates, 2011; Hiatt, 2009; Chapter 2.

[11]Card and Krueger, 1992; Hoxby, 2000; Woessman, 2005.

[12]We make robustness exercises using alternative specifications in the production function.

$$\widehat{w}_0 D \leq G_0. \tag{3.11}$$

where $\widehat{w}_0$ represents the teacher wage, D is the number of teachers hired, and G_0 is the exogenous maximum amount of money to spend in salary compensations.

Then, all the combinations of teacher wages ($\widehat{w}_0$) and number of teachers hired (D) which satisfy the budget constraint of equation (3.11) are considered available for the school board. As mentioned above, this work focuses on the efficient allocation of the wage bill and not on its absolute magnitude. Therefore, the importance of considering the budget constraint is because some education systems could achieve high student scores due to a high expenditure while still being inefficient.

Defining the parameter γ as the share of teachers in total employment, we can rewrite our modified version of the model in Chapter 2 using their parameters. Then, we can use the calibration carried out in the previous chapter for 22 OECD countries.

That is:

$$\gamma = \frac{D}{N}, \tag{3.12}$$

where N is the total employment which is assumed exogenous.

Dividing both sides of equation (3.10) between N, we can write the budget constraint of the education system in term of the parameters γ and $\widehat{w}_0$.

$$\widehat{w}_0 \gamma < g_0, \tag{3.13}$$

where g_0 is the educational wage bill per worker (G_0/N).

A final issue to take into account is the selection strategy used by the school board to hire teachers. As is discussed in depth in Chapter 2, the strategy of the school board to select their teachers basically consist of two steps: i) ranking the teacher supply based on the individual's observable ability (θ), and ii) hiring the fraction γ of individuals which displays greatest ability. Since we assume a positive correlation between the teacher and general skills, this strategy leads to maximising the expected quality of the teaching staff.

This strategy determines that the correlation between the general skill θ and the teacher skill t within the teacher supply ($\widetilde{\rho}_{\theta t}$) becomes a key parameter to estimating the expected quality of the teaching staff. Indeed, a higher correlation implies better results of the selection strategy because the proxy used to predict the quality of teachers will be more powerful. On the contrary, a lower correlation implies less capacity for selection because schools cannot identify the best teachers. In the extreme case in which the correlation among skills within the teaching supply is zero, the school board does not have any information regarding the teaching ability of the individuals and therefore, the expected quality of the teaching staff will coincide with the average ability of the teacher supply. This case would be equivalent to a random selection strategy among those individuals who apply for a teaching position.

It is important to note that the correlation of skills within the teacher supply is an endogenous result of the model and does not coincide with the correlation of skills in the total population, which is an exogenous parameter. The correlation of skills within the teaching supply is computed as follows:

$$\widetilde{\rho}_{\theta t} = \frac{\widetilde{\sigma}_{\theta t}}{\widetilde{\sigma}_t \widetilde{\sigma}_\theta}, \tag{3.14}$$

where $\widetilde{\sigma}_{\theta t}$ represents the covariance between the teacher and general skill within the teacher supply and $\widetilde{\sigma}_t$ and $\widetilde{\sigma}_\theta$ are the standard deviations of the teacher and general skill respectively within the teacher supply.[13]

As an endogenous result of the model, $\widetilde{\rho}_{\theta t}$ is affected by the decisions taken by the school board regarding the teacher wages $\widehat{w}_0$. That is, the power of the signal used in the process of selection is a function of teacher wages ($\widetilde{\rho}_{\theta t} = g(\widehat{w}_0)$).

[13] See Rao (1989) for details regarding the computation of the restricted variances and covariance.

Particularly, if $\rho_{\theta t}$ is relatively low, $\widetilde{\rho}_{\theta t} > \rho_{\theta t}$ holds for any teacher salary. On the other hand, if $\rho_{\theta t}$ is relatively high, the inequality $\rho_{\theta t} > \widetilde{\rho}_{\theta t}$ holds for any teacher salary. Additionally, when $\widetilde{\rho}_{\theta t} \neq \rho_{\theta t}$, the distance between the restricted and unrestricted correlation coefficients decreases with the supply of teachers, which in turn, depends positively on wages. Therefore, a rise in teacher wages determines the convergence between the restricted and the unrestricted correlation.[14]

Since the convergence between the restricted and the unrestricted correlation could be from above or from below, the sign of the relationship between teacher salary $\widehat{w}_0$ and the effectiveness of the proxy $\widetilde{\rho}_{\theta t}$ is not theoretically defined. Specifically, if $\widetilde{\rho}_{\theta t} < \rho_{\theta t}$ holds for any level of $\widehat{w}_0$, a positive relationship between the teacher salary and the quality of the proxy, ($\widetilde{\rho}_{\theta t}$) is obtained. In this case, when schools set a higher salary, the proxy to identify the best teachers becomes powerful. On the contrary, when $\widetilde{\rho}_{\theta t} < \rho_{\theta t}$ holds for any $\widehat{w}_0$, a negative relationship between $\widetilde{\rho}_{\theta t}$ and $\widehat{w}_0$ is obtained. In this case, when schools set a higher salary, the proxy to identify the best teachers becomes weaker.

Considering all the previous issues, the maximization problem faced by the school board is summarized as follows:

$$\begin{cases} \max\limits_{\widehat{w}_0,\gamma} y = f(TQ, STR) \\ st \\ \widehat{w}_0\gamma < g_0 \\ P(I=1) = \Phi(\frac{w_0-\mu_v}{\sigma_v}) \\ E(t|I=1) = E\left(t|\frac{v-\mu_v}{\sigma_v} < \frac{w_0-\mu_v}{\sigma_v}\right) \\ \widetilde{\rho}_{\theta t} = g(\widehat{w}_0) \\ STR = \frac{1}{\gamma} * \frac{stud}{N} \\ TQ = TQ[P(I=1), E(t|I=1), \widetilde{\rho}_{\theta t}, \gamma] \end{cases}$$

The optimization problem implies that the school board will choose the teacher wage ($\widehat{w}_0$) and the number of contracted teachers (γ) according to their budget constraint, and taking into account that: i) the size of the

[14] In the extreme, when w_0 tends to infinite and thus, the teacher supply tends to the total population, i.e. $\widetilde{\rho}_{\theta t}$ tends to $\rho_{\theta t}$.

teacher supply (and therefore the possibilities of selection) is affected by decisions regarding teacher salaries. ii) the average quality of the teacher supply is affected by decisions regarding teacher salaries. iii) the powerful of the signal used to select teachers is also affected by decisions regarding teacher salaries. iv) The student-teacher ratio depends negatively on the number of teachers hired and, v) The final quality of the teacher staff depends on the quantity and quality of the teacher supply, the power of the signal used in the process of selection and the number of teachers to hire.

3.2.3 Equilibrium of the model

The equilibrium of the model consists of an optimal teacher wage (w^*), an optimal share of teachers in the total employment (γ^*) and an optimal expected teacher quality TQ^* such that:

- No individuals wish to change occupation from the teaching sector to the market sector, given the market wages.
- The school board maximises the student outcomes given its budget constraint.

Note that some individuals that choose to apply for a teacher position in the self-selection stage could not be hired, so that, an excess of supply in the teacher market could be observed in equilibrium.[15] Nevertheless, no agents have incentives to change their decisions.

3.2.4 Estimation of the Equilibrium

The proposed model does not have a closed numerical solution, so it is obtained from simulations. In what follows we present the solution of the model obtained from the simulation of a population of 1,000,000 individuals for which the distribution of skills follows the log-normal distribution of equation (3.1).

[15] Recall that individuals who are not selected for a teacher position can apply for a job in the market sector like any other individual.

Our strategy to solve the model is based on four steps. First, we consider a grid of teacher wages and share of teachers in the total employment large enough to include most of the available combinations.[16] Second, we compute the expected teacher quality for each combination of γ and $\widehat{w}_0$ in the grid based on our theoretical model.[17] Third, we compute the expected student outcomes for each available combination of γ and $\widehat{w}_0$ based on the educational production function of equation (3.10) and the computed values for teacher quality. Finally, considering only the combinations available to the budget constraint, we search for the allocation which leads to the highest student achievement.

As an example, Figures 3.1 and 3.2 present the results obtained for a baseline economy based on the parameters of Table 3.1. The parametric values assumed for the purposes of computing the equilibrium of the model were chosen in order to work with a simple economy where: i) the marginal distributions of both skills are standardized normal (in their logarithm); ii) the individual utility derived from the occupational choice is more affected by wages than motivational factors ($\alpha > \tau$); iii) there is a positive but not extremely strong correlation between both utilities, which determines an imperfect proxy for the teacher skill in the process of selection; iv) it is assumed that an increase of one standard deviation in the teacher quality has an identical effect on the educational results that a reduction of one standard deviation in student-teacher ratio, and; v) the effect of the student-teacher ratio on educational outcomes does not have non-linear effects.

Figure 3.1 assumes that the budget constraint is not binding and then, all points in the grid are available to the school board. The figure shows that student outcomes rise with teacher wages. This quite intuitive result follows from the fact that in the considered economy a higher level of teacher wages allows attracting to the profession individuals with higher abilities and therefore the average quality of the teaching staff increases. In turn, the higher teacher quality translates into better student achievements. However, it is important to note that the effect of teacher salaries on student outcomes

[16] The initial grid includes all the values of relative teacher salary and teacher participation in the labour force observed in the set of 22 countries considered in this work. In case of obtaining a corner solution, we enlarge the grid.

[17] Each point of the grid implies a exogenous combination of teacher wages and number of teachers. Therefore, for each point of the grid, we solve the model like in chapter 2 to obtain the expected quality of the teaching staff.

Table 3.1: Parameters of a baseline Economy

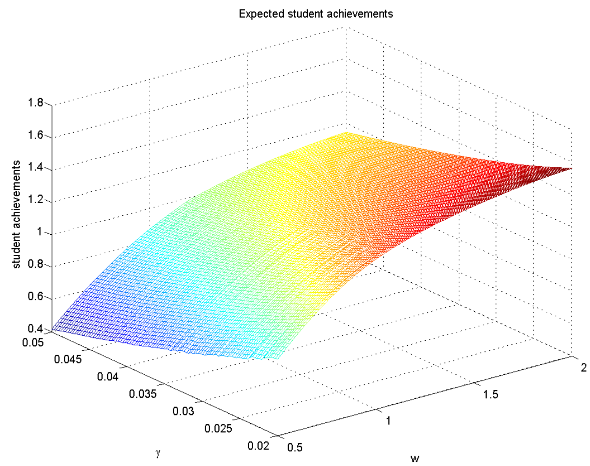
Parameter	Definition	Value
μ_t	mean of the teacher skill distribution	0
σ_t^2	variance of the teacher skill distribution	1
μ_θ	mean of the general skill distribution	0
σ_θ^2	variance of the general skill distribution	1
$\rho_{\theta t}$	correlation between the teacher and general skill	0.5
α	elasticity of wages with respect to the general skill	1
τ	elasticity of the non-pecuniary utility with respect to the teacher skill	0.1
β_1	partial effect of teacher quality on student outcomes	1
β_2	partial effect of student teacher ratio on student outcomes	-1
β_3	partial effect of student teacher ratio on student outcomes (quadratic)	0

is non-linear, with a decreasing marginal effect.

Less intuitive is the observed effect in terms of the share of teachers in the total of employment (γ). Given that the total employment is assumed exogenous, a rise of γ implies a greater number of teachers hired and therefore a smaller student-teacher ratio. Considering that we assume a negative direct effect from the student-teacher ratio to the student outcomes ($\beta_2 = -1$), intuitively, a rise in the number of teachers hired (a rise on γ) should be associated with improvements in the student achievements.

However, in our model, a greater number of teachers hired, ceteris paribus, generates an adverse effect on the average quality of the teaching staff. Indeed, given the strategy of selection used by the school board, if there is no additional change, hiring a greater number of teachers will involve hiring individuals with a lower level of the observable ability (θ) and therefore, with a lower expected level of teacher skill (t). It is precisely this decrease of the average quality of the teaching staff what explain the negative indirect effect on student outcomes linked to the decision of hiring additional teachers.

Figure 3.1: Expected student outcomes for different combinations of teacher wages and share of teachers into total employment

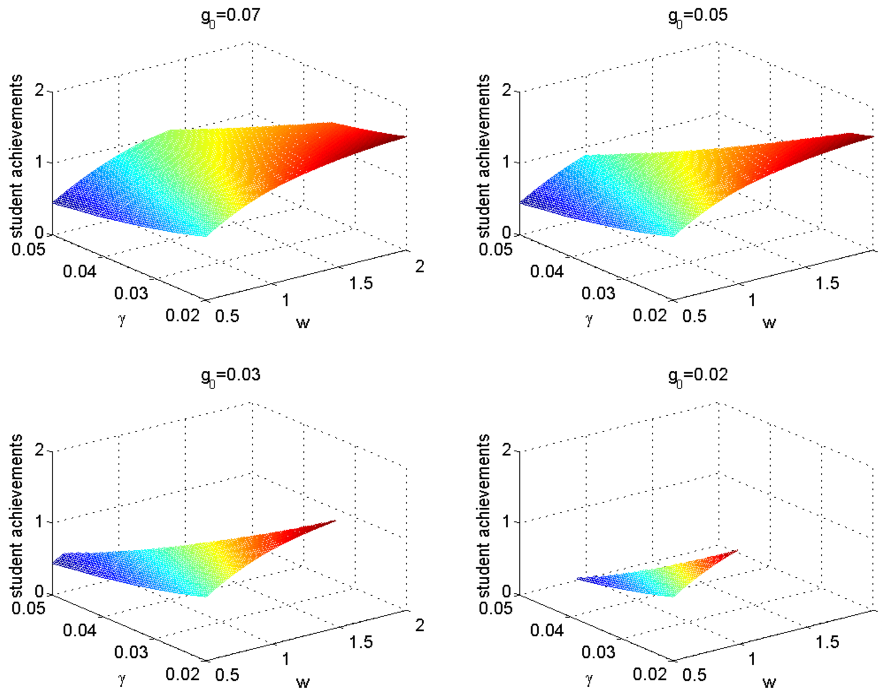


In our baseline economy, the indirect effect of a rising in γ on the average quality of teachers is greater than the direct effect derived from the reduction of the student-teacher ratio, determining that the expected student outcomes decrease in γ. In this sense, our baseline economy emphasizes the importance of considering not only the partial effects but also the general equilibrium effects when evaluating the optimal allocation of the wage bill.

Figure 3.2 shows how the grid of values is restricted when we assume more limited budgets to hire teachers. Specifically, there are four alternative scenarios where the exogenous budget constraint expressed in terms of wage compensations per worker (g_0) is getting smaller. In the figures, we observe that once the budget constraint becomes active, combinations of higher salaries ($\widehat{w}_0$) and a larger number of teachers (γ) becomes not available.

The optimal allocation for the wage bill in each scenario is the one that maximize student outcomes among the available points of the grid. As is expected, the optimal allocation associated to higher budgets leads to better student outcomes. Therefore, higher student achievements not necessarily implies a higher efficiency in the allocation of the wage bill.

Figure 3.2: Available combinations of teacher wages and share of teachers under different levels of salary expenditures



3.3 Inefficiency in the allocation of the educational wage bill in OECD countries

Based on the theoretical model of the previous section, we computed for a set of 22 OECD countries the efficient allocation for the educational salary budget, that is, the combination of teacher salaries and number of teachers that maximises student outcomes given the budget constraint.

The computation of the optimal combination of γ and $\widehat{w}_0$ for each country is mostly based on the calibration of the model for our set of countries carried out in Chapter 2. Additionally, in order to quantify the impact of TQ and STR on student outcomes, the following educational production function based on PISA micro data in mathematics was estimated using the same sample of 22 OECD countries between 2006 and 2015:

$$y_i = B_1 I_i + B_2 F_i + B_3 SCH_i + \beta_1 TQ_{ct} + \beta_2 STR_i + \beta_3 STR_i^2 + C_c + T_t + u_i, \quad (3.15)$$

where y_i represents the score in PISA for individual i, I represents a set of individual characteristics like age, gender, migration status, language[18] and if the individual repeat a grade; F is a set of family inputs summarized in the index of economic, social and cultural status (ESCS index) of PISA[19]; SCH includes characteristics of the school to which the individual i attends, like the academic and budget autonomy, the school size, ownership (public or private) and the size of the population in which is located; $TQ_{c,t}$ represents the average teacher quality for country c in period t which is estimated based on the theoretical model and STR represents the student-teacher ratio in the school to which individual i attends. Note that the specification allow for non-linearities in the effect of STR on student outcomes. Finally, C_c and T_t are fixed effects corresponding to counties and years respectively.

[18] We consider the correspondence between the native language and the language of the test.

[19] This index was created on the basis of the highest levels of education and occupational status of the student's parents; the number of books at home; and an index of other home resources. The index of other home resources was created on the basis of whether there is a quiet study space, internet access, TV, and stories and novels at home. For more details on the ESCS, see the Annex I of PISA (2015)- OECD.

The objective of the estimation is to identify the parameters associated with the impact of teacher quality (β_1), and the student-teacher ratio (β_2 and β_3) on student outcomes. Those values are presented in table 3.3 together with the rest of parameters which are assumed fixed across countries in the calibration of Chapter 2.[20] Based on these estimated coefficients, and the rest of the parameters of the model calibrated in Chapter 2 presented in table 3.2, we are able to estimate the efficient allocation for each one of the 22 countries considered in our sample. All the parameters values used for each country in the simulation exercises are specified in tables 3.2 and 3.3.

In turn, comparing the expected student outcomes when adopting the optimal combination suggested by our model with the expected results by adopting the observed values of teacher salaries and the number of teachers, we computed an index of Inefficient Allocation (IA index) for this group of countries. Table 3.4 presents for 2015 the observed values of teacher salaries ($\widehat{w}_0$) and the share of teachers in the total employment (γ) together with the optimal values.[21]

Table 3.4 shows that, in most countries, the efficiency gap is generated by a bias towards prioritising quantity over the quality of teachers. Indeed, in most of the countries the number of teachers hired is larger than its optimal value, and, conversely, teacher salaries are lower than the optimal ones. The only exceptions are Korea and Japan which show an allocation very close to the optimal point, but, with a slight bias towards quality instead of quantity.

Once the optimal allocation has been computed, we are able to estimate our measure of the Inefficient Allocation of the wage bill (IA index). We will use as an indicator of efficiency in the allocation of the salary budget the ratio between the educational score predicted by the EPF of equation (3.10) in the observed scenario for $\widehat{w}_0$ and STR and the predicted score under the efficient allocation. This efficiency indicator varies between zero and one. The value one indicates efficiency.

At the same time, we will adopt the complement of the Efficiency measure, that is, IA = 1-Efficiency as an indicator of Inefficient Allocation of the salary

[20] Details on the estimate, including the coefficients and significance of all the variables considered, is included in the Appendix II of this Chapter. The results for β_2 and β_3 are robust to changes in the sample of the estimation.

[21] The same tables for 2006, 2009 and 2012 are included in the Appendix I of the chapter.

Table 3.2: Specific parameters by countries

	μ_t	σ_t	μ_θ	σ_θ	α			
					2006	2009	2012	2015
Australia	0.2532	0.7666	0.4072	0.7666	0.89	0.92	0.91	0.92
Austria	0.6014	0.6919	0.1851	0.6919	1.06	1.05	1.16	1.02
Belgium	1.3791	0.7033	0.6748	0.7033	0.90	0.89	0.87	0.92
Canada	1.6046	0.6070	-0.0821	0.6070	0.93	0.95	0.94	0.94
Czech. R	0.1179	0.7972	0.3980	0.7972	1.24	1.27	1.19	1.30
Denmark	1.4871	0.6223	0.3640	0.6223	0.85	0.86	0.86	0.85
Estonia	1.8271	0.6216	0.2412	0.6216		0.93	0.91	0.87
Finland	1.4981	0.6338	1.3688	0.6338	1.01	0.99	1.00	0.91
France	0.3782	0.5958	-1.2216	0.5958	1.01	0.99	1.04	0.95
Germany	1.0954	0.7941	0.0266	0.7941	1.11	1.06	1.18	1.07
Ireland	0.9893	0.8007	-0.9330	0.8007	1.14	1.11	1.19	1.10
Italy	-0.0108	0.8795	-2.1209	0.8795	1.11	1.01	0.99	0.96
Japan	2.7245	0.6747	2.0886	0.6747		1.00	1.03	1.03
Korea	2.2649	0.6121	-0.2139	0.6121	0.95	0.89	1.00	0.94
Netherlands	1.6097	0.6414	1.0773	0.6414	1.00	1.08	1.06	1.00
Norway	1.0570	0.6299	0.7556	0.6299	0.87	0.86	0.88	0.85
Poland	1.0552	0.6926	-0.7740	0.6926	1.17	1.13	1.16	1.10
Slovak, R.	-1.0269	0.6451	0.1121	0.6451		1.25	1.17	1.15
Spain	-0.0235	0.6280	-1.7549	0.6280	0.89	0.96	0.95	0.95
Sweden	0.5233	0.6554	0.6816	0.6554	0.86	0.85	0.87	0.83
UK	0.2708	0.8947	-0.3772	0.8947	1.08	1.08	1.05	1.00
US	-1.2038	0.9051	-0.9032	0.9051	1.19	1.21	1.18	1.14

Note: Parameter values are based on the calibration carried out in Chapter 2. Parameters μ_θ, σ_θ (mean and standard deviation of the distribution of the general skill among the total population) and α (wage returns to the general skill in the non-teaching sector) are observables. The sources for those parameters are the PIAAC survey and OECD. The calibration of the unobservable parameters μ_t and σ_t is explained in section 2.3.2 of the previous chapter.

Table 3.3: General Parameters

Parameter	Definition	Value
$\rho_{\theta t}$	correlation between teacher and general skill	0.57
τ	elasticity of non-pecuniary utility with respec to the teacher skill	0.24
β_1	partial effect of teacher quality on student outcomes	9.2
β_2	partial effect of student teacher ratio on student outcomes	2.46
β_3	partial effect of student teacher ratio (cuadratic) on student outcomes	-0.79

Note: Parameters $\rho_{\theta t}$ and τ (correlation of teaching and general skills among the total population and the elasticity of the non-pecuniary utility with respect to the individual teaching skill respectively) are based on the calibration carried out in Chapter 2. Parameters β_1, β_2 and β_3 are based on the estimation of the Educational production function of equation (3.15). Details of the estimation are presented in the Appendix II.

budget. Therefore, the IA index also varies between zero and one, where zero indicates efficiency.

The computation of the score in the observed scenario is based on the observed value of the student-teacher ratio and the estimated teacher quality from our theoretical model with the parameters calibrated for each country. In turn, the computation of the score in the optimal scenario considers the student-teacher ratio compatible with the optimal value of γ (γ^*) and the predicted teacher quality from the model using all the observed parameters except in the cases of $\widehat{w}_0$ and γ which are replaced by their optimal values ($w^*; \gamma^*$).

In this way, the proposed index of Inefficient Allocation of the wage bill is expressed as follows:

$$IA_{ct} = 1 - \frac{y(w_{ct}; \gamma_{ct})}{y(w^*_{ct}; \gamma^*_{ct})} \tag{3.16}$$

where IA_{ct} represents the index of inefficient allocation for country c in

Table 3.4: Wages and share of teachers in total employment (observed and optimal(*) values for 2015)

	2015			
	w	w*	γ	γ*
Australia	1.11	1.470	2.30%	1.71%
Austria	1.06	1.530	2.60%	1.78%
Belgium	1.11	1.803	3.60%	1.96%
Canada	1.26	1.364	1.70%	1.57%
Czech. R	0.62	0.833	2.10%	1.54%
Denmark	1.13	1.500	2.80%	2.10%
Estonia	0.50	0.727	2.50%	1.71%
Finland	1.00	1.606	2.40%	1.50%
France	0.99	1.379	2.70%	1.92%
Germany	1.45	1.712	1.90%	1.61%
Ireland	0.99	1.273	2.80%	2.17%
Italy	1.04	1.758	2.90%	1.71%
Japan	1.24	1.227	1.50%	1.50%
Korea	1.40	1.303	1.40%	1.50%
Netherlands	1.18	1.188	2.80%	2.70%
Norway	0.66	1.121	3.70%	2.17%
Poland	0.87	1.439	2.50%	1.50%
Slovak, R.	0.54	0.788	2.50%	1.71%
Spain	1.45	1.924	2.70%	2.03%
Sweden	0.82	1.197	2.80%	1.92%
UK	0.99	1.167	2.40%	2.03%
US	1.06	1.17	2.20%	1.99%

Note: Teacher wages are expressed in terms of the GDP per capita.

period t; $y(w_{ct};\gamma_{ct})$ indicates the predicted educational score for country c in period t using the observed values for teacher wages and number of teachers, and $y(w^*_{ct};\gamma^*_{ct})$ states the score predicted for country c in period t assuming an optimal allocation of the educational wage bill $(w^*;\gamma^*)$. We estimate the index of inefficient allocation for a group of 22 OECD countries for the years 2006, 2009, 2012 and 2015. These years were chosen because of the availability of PISA data.[22] The results are presented in table 3.5.

Table 3.5 shows that on average our set of countries evidence an inefficiency in the allocation of the wage bill of the order of 16% between 2006 and 2015.[23] That is, the contribution of the wage bill to the student outcomes could be, on average, 16% higher than its observed contribution. Japan, Korea, and Canada are the countries with the most efficient allocation of the wage bill while the Slovak Republic, US, and Norway have the less efficient allocations. In all cases, countries which evidence the less efficient allocation are characterized by a clear bias toward quantity in the allocation of the wage bill.

The ranking of countries in terms of their IA index remains fairly stable between 2006 and 2015. Indeed, most of the countries do not show significant changes in the IA index in the considered period. The main exceptions are Italy, which shows a reduction in the inefficiency index associated to a rise in the teacher salaries and a small rise in the student-teacher ratio, and Czech Republic, Slovak Republic, and Poland which present a rise in the IA index due to a rise in the quantity bias.

Although there are several similarities between our ranking in terms of the IA index with respect to the ranking developed by Dolton and Marcenaro Gutierrez (2014), there are also important differences. The differences are not only manifested with respect to the ranking of results but fundamentally to

[22]As described in the next section, PISA data base will allows us to make an empirical estimation of the inefficiency of the education systems in order to evaluate the results of our model.

[23]Note that this paper focuses solely on the inefficiency related to the process of hiring teachers, and does not consider the inefficiencies that could occur in the performance of the teaching function like teacher absence. That is, we work under the assumption that decisions regarding the allocation of the wage bill are not correlated with this kind of inefficiencies. Muralidharan et al. (2015) highlights the importance of this kind of inefficiencies and its relationship with the governance of schools.

Table 3.5: Index of Inefficient Allocation of the wage bill (IA)

	2006	2009	2012	2015
Australia	13.5%	13.7%	14.1%	13.0%
Austria	16.3%	15.4%	17.3%	15.8%
Belgium	17.7%	18.1%	16.7%	17.1%
Canada	na	na	5.3%	5.5%
Czech. R	12.1%	13.7%	15.0%	18.4%
Denmark	11.3%	9.4%	9.2%	9.0%
Estonia	na	8.8%	12.6%	12.7%
Finland	11.9%	11.7%	13.4%	13.4%
France	17.4%	16.9%	17.7%	18.2%
Germany	8.8%	7.9%	8.6%	8.3%
Ireland	10.3%	9.0%	9.4%	12.0%
Italy	35.1%	30.0%	27.5%	26.4%
Japan	na	3.2%	2.9%	2.7%
Korea	6.3%	7.5%	5.5%	4.9%
Netherlands	7.3%	7.1%	7.2%	7.4%
Norway	19.7%	17.5%	19.7%	20.0%
Poland	na	16.5%	19.9%	20.2%
Slovak, R.	na	40.2%	50.7%	53.0%
Spain	17.5%	16.6%	18.3%	17.0%
Sweden	15.6%	14.6%	15.8%	17.4%
UK	11.0%	11.2%	11.2%	9.6%
US	33.1%	33.3%	33.7%	31.2%

Note: na indicates that it was not possible to calculate the efficiency due to lack of information regarding some parameter of the model. The IA index also varies between zero and one, where zero indicates efficiency.

the policy recommendations that are derived from them. While Dolton and Marcenaro Gutierrez (2014) find that slightly more than half of the countries analysed should reduce their teaching salaries in order to be more efficient, in this work, as mentioned above, a clear bias to prioritize the quantity more than the quality of teachers is identified, and then it would be better to reallocate resources through quality of teachers instead. As an example, the work of Dolton and Marcenaro Gutierrez suggests that countries like the US, UK, Norway, Denmark, Ireland, Belgium, Germany and Spain should reduce their teaching salaries in order to obtain greater efficiency, while our results suggest otherwise.

We identify two main reasons for the differences between our results and those of Dolton and Marcenaro Gutierrez (2014). The first one appears as a consequence of measuring differently the impact of teacher salaries on student outcomes. Specifically, in our work, we calibrate the theoretical model for each one of the 22 OECD countries which allow us to measure the specific impact of changes in teacher wages and the number of teachers on students test scores (as seen in figure 3.1). Indeed, we have a total of 22 figures for each country of the data base, all of them with a similar shape to the one presented in figure 3.1. Recall that in our work, the impact of teacher salaries and class size on the expected teacher quality is specific in each country because it depends on: i) the average and variance of the population skills (parameters μ_t, μ_θ, σ_t, and σ_t); ii) the wage returns in the non-teaching sector (parameter α) and; iii) the observed level of teacher wages because the curve that relates salaries (parameter $\widehat{w}_0$)to teacher quality is non-linear in all the countries considered according to our calibration of the model. In contrast, the work of Dolton and Marcerano (2014) measure the effect of wages on student scores based on an elasticity obtained from a panel estimation. Their approximation determines that: first, the impact of wages on student test scores is the same for all countries and second, the effect of wages on student scores is independent of the level of teacher wages (that is, different from our theoretical results, it is a linear effect).

The second source of differences with respect to the results in Dolton and Marcenaro Gutierrez (2014) stems from the fact that our work takes into account the indirect effect that operates on teacher quality when the number of teachers hired is modified. Omitting this general equilibrium effect clearly generates a favourable bias towards recommending a distribution of the salary budget more oriented to quantity than to wages.

3.4 Empirical approximation to the inefficiency in education systems

Once we build the inefficient allocation index (IA) based on our model, the main question is: Are our theoretical results reasonable? To answer this question, we study the correlation between the IA index with an empirical estimation of the overall inefficiency of the education system which is totally independent of our theoretical approach.

The empirical inefficiency is based on an alternative estimation of the educational production function proposed in equation (3.16). Particularly, we replaced the theoretical measure of TQ by the observed data of the relative teacher wage in order to ensure that our estimate of inefficiency was not affected by inputs derived from our theoretical model. Additionally, country fixed effects were removed from the specification because they capture not only omitted inputs but also differences in the average efficiency among the countries. In this way, the empirical efficiency was based on the following specification:

$$y_i = B_1 I_i + B_2 F_i + B_3 SCH_i + b_1 w_{ct} + b_2 w_{ct}^2 + b_3 STR + b_4 STR^2 + T_t + u_i, \quad (3.17)$$

where w_{ct} represents the teacher wage relative to the median wage in the market sector and all the other inputs are the same than in equation (3.16).

Like the Solow residual in the literature of growth, we define the empirical inefficiency of an educational system as the ratio between the educational score estimated from equation (3.17) and the observed educational score.[24] In consequence, a higher value of the ratio indicates that the observed perfor-

[24] As a robustness exercise, we make alternative estimations of inefficiency based on the frontier model proposed in Battese and Coelli (1995). The results are qualitative similar to those obtained by the strategy used here.

mance is lower than its expectation using the observed determinants. That is, a higher value of the ratio states a less efficient use of resources.[25]

The indicator of empirical inefficiency is computed as follows:

$$EI_{ct} = \frac{\hat{y_{ct}}}{y_{ct}} \tag{3.18}$$

where $\hat{y_{ct}}$ indicates the estimated education score for country c in period t using the fitted value from equation (3.17) and y_{ct} indicates the observed score in PISA for country c in period t.

It should be noted that the index of empirical inefficiency (EI) measures the overall inefficiency of the education system and not only the inefficiency derived from the allocation of the wage bill. In this sense, even in the case of a perfect performance of our theoretical model to capture the inefficiency in the allocation of the wage bill, there should not be a total coincidence between the IA and EI indicators since the IA index captures only a part of the complete inefficiency of the system.

However, taking into account the importance of the wage bill within the educational budget and the importance of teacher quality as school input, it is expected that inefficiencies in the allocation of the wage bill determines a significant share of overall inefficiency. In this sense, if our theoretical model is able to adequately capture the inefficiencies in the allocation of the wage bill, the index of inefficient allocation of the wage bill (IA) should show a significant correlation with our empirical estimate of overall inefficiency of the education system (EI).

Table 3.6 presents the results of the EI index for the same set of 22 countries and the same period for which the index of inefficient allocation of the wage bill was computed. Figure 3.3 shows the correlation between both indicators, IA and EI, which is 0.47 for our set countries and the considered period.

Looking for a more rigorous approximation to the relationship between the EI and IA measures, we regress the EI index as the dependent variable of

[25] Note that, the value 1 represents the average level of efficiency for the set of considered countries between 2006 and 2015.

Table 3.6: Empirical Inefficiency of Education Systems (EI)

	2006	2009	2012	2015
Australia	0.98	1.01	1.03	1.05
Austria	1.00	1.05		1.04
Belgium	0.93	0.99	0.96	1.00
Canada			1.00	1.01
Czech. R	0.96	0.99	0.95	0.94
Denmark	1.02	1.05	1.07	1.06
Estonia	0.87	0.96	0.89	
Finland	0.93	0.98	1.01	1.01
France	1.00	1.02	1.02	1.03
Germany	1.02	1.03	1.02	1.03
Ireland	1.02	1.05	1.04	1.03
Italy	1.07	1.06	1.06	1.05
Japan	0.94	0.95	0.92	0.91
Korea	0.92	0.93	0.90	0.94
Netherlands	0.97	0.99	0.99	1.02
Norway	1.04	1.07	1.06	1.07
Poland		0.98	0.95	0.97
Slovak, R.		0.94	0.95	0.99
Spain	1.04	1.02	1.07	1.02
Sweden	1.01	1.06	1.08	1.05
UK	1.03	1.06	1.05	1.04
US	1.04	1.04	1.04	1.09

Note: The value 1 represents the average level of efficiency for the set of considered countries between 2006 and 2015.

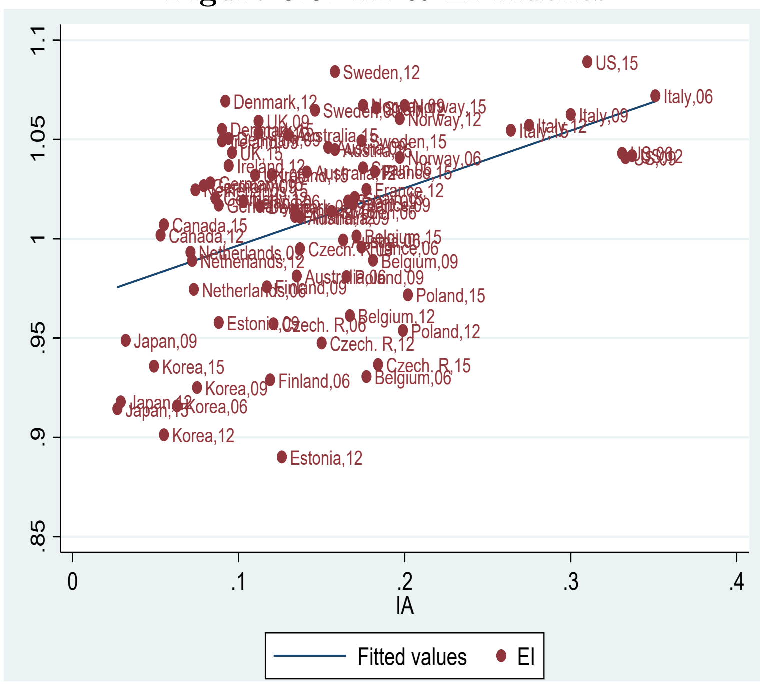
the model and the IA index along with a set of control variables were included as explanatory variables. The selected controls were included following some previous results in the literature.

For example, Muralidharan, et al. (2015) highlights the importance of inefficiencies in the teacher performance, measured by teacher absence, and its relationship with the governance of schools. In this line, we include controls related to school organization in order to capture this kind of inefficiencies. The report of OECD (2017) emphasizes the importance of the number of classroom hours as a way to evaluate the working conditions of teachers and their availability of time for non-teaching tasks such as preparing classes, correcting tasks, etc. That is, given the same student-teacher ratio, differences in the number of classroom hours could imply a different quality of teaching. Additionally, Hanushek et al. (2013) highlight the importance of school autonomy to improve student outcomes. Therefore, school autonomy could be another characteristic of the school organization potentially related to the inefficiencies in the performance of the teachers. In a similar line, West and Woessman (2010) discuss if the ownership of schools is related to student outcomes. Taking into account this previous results, we include as control variables in the estimations the number of classroom hours of teachers (Classroom hours), the autonomy grade of educational institutions (Sch. Autonomy), the share of private institutions in the system (% of private) and the average size of the institutions (Sch. Size).[26]

In addition to school organization, Temming (2002) and Bacolod (2003) discuss the role of the female labour market in the determination of teacher quality. Greater gender inequality in the labour market could limit alternative options for women, determining that highly qualified women join the education sector. In this way, a greater female participation could be associated with a higher teaching quality for the same teacher salary offered. Since in our model, we do not control for differences in the gender gap of the market wage across countries, the share of female teachers could explain part of the residual of the EPF. For this reason, we include in our estimation the

[26]The information regarding the number of classroom hours per country was taken from Education at a Glance, OECD. The index of school autonomy is calculated as the percentage of tasks included in the questionnaire of school for which the principal, teachers or the school governing board have considerable responsibility. See the Annex A1 of PISA (2015)- OECD Volume II for details of the index of school autonomy. The school size is measured as the total student enrolment.

Figure 3.3: IA & EI indexes



variable (% Women).[27]

From table 3.7 we observe that across all the specifications the coefficient associated to the IA measure presents a positive and significant correlation with de EI index. As expected, these results indicate that the measure of inefficiency in the allocation of the wage bill constructed from our theoretical model is able to explain part of the estimated overall inefficiency of education systems for the OECD countries included in this analysis.

All in all, the estimations of table 3.7 support our theoretical measure of inefficiency in the allocation of the wage bill. This results is important for at least two reasons. Firstly, because having a theoretical model behind allow us to better understand the trade-off between quantity and quality in the teacher selection considering not only the direct effects but also the associated

[27]The information regarding the percentage of women in the teaching staff were taking from Education at a Glance, OECD.

Table 3.7: Determinants of the Inefficiency in Education Systems, EI index

	(1)	(2)	(3)	(4)
IA	0.288***	0.267***	0.202**	0.217**
Sch. Autonomy		-0.004	-0.013	-0.11
% of private		-0.021	-0.002	0.001
Sch. Size		0.00	-0.00	-0.00*
Classroom hours			0.0002***	0.000***
% Women			0.000	0.000
Year effect	no	no	no	yes
Observations	77	71	60	60
Adj. R2	0.195	0.206	0.389	0.407

Note: Significance levels: *p<0.1, **p<0.05, ***p<0.001. Data source: PISA, OECD, and our own computations of the theoretical inefficient allocation index (IA).

general equilibrium effects. Secondly, because our model calibrated for each one of the 22 OECD countries allow us to measure the impact of changes in teacher wages and number of teacher on students test scores (as in figure 3.1). Indeed, for each country we obtain a different figure –instead of assuming an average effect of teacher wages on test scores and an average effect of class size on average test scores as is assumed in Dolton and Marcerano (2014).

3.5 Conclusions

This chapter proposes a theoretical model of teacher selection which, together with the empirical estimation of an educational production function, allows us to estimate the inefficiency in the allocation of the educational wage bill. The proposed theoretical model allows us to consider the existing trade-off when allocating the educational wage bill between quality and quantity of teaching hours. The consideration of this trade-off in our theoretical model as well as the general equilibrium effects that it involves represents the greatest contribution of this research with respect to the previous literature.

Our model show us that the efficient allocation of the wage bill in each country depends on a set of variables (related to the distribution of skills among the population, the wage returns in the non-teaching sector and the teacher wage) that affect the process of teacher selection and therefore the link between teacher quality, teacher salaries and the number of teachers hired.

After calibrating our model for a set of 22 OECD countries between 2006 and 2015, we compute the optimal allocation of the wage bill for those countries. Then, based on the predicted student outcomes imposing the observed and the optimal values for teacher salaries and number of teachers respectively, we build an index of inefficient allocation of the salary budget. The results suggest that, the contribution of the wage bill to the student outcomes could be, on average, 16% higher than its current contribution. Moreover, in most countries, the efficiency gap is generated by a bias to prioritise the quantity more than the quality of teachers.

Finally, in order to evaluate the results of our model, we analyse the correlation between the proposed index of inefficient allocation with an empirical estimate of the overall inefficiency of the education system which is built independently of the model. Given the importance of the wage bill inside the educational costs and of the teaching quality as school input, it is expected that the inefficiency in the allocation of the salary expenditure explains a significant portion of the overall inefficiency of the education system. The estimations, including several control variables, confirm a positive and significant correlation between the indicator of the allocative inefficiency of the wage bill obtained from our theoretical model and the empirical estimate of educational inefficiency which is built independently of the model.

3.6 References

Bacolod, M. P. (2003). Do alternative opportunities matter? The role of female labor markets in the decline of teacher quality, 19602000. UCLA Department of Economics Working Paper, September.

Battese, G.E. and T.J. Coelli (1995), "A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data", Empirical Economics, Vol. 20, pgs. 325-332.

Borjas, G. (1987). "Self-Selection and the Earnings of Immigrants," American Economic Review, Vol. 77, No. 4, pp. 531-553.

Borjas, G. (2002). "The Wage Structure and the Sorting of Workers into the Public Sector," NBER Working Papers 9313, National Bureau of Economic Research, Inc.

Card, D. and A. Krueger (1992), "Does school quality matter? Returns to education and the characteristics of public schools in the United States", Journal of Political Economy, 100(1),1?40.

Dolton, P. and O. Marcenaro-Gutierrez. (2011). "If you pay peanuts do you get monkeys? A cross-country analysis of teacher pay and pupil performance." Economic Policy 26 (65): 5-55.

Dolton, P. and O. Marcenaro-Gutierrez. (2014). "The efficiency index. Which education systems deliver the best value of money?". GEMS, Education Solutions.

Evans and Jovanovic (1989). "An Estimated Model of Entrepreneurial Choice under Liquidity Constraints" Journal of Political Economy, Vol. 97, No. 4, pp. 808-827.

Gates, B. (2011)."How Teacher Development Could Revolutionize Our Schools", The Washington Post

Hanushek, E. (2003). "The Failure of input-based schooling policies". The Economic Journal, 113, Febraury p.64-98.

Hanushek, E. (2010). "The economic value of higher teacher quality". CALDER Working Paper N 56, December, Urban Institute.

Hanushek, E., S. Link, and L. Woessmann. (2013). "Does school autonomy make sense everywhere? Panel estimates from PISA." Journal of Development Economics 104(September): 212-232.

Hanushek, E.; M. Piopiunik, and S. Wiederhold (2014). "The value of smarter teachers: International evidence on the teacher cognitive skills and student performance". Working Paper 20727, NBER.

Hanushek, E., G. Schwerdt, S. Wiederhold, and L. Woessmann (2015).

"Returns to Skills around the World: Evidence from PIAAC". European Economic Review, Vol. 73, pp. 103-130.

Heckman, J. (1985). "Heterogeneity, Aggregation and Market Wage Functions: An Empirical Model of Self-Selection in the Labor Market". Journal of Political Economy, Vol 93, No 6, 1077-1125.

Hiatt, F. (2009). "How Bill Gates Would Repair Our Schools", The Washington Post, March 30 2009.

Hoxby, C. (2000). "The effects of class size on student achievement: new evidence from population variation", Quarterly Journal of Economics, 115(4), 1239?85.

Klein, J., M. Rhee, P. C. Gorman, R. Huberman, C. R. Johnson, A. Alonso, T. Boasberg, A. Ackerman, W. Hite Jr., JC. Brizard, J. Torres, J. Covington, T. Grier, P. Vallas, E. White, and L. Sheffield (2010). "How to Fix Our Schools: A Manifesto by Joel Klein, Michelle Rhee and Other Education Leaders", The Washington Post, October 10 2010.

Loeb, S. and M. Page (2000). 'Examining the link between teacher wages and student outcomes: The importance of alternative labor market opportunities and non-pecuniary variation', Review of Economics and Statistics, 82(3), 393–408.

Muralidharan, K., J. Das, A. Holla and A. Mohpal (2017). "The fiscal cost of weak governance: Evidence from teacher absence in India," Journal of Public Economics, Elsevier, vol. 145(C), pages 116-135.

OECD (2017), "Education at a Glance (2017): OECD Indicators", OECD Publishing, Paris.

Rao (1989). "A note on corrected correlation coefficients when observation on one variable is restricted". Biometrical Journal31. 6, 677-680.

Rothstein, J. (2015). "Teacher quality policy when supply matters". American Economic Review, Vol, 105, No 1, January, pp 100-130.

Temin, P. (2002). "Teacher quality and the future of America". Eastern Economics Journal, 28, 285300.

West, M. and L. Woessmann. (2010). "Every Catholic child in a Catholic school: Historical resistance to state schooling, contemporary private competition and student achievement across countries." Economic Journal 120, no. 546: F229-F255.

Woessman, L. (2005). "Educational production in Europe", Economic Policy, 20 (Issue 43), 445?504.

3.7 Appendix

3.7.1 Appendix I. Optimal allocations (2006-2012)

Table 3.8: Observed and optimal allocations for 2012

	2012			
	w	w*	γ	γ*
Australia	1.18	1.576	2.30%	1.71%
Austria	1.07	1.652	2.60%	1.68%
Belgium	1.18	1.742	3.60%	1.92%
Canada	1.38	1.379	1.70%	1.54%
Czech. R	0.72	0.939	2.10%	1.61%
Denmark	1.21	1.652	2.80%	2.03%
Estonia	0.50	0.758	2.50%	1.64%
Finland	1.06	1.697	2.40%	1.50%
France	0.94	1.394	2.70%	1.82%
Germany	1.58	1.833	1.90%	1.64%
Ireland	1.21	1.500	2.80%	2.24%
Italy	1.06	1.864	2.90%	1.64%
Japan	1.34	1.333	1.50%	1.50%
Korea	1.54	1.439	1.40%	1.50%
Netherlands	1.47	1.500	2.80%	2.74%
Norway	0.61	1.015	3.70%	2.21%
Poland	0.92	1.515	2.50%	1.50%
Slovak, R.	0.51	0.727	2.50%	1.75%
Spain	1.44	2.000	2.70%	1.92%
Sweden	0.85	1.197	2.80%	1.99%
UK	1.17	1.364	2.40%	2.07%
US	0.91	1.06	2.20%	1.89%

Table 3.9: Observed and optimal allocations for 2009

	2009			
	w	w*	γ	γ*
Australia	1.19	1.561	2.30%	1.75%
Austria	1.11	1.652	2.60%	1.75%
Belgium	1.20	1.788	3.60%	1.85%
Canada			1.70%	
Czech. R	0.96	1.303	2.10%	1.54%
Denmark	1.36	1.636	2.80%	1.96%
Estonia	0.77	1.076	2.50%	1.78%
Finland	1.19	1.818	2.40%	1.57%
France	0.99	1.439	2.70%	1.85%
Germany	1.70	1.849	1.90%	1.75%
Ireland	1.40	1.773	2.80%	2.21%
Italy	1.15	2.000	2.90%	1.57%
Japan	1.55	1.515	1.50%	1.50%
Korea	1.90	1.409	1.40%	1.50%
Netherlands	1.37	1.470	2.80%	2.60%
Norway	0.73	1.212	3.70%	2.21%
Poland	0.91	1.500	2.50%	1.50%
Slovak, R.	0.62	0.818	2.50%	1.89%
Spain	1.70	2.000	2.70%	1.85%
Sweden	0.98	1.394	2.80%	1.96%
UK	1.34	1.530	2.40%	2.10%
US	0.95	1.11	2.20%	1.89%

Table 3.10: Table 10 - Observed and optimal allocations for 2006

	2006			
	w	w*	γ	γ*
Australia	1.16	1.515	2.30%	1.75%
Austria	1.04	1.576	2.60%	1.71%
Belgium	1.11	1.788	3.60%	1.89%
Canada			1.70%	
Czech. R	1.04	1.318	2.10%	1.64%
Denmark	0.99	1.424	2.80%	1.92%
Estonia			2.50%	
Finland	1.04	1.546	2.40%	1.61%
France	0.96	1.424	2.70%	1.82%
Germany	1.46	1.470	1.90%	1.89%
Ireland	1.06	1.394	2.80%	2.14%
Italy	0.95	1.833	2.90%	1.50%
Japan			1.50%	
Korea	2.14	1.515	1.40%	1.50%
Netherlands	1.13	1.212	2.80%	2.60%
Norway	0.60	0.985	3.70%	2.40%
Poland			2.50%	
Slovak, R.			2.50%	
Spain	1.41	1.970	2.70%	1.92%
Sweden	0.85	1.212	2.80%	1.96%
UK	1.29	1.500	2.40%	2.07%
US	0.92	1.09	2.20%	1.85%

3.7.2 Appendix II. Estimations

Table 3.11: Educational Production Function

	Parameter	Coeff.
TQ	β_1	9.421***
Student-teacher ratio	β_2	2.463***
Student-teacher ratio (quadratic)	$\beta 3$	-0.791**
female		-14.33***
F. Gen. Migrant		-1.114***
Diff. Language		-0.652
Age		16.078***
Repetition		-69.001***
ESCS		32.208***
Sch. Size		0.0061***
Sch Autonomy		0.898
% of private		10.083***
GDP growth		1.3377***
GDP per capita		-0.0019***
Expenditure on Educ (% of GDP)		-1.532***
Country fixed effects		yes
Time dummies		yes
R-Squared		0.243
Sample		2006-2015
Observations		478830

Note: Significance levels: *p<0.1, **p<0.05, ***p<0.001. Data source: PISA 2006-2015; OECD, IMF.

Overall Conclusions

From the research carried out in this dissertation, several relevant conclusions are drawn that imply a contribution to the previous literature and could be of interest to politicians and policy makers.

Firstly, my research finds that in Latin American and Caribbean countries a process of change in the profile of tasks developed by workers is taking place, which is in line with the existing evidence for developed countries. My empirical exercise shows that non-routine cognitive tasks are becoming increasingly important to the detriment of manual tasks. Furthermore, occupations in the higher income deciles present a clear cognitive task profile.

The evidence found for Latin American and Caribbean countries suggests that the process of labour market transformation is a result of technological change. The pattern in these emerging countries is similar in developed countries, despite the structural differences that exist between both types of economies.

In this sense, the challenge for both developed and emerging countries is similar and consists in trying to provide the workforce with the greater number of cognitive skills required to satisfy the rise in demand for non-routine cognitive tasks. Therefore, increasingly, an educational system that develops these cognitive abilities is crucial for good job placement and a high remuneration (from the individual point of view) as well as for stimulating economic growth (from the aggregate point of view).

This challenge puts particular pressure on educational systems since it is in the educational process where most of the skills needed to adapt to the new labour reality are acquired. Thus, it is critical to understand why educational systems show a significant disparity in cognitive abilities, in order to identify the key inputs for the educational process. Additionally, in a context of limited resources, it is key to understand how to use educational resources in the most efficient way to maximize student achievement. This dissertation presents evidence in both directions.

Indeed, the second relevant conclusion that emerges from this research is the importance of teaching quality as an educational input in explaining the cognitive abilities of the students. The results obtained in this research indicate that differences in teaching quality between countries are a key factor in understanding the differences observed in educational results. Indeed, differences in teaching quality explain a proportion of differences in educational outcomes between countries similar to that explained by differences in family background and clearly higher than the proportion explained by differences in any other school input like school organisation (proxy by school autonomy and school size), student teacher ratio and educational expenditures. Since the effect size estimated for teacher quality is really large, compared to other school inputs, educational programs that promote good teachers will be really effective and may be not too costly to implement. This is why the last part of this dissertation analyses the trade-off between quantity and quality of teacher. When faced with a lack of resources, policy makers need to choose between both alternatives.

In this way, the final relevant empirical finding from this dissertation is that most of the OECD countries present a bias towards the quantity instead of the quality of the teaching staff that makes them inefficient in the allocation of the educational wage bill. That is, a prioritization of teacher salaries instead of the number of hours hired would allow a better educational result to be obtained, using the same level of resources.

Conclusiones Generales (Spanish)

A partir de la investigación llevada a cabo en esta tesis doctoral, se extraen varias conclusiones relevantes que proporcionan una contribución a la literatura previa, a la vez que resultan de interés general para los responsables en la formulación de políticas educativas.

En primer lugar, mi investigación encuentra que en los países de Amrica Latina y el Caribe se está produciendo un cambio en el perfil de las tareas desarrolladas por los trabajadores, lo que se encuentra en línea con la evidencia existente para los países desarrollados. El ejercicio empírico desarrollado en el primer capítulo muestra que las tareas cognitivas no rutinarias son cada vez más importantes en el mercado laboral al tiempo que las tareas manuales pierden importancia. Además, las ocupaciones en los deciles de mayores ingresos presentan un claro perfil de tareas cognitivas, particularmente no rutinarias. La evidencia encontrada para los pases de América Latina y el Caribe sugiere que el proceso de transformación del mercado laboral es resultado de un proceso de cambio tecnológico. El patrón en estos países emergentes es similar al observeado en los países desarrollados, a pesar de las diferencias estructurales que existen entre ambos tipos de economías.

En este sentido, el desafío para los países desarrollados y emergentes es similar y consiste en tratar de proporcionar a la fuerza laboral el mayor número de habilidades cognitivas requeridas para satisfacer el aumento de la demanda de tareas cognitivas no rutinarias. Por lo tanto, cada vez más, un sistema educativo que desarrolle estas capacidades cognitivas es crucial para una buena inserción laboral y una alta remuneración (desde el punto de vista individual), así como para estimular el crecimiento económico (desde el punto de vista agregado).

Este desafío ejerce una presión particularmente importante sobre los sistemas educativos, ya que es en el proceso educativo donde se adquieren la mayoría de las habilidades necesarias para adaptarse a la nueva realidad laboral. Por lo tanto, es fundamental entender por qué los sistemas educativos muestran una disparidad significativa en las capacidades cognitivas, con el fin de identificar los imputs claves en el proceso de aprendizaje. Además, en un contexto de recursos limitados, es clave para comprender cómo usar los recursos educativos de la manera más eficiente para maximizar el rendimiento estudiantil. Esta tesis doctoral presenta evidencia en ambas direcciones.

En efecto, la segunda conclusión relevante que surge de esta investigación es la importancia de la calidad del profesor para explicar las capacidades cognitivas de los estudiantes. Los resultados obtenidos en esta investigación indican que las diferencias en la calidad del profesorado entre países resulta un factor clave para comprender las diferencias observadas en los resultados educativos medidos con los datos de PISA. De hecho, las diferencias en la calidad del profesor explican una proporción de diferencias en los resultados educativos entre países similar a la explicada por las diferencias en el entorno familiar y claramente más alta que la proporción explicada por diferencias en cualquier otro input o característica de organización escolar (por ejemplo autonomía escolar o tamaño de la escuela), el tamaño de la clase y el gasto educativo. Dado que el efecto estimado para la calidad del docente es realmente significativo en comparación con otros inputs escolares, los programas educativos que promuevan buenos docentes en su plantilla serán realmente efectivos y pueden no ser demasiado costosos de implementar. Esta es la razón por la cual la última parte de esta tesis analiza la disyuntiva entre la cantidad y la calidad del profesor. Ante la falta de recursos, los responsables de las políticas deben elegir entre ambas alternativas.

De esta forma, el ltimo hallazgo empírico relevante de esta tesis doctoral es que la mayora de los países de la OCDE presentan un sesgo hacia la cantidad en lugar de la calidad docente que los hace ineficientes en la asignación de la masa salarial educativa. Es decir, una priorización de los salarios de los docentes en lugar del número de horas contratadas permitiría obtener un mejor resultado educativo, utilizando el mismo nivel de recursos.