TALLINN UNIVERSITY OF TECHNOLOGY DOCTORAL THESIS 60/2018

# Essays on Education and Labour Economics

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#### Defence of the thesis: 25 October 2018, Tallinn

#### **Declaration:**

Hereby I declare that this doctoral thesis, my original investigation and achievement, submitted for the doctoral degree at Tallinn University of Technology has not been submitted for doctoral or equivalent academic degree.

Simona Ferraro



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TALLINNA TEHNIKAÜLIKOOL DOKTORITÖÖ 60/2018

# Uurimusi haridus- ja tööjõuökonoomikast

SIMONA FERRARO



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## **List of Publications**

The list of author's publications, on the basis of which the thesis has been prepared:

- I Ferraro S., Põder K., 2017. School-level policies and the efficiency and equity tradeoff in education. *Journal of Policy Modeling*, vol. xxx, no. xxx, pp. xxx-xxx. DOI: https://doi.org/10.1016/j.jpolmod.2017.11.001 (ETIS 1.1)
- II Ferraro S., 2018. Is information and communication technology satisfying educational needs at school? *Computers & Education*, vol. 144, pp. 194-204. DOI https://doi.org/10.1016/j.compedu.2018.04.002 (ETIS 1.1)
- III Ferraro S., Meriküll J., Staehr K., 2018. Minimum Wages and the Wage Distribution in Estonia. *Applied Economics*, vol. 50, no. 49, pp. 5253-5268. DOI: https://doi.org/10.1080/00036846.2018.1486017 (ETIS 1.1)
- IV Ferraro S., Hänilane B., Staehr K., 2018. Minimum Wages and Employment Retention. A Microeconometric Study for Estonia. *Baltic Journal of Economics*, vol. 18, no. 1, pp. 51-67. DOI: https://doi.org/10.1080/1406099X.2018.1485422. (ETIS 1.1)

## Author's Contribution to the Publications

Contribution to the papers in this thesis are:

- I The author of the thesis had a leading role in systemising the literature, preparing the dataset, running the estimations and writing the paper. The author of the thesis acted as the corresponding author in the publishing process.
- II The author of the thesis is the sole author of the article.
- III The author of the thesis prepared the dataset, ran the estimations and co-wrote the article.
- IV The author of the thesis prepared the dataset, ran the estimations and acted as the corresponding author in the publishing process.

### Introduction

How governments set their goals and enact their policies has also been a stimulus for shedding light on how some of these institutional policies have impacted on society. Empirical economic research can help to extend the understanding of their effect on the welfare of society by providing new insights to researchers and institutions.

The overall attainment and achievements in education have improved, and interest in issues of efficiency and equity has risen together with those achievements, making these important themes in any evaluation of policy (Barro and Lee, 2001). Equity means the inequality of outcomes among people while efficiency is the overall level of the outcomes (Okun, 2015). The economic analysis has also underlined the existence of equity-efficiency trade-offs.

Equity and efficiency concerns have also been debated in the context of labour market outcomes. Governments introduce and increase minimum wages in order to ensure that low-paid workers, usually workers with a low level of education and skills, earn a fair wage. This means minimum wages are institutional tools that affect the distribution of resources within society (Stigler, 1946). High minimum wages may however also affect efficiency as they may harm the employment prospects of low-income workers.

This thesis "Essays on Education and Labour Economics" consists of four selfcontained essays that all focus on equity-efficiency trade-offs in economic policy making. The first two essays (articles I and II) are from the field of Economics of Education and discuss the Italian education system, while the other two (articles III and IV) are from Labour Economics and discuss labour market outcomes for Estonia. The studies are motivated by the involvement and intervention of governments and their policies on educational and labour market outcomes, and by the impact of these policies on society.

The thesis seeks to extend the understanding of how some specific institutional policies affect the Italian education system and the Estonian labour market. Common themes among the studies are their policy considerations, the micro-data analyses and the use of surveys. The Programme for International Students Assessment (PISA) survey was used for Italy and the Estonian Labour Force Survey (ELFS) for Estonia.

The thesis considers two areas of research that are closely related, education economics and labour economics. Moreover, different econometric models have been used to reflect the specific research questions and dataset used for each study. All of the studies use surveys and not administrative data. A further detailed discussion on the strengths and limitations of using surveys is presented in Section 3.

Two individual countries are considered, Italy and Estonia. I have been interested in the Italian education system because of my experience both as a student and as a teacher. The poor performance of Italian students in international surveys such as PISA (OECD reports 2010c, 2013) next to their peers in other developed European countries and members of the Organisation for Economic Co-operation and Development (OECD) has driven my interest in investigating at the micro level which policies can be designed and used to improve the performance of Italian students (articles I and II).

Studies on efficiency and equity are not restricted only to education systems. Equity concerns about labour market outcomes are also debated. Estonia is a country that presents high levels of inequality within society and it has also introduced and increased a minimum wage in recent decades. Minimum wages are usually introduced and

increased by governments to ensure a better standard of living for citizens and to compress the spread of income inequality.

Essay III is linked to my work experience in the Bank of Estonia where the research sought to understand how institutional policies relate to equity considerations. The essay discusses inequality in wage and income distributions within the Estonian labour market and how the rise in the minimum wage helped to reduce inequality (OECD, 2015). My interest in labour economics became more intense after that work experience and another study of the Estonian labour market, specifically the impact of the minimum wage on job retention, which was investigated in Essay IV.

The empirical research uses different and appropriate econometric models to suit the outcome of the study and the structure of the data. Econometric models vary from parametric models such the Multilevel Modelling adopted in Essay I and the Ordinary Least Squares (OLS) in Essay IV to the semi-parametric Difference-in-Differences (DID) model applied in Essay III and non-parametric models like the Bayesian Additive Regression Trees (BART) used in Essay II. It was possible to use these econometric approaches because of my studies as a Ph.D. student, several relevant courses, workshops attended in Estonia and abroad, and exchanges with colleagues when I was working in the Bank of Estonia.

The thesis proceeds as follows. Section 1 gives a short review of the Education Production Function and school policies underlying Publications I and II, while Section 2 presents a review of labour market theory and empirics together with the aims and results of Publications III and IV. Section 3 provides conclusions and plans for further research. Appendices I-IV reprint the four essays.

### **1** School Level Education Policies

Issues of quality in education have led to debates about the improvements and educational policies that are needed but the path to follow has not been clear (Woessmann et al., 2009). Market elements like increasing consumer choice and competition, publishing performance indicators and giving financial rewards, which are found in some areas of public policy, have also been introduced in education (Gorard et al., 2003 p. 3). Competition is suggested as one of the market policies that should improve performances, but how it should do so is still debatable.

Market elements and the word competition have been introduced in the education sector (Gorard et al., 2003; Wiseman, 1959). In 1962, the idea was proposed that schools should compete to put pressure on themselves and so to increase the quality of education. Competition, however, was also seen as a cause of social segregation if schools can select students (Friedman, 2002).

The analysis of what determines the achievement of students and the role that schools and governmental policies have in this shows a complex picture. It is clear that educational policies are a major concern for policy-makers because the growth of a country and its competitiveness depend on there being an educated workforce. Education is important and governments have tried to do more with little, pushing the debate in education around the concept of efficiency while keeping levels of equity high (Bessent and Bessent, 1980).

#### **1.1 Education Production Function**

The classical economist Adam Smith discussed the role of education in his famous book *The Wealth of Nations*, where he stated that education is important for its contribution to increasing the productivity of workers (Smith, 1776 [2010]).

Understanding how students perform within each country, comparing students' results across countries and understanding how an education system works to increase its educational quality implies knowing which factors are involved in the educational production process. An understanding of that process can be gained by estimating the effects of some inputs on students' achievements defined using the Education Production Function or EPF (Bowles, 1970).

The empirical literature on education production is linked to the report on *Equality* of *Education Opportunity* (1966), which is also known as the Coleman Report (Coleman et al., 1966). Developed in the US in 1964, the results from the first pioneer study in education suggested that cognitive achievements expressed in terms of students' outcomes by standardised test scores were not affected by the inputs from schools.

The report discussed how family background and the effect of peers were the main determinants of students' achievement while schools played only a very small role. The report motivated a broad inquiry into the role of schools despite the complexity of the methodology. There were, however, some criticisms of Coleman's work and further studies were conducted (Bowles and Levin, 1968; Cain and Watts, 1970; Hanushek and Kain, 1972). The main reason is that education has been seen as a service that transforms inputs such as individuals into outputs that are still individuals but of a different quality.

Over the past fifty years, empirical models of education production have been developed where inputs have usually been family background characteristics, characteristics of peers and school resources. Educational outputs have been measured

through the performance of students in standardised tests (Hanushek, 1979; Woessmann, 2005).

Conceptually, a standard EPF can be formalised as in Hanushek (1979):

$$A_{it} = f(B_{it}, P_{it}, S_{it}, I_i) \tag{1}$$

where, for the  $i^{th}$  student,  $A_{it}$  is the student's achievement usually measured by standardised test scores, but also by other measures such as student attitudes, attendance rates, college continuation or dropout rates;  $B_{it}$  is a vector of family background at time t;  $P_{it}$  is a vector of the influence of peers at time t;  $S_{it}$  is a vector of school inputs at time t, and  $I_i$  is a vector of innate abilities, which is assumed to be time-invariant.

Standardised test scores have become an important way to measure the capacity of human capital in different age groups. The use of test scores is widely recognised around the world as a good output measure because they measure the quality of educational output and not the quantity, as occurs when numbers of graduates or the teacher-student ratio are used (Worthington, 2001). Moreover, since the achievements of students are available in international datasets, the role of educational institutions and educational policies on students' achievement can be focused on efficiency and equity. Some limitations can arise in using test scores when there is time discontinuity in the collection of the data. The Programme for International Student Assessment (PISA), an international survey that assesses the levels reached by 15-year-old students in reading, mathematics and science skills is carried out only every three years in a rotation (OECD 2007, 2010a, 2013, 2017).

The EPF provides the theoretical frame for Essays I and II, and the analysis in both cases is concentrated on school level factors  $S_{it}$ . The literature, however, has several perspectives as part of it focuses only on school management, meaning how resources are used within schools, while the other part looks at wider policies that schools might execute at the school level if they have autonomy. Essay I focuses on school level policies where  $S_{it}$  is operationalised by the measure of competition between schools, while Essay II focuses on school management where  $S_{it}$  is operationalised as Informational and Communication Technologies (ICT) used at school. In both cases, intensive school level controls are applied.

#### 1.2 Efficiency and equity in education

Since the report by Coleman et al. (1966), the literature has investigated the role of school inputs and outputs. The report combined schools' inputs such as family characteristics and school characteristics and the educational outputs measured with test scores, and it showed that the family characteristics were more important than the school characteristics. Its central point said that Family Background (FB) characteristics identified as  $B_{it}$  in eq. (1), are more important for producing outcomes than any other input. Moreover, the school inputs that have been operationalised in monetary terms as school financing  $S_{it}$  in eq. (1) did not matter.

Since the work by Hanushek (1986), there has been no consensus in the literature about the effect that school resources have in increasing the efficiency level as measured by test scores. Different results from studies across several countries by Hanushek (1997), Hanushek and Luque (2003), Häkkinen et al. (2003), in the USA by Hanushek (1996), and for developing countries also by Hanushek (1995) conclude that the

educational resources of schools do not have an effect on the academic results of the students.

Other more recent empirical studies show that not only school level policies or management decisions but also resources devoted to the classroom have large and positive effects (LaFortune et al., 2018; Krueger, 2003; Greenwald et al., 1996; Card and Krueger, 1996; Fuller and Clarke, 1994). A detailed and extensive review of studies on efficiency is provided by De Witte and López-Torres (2017).

The debate still remains whether FB Effects (FBE) are more influential than other inputs in efficiency studies. This dispute also has normative implications because in most studies, the dependency on FB is given as the measure of educational inequality (Hanushek and Woessmann, 2010; Hanushek et al., 2016; Krueger, 2003; Todd and Wolpin, 2003). For this reason, education economists refer to equity in terms of equality of opportunity, but they also consider the ability of the education system to minimise students' dependency on their family background (Roemer, 1998; Betts and Roemer, 2006; Lauer, 2003).

The concept of equity in educational outcomes consequently has a broader meaning than the concept of efficiency. The literature is unanimous in claiming that FBE is positive in all countries but its size differs (Schuetz et al., 2008). This difference in size can be related to factors like the institutional characteristics of school systems, for example the level of autonomy of a school, the level of competition between schools or how school resources are allocated (Woessmann et al., 2009; Hanushek and Luque, 2003). Essays I and II in this thesis concentrate on school level policies and their effects on Italian PISA test scores.

#### 1.3 Implications of policies for efficiency and equity

In education, the literature typically defines good education policies as policies that can bring about both efficiency, through increases in outputs  $A_{it}$  as in eq. 1, and equity. The studies of school level policies have looked at the correlations between efficiency measured by students' achievements and the implementation of some policies. Arguably the most interesting debate focuses on the trade-off between efficiency and equity and on which school level policies lead to higher efficiency without harming equity. Competition between schools and school choice in general are considered "good" candidates that demonstrate the positive effect of efficiency (Belfield and Levin, 2002; Woessmann et al., 2009; Woessmann, 2008; Hanushek and Luque, 2003).

Essays I and II discuss the school policies in the Italian education system. How school policies like increasing competition between schools affect Italian educational outcomes as measured by the PISA test score is discussed in Essay I. Starting from the standard EPF as in Hanushek (1979), the first article "School-level policies and the efficiency and equity trade-off in education" (Ferraro and Põder, 2017) studies how the increase in competition between schools has an effect on the levels of efficiency and equity.

The motivation for this study is the study by Põder et al. (2013) that shows from a cross-country analysis that there is a high level of equity within the Italian education system but a low level of efficiency. The research question of Essay I is then to evaluate whether there is room to increase efficiency, defined as the mean result orientation in the educational outcomes measured by PISA test scores, without negatively affecting equity. Specific country studies by Agasisti (2011a, 2011b) indicate that competition does not show a clear and strong effect on students' achievements.

The paper uses data from the OECD-PISA 2012 survey for Italy and adopts the methodology of parametric multilevel modelling. The multilevel model takes account of the nested structure of the PISA data and provides an accurate representation of the sources of variability in the data, thus giving consistent test statistics, p-values and confidence intervals (Goldstein, 2011). Some limitations of the multilevel models arise because of the population of clusters from which the sample of clusters is selected at random or because hierarchies compete with each other and they are not nested (Gorard, 2003).

The main contribution of Essay I to the existing academic literature is its extension of new evidence for the effect of competition between schools on both efficiency in terms of maximisation of output and equity as measured by the dependence on family background. The results show that competition between schools increases social inequality and segregation without having any effect on the level of efficiency.

The paper is forthcoming but has already been published online in the *Journal of Policy Modeling*<sup>1</sup>. The preliminary results of the paper were presented at the 5<sup>th</sup> Workshop on Efficiency in Education "Efficiency in education and performance measurement in the public sector", 19-20 October 2017, Budapest, Hungary; the Seventh ECINEQ Meeting 2017 at The Graduate Center City University of New York, 17-19 July 2017, New York; the Emerging Researchers' Conference 22-23 August 2016, Dublin, Ireland; and The European Conference on Educational Research 23-26 August 2016, Dublin, Ireland.

The improvement in the performance of Italian students when the PISA survey was based on Computer-Based Assessment (CBA) in 2012 (OECD, 2014) inspired me to investigate the causal relationship between another school policy, the integration of the use of Information and Communication Technologies at school, and students' outcomes.

The use of computers has increased and has become important, introducing large changes within modern societies (Lindbeck and Snower, 2000; Angrist and Lavy, 2002). Computers have been introduced at home but not only there. Governments have used resources to equip their schools with classroom computers and internet connections, and the rates of computer access in schools have increased in European countries (European Commission, 2013).

Understanding how ICT affects educational outcomes is critical because it can show whether this educational input is an important predictor in the educational production process and whether inequalities can arise from disparities in access to it.

The effect of ICT on student achievement has received attention during the last decade but the evidence is not conclusive. The OECD (2010b, 2010c) has underlined how important the role of Information and Communication Technology (ICT) is in education. There is a negative relationship between the use of computers at school and students' outcomes in the studies by the OECD (2006) using the PISA survey.

In the UK, the work by Machin et al. (2007) shows that higher investment in ICT leads to better educational outcomes for some subjects but not for others. Banerjee et al. (2007) in India find that the use of ICT at school is beneficial for students' performance. Another study from Canada by Luu and Freeman (2011) also shows that ICT use has a positive effect on students' test scores. In the Italian education system, results from

<sup>&</sup>lt;sup>1</sup> Ferraro, Põder (2017) available online from 27 November 2017 https://www.sciencedirect.com/science/article/pii/S0161893817301199

Ponzo (2011) and Agasisti et al. (2017) show that students' achievements are negatively affected when they use computers at school.

Essay II in this doctoral thesis, "Is Information and Communication Technology satisfying educational needs at school?" (Ferraro, 2018), presents the results of the integration of ICT tools in schools in Italy and their effect on the 2012 OECD-PISA test scores.

The study uses a new non-parametric methodology known as Bayesian Additive Regression Trees (BART), applied by Chipman et al. (2010) and Cabras and Tena-Horrillo (2016). It allows for causal estimation without two different models needing to be estimated, one to capture the endogeneity of the treatment variable and another to estimate the performance of students. BART is a model-based approach and it produces credible intervals compared to other ensemble methods. BART, however, becomes very computationally demanding when used on high-dimensional data (Chipman et al., 2010).

The contribution of Essay II is twofold. It seeks to evaluate the beneficial effects of ICT on students' learning and on their performance, and it demonstrates the applicability of the BART approach to analyses of economic outcomes without imposing a specific parametric form that a priori has additional advantages over traditional parametric models.

The essay aims to encourage further research in this field, given that ICT is becoming an important component of larger educational reforms that seek to enable and support traditional teaching and learning processes. The paper has been published in *Computers* & *Education*, vol. 122. The preliminary results of the paper were presented at seminars at Tallinn University of Technology.

### 2 Labour Markets and Minimum Wages

The literature and empirical studies have shown the well-established relationship between education and earnings. Earnings growth increases with final education level and the present value of lifetime earnings minus average expenditure on education increases with education.

Differences in earnings may reflect labour market discrimination (Blaug, 1972; Layard and Psacharopoulos, 1974; Mincer, 1974, 1976, 1980) and it has also raised concerns about the distribution of incomes and wages. Policy-makers have consequently focused on redistributive policies to reduce inequality, and an institutional policy within labour economics that has taken an increased role in reducing inequality in wages and income distributions is the minimum wage (Piketty, 2014; Schulten, 2012).

Adam Smith emphasised as early as 1776 the importance of introducing an appropriate wage for workers at the bottom of the wage distribution. He said: "It is but equity, besides, that they who feed, clothe, and lodge the whole body of the people, should have such a share of the produce of their own labour as to be themselves tolerably well fed, clothed and lodged" (Smith, 1776 [2010], Book I, Chapter 8, p. 66).

Some scholars have been in favour of minimum wages, while others have not, with Milton Friedman, Nobel Prize winner in 2006, claiming: "The high rate of unemployment among teenagers, and especially black teenagers, is both a scandal and a serious source of social unrest. Yet it is largely a result of minimum wage laws. We regard the minimum wage law as one of the most, if not the most, antiblack laws on the statute books" (Friedman and Friedman, 1990 p. 237).

Minimum wages have been set in a large number of countries around the world. In the European Union, 22 out of 28 countries have a minimum wage but scale, eligibility, and operational details vary from country to country, making cross-country analysis difficult (Boeri and van Ours, 2008).

Minimum wages are set differently around the world. In some countries, such as Estonia, there is a statutory minimum wage set by the government after negotiations with parties representing employers and workers. In other countries, like the UK, there is a national minimum wage meaning that the minimum wage is set nationally with no decision at local levels. Finally, in other countries trade unions impose floors for wages through collective wage agreements in specific industries. The minimum wages can be set on an hourly, daily, weekly or monthly basis (Eurofund, 2018).

How the minimum wage affects employment is, next to the discussion on equity considerations, still a hot topic for economic theory as well as for empirical studies. Efforts have been made to answer the question of how minimum wages affect labour outcomes and these questions and effects are probably the most debated topic in labour economics (Dickens et., 1999).

The last two essays of this thesis discuss the role that the statutory minimum wage has had in reducing inequality by increasing the wages of low-paid workers (Essay III) and its role in the probability of workers retaining a job in the Estonian labour market (Essay IV).

#### 2.1 Minimum Wages and the Wage Distribution

One of the motivations for introducing a minimum wage is to help low-wage workers and address the rise of wage inequality. Several studies have focused on the impact of minimum wages on wage distribution around the world to estimate whether an increase in the minimum wage has large or small spill-over effects on wages across the wage distribution.

Spill-over effects may arise (i) if employers substitute low-skilled workers with highskilled workers, or (ii) the increase in the wage floor means those who earn above the minimum wage are pushed up by the increase in demand. The same may happen for those who have wages between these two categories of workers. The spill-over effect from an increase in the minimum wage may be seen as a tool for raising the incomes of low-wage workers who earn a little more than the minimum.

The literature on the effects of minimum wages on the wage distribution is not extensive and it is also inconclusive compared to other studies that focus on how minimum wages affect employment. The international literature, however, can be divided into geographical areas.

Studies from the USA, for example, show that the introduction of the minimum wage or a rise in it led to large increase in the wages in the upper tail of the distribution, meaning large spill-over effects were found (Gramlich, 1976; Grossman, 1983; DiNardo et al., 1996; Lee, 1999). In contrast, studies for the UK present evidence of small spillover effects or no spill-over effect (Neumark et al., 2004; Dickens and Manning, 2004a, 2004b; Autor et al., 2016).

Essay III "Minimum wages and the wage distribution in Estonia" (Ferraro et al., 2018) assesses the impact of the rise in the minimum wage on the wage distribution in Estonia.

Studies for the Central and Eastern European countries are scarce and the main conclusion is that rises in the minimum wage have a strong effect on the wage distribution (see for Ukraine Ganguli and Terrell, 2006; in Poland Lukiyanova, 2011 and in Slovenia Laporšek et al., 2015). The first study on the impact of the Estonian minimum wage on the wage distribution in Estonia is by Hinnosaar and Rõõm (2003), who showed for the years 1995-2000 that a rise in the minimum wage had no strong effect on the wage distribution. However, Hinnossar and Rõõm (2003) compared kernel densities while Essay III adopts the Lee model (1999) modified for the Estonian case in order to take account of the lack of cross-sectional variation in the minimum wage in Estonia.

The model makes it possible to study the variability across percentiles in the wage distribution. Moreover, since the median wage is present in both the left and right sides of the identification model as a measure of dispersion and is also used to construct the relative minimum wage variable, it may exaggerate the impact of the minimum wage for two reasons: (i) sampling error; and (ii) variability in the median rather than in the percentiles of the lower or upper tails.

The empirical analysis uses the Estonian LFS micro-data for the years 2001-2014, dividing the income distribution into different percentiles so as to disentangle better the effect of the rise in the minimum wage in each labour market or cell, depending on the position of the workers in the income distribution.

Essay III offers three different contributions to the existing academic literature. The paper addresses for the first time the distributional effects of the minimum wage in a Central and Eastern European country like Estonia. Secondly, the empirical method developed by Lee (1999) was redefined to represent dimensions such as sectors of activity and occupation status, and to apply to a small country like Estonia. Finally, the

dataset presents a long time-series from 2001 to 2014, allowing the business cycle to be studied together with how the minimum wage affected the wage distribution. The paper has been published in *Applied Economics*, vol. 50, no. 49.

#### 2.2 Minimum Wages and Employment

The large body of empirical research shows that the minimum wage can have significant effects on both job-finding and job-loss probabilities (Card and Krueger, 1995). Economic theory offers unambiguous predictions about the effects of a minimum wage in a competitive labour market, or presents elements of monopsony (Stigler, 1946; Burdett and Mortensen, 1998; Manning, 2003).

Defining the wage in equilibrium  $w^*$ , the minimum wage  $\underline{w}$ , the supply curve  $L^s$  and the demand curve  $L^D$ , with the employment level in equilibrium  $L_1$ , in a competitive labour market as shown in Figure 1 (Boeri and van Ours, 2008), a minimum wage  $\underline{w}$  set above the market clearing wage  $w^*$  has a negative effect on employment that moves from  $L_1$  to  $L_0$ .



Figure 1. Competitive labour market

The wage paid after the introduction of the minimum wage is above the wage in equilibrium and the employment level is lower. In this new situation, some workers who earned the equilibrium wage  $w^*$  will be out of the labour market while other workers who were not supplying labour at  $w^*$  enter the labour market at the minimum wage. The result of these two effects will be some level of unemployment.

When firms have monopsony power in setting the wage, the introduction of a minimum wage may have a positive effect on the employment level. In Figure 2, the wage in equilibrium is set in  $w^*$ , the minimum wage is  $w^m$ ,  $L^s$  is the supply curve, and *mhc* is the marginal hiring cost. The monopsonist in the labour market has a marginal cost of hiring a worker that is higher than the reservation wage of any additional worker. The marginal hiring cost (*mhc*) of a monopsonist is above the  $L^s(w)$  curve and deviates because an additional worker implies a wage increase for a larger workforce (Rebitzer and Taylor, 1995).



Figure 2. Monopsony labour market

In any case, the statutory minimum wage may not always be enforced in practice, so wages may still be below the minimum wage in some cases, potentially limiting any effect on employment (Basu et al., 2010).

There have been numerous empirical studies of the effect of the minimum wage on employment. Increases in the minimum wage in the USA, for example, have a negative effect on the level of employment in the studies by Brown et al. (1982) and Neumark and Wascher (2008, 1992), while Card (1992), Card and Krueger (1994), and Katz and Krueger (1992) present results showing that the rise in the minimum wage does not have any negative employment effects. In the UK, studies by Dickens et al. (1999), Stewart (2002), and Metcalf (2004) find that the increase in the minimum wage did not have adverse effects on employment.

Other studies for developed and developing countries also present mixed results (Broecke et al., 2017; OECD, 2015; Nataraj et al., 2014). The literature is scarce for Central and Eastern European countries. For Slovenia, Vodopivec (2015) find a negative effect on employment and for Poland, Majchrowska et al. (2015) find no negative employment effects, while for Estonia, Hinnosaar and Rõõm (2003) use data from the Estonian LFS survey for 1995-2000 and the model by Neumark et al. (2004) and show that there is a strong negative effect on employment for workers directly affected by the increase in the minimum wage.

Essay IV "Minimum wages and employment retention. A Microeconometric study for Estonia" (Ferraro et al., 2018) shows the effect of the rises in the minimum wage on the probability of full-time wage-earning workers retaining a job in the years 2013-2016.

The study was motivated by the sharp rise in the minimum wage faster than the average rate of wage growth in the years 2013-2016. The micro-data of the Estonian LFS were used in the semi-parametric DID model. The wage distribution was divided into groups according to the position of workers in the wage distribution before the increase in the minimum wage. This allows estimation of whether the probability of employment retention was different for the individuals in each group in the years 2013–2016, when the minimum wage was raised, from what it was in the years 2009–2011, when there were no changes. The DID model found in Neumark et al. (2004), Stewart (2004a, 2004b), and Stewart and Swaffield (2008) was applied in this work. The DID model obtains an

appropriate counterfactual to estimate a causal effect but as with all experiments and quasi-experimental methods, extrapolation is not easy.

The contribution of the study is its new insight for the Estonian labour market given the lack of an organised labour market, the weak employment protection, and the limited role that collective wage bargaining plays within the country. The paper has been published in the *Baltic Journal of Economics*, vol. 18, no. 1. The results of the paper were presented at the 9<sup>th</sup> international conference "Economic Challenges in an Enlarged Europe" held on June 11-16, 2017 in Tallinn and also at a seminar of the Department of Economics and Finance in March 2018.

### **3 Final Comments**

The essays in this thesis contribute to the literature on the economics of education and labour economics but as always they do not provide conclusive results. They provide further elements for new research and debates. Several other datasets and topics can be investigated to bring new approaches and contributions to the topic.

Measuring educational performance and understanding its determinants are important factors for designing and implementing educational policies. As quality matters at least as much as quantity in education, it is necessary to understand which factors or actors contribute to and affect the amount and quality of human capital.

Distributional concerns have driven governments to introduce institutional tools to reduce inequality within income and wage distributions. The empirical literature does not provide unambiguous results for the effect of the minimum wages, which explains why some researchers advocate raising the minimum wage, while others argue in favour of marked reductions in the minimum wage.

All four essays use micro-data from either the PISA Survey by the OECD for Italy or the Estonian LFS for Estonia. The PISA survey presents some positive characteristics but also has limitations. It produces a huge amount of data, for example, and the sample for the Italian PISA data consists of some 30,000 students and 2,000 schools. It shows policymakers what they want to know, such as the strengths or weaknesses of their country's education system, which demographic groups or regions or schools policies should be addressed to, what should be changed within the educational system, how the change can be introduced, and which policies should be introduced. There are, however, some limitations in using the PISA survey. Although PISA illustrates the quality of an education system, it does not provide any solution to address some of the problems that can arise within each education system and it does not provide a measure of the value added of the system. Other limitations are linked to the sample design, while some degree of uncertainty can arise together with a lack of accuracy because the information comes from the respondents to the survey questionnaire.

The Estonian LFS equally presents some positive elements and some limitations. Its positives are that it collects a wide range of different information on the labour force using longer questionnaires each year for panel or longitudinal data, and it allows the high costs of population censuses to be overcome. Because the LFS covers all the individuals in the sampled households whatever their labour market status or occupation, the survey provides a consistent framework for simultaneously studying employment, unemployment and other variables of interest for researchers. The limitations of the LFS are that it is not representative of the population as a whole and there may also be some sampling errors during the survey. The Estonian LFS also has the same limitations of lack of accuracy and degree of uncertainty as the PISA survey.

This thesis consists of four essays, three published and one in process of publication, and it discusses some educational policies for the Italian education system and labour market policies for the Estonian labour market. Using micro-level data for the two countries and different econometric approaches, all four essays contribute to the academic literature in their specific fields.

Essay I contributes to the academic literature by studying whether there is room to improve efficiency in terms of test scores for Italian students without harming the equity of which the Italian education system has high levels. Using OECD-PISA 2012 and multilevel modelling to take account of the hierarchical structure of the survey, the study

focuses on how increased competition between schools affects efficiency and equity. The results show that when schools compete against each other, there is an increase in the level of inequality and social segregation and no effect on efficiency in terms of PISA test scores.

Essay II analyses how the integration of ICT in schools affects Italian students' performance. The debate over the use of ICT in schools and at home has seen different arguments and conclusions from different models. The essay applied the non-parametric model BART from the Bayesian family, which is able to tackle the endogeneity problem that arises from the PISA survey. The main conclusion is that ICT has a positive effect on test scores for Italian students.

Essay III studies how the minimum wage affects the wage distribution in Estonia. The literature is scarce for emerging economies in the Central and Eastern European countries and for Estonia. Using the Estonian Labour Force Survey (LFS) and revising Lee's model (1999), we show that the increase in minimum wages has led to an increase in wages for the lower tail of the wage distribution, but the effect has also reached workers at higher percentiles up to the 40<sup>th</sup> percentile.

Essay IV discusses how the rise in the minimum wage affected job retention following the sharp increase in the minimum wage by more than the average wage in 2013-2016 in Estonia. Using the Estonian LFS and a DID model, the conclusion of this study is that the rise in the minimum wage did not have negative effects on the probability of workers retaining their jobs.

These essays, however, do not close any research topic but are expected to open new debates and questions to give a new start for further research and keep interest in these topics alive.

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# Acknowledgements

I sincerely thank my supervisor, Associate Professor Karin Jõeveer, for her supervision and comments during the last part of my doctoral studies.

I wish to thank my co-supervisor, Professor Karsten Staehr for his feedback and advice throughout the path of my doctoral studies and my internship at the Bank of Estonia and for his contribution as co-author of our articles. I very much appreciated his patience and his suggestions for the academic research. I would also like to thank Professor Staehr for his financial support during the first year of my studies.

I am truly and deeply grateful to my co-supervisor Professor Kaire Põder for being my supervisor when I decided to join this doctoral programme, for her excellent supervision, inspirational and helpful feedback, support and encouragement, and for the many constructive and valuable discussions throughout my time as her doctoral student. She led me down the correct path to accomplishing my personal and professional goals and it has been an honour and a privilege to be her student and co-author.

I would like to thank Professor Aaro Hazak for the productive teaching experience as his teaching assistant.

I wish to thank Merike Kukk, Associate Professor, and Kirsti Rumma Ph.D. for their remarkable comments and advices expressed on their reviews, on the preliminary version of my doctoral thesis.

I am indebted to Tallinn University of Technology in the persons of Professor Enn Listra, the Dean of the School of Business and Governance, and Professor Kadri Männasoo, the Head of the Department of Economics and Finance (DEF) and Professor Kaie Kerem, the former Head of the DEF, for giving me the opportunity to be a doctoral student and be a part of the department staff as a lecturer. I must also thank them for providing the funding which allowed me to undertake this research, and for giving me the opportunity to attend conferences and create a network for my future career.

I also would like to thank Jaanika Meriküll Ph.D. for being my supervisor at the Bank of Estonia and for introducing me to the field of labour economics. That experience allowed me to improve my knowledge and skills a great deal and I am very grateful to her for sharing her knowledge with me.

I would also like to thank Professor Tairi Rõõm, Head of the Research Department at the Bank of Estonia, for the chance to spend an internship in Eesti Pank surrounded by great economists.

I thank all the departmental staff, Tiia Sarv, Anneli Kalm and Eva Laura Auling, for their help in all administrative and bureaucratic matters.

I thank Ingrida Tatolyte for her valuable comments and feedback during her course on academic writing together with Robin Hazlehurst, who provided important comments and advice and who has done excellent language editing.

I thank all the doctoral students and colleagues at the Department of Economics and Finance whom I have met during these years of my studies and with whom I have shared this path.

I am grateful to all institutions that have provided financial support to attend courses, conferences, workshops to present the results of the papers, during my studies: the European Union's Horizon 202 research and innovation programme under the Marie Sklodowka-Curie grant agreement No 734712; the Doctoral School in Economics and Innovation; the Estonian Research Grant PUT315 "Towards the Knowledge Economy: Incentives, Regulation and Capital Allocation"; the Research Grant B45 "Economic crises in Europe: information, risks and government policy"; the European Union Social Fund and the DoRa Plus programme.

I would also thank all my friends who have been close to me and support me during my doctoral studies.

Last, but most importantly, I would like to thank my parents and my brother for always being close to me despite the distance, encouraging me and supporting me.

# Abstract Essays on Education and Labour Economics

The thesis "Essays on Education and Labour Economics" presents empirical studies in two areas. First, the thesis seeks to extend the understanding of the effect of some institutional policies on Italian educational outcomes, and second, it studies and gives further results on labour market outcomes for the Estonian labour market and the rise in the statutory minimum wage.

The thesis consists of four essays. Essay I is entitled "School-level policies and efficiency and equity trade-off in education". The purpose of the paper is to investigate if it is possible to increase the level of efficiency by improving students' performance within the Italian education system without reducing the level of equity, which it is high within the country. The level of competition among schools is discussed as one market policy that is identified as an element that can reach both levels without making any trade-off. The results show that increasing the level of competition among schools within the Italian education system, does not lead to an increase in efficiency, but rather it harms equity. Essay I extends the understanding of the implications of a market policy such as competition on educational outcomes.

Essay II "Is Information and Communication Technology satisfying educational needs at school?" studies the integration of ICT in schools to understand the impact of the technological tools on students' performance. The essay seeks to evaluate the beneficial effects of ICT on students' performance measured by PISA test scores. The nonparametric model BART is used for its greater flexibility than found in traditional models. The findings show the positive effect of ICT on Italian PISA scores. The contribution of this essay is to encourage new debates, given that ICT is becoming an important component of larger educational reforms in supporting traditional teaching and learning processes.

Essay III is entitled "Minimum wages and the wage distribution in Estonia". The purpose of the paper is to estimate the impact of the rise in the Estonian minimum wage on the wage distribution. Using the methodology by Lee (1999) revised to address the specificities of the Estonian labour market, the results show that the higher minimum wage increases the wage for the bottom part of the distribution with the increase running up to the 40<sup>th</sup> percentile. The essay contributes to the public discussion about the introduction of a minimum wage or a rise in it, and about whether the tool can be considered effective at helping workers with low wages and reducing the wage differential and inequality within society.

Essay IV "Minimum wages and employment retention. A Microeconometric study for Estonia" explores how rises in the minimum wage impacted the probability of full-time wage-earner workers retaining their job in the years 2013-2016, a time when there was a steep increase in the minimum wage above the average rate of wage growth. The findings show that there was no difference in the probability of job retention among workers. The contribution of the study is its new insight for the Estonian labour market given the unorganised labour market, the weak employment protection and the limited role that collective wage bargaining plays within the country.

All four essays have studied some policy implications for society in the area of education and labour economics. Each essay has provided empirical results on the effect of these policies, but several new plans and directions for further studies have emerged. In the field of education, for example, it would be interesting to extend the analysis of

the impact of ICT on students' PISA test scores by comparing different countries and comparing the expenditure on educational technology.

For the study of the impact of the minimum wage, a new study might also introduce a firm-level dataset to understand how the minimum wage in Estonia, for example, has affected the firm productivity.

Additionally, future researches using other approaches and methods may be fruitful.

# Lühikokkuvõte Uurimusi haridus- ja tööjõuökonoomikast

Antud väitekiri "Uurimusi haridus- ja tööjõuökonoomikast" koosneb neljast iseseisvast esseest, mis keskenduvad majanduspoliitika kujundamisele nimetatud valdkondades. Kaks esimest esseed (artiklid I ja II) on haridusökonoomika suunitlusega ja keskenduvad Itaalia haridussüsteemi probleemidele. Ülejäänud kaks esseed (III ja IV artikkel) on tööjõuökonoomika valdkonnas ja käsitlevad Eesti tööturu probleeme. Uuringute läbiviimist motiveeris nii juhtumitega (Eesti tööjõuturuga ja Itaalia hariduspoliitikaga) seotud spetsiifilised probleemid, kui akadeemilise kirjanduse vastuolulisus, mis ajendas leidma empiirilisi vastuseid ehk poliitikate mõju teatud spetsiifilistes ühiskondades.

Doktoritöö eesmärk on laiendada arusaamist konkreetsete institutsionaalsete poliitikate mõjust Itaalia haridussüsteemile ja Eesti tööjõuturule. Uuringute ülesed teemad on seotud poliitiliste kaalutlustega, mikroandmete analüüsimisega ja küsitlustel baseeruva uuringute disainiga. Itaalia hariduspoliitika mõjusid on uuritud toetudes PISA (*The Programme for International Student Assessment*) andmetele ja Eesti puhul tööjõu-uuringu ELFS (*Estonian Labour Force Survey*) andmetele. Kuigi antud töös kajastatud haridusökonoomika kaasused on keskendunud tõhususe ja õigluse aspektidele hariduses, ei puuduta need teemad mitte ainult haridussüsteeme. Sarnased dilemmad on aktuaalsed ka tööjõuturgude poliitikate kujundamisel. Eesti tööjõuturg paistab silma mitme terava probleemiga, näiteks sissetulekute ebavõrdsus, mis on viimastel aastakümnetel teravnenud ja mille vastukaaluks on rakendatud miinimumpalga tõstmist.

Seega peegeldab antud doktoritöö kahte uurimisvaldkonda, mis on tihedalt seotud: haridus- ja tööjõuökonoomikat. Lisaks sellele on iga artikkel keskendunud konkreetsele uurimisküsimusele ja iga uuringu puhul on kasutatud erinevat andmekogumit ning sellele vastavaid ökonomeetrilisi mudeleid. Kõik uuringud kasutavad algallikatena ankeetküsitlusi, mitte administratiivseid andmeid. Nagu mainitud, on uuringud keskendunud kahele riigile: Itaalia ja Eesti. Olen huvitatud Itaalia haridussüsteemist, kuna olen olnud Itaalias nii üliõpilane kui ka õpetaja. Rahvusvaheliste uuringute andmetel, nagu PISA (OECD 2010c, 2013), on Itaalia õpilaste tulemus nõrk, seda eriti teiste arenenud Euroopa riikide ja Majanduskoostöö ja Arengu Organisatsiooni (OECD) liikmete valguses. Seega on I ja II artikli keskmes küsimused sellest, mida saaks mikrotasandil (koolide tasand) muuta ehk milliseid poliitikaid rakendada, et parandada Itaalia õpilaste saavutusi ilma suurendamata õpitulemuste ebavõrdust.

Empiirilises uuringus kasutatakse uuringu eesmärkidele vastavaid ja andmete struktuurile sobivaid ökonomeetrilisi mudeleid. Ökonomeetrilised mudelid erinevad – alustame parameetrilistest tehnikatest nagu I artiklis kasutatud hierarhiline modelleerimine ja IV artiklis kasutatud vähimruutude meetod (OLS), kuni poolparameetriliste meetoditeni IV artiklis (*differences in differences*), lõpetades II artiklis rakendatud mitteparameetrilise modelleerimisega ehk Bayesi regressioonipuudega (BART). Sellise metoodilise pagasi rakendamine on saanud võimalikuks läbides mitmeid kohustuslikke ja vabatahtlikke doktoritasemel metoodikaõppeid nii Eestis kui välismaal. Lisaks töötasin ühel semestril Eesti Pangas, kus sain õppida parimatelt kolleegidelt.

Minu doktoritöö lähtepunktiks on tees, et valitsuste poliitikad tekitavad stiimuleid ja ajendeid, mis võivad oluliselt mõjutada institutsioonide, sh turgude toimet läbi indiviidide erinevate valikute. Minu empiirilised majandusuuringud aitavad mõista nende poliitikate mõju ühiskonna heaolule, pakkudes teadlastele ja institutsioonidele uusi teadmisi. Kuigi üldiselt on õpitulemused ajas suurenenud, siis koos nendega on huvi mitte ainult hariduse tõhususe, vaid ka võrdsuse küsimuste üle kasvanud, muutes tõhususe-võrdsuse dilemma poliitika kujundamise raskuspunktiks (Barro ja Lee, 2001). Ka tööjõuturul on sarnased dilemmad esindatud. Valitsused kehtestavad ja suurendavad miinimumpalka, et tagada madala palgaga töötajatele, kes on harilikult madalama haridustasemega, elamisväärne sissetulek. Seepärast on miinimumpalk institutsioon, mis mõjutab ressursside jagamist ühiskonnas (Stigler, 1946). Samas võib kõrge miinimumpalk mõjutada ka turgude tõhusust ressursside kasutamisel, kuna see võib ohustada madala sissetulekuga töötajate hõivevõimalusi.

Hariduses määratleb teaduskirjandus tavaliselt "head" hariduspoliitikat kui poliitikat, mis võib viia nii efektiivsuse kui ka võrdsete võimalusteni. Sellises teoreetilises empiirilises kirjanduses keskendub kõige huvitavam arutelu efektiivsuse ja võrdsete võimaluste kompromissile ning kooli tasemel läbiviidavale poliitikale, mis tooks kaasa suurema efektiivsuse, kuid samas ei kahjustaks võrdseid võimalusi. Üldiselt peetakse selliste poliitikate "headeks" kandidaatideks koolivalikut ja koolidevahelist konkurentsi (Belfield ja Levin, 2002; Woessmann jt, 2009; Woessmann, 2008; Hanushek ja Luque, 2003). Sellisest teesist lähtuvalt käsitlevadki I ja II artikkel kooli tasemel läbiviidavaid poliitikate rakendusi Itaalia haridussüsteemis. I artikkel (Ferraro ja Põder, 2017) keskendub koolidevahelise konkurentsi mõjule õpilaste haridustulemustele (väljendatud PISA testi matemaatika tulemusena). Uuring on ajendatud Põder jt (2013) tulemustest, mis näitab, et Itaalia haridussüsteemis on kõrge hariduslik õiglus, kuid madal efektiivsus.

I Artikli uurimisküsimus: kas koolidevaheline konkurents suurendab õpilaste tulemusi ilma, et see tooks omakorda kaasa negatiivset mõju hariduslikule õiglusele. Eelnevad Agasisti uuringud (2011a, 2011b) näitavad, et konkurents ei avalda selget ja tugevat mõju üliõpilaste tulemustele. Kasutatud hierarhiline mudel võtab arvesse PISA andmete klastervalimile omast struktuuri (Gorard, 2003) ja annab nihutamata hinnangud regressiooni koefitsentidele (Goldstein, 2011). I Artikli peamiseks panuseks olemasolevasse akadeemilisse kirjandusse on uute tõendite toomine koolidevahelise konkurentsi mõju kohta nii efektiivsuse kui ka õigluse mõttes. Viimast defineerime kui haridustulemuste sõltuvust perekonna taustakarakteristikutest. Tulemused näitavad, et koolidevaheline konkurents suurendab sotsiaalset ebavõrdsust ja vanemate haridustulemustest lähtuvat õpilaste selektsiooni ilma, et see mõjutaks efektiivsuse taset.

Käesoleva doktoritöö II artikkel (Ferraro, 2018) näitab, kuidas IKT-tööriistade kasutamine koolis avaldab mõju õpilaste tulemustele. Kusjuures õpilaste tulemused on jällegi väljendatud PISA testide tulemustena. 2012. aastal viidi sisse arvutipõhine PISA testimine, mis parandas ka Itaalia õpilaste testide tulemusi (OECD, 2014). Antud empiiriline fakt inspireeris mind uurima koolikesksete poliitikate rakendamise põhjuslikke seoseid. Selline uurimisküsimus ei ole triviaalne, kuna IKT-sisend võib olla nii õppeprotsessi tõhususe näitajaks, kui võib ka osutuda nn ise-selektsiooni probleemile – rikkamatel on ligipääs IKT-ressurssidele ja seega ei tulene nende paremus mitte tehnilistest võimalustest, vaid õpilaste taustakarakteristikutest. IKT mõju õpilaste tulemustele on viimasel kümnendil akadeemilises kirjanduses suurt tähelepanu pälvinud, kuid tõendid ei ole lõplikud. OECD (2010b, 2010c) on rõhutanud info- ja sidetehnoloogia positiivset rolli, kuid OECD varasemad uuringud (2006) on näidanud, et arvutite kasutamine koolis vähendab õpilaste tulemuslikkust. Lisaks

näitavad Machin jt (2007), et suuremad investeeringud IKT-sse võivad osadele õpilastele kaasa tuua paremaid õpitulemusi, kuid mitte teistele. Itaalia andmeid kasutades on Ponzo (2011) ja Agasisti jt tulemused (2017) näidanud, et õpitulemused vähenevad, kui õpilased kasutavad koolis arvutit. Antud uuringus (Ferraro, 2018) kasutatakse Chipmani jt (2010) poolt rakendatud uut mitteparameetrilist metoodikat, mida nimetatakse Bayesi lisandväärtusega regressioonipuudeks (BART). See võimaldab põhjuslike seoste uuringut ilma, et hinnataks kahte erinevat mudelit: ühte, mis saab hakkama mudelile omase IKT muutuja endogeensusega ja teist, mis hindab õpilaste tulemuslikkuse sõltuvust IKT-st (Chipman jt, 2010). II Artikli panust võib lugeda kahesuguseks. Esiteks metoodiline panus, mis võimaldab hinnata IKT mõju õpitulemustele. Teiseks näidatakse, et selline mittenihutatud hinnang on positiivne – IKT kasutamine koolis suurendab õpilaste haridustulemusi.

Kuidas minimaalne palk mõjutab tööhõivet? Viimane on sissetulekute jaotuse ja palgalõhede probleemide kõrval senini üks oluline teema nii majandusteoorias kui empiirilistes uuringutes. Akadeemilises kirjanduses (näiteks Dickens jt, 1999) näidatakse teema olulisuse kõrval ka seda, et miinimumpalk mõjutab palgajaotust. Paraku on ebaselge nii selle mõju ulatus kui ka unikaalsus või mõju üldistatavus näiteks geograafiliselt. III Artikkel "Miinimumpalk ja palgajaotus Eestis" (Ferraro jt, 2018) hindab miinimumpalga tõusu mõju Eesti palgajaotuse kujunemisel. Kuigi vähestes uuringutes, mis Kesk- ja Ida-Euroopa riikides on läbi viidud, on peamine järeldus, et miinimumpalgal on suur mõju palgajaotuse kujunemisele (vt Ukraina Ganguli ja Terrell, 2006; Poolas Lukiyanova, 2011 ja Sloveenias Laporšek jt, 2015) näitab selleteemaline esimene uuring Eestis (Hinnosaar ja Rõõm, 2003) teisiti, et aastatel 1995-2000 ei avaldanud miinimumpalga tõus palgatulemusele tugevat mõju. Artikkel III kasutab erinevat lähenemist kui Hinnossaar ja Rõõm (2003), rakendades Lee (1999) mudelit, mida on kohendatud Eesti juhtumi jaoks selleks, et võtta arvesse andmete omapära. Selline kohendatud mudel võimaldab uurida protsentiilide varieeruvust palgajaotuses. Kuna keskmine palk on identifitseeritud mudeli vasakus ja paremas osas dispersioonimõõduna ning seda kasutatakse ka suhtelise miinimumpalga muutuja konstrueerimiseks, siis võib see miinimumpalga mõju ülehinnata kahel põhjusel: (i) valimi valikust tulenev viga; (ii) mediaani varieeruvus võrreldes ülemistes ja alumistes protsentiilides (jaotuse sabades) leiduvaga. Mudeli hindamisel kasutasime Eesti tööjõu-uuringu (LFS) mikroandmeid aastatel 2001-2014. III Artikkel panustab kolmel tasandil. Esiteks käsitletakse esmakordselt miinimumpalga mõjusid palgajaotusele Eestis. Teiseks, kasutades täiendatud Lee (1999) väljatöötatud empiirilist mudelit, haarati analüüsi uusi tegureid nagu majandusvaldkond, hõivestaatus ims. Kolmandaks kasutatakse andmestikku, mis sisaldab 2001 kuni 2014 aasta vahemikus kogu majandustsüklit ja seega näitab miinimumpalga tõstmise mõju dünaamikat.

Hoolimata eelnevast kirjandusest, ei pruugita seadusjärgset miinimumpalka alati praktikas rakendada, mistõttu palgad võivad mõnedel juhtudel ikkagi miinimumpalgast madalamaks jääda ja nii tööhõivet tõsta (Basu jt, 2010). Miinimumpalga mõjust tööhõivele on tehtud arvukalt empiirilisi uuringuid. Sellised uuringud näitavad, et miinimumpalga tõus on Browni jt (1982) uuringus avaldanud negatiivset mõju tööhõive tasemele, sama näitavad ka Neumark ja Wascher (2008, 1992), samas kui Card (1992), Card ja Krueger (1994), Katz ja Krueger (1992) saavad tulemuseks, et palga alammäära suurenemine ei avalda negatiivset mõju tööhõivele. Ühendkuningriigis näitavad Dickensi jt (1999), Stewart (2002) ja Metcalf (2004), et miinimumpalga tõus ei mõjutanud

tööhõivet negatiivselt. Oluline on, et arenenud riikides ja arengumaades tehtavad uuringud pakuvad erinevaid tulemusi (Broecke jt 2017; OECD, 2015; Nataraj jt, 2014). Kesk- ja Ida-Euroopa riikidest on akadeemilist kirjandust vähe. Sloveenias leiab Vodopivec (2015), et vastav mõju on negatiivne ja Poola kohta leiavad Majchrowska jt (2015), et mõju puudub. Eestis on Hinnosaar ja Rõõm (2003) kasutanud LFS-i uuringut aastatel 1995-2000 ning Neumarki jt (2004) mudelit. Nimetatud uuring näitab, et miinimumpalga tõusu mõju on otsene ja suur ehk miinimumpalga kasv viib alla tööhõive. Antud doktoritöö IV Artikkel "Miinimumpalk ja tööhõive säilitamine. Eesti mikroökonomeetriline uuring" (Ferraro jt 2018) näitab miinimumpalga tõusu mõju täistööajaga palgatöötajate töötamise tõenäosusele aastatel 2013-2016. Uuring on ajendatud majanduskeskkonna muutusest ehk miinimumpalga järsust tõstmisest, mis oli kiirem kui palgatõusu keskmine tase aastatel 2013-2016. Modelleerimisel kasutati Eesti LFS-i mikroandmeid ja analüüsimeetodina kasutati poolparameetrilist DIDmudelit. Sarnast DID-mudelit on kasutanud Neumark jt (2004), Stewart (2004a, 2004b), Stewart ja Swaffield (2008). Oluline on see, et DID-mudel annab põhjusliku mõju hindamiseks sobiva uuringudisaini, kuigi kõigi eksperimentaalsete ia kvaasieksperimentaalsete meetodite puhul ei ole mudeli spetsifitseerimine triviaalne. Selleks klassifitseeriti palgajaotuse alusel rühmad vastavalt palgatöötajate positsioonile enne, kui alampalka tõsteti. See võimaldab hinnata, kas tööhõive säilitamise tõenäosus nende rühma iga üksikisiku puhul oli erinev aastatel 2013-2016 ehk siis kui miinimumpalk suurenes võrreldes 2009-2011 aastaga, kui muudatusi ei tehtud. Uuring panustab akadeemilisse kirjandusse luues empiirilise kaasuse, mis lisaks Eesti tööjõuturu ülevaatele käsitleb kaasust, kus puudub organiseeritud ametiühinguliikumine, riigi roll on kollektiivsete palgarääkimiste näol piiratud ning tööjõu kaitse on pigem nõrk.

Kõik neli doktoritöö aluseks olnud artiklit on käsitlenud haridus- ja tööjõupoliitika meetmete mõjusid. Iga artikkel keskendub poliitika mõju uurimisele läbi majandusagentide ja pakub empiirilisi kinnitusi poliitikate mõjust. Muidugi jäävad uuringud oma aega ja paljud teemad nõuaksid lisauuringuid. Näiteks hariduse valdkonnas oleks huvitav laiendada IKT mõju analüüsi võrreldes erinevaid riike ja haridustehnoloogiale tehtavaid kulutusi. Hariduspoliitika kooli taseme mõjude analüüsis on palju avatud otsi seoses mõjude heterogeensusega ehk riigi või haridussüsteemi spetsiifilisusega. Miinimumpalga mõju uurimisel võiks keskenduda firma-tasemel andmete analüüsile ja näidata, kuidas ja kas miinimumpalga muutused on mõjutanud ettevõtete tootlikkust. Metoodiline ja andmestikuline rikkus võib panustada antud teemade uurimisse jätkuvalt.
# Appendix

# Paper I

# SCHOOL - LEVEL POLICIES AND THE EFFICIENCY AND EQUITY TRADE-OFF IN EDUCATION

# Publication:

Ferraro Simona, Kaire Põder, 2017 (forthcoming). School-level policies and the efficiency and equity trade-off in education. *Journal of Policy Modeling*, available online from 27 November 2017 at https://www.sciencedirect.com/science/article/pii/S0161893817301199 DOI: https://doi.org/10.1016/j.jpolmod.2017.11.001

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# Draft as conference proceedings:

Ferraro, S., Poder, K. 2017. School-level policies and the efficiency and equity trade-off in education. 5<sup>th</sup> Workshop on Efficiency in Education "Efficiency in education and performance measurement in public sector", 19-20 October 2017, Budapest, Hungary.

Ferraro, S., Poder, K. 2017. School-level policies and the efficiency and equity trade-off in education. Seventh ECINEQ Meeting 2017 – The Graduate Center City University of New York, 17-19 July 2017, New York, New York.

Ferraro, S., Poder, K. 2016. School-level policies and the efficiency and equity trade-off in education. Emerging Researchers' Conference 22-23 August 2016, Dublin, Ireland.

Ferraro, S., Poder, K. 2016. School-level policies and the efficiency and equity trade-off in education. The European Conference on Educational Research 23-26 August 2016, Dublin, Ireland





Available online at www.sciencedirect.com





Journal of Policy Modeling xxx (2017) xxx-xxx

www.elsevier.com/locate/jpm

# School-level policies and the efficiency and equity trade-off in education

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Received 24 July 2017; received in revised form 28 October 2017; accepted 9 November 2017

### Abstract

This paper identifies the relationship between pupils' Family Background, their mathematics scores, and school-level policies, using the 2012 Programme of International Student Assessment for Italy and multilevel modelling. School-level policies have played a leading role in recent school reforms in many countries, but there is no straightforward empirical evidence for how they affect pupils' outcomes and the equality of educational outcomes. Our findings show that that only some school policies intensify the Family Background Effect – (educational equity) and affect student outcomes (educational efficiency) simultaneously. We find that competitive schools are able to screen students by selecting higher socio-economic status parents, which mainly harms equity without having much effect on efficiency. There are some policies which allow some trade-off between aforementioned objectives, mainly policies related to management schools. © 2017 The Society for Policy Modeling. Published by Elsevier Inc. All rights reserved.

JEL classification: I21; I24; C19

Keywords: School-level policies; Equity; Efficiency PISA2012; Multilevel modelling

# 1. Introduction

Increasing cross-country evidence supports the normative platform from the Organization of Economic Cooperation and Development (OECD) and it shows that institutional structures of

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https://doi.org/10.1016/j.jpolmod.2017.11.001

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school systems are important for the efficiency and equity of educational outcomes. We indicate these institutional structures as school-level policies.

In recent decades, the most hotly disputed debates have centred around choice policies such as public or private school, competition between schools, ability grouping (students are grouped by their ability) and management policies such as *assessment* (assessment by national performance or assessment by other schools); *accountability – external evaluation* or the process of evaluating schools on the basis of the performance of their pupils considering them responsible for their performance; *autonomy* or decentralisation of decision-making power that we study by principal as responsible for disciplinary policy and for budget; and *achievements*, and these groups of policies play a leading role in recent school reforms in many countries that in our study we identify as achievement posted publicly. These disputes supported by empirical insights have in general stressed the role of all aforementioned school-level policies in promoting educational efficiency.

The OECD (2013) study, supported by Woessmann (2007) and Woessmann, Luedemann, Schuetz and West (2007), shows that where schools have more autonomy over curricula and assessments, they tend to perform better overall. Looking at accountability, Woessmann (2007) argues that pupils perform better when policies are in place, such as external exit exams or publicly funded private schools; autonomous teachers, through monitoring of lessons; and accountability of schools, such as assessment-based comparisons. Moreover, pupils perform better in countries with more choice and competition as measured by the share of privately managed schools, the share of total school funding from government sources, and the equality of government funding between public and private schools.

This paper proposes a case specific insights of school-level policies and how they affect pupils' achievement and educational equity in Italy. The Italian educational system is an interesting case to study: Põder, Kerem and Lauri (2013) using cross-country estimates and calibrating scores of efficiency and equity and show that the Italian educational system is a distinct case characterised by high equity and low efficiency scores. However, this outlier position underlines the possible trade-offs between efficiency and equity. We address the question whether there is a room for increasing efficiency as student scores while not harming equity that we express as outcome dependence of families background characteristics.

We discuss previous policy decisions and why despite several reforms, the educational system of Italy is close to a breaking point and gives some suggestions based on our findings to get the resources to respond more positively in terms of performance as well as equity. Without discovering the causal mechanism for how Family Background Effect (FBE) is determined, we show that some school-level policies intensify it. Moreover, we contribute to the empirical literature by giving evidence that some school-level policies related to school-choice not only lead to efficiency, but also have a negative effect on equity, while some management policies bring along efficiency without hurting equity.

The motivation for the single case study – Italy – is not relying only on "outliers' logic" of research design, it treats the problem of unobserved country heterogeneity. Our analyses of single case is to study school system within one country with the same language, same legal system and same general culture, and the like, to test whether school-level policies have effects on efficiency and equity on particular case and avoid biases from other system level characteristics.

The analysis focuses on Italy using the 2012 PISA-OECD standardised test scores, which originate from a test and survey of 15-year-old pupils accompanied by intensive family and school-level controls. Our dataset consist of more than 30,000 observations. We apply the multilevel method, given the nested nature of the dataset. For the efficient regression estimation the effects

of variables of different hierarchies – school and region – can be studied simultaneously, taken account the correlation between the variables of those units in the same group, whether school or region.

The article proceeds as follows: in Section 2 the background with the empirical studies and an overview of the case specificities of Italian education system. Section 3 explains the research design while in Section 4 we present our findings. In Section 5 we elaborate our findings by giving policy discussion.

# 2. Background

### 2.1. Empirical studies

Human capital approach to the socio-economic development of countries (Asteriou & Agiomirgianakis, 2001; Hanushek & Kimko, 2000; Hanushek & Woessmann, 2012) is defining the goals of education policy as a two-fold coin – efficiency and equality of opportunity. The debate on school choice and competition among schools is still very much alive, indicating that empirical international evidence (e.g. Fertig & Schmidt, 2002; Raitano & Vona, 2010) produce mixed results.

The Italian debate traditionally focuses on the public financing of private schools even though it is not clear whether competition influences the average level of achievement in Italian schools (Agasisti, 2010). On the other hand, empirical insights have increased significantly when cross-country international studies of students' performance such as PISA have been run. Whitty (1997), Clark (2009), and Machin and Vernoit (2011) have shown that there has also been an international trend towards giving schools increased authority in making autonomous decisions on curricula and resource allocation in order to raise performance levels by encouraging responsiveness to student and school needs at the local level.

Assuming that pupils and parents have sufficient information to be able to choose schools based on academic criteria or the programme quality, competition for schools promises to create incentives for institutions to organise programmes and teaching in ways that better meet diverse student requirements and interests, thus reducing the cost of failure and mismatches. For instance, Bishop (2006) indicates that signalling student achievement to institutions of higher education or potential employers using external school-leaving exams boosts both students' rewards for learning and parents' interest in monitoring the education process interpreted as an accountability device. Using PISA 2000 and 2003 and micro-econometric cross-country analysis, Woessmann (2005a, 2005b), Fuchs and Woessmann (2007) control for FB and school input factors at the student level, confirm Bishop's (2006) findings.

Another study based on PISA (Woessmann, 2003) show that students perform significantly better in schools that have autonomy in decisions about processes and personnel such as the purchase of supplies, budget allocations within schools, the hiring and rewarding of teachers, and the choice of textbooks or instructional methods. Fuchs and Woessmann (2007) find that private school management tends to be positively associated with student achievement in PISA 2000, while Woessmann, Luedemann, Schuetz, and West (2009) find similar results for PISA 2003 but claim that the pattern is not uniform across countries.

Similarly, Vandenberghe and Robin (2004) study the effect of private school operation in eight countries in PISA 2000, finding positive effects only in some countries. Similarly, Corten and Dronkers (2006) show a positive association between the achievement of students with low

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socio-economic status and private government-dependent schools, but no significant differences between public and private-independent schools.

Studies on competition between schools show that none can refute the potential benefit of competition because the main advantage stems from the incentive for "technical" efficiency. Schools which operate in a competitive environment usually tend to be more productive (Belfield & Levin, 2002). Hoxby (1994, 1996, 2001) also indicates positive effects of school-level policies showing that competition between public and private schools increase the quality of public schools and students' productivity which is indicated as students' achievements.

Advocates of the decentralization or school-level policies often argue that the introduction of market mechanisms in education allows equal access to high quality schooling for all, as the expansion of school choice opportunities allows all pupils, including disadvantaged ones and those attending low performing schools, to change to better schools, thus increasing equity (Põder & Kerem, 2012). Teacher autonomy over the subject matter in the class and school autonomy over the budget negatively affects students' achievement; by contrast, school autonomy in staffing decisions and in hiring teachers has a positive effect (Hanushek & Woessmann, 2011). However, the interaction between school autonomy embodies the functions already mentioned as negatively associated with student's achievements but there are also external exit exams, the positive effect is larger than when there is accountability but no formulating of the budget and teachers' autonomy (Woessmann et al., 2009).

In cross-country evidence, using various surveys about international students' achievements, is indicated that students perform better with external exit exams, school autonomy in process and personal decisions, and under publicly financed private schools. In terms of equity, less intensive tracking has a significant effect (Ponzo & Scoppa, 2014). Most studies show little trade-off between policies (Hanushek & Woessman, 2006; Schuetz, Ursprung & Woessmann, 2008). While in Italian case specific contributions are on Family Background Effects (FBEs) and pupils' outcomes (Bratti, Checchi, & Filippin, 2007; Checchi, 2004; Quintano, Castellano, & Longobardi, 2009; Tramonte, 2004) or on efficiency by Agasisti and Cordero Ferreira (2013) showing the gap between the North and the South of Italy, with differences between school types, and that socio-economic background has a major impact in predicting students' results.

# 2.2. Case specification

Incentivized by "outlier" position and competitive-status of OECD policy platform, Italian educational system has been challenged by several reforms. In 2015, Renzi's Government implemented the latest reform "La Buona Scuola".<sup>1</sup> The reform intended to "fully implement" the law on school autonomy proposed already in March 1997. It has as main objective to increase autonomy, transparency, responsibility, fair valuation and merits in the educational system. The educational goals (aims) have turned into de facto market purposes.

During the last ten decades, the Italian schooling system has been centrally managed and financed. Since the unification of the country in the nineteenth century, the long Italian heritage was enclosed through the education system. This created a national identity where the national government has had the main responsibility for regulating and funding education and the high

<sup>&</sup>lt;sup>1</sup> "Reform of the national system of education and training and for the reorganisation of the laws in force" is Decree no. 107 of 13 July 2015 of the Italian Ministry of Education, University and Research (MIUR).

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number of education Ministers has generated an arising instability delaying necessary reforms into the educational system (OECD, 1998).

A process of giving schools more autonomy in financial management, teacher evaluation and teaching organisation has been underway since 2000. Thus, the topic of the autonomy of schools, both public and private, has been a hot topic for same years in Italy where private schools have higher margins of autonomy than public schools do. This factor is particularly evident in international comparisons (OECD, 2007).

The concern is that the present public monopoly on schooling is not able to guarantee high-level results, Italian pupils have lower performance than other OECD counterparts and the "catchment areas" of the schools, dismantled without any debate (Italian Ministry of Education, 1998) and replaced with the introduction of the Piano di Offerta Formativa, through which schools offer their educational products to all potential recipients without geographic limitation beyond the availability of classrooms, have not given the outcomes that were hoped for.

In the last decades, Italy has experienced a generalised increase in the level of education but the growth in the percentage of individuals with a secondary education over the years, has not been enough to close the educational gap between the North and the South of the country (Brunello, Lucifora, & Comi, 1999). Parents are free to choose any school to send their children but, limitations may be arise due to a lack of available facilities or the lack of school staff assigned to each school by the school administration. Each school will establish its own criteria for the enrolment of students in case applications exceed the number of places available and schools and local authorities must work closely together to guarantee the right of all to study (Eurydice, 2014).

# 3. Research design

### 3.1. Model specification

Economists have studied education production functions since the release of the Coleman report (Coleman et al., 1966) in the 1960s but Hanushek (1979) conducted the most comprehensive study of this literature. PISA data, as cross-sectional data, are affected by omitted variables and one way of reducing bias in the estimate is to control for several characteristics.

The general form of the education production function indicates the following structure (Hanushek, 1979):

$$T_i = f(I_i, F_i, C_i, S_i) \tag{1}$$

where  $T_i$  is their achievement;  $I_i$  is the vector of innate abilities;  $F_i$  is the family background influence;  $C_i$  is the vector of influences of peers; and  $S_i$  is the vector of school level policies while the subscript *i* is pupils. A student's school achievement is operationalised by test scores, while inputs such as teacher's efforts and quality, and other family characteristics are operationalised by a variety of measures.

This paper focuses on schools-level policies, controlling for individuals, family-level and schools measures. The analysis includes school-level variables and takes the school effect into account by using the estimation technique. The specification of our final model was carried out in the conventional form (Hox, 2002; Raudenbush & Bryk, 2002).

The starting point was a null model (without explanatory variables) to evaluate the variance decomposition of the dependent variables between the proposed levels of choice and management,

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then explanatory variables of different levels and types of effects were added to give the final model, which is formally expressed in Eq. (2):

$$\Psi_{\iota\varphi}\beta_{0j} + \sum_{p=1}^{p}\beta_{p_0}X_{p_{ij}} + \sum_{q=1}^{q}\beta_{qj}Z_{q_{ij}} + U_{oj} + \alpha_{0j} + \sum_{p=1}^{p}\alpha_{p_0}X_{p_{ij}} + \sum_{q=1}^{q}\alpha_{qj}Z_{q_{ij}} + e_{ij}$$
(2)

where  $Y_{ijr}$  is the expected educational result of student *i* at school *j*;  $\beta_{0j}$  ( $\alpha_{0j}$ ) is the intercept of the regression line for school *j*;  $X_{pji}$  is the set of *S* independent variables at level 2 with fixed effects;  $\beta_{p0}$  ( $\alpha_{p0}$ ) is the coefficient that accompanies the explanatory variables *X* and so does not vary between mean;  $Z_{qij}$  is the set of *Q* independent variables at level 2 with random effects;  $\beta_{qj}$  ( $\alpha_{qj}$ ) is the coefficient that accompanies the explanatory variables *X* and so does not vary between mean;  $Z_{qij}$  is the set of *Q* independent variables at level 2 with random effects;  $\beta_{qj}$  ( $\alpha_{qj}$ ) is the coefficient that accompanies the explanatory variables *Z* and so varies between mean; and  $U_{0j}$  ( $e_{ij}$ ) is the random deviation of student *i* with regard to the school average within each mean *j*.

The statistical methodology used is multilevel modelling with random intercept which estimates a regression line for each higher level unit, here schools, studying the effects of variables of different hierarchies simultaneously. It also takes account of the existence of a greater correlation between the variables of those units in the same group, obtaining more efficient estimations (Levacic & Vignoles, 2002; OECD, 2010).

Simple linear regression techniques did not properly account for the shared variance that is inherent when dealing with a nested structure and since the structure of the PISA dataset has one, multilevel modelling is the most appropriate model for investigating it as a powerful and flexible extension to traditional regression frameworks for exploring how micro-level variables are affected by structural micro and macro-level variables (Goldstein, 1995; Snijders & Bosker, 2012).

The procedure adopted is useful for analysing the performances at different levels such as student-level, school-level, and school macro areas, controlling for the variance across levels. This model allows us to decompose the variance of our dependent variable at the different levels of aggregation to assess the relative weight of the attributes at each level. We observe the decomposition of the variation in mathematic score between schools ("between schools") and among pupils within schools ("within schools").

The paper adopts a two-level approach in order to take account of the divergences among schools. We have two different stages.

*Stage a*: the null model is specified as:

$$Y_{ijr} = \gamma_0 + U_{0jr} + \varepsilon_{ijr} \tag{3}$$

where  $Y_{ijz}$  is the dependent variable (maths score) for the *i*th student in the *j*th school and *r*th regions;  $\gamma_0$  is the *Y* mean calculated from all pupils;  $U_{0jz}$  is the distance between the mean of the *j*th school and the overall mean or grand-mean (level-2 error); and  $\varepsilon_{ijr}$  is the level-1 error, which is defined as the difference between the mean of the *i*th student and the mean of the *j*th school. We can decompose the variance:  $\sigma^2$  which represents the variance within schools and  $\tau_u^2$  is the variance among schools.

The "Intraclass Coefficient of Correlation" (ICC) allows us to see the proportion of total variance that is due to differences between groups, by dividing the variance between schools and the total variance:

$$\rho = \frac{\tau_u^2}{\tau_u^2 + \sigma_e^2} \tag{4}$$

Please cite this article in press as: Ferraro, S., & Põder, K. School-level policies and the efficiency and equity trade-off in education. *Journal of Policy Modeling* (2017), https://doi.org/10.1016/j.jpolmod.2017.11.001

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The coefficient represents the part of the total variance that could be imputed to the "between schools" variance. If  $\rho \neq 0$ , a multilevel model will be adopted to account for the hierarchical nature of the data.

Stage b: the "Full" model - multilevel model with random intercept

At this stage we add some explanatory variables, or covariates, to the empty model in order to explain the between-schools and within-school variance. A two-level structure of the data is assumed in this paper, with pupils nested within schools and one covariate at the student level  $(x_{1ijr})$  and one at the school-level $(z_{1jr})$ .

The equation for the multilevel model with random intercept is:

$$Y_{ijr} = \alpha_{0jr} + \alpha_1 x_{1ijr} + \varepsilon_{ijr} \tag{5}$$

$$\alpha_{0jr} = \gamma_0 + \alpha_2 z_{ijr} + U_{0jr}$$

The random intercept  $\alpha_{0j}$  is also explained by considering the effect of  $z_{ijr}$ . From the two equations, a single equation can be formulated:

$$Y_{ijr} = \gamma_0 + \alpha_1 x_{1ijr} + \alpha_2 z_{ijr} + U_{0jr} + \varepsilon_{ijr}$$
(6)

In the previous two equations, two components can be identified: (i) a "fixed" part represented by  $\gamma_0 + \alpha_1 x_{1ijr} + \alpha_2 z_{ijr}$ ; and (ii) a "random" part with the error terms  $U_{0jr} + \varepsilon_{ijr}$ . Here it is assumed that the observations within schools are correlated.

Our final model is presented assuming s student-level variables and s school-level variables:

$$Y_{ijr} = \alpha_i \sum_{i=1}^{6} F_{ijr} + \beta_i \sum_{s=1}^{6} S_{jr} + \sum_{s=1}^{6} \gamma_i \left( F_{ijr} \cdot S_{jr} \right)$$
$$+ \delta_i \sum_{i=1}^{N} I_{jr} + \varepsilon_i \sum_{j=1}^{6} S_{jr} + \theta_i \sum_{r=1}^{5} M_{ij} + U_{ijr} + \varepsilon_{ijr}$$
(7)

where *i* indicates an individual at the school *j* from region *r*. Family background characteristics is indicated by  $\alpha_i$  while school-level policies  $S_{jr}$  are indicate by  $\beta_i$ . The interaction effect between FBE and school-level policies (choice and management) is expressed by  $\gamma_i$ . We also add the vector for individual level control variables  $I_{jr}$  such as gender, attended pre-primary school, immigration status and for school characteristics  $S_{jr}$  such as location and for regions  $M_{ij}$ .

The final estimated model has one response variable, which is the pupils' mathematics score (pv1math). Each observation unit has one value that forms the lowest hierarchy level (level 1).

# 3.2. Data

PISA-OECD 2012 is used in our analysis and the sample for Italy covers 31,073 pupils and 1194 schools. The dataset contains a lot of information that is useful for our analysis at the individual level and the family level, and for school characteristics and geographical areas (north, centre, south, and islands). We use as the dependent variable the mathematics score expressed by "pvImath". The descriptive statistics are presented in Table A1 in Appendix A. The data come from the National Institute for the Educational Evaluation of Instruction and Training (INVALSI),<sup>2</sup>

<sup>&</sup>lt;sup>2</sup> INVALSI: http://www.invalsi.it/invalsi/eng/echisiamo.htm.

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### Table 1

School-level policies, descriptive statistics.

| School-level policies   | % of students | % of schools |  |
|---|---------------|--------------|--|
| Choice policies   |               |              |  |
| Public or private school (public = 1)                         | 95.25         | 93.41        |  |
| Competition (two or more schools $= 1$ )                      | 29.50         | 30.49        |  |
| Students grouped by ability (for all classes = 1)             | 32.36         | 34.72        |  |
| Management policies   |               |              |  |
| Assessed by national performance $(yes = 1)$                  | 60.58         | 59.78        |  |
| Assessed by other schools (yes $= 1$ )                        | 34.77         | 33.82        |  |
| Achievements posted publicly $(yes = 1)$                      | 36.55         | 34.27        |  |
| Responsibility for disciplinary policy – principal (tick = 1) | 27.54         | 69.99        |  |
| Responsibility for budget – principal (tick = 1)              | 27.54         | 46.64        |  |
| External evaluation (yes = 1)                                 | 30.21         | 30.83        |  |

Source: PISA 2012, school questionnaire.

which carries out periodic and systematic checks of pupils' knowledge and skills, and of the overall quality of the educational offering of schools and vocational training institutes in Italy (INVALSI, 2012). The step-win specifications of the models are the following:

- a. Model 1 contains our main variables related to family background characteristics that indicates the highest level of education of both parents (hisced) and school-level policies such as choice and management. *Choice policies* are those such as competition between schools and grouped pupils by ability while *management policies* are indicated as assessment (assessed by national performance and assessed by other schools); accountability (external evaluation); achievement (achievement posted publicly); autonomy (responsibility for disciplinary policies and for budget allocation by the principal). We also have students, family and school variable controls.
- b. Model 2 includes the geographical areas of north, east, west, south and islands (MAREA);
- c. Model 3 includes several interaction terms which are related to the highest educational level of the parents and different school-policies such as competition between schools (HC), disciplinary policy (HDP), students grouped by ability (HAG), achievement posted publicly (HAC), external evaluation (HEE) and responsibility for budget (HRB) that we include to test how they affect our hypothesis.

Descriptive statistics of the school – level policies are presented in Table 1.

# 4. Results

# 4.1. Baseline results

Multilevel analysis is revealed in Tables 2 and 3. The decomposition of the variance in the empty model (Table 2) shows the total variance in the maths score, which is explained mostly by the differences between schools ( $0.535 \approx 54\%$ ). It is observed that the relative role of schools is greater than the relative role that personal and family characteristics (46%).

Regarding the analysis of the variance, coefficients indicate for the intercept that is the average maths score for all pupils in all schools. It is interesting in these models that the analysis of

| Table 2    |                     |         |
|------------|---------------------|---------|
| Multilevel | regression - random | effects |

|   | Null model       |
|---|------------------|
| Variance between schools $\tau_{\mu}^2$   | 4722.683 (47.3%) |
| Variance between pupils within schools $\sigma_e^2$   | 4118.414         |
| Total variance: $\tau_{\mu}^2 + \sigma_e^2$   | 8814.097         |
| Percentage of the residual variance that is explained by the variables over<br>the null model: school level | 54%              |

Source: authors' estimation based on the PISA 2012.

variance confirms how differences between and within schools exist. The variance within schools is lower than the variance between schools. The largest part of the variance is at school level, rather than at student level.

Our main results are presented in Table 3, column 4 which enables us to find out which factors related to school policies affect equity. The variable we are interested in, final model in column 4 is "Competition" and it has no significant effect on outcomes. Moreover, adding the interaction term – highest level of education of both parents and competition between schools (HC) – the same variable shows a positive coefficient but not statistically significant. We interpret it as having competition between schools creates additional efficiency that increases students' scores, but it comes at the expense of equity.

Thus, competition works by increasing FBE not by increasing efficiency and we can say that better pupils with better background characteristics are pulled together in highly competitive schools via choice and competition harm equity. We show that competition does not bring only efficiency, it just makes schools segregated as better FB pupils are grouped together by the selective practices of schools. For our study, we also introduce other interaction terms as already discussed in sub-Section 3.2 for Model 3. All coefficients for our interactions, with the exception of the interaction HC (hisced and competition) are statistically not significant and this means that they do not have any effect on efficiency.

The other variable "pupils grouped by ability" gives us an interesting and unexpected result: its coefficient is negative and statistically significant. Ability grouping has a positive effect on efficiency and a negative effect on equity and it is a surprising result given the literature. The results for school-level variables – *management* – show that assessment policies expressed by the variable "achievement posted publicly" has a positive effect and it increases the pupils' score. From assessment with the variables "assessed by national performance" and "assessed by other schools", only the first shows a significant impact on pupils' outcomes. These policies produce efficiency with no statistically significant moderating effect on equity and this argument is supported in our model 3. They do not produce additional inequality even as they boost efficiency.

School-level policies related to *autonomy* – responsible for budget allocation and responsible for school policy – have an opposite effect, as they reduce efficiency with no effect on equity. Introducing school characteristics do contribute to a reduction in between-schools variance, furthermore, considering all the interactions tested, the results show that none of them are statistically significant for our analysis.

The ownership of schools as public or private does not have a relevant impact on determining the PISA score, but the location of the school seems very important for a higher performance to be achieved among pupils. If schools are located in a "town" or "large city" there is a positive and statistically significant effect as the pupils' scores increase by about 40% and 52%.

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# Table 3

Multilevel model with random intercept.

| Variables  | Model 1<br>"Individual-school<br>level" | Model 2<br>"School policies" | Model 3<br>"Full model" |  |
|--|---|------------------------------|-------------------------|--|
| Highest aducational lavel of parents Hispad (refe  | ranca catagory - ISCE                   | <b>D1</b> )                  |                         |  |
| ISCED 2  | 13 820**                                | 14 042**                     | 13 544**                |  |
| ISCED 2  | (4 341)                                 | (4 339)                      | (4 362)                 |  |
| ISCED 3B C   | 26 313***                               | 26 253***                    | 25 112***               |  |
| iscel 5b, c  | (4 565)                                 | (4 562)                      | (4 650)                 |  |
| ISCED 3A ISCED 4                                   | 24 980***                               | 25 107***                    | 23 084***               |  |
|  | (4.307)                                 | (4.305)                      | (4.530)                 |  |
| ISCED 5B   | 8.611*                                  | 8.840*                       | 5.995                   |  |
|  | (4.496)                                 | (4.494)                      | (4.876)                 |  |
| ISCED 5A. 6  | 20.904***                               | 21.133***                    | 17.238***               |  |
|  | (4.335)                                 | (4.333)                      | (4.951)                 |  |
| Choice policies                                    |   |                              |                         |  |
| Public or private school (public = 1)              | 3.760                                   | 16.703**                     | 16.909**                |  |
|  | (8.527)                                 | (8.008)                      | (8.005)                 |  |
| Competition  | 11.671**                                | 10.988**                     | 4.786                   |  |
|  | (4.408)                                 | (4.100)                      | (4.915)                 |  |
| Students grouped by ability                        | -26.897***                              | -27.781***                   | -24.007***              |  |
|  | (4.261)                                 | (3.966)                      | (4.916)                 |  |
| Management policies                                |   |                              |                         |  |
| Responsibility for disciplinary policy – principal | 11.287**                                | 10.144**                     | 10.839**                |  |
| (tick=1)   | (4.907)                                 | (4.567)                      | (4.740)                 |  |
| Responsibility for budget – principal (tick=1)     | 0.539                                   | -3.230                       | -5.684                  |  |
|  | (4.433)                                 | (4.135)                      | (4.833)                 |  |
| Achievement posted publicly $(yes = 1)$            | 20.508***                               | 15.883***                    | 14.035***               |  |
|  | (4.383)                                 | (4.119)                      | (4.896)                 |  |
| External evaluation (tick = 1)                     | 2.055                                   | -2.538                       | -5.037                  |  |
|  | (4.409)                                 | (4.407)                      | (4.915)                 |  |
| Assessed by national performance ( $yes = 1$ )     | 1.558                                   | 8.543**                      | 8.529**                 |  |
|  | (4.590)                                 | (4.301)                      | (4.298)                 |  |
| Assessed by other schools (yes = 1)                | 4.295                                   | 2.933                        | 2.932                   |  |
|  | (4.713)                                 | (4.377)                      | (4.3/4)                 |  |
| HC (hisced*competition between schools)            | -                                       | -                            | 1.4//**                 |  |
|  |   |                              | (0.645)                 |  |
| HAG (hisced*student grouped by ability)            | -                                       | -                            | -0.902 (0.632)          |  |
| HSP (hisced*responsible for disciplinary           | -                                       | -                            | 0.302                   |  |
| policies – principal)                              |   |                              | (0.570)                 |  |
| HKB (nisced*responsible for                        | -                                       | -                            | 0.541                   |  |
| budget – principal)                                |   |                              | (0.018)                 |  |
| HAC (msced*achievement posted publicity)           | -                                       | -                            | (0.514)                 |  |
| HEE (hissad*autamal avaluation)                    |   |                              | (0.018)                 |  |
| THEE (Inscent external evaluation)                 | -                                       | -                            | (0.647)                 |  |
| Student level                                      |   |                              |                         |  |
| Gender (female = 1)                                | -26.535***                              | -26.490***                   | -26.469***              |  |
| · /  | (0.886)                                 | (0.886)                      | (0.886)                 |  |

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| Table 3 | (Continu | ed) |
|---------|----------|-----|
|---------|----------|-----|

| Variables   | Model 1<br>"Individual-school<br>level" | Model 2 "School<br>policies" | Model 3 "Full<br>model" |
|---|---|------------------------------|-------------------------|
| Attended pre-primary school (yes = 1)                 | 26.452***                               | 26.872***                    | 26.808***               |
|   | (2.176)                                 | (2.175)                      | (2.175)                 |
| Immigration status (native = 1)                       | 21.650***                               | 22.313***                    | 22.326***               |
|   | (1.520)                                 | (1.520)                      | (1.520)                 |
| Family structure (single parent = 1)                  | -0.965                                  | -1.261                       | -1.249                  |
|   | (1.346)                                 | (1.346)                      | (1.346)                 |
| School location (reference category = village)        |   |                              |                         |
| Small town  | 17.336                                  | 28.796**                     | 28.857**                |
|   | (10.783)                                | (10.071)                     | (10.066)                |
| Town  | 30.857**                                | 40.535***                    | 40.637***               |
|   | (10.302)                                | (9.663)                      | (9.659)                 |
| City  | 29.760**                                | 35.983***                    | 36.011***               |
| -   | (10.778)                                | (10.046)                     | (10.042)                |
| Large city  | 39.861**                                | 53.038***                    | 52.738***               |
|   | (14.624)                                | (13.886)                     | (13.881)                |
| MAREA (reference category = North West)               |   |                              |                         |
| NORD EST (North East)                                 | -                                       | 19.515**                     | 19.387**                |
|   |   | (5.745)                      | (5.743)                 |
| Centro (Centre)                                       | -                                       | -8.861                       | -8.832                  |
|   |   | (6.414)                      | (6.410)                 |
| Sud (South)   | -                                       | -34.621***                   | -34.722***              |
|   |   | (6.350)                      | (6.349)                 |
| SUD ISOLE (Islands)                                   | -                                       | -42.990***                   | -43.101***              |
|   |   | (6.316)                      | (6.315)                 |
| Between-schools variance $(\tau^2)$                   | 3824.59                                 | 3254.83                      | 3249.23                 |
| Within-schools between students variance $(\sigma^2)$ | 3832.48                                 | 3834.06                      | 3832.85                 |
| % between (ICC)                                       | 50%                                     | 46%                          | 46%                     |
| No. of observations (pupils)                          | 25706                                   | 25706                        | 25706                   |
| No. of groups (schools)                               | 1028                                    | 1028                         | 1028                    |

Notes: \*\*\*1%; \*\*5%; \*10% SE in parentheses. Author's elaboration based on OECD-PISA2012 data.

We do not confirm or reject the empirical evidence that school autonomy in financing decisions improves the average scores of the students, while autonomy in contents has the opposite effect. Accountability policy in terms of external evaluation, shows a negative effect. Finally, the geographical areas (MAREA) show the clear gap between North and South Italy where the effect in the south is much larger, in negative values, than the northern areas.

# 5. Conclusions

This paper investigates the relationship between pupils' mathematics scores, family background characteristics and school-level policies, employing a multilevel modelling for Italy using PISA data 2012. The topic is relevant given that multi-cultural communities are rapidly populating Europe and leading to increasing diversity, which is obviously challenging for policies that strive to promote socio-economic inclusion and prevent segregation.

We can summarise two different conclusions at the family level and at the school level. Our main conclusions from the empirical modelling (Table 3) are partially in alignment with theory

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Fig. 1. Caterpillar for schools. Source: authors' elaboration based on the OECD-PISA 2012 data.

and intuition. Firstly, a highly interesting result is the positive significant interaction between the parental educational attainment level and competition between schools, stressing that in a competitive environment the family background characteristics matter even more, which might lead to higher between-school segregation.

Competitive schools are able to screen students by selecting higher socio-economic status parents, which does not affect efficiency but harms equity. Secondly, we show that accountability and autonomy not only improve efficiency, but also have no effect on equity. This finding is the novelty in our research. We showed that ability grouping hurts efficiency without significant effects on equity, while some management policies affect efficiency positively without any effect on equity. Also the size of some management policies mainly achievement posted publicly is approximately 14 PISA points which is remarkable approximately half year progression of the student.

At the regional level, our results also indicate as expected that students in the north perform better while results are worse in the south. This shows a further evidence of the disparity within the Italian educational system. The school residuals might be regarded as a school effect – expressed by the term 'value added' – in school effectiveness and represents the difference from the observed level of school performance. A positive "value added score" expressed as a residual indicates that a school may be performing above expectations while a negative value added score indicates that a school may be performing below expectations as we also highlight in Appendix A – Fig. 1.

Despite of several reforms, there is comparative evidence that Italy has disperse geographical divide in both dimensions – students' outcomes and equity of educational opportunity. From a policy point of view, highlighting that the educational policy platform has to rest on two pillars such as equity and efficiency, our findings suggest that the reform towards decentralization and school autonomy indicate that competition between schools groups better peers and allows cream-skimming without any effect on efficiency in the system level. So we advocate against choice policies. However, we find three policies (achievement posted publicly, responsibility for disciplinary policy and assessed by national performance) that do not have significant effect on equity while increasing efficiency. Thus, we advocate for management policies.

Please cite this article in press as: Ferraro, S., & Põder, K. School-level policies and the efficiency and equity trade-off in education. *Journal of Policy Modeling* (2017), https://doi.org/10.1016/j.jpolmod.2017.11.001

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It may be argued that decentralization empowers people and creates innovation meaning that more autonomy for schools is a valuable tool for adapting education goals in specific context, but it cannot be an end in itself. Autonomy of schools brings along competitive environment, where schools compete for the "input", which has widen the outcome gap between "good" and "not so good" family background students without statistically significant effect on efficiency. However, management reforms that have been implemented in Italy, has given more decision-making power to the schools but it may be argued at normative ground that there is still much to do in increasing families' participation, incentivising school teachers to improve quality and mainly, financing education through using resources more efficiently.

The main message that emerged from our findings is that pupils' outcomes are driven not only by their socio-economic background and other student characteristics, but also by how schoollevel policies are executed. The effect of schools' policies, upon pupils' achievement and the size of FBEs reflects on efficiency at the individual level, while the size of the FBE indicates inequality, as the bigger the FBE is, the worse equality is. School policy features show that some school policies are able to obtain good results while others are not where the high level of betweenschools variance also suggests that some schools' characteristics are likely to play an effective role in influencing students' results.

# Acknowledgements

We are grateful to the Italian Institute for the Evaluation of Education (INVALSI) which kindly provided us the dataset. The authors would like to thank Prof. Karsten Staehr for extensive suggestions. We want to thank anonymous referees for their useful comments. This research was supported by project PUT315 "Towards the Knowledge Economy: Incentives, Regulation and Capital Allocation".

# Appendix A.

### Table A1 Descriptive statistics.

| Variables   | # obs  | Mean | Std. dev. | Min | Max |
|---|--------|------|-----------|-----|-----|
| PISA OECD (34 OECD countries <sup>a</sup> )                               |        | 494  | 94        |     |     |
| PISA Italy  | 31,073 | 485  | 92        | 108 | 811 |
| Dependent variable  |        |      |           |     |     |
| pv1math   | 31,073 | 492  | 91        | 109 | 812 |
| Individual level  |        |      |           |     |     |
| Gender (female = 1)   | 31,073 | 0.49 | 0.50      | 0   | 1   |
| Attended pre-primary school (yes $= 1$ )                                  | 31,073 | 0.96 | 0.19      | 0   | 1   |
| Immigration status (native = 1)   | 31,073 | 0.09 | 0.29      | 0   | 1   |
| Family structure (single parent $= 1$ )                                   | 29,719 | 0.10 | 0.30      | 0   | 1   |
| Highest educational level of parents – Hisced (reference category ISCED1) | 30,594 | 4.23 | 1.43      | 1   | 6   |

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### Table A1 (Continued)

| Variables   | # obs  | Mean | Std. dev. | Min | Max |
|---|--------|------|-----------|-----|-----|
| School-level  |        |      |           |     |     |
| Public or private school (public = 1)                         | 29,250 | 0.95 | 0.21      | 0   | 1   |
| School location (reference category village)                  | 29,018 | 3.03 | 0.83      | 1   | 5   |
| Small town  | 29,018 | 0.20 | 0.40      | 0   | 1   |
| Town  | 29,018 | 0.52 | 0.50      | 0   | 1   |
| City  | 29,018 | 0.22 | 0.41      | 0   | 1   |
| Large city  | 29,018 | 0.04 | 0.19      | 0   | 1   |
| Competition between schools                                   | 31,073 | 0.29 | 0.46      | 0   | 1   |
| Students grouped by ability                                   | 28,282 | 0.32 | 0.47      | 0   | 1   |
| School-level – management                                     |        |      |           |     |     |
| Assessed by national performance $(yes = 1)$                  | 28,607 | 0.61 | 0.49      | 0   | 1   |
| Assessed by other schools $(yes = 1)$                         | 28,639 | 0.35 | 0.48      | 0   | 1   |
| Achievement posted publicly $(yes = 1)$                       | 28,813 | 0.37 | 0.48      | 0   | 1   |
| Responsibility for budget – principal (tick = 1)              | 29,244 | 0.45 | 0.50      | 0   | 1   |
| Responsibility for disciplinary policy – principal (tick = 1) | 29,250 | 1,72 | 0.45      | 0   | 1   |
| External evaluation (tick = $1$ )                             | 28,220 | 0.30 | 0.46      | 0   | 1   |
| MAREA   |        |      |           |     |     |
| NORD EST (North East)   | 31,073 | 0.27 | 0.45      | 0   | 1   |
| CENTRO (Centre)   | 31,073 | 0.19 | 0.39      | 0   | 1   |
| SUD (South)   | 31,073 | 0.18 | 0.39      | 0   | 1   |
| SUD ISOLE (Islands)   | 31,073 | 0.19 | 0.39      | 0   | 1   |

<sup>a</sup> Source: OECD – PISA2012 data.

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# Paper II

# IS INFORMATION AND COMMUNICATION TECHNOLOGY SATISFYING EDUCATIONAL NEEDS AT SCHOOL?

# **Publication:**

Ferraro Simona, 2018. Is information and communication technology satisfying<br/>educational needs at school? Computers and Education, vol. 122, pp. 194-204, available<br/>online from 2 April 2018 at<br/>https://www.sciencedirect.com/science/article/pii/S0360131518300824<br/>DOI: 10.1016/j.compedu.2018.04.002 (ETIS 1.1)

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Computers & Education 122 (2018) 194-204

Contents lists available at ScienceDirect



# **Computers & Education**

journal homepage: www.elsevier.com/locate/compedu

# Is information and communication technology satisfying educational needs at school?



Computer Education

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#### ARTICLE INFO

Keywords: ICT Bayesian additive regression tree Posterior distribution PISAJEL Classification: I20 O33 C25

#### ABSTRACT

This paper assesses how the integration of ICT in education has affected the mathematics test scores for Italian students measured by the Programme for International Student Assessment 2012 data. The problem of endogeneity that affects survey data in this area, is addressed by applying the Bayesian Additive Regression Trees (BART) methodology as in Cabras & Tena Horrillo (2016). The BART methodology needs a prior and likelihood functions using the Markov Chain Monte Carlo (MCMC) algorithm to obtain the posterior distribution. Controlling for socio-economic, demographic and school factors, the predicted posterior distribution implies an increase, on average, of 16 points in the test scores. The result indicates that the use of ICT at school has a positive and strong impact on mathematic test scores.

### 1. Introduction

Since the beginning of the 1990s, Information and Communication Technology (ICT) and its impact on students' achievements have interested educators and policy makers. Alike with the aim to improve digital skills among students, the Organization for Economic-Cooperation and Development (OECD, 2010a, 2010b, p. 102) has advanced its use with the argument that there is "a significant influence or effect of ICT on the measured or perceived quality of (parts of) education".

The United Nations Educational, Scientific and Cultural Organization (UNESCO) states that "ICT adds value to the processes of learning, and in the organization and management of learning institutions. The Internet is a driving force for much development and innovation in both developed and developing countries" (UNESCO, 2002, p. 9). ICT may indeed be seen as important for the quality of the education systems. Through education, a country creates human capital needed to lead to a higher economic growth (Barro, 2001; Hanushek & Kimko, 2000).

Following the OECD guidelines, European countries has made substantial investments in ICT for educational purposes (OECD, 2015). The European Commission highlighted the use of ICT for work, leisure and communication as among the key abilities and strengths that students need to improve (European Commission, 2006). According to the PISA results from 2009, one computer was available for every two students within schools for most of the OECD countries except for Italy. The disparity within the Italian country is high and only one computer was available up to eight students. In 2012, the gap had decreased and the students-computer ratio was 4.1 to 1 meaning one computer available at school for every four students (Eurydice, 2011 Figure E3; OECD, 2015).

The European Union (EU) has also advised its Member States to invest in digital technologies within their education systems. The Member States agreed to promote the use of new ICT tools within the first cycle of the Strategic Framework for Education and Training known as 'ET 2020' (Eurydice, 2011). This initiative followed the eLearning initiative promoted in 2000 by the European Commission (2000) with the goal to improve the effectiveness of European education systems, and also the competitiveness of the

https://doi.org/10.1016/j.compedu.2018.04.002

Received 30 May 2017; Received in revised form 31 March 2018; Accepted 3 April 2018 Available online 06 April 2018 0360-1315/ $\odot$  2018 Published by Elsevier Ltd.

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European economy. The integration of ICT at school has seen as a powerful tool to improve technology-related competencies for all students.

The literature regarding the impact of ICT on students' achievements is quite extensive. Several meta-analyses, experimental and parametric studies have been produced but the literature is not unanimous with regard to the effect of ICT on educational outcomes. Cheung and Slavin (2013) provide a meta-analysis study showing that the use of technological applications in education have, in general, a positive impact on students' outcome. Another study from Germany adopting the Programme for International Students Assessment (PISA) survey shows that there is no effect of the use of ICT on PISA test scores (Wittwer & Senkbeil, 2008). The divergent outcomes of those studies suggest that new evidences and approaches are warranted.

This paper assessed whether the use of ICT have had an impact on test scores using large-scale data such as OECD-PISA survey by a new flexible nonparametric model. PISA 2012 survey is a very rich data which also contains questions on the use of ICT among students. As Rojano (1996) states in her work, technology allows students to have the perception of owning the subject. Using a computer with the appropriate software, students can present and observe solutions in real time, for example, how the shape of a geometric object can change.

The paper contributes to the literature by providing new evidences with the application of a new non-parametric methodology compared to what previous researchers have applied (https://www.sciencedirect.com/science/article/pii/S0360131514000463; Angrist & Lavy, 2002; Cheung & Slavin, 2013; Machin, McNally, & Silva, 2007). Moreover, students from 32 OECD countries included Italy, who participated in the PISA 2012 Paper-Based Assessment (PBA) were also invited to take a reading and mathematics test on computers.<sup>1</sup> The case of Italy is interesting given the results of Italian PISA 2012 test scores above the OECD average using the Computer-Based Assessment (CBA) compared to the results obtained in PISA 2012 using the Paper-Based Assessment (PBA). It is worth to mention that Italian PISA scores using PBA test have usually been below the OECD average in all different set of tests such as reading, mathematics and science (OECD, 2015).

The paper uses a new nonparametric methodology known as Bayesian Additive Regression Trees (BART). The BART model was developed by Chipman, George, and McCulloch (2010) and Hill (2011) and, first applied by Cabras and Tena Horrillo (2016) using Spanish PISA 2012 data. It is a new flexible econometric model which makes it possible to deal with the problem of endogeneity that arises using surveys such as PISA. From an econometric perspective, student and school characteristics may be correlated and the omission of some variables may generate endogeneity bias.

The motivation to adopt the BART model in the field of economics of education is, mainly related to the fact that learning processes are complex, unknown and very heterogeneous. The model relaxes the parametric assumptions and addresses the sample selection problems in survey data as PISA data. The BART model has the aim of providing new results on a single country perspective and stimulate further debates among researchers. The focus, then, on student performance in mathematics is highly correlated to results in reading so that the results presented for mathematic test score can be generalized also to reading.

The rest of the paper is organised as follows. Section 2 reviews the literature, Section 3 presents a review of the Bart Additive Regression Trees and data used in the empirical study, Section 4 provides the main estimation results and robustness check, and Section 5 summarises the results.

#### 2. Literature

The study of the impact of ICT use on mathematics test score in primary and secondary schools has gained interest in the academic literature since the beginning of the '90s. Meta-analyses and single studies have been published but, results are still mixed as several studies have shown (Balanskat, Blamire, & Kefala, 2006; Pedrò, 2006; Hakkarainen et al., 2000; Hatlevik, Ottestad, & Throndsen, 2015b, 2015a; Kulik & Kulik, 1991; Luu & Freeman, 2011; Rutten, van Joolingen, & van der Veen, 2012; Tamim, Bernard, Borokhovski, Abrami, & Schmid, 2011).

The existing literature can be grouped into three main areas according to the methodology applied in the study. Some studies have adopted parametric models (Angrist & Lavy, 2002; Goolsbee & Guryan, 2006; Machin et al., 2007), a study was conducted through experiment as in Banerjee, Cole, Duflo, and Linden (2007) while others adopted non-parametric models (Cabras and Tena Horrillo, 2016; Fuchs & Woessmann, 2004; Spieza, 2010). This literature review, however, provides a short survey of the numerous studies on the topic.

Angrist and Lavy (2002) adopt Ordinary Least Squared and the Instrumental Variables (IV) strategy using test scores for Israeli for 1998. They find a negative impact for mathematic test scores after the introduction of computers at school. In the UK, Machin et al. (2007) also using IV strategy show that higher investment in ICT leads to better educational outcomes for reading and science but not for mathematics. Regarding studies using experiment, Banerjee et al. (2007) conduct a randomized experiment in India to study the causal impact of computers on students' performance. They compare the change in the test scores among students who received the treatment and students who did not receive it represented by the use of a computer. They find that students who were able to use a computer have also higher mathematic test score compared to their peers.

Among some studies that have applied non-parametric methods and PISA data, there are works by Spieza (2010), Fuchs and Woessmann (2004), Shewbridge, Ikeda, and Schleicher (2005). Using PISA 2006 for science score in OECD 33 countries, Spieza (2010) shows a positive correlation between the availability of computers at school and school performance. He estimates an endogenous treatment model where the frequency of computer use is modelled on specific students' characteristics. In their study, Fuchs

<sup>&</sup>lt;sup>1</sup> Computer-Based Assessment for PISA 2012 did not include science literacy.Cabras and Tena Horrillo (2016)

and Woessmann (2004) control for numerous variables with a known impact on achievement using PISA 2000 and two stage least squares. They show that there is a positive correlation of the home computer use but this effect is almost neutral or even negative for the use of computer at school.

In their studies, Shewbridge et al. (2005) find no effect of the use of ICT at school and PISA 2003 test scores such as reading, mathematics and science. A new flexible non-parametric approach from the Bayesian family, has been employed with PISA data by Cabras and Tena Horrillo (2016). They study the causal impact of ICT on educational outcomes adopting a new model from the Bayesian models for Spanish PISA 2012 data that represent a general survey for the whole student population including a rich collection of information on individual, family and school levels. The BART model allows them to overcome the endogeneity problem that arises from the survey and using some control variables, their findings show that the use of ICT has a strong positive effect on students' achievements. This paper follows the methodology in Cabras and Tena Horrillo (2016) for Italian data.

In Italy, the investment in ICTs and its introduction at all levels of compulsory education, is crucial for the development of digital skills (Annali della Pubblica Istruzione, 2012). The Ministry of Education have released a survey known as 'Teaching Multimedia Equipment Survey' to individuate technological instruments adopted by schools such as the use of the Internet, amount and speed of Internet connections, ratio of classrooms equipped with wireless connectivity, total number of computers (desktop and laptop), mobile devices. The data are available and uploaded on the "Scuola in Chiaro platform". Despite of the geographical gap between North and South, the Italian National Statistics Office (Istat, 2015) showed that the gap is also present in digital infrastructures but, it underlines that during last years the Southern regions received specific funds from the National Operational Program showing a reduction in the gap. A detailed study of the Italian Strategy for Digital Schools can be found in Avvisati, Hennessy, Kozma, and Vincent-Lancrin (2013).

The Italian literature in education has been focused mainly on the Family Background effects, school level peer effects and also on the causes of the regional disparities using PISA data or INVALSI administrative data (Agasisti & Vittadini, 2012; Bratti, Checchi, & Filippin, 2007; Checchi, 2004; Montanaro, 2007). Focusing on both the use of computer at home and at school with PISA 2006 data, Ponzo (2011) shows that students' achievements are negatively affected when students use computer at school compared to using a computer at home. A more recent study that focuses on the impact of ICT on students' outcome which includes Italian data is by Agasisti, Gil-Izquierdo, and Han (2017). They employ data from the OECD-PISA 2012 for 15 European countries. Despite they focus mainly on the effect of using ICT at home for school related tasks, they also show that for higher values of ICT used at school, there is a decrease in the test score.

### 3. Research method

This section discusses data collection and the research design represented by the econometric model for estimating the causal effect of some treatment variables identified with the use of computer or laptop or tablet at school, on students' mathematic test scores. It also includes the data analysis and all variables used in the study.

#### 3.1. Participants

This article uses the fifth wave of PISA survey conducted by the OECD in 2012. PISA survey is administrated by the Italian National Evaluation Committee (INVALSI) and subsequentially is elaborated by the OECD. The PISA survey is a cross-national survey, carried out every three years and since 2000, its main goal is to assess 15 year-old students' performance in reading, mathematics and science literacy as well as problem-solving skills.

Since 2009, the survey contains a questionnaire on students' familiarity with ICT where students give information on which kinds of technology they have at their disposal at home and also at school; whether they use them and how often they use them and for what purposes. The survey also contains questions for self-assessment, in other words it askes the level of proficiency and confidence of students using a ICT tool. The database contains detailed information on students' characteristics as well as on family and schools characteristics.

The Italian PISA results are interesting to study because, in 2012, the survey was also conducted by CBA test and Italian students improved their test scores compare to the PBA test). Results from PISA 2012 survey showed an improvement of students' scores: 504 points for reading and 499 for mathematics in the CBA test against 490 points for reading and 485 points for mathematics in the PBA test (OECD, 2015). It is, hence, interesting to conduct this study on Italian case. A description of PBA and CBA scores are presented in Table 1.

#### Table 1

Italian PISA 2012 test scores.

|                           | Math | SE  | Reading | SE  | Science | SE  |  |  |
|---------------------------|------|-----|---------|-----|---------|-----|--|--|
| Paper-Based Assessment    | 485  | 2.0 | 490     | 2.0 | 494     | 1.9 |  |  |
| OECD Average              | 494  | 0.5 | 496     | 0.5 | 501     | 0.5 |  |  |
| Computer-Based Assessment | 499  | 4.2 | 504     | 4.3 | -       | -   |  |  |
| OECD Average              | 497  | 0.7 | 497     | 0.7 | -       | -   |  |  |
|                           |      |     |         |     |         |     |  |  |

Notes: In 2012, the Computer-Based Assessment (CBA) was only for reading, mathematics and problem solving.

### 3.2. Research design (review of Bayesian Additive Regression Trees)

Causality defines the causal relationship in terms of potential outcome frameworks for describing what would happen to a given individual in a hypothetical comparison of alternative scenarios. In the first case, there is the factual situation while in the other case the counterfactual situation. In this paper, counterfactual situations are operationalized by using the notation suggested by Rubin (1978). The potential outcomes are:

Potential outcome = 
$$\begin{cases} Y_{1i} = outcome \text{ for } i_{th} \text{ student if treated} \\ Y_{0i} = outcome \text{ for the } i_{th} \text{ student if not treated} \end{cases}$$
(1)

The dependent variable is the OECD-PISA mathematic test score, while the treatment is a binary variable expressed by Z = 1 whether a student uses a computer, a laptop or a tablet at school or Z = 0 otherwise. The potential outcome  $Y_{1i}$  measures the mathematics test scores where the subscript 1 indicates whether the computer, laptop, tablet exist and are in use at school for the individual *i* while  $Y_{0i}$  where the subscript 0 indicates whether the computer, laptop, tablet exist and are not used at school. In other words,  $Y_{1i}$  and  $Y_{0i}$  are the potential outcomes for individual *i* and the casual effect of the treatment variable Z for using ICT at school, on test scores.

The observed outcome  $Y_i$  can also be expressed by  $Y_i = Y_{0i} + (Y_{1i} - Y_{0i}) Z_i$  in terms of potential outcomes and treatment effect, where  $Z_i$  is a treatment dummy variable. In studies as OECD-PISA survey, scholars face the endogeneity problem because potential results are not independent from the treatment variable. An endogeneity problem may arise, for example, when families with high socio-economic status enrol their children in schools that have better and well-equipped informatics rooms compared to families with low socio-economic status who can decide to enrol their children in schools that invest less in informatics infrastructures. Therefore, it is more likely that family decisions and socio-economic status affect students' test scores.

To overcome the endogeneity problem and assuming independency among outcomes and treatment variables, several covariates should be included in the model controlling for some individual characteristics. The recent use of non-parametric methodologies like the BART model discussed in sub-section 3.2, avoid to have several different models to capture the endogeneity as classical approaches such as linear regression models or propensity score do not allow, indeed, to overcome the problem as treatment and not treatment are not observable for a specific characteristic of the individual indicated with *X*. Given that treatment and no treatment are not observable for the same value of *X*, the estimation of the score assigned to each individual becomes difficult and as alternative, the nonparametric methods are more flexible compared with linear models.

The Average Treatment Effect (ATE) is computed as the difference between  $Y_{1i} - Y_{0i}$  cannot be computed as direct measure because  $Y_{1i}$  and  $Y_{0i}$  are not directly observable. For a given treatment and control condition, each student *i* can have two potential outcomes: Y(0) and Y(1) where Y(Z = 1) = Y(1) if students receive the treatment while Y(Z = 0) = Y(0) otherwise. The ATE equals E(Y(1) - Y(0)) and it defines the expected value with respect to the probability distribution of the dependent variable for all the individuals. The variables of interest is the expected value of potential outcomes conditional to the treatment E(Y(1) - Y(0)|Z = 1). To address a possible bias, the model uses the Conditional Independence Assumption (CIA) conditional on observed individual characteristics indicated by  $X_i$ .

Looking at individuals with the same characteristics,  $\{Y_{1i}, Y_{0i}\}$  and the treatment  $Z_i$ , the dependent variable Y is conditional independent:

### $\{Y_{1i}; Y_{0i}\}$ independent of $Z_i$ , conditional on $X_i$

(2)

The Bayesian Additive Regression Trees (BART) provides a framework for flexible nonparametric modelling of the relationships of covariates to outcomes and it is a tree-based variable selection making use of the internals of the decision tree structure.

### 3.3. Estimation of the model BART

Decision tree ensembles have become a popular tool for obtaining high quality predictions in nonparametric regression problems, also motivated by the success of methodological approaches such as boosting (Chipman et al., 2010; Denison, Mallick, & Smith, 1998). They use an algorithm to learn the relationship between the response and its predictors (Breiman, 2001) assuming that the data-generating process is complex and unknown. In this framework, the approach of the BART model allows to estimate the response outcome and the counterfactual result using an extension of a non-parametric Bayesian model that performs conditional inference without making any pre-assumption on the distribution as classical inference does.

The BART model consists of a collection of regression tree models. Considering  $y_i$  as the outcome and  $x_i$  as a vector of covariates where their relationship is given by the function  $y_i = g(x_i; T, M) + \varepsilon_i$  where  $g(x_i; T, M)$  is a binary tree function, T indicates the tree structure that consists of two sets of nodes: an interior and a terminal node and, a branch decision rule at each interior node. The branch decision rule is typically a binary split based on a single component of the covariate vector. The second tree component is  $M = \{\mu_1, ..., \mu_b\}$  is made up of the function values at the terminal nodes. An example is provided in Fig. 1.

This paper follows the application of the BART methodology for Spanish PISA data in the study by Cabras and Tena Horrillo (2016). Their study is the first that applies a non-parametric model within the framework of Bayesian models in educational studies. The aim of BART is to estimate the posterior probability distribution of the causal effect conditional to some covariates  $\pi$  (ATE|X) using its flexibility in high non-linear response surfaces even with a large number of predictors (with great out-of-sample prediction properties).



Fig. 1. Example of single binary tree with branch decision rules (circles) and terminal nodes (rectangular).

For this BART model, there are a sum of trees with a prior distribution over the depth of the splits and the values at the leaf nodes. The a sum of trees is fitted in the context of the rest and on the iterative algorithm and each tree is modified one by one based on the residuals from the generation of previous trees (unlike random forests, where each tree is independent). This means that there is an informative prior and allows BART to better captures additive effects.

Formally, all observations begin in a single root node and then, the root node's splitting rule is chosen by the algorithm and consists of a splitting variable  $x_k$  and a split point c. The observations in the root node are split into two groups, based on whether the splitting variable is greater or smaller than the split point  $x_k \ge c$  or  $x_k < c$ . The two groups become a right daughter node and a left daughter node while within each of the two nodes, additional binary splits can be chosen.

The equation for the basic BART model also defined as likelihood function is the following:

$$Y = \sum_{j=1}^{m} g(x_k, z; T_j, M_j)$$
(3)

where  $g(x_k)$  is a Bayesian decision tree model as described in Chipman et al. (2010, 1998) with  $x_k$  as splitting variables, z is the treatment effect that belongs to the individual whose response is Y and have the error term normally distributed  $\varepsilon \sim N(0, \sigma^2)$  where  $\sigma^2$  the residual variance. The term  $T_j$  refers to decision tree where j refers to the number of trees which goes from 1 to m, where m is the total number of trees in the model while  $M_i$  is the function values at the terminal nodes.

The Additive Regression Trees employs an ensemble of such trees in an additive fashion, that is, it is the sum of *m* trees where *m* is typically large such as 200, 500, or 1000. The model is fitted via a back-fitting Gibbs sampler that draws from the joint posterior distribution of all the trees and terminal node parameters and the standard deviation, given the data (Chipman et al., 2010). Each tree  $T_j$  is iteratively fitted and based on the residuals generated from the previous trees, at the current iteration of the Gibbs sampler until a predetermined number of iterations is reached. The prior on  $T_j$  and  $M_j$  strongly favours small trees and leaf parameters that are near zero, constraining each term in the sum to be a "weak learner".

Starting from the root node, the probability that a node at depth *d* splits (is not terminal) is given by  $\alpha(1 + d)^{-\beta}$  where  $\alpha \in (0.1)$ ,  $\beta \in [0, \infty)$  where *d* is the depth of internal node *i* and,  $\alpha$ ,  $\beta$  are parameters that determine both the size and shape of the trees. This paper employs the standard values with  $\alpha = 0.95$  and  $\beta = 5$  as indicated in Chipman et al. (2010) and in Cabras and Tena Horrillo (2016). Such values assure that trees do not grow too much and each tree with more than 5 terminal nodes has a probability of 3 per cent. The model also uses the Markov Chain Monte Carlo (MCMC) and the Metropolis Hastings within Gibbs for simulating samples from the posterior distribution with a non-excessive computational effort. For this study, m = 200 trees and 5000 MCMC steps after an initial burn-in of 1000 steps are used. Interactions are estimated from the data by the 500<sup>th</sup> tree and they are not specified in the model a priori. For the estimation, R software was used and the package "bartMachine" recently developed by Kapalner and Bleinch (2016).

#### 3.4. Data analysis

The sample consists of 21,520 observations and 925 variables. The final PISA sample was chosen randomly and the selection probabilities of students vary so weights must be used to be sure that the sample represents correctly the full PISA population (OECD, 2014). The final sample consists of 21,520 observations and 17 variables chosen for the study. It is a sub-sample created to estimate the prediction model for the dependent variable that it is the PISA test score in mathematics defined as plausible values (pv1math).

The estimation uses variables related to students' characteristics such as gender, relative age related to whether the student is born before the first half of the year (before June) or after, whether the student attended or not the pre-primary school, the immigration status, family structure and how much time a student spend using internet (time internet). The socio-economic status of students is also included and it is expressed in the ESCS index constituted of several indicators: International Socio-Economic Index of Occupational Status (ISEI), the Highest level of education of the student's parents (HISCED), converted into years of schooling. It also includes the index of family wealth (WEALTH), the index of Home Educational Resources (HEDRES) and, the index of possessions related to classical culture in the family home (Home Possession).

Other variables are included to control school characteristics such as the quality of educational resources at school expressed by the variable school\_resources, the student-teacher ratio, whether the school is a public or private school. Then, the index of availability of computers with the variable computer\_ratio obtained by dividing the number of computers at school by the number of students at school, class size related to the number of students in each class and mathematics teacher-students ratio. Descriptive



Fig. 2. Histogram for distribution of PISA scores conditional to the treatment Z.

Notes: Author's calculation. The treatment Z = 1 indicates students who use a computer, laptop or tablet at school, while Z = 0 indicates students who do not use a computer, laptop or tablet.

Source: OECD-PISA data 2012 for Italy

### statistics are summarised in Table 2 in Appendix A.

The treatment variable is the use of computer, laptop, tablet at school indicated by the variable "Treatment" that has value 1 if the student use, at least, a computer, a laptop or a tablet at school. The treatment variable is used to compute the causal effect on the dependent variable, the mathematic test score. The sample histogram for the dependent variable (math test score) for students who use or not use a computer, laptop, tablet (treatment variable) is shown in Fig. 2.

The histogram shows the distribution of the use of computer, laptop or tablet among students at school. The treatment variable Z = 1 indicates 14,937 students who use it and 6583 students who do not use it. Therefore, 14,937 out of 21,520 students use ICT and it is an unbalanced sample that classical parametric approaches can estimate without problems.

### 4. Estimation results

This section presents the main results of the impact of the ICT on Italian mathematic test scores using PISA 2012 data and the flexible BART model discussed in Section 3. After the construction of trees, the fitted values are assigned to each terminal node. The fitted values will be the average of response values for the regression tree and the majority class for the node in the classification trees. Fig. 3 shows three steps in the growth of a classification tree for response y with levels "0" and "1" and predictor Z.

The classification tree above shows how the root - that is the starting point of the tree - is split. If half of students use a computer at



Fig. 3. Three Steps in the growing process of a classification tree. *Notes:* Author's own calculation. *Source:* PISA 2012 data



Fig. 4. Approximation of the posterior distribution for Italy. Notes: Elaboration by author using R software. Source: OECD-PISA data 2012

school (> = 0.5) the predicted number of test scores will be 2 with probability of 66.1%. For the other half of students who do not use a computer at school, there is no final prediction but rather there is another split. The process continues until there are no splitting points. The end part of the tree consists of "leaves". In between root and leaves, there are decision nodes from where new splits are generated. The percentages represents the percentage of the total sample which must be 100%.

The posterior distribution of the marginal causal effect in Fig. 4 is derived by the simulated differences between the mean of the posterior predictive distribution for students that use or not use a computer or laptop, or tablet at school at school. The approximation is generated by means of MCMC draws, of the posterior distribution  $\pi(ATE|D)$ . The posterior distribution for the Italian case shows a positive effect of 99%. The size of the posterior distribution is given by the ratio of the posterior probability and its magnitude which indicates that it is on average, 16 times more likely that ICT, such as the use of a computer or a laptop or a tablet at school, has a positive impact on educational outcomes.

In particular, taking a closer look at the confident interval at 99%, results also show that the effect of ICT is within the interval 2.97 and 9.23 meaning that the effect is substantially strong positive. For the immigration status, meaning whether ICT is more beneficial for native or immigrants students, estimating the ATE and the posterior distribution for both of them the effect is around 99.8% for non-native students and 99.7% for native students. Students who are not natives have also beneficial effects from the use of ICT. It is possible to say that the ICT has anyway a strong impact on immigrants and may be helpful for them for filling some gaps.

The final model aggregates four post-burn-in chains for the four cores indicated in the parameter that yields the 1000 total postburn-in-samples. This gives the drawback of effectively running the burn-in serially and add the benefit to reduce auto-correlation of the sum-of-trees samples in the posterior distribution since the chains are independent giving a greater predictive performance. The pseudo- $R^2$  for in-sample is 0.53 and higher compared to 0.24 of the parametric study adopting the Ordinary Least Squared (Table A2 – Appendix A). Fig. 5 illustrates that predictive performance levels off around m = 20 with an improvement with the further trees.



Fig. 5. Out-of-Sample predictive performance by number of tree.

Notes: The starting point is set to m = 200 as in Chipman et al. (2010) and not m = 500 as in Cabras and Tena Horrillo (2016) to reduce computational time and memory requirements. Performance results are very similar. Source: OECD-PISA 2012





Fig. 6. Assessment of normality. *Notes:* Author's calculation.

The summary of the posterior distribution in Fig. 6 shows the p-value for Shapiro-Wilk test of normality of residuals. Fig. 5 displays that the predictive performance levels are off around 50 trees and there is a stationary trend.

Fig. 6 shows that the assumption of normality is not violated. To check also the convergence of the Gibbs sampler, Fig. 7 displays four plots which features the convergence diagnostics.

The first panel on the top-left is the sigma-squared by MCMC iteration and the plot shows five boxes. The first box on the left indicates burn-in from the first computing core's MCMC chain while the following four plots show the post-burn-in iterations from each of the four computing cores. The second plot on the top-right indicates the percent acceptance of Metropolis-Hastings proposals for all trees where each point represents one iteration. It is possible to see two boxes: the box on the left illustrates burn-in iterations and points after illustrate post-burn-in iterations. For last two plots on the bottom, the plot on the bottom-left shows the average number of leaves across the m trees by iteration while the plot on the bottom-right shows the average tree depth across the m trees by iteration. It is visible that the model has burned-in quite nicely and each plots exhibits a stationary process.

In conclusion, it is possible to check which variables are the most important in the model counting how many times a variable appear in a tree indicating which variables have a more important role in affecting students' results. Fig. 8 indicates the average variable inclusion proportions.

This figure shows the results after assessing the splitting rules in the *m* trees across the post-burn-in MCMC iterations. This process is also known as inclusion proportions (Chipman et al., 2010) and it represents for a given predictor or covariate, the proportion of times



Fig. 7. Convergence diagnostic. *Notes:* Author's calculation.



**Fig. 8.** Average inclusion proportion. *Notes:* Author's calculation using R software.

that the variable has been chosen as a splitting rule out of all splitting rules among the posterior draws of the sum-of-trees model.

For this study, the variable which appears several times and is the most important for explaining the response is the variable determining whether school is a public or private school. In this study, the variable assumes dummy characteristics with public school taking value 1. It is possible to conclude that public school variable has more weight in predicting results in test score. A robustness check is presented comparing the BART model with the traditional parametric model such as the linear regression. Estimation results of the linear regression are presented in Table 2A in Appendix A. Results indicate that the use of ICT at school increase PISA test scores for 6.5 points but the goodness-of-fit model is low. The interpretation for the low value compared to what the Bayesian analysis computed, shows the low power of the linear model to fit all variables.

The analysis and interpretation of the results from the Bayesian analysis suggest the positive impact of the ICT on students' test scores and the predictive power of the model to explain the causal effect.

### 5. Conclusion

This paper studies the impact of ICT expressed as the use of a computer, laptop or tablet at school on the mathematic test scores for Italian students. The Italian PISA 2012 data was employed and the BART model was applied. The Italian case was an interesting case to study after the improvement of Italian students' scores in reading and mathematics when the Computer-Based Assessment test was carried out by OECD, in 2012. Italian PISA scores have usually been below the OECD average as confirmed by OECD reports (2007, 2010a, 2010b, 2016). The BART model was applied as flexible Bayesian methodology with some advantages compared with other classical parametric model such as: (i) overcomes the problem of endogeneity and (ii) uses less assumptions in the specification of the model. Moreover, as Cabras and Tena Horrillo (2016) say in their study, the interpretation of the coefficient in the Ordinary Least Squares is challenging because of the difficulty to introduce in the model, all relevant covariates with all the interactions.

The analysis has shown that computer use does increase student performance. This study is also innovative in that because it moves beyond the descriptive analysis of the country. The study applies a different econometric model that is not based on parametric assumptions. As in Cabras and Tena Horrillo (2016) who used BART model for Spanish PISA 2012 data showing a positive effect of the use of ICT on Spanish students' outcomes, the posterior distribution ATE for Italian data in Fig. 4 underlined the positive and strong effect of the treatment variable – use of computer or laptop or table at school - on mathematic test scores. The impact can be computed in almost 16 times more likely for students who use ICT to improve their test score. In this respect, results from this study are in line with those in Cabras and Tena Horrillo (2016).

The paper shows that using ICT at school leads to better learning and knowledge acquisition among students and leads to better results among the students' mathematics scores. The non-parametric analysis as the Bayesian analysis is able to overcome the issue in PISA when the number of potential confounding variables is large. As it does not require any subjective decision by the scholar expect for the indication of the treated variable, BART allows to be also implemented also in different contexts.

Analysis of normality but also the analysis of the converge diagnostics showed that BART and the burned-in MCMC iterations provided a good approximate posterior distribution. A robustness check using the parametric model is also presented showing the effect of the treatment, on the sample of Italian students. The positive sign of the treatment variable is statistically significant at 1 per cent level but the coefficient of determination is lower compared to what the Bayesian analysis showed. However, as Cabras and Tena Horrillo (2016) pointed out, the interpretation of the coefficient in the Ordinary Least Squares is challenging because the difficulty in introducing all relevant covariates with all the interactions in the model. The BART model seems, hence, an effective model for causal inference as Hill (2011) showed as there is no need to estimate several models as traditional parametric analysis such as propensity score matching can require. However, BART model can be demanding in terms of computational algorithm and there is a need for further applications and improvement of the model using also different data.

### Acknowledgment

The author would like to thank Karin Jõeveer, Kaire Põder, Karsten Staehr, Ingrida Tatolyte and two anonymous referees for very useful comments to earlier versions of the paper. The author would also like to thank INVALSI for providing the dataset.

### Appendix A

### Table A.1 Descriptive Statistics. Source: OECD-PISA 2012

|  | Use of computer $= 1$ |       |       |       | Use of computer $= 0$ |      |       |       |       |       |
|--|-----------------------|-------|-------|-------|-----------------------|------|-------|-------|-------|-------|
|  | Obs                   | Mean  | S.D.  | Min   | Max                   | Obs  | Mean  | S.D.  | Min   | Max   |
| Relative age                               | 14,937                | 0.50  | 0.50  | 0     | 1                     | 6583 | 0.49  | 0.50  | 0     | 1     |
| Gender                                     | 14,937                | 0.49  | 0.50  | 0     | 1                     | 6583 | 0.53  | 0.50  | 0     | 1     |
| Attended pre-primary school                | 14,937                | 0.96  | 0.19  | 0     | 1                     | 6583 | 0.97  | 0.17  | 0     | 1     |
| ESCS                                       | 14,937                | -0.08 | 0.93  | -0.75 | 2.70                  | 6583 | 0.12  | 0.97  | -4.7  | 2.7   |
| Family structure                           | 14,937                | 0.90  | 0.30  | 0     | 1                     | 6583 | 0.90  | 0.30  | 0     | 1     |
| Immigration status                         | 14,937                | 1.10  | 0.42  | 1     | 3                     | 6583 | 1.09  | 0.40  | 1     | 3     |
| Time spent on internet (TIMEINT)           | 14,937                | 40.44 | 33.68 | 0     | 206                   | 6583 | 37.46 | 32.94 | 0     | 206   |
| Resources at school (SCMATEDU)             | 14,937                | 0.09  | 0.88  | -3.59 | 1.98                  | 6583 | -0.12 | 0.87  | -3.59 | 1.98  |
| Teacher-student ratio (STRATIO)            | 14,937                | 9.62  | 3.82  | 0.63  | 72.54                 | 6583 | 10.78 | 3.30  | 0.63  | 28.18 |
| School type                                | 14,937                | 0.97  | 0.16  | 0     | 1                     | 6583 | 0.98  | 0.13  | 0     | 1     |
| Computer-student ratio (RATCOMP)           | 14,937                | 0.59  | 0.45  | 0     | 4.5                   | 6583 | 0.41  | 0.33  | 0     | 4.5   |
| Mathematic teacher-student ratio (SMRATIO) | 14,937                | 92,74 | 38.82 | 5.65  | 651                   | 6583 | 90.63 | 34.90 | 5.65  | 335   |

### Table A.2 Linear Regression analysis. Source: OECD-PISA 2012 data

| Variables                          | (2.1)         |
|------------------------------------|---------------|
| Relative age                       | 6.891***      |
|                                    | (1.061)       |
| Gender (female $= 1$ )             | -22.290***    |
|                                    | (1.069)       |
| Pre-primary school (yes $= 1$ )    | 33.994***     |
|                                    | (2.933)       |
| ESCS                               | 19.831***     |
|                                    | (0.579)       |
| Family structure (nuclear $= 1$ )  | 0.172 (1.775) |
| Immigration status (native $= 1$ ) | -9.033***     |
|                                    | (0.646)       |
| Time spent on internet (TIMEINT)   | -0.275***     |
|                                    | (0.016)       |
| Resources at school (SCMATEDU)     | 9.469***      |
|                                    | (0.646)       |
| Teacher-student ratio (STRATIO)    | 8.251***      |
|                                    | (0.179)       |
| School type (public $= 1$ )        | 39.511***     |
|                                    | (3.801)       |
| Computer – student ratio (RATCOMP) | 8.251***      |
|                                    | (0.179)       |
| Student-Teacher mathematics ratio  | -0.312***     |
| (SMRATIO)                          | (0.014)       |
| Treatment variable as use of ICT   | 6.499***      |
| (yes = 1)                          | (1.224)       |
| No. obs                            | 21,520        |
| R-squared                          | 0.24          |

*Note:* Result of linear regression with mathematic test score as the dependent variable. Cells show the marginal effects evaluated at the means of all explanatory variables. Robust standard errors are shown in brackets below. Superscripts \*\*\*, \*\*, \* denote statistical significance at the 1, 5 and 10 per cent levels respectively.

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# Paper III

# MINIMUM WAGES AND THE WAGES DISTRIBUTION IN ESTONIA.

# **Publication:**

Ferraro Simona, Jaanika Meriküll, Karsten Staehr, 2018. Minimum wages and the wages<br/>distribution in Estonia. Applied Economics, vol. 50, no. 49, pp. 5253-5268, available online<br/>from 23 June 2018 at<br/>https://www.tandfonline.com/doi/full/10.1080/00036846.2018.1486017?scroll=top&n<br/>eedAccess=true<br/>DOI: https://doi.org/10.1080/00036846.2018.1486017 (ETIS 1.1)

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# Draft as conference proceedings:

Minimum wages and the wages distribution in Estonia, 8<sup>th</sup> International Conference "Economic Challenges in Enlarged Europe", Conference Proceedings, 17-19 June 2016, Tallinn, Estonia.



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# Minimum wages and the wage distribution in Estonia

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#### ABSTRACT

Abstract: This article studies how changes in the statutory minimum wage have affected the wage distribution in Estonia, a post-transition country with little collective bargaining and relatively large wage inequality. The analyses show that the minimum wage has had substantial spillover effects on wages in the lower tail of the distribution; the effects are most pronounced up to the twentieth percentile and then decline markedly. The minimum wage has contributed to lower wage inequality and this has particularly benefitted low-wage segments of the labour market such as women and the elderly. Interestingly, the importance of the minimum wage for the wage distribution was smaller during the global financial crisis than before or after the crisis.

### **KEYWORDS**

Minimum wage; wage distribution; spillover effects; inequality; Central and Eastern Europe; global financial crisis

JEL CLASSIFICATION J31; J38; D31; P36

### I. Introduction

This article studies the effect of the minimum wage on the wage distribution in Estonia, a country from Central and Eastern Europe (CEE) that joined the European Union in 2004. Estonia is a particularly interesting case for such an analysis since the country has relatively unequal wage and income distributions compared to those in other EU countries, in part reflecting the virtual absence of collective bargaining, a modest social safety net and a flat income tax system.<sup>1</sup>

Concerns about the distribution of incomes and wages have increased after the global financial crisis and the resulting economic setback in many countries. Studies on the causes and consequences of inequality have become bestsellers and constitute the backdrop for debates in academics and policymaking (Piketty 2014). International organisations have similarly entered the debate and have emphasised that distributional concerns should be taken into account when devising economic policies (Dabla-Norris et al. 2015). Wages and the distribution of wages have similarly become a key issue on the European policy agenda (Schulten 2012).

The minimum wage is an instrument that can potentially influence the wage distribution. Policymakers have seen the minimum wage as a means of reducing poverty and improving living standards for low-wage workers. Minimum wages were first adopted in New Zealand and Australia in the 1890s and later in numerous other countries. In 2014, in total 21 EU Member States had a national minimum wage (Schulten 2014a). Some countries have a single national minimum wage, while others set minimum wages only at, say, the sectoral or occupational level.

The effects of the minimum wage on the wage distribution are not only important from a distributional viewpoint but also from a macroeconomic perspective. This can be the case if policymakers are concerned that an increase in the minimum wage will increase the *average* wage level and hence possibly be detrimental to international competitiveness. The spillover effects to wages above the minimum wage are important in this context as these higher wages have a larger weight in the average wage level than the wages below the minimum wage.

A rise in the minimum wage may affect the wage distribution in various ways. The rise is intended to lift wages for those directly affected by the minimum

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<sup>&</sup>lt;sup>1</sup>The Gini coefficient of equivalised disposable income in Estonia is 0.35 which is substantially above the EU28 average of 0.31 (Eurostat 2017: *tessi190*). The Gini coefficient of is also high in several other CEE countries as well as many post-Soviet countries.

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wage, who are those that initially earn wages below the new minimum wage, but it may also affect the wage distribution for those with wages above the new minimum wage. The latter effect is called the *spillover* or *ripple* effect. A positive spillover effect may occur because of employers substituting away from the low-income workers affected by the rise in the minimum wage to higher-paid workers. It may also result from the minimum wage being taken as a benchmark in wage setting above the minimum wage. Employers may also seek to maintain a given wage structure or 'hierarchy' if the efforts of employees depend on their relative wage (Grossman 1983; Akerlof and Yellen 1990).

It is generally challenging to determine the distributional impact of changes in the minimum wage because such changes typically apply to all wage earners. A number of empirical methods have been developed to address this identification problem of which the one by Lee (1999) is the most commonly used. The methodology proposed by Lee (1999) is applicable when the minimum wage exhibits little cross-sectional variation and it is the method used in most studies of spillover effects. The underlying idea is that the effect of the minimum wage on the wage distribution will vary depending on the existing wage distributions in different well-defined labour markets. The effective minimum wage is thus the minimum wage relative to the median or another measure of centrality of the wage distribution in the given labour market. The effective minimum wage will exhibit substantial cross-sectional variation and hence facilitate the identification of the distributional effect of the minimum wage.

Section II provides a comparative survey of studies assessing the effects of changes in the minimum wage on the wage distribution in highincome, transition and developing countries. The conclusion is that there is generally some spillover to wages above the minimum wage, but the extent appears to vary across countries, likely reflecting different institutional and economic environments.

This article contributes to the literature in three main areas. First, the article uses the method developed by Lee (1999) but adapts the identification strategy by depicting labour markets not only by their time and region but also by an additional dimension, either the sector of activity or the

occupation of the wage earners. This elaboration allows applying the Lee (1999) methodology also to small countries where the number of regions with sufficient size is limited. Second, the article is one of the first to address the distributional effects of the minimum wage in an EU member from CEE. Research on the effects of the minimum wage on wage inequality in the region is limited, which is surprising given that many post-transition countries have very unequal wage and income distributions (Schulten 2014b). Finally, data are for the period 2001-2014 and this relatively long sample makes it possible to investigate whether the effect of the minimum wage on the wage distribution changes over the business cycle, in particular between the pre-crisis boom before the global financial crisis, the period of crisis and the period of post-crisis recovery.

We estimate spillover effects in Estonia using data for the full-time employed from the Estonian Labour Force Survey (LFS) for the years 2001-2014. The analyses for the full sample show that there are substantial spillover effects from the minimum wage to the lower percentiles of the wage distribution, but the spillover effects decline markedly as the wage approaches the median wage. When the effects are aggregated to the macro level, the result is that an increase in the minimum wage of 1 euro is associated with an increase in 0.11 euro in the average wage of all full-time wage earners. The spillover at given percentiles of the wage distribution is larger for women than for men and also larger for older wage earners than for younger ones. The analyses also show that the spillover effects on the lower tail of the wage distribution were smaller during the global financial crisis than before or after the crisis. Notably, the results are very similar irrespective of whether the sector of activity or the occupation of the wage earners is used to construct the individual labour markets or cells.

The rest of the article is organised as follows. Section II discusses the related literature. Section III provides information on the Estonian labour market and the minimum wage. Section IV discusses the methodology. Section V presents the data and summary statistics. Section VI provides the main results in the article including the effect of the minimum wage for different subgroups of
the sample. Section VII contains some robustness analyses. Finally, Section VIII discusses the results of the article.

#### II. Review of empirical studies

The literature on the role of minimum wages and their spillover effects focused initially on the USA and the issue of whether declines in the real value of the minimum wage contributed to increasing wage inequality. Spillover effects have since been studied in the UK particularly but also in a number of emerging-market and transition economies. This allows for a comparative analysis of the results.

Early studies generally find substantial spillover effects from changes in the minimum wage in the USA. Gramlich (1976) reaches this conclusion by simply inspecting the wage distribution before and after changes in the minimum wage, and Grossman (1983) includes the minimum wage in time-series wage regressions.

Later studies confirm these results using increasingly complex identification methods. DiNardo, Fortin, and Lemieux (1996) propose a semi-parametric Oaxaca-type methodology that decomposes differences in wage distributions over time into contributions stemming from changes in coefficients, changes in endowments and residuals. They study the role of supply and demand shocks and labour market institutions and find that the decline in the real minimum wage was a key factor behind the higher wage inequality in the USA from 1979 to 1988.

Lee (1999) estimates the effect of the minimum wage at different percentiles of the wage distribution by considering the minimum wage relative to the median wage across different labour markets. The conclusion is that declines in the real minimum wage played an important role in the increase in wage inequality observed for the USA in the 1980s. Autor, Manning, and Smith (2016) update and augment the study by Lee (1999) by including more data and by instrumenting the minimum wage to account for possible reverse causality and measurement errors. The result is smaller spillover effects, especially for males, suggesting that changes in the minimum wage may in part reflect other factors affecting the wage distribution.

Neumark, Schweitzer, and Wascher (2004) regress changes in the wage income of individuals on changes in the time and the minimum wage along with a number of control variables. The effect of the minimum wage is substantial for low-income earners, but since the employment is adversely affected, the net effect on total income is negative for low-wage earners.

In contrast to the results for the USA studies using UK data generally find no or rather small spillover effects. Dickens and Manning (2004a) consider the effects of the introduction of the national minimum wage in 1999 by inspecting wage distributions before and after. The conclusion is that there are virtually no spillover effects on wage earners who have not been directly affected.

Dickens and Manning (2004b) use the methodology of Lee (1999) to estimate spillover effects for wage earners in UK care homes, a group of lowwage earners. The result is that the effects on wages above the minimum wage are negligible. Stewart (2012) estimates the wage growth of individual wage earners in different wage brackets, identifying the effects of the UK minimum wage using difference-in-differences and the size of minimum wage changes. There appear to be no spillover effects.<sup>2</sup>

There are very few studies from other Western European countries, in part because many of these countries have not applied a statutory minimum wage. An exception is France; Aeberhardt, Givord, and Marbot (2015) use data from this country and find that increases in the minimum wage affect the wage distribution up to the seventh decile, a surprisingly strong effect. The article uses a unique method where a Mincer-type regression is augmented with the minimum wage and estimated using unconditional quantile regression.

Minimum wages have been found to have strong equity-enhancing effects on the wage distribution in emerging-market countries. For Mexico, Bosch and Manacorda (2010) study the effect on income inequality of the minimum wage, which varies across municipalities, using the

<sup>&</sup>lt;sup>2</sup>Butcher, Dickens, and Manning (2012) consider panel data models for the UK where wage changes at different percentiles are regressed on changes in the national minimum wage along with control variables. They find larger spillover effects than in other studies for the UK, reaching the 10<sup>th</sup> percentile and in one particular specification the 25<sup>th</sup> percentile.

methodology by Lee (1999). They show that changes in the real minimum wage can explain a large part of the changes in wage inequality, especially at the bottom of wage distribution. Minimum wages have also had an important role in reducing wage inequality in Brazil (Lemos 2009). Moreover, the wages of workers in the formal and informal sectors are equally affected, suggesting that the formal and informal sectors are very integrated.

Few studies have focussed on transition countries. Ganguli and Terrell (2006) study the impacts of minimum wages on the wage distribution in Ukraine for 1996-2003, using kernel density techniques. They find that increases in the minimum wage have played an important role in lowering inequality, more so for women than for men. For Russia, Lukiyanova (2011) uses the methodology by Lee (1999) to study the effect of the threefold increase in the real value of the minimum wage between 2005 and 2009. The minimum wage can account for the bulk of the decline in the lower tail wage inequality, particularly for females. Laporšek, Vodopivec, and Vodopivec (2015) use a difference-in-differences methodology on Slovenian data and find changes in the minimum wage to have spillover effects on wage earnings of up to 150 per cent of the minimum wage.

No studies have formally investigated the spillover effects of the minimum wage in Estonia. Hinnosaar and Rõõm (2003) compare kernel estimations of the wage distribution in 1995 and in 2000 and conclude that the wage distribution remained unaltered despite increases in the minimum wage. Masso and Krillo (2008) provide data on the Estonian labour market and argue that changes in wage inequality are mainly attributable to factors other than the minimum wage.

#### III. The Estonian economy and labour market

Estonia is a small country in Northern Europe with around 1.3 million inhabitants. It regained its independence from the Soviet Union in 1991 and embarked immediately on far-reaching political and economic reforms (Staehr 2004). The reforms exhibited a strong market orientation and comparatively little emphasis on distributional issues. The business cycle in Estonia could be likened to a rollercoaster. A boom from 2001 until 2007 produced growth rates of around 5–10 per cent. The global financial crisis affected the country disproportionately, with GDP declining by 5 per cent in 2008 and 14.3 per cent in 2009, and then increasing by 1.8 per cent in 2010. The period since 2011 has exhibited a recovery with moderate but positive growth rates. Developments in the labour market have evidently reflected the very strong business cycle, as unemployment declined during the pre-crisis boom increased rapidly during the crisis and then declined gradually during the recovery.

At the beginning of our sample in 2001, the economic transition in Estonia was largely complete, but the country nevertheless features some particularities throughout the sample period. The country has a flat personal income tax with a modest tax-free deductible, implying relatively little redistribution through the tax system. The social welfare system is among the least generous in Europe and is in many ways comparable to the systems often associated with Anglo-Saxon countries (Põder and Kerem 2011). Moreover, the ability to implement counter-cyclical policies is severely limited by a policy of annually balanced budgets and by a strictly fixed exchange rate prior to 2011 when Estonia joined the euro area.

The 1990s was a period of rapid economic and structural change but the transition was largely completed by the end of the 1990s. Worker reallocation had by the early 2000s fallen to levels comparable with those in Western European countries (Meriküll 2016). The wage distribution is however very wide compared to the peers in Western Europe. Moreover, the wage gap that cannot be explained by standard controls such as education and labour market experience is very large across the genders (Meriküll and Mõtsmees 2017). Estonia has become a country with a high degree of nominal wage flexibility in Europe (Druant et al. 2012) and external shocks appear in large part to be accommodated through adjustment in wage costs (Babetskii 2006).

The market reforms introduced substantial regional differences in unemployment and wage levels. Like in other CEE countries, internal migration has been low in spite of the sizable and persistent regional disparities. Paci et al. (2010) find the internal migration in the CEE countries to be below the OECD average and comparable to the levels of Southern Europe and Austria. They also find that internal migration is concentrated among individuals that are young, better-educated and single, while other individuals react little to regional inequality. Jurajda and Terrell (2009) posit that the internal migration of high-skilled rather than low-skilled workers is likely to reflect the higher opportunity costs of not working for the high-skilled. Only 1–2 per cent of economically active individuals change their place of residence each year in Estonia (Meriküll 2016).

The job-to-job mobility rate in Estonia is also one of the lowest among OECD countries, as around 6–9 per cent of workers change their job within a year and fewer than 50 per cent of those that change their job within a year also change their field of activity or occupation (Meriküll 2016; OECD 2010). The low mobility of workers is consistent with the finding that overall labour productivity growth is almost entirely the result of productivity growth within sectors and only to a limited extent due to sectoral reallocation of labour (Kuusk, Staehr, and Varblane 2017).

The main institutional reforms in Estonia during our sample period were the introduction of an unemployment insurance system in 2002 and a major relaxation in employment protection legislation in 2009. The introduction of an unemployment insurance system increased replacement rates for separated workers and led to a lengthening of the tenure of unemployment (Lauringson 2011). Reform of the employment legislation system also contributed to a reduction in job-to-job flows (Malk 2014).

The institutional framework for setting the minimum wage has remained unchanged throughout the sample period. The system can be described as collective or tripartite bargaining where minimum wages are set in negotiations between employers, trade unions and the government. The pre-tax minimum wage was increased gradually from 102 euros in 2001 to 278 euros in 2008. The minimum wage was kept unchanged during the global financial crisis but was increased to 290 euros in 2012 and then to 320 euros in 2013 and 355 euros in 2014. If the minimum wage is

changed, the new rate always comes into force from 1 January.

The Estonian minimum wage is relatively low and not binding for a very large share of the employed (Schulten 2012). The share of employed earning the minimum wage or less has declined during the sample period and reached 3–5 per cent in 2005–2014. This may reflect the substantial bargaining power that employers have in tripartite negotiations. Unions are generally perceived to be of little importance as union membership is low and exhibits a declining trend (Kallaste and Woolfson 2009).

#### IV. Methodology

We use the methodology by Lee (1999) to estimate the effect of the minimum wage on different percentiles of the income distribution. The method has been used in key studies, as discussed in Section II. There are some challenges in using the method in the case of Estonia because there is no cross-sectoral variation in the minimum wage and, more importantly, because the relatively small population limits the number of geographical locations applicable for the empirical analysis. We address these challenges by exploiting that the mobility between economic sectors (and between occupations) is relatively modest in Estonia.

The underlying idea in Lee (1999) is that the effect of the minimum wage will vary depending on the wage distribution in each individual labour market. In labour markets where wages are typically high, few workers will be affected and so the minimum wage will have little impact on the wage distribution. In contrast, labour markets with typically low wages will see many workers affected and the minimum wage will have a substantial impact on the wage distribution. In other words, the *effective* minimum wage varies across different labour markets and this makes it possible to identify the effect of the minimum wage even when there is little or no regional variation in the head-line minimum wage.

Lee (1999) defines each labour market or 'cell' in terms of its location and time. To attain a sufficient number of observation points, we define each cell using its location, time and sectoral activity, and in some robustness analyses, the occupation instead of the sector. As discussed in detail in Section III there is relatively little mobility in the Estonian labour market, not only geographically within Estonia but also across sectors and occupations. The low level of mobility allows us to use the sectoral or occupational distribution as an additional margin of identification when estimating the effect of the minimum wage.

It is assumed that the *latent* log wage,  $w_{ijt}^*$ , the wage in the absence of a minimum wage, in a cell or labour market can be depicted by the cumulative distribution function  $F((w_{ijt}^* - \mu_{ijt})/\sigma_{ijt})$ , where  $\mu_{ijt}$  is a centrality measure and  $\sigma_{ijt}$  is a scale or dispersion measure. Subscript *i* indicates the region, *j* indicates the sector and *t* indicates the time. The *p*th percentile of the log wage in a cell is denoted  $w_{ijt}^p$ , so for instance the tenth percentile is  $w_{ijt}^{10}$  and the median is  $w_{ijt}^{50}$ . Given the distributional assumption, the *p*th percentile of the *latent* log wage for the particular cell or labour market can then be found as  $w_{ijt}^{*p} = \mu_{ijt} + \sigma_{ijt}F^{-1}(p)$ .

If it is possible to find a centrality measure  $\mu_{ijt}$  that is independent of the scale measure  $\sigma_{ijt}$ , then the centrality measure and the wage distribution will also be independent since it is assumed that *F*(.) is the same across all cells. We follow Lee (1999) and assume that the log median wage of the *observed* distribution,  $w_{ijt}^{50}$ , is a good candidate. The argument is that the log minimum wage,  $\underline{w}_t$ , is typically so low that it is unlikely that it will affect the log median wage. This independence assumption implies that the following holds for any given cell:

$$\begin{aligned} & \operatorname{cov}(\sigma_{ijt}F^{-1}(p),\underline{w}_t - \mu_{ijt}) \\ &= & \operatorname{cov}(w_{ijt}^{*p} - w_{ijt}^{50},\underline{w}_t - w_{ijt}^{50}) = 0 \end{aligned} \tag{1}$$

The difference between the log minimum wage and the log median wage,  $\underline{w}_t - w_{ijt}^{50}$ , is the *effective* log minimum wage which reflects the 'bindingness' of the minimum wage, the degree to which the minimum wage is binding in a given cell.

The implication of Eq. (1) is that any covariation between the effective log minimum wage and the difference between the observed *p*th percentile of the log wage and the log median wage must stem from the minimum wage affecting the *observed p*th percentile or, alternatively, from some other factors that may be captured by control variables. The reason is that the covariance between the latent distribution and minimum wages is zero given the assumptions so that any nonzero covariance is related to the minimum wage or some control variable. The exact functional form of the relationship is of course unknown, but Lee (1999) suggests that the following empirical specification provides sufficient flexibility:

$$w_{ijt}^{p} - w_{ijt}^{50} = \beta_1 (\underline{w}_t - w_{ijt}^{50}) + \beta_2 (\underline{w}_t - w_{ijt}^{50})^2 + controls + \varepsilon_{ijt}$$
(2)

The terms  $\beta_1$  and  $\beta_2$  are the coefficients to be estimated and  $\varepsilon_{it}$  is a conventional error term. The control variables may include cell-specific features, including the business cycle stance. The nonlinear specification implies that the marginal effect of the effective minimum wage may depend on the level of the effective minimum wage.

Eq. (2) can be estimated for any percentile p, but given the assumption that the minimum wage has no effect on the median wage, the marginal effects for p > 50 must also be negligible. This provides a test of the assumption that the median wage is a centrality measure that is not affected by the minimum wage. We will generally compute the marginal effects for percentiles above the median and examine whether the effects are insignificant in statistical and economic terms.

Given the assumptions of the model and the way we estimate eq. (2), it is possible to pinpoint how the effect of the minimum wage on the wage distribution is identified. As discussed, there is no cross-sectional variation in the headline minimum wage in Estonia, so that type of variation does not contribute to the identification. Moreover, we always include year fixed effects (FE) in eq. (2) and this implies that the rest of the changes in wage distribution from year to year that are not related to minimum wages will be absorbed by the year FEs. The upshot is that the effect of the minimum wage is identified from the variation in the effective minimum wage across regions and sectors and this variation stems only from different median wages across the regions and sectors.

Many studies relying on the methodology by Lee (1999) use data where there is some crosssectional variation in the headline minimum wage, but this variation may not be very important given that there is typically substantial variation in the median wage. Moreover, some studies identify the effect entirely from the variation in the effective minimum wage afforded by the variation in the wage distributions across different cells. In fact, Lee (1999) carries out robustness analyses with a sample of the 36 US states that do not have a state-specific minimum wage and where the federal minimum wage is binding, and finds the results to be qualitatively similar to those obtained using all 50 states. Dickens and Manning (2004b) analyse the distributional effects within the home care sector in the UK and estimate the distributional effects within the negotiated common minimum wage for the sector.

### V. Data

We use data from 2001 to 2014 from the Estonian LFS by Statistics Estonia.<sup>3</sup> The LFS data follow the definitions of the International Labour Organization for the labour market statuses and are used as the main source of labour market statistics internationally and in Estonia. The LFS is a quarterly survey with a rotating panel and covers 15,000–20,000 individual-level observations each year (Statistics Estonia 2013).

We consider full-time wage earners who are Estonian residents, meaning we exclude those who work part time, whose main employment status is self-employment, or whose current residence is abroad. The net wage has been used, which comprises the take-home pay after income tax, pension contributions and unemployment insurance contributions. Beyond the net wages, individual data on each person's sector of activity, occupation, gender and age are also used, resulting in 6000–7000 observations for each year.

While the net wage is self-reported by respondents, the minimum wage is set in gross terms and it has therefore been converted into net terms using the statutory income tax and unemployment insurance rates. The simple Estonian tax system with flat taxes makes the conversion from gross to net a relatively straightforward exercise.<sup>4</sup>

(Figure 1) shows the ratios of the Estonian net minimum wage to the net average and median wages for full-time employees using data from the LFS.<sup>5</sup> The ratios have been relatively stable except at the beginning of the pre-crisis boom in 2003–2005. Using LFS data, the Gini index for the wage distribution for full-time employees has remained relatively stable at around 0.3 over the years from 2001 to 2014 with only a small increase in 2011–2012 in the aftermath of the crisis.<sup>6</sup>

The original individual-level data have been collapsed to an aggregate database with a year, region and sectoral dimension. As discussed in the methodology section, this dimension defines our individual labour market in this article. The database covers 14 years, 5 regions at the NUTS3 level, and 11 sectors.<sup>7</sup> The year  $\times$  region  $\times$  sector dimension has been used in the baseline specification, but we also test an alternative specification where occupation replaces the very last dimension. The minimum number of observations for each cell is set at 20 observations; if the cell is based on fewer than 20 observations, the cell is omitted from the analysis.

<sup>6</sup>Table A.1 in Appendix A shows summary statistics for the minimum wage and the wage distribution for the data in the database before it is collapsed to cells using the year, region and sectoral dimensions.

<sup>&</sup>lt;sup>3</sup>The LFS data for 2015 and 2016 are not available in the format of earlier data due to a change in the way Statistics Estonia makes data available for research organisations.

<sup>&</sup>lt;sup>4</sup>A minor source of measurement error arises from the Estonian pension system where some individuals pay contributions to a funded second pillar funds. It is not possible to identify the individuals that contribute to the second pillar and the second pillar contributions are therefore not deducted when the net minimum wage is computed from the gross minimum wage. However, as these contributions are very small compared to the income tax, it is unlikely that this omission will affect the findings of the article.

<sup>&</sup>lt;sup>5</sup>The ratio of the minimum wage to the mean wage is somewhat higher than the ratio reported in the official statistics. There are two reasons for this. First, this article reports the ratio of the minimum wage to the mean wage *net of taxes*. The tax-free minimum makes the minimum wage largely exempt from taxation, which the average wage is not, and this results in a higher ratio than if pre-tax wages had been used. Second, the Estonian LFS is used for the official unemployment and employment statistics, but *not* for the official wage statistics. The average wage in the LFS is somewhat lower than in the official statistics; the official statistics are based on a survey of employeers and the missing observations have been imputed unlike in the LFS.

<sup>&</sup>lt;sup>7</sup>The 11 sectors are defined according to NACE 2003: 1) primary sector; 2) manufacturing and electricity, gas and water supply; 3) construction; 4) trade; 5) hotels and restaurants; 6) transport and communication; 7) financial intermediation, and real estate and business activities; 8) public administration; 9) education; 10) health; 11) other services.



Figure 1. Ratios of the net minimum wage to the net average wage and the net median wage for full-time employees in Estonia, 2001–2014.

Source: Authors' calculations based on the Estonian LFS.

#### VI. Estimation results

#### Estimations on the full sample

We use data from the Estonian LFS as discussed in Section V and let each labour market or cell be described by its year, region and sector. Using the full sample, a total of 742 cells out of the maximum 770 have 20 or more observations, and the distributional data from these cells are used to estimate eq. (2) separately for different percentages of the distribution.

For each of the estimations, the dependent variable is the difference between the log wage of the percentage and the log median wage, while the explanatory variables are the difference between the log minimum wage and the log median wage in linear and squared forms in addition to control variables. The log differences of the wage expressions imply that there is no need to deflate the wage variable. For our baseline estimation, we follow Lee (1999) and use only time FEs as a control variable. We examine the importance of this choice by including regional FEs and the annual growth rate of regional real GDP and the regional unemployment rate as additional control variables in some specifications.8 We have experimented with various other control variables and generally find that the qualitative results are not very sensitive to the choice of controls.<sup>9</sup>

In line with almost all other studies, we estimate eq. (2) using OLS. Autor, Manning, and Smith (2016) argue that there may be measurement errors and possible endogeneity issues and therefore use instrumental variables estimation. We prefer to use OLS in our case as good instruments are rarely available, and invalid or weak instruments may lead to biased estimations or erroneous inferences.

(Table 1) shows the results when eq. (2) is estimated with only year FEs as control variable. The estimates of the coefficients  $\beta_1$  and  $\beta_2$  become smaller as the dependent variable – the difference between the *p*th percentile and the median – increases. The coefficient of determination similarly decreases with the percentiles increase, suggesting that the degree to which the minimum wage binds is disproportionately important for wages in the lower tail of the distribution.

The model in eq. (2) is nonlinear and to ease the interpretation of the results, we compute the marginal effects at the means of the explanatory variables. (Table 2) shows the marginal effects for models with different control variables. Column (2.1) shows the marginal effects for the baseline model with year FEs, for which the estimation results were presented in (Table 1). The computed effect at the fifth percentile is 0.622, so an increase in the minimum wage of 1 per cent is associated

 $<sup>^{8}</sup>$ Regional data on GDP growth and the unemployment rate are from Statistics Estonia (2017, tables RAA0053 and TT50).

<sup>&</sup>lt;sup>9</sup>We refrain from including control variables for region and sectoral activity, and occupation in some robustness analyses, partly so as to avoid having an excessive number of control variables. Sectors are correlated with the effective minimum wage and with the wage distribution and would seem like sound controls. However, these variables share features that cause the problem of too much control. As discussed by Angrist & Pischke (2015) variables such as occupation may not perform well as controls in wage equations, and the field of activity of the worker shares the same features.

 Table 1. Estimations of eq. (2) for percentiles of log wages, full sample.

|                      | (1.1)                | (1.2)            | (1.3)          |
|----------------------|----------------------|------------------|----------------|
|                      | (minw – <i>p</i> 50) | $(minw - p50)^2$ | R <sup>2</sup> |
| p5–p50               | 1.106***             | 0.375***         | 0.441          |
|                      | (0.100)              | (0.085)          |                |
| p10-p50              | 1.161***             | 0.516***         | 0.575          |
|                      | (0.089)              | (0.079)          |                |
| p15–p50              | 1.027***             | 0.519***         | 0.428          |
|                      | (0.085)              | (0.075)          |                |
| p20–p50              | 0.819***             | 0.442***         | 0.316          |
|                      | (0.076)              | (0.066)          |                |
| p25 <del>-</del> p50 | 0.662***             | 0.363***         | 0.244          |
|                      | (0.075)              | (0.065)          |                |
| p30 <b>-</b> p50     | 0.488***             | 0.282***         | 0.182          |
|                      | (0.064) (0.056)      |                  |                |
| p40 <del>-</del> p50 | 0.183***             | 0.091*           | 0.087          |
|                      | (0.046)              | (0.039)          |                |
| p60 <del>-</del> p50 | 0 -0.160*** -0.116** |                  | 0.035          |
|                      | (0.046) (0.03        |                  |                |
| p70 <del>_</del> p50 | -0.178* -0.114*      |                  | 0.031          |
|                      | (0.072) (0.056)      |                  |                |
| p80 <del>-</del> p50 | -0.289*              | -0.189** 0.036   |                |
|                      | (0.082)              | (0.065)          |                |
| p90 <b>-</b> p50     | -0.260*              | -0.178           | 0.036          |
| · · ·                | (0.119)              | (0.094)          |                |

Note: Each row reports the results of a separate OLS regression of eq. (2) with the dependent variable being the difference between the percentile indicated in the first column and the median. Year fixed effects are included as the control variable. The number of observations is 742 in all cases. Robust standard errors are shown in brackets. Superscripts \*\*\*, \*\* and \* denote that the effect is statistically significant at the 1, 5 and 10 per cent levels, respectively.

with a wage increase of a bit more than 0.6 per cent at this percentile. The computed marginal effects are positive and statistically significant for wages up the fortieth percentile, but the effects decline relatively fast and are modest for the thirtieth and fortieth percentiles. The marginal effects are typically statistically or economically insignificant in the estimations above the fiftieth percentile.<sup>10</sup>

Column (2.2) shows the effects when both year and region FEs are included as a control variable and Column (2.3) shows the effects when the control variables also include regional GDP growth and unemployment. The results are virtually indistinguishable from those for the baseline model in Column (2.1) with only year FEs.

(Figure 2) provides a graphical representation of the effects of the minimum wage for the baseline model. The gradual decline in the effect for increasing percentiles below the median wage is evident and, as expected, there is virtually no effect for the percentiles above the median wage. The relatively

| Table  | 2. Marginal | effects | for | percentiles | of | log | wages, | full |
|--------|-------------|---------|-----|-------------|----|-----|--------|------|
| sample | 2.          |         |     |             |    |     |        |      |

| (2.1)    | (2.2)  | (2.3)   |
|----------|--|---|
| 0.622*** | 0.605***   | 0.605***  |
| (0.027)  | (0.028)  | (0.028)   |
| 0.494*** | 0.478***   | 0.478***  |
| (0.021)  | (0.024)  | (0.024)   |
| 0.356*** | 0.342***   | 0.342***  |
| (0.020)  | (0.023)  | (0.024)   |
| 0.248*** | 0.240***   | 0.239***  |
| (0.019)  | (0.021)  | (0.021)   |
| 0.192*** | 0.196***   | 0.196***  |
| (0.017)  | (0.021)  | (0.021)   |
| 0.124*** | 0.130***   | 0.130***  |
| (0.015)  | (0.017)  | (0.017)   |
| 0.065*** | 0.074***   | 0.074***  |
| (0.010)  | (0.012)  | (0.012)   |
| -0.010   | 0.005  | 0.005   |
| (0.011)  | (0.012)  | (0.012)   |
| -0.031   | -0.007   | -0.006  |
| (0.017)  | (0.019)  | (0.019)   |
| -0.045*  | -0.004   | -0.004  |
| (0.021)  | (0.024)  | (0.024)   |
| -0.031   | 0.040  | 0.040   |
| (0.031)  | (0.034)  | (0.034)   |
| Yes      | Yes  | Yes   |
| No       | Yes  | Yes   |
| No       | No   | Yes   |
| 742      | 742  | 742   |
|          | (2.1)<br>0.622***<br>(0.027)<br>0.494***<br>(0.021)<br>0.356***<br>(0.019)<br>0.122****<br>(0.015)<br>0.124***<br>(0.015)<br>0.055***<br>(0.010)<br>-0.010<br>(0.011)<br>-0.031<br>(0.031)<br>Yes<br>No<br>742 | (2.1)         (2.2)           0.622***         0.605***           (0.027)         (0.028)           0.494***         0.478***           (0.021)         (0.024)           0.356***         0.342***           (0.021)         (0.023)           0.248***         0.240***           (0.019)         (0.021)           0.192***         0.196***           (0.017)         (0.021)           0.124***         0.130***           (0.015)         (0.017)           0.055***         0.074***           (0.010)         (0.012)           -0.010         0.005           (0.011)         (0.012)           -0.031         -0.007           (0.017)         (0.019)           -0.045**         -0.004           (0.021)         (0.024)           -0.031         0.040           (0.031)         (0.034)           Yes         Yes           No         No           No         No           No         No |

Note: Each row reports the results of a separate OLS regression of eq. (2) with the dependent variable being the difference between the percentile indicated in the first column and the median. The included control variables are indicated in the table. Robust standard errors are shown in brackets. Superscripts \*\*\* and \* denote that the effect is statistically significant at the 1 and 10 per cent levels, respectively.

large spillover effects in Estonia place the country alongside the USA, and many emerging markets and transition economies, where similarly large effects have been found, but it sets the country apart from the UK and some continental European countries where the effects have generally been small. We return to possible factors behind these findings in the final comments in Section VIII.

The marginal effects in (Table 2) and (Figure 2) are elasticities depicting the percentage increase in the wage at various percentiles when the minimum wage increases by 1 per cent. It may also be useful to consider the effect in monetary terms, i.e. the change in the wage in euros at various percentiles for an increase of 1 euro in the minimum wage. (Table 3) shows the average wage in 2014 for various percentiles, the marginal effects from the baseline model in Column (2.1) and, finally, the marginal effects in euros for the corresponding percentiles given an increase of 1 euro in

<sup>&</sup>lt;sup>10</sup>The marginal effects above the 50<sup>th</sup> percentile are typically statistically insignificant despite the often statistically significant coefficients in (Table 1). Since the marginal effect is derived from the coefficients of the linear and quadratic terms, the standard error of the marginal effect will also comprise the nonzero covariance of these two coefficients.



Figure 2. Marginal effects with confidence intervals for percentiles of log wages, baseline model.

 Table 3. Marginal effects in euros for percentiles of log wages,

 2014, baseline model.

|         | (3.1)        | (3.2)           | (3.3)                    |
|---------|--------------|-----------------|--------------------------|
|         | Average wage | Marginal effect | Marginal effect in euros |
| p5–p50  | 319          | 0.605           | 0.631                    |
| p10–p50 | 355          | 0.478           | 0.556                    |
| p15-p50 | 398          | 0.342           | 0.446                    |
| p20–p50 | 428          | 0.240           | 0.336                    |
| p25-p50 | 460          | 0.196           | 0.296                    |
| p30-p50 | 493          | 0.130           | 0.210                    |
| p40–p50 | 550          | 0.074           | 0.134                    |

*Note*: The marginal effect in euros depicts the change in the wage in euros given an increase of 1 euro in the minimum wage.

the minimum wage. The minimum wage in 2014 was 305.08 euros net of taxes, or just below the fifth percentile of the wage distribution.

It is notable that the marginal effect is substantially below 1 euro even for those at the fifth percentile with wages just at or above the minimum wage. Moreover, although they clearly decline when the wages increase, the marginal effects in euros for, say, the twentieth or twenty-fifth percentiles are not negligible. These relatively large marginal effects prove that the spillover of the minimum wage to wages above the minimum wage is substantial, perhaps because the minimum wage is used as a benchmark or reference measure for wage setting at levels above the minimum wage.

Extending (Table 3) by calculating the marginal effects in euros for every fifth percentile of the wage distribution makes it possible to derive a proxy wage distribution with and without the minimum wage increase. Comparing the average wages based on these distributions shows that a minimum wage increase of 1 euro in 2014 is

related to an increase in the *average* wage of 0.11 euro. This back-of-the-envelope exercise demonstrates that although the rise in the minimum wage mostly affects workers in the lower part of the wage distribution, the effect on the average wage may also be non-negligible.

#### Gender and age

This subsection presents the results from estimations when the wage distributions of men and women are considered separately and when the wage distributions for different age groups are considered separately. (Table 4 shows the results).

Columns (4.1) and (4.2) present the estimation results of equation (2) when the distributions for men and women are considered separately. The results demonstrate that the spillover effects from the minimum wage are larger for women than for men up to the thirtieth percentile. The economic size of the difference is also sizeable in the lower part of the wage distribution; the difference in elasticity is roughly twice as large for women from the tenth percentile of wage distribution for example. These results are the consequence of the very different wage distributions for men and women in Estonia. The gender wage gap is very large in Estonia (Meriküll and Mõtsmees 2014). This means that a man at, for instance, the twentieth percentile of the wage distribution for men earn much more than a woman at the twentieth percentile of the distribution for women.

The results demonstrate that the spillover effects from the minimum wage are larger for women than

Table 4. Marginal effects for percentiles of log wages; gender and age groups.

|                                      | (4.1)    | (4.2)    | (4.3)          | (4.4)        |
|--------------------------------------|----------|----------|----------------|--------------|
|                                      | Men      | Women    | Age 45 or less | Age above 45 |
| p5–p50                               | 0.548*** | 0.729*** | 0.542***       | 0.709***     |
|                                      | (0.048)  | (0.034)  | (0.038)        | (0.040)      |
| p10 <del>-</del> p50                 | 0.387*** | 0.607*** | 0.408***       | 0.570***     |
|                                      | (0.045)  | (0.025)  | (0.034)        | (0.029)      |
| p15 <b>-</b> p50                     | 0.272*** | 0.508*** | 0.298***       | 0.436***     |
|                                      | (0.041)  | (0.023)  | (0.027)        | (0.024)      |
| p20 <del>-</del> p50                 | 0.190*** | 0.390*** | 0.233***       | 0.334***     |
|                                      | (0.037)  | (0.022)  | (0.024)        | (0.022)      |
| p25 <del>-</del> p50                 | 0.133*** | 0.299*** | 0.173***       | 0.235***     |
|                                      | (0.032)  | (0.021)  | (0.021)        | (0.021)      |
| p30 <del>_</del> p50                 | 0.108*** | 0.214*** | 0.128***       | 0.170***     |
|                                      | (0.026)  | (0.018)  | (0.019)        | (0.021)      |
| p40 – p50                            | 0.068**  | 0.105*** | 0.080***       | 0.072***     |
|                                      | (0.021)  | (0.012)  | (0.015)        | (0.015)      |
| <i>p</i> 60 <del>_</del> <i>p</i> 50 | 0.042*   | -0.023   | 0.008          | 0.034*       |
|                                      | (0.018)  | (0.012)  | (0.014)        | (0.016)      |
| p70 <del>_</del> p50                 | 0.062*   | -0.038   | -0.019         | 0.056**      |
|                                      | (0.027)  | (0.018)  | (0.021)        | (0.022)      |
| p80–p50                              | 0.036    | -0.014   | -0.043         | 0.102***     |
|                                      | (0.036)  | (0.029)  | (0.028)        | (0.027)      |
| p90 <b>-</b> p50                     | 0.093    | 0.000    | -0.027         | 0.091*       |
|                                      | (0.059)  | (0.038)  | (0.037)        | (0.038)      |
| Obs.                                 | 497      | 588      | 639            | 593          |

Note: Each row reports the results of a separate OLS regression of eq. (2) with the dependent variable being the difference between the percentile indicated in the first column and the median. Year fixed effects are included as a control variable. Robust standard errors are shown in brackets. Superscripts \*\*\*, \*\* and \* denote that the effect is statistically significant at the 1, 5 and 10 per cent levels, respectively.

for men up to the thirtieth percentile. The economic size of the difference is also sizeable in the lower part of the wage distribution; the difference in elasticity is roughly twice as large for women from the tenth percentile of wage distribution for example. The large difference in elasticities corresponds to large differences in monetary returns; the marginal effects in euros are around 0.20 euro higher for women than for men between the tenth and the twenty-fifth percentiles in 2014. As expected, we find that an increase in the minimum wage benefits women more than men and contributes more to wage compression among women than among men. This also suggests that a rise in the minimum wage can help reduce the gender wage gap.

The large difference in elasticities corresponds to large differences in monetary returns; the marginal effects in euros are around 0.20 euro higher for women than for men between the tenth and the twenty-fifth percentiles in 2014. As expected, we find that an increase in the minimum wage benefits women more than it benefits men and contributes more to wage compression among women than among men.

Most studies on spillover effects find that the wages of women are more affected by a rise in the minimum wage than are the wages of men.<sup>11</sup> Women usually earn lower wages than men and the minimum wage is therefore much more binding for women. The greater spillovers for women are therefore typically a reflection of different wage distributions. The results for Estonia are in line with those from the literature and are consistent with the fact that the gender wage gap in Estonia is unusually large.

The wage distribution and the spillover effects may also vary across different age groups. Columns (4.3) and (4.4) in (Table 4) show the results when the sample is split along the age of the employees. The wage income for those under aged 45 years is higher than for those aged over 45 years. Given that the minimum wage is less binding for young workers, it is arguably not surprising that we find that the minimum wage affects the lower part of the wage distribution to a greater extent for older wage earners than for younger ones.

#### Boom, bust and recovery

We examine in this subsection whether the effects of the minimum wage on the wage distribution differed across the different phases of the business cycle in Estonia as discussed in Section III. We split the original year, region and sector-level data between three subsamples, the boom years 2001–2007, the crisis years 2008–2010 and the recovery years 2011–2014. (Table 5) shows the results when eq. (2) is estimated for the three subsamples separately.

It follows from (Table 5) that the spillover effects are smaller and decay more rapidly across the lower percentiles for the crisis period 2008–2010 than for the boom and recovery periods, although the confidence intervals are relatively wide and largely overlapping. The smaller spillover effects during the crisis period are consistent with the observation that nominal wages were declining across most of the wage distribution during the crisis years in spite of the headline

<sup>&</sup>lt;sup>11</sup>See for instance DiNardo, Fortin, and Lemieux (1996) & Lee (1999) for the USA and Ganguli and Terrell (2006) and Lukiyanova (2011) for transition countries.

 Table 5. Marginal effects for percentiles of log wages; before, during and after the global financial crisis.

|                          | (5.1)                        | (5.2)                       | (5.3)                         |
|--------------------------|------------------------------|-----------------------------|-------------------------------|
|                          | The boom<br>period 2001–2007 | The crisis period 2008–2010 | The recovery period 2011–2014 |
| p5–p50                   | 0.652***                     | 0.482***                    | 0.584***                      |
|                          | (0.034)                      | (0.086)                     | (0.050)                       |
| p10-p50                  | 0.508***                     | 0.360***                    | 0.474***                      |
|                          | (0.027)                      | (0.046)                     | (0.049)                       |
| p15-p50                  | 0.371***                     | 0.247***                    | 0.329***                      |
|                          | (0.028)                      | (0.048)                     | (0.047)                       |
| p20–p50                  | 0.254***                     | 0.175***                    | 0.232***                      |
|                          | (0.027)                      | (0.039)                     | (0.042)                       |
| p25–p50                  | 0.200***                     | 0.127**                     | 0.202***                      |
|                          | (0.025)                      | (0.041)                     | (0.040)                       |
| p30–p50                  | 0.123***                     | 0.010*                      | 0.140***                      |
|                          | (0.022)                      | (0.037)                     | (0.032)                       |
| p40–p50                  | 0.068***                     | 0.048                       | 0.089***                      |
|                          | (0.015)                      | (0.029)                     | (0.020)                       |
| <i>p</i> 60– <i>p</i> 50 | 0.006                        | 0.013                       | 0.005                         |
|                          | (0.016)                      | (0.034)                     | (0.022)                       |
| p70–p50                  | -0.001                       | -0.002                      | -0.012                        |
|                          | (0.025)                      | (0.048)                     | (0.034)                       |
| p80–p50                  | 0.002                        | -0.062                      | 0.020                         |
|                          | (0.034)                      | (0.054)                     | (0.043)                       |
| p90–p50                  | 0.114*                       | -0.109                      | 0.029                         |
|                          | (0.046)                      | (0.078)                     | (0.062)                       |
| Obs.                     | 377                          | 156                         | 209                           |

Note: Each row reports the results of a separate OLS regression of eq. (2) with the dependent variable being the difference between the percentile indicated in the first column and the median. Year fixed effects are included as a control variable. Robust standard errors are shown in brackets. Superscripts \*\*\*\*, \*\* and \* denote that the effect is statistically significant at the 1, 5 and 10 per cent levels, respectively.

minimum wage remaining constant. These results also apply if the GDP growth rate and the unemployment rate are included as additional control variables (not shown). The upshot is that the effects of the minimum wage on the wage distribution may vary across boom, crisis and recovery periods, in all likelihood reflecting changing wage setting behaviour across the business cycle.

#### VII. Robustness

The estimations have so far considered labour markets or cells based on the year, region and sector. Although there is limited mobility of labour between sectors in Estonia, it is nevertheless advisable to assess whether the use of the sector as an additional margin of identification is appropriate. We have therefore repeated the estimations from (Table 2) replacing the sector with the occupation in the definition of the cells. Data suggest that mobility between occupations is of broadly the same range as mobility between sectors, although it is even slightly lower between occupations. There are nine occupation groups at the ISCO 1-digit level of aggregation, which covers all occupations from elementary workers to managers but excludes the military. The change results in 590 cells with 20 or more individuals out of a maximum of 630 possible cells.

(Table 6) shows the results when cells are formed from the year, region and occupation with different sets of control variables. When the results are compared with those in (Table 2), it is clear that the change of identification margin is of very little importance. The results obtained are robust to the exact specification of the labour markets or cells in the aggregate data set.

We have also run a number of other robustness checks. Until this stage cells with less than 20 observations have been dropped, so that all cells have 20 or more individual observations. This relatively low number has been chosen to preserve observations in the aggregate data set. We have examined the sensitivity of the results to this cut-off point and raised it to 50, but the results did not change in qualitative terms (not reported).

The monthly wage reported in the Estonian LFS is the most recent wage received by the individual interviewed. Temporary absence from work or overtime work may make the wage reported extraordinarily low or high and this may affect the tails of the wage distribution and also the results obtained. We can assess the robustness of the results to extraordinary fluctuations in wage income by using a question in the Estonian LFS in which the person interviewed is asked whether or not the wage reported is the 'ordinary wage'. This question has been available in the LFS since 2007. We have repeated the estimations in (Table 2) for the period 2007-2014 for the full sample with all interviewed individuals and for a sample where we have excluded individuals whose reported wage is not the 'ordinary wage'. The results for the two samples are virtually identical (not reported).

As a final robustness check, we have run estimations where the median has been replaced as the centrality measure by the fortieth percentile and by the sixtieth percentile (not reported).<sup>12</sup> The

<sup>12</sup>The requirement is that the centrality measure must be independent of the scale measure, and this may not be satisfied if a very high percentile of the wage within the cell is chosen as the centrality measure. Lee (1999) uses the median as the centrality measure and this is customary in the literature.

| Table 6.  | Marginal   | effects | for | percentiles | of | log | wages, | occupa- |
|-----------|------------|---------|-----|-------------|----|-----|--------|---------|
| tion inst | ead of see | ctor.   |     |             |    |     |        |         |

|                          | (6.1)    | (6.2)    | (6.3)    |
|--------------------------|----------|----------|----------|
| p5–p50                   | 0.565*** | 0.555*** | 0.555*** |
|                          | (0.019)  | (0.019)  | (0.019)  |
| p10-p50                  | 0.419*** | 0.416*** | 0.416*** |
|                          | (0.012)  | (0.013)  | (0.013)  |
| p15–p50                  | 0.319*** | 0.316*** | 0.316*** |
|                          | (0.011)  | (0.012)  | (0.012)  |
| p20–p50                  | 0.238*** | 0.238*** | 0.239*** |
|                          | (0.010)  | (0.011)  | (0.011)  |
| p25–p50                  | 0.169*** | 0.168*** | 0.168*** |
|                          | (0.009)  | (0.010)  | (0.010)  |
| p30–p50                  | 0.122*** | 0.123*** | 0.123*** |
|                          | (0.008)  | (0.009)  | (0.009)  |
| p40-p50                  | 0.057*** | 0.056*** | 0.056*** |
|                          | (0.006)  | (0.007)  | (0.007)  |
| <i>p</i> 60– <i>p</i> 50 | -0.006   | -0.007   | -0.007   |
|                          | (0.008)  | (0.008)  | (0.008)  |
| p70–p50                  | -0.026*  | -0.022*  | -0.022*  |
|                          | (0.010)  | (0.011)  | (0.011)  |
| <i>p</i> 80– <i>p</i> 50 | -0.032*  | -0.027   | -0.027   |
|                          | (0.016)  | (0.016)  | (0.016)  |
| <i>p</i> 90– <i>p</i> 50 | -0.055*  | -0.055*  | -0.056*  |
|                          | (0.022)  | (0.023)  | (0.023)  |
| Year FE                  | Yes      | Yes      | Yes      |
| Region FE                | No       | Yes      | Yes      |
| Growth and unempl.       | No       | No       | Yes      |
| Obs.                     | 590      | 590      | 590      |

Note: Each row reports the results of a separate OLS regression of eq. (2) with the dependent variable being the difference between the percentile indicated in the first column and the median. The control variables are indicated in the table. Robust standard errors are shown in brackets. Superscripts \*\*\* and \* denote that the effect is statistically significant at the 1 and 10 per cent levels, respectively.

results are qualitatively in line with the results when the median is chosen as the centrality measure. In neither of the new specifications are there any statistically significant marginal effects above the new measure of centrality. This indicates that higher percentiles do not seem to be affected by the minimum wage, confirming the choice of the median as the centrality measure.

#### VIII. Discussion

This article analyses the effect of the statutory minimum wage on the wage distribution of the full-time employed in Estonia using data from the LFS from 2001 to 2014. The minimum wage in Estonia is uniform and this complicates the identification of the effect on the wage distribution. We use instead a modified version of the methodology developed by Lee (1999).<sup>13</sup>

The analyses for the full sample show that there are substantial spillover effects from the minimum

wage to the lower percentiles of the wage distribution. The effects are most pronounced up to the twentieth percentile and then decline relatively fast as the wage approaches the median wage. The conclusion is that the minimum wage appears to have contributed to lower wage inequality in Estonia.

The marginal effect in monetary terms is less than the increase in the minimum wage at all percentiles, even at the fifth percentile of the wage distribution, just above the minimum wage. The estimated spillover effects imply for 2014 that an increase of 1 euro in the minimum wage is associated with an increase of 0.11 euro in the *average* wage of all full-time wage earners.

The spillover at given percentiles of the wage distribution is larger for women than for men. The spillover is similarly larger for wage earners over 45 years than for those below 45 years. These results reflect that the wage distributions for men and women and for younger and older workers are very different. The spillover effects at the lower tail of the wage distribution were smaller at the height of the global financial crisis in 2008–2010 than before or after the crisis.

In a comparative context, it is clear that the overall substantial spillover effects for Estonia bear clear resemblance to those found in earlier studies for the USA, emerging-market economies in Latin America and some Eastern European transition countries, but are larger than those found for the UK and some continental European countries. The substantial effects in Estonia may be tied to a number of structural features of the economy and the role played by the minimum wage in wage and price setting in the country.

First, the absence of collective bargaining in Estonia makes the minimum wage the arguably most important institutional measure affecting wages and employment in Estonia. This is compounded by the flat income tax system which means that the marginal tax rate remains unchanged at higher income levels.

Second, changes to the minimum wage are announced in advance and take effect from 1 January of the following year. Survey evidence on wage setting in Estonia shows that when wages are

<sup>&</sup>lt;sup>13</sup>The baseline results are derived using the sector of activity to construct the individual labour markets or cells, but the results are very similar if the occupation of the wage earners is used.

changed on a regular basis, it typically occurs in January or one of the immediately following months (Dabušinskas and Rõõm 2011). Changes in the minimum wage are thus typically known when the wage setting takes place and the information on the minimum wage is thus easy to take into account.

Third, a number of fees and prices are indexed to the minimum wage in Estonia; these include kindergarten fees, child support and traffic fines. In this way, changes in the minimum wage become very visible and directly affect the spending and wage expectations of many Estonians.

Finally, the level of wages is relatively low in Estonia in comparison to many Western European countries. It may therefore be quite affordable to raise wages at levels above the minimum wage and the incentive for employers to resist wage increases for these groups of employees may thus be limited if their productivity makes wage increases feasible.

This study could be extended in a number of ways. One direction would be to seek to validate or cross-check the results using other empirical methods, preferably incorporating possible effects on employment. The challenge in this context is to account for the lack of cross-sectional variability in the headline minimum wage in Estonia. Another interesting direction would be to produce similar analyses for other European countries with the aim of facilitating a direct comparison of spillover effects across countries. We leave these questions for future research.

### Acknowledgment

The authors would like to thank Tairi Rôōm and seminar participants at the University of Warsaw and Eesti Pank for their useful comments. The views expressed are those of the authors and not necessarily those of Eesti Pank or other parts of the Eurosystem.

#### **Disclosure statement**

No potential conflict of interest was reported by the authors.

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### Appendix

|      | Gross minimum | Net minimum | Median of net | Std. dev. of net |
|------|---------------|-------------|---------------|------------------|
|      | wage          | wage        | wage          | wage             |
| 2001 | 102           | 92.12       | 192           | 155              |
| 2002 | 118           | 103.09      | 211           | 166              |
| 2003 | 138           | 117.74      | 224           | 163              |
| 2004 | 159           | 139.62      | 256           | 177              |
| 2005 | 172           | 155.57      | 288           | 220              |
| 2006 | 192           | 176.39      | 345           | 262              |
| 2007 | 230           | 206.48      | 447           | 307              |
| 2008 | 278           | 248.54      | 511           | 356              |
| 2009 | 278           | 246.03      | 511           | 365              |
| 2010 | 278           | 243.71      | 511           | 384              |
| 2011 | 278           | 243.71      | 510           | 483              |
| 2012 | 290           | 252.93      | 550           | 425              |
| 2013 | 320           | 277.98      | 600           | 447              |
| 2014 | 355           | 305.08      | 650           | 450              |

### Table A.1. Summary statistics, full-time wage earners.

Note: The wages are expressed in euros per month. For 2001–2010 the wages have been converted from EEK to EUR using the fixed exchange rate 1 EUR = 15.6466 EEK Source: Own calculations using data from the LFS (2001–2014).

# Paper IV

# MINIMUM WAGES AND EMPLOYMENT RETENTION. A MICROECONOMETRIC STUDY FOR ESTONIA

### **Publication:**

Ferraro Simona, Hänilane Birgit, Staehr Karsten, 2018. Minimum wages and employment retention across the wage distribution. A Microeconometric study for Estonia. *Baltic Journal of Economics*, vol. 18, no. 1, pp. 51-67, available online from 26 June 2018 at https://www.tandfonline.com/doi/full/10.1080/1406099X.2018.1485422 DOI https://doi.org/10.1080/1406099X.2018.1485422 (ETIS 1.1)

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### Draft as conference proceedings:

A Microeconometric Study of Minimum Wages and Employment Probabilities in Estonia, 9<sup>th</sup> International Conference & Summer School *Economic Challenges in Enlarged Europe*, 11-16 June 2017, Tallinn (Estonia)

Department of Economics and Finance, Tallinn University of Technology, 20 September 2017

BALTIC JOURNAL OF ECONOMICS 2018, VOL. 18, NO. 1, 51–67 https://doi.org/10.1080/1406099X.2018.1485422



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# Minimum wages and employment retention: A microeconometric study for Estonia

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#### ABSTRACT

This paper assesses the effect of increases in the Estonian minimum wage in 2013–2016 on the probability of workers at different wage levels retaining employment. The effect is identified by comparing the probability of workers remaining employed after increases in the minimum wage in 2013–2016 with the probability of workers at comparable wage levels remaining employed in the 2009–2011 when the minimum wage was left unchanged. Estimations on data from the Estonian Labour Force Survey show that the increases in the minimum wage in 2013–2016 had no or small and imprecisely estimated effects on employment retention for the directly affected workers are robust to the choice of control variables, to refinements of the treatment group and to changes in the time sample.

#### ARTICLE HISTORY

Received 10 July 2017 Accepted 21 May 2018

#### **KEYWORDS**

Minimum wage; employment retention; wage distribution

CODES: J31; J63; D68

#### 1. Introduction

Distributional concerns and poverty alleviation have attracted increased attention since the global financial crisis. Raising the minimum wage may be seen as one way to support low-wage workers, but a key concern is whether it will reduce the job prospects of the workers directly affected and possibly also those of workers who may be indirectly affected through wage spill-overs and shifting employment patterns. The gains from a higher minimum wage may be wiped out if it becomes harder for the workers directly or indirectly affected to retain employment. This suggests that it is important to examine the effects of increases in the minimum wage on employment retention.

Estonia is a country in post-communist Europe with substantial wage inequality. The statutory minimum wage in Estonia is set each year by the government after negotiations with representatives of employers and workers. Changes in the minimum wage take effect from 1 January the following year. The minimum wage was constant in 2008–2011 and raised moderately in 2012, but increased by around 10% each year from 2013 to 2016.<sup>1</sup> The annual increases were considerably above both the inflation rate and the average rate of wage growth, implying a substantial increase in the minimum wage in real

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terms and relative to the average wage. Figure A1 in Appendix A shows the minimum wage in per cent of the average wage over the period 2000–2016.

The substantial rises in the minimum wage in Estonia in 2013–2016 provide an excellent backdrop for analysing the effects on the likelihood of directly or indirectly affected workers remaining employed. This paper estimates the probability of employment retention for full-time wage-earners across the wage distribution after the substantial rises in the minimum wage in 2013–2016. The analysis considers whether workers retain full-time employment, *not* whether they retain the job which they had when the minimum wage was increased.

The analysis uses a difference-in-differences methodology derived from key microeconometric studies of the effect of minimum wage rises on employment, principally Neumark, Schweitzer, and Wascher (2004), Stewart (2004a, 2004b) and Stewart and Swaffield (2008). Data are from the Estonian Labour Force Survey (ELFS) and we consider individuals in the ELFS who are employed full-time in the fourth quarter and are interviewed again in the fourth quarter of the following year. The individuals are divided into wage groups by their wage income in the first round of interviews. The outcome of increases in the minimum wage is identified by comparing the probability of full-time workers remaining employed after the rises in the minimum wage in 2013–2016 with the probability of workers in the same part of the wage distribution remaining employed in the period 2009–2011 when the minimum wage was constant.

Economic theory provides conflicting predictions for how a statutory minimum wage influences employment, including the employment retention of those directly affected by rises in the minimum wage (Dickens, Machin, & Manning, 1999). The standard competitive labour market model predicts that employment will decline among those directly affected by the minimum wage. The monopsony model in contrast may lead to the opposite conclusion if the minimum wage prevents companies from exploiting their market power. A minimum wage may also increase employment in a competitive model if the minimum wage enhances productivity as posited in the efficiency wage model (Rebitzer & Taylor, 1995). Finally, the statutory minimum wage may not always be enforced in practice, so wages may still be below the minimum wage in some cases, potentially limiting any effect on employment (Basu, Chau, & Kanbur, 2010). How the minimum wage influences employment and employment retention is evidently an empirical question.

The effect of minimum wages on employment is of importance for economic and social policies and so the empirical literature on the topic is extensive. Studies are particularly plentiful for the USA and the UK but there are also studies from other high-income countries, for emerging economies and for developing countries. The literature is summarised in several surveys and meta-analyses.<sup>2</sup> The main conclusion is that the employment effect is negligible or in some cases negative, depending on the labour markets considered and the level of the minimum wage relative to the general wage level. We may discuss some studies of particular relevance for our empirical analysis.

Stewart (2004a) studies the probability of low-paid workers remaining employed after the introduction of the National Minimum Wage (NMW) in the UK in 1999. He compares the retention of employment by workers with wages just below the NMW with the retention probability for those who have wages slightly above. The introduction of the NMW had no effect on the probability of the directly affected workers remaining employed. Stewart (2004b) uses the same methodology to update his previous study by including the rises in the NMW in 2000 and 2001. The study finds no adverse effect on employment retention from the introduction of the NMW and the subsequent increases in it.  $^3$ 

The study for the USA by Neumark et al. (2004) estimates the effects of the minimum wage on employment retention for different points in the wage distribution using data on individuals from the Current Population Survey for the years 1979–1997. The argument for examining the effects across the wage distribution is that changes in the minimum wage may also have consequences for workers that are not directly affected. They identify the effect using variation in the minimum wage over time and over the 50 states. Workers with wages at or just above the previous minimum wage is raised, while the effects are negligible for workers higher up the wage distribution.

Meta-analyses on emerging economies from Europe, Asia, Latin America and Africa suggest that the employment effects there are stronger than those that are typically found for advanced economies, perhaps because the minimum wage in many emerging economies is often comparatively high relative to the average wage (Broecke, Forti, & Vandeweyer, 2017; Nataraj, Perez-Arce, Kumar, & Srinivasan, 2014). Moreover, some studies find that higher minimum wages lead to a shift from formal to informal employment.

Estonia shares many economic and institutional features with other European postcommunist countries but there are very few studies from this region. A survey conducted within the framework of the ECB Wage Dynamics Network asked firms in a number of CEE countries how they had reacted to increases in the minimum wage in the period 2010– 2013 (Bodnár et al., 2018). The most important adjustment channels were increases in productivity, cuts in non-labour costs and price increases, while the least important channel was firing of staff. The relative unimportance of firing of staff was particularly prevalent in Estonia where less than 10% of the interviewed firms stated that this was a relevant adjustment channel.

Country-specific studies include Vodopivec (2015) who uses administrative data from Slovenia and a difference-in-differences methodology to study employment retention after an increase in the minimum wage in 2010. It is found that the increase had a negative effect on employment retention for the workers directly affected by the rise.

Poland is a comparatively large country with large regional differences. This is exploited by Majchrowska, Broniatowska, and Żółkiewski (2016) to identify the overall employment effects of changes in the minimum wage in the period 1999–2012. They find no effect for the labour market as a whole but do find negative effects for young workers in disadvantaged regions. Baranowska-Rataj and Magda (2015) focus on young workers in Poland and apply a difference-in-differences estimation on a matched sample. They discover a substantial negative effect on the employment of the young workers.

The only formal econometric analysis of the employment effects of the minimum wage for Estonia is the study by Hinnosaar and Rõõm (2003) for Estonia. They use micro data from the ELFS for 1995–2000 and a difference-in-differences methodology derived from the working paper version of Neumark et al. (2004). They find substantial negative effects on employment retention for those directly affected but little effect for other groups.<sup>4</sup> It is interesting to revisit this result given that worker reallocation was very intensive in the 1990s but subsided to the levels of western European countries in the 2000s (Meriküll, 2016).

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This paper considers the effects on employment retention in Estonia after the substantial minimum wage rises in 2013–2016. Studies of the Estonian labour market suggest that Estonia represents an interesting case study. It is an EU country from Central and Eastern Europe with largely unorganised labour markets and weakly enforced employment protection (Eamets, Masso, & Altosaar, 2005). Collective wage bargaining plays a very limited role, the participation rate is high, and the unemployment rate exhibits substantial variation over time. Malk (2014) finds, however, that a strengthening of employment protection laws at the end of the 2000s had a negative influence on employment.

The rest of the paper is organised as follows. Section 2 presents the methodology and data used in the empirical study, Section 3 provides the main estimation results, Section 4 shows the results of robustness analyses, including a refinement of the treatment group, and finally Section 5 summarises the results.

#### 2. Methodology and data

This section discusses the methodology that the empirical analysis uses to identify the effect of increases in the minimum wage in Estonia in 2013–2016 on employment retention.

Rises in the minimum wage may not only impact the employment retention of those directly affected. One channel through which the impact can be felt more widely is spill-over effects, where rises in the minimum wage lead to upwards wage drift further up the wage distribution.<sup>5</sup> Ferraro, Meriküll, and Staehr (forthcoming) find for Estonia that although the minimum wage after tax is typically around the 5th percentile of the wage distribution, there are substantial spill-over effects up to the 20th percentile and some effects up to the 40th percentile.

Another channel goes through substitution and complementarity effects. Substitution effects occur if employers shift away from the workers directly affected and instead employ workers elsewhere in the wage distribution, while complementarity effects occur when directly affected workers being laid off leads to workers at higher wage levels being made redundant. These effects are most likely to touch workers with wages fairly close to the wage of the workers directly affected by the new minimum wage.

The net effect of spill-over, substitution and complementarity effects on employment retention for the workers that are indirectly affected cannot be ascertained ex ante (Stewart, 2004a). The possibility of these effects suggests that we should consider the impact on employment retention not only for those directly affected by rises in the minimum wage but also for workers that may be affected indirectly. These may be workers who had wages higher than the new minimum wage but may also, be workers with wages lower than the initial minimum wage. In other words, we should consider how employment retention is impacted across the wage distribution up to the point where it is unlikely there are any effects.

The sample of the ELFS is relatively small and the number of observations is, therefore, limited, especially of those directly affected by increases in the minimum wage. This would suggest that we should use several years of observations in the estimations. Fortuitously, the pattern of changes in the minimum wage in Estonia makes this possible. The minimum wage was held constant in the years 2008–2011, while a minor increase in 2012 was followed by rises of approximately 10% each year in 2013–2016. We seek to identify the

effect of the rises in the minimum wage using a standard difference-in-differences methodology comparing employment retention across the wage distribution in 2013–2016, with retention at comparable wage levels when the minimum wage was constant in 2009–2011. The rise of around 10% every year in the minimum wage in the treatment period facilitates the comparison of the wage distributions across the reference period and the treatment period.<sup>6</sup>

The difference-in-differences methodology we use draws on Neumark et al. (2004), Stewart (2004a, 2004b) and Stewart and Swaffield (2008). All working individuals are divided into groups by their wage before the minimum wage was raised and then we test whether the probability of employment retention for individuals in the different wage groups was different in the years 2013–2016 when the minimum wage was increased from what it was in the years 2009–2011 when there were no changes. The null hypothesis is that raising the minimum wage does not lower the probability of individuals in the treatment period remaining employed. Note that the comparison of employment retention can be carried out for workers in groups directly affected and for workers in groups indirectly affected through the spill-over and substitution effects.

The paper uses micro data from the ELFS for 2008–2016, documented in Statistics Estonia (2013).<sup>7</sup> The survey has a panel dimension with four interview rounds over two years. Individuals are interviewed two quarters in a row in the first year and in the same two quarters in the second year. Our sample consists of individuals who were full-time employed and reported positive wage income in the fourth quarter one year and were interviewed again in the fourth quarter of the following year.

The baseline estimations are run for a cross-sectional model with the observations for all individuals pooled across the years 2013–2016, when the minimum wage was raised, and the reference years 2009–2011, when it was constant. The time index *t* denotes the second year the individual is interviewed and t - 1 denotes the first interview year. The index *i* depicts the individuals included in the sample, which are those in full-time employment with non-missing wage data in year t - 1.

Data on gross or pre-tax monthly wage income in year t - 1 are available in the ELFS for all the individuals in the sample. We define eight different wage groups, labelled Group1 to Group8, into which individuals are placed depending on their wage income in the fourth quarter of year t - 1.

For the treatment period 2013–2016, when the minimum wage was increased every year, individuals are placed in Group2 if their wage in the fourth quarter of year t - 1 is above the minimum wage in that year but below the minimum wage in year t. This implies that individuals in Group2 are those directly affected or treated by the increase in the minimum wage from year t - 1 to year t. The monthly gross minimum wage for the full-time employed was 290 euros in 2012, 320 euros in 2013, 355 euros in 2014, 390 euros in 2015 and 430 euros in 2016 (EMTA, 2017).

Group1 consists of individuals whose wage income is already lower than the minimum wage in year t - 1. Given that the criteria for choosing the individuals in the sample are that they work full-time and report positive wage income in year t - 1, there should in principle not be anybody in Group1. There are, however, a number of individuals who report wages below the minimum wage. This may be caused by erroneous reporting, with people stating lower wage income than they actually received, but the reporting may also reflect imperfect enforcement of the minimum wage regulation (Basu et al.,

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2010). In any case, Group1 contains individuals who report wage income just below the minimum wage.

Group3 contains individuals who had wage income in year t - 1 and who received wage income in year t above the new minimum wage but below 1.4 times the new minimum wage. The wage of the individuals in Group3 implies that they are not directly affected or treated by the increased minimum wage, but their wage is close to the wage of those in Group2. This may make Group3 particularly susceptible to spill-over, substitution and complementarity effects.

Group4 consists of individuals with wage income in year t - 1 and with income in period t that is more than 1.4 times the new minimum wage but less than 1.8 times the new minimum wage. Group5 to Group8 contain individuals with even higher wage incomes. Table 1 shows the intervals of the eight different wage groups. The thresholds are chosen so that the number of individuals is relatively similar in each of the groups from 3 to 8.

For the reference sample of the years 2009–2011, the groups are constructed so that the relative wage distribution is as similar as possible to the distribution for the treatment sample 2013-2016. The minimum wage increased by 10.4% per year on average in 2013-2016 and there was little difference between the years. We seek to make Group2 for the reference period when the minimum wage was constant comparable to Group2 for the treatment period, and so we let Group2 for the reference period consist of individuals who had wage income in the fourth guarter of year t - 1 above the minimum wage in year t = 1 but below the minimum wage times 1.104. Group for the reference period can be seen to contain those who would have been directly affected if the minimum wage had been increased by 10.4%.

As before Group1 consists of individuals with wage income below the minimum wage in year t = 1. Group3 contains individuals with wage income in year t above 1.104 times the constant minimum wage but lower than 1.4 times the minimum wage. Group4 and above are defined as for the treatment period. Table B1 in Appendix B shows the average wage and the number of observations for each group for each of the years 2009-2011 and 2013-2016.

We use a difference-in-differences approach with a dummy variable for the treatment period to estimate the effect of rises in the minimum wage on the probability of individuals in different wage groups retaining employment. The dummy variable Treat, takes the value 1 for the treatment years t = 2013 - 2016 and 0 for the reference years t = 2009 - 2011. The employment indicator  $L_{it}$  takes the value 1 if individual i is full-time employed in year t

| Table  | Table 1. Delinition of wage groups.                        |  |  |  |  |  |
|--------|--|--|--|--|--|--|
|        | Reference period, 2009–2011                                | Treatment period, 2013-2016                              |  |  |  |  |
| Group1 | $w_{it-1} < mw_{it-1}$                                     | $w_{it-1} < mw_{it-1}$                                   |  |  |  |  |
| Group2 | $mw_{it-1} \le w_{it-1} < 1.104 \times mw_{it-1}$          | $mw_{it-1} \leq w_{it-1} < mw_{it}$                      |  |  |  |  |
| Group3 | $1.104 \times mw_{it} \leq w_{it-1} < 1.37 \times mw_{it}$ | $mw_{it} \leq w_{it-1} < 1.37 \times mw_{it}$            |  |  |  |  |
| Group4 | $1.37 \times mw_{it} \leq w_{it-1} < 1.79 \times mw_{it}$  | $1.37 \times mw_{it} \le w_{it-1} < 1.79 \times mw_{it}$ |  |  |  |  |
| Group5 | $1.79 \times mw_{it} \leq w_{it-1} < 2.15 \times mw_{it}$  | $1.79 \times mw_{it} \le w_{it-1} < 2.15 \times mw_{it}$ |  |  |  |  |
| Group6 | $2.15 \times mw_{it} \leq w_{it-1} < 2.52 \times mw_{it}$  | $2.15 \times mw_{it} \le w_{it-1} < 2.52 \times mw_{it}$ |  |  |  |  |
| Group7 | $2.52 \times mw_{it} \leq w_{it-1} < 3.58 \times mw_{it}$  | $2.52 \times mw_{it} \le w_{it-1} < 3.58 \times mw_{it}$ |  |  |  |  |
| Group8 | $3.58 \times mw_{it} \le w_{it-1}$                         | $3.58 \times mw_{it} \le w_{it-1}$                       |  |  |  |  |

| Table 1. | Definition of | of wage | groups. |
|----------|---------------|---------|---------|
|----------|---------------|---------|---------|

Note: The term  $w_{it-1}$  is the wage of individual i in year t-1,  $mw_{it-1}$  is the minimum wage in year t-1 and  $mw_{it}$  is the minimum wage in year t after the rise of the minimum wage

and 0 if the individual is not full-time employed. The term  $Pr(L_{it} = 1|Group n_{it-1})$  is then the probability of individual *i* retaining full-time employment in year *t* given that the individual was employed and belonged to wage group Group  $n_{it-1}$  in year t - 1. The employment probability is estimated using the follow specification:

$$\Pr(L_{it} = 1|\operatorname{Group} n_{it-1}) = \alpha + \sum_{n \neq 7} \beta_n \operatorname{Group} n_{it-1} + \sum_{n \neq 7} \gamma_n \operatorname{Group} n_{it-1} \times \operatorname{Treat}_t + \tau_t + \delta X_{it-1} + \varepsilon_{it}$$
(1)

The  $\beta$ -coefficients of the group dummies Group  $n_{it-1}$  capture the overall differences in employment retention across the wage groups, while the  $\gamma$ -coefficients of the interaction terms Group  $n_{it-1} \times$  Treat<sub>t</sub> capture the additional effects of the treatment period. The term  $\alpha$  is a constant and to avoid perfect multicollinearity, Group7 is omitted so that the  $\beta_n$  and  $\gamma_n$  coefficients must be interpreted as the additional effect relative to that of Group7. Group7 is chosen as the omitted group because changes in the minimum wage are unlikely to influence employment retention so high in the wage distribution. Group8 could have been chosen but it contains individuals with very high wages and they may experience idiosyncratic changes in employment retention without relevance to changes in the minimum wage.

The control variables include the year dummies  $\tau_t$  which are meant to absorb business cycle effects that impact the employment probabilities of the eight wage groups in equal proportion. The rest of the control variables are collected in the vector  $X_{it-1}$  and are specific to the individual for year t - 1. The controls are for the region of residence, gender, ethnicity, age, education level, sector of activity and occupation. The vector of coefficients of the control variables  $X_{it-1}$  is labelled  $\delta$ . Finally,  $\varepsilon_{it}$  is the error term.

The employment indicator  $L_{it}$  takes the values 0 and 1 so the model in Eq. (1) is estimated using Probit and we report the marginal effects evaluated at the means of all explanatory variables. The results are very similar if the model is estimated as a linear probability model using ordinary least squares (not shown).

#### 3. Estimation results

This section presents the results of the analyses using the difference-in-differences methodology developed in Section 2. The estimation results are presented separately for the full treatment sample and for subsamples.

#### 3.1. Full sample

Table 2 shows the results when Eq. (1) is estimated with Probit using different sets of control variables. The marginal effects presented are relative to the omitted variable, the Group7 dummy, and the interaction of the Group7 dummy and the treatment dummy for the years 2013–2016. Column (2.1) provides the baseline results where the control variables are year dummies together with the region of residence, gender, ethnicity, age, education level, sector of activity and occupation of the worker during the first interview round.

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|                                 | (2.1)     | (2.2)             |
|---------------------------------|-----------|-------------------|
|                                 | Baseline  | Only year dummies |
| Group1                          | -0.056**  | -0.051**          |
|                                 | (0.026)   | (0.025)           |
| Group2                          | -0.088*** | -0.085***         |
|                                 | (0.024)   | (0.024)           |
| Group3                          | -0.041**  | -0.039**          |
|                                 | (0.020)   | (0.019)           |
| Group4                          | -0.026    | -0.026            |
|                                 | (0.019)   | (0.019)           |
| Group5                          | 0.013     | 0.011             |
|                                 | (0.021)   | (0.021)           |
| Group6                          | -0.001    | -0.004            |
|                                 | (0.020)   | (0.021)           |
| Group7 (omitted)                | 0.000     | 0.000             |
| Group8                          | -0.009    | -0.015            |
|                                 | (0.020)   | (0.021)           |
| Group1 × Treat                  | -0.057*   | -0.061*           |
|                                 | (0.032)   | (0.032)           |
| Group2 × Treat                  | -0.006    | 0.002             |
|                                 | (0.032)   | (0.033)           |
| Group3 × Treat                  | -0.032    | -0.029            |
|                                 | (0.024)   | (0.025)           |
| Group4 × Treat                  | -0.012    | -0.006            |
|                                 | (0.025)   | (0.025)           |
| Group5 × Treat                  | -0.040    | -0.032            |
|                                 | (0.027)   | (0.028)           |
| Group6 × Treat                  | -0.012    | -0.005            |
|                                 | (0.025)   | (0.028)           |
| Group7 $\times$ Treat (omitted) | 0.000     | 0.000             |
| Group8 × Treat                  | 0.048     | 0.055*            |
|                                 | (0.030)   | (0.030)           |
| Pseudo R <sup>2</sup>           | 0.064     | 0.051             |
| Obs.                            | 5063      | 5091              |

Table 2. Group dummies and treatment effects 2013-2016.

Notes: Probit estimations with employment dummy as dependent variable. Cells show the marginal effects evaluated at the means of all explanatory variables. Robust standard errors are shown in brackets below. Superscripts \*\*\*, \*\* and \* denote statistical significance at the 1%, 5% and 10% levels respectively. The control variables in Column (2.1) are year dummies, region of residence, gender, ethnicity, age, education level, sector of activity and occupation are used as control variables; in Column (2.2) only year dummies.

Taking first the results for the group dummies it is notable that the estimated probabilities of employment retention increase quite consistently with the wage income of the groups, especially from Group2 upwards. Individuals with high wages have a substantially higher probability of retaining employment than do those with lower wages, even in the presence of year dummies and control variables for a large number of individual characteristics. Taken literally this would suggest that a higher wage by itself is a factor in employed workers retaining employment. One possible explanation may be that a higher wage makes workers strive harder to avoid dismissal but other factors might also be in play. Similar patterns of employment retention increasing over the wage distribution even with numerous control variables are found for the UK by Neumark et al. (2004), for China by Sun, Wang, and Zhang (2015) and for Estonia by Hinnosaar and Rõõm (2003).

The marginal effects of the group dummies interacted with the treatment dummy show the treatment effect, the effect of the higher minimum wage in 2013–2016 on employment retention relative to what it is for Group7. The estimated marginal for Group2, which contains those directly affected by the minimum wage increases, is negative but statistically and economically insignificant. The probability of those paid the minimum wage and up to 10.4% more retaining their employment remains virtually unchanged from the reference period with no changes in the minimum wage to the treatment period with increases in the minimum wage.

The estimated treatment effects for Group3 to Group6 are similarly statistically insignificant although they are negative in all cases. This suggests that spill-over and substitution effects do not have a discernible effect on employment retention for the groups comprising individuals with wages above the wage level in Group2. Remarkably, there may be an effect on Group1, which contains the workers who report wage income below the minimum wage *before* the minimum wage is increased. The effect is however only statistically significant at the 10% level and anyway applies to a small group of workers who may not be employed in the formal labour market.

Column (2.2) in Table 2 shows the results when only year dummies are included as control variables while all the individual control variables are left out. The results are very similar to those obtained with the broader set of control variables but the pseudo coefficient of determination declines somewhat. The upshot is that the results in the base-line estimation are robust to a smaller set of control variables.

#### 3.2. Changing treatment years

The effects of raising the minimum wage may differ over time as economic conditions change. This may be particularly important for Estonia where the minimum wage relative to the average wage increased markedly over the years 2013–2016 as shown in Figure A1 in Appendix A. Given the low number of treated or directly affected workers, it is not feasible to estimate the treatment effects for individual years, so instead we split the treatment sample of four years into two subsamples of two years each, 2013–2014 and 2015–2016. Table 3 shows the estimation results with the baseline results repeated for ease of comparison.

It follows from Columns (3.2) and (3.3) that the estimated treatment effects for the directly treated in Group2 and for the indirectly treated in Group3-Group6 are quite similar across the two subsamples. The main notable difference between the two subsamples is in the treatment effects for Group1, for which the effects are negative and economically and statistically significant in 2013–2014 but statistically insignificant in 2015–2016. The importance of this result is difficult to assess given the marginal status of the workers in Group1, but it may suggest that the early rises in the minimum wage led to disruptions in the lowest paid segments of the labour market. These results are in any case estimated on a group with relatively few individuals.

We repeat the baseline estimation in Column (2.2) for men and women separately to ascertain whether minimum wage increases have different effects on the eight groups, but the result is again that no differences can be found (not shown). The same applies when the sample is split along age groups (not shown). The absence of any differences between gender and age groups should however be considered in light of the very low number of observations in some of wage groups, especially Group1 and Group2.

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|                          | (3.1)     | (3.2)     | (3.3)     |
|--------------------------|-----------|-----------|-----------|
|                          | Baseline  | 2013-2014 | 2015-2016 |
| Group1                   | -0.056**  | -0.056**  | -0.052*   |
| ·                        | (0.026)   | (0.027)   | (0.027)   |
| Group2                   | -0.088*** | -0.091*** | -0.086**  |
|                          | (0.024)   | (0.026)   | (0.026)   |
| Group3                   | -0.041**  | -0.041**  | -0.039*   |
|                          | (0.020)   | (0.021)   | (0.021)   |
| Group4                   | -0.026    | -0.026    | -0.025    |
|                          | (0.019)   | (0.020)   | (0.020)   |
| Group5                   | 0.013     | 0.016     | 0.016     |
|                          | (0.021)   | (0.022)   | (0.023)   |
| Group6                   | -0.001    | 0.000     | 0.001     |
|                          | (0.020)   | (0.021)   | (0.021)   |
| Group7 (omitted)         | 0.000     | 0.000     | 0.000     |
| Group8                   | -0.009    | -0.009    | -0.009    |
|                          | (0.020)   | (0.021)   | (0.021)   |
| Group1 $\times$ Treat    | -0.057*   | -0.091**  | -0.031    |
|                          | (0.032)   | (0.039)   | (0.039)   |
| $Group2 \times Treat$    | -0.006    | -0.029    | 0.028     |
|                          | (0.032)   | (0.038)   | (0.045)   |
| Group3 × Treat           | -0.032    | -0.045    | -0.020    |
|                          | (0.024)   | (0.030)   | (0.030)   |
| Group4 $\times$ Treat    | -0.012    | -0.007    | -0.018    |
|                          | (0.025)   | (0.031)   | (0.031)   |
| Group5 $\times$ Treat    | -0.040    | -0.012    | -0.060*   |
|                          | (0.027)   | (0.037)   | (0.033)   |
| Group6 $	imes$ Treat     | -0.012    | -0.027    | 0.003     |
|                          | (0.025)   | (0.034)   | (0.036)   |
| Group7 × Treat (omitted) | 0.000     | 0.000     | 0.000     |
| Group8 × Treat           | 0.048     | 0.028     | 0.089**   |
| _                        | (0.030)   | (0.036)   | (0.045)   |
| Pseudo R <sup>2</sup>    | 0.064     | 0.073     | 0.069     |
| Obs.                     | 5063      | 3566      | 3492      |

 Table 3. Group dummies and treatment effects for treatment periods.

Notes: Probit estimations with the employment dummy as the dependent variable. Cells show the marginal effects evaluated at the means of all explanatory variables. Robust standard errors are shown in brackets below. Superscripts \*\*\*, \*\* and \* denote statistical significance at the 1%, 5% and 10% levels respectively. The control variables are year dummies, region of residence, gender, ethnicity, age, education level, sector of activity and occupation.

### 4. Robustness checks

This section examines whether the results obtained in Section 3 are robust to changes in the way the treatment effects are identified.

#### 4.1. Changing reference years

The reference years when the minimum wage was left unchanged are the years when the global financial crisis affected the Estonian economy and the Estonian labour market very severely. The year 2009 saw a deep decline in output, lower employment and rapidly rising unemployment, while this picture was reversed in 2011. This pronounced cyclical pattern raises the question of whether the years 2009–2011 are an appropriate choice of reference period. If the macroeconomic developments impacted the probabilities of employment retention equally for the different wage groups, then the year dummies will pick the effect up and the cyclical pattern in 2009–2011 should be inconsequential. If, however,

the developments impacted on employment retention differently for different wage groups, then the treatment effects may be estimated incorrectly.

To examine whether these concerns are warranted, we repeat the baseline estimation of Equation (1) but remove the years of the reference period sequentially one at a time. Table 4 presents the results. Column (4.2) shows the results when the crisis year 2009 is removed from the sample, Column (4.3) when 2010 is removed and Column (4.4) when the rebound year 2011 is removed.

The results are very similar to the results of the baseline estimation and this applies also for the treatment effects of Group2, the group directly affected by the rises in the minimum wage in 2013–2016. The only partial exception is the estimated employment probability and treatment effect for Group1 if 2011 is left out of the reference period. It should be noted however Group1 contains very few individuals and removing a year from the reference period may thus be of particular importance for the results for this group. The overall conclusion is nevertheless that the employment retention probabilities do not seem to be impacted in any discernible way by the particularly volatile macroeconomic environment in the reference period.

|                          | (4.1)     | (4.2)        | (4.3)        | (4.4)        |
|--------------------------|-----------|--------------|--------------|--------------|
|                          | Baseline  | Without 2009 | Without 2010 | Without 2011 |
| Group1                   | -0.056**  | -0.078**     | -0.062**     | -0.038       |
|                          | (0.026)   | (0.031)      | (0.031)      | (0.030)      |
| Group2                   | -0.088*** | -0.095***    | -0.092***    | -0.081***    |
|                          | (0.024)   | (0.031)      | (0.029)      | (0.028)      |
| Group3                   | -0.041**  | -0.052**     | -0.043*      | -0.035       |
|                          | (0.020)   | (0.026)      | (0.023)      | (0.022)      |
| Group4                   | -0.026    | -0.037       | -0.033       | -0.012       |
|                          | (0.019)   | (0.026)      | (0.021)      | (0.022)      |
| Group5                   | 0.013     | -0.004       | 0.012        | 0.021        |
|                          | (0.021)   | (0.030)      | (0.024)      | (0.024)      |
| Group6                   | -0.001    | 0.040        | 0.012        | 0.015        |
|                          | (0.020)   | (0.026)      | (0.024)      | (0.023)      |
| Group7 (omitted)         | 0.000     | 0.000        | 0.000        | 0.000        |
| Group8                   | -0.009    | -0.021       | -0.013       | 0.001        |
|                          | (0.020)   | (0.029)      | (0.022)      | (0.023)      |
| Group1 × Treat           | -0.057*   | -0.026       | -0.049       | -0.076**     |
|                          | (0.032)   | (0.036)      | (0.035)      | (0.036)      |
| Group2 × Treat           | -0.006    | 0.010        | -0.002       | -0.015       |
|                          | (0.032)   | (0.036)      | (0.035)      | (0.035)      |
| Group3 × Treat           | -0.032    | -0.015       | -0.030       | -0.040       |
|                          | (0.024)   | (0.029)      | (0.026)      | (0.027)      |
| Group4 $\times$ Treat    | -0.012    | 0.003        | -0.006       | -0.026       |
|                          | (0.025)   | (0.029)      | (0.026)      | (0.027)      |
| Group5 $\times$ Treat    | -0.040    | -0.020       | -0.039       | -0.048       |
|                          | (0.027)   | (0.034)      | (0.029)      | (0.030)      |
| Group6 × Treat           | -0.012    | 0.028        | -0.026       | -0.029       |
|                          | (0.025)   | (0.031)      | (0.030)      | (0.030)      |
| Group7 × Treat (omitted) | 0.000     | 0.000        | 0.000        | 0.000        |
| Group8 × Treat           | 0.048     | 0.057        | 0.050        | 0.038        |
| 2                        | (0.030)   | (0.035)      | (0.030)      | (0.032)      |
| Pseudo R <sup>∠</sup>    | 0.064     | 0.056        | 0.071        | 0.067        |
| Obs.                     | 5063      | 4272         | 4475         | 4447         |

Table 4. Group dummies and treatment effects 2013-2016.

Notes: Probit estimations with the employment dummy as the dependent variable. Cells show the marginal effects evaluated at the means of all explanatory variables. Robust standard errors are shown in brackets below. Superscripts \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5% and 10% levels respectively. The control variables are in year dummies, region of residence, gender, ethnicity, age, education level, sector of activity and occupation. 62 👄 S. FERRARO ET AL.

#### 4.2. Refinement of treatment group

The nominal wage growth in the ELFS sample used in this paper was on average 7.0% in 2013, 5.9% in 2014, 6.0% in 2015 and 7.6% in 2016. If the wage increases were evenly distributed across the wage distribution, some low-wage workers may have received substantial wage increases without these being related to or caused by the minimum wage rises. Workers in Group2 may thus have received wage increases due to the overall wage drift in the labour market and not because of the higher minimum wage. This subsection seeks to assess whether this could be behind the muted effect on employment retention for Group2. The idea is to refine the treatment group so that it is more likely to contain workers that have effectively been treated by higher minimum wages.

We split Group2 into two groups, Group2A and Group2B. Group2A consists of the individuals in Group2 with the lowest wages of the group while Group2B is composed of those with highest wages. Group2B is then those who would have ended up with a wage exceeding the new minimum wage *if* they had received the average wage increase of that year. Group2A then consists of those who would *not* have reached the new minimum wage even if they had received the average wage increase of that year. Group2A is thus more likely to have been directly affected or 'treated' by the higher minimum wage than Group2B is.

For each of the years of the treatment sample, the cut-offs between Group2A and Group2B are computed using the average wage growth of the year. For 2013, Group2B contains individuals who would reach or surpass the minimum wage for 2014 if they received 7.0% higher wage income, while Group2A consists of the remaining individuals from Group2. The wage growth used to compute the cut-off is 5.9% in 2014, 6.0% in 2015 and 7.6% in 2016. For the reference period, the cut-offs are 1.1% in 2009 and 5.9% in 2010.

The drawback of this refinement is that the number of observations is very small in Group2A and especially in Group2B. Over the four years of the treatment sample there are 73 observations in Group2A and 58 in Group2B. Of even greater concern is that over the three years in the reference sample there are 95 observations in Group2A but only 5 in Group2B. The lack of observations for Group2B in the reference period means that the results for this group are inconsequential and should not be given any attention.

Table 5 shows the results when the baseline estimation is modified so that Group2 and its interaction with the treatment dummy are replaced by Group2A and Group2B and their interactions with the treatment dummy. The set of control variables differs across the columns but corresponds to those in Table 2. The main issue is whether the results for the low-paid workers in Group2A, the workers most likely to have been directly affected by the minimum wage increases in 2013–2016, are different from those for Group5 reported in Table 2.

The estimated treatment effects for Group2A reported in Table 5 are in all cases negative and in numerical terms larger than the effects for Group2 reported in Table 2. This suggests that refining Group2 so that it consists of the workers most likely to have been affected by the rises in the minimum wage did change the estimation results somewhat. However, the treatment effects for Group2A are still very small and statistically insignificant, suggesting that the results reported for Group2 in Table 2 are not substantially influenced by any imprecision in the definition of the group of workers directly affected by rises in the minimum wage.

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|                                 | (5.1)         | (5.2)             |
|---------------------------------|---------------|-------------------|
|                                 | Main controls | Only year dummies |
| Group1                          | -0.056**      | -0.051**          |
|                                 | (0.026)       | (0.025)           |
| Group2A                         | -0.081**      | -0.079**          |
|                                 | (0.025)       | (0.025)           |
| Group2B                         | -0.198**      | -0.185**          |
|                                 | (0.074)       | (0.076)           |
| Group3                          | -0.041**      | -0.039**          |
|                                 | (0.020)       | (0.019)           |
| Group4                          | -0.026        | -0.026            |
|                                 | (0.019)       | (0.019)           |
| Group5                          | 0.013         | 0.011             |
|                                 | (0.021)       | (0.021)           |
| Group6                          | -0.001        | -0.004            |
|                                 | (0.020)       | (0.021)           |
| Group7 (omitted)                | 0.000         | 0.000             |
| Group8                          | -0.009        | -0.014            |
|                                 | (0.020)       | (0.021)           |
| Group1 × Treat                  | -0.057*       | -0.060*           |
|                                 | (0.032)       | (0.032)           |
| Group2A × Treat                 | -0.020        | -0.009            |
|                                 | (0.036)       | (0.036)           |
| $Group2B \times Treat$          | 0.114         | 0.108             |
|                                 | (0.079)       | (0.082)           |
| Group3 × Treat                  | -0.032        | -0.029            |
|                                 | (0.024)       | (0.025)           |
| Group4 $	imes$ Treat            | -0.012        | -0.006            |
|                                 | (0.025)       | (0.025)           |
| Group5 $\times$ Treat           | -0.040        | -0.032            |
|                                 | (0.028)       | (0.028)           |
| Group6 × Treat                  | -0.013        | -0.005            |
|                                 | (0.028)       | (0.028)           |
| Group7 $\times$ Treat (omitted) | 0.000         | 0.000             |
| Group8 × Treat                  | 0.047         | 0.055*            |
|                                 | (0.030)       | (0.030)           |
| Pseudo R <sup>2</sup>           | 0.065         | 0.052             |
| Obs.                            | 5063          | 5091              |

Table 5. Group dummies and treatment effects 2013-2016.

Notes: Probit estimations with the employment dummy as the dependent variable. Cells show the marginal effects evaluated at the means of all explanatory variables. Robust standard errors are shown in brackets below. Superscripts \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5% and 10% levels respectively. The control variables in Column (5.1) are year dummies, region of residence, gender, ethnicity, age, education level, sector of activity and occupation; in Column (5.2) only year dummies.

### 5. Final comments

This paper assesses whether the rises in the Estonian minimum wage in 2013–2016 changed the probability of workers across the wage distribution retaining full-time employment, either in the job they had when the minimum wage was increased or in another job. The effect is identified using a difference-in-differences methodology in which the probability of a worker retaining employment during the treatment period 2013–2016 is compared with the probability in the reference period 2009–2011 when the minimum wage was constant.

The estimations show that the probability of retaining employment for different wage groups during the period of rises in the minimum wage was not different from the probability of retaining employment for comparable wage groups during the years 2009–2011

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when there were no increases in the minimum wage. This suggests that the increases in 2013–2016 had no, or only indiscernible, effects on employment retention in the period. The result is very robust and holds irrespective of the set of control variables used in the estimations, and also holds if the early stage and the later stage of the rises in the minimum wage are considered separately, if the reference period is altered, or if the group of the directly treated is refined.

The results are not in line with the negative effect for those directly affected found in Hinnosaar and Rõõm (2003), who use Estonian data for the period 1995–2000. Hinnosaar and Rõõm (2003), however, identify the effect from year-on-year changes in the minimum wage, while we use a traditional difference-in-differences methodology. Moreover, there were very large rises in the minimum wage and intensive worker reallocation during the period 1995–2000, while our sample comprises a period of moderate increases and less intensive reallocation of workers (Meriküll, 2016).

The results are, however, in accordance with the finding in Bodnár et al. (2018) where only a few firms in Estonia report that they find firing of staff a relevant adjustment channel after hikes in the minimum wage. The results are also in line with a number of studies from other countries, which find little or no effect of minimum wages on employment or employment retention, at least as long as the minimum wage remains at moderate levels (see the reviews by Belman & Wolfson, 2014, ch. 4; Doucouliagos & Stanley, 2009; de Linde Leonard, Stanley, & Doucouliagos, 2014). Schmitt (2015) posits that the effect on employment is likely to be small because employers have many adjustment channels available to them when faced with a higher minimum wage.

The absence of any effects from minimum wage hikes on employment retention as found by this study does not necessarily mean that a higher minimum wage has no overall employment effects. The minimum wage could for instance make it harder for the unemployed to enter the labour market, or the labour market could be subject to substitution and complementarity effects that are not captured in this study. These considerations suggest that it would be useful to consider the broader effects of rises in the minimum wage using other empirical models. Such exercises are left for future research.

#### Notes

- 1. The monthly gross minimum wage for the full-time employed was 278.02 euros in 2008–2011, 290 euros in 2012, 320 euros in 2013, 355 euros in 2014, 390 euros in 2015 and 430 euros in 2016 (EMTA 2017).
- For reviews of the empirical literature on developed economies, see Card and Krueger (1995a, 1995b), Doucouliagos and Stanley (2009), Belman and Wolfson (2014, ch. 4) and OECD (2015).
- 3. Stewart and Swaffield (2002) distinguish between the extensive and intensive margins as impact on employment or impact on hours per worker. The authors find no reduction in employment but do find a reduction in hours worked.
- 4. These results are in line with the findings in Neumark et al. (2004). The impact on the directly affected is so large that it affects overall employment, as an increase of 10% in the minimum wage reduced overall employment retention by around 0.5%.
- Empirical studies of such spill-overs go back to the 1970s (Gramlich, 1976). Subsequent studies have found sizeable spill-over effects for some countries, including the USA and several emerging markets, but limited spill-overs for other countries such as the UK (Ferraro et al. Forthcoming).
- 6. We do not use the data for 2012 in the analysis in order to ensure that the treatment group is as homogenous as possible over the years.

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7. The summary statistics and estimations are produced using the sample data of the ELFS and as such pertain to the data of the ELFS databases. We have also produced summary statistics and estimations using sampling weights (the results are available from the corresponding author upon request). The results are, however, qualitatively similar to those of the unweighted data with only insignificant differences at the upper and lower wage levels and so we choose to present the results using the results from the unweighted data set; see also Solon, Haider, and Wooldridde (2015).

#### Acknowledgement

The authors would like to thank Jaanika Meriküll, Tairi Rõõm, the editor of *Baltic Journal of Economics*, Konstantins Benkovskis, and two anonymous referees for very useful comments to earlier versions of the paper. The usual disclaimer applies. This study has received funding from the European Union's Horizon 2020 research and innovation programme under Marie Skłodowska-Curie grant agreement no. 734712. The views expressed are those of the authors and not necessarily those of the Ministry of Finance of the Republic of Estonia or Eesti Pank or other parts of the Europystem.

#### **Disclosure statement**

No potential conflict of interest was reported by the authors.

#### Funding

This study has received funding from the European Union's Horizon 2020 Research and Innovation Framework Programme under Marie Skłodowska-Curie grant agreement no. 734712.

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### **Appendices**

Appendix A



Figure A1. Gross minimum wage in per cent of the gross average wage, 2000–2016. Source: EMTA (2017), Statistics Estonia (2017, codes: WS5211, WS5311), authors' calculations.

### Appendix B

| Table B1. Mean c | pross wage and t | the number of | observations in    | the eigh | it wage groups. |
|------------------|------------------|---------------|--------------------|----------|-----------------|
|                  |                  |               | 0.0000110110110110 |          |                 |

|        |           | 2009 | 2010 | 2011 | 2013 | 2014 | 2015 | 2016 |
|--------|-----------|------|------|------|------|------|------|------|
| Group1 | Mean wage | 242  | 219  | 203  | 187  | 171  | 307  | 342  |
|        | Obs.      | 31   | 41   | 33   | 39   | 23   | 37   | 39   |
| Group2 | Mean wage | 288  | 287  | 286  | 304  | 333  | 363  | 402  |
|        | Obs.      | 32   | 38   | 29   | 27   | 50   | 32   | 22   |
| Group3 | Mean wage | 366  | 359  | 358  | 366  | 428  | 467  | 520  |
|        | Obs.      | 105  | 114  | 88   | 102  | 125  | 138  | 131  |
| Group4 | Mean wage | 489  | 486  | 483  | 493  | 569  | 611  | 690  |
|        | Obs.      | 153  | 102  | 137  | 106  | 146  | 120  | 95   |
| Group5 | Mean wage | 610  | 613  | 606  | 617  | 699  | 742  | 834  |
|        | Obs.      | 124  | 72   | 82   | 96   | 103  | 128  | 98   |
| Group6 | Mean wage | 744  | 735  | 735  | 743  | 828  | 915  | 979  |
|        | Obs.      | 121  | 89   | 93   | 100  | 91   | 122  | 71   |
| Group7 | Mean wage | 924  | 939  | 931  | 955  | 1075 | 1174 | 1246 |
|        | Obs.      | 111  | 72   | 84   | 155  | 170  | 160  | 137  |
| Group8 | Mean wage | 1563 | 1589 | 1539 | 1710 | 1954 | 1927 | 2225 |
|        | Obs.      | 120  | 63   | 73   | 134  | 110  | 103  | 74   |
| All    | Mean wage | 653  | 653  | 643  | 672  | 757  | 813  | 905  |
|        | Obs.      | 797  | 591  | 619  | 759  | 818  | 840  | 667  |

Note: The mean wage is the mean of the nominal pre-tax wage in euros of the group.

# Curriculum vitae

# 1. Personal data

| Name                    | Simona Ferraro            |
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| Date and place of birth | 19.04.1981, Agrigento     |
| Citizenship             | Italian                   |
| E-mail address          | simona.ferraro@taltech.ee |

# 2. Education

| Educational institution                                       | Graduation<br>year | Education (field of study/degree)           |
|---|--------------------|---|
| Tallinn University of<br>Technology                           | (2018)             | Economics / Doctor of Philosophy            |
| Politecnico di Milano   | 2018               | Visiting Doctoral student                   |
| University of Palermo   | 2014               | Economics / Bachelor of Arts                |
| Ministry of Justice   | 2009               | Chartered Accountant                        |
| Ministry of Justice   | 2009               | Auditor                                     |
| Libera Università degli<br>Studi Maria Ss. Assunta di<br>Roma | 2007               | Marketing / Second Level Master's<br>Degree |
| Università degli Studi di<br>Palermo                          | 2005               | Laurea Degree in Economics and<br>Business  |

# 3. Language

| competence/skill |
|------------------|
|------------------|

| Language | Level        |
|----------|--------------|
| Italian  | Native       |
| English  | Fluent       |
| French   | Advanced     |
| Spanish  | Basic skills |
| Estonian | Basic skills |

# 4. Special courses

| Period | Course |
|--------|--------|
| Period | Course |

Educational or other organisation

| March 2017 | Introduction to R                   | University of Bamberg                    |
|------------|-------------------------------------|--|
| March 2016 | Bayesian Econometrics               | Eesti Pank (Bank of<br>Estonia), Tallinn |
| June 2015  | Introduction to Multilevel Modeling | University of Tartu                      |
| May 2015   | Applied Spatial Econometrics with R | University of Tartu                      |

# 5. Professional employment

-

| Period      | Organisation                         | Position   |
|-------------|--------------------------------------|--|
| 2017        | Tallinn University of Technology     | Lecturer, Department of<br>Economics and Finance         |
| 2016 – 2017 | Tallinn University of Technology     | Visiting Lecturer, Department of Economics and Finance   |
| 2016 – 2016 | Bank of Estonia                      | Intern, Research Department                              |
| 2010-2013   | Simona Ferraro                       | Self-Employed, Chartered<br>Accountant                   |
| 2012-2013   | Alin S.p.A.                          | External Auditor   |
| 2009 - 2009 | Banca Popolare Sant'Angelo di Licata | Collaborator, Headquarters Banca<br>Popolare Sant'Angelo |
| 2008 - 2008 | Eureka S.p.A.<br>(Vocational school) | Teacher  |
| 2006 - 2007 | GE.I.S. S.r.L.                       | Teacher  |

# 6. Research activity, including honours and thesis supervised

2018 – Doctoral School scholarship for participating in the Barcelona Graduate Summer School, July 2-6, 2018, Barcelona (Spain)

2018 – Dora Plus doctoral scholarship for semester of research at Politecnico di Milano, Italy.

2017 – Scientific award named after prof. Vello Vensel by Estonian Economic Association for article "Is there a Trade-off between Efficiency and Equity in Education?" (co-authored by Kaire Põder)

2017 – Doctoral School scholarship for the article "School-level policies and the efficiency and equity trade-off in education" presentation in 5<sup>th</sup> Workshop on Efficiency in Education "Efficiency in education and performance measurement in public sector", 19-20 October 2017, Budapest, Hungary.

2017 – Doctoral School scholarship for the article "School-level policies and the efficiency and equity trade-off in education" presentation in the Seventh ECINEQ Meeting 2017 – The Graduate Center City University of New York, 17-19 July 2017, New York, New York.

2016 – Dora Plus scholarship for the article "School-level policies and the efficiency and equity trade-off in education" in the Emerging Researchers' Conference 22-23 August 2016, Dublin, Ireland.

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## Publications

Dutt Pawan, Simona Ferraro, Archil Cochilla and R. Muljar, 2018. Using Patent Development, Education Policy and Research and Development Expenditure Policy to Understand Differences Between Countries – The Case of Estonia and Finland. *Baltic Journal of European Studies*, vol. 8, no. 1, pp. 123–153. (ETIS 1.1)

Ferraro Simona, 2018. Is information and communication technology satisfying educational needs at school? *Computers and Education*, vol. 122, pp. 194-204. (ETIS 1.1)

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Supriya Banerjee, Mike Franz Wahl, Jelena Hartsenko, Simona Ferraro, 2017. Towards mitigating conflicts of interest: An empirical study of typology of corporate governance systems including values, *International Journal of Development and Sustainability*, vol. 6, no. 7, pp. 488-499. (ETIS 1.1)

## Working Papers

Ferraro Simona, Jaanika Meriküll, Karsten Staehr (2016). Minimum wages and the wage distribution in Estonia, Eesti Pank Working Paper Series 6/2016 (ETIS 3.3).

# *Conference presentations / Conference proceedings*

July 2018 - Labour Economics Summer School at Barcelona Graduate School of Economics, July 2-6 2018. Courses attended: Economics of Education with Prof. Derek Neal (School of Chicago) and Labour Market Outcomes with Prof. Robert Schimer (School of Chicago)

October 2017 - 5<sup>th</sup> Workshop on Efficiency in Education "Efficiency in education and performance measurement in public sector", Budapest, Hungary. Article presented "School-Level Policies and the Efficiency and Equity Trade-off in Education"

October 2017 - Summer School on Applied Techniques "Hands-on data in education research", Education Economics Network (EdEN) Budapest, Hungary.

July 2017 - Seventh ECINEQ Meeting 2017, The Graduate Center City University of New York - New York City. Article presented "Is there a Trade-off between Efficiency and Equity in Education?"

June 2017 - PhD Summer School in Economics, Management, Governments and Politics, Political Science, Law and Public Administration. Article presented "Is there a Trade-off between Efficiency and Equity in Education?" Saka Manor (Estonia)

June 2017 - 9<sup>th</sup> international conference "Economic Challenges in Enlarged Europe", Tallinn. Article presented "A Microeconometric Study of Minimum Wages and Employment Probabilities in Estonia".

April 2017 - Pre- and Post-Doc Colloquium "Amici come prima? Social Science Perspectives on Germany, Italy and the European union in Contemporary Crises", Menaggio (Italy). Article presented "The Italian and the German Labour Market: Perception, fiction and reality".

August 2016 - EERA-ECER (The European Conference on Educational Research) Emerging

Researchers' Conference, University College Dublin, Ireland. Article presented "School Level Policies and Efficiency and Equity Trade-off in Education".

August 2016 - EERA-ECER (The European Conference on Educational Research) Main Conference, University College Dublin, Ireland. Article presented "School Level Policies and Efficiency and Equity Trade-off in Education", August 23-26, 2016.

# August 2015 - Doctoral Summer School in Economics and Innovation, Pühajärve (Estonia).

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#### Teaching

Economics II (Microeconomics), Bachelor program in English - Department of Economics and Finance, Tallinn University of Technology.

Intermediate Microeconomics, Master program in English - Department of Economics and Finance, Tallinn University of Technology.

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Microeconomics I, Bachelor program in English - Department of Economics and Finance, Tallinn University of Technology.

#### 7. Defended theses

The role of the United Nations, Bachelor's Thesis, supervisor Prof. Anna Li Donni, Università degli Studi di Palermo

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#### 8. Main research topics

Economics of Education, Labour Economics, Microeconomics, Microeconometrics

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| Tallinnna Tehnikaülikool                                      | (2018)            | Majandusteaduse doktor                            |
| Politecnico di Milano   | 2018              | Külalisdoktorant                                  |
| University of Palermo   | 2014              | Ökonoomika / BA                                   |
| Ministry of Justice   | 2009              | Raamatupidaja litsent                             |
| Ministry of Justice   | 2009              | Audiitori litsent                                 |
| Libera Università degli<br>Studi Maria Ss. Assunta di<br>Roma | 2007              | Turundus / Magistrikraad                          |
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## 12. Keelteoskus (alg-, kesk- või kõrgtase)

| Keel      | Tase                     |
|-----------|--------------------------|
| Itaalia   | Emakeel                  |
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| Prantsuse | Kesktase                 |
| Hispaania | Algtase                  |
| Eesti     | Algtase                  |

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| Õppimise aeg | Täiendusõppe korraldaja nimetus          |
|--------------|--|
| 2017 Märts   | Sissejuhatus R-i, University of Bamberg, |
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| -          |  |
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| 2015 Juuni | Sissejuhatus mitmetasandilisse<br>modeleerimisse, Tartu Ülikool, Eesti |
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# 14. Teenistuskäik

| Töötamise aeg | Tööandja nimetus/ametikoht<br>(koormus)  |
|---------------|--|
| 2017          | Tallinna tehnikaülikool / Lektor,<br>Majandusanalüüsi ja rahanduse<br>instituut                        |
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| 2016 – 2016   | Eesti Pank / Praktikant-külalisuurija,<br>Majandusuuringute osakond                                    |
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\*esitatud on inglisekeelsete teoste pealkirjade eestikeelsed tõlked

## Publikatsioonid

Dutt Pawan, Simona Ferraro, Archil Cochilla ja R. Muljar, 2018. Using Patent Development, Education Policy and Research and Development Expenditure Policy to Understand Differences Between Countries – The Case of Estonia and Finland. *Baltic Journal of European Studies*, vol. 8, no. 1, pp. 123–153. (ETIS 1.1)

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Ferraro Simona, Hänilane Birgit ja Karsten Staehr, 2018. Minimum wages and employment retention across the wage distribution. A microeconometric study for Estonia. *Baltic Journal of Economics*, vol. 18, no. 1, pp. 51-67 (ETIS 1.1)

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Ferraro Simona, Pawan Kuman Dutt, Tanel Kerikmae, 2017. Using Patent Development, Education Policy and Research and Development Expenditure Policy to Increase Technological Competitiveness of Small European Union Member States, *Croatian*  International Relations Review, vol. XXIII, no. 78, pp. 97-126. https://doi.org/10.1515/cirr-2017-0009 (ETIS 1.1)

Supriya Banerjee, Mike Franz Wahl, Jelena Hartsenko, Simona Ferraro, 2017. Towards mitigating conflicts of interest: An empirical study of typology of corporate governance systems including values, *International Journal of Development and Sustainability*, vol. 6, no. 7, pp. 488-499. (ETIS 1.1)

## Toimetised

Ferraro Simona, Jaanika Meriküll, Karsten Staehr (2016). Minimum wages and the wage distribution in Estonia, Eesti Pank Working Paper Series 6/2016 (ETIS 3.3).

## Konverentsiettekanded / eelpublitseerimine konverentsimaterjalidena

2018 juuli - Labour Economics Summer School, Barcelona Graduate School of Economics, 2.-6. juuli 2018. Osavõtt kursustest : Economics of Education, Prof. Derek Neal (School of Chicago) ja Labour Market Outcomes, Prof. Robert Schimer (School of Chicago), Hispaania

2017 oktoober - 5<sup>th</sup> Workshop on Efficiency in Education "Efficiency in education and performance measurement in public sector", Budapest, Ungari. Ettekanne "School-Level Policies and the Efficiency and Equity Trade-off in Education"

2017 oktoober - Summer School on Applied Techniques "Hands-on data in education research", Education Economics Network (EdEN), Budapest, Ungari.

2017 juuli - Seventh ECINEQ Meeting 2017, The Graduate Center City University of New York , New York, USA. Ettekanne "Is there a Trade-off between Efficiency and Equity in Education?"

2017 juuni – Majanduse ja innovatsiooni doktorikooli suvekool (MIDOK). **Ettekanne** "Is there a Trade-off between Efficiency and Equity in Education?" Saka 'Mõis, Eesti.

2017 juuni - 9<sup>th</sup> international conference "Economic Challenges in Enlarged Europe", Tallinn, Eesti. Ettekanne "A Microeconometric Study of Minimum Wages and Employment Probabilities in Estonia".

2017 aprill - Pre- and Post-Doc Colloquium "Amici come prima? Social Science Perspectives on Germany, Italy and the European union in Contemporary Crises", Menaggio, Itaalia. Ettekanne "The Italian and the German Labour Market: Perception, fiction and reality".

2016 august - EERA-ECER (The European Conference on Educational Research) Emerging Researchers' Conference, University College Dublin, Iirimaa. Ettekanne "School Level Policies and Efficiency and Equity Trade-off in Education".

2016 august - EERA-ECER (The European Conference on Educational Research) Main Conference, University College Dublin, Iirimaa. Ettekanne "School Level Policies and Efficiency and Equity Trade-off in Education", 23.-26. august.

2015 august - Majanduse ja innovatsiooni doktorikooli suvekool (MIDOK), Pühajärve, Eesti.

2015 juuni - 7<sup>th</sup> international conference "Economic Challenges in Enlarged Europe", Tallinn, Eesti. Ettekanne "Tale of one culture: Family Background Effects in Educational Achievements in Northern and Southern Italy".

# Õppetöö

Ökonoomika II (Microeconomics), Inglisekeelne bakalaureuseprogramm – Majandusteooria ja Rahanduse instituut, Tallinna Tehnikaülikool.

Mikroökonoomika keskkursus (Intermediate Microeconomics), Inglisekeelne magistriprogramm – Majandusteooria ja Rahanduse instituut, Tallinna Tehnikaülikool.

Arenguökonoomika (Development Economics), Inglisekeelne magistriprogramm – Majandusteooria ja Rahanduse instituut, Tallinna Tehnikaülikool

Mikroökonoomika I (Microeconomics I), Inglisekeelne bakalaureuseprogramm – Majandusteooria ja Rahanduse instituut, Tallinna Tehnikaülikool

# 16. Kaitstud lõputööd

The role of the United Nations, Bachelor's Thesis, juhendaja Prof. Anna Li Donni, Università degli Studi di Palermo

L'impatto dei servizi turistici in Italia [Itaalia turismiteenuste mõjuuuring], Laurea's Thesis, juhendaja Prof. Vincenzo Lo Jacono, Università degli Studi di Palermo

# 17. Teadustöö põhisuunad

Haridusökonoomika, tööjõuökonoomika, mikroökonoomika, mikroökonomeetria

# 18. Lisainfo

2017 – Itaalia Ökonomeetria seltsi liige

2017 – Doktorantide õpilasesindaja, Majandusteooria ja Rahanduse instituut, Tallinna Tehnikaülikool