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The Returns to Preschool Attendance

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Abstract

Preschool attendance is widely recognized as a key ingredient for later socioeconomic success, mothers' labor market participation, and leveling the playing field for children from disadvantaged backgrounds. However, the empirical evidence for these claims is still relatively scarce, particularly in Europe. Using data from the 2011 Austrian European Union Statistics of Income and Living Conditions (EU-SILC), we contribute to this literature in all mentioned dimensions. In particular, we investigate the effect of preschool attendance on an individual's later educational attainment, the probability that they work full time and their hourly wages, the likelihood of the mother working when the child is 14 years old, and on the overall distribution of wages. We find strong and positive effects of preschool attendance on educational attainment, the probability of working full time, hourly wages, and the probability that the mother is in the labor market. Full time workers at the bottom and the top of the distribution tend to benefit less than those in the middle. Women in particular benefit more in terms of years of schooling and the probability of working full time. Other disadvantaged groups (second migration migrants; people with less educated parents) also often benefit more in terms of education and work.

JEL Classifications: I26, J62, I24, H52, I38

Key Words: returns to preschool/kindergarten, early childhood education, education, inequality

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1 Introduction

Preschool[1] is widely discussed as a potential tool to give children the best opportunities for success and to combat socioeconomic inequality. The literature does indeed show that preschool has many positive impacts on individuals in terms of their social, cognitive, and economic development.

This paper contributes to the literature on early childhood education and economic inequality by studying the economic and social effects of preschool attendance in Austria. Using a broad set of econometric methods, we look at the effect of preschool attendance on a battery of economic outcomes, for different groups of individuals (men/women; native/migrant; and descendants of high versus low educated parents). In particular, we study the effects of preschool attendance on education (total years of schooling and the probability of completing university), on labor market outcomes (the probability of working full time and hourly wages), on the probability that the respondent's mother participated in the labor force when the respondent was 14, and on wage inequality. This is the first study to examine the effects of preschool attendance for people in Austria, making it a contribution to our knowledge of European educational systems and the impact of early childhood education in an institutional context of relatively early tracking ages. The tracking age in Austria and Germany is 10, as compared to 15-16 in the other European countries discussed throughout this paper (France, the UK, and Norway) (European Commission, 2015a,b). In this context, preschool may be particularly helpful for later socioeconomic outcomes, since it could affect the decision about which schooling track to follow and thus the chances for finishing tertiary education and having higher wages.

We find that across the board, preschool attendance has positive effects on later outcomes at the personal (education, labor force attachment, and wages), familial (mother's labor force participation), and social (inequality in hourly wages) levels. Attending preschool leads to both a quantitative improvement in educational outcomes, via a 0.4 year increase in the years of schooling completed, and a qualitative improvement, by raising the probability of finishing a higher education degree by 4.9 percentage points. Preschool attendance also increases the chances of working full time by 5.3 percentage points and hourly wages by 7.3 percent, on average. The effects on years of schooling and probability of working full time are stronger for women; indeed preschool attendance almost halves the gender gap in the probability of working full time. Another significant gender effect of preschool is that the probability of a mother working when her child is 14 is 10.8 percentage points higher when the child had attended preschool. Finally, preschool has the strongest wage impact for people in the middle of the income distribution, and it lowers inequality in the upper half of the income distribution.

[1]Throughout this paper, we call all forms of schooling before primary school, including kindergarten, "preschool."

The paper presents our analysis as follows. Section 2 gives a brief overview of existing literature on the preschool effects on the outcomes of interest in European countries. Section 3.1 introduces the data set and its main properties, while section 3.2 lays out the identification and estimation strategies used. Section 4 presents the results of our empirical exercises, and section 5 discusses the results and concludes.

2 Background

There is a large literature on the effects of early childhood education on one's later outcomes, particularly for the U.S. Although dated, Currie (2001) gives an excellent review of the (primarily U.S.) literature, showing that preschool attendance leads to a wide range of positive effects, from higher IQ, better scores on academic tests, stronger grade retention, and higher graduation rates to lower probabilities of being unemployed, on welfare, in jail, or pregnant as a teen. Given that the present study focuses in particular on the effects of preschool attendance on educational attainment, labor force attachment and wages earned, mother's labor force participation, and wage inequality in Austria, we restrict our review of this literature to studies from other European countries with similar outcome measures. While several studies look at the benefits of preschool to children's general social, emotional, and cognitive development in various European countries and for heterogeneous groups (e.g. Felfe and Lalive (2013) for Germany, Esping-Andersen et al. (2012) and Bauchmüller et al. (2014) in Denmark, Leuven et al. (2010) in the Netherlands, and Fredriksson et al. (2010) for Sweden), we focus on literature which has similar individual-level outcome variables to our own.

Turning first to the effect of preschool attendance on a person's later educational attainment and earnings, the literature fairly consistently reports positive impacts, albeit with differing degrees of strength for people in various socio-demographic groups. In studying the effects of a reform expanding preschool availability in Norway, for example, Havnes and Mogstad (2011) find that the expansion resulted in 0.35 more years of schooling, on average; an increase of college attendance rates of 6.8 percentage points; and a decrease in high school drop-out rates of 5.8 percentage points. Most of these positive effects are driven by exceptionally strong results for children with less educated mothers, and for girls, who are about seven percentage points less likely to become low earners if they received the preschool treatment. The same authors show in a later study that attending preschool leads to higher earnings, particularly for women and for people from a lower socioeconomic background. Indeed girls who were exposed to the child care reform had higher earnings than girls who did not, while boys who got a preschool education actually had lower earnings than boys without a preschool education (although these findings are not statistically significant) (Havnes and Mogstad, 2015).

Using a similar estimation framework as ours with data from the U.K., Goodman and Sianesi (2005) show that pre-compulsory school attendance increases the probability of obtaining a degree or other higher education qualification for women (but not men), though the magnitude of this effect is not reported.[2] Further, Goodman and Sianesi (2005) find that preschool attendance is related to an increase of three percent in wages for women (only) up through age 33. When respondents were surveyed at age 42, the positive effect of preschool on earnings had disappeared.

Further, Dumas and Lefranc (2010) study the effects of reforms which expanded preschool enrollment in France in the 1960s and 70s, finding that an additional year of preschool reduced the probability of needing to repeat a grade later on by two percentage points and increased the probability of graduating from high school by almost three percentage points. This result is driven by positive effects found for people from lower- and middle-class backgrounds. Moreover, the authors find that starting preschool a year earlier increases monthly wages by about three percent. These results hold only for people from lower and middle class backgrounds. Finally, in West Germany, an analysis of a rich dataset (the German Socio-Economic Panel) by Spiess et al. (2003) suggests that attending preschool leads to a tremendous increase in the probability of being assigned to an academic school track for second generation migrant children, but not for native German children.

Aside from later educational attainment and earnings, we are also interested in knowing if preschool attendance has an impact on one's mother's labor force participation. The authors know of only two papers which study this effect in European countries; both Havnes and Mogstad (2011) and Black et al. (2014) find no net effect of preschool on mothers' labor force participation in Norway. The seminal paper in the U.S. literature, though, suggests that at least in some states (those in which there are data and policy reforms which allow an experimental design), preschool boosts the probability of a mother working (by about seven percent) if the mother is married or, in the case of single mothers (by about six percent), if the child in preschool is the youngest in the household (Gelbach, 2002). Cascio (2009) confirms these findings for single mothers (the probability of having worked last week increases by 7.5 percent), but finds less strong effects for married women. While an early analysis found that there was no effect of the implementation of universal preschool on mother's labor force participation (Fitzpatrick, 2010), the same author later used a different estimation technique and could confirm that the implementation of free preschool increases the probability of working of (only) single mothers whose youngest child is preschool age by between 15 and 20 percentage points (Fitzpatrick, 2012). Preschool and preschool availability have also been shown to have a positive impact on mothers' labor force participation in Argentina (seven to 14 percentage point increase in the probability of working) (Berlinski and Galiani, 2007), Québec, Canada (6.5 percentage points for mothers with a high school diploma; 7.9 percentage points for all

[2]Similarly, in the U.S., Anderson (2008) found that the Perry Preschool, Abecedarian, and the Early Training Project Programs had a statistically significant positive relationship with the cognitive development and later economic success of girls, but not boys. This study corrected for the potential for rare events in the multiple inference framework in earlier analyses which had found positive results for boys only.

mothers) (Lefebvre and Merrigan, 2008), and on Arab mothers in Israel (seven percentage points) (Schlosser, 2005).

Finally, three European papers look explicitly at the impact of expanded preschool access on wage inequality and find an equalizing effect of preschool on the wage distribution. Havnes and Mogstad (2011) show that both boys and girls who attended preschool are 2.2 percentage points less likely to become top earners, while girls are seven percentage points less likely to become low earners. Preschool attendance also increases the probability of girls becoming average earners by almost 8.5 percentage points. The same authors later show that attending preschool increases the earnings of people from a low socioeconomic background by almost three percent and decreases them for people from a high socioeconomic background by about two percent (Havnes and Mogstad, 2015, table 2). Further, the wage effects of preschool attendance are highest for people from lower earnings households, with a peak in the effect at about the 11^{th} percentile of the household earning distribution and negative effects after the 82^{nd} percentile. Finally, the analysis in Dumas and Lefranc (2010) reveals that preschool increases monthly earnings for people whose parents were in social group one (farmers and manual workers) and social group two (non-manual workers), while decreasing wages for those whose parents were higher-grade professionals.

3 Empirical Set-up

3.1 Data

We employ data from the 2011 Austrian European Union Statistics on Income and Living Conditions (EU-SILC) dataset (Statistik Austria, 2014) for this analysis. The data provide information on demographic, economic, and family background characteristics of 13,933 individuals.

Our main variable of interest is preschool attendance. The relevant survey question asked respondents if they had attended kindergarten or preschool (*"Kindergarten" or "Vorschule"*) (answers were either simply yes or no, meaning that there is no information on the length of preschool attendance or the characteristics of the institution visited). Only individuals aged 25-59 were given the special module asking about preschool, which is an unproblematic restriction because we are mainly interested in labor market outcomes. We further dropped all individuals who were not born in Austria or who moved to Austria before the age of four (1,085 observations), in order to avoid conflating the effects of kindergarten attendance in other countries with those in Austria. Of the remaining 5,707 observations, we drop 16 who stated that they did not live in Austria at age of 14, and 12 further individuals who did not provide information on their kindergarten attendance. The final sample comprises 5,679 individuals.

Table 1 presents main descriptive statistics for our sample. About 60% of the the adult

Austrian population aged 25 to 59 attended preschool as a child. The share of individuals enrolled in preschool slightly increased over time. Among the population without preschool, only about 6% are younger than 35, while this youngest cohort represents 23% of the population but comprises 34% of all people who attended preschool. Males and females were almost equally likely to attend preschool, but the distribution of preschool attendance varies greatly by (later) educational attainment. Overall, about 15% of the population has a tertiary education, but 19% of preschool goers and only 9% of people without preschool have a tertiary education. Accordingly, average years of schooling is lower in the population without preschool attainment. Two percent of our sample is second generation migrants. The small share of second generation migrants is due to the fact that the major recent migration waves into Austria occurred in the 1960s and 1970s, as "guest workers" came from Yugoslavia and Turkey, and in the 1990s, because of the Yugoslavian war. The large majority of the children of these migrants will have been born after the cutoff dates for participation in this module of the SILC survey.[3]

3.2 Identification and estimation strategy

To estimate the effect of preschool enrollment on later economic outcomes, we draw on the recent microeconometric literature on causal effects, program evaluation, and decomposition methods. The workhorse for our analysis of preschool effects is a fully integrated linear model with a functional form allowing for heterogeneous treatment effects and straight forward interpretation, which was proposed in Imbens and Rubin (2015). However, for our analyses beyond the average effect we also use the propensity score (Rosenbaum and Rubin, 1983), and re-centered influence function regressions (Fortin et al., 2009) to estimate the returns to preschool attendance. Most of these decomposition techniques are summarized in, for example, Fortin et al. (2011). We also include estimates of the mediation effects in our prediction of the effect of preschool on wages, where we use standard approaches discussed in Pearl (2009) or VanderWeele (2015).

As in other studies that measure the returns to educational attainment, we are faced with potential selection bias in our estimates. We observe the differences in outcomes Y between those individuals $i \in I$ who attended preschool ($T_i = 1$) and those who did not ($T_i = 0$), as shown in the left hand side of equation (1). These observed differences can be split up into two parts. First, there is the causal effect of preschool, which is what we are interested in measuring. Second, there is also potential selection bias, arising from the fact that potential outcomes under the condition of no preschool attendance (Y_{0i}) might be different for those who attend preschool and those who do not. This idea is expressed in the second expression on the right hand side of equation (1). Therefore, the observed differences in outcomes for

[3]The respondents in our sample were 25-59 in 2010 (and thus born between 1951-1985).

Table 1: Descriptive Statistics

	All	Preschool	No Preschool
Preschool	0.60	1.00	0.00
	(0.007)		
Mean age	43.0	39.8	47.9
	(0.142)	(0.183)	(0.168)
Age 25-34	0.23	0.34	0.06
	(0.006)	(0.009)	(0.006)
Age 35-44	0.29	0.33	0.24
	(0.006)	(0.009)	(0.010)
Age 45-59	0.48	0.33	0.71
	(0.007)	(0.009)	(0.011)
Female	0.50	0.49	0.50
	(0.007)	(0.009)	(0.012)
Primary education	0.13	0.09	0.19
	(0.005)	(0.005)	(0.010)
Lower secondary education	0.42	0.38	0.49
	(0.007)	(0.009)	(0.012)
Upper secondary education	0.30	0.34	0.24
	(0.007)	(0.009)	(0.010)
Tertiary education	0.15	0.19	0.09
	(0.005)	(0.007)	(0.006)
Years of schooling	11.49	11.93	10.83
	(0.036)	(0.049)	(0.049)
Second Generation Migrant	0.02	0.02	0.02
	(0.002)	(0.003)	(0.003)
Number of Observations	5,679	3,429	2,250

Notes: This table shows the means of the main variables used in the sample. Standard errors are given in parentheses. *Source*: Authors' calculations on EU-SILC 2011.

those with versus those without preschool attendance may not be the effect of preschool. As we cannot observe the counterfactual outcomes Y_{0i} for those who did attend preschool or Y_{1i} for those who did not, we cannot empirically decompose the left into the right hand side of equation (1).

$$\underbrace{\mathbb{E}\left[Y_i|T_i=1\right]-\mathbb{E}\left[Y_i|T_i=0\right]}_{\text{Difference in Outcome}}=\underbrace{\mathbb{E}\left[Y_{1i}|T_i=1\right]-\mathbb{E}\left[Y_{0i}T_i=1\right]}_{\text{Average effect of Pre-School}}+\underbrace{\mathbb{E}\left[Y_{0i}|T_i=1\right]-\mathbb{E}\left[Y_{0i}|T_i=0\right]}_{\text{Selection Bias}} \quad (1)$$

As in all observational studies,[4] we thus need to rely on assumptions about the assignment of preschool attendance in order to decompose the observed differences in economic outcomes into causal treatment effects and selection bias. The Conditional Independence Assumption (CIA) given in equation (2) is such an identification strategy. It states that once controlling for observable characteristics X, treatment assignment is random and selection bias disappears:

$$\{Y_{0i}, Y_{1i}\} \perp\!\!\!\perp T_i|X_i. \quad (2)$$

This assumption states that there is no (self-)selection into preschool correlated with potential economic outcomes, conditional on the covariates X. This assumption is not unproblematic, but reasonably credible with a rich set of covariates that determine selection into treatment, such as the ones we work with in this study. In our choice of covariates, we look for controls which ensure the CIA reasonably well without introducing bad control bias, which is another form of selection bias.[5] Good controls are variables which are themselves not an outcome of preschool attendance; the background characteristics on which we want to control are strictly exogenous to preschool attendance (Imbens, 2009).

The most important background characteristics in our data are the educational attainment of the mother and the father. Parental education explains a large part of an individual's later outcomes, since it is highly correlated with parental wealth, income, and health, which all affect descendant outcomes in a positive way (Haveman and Wolfe, 1995). Parental education is thus an important and credible proxy for social background. Highly educated parents are also more likely to (1) value schooling and (2) be attached to the labor market, which would make them more likely to enroll their children in preschool. At the same time, parental education is typically fixed well before the decision to send children to preschool. It is thus an ideal candidate for a covariate determining treatment assignment. Other important covariates in our data are age (and its square) and regional dummies for the nine provinces of Austria in

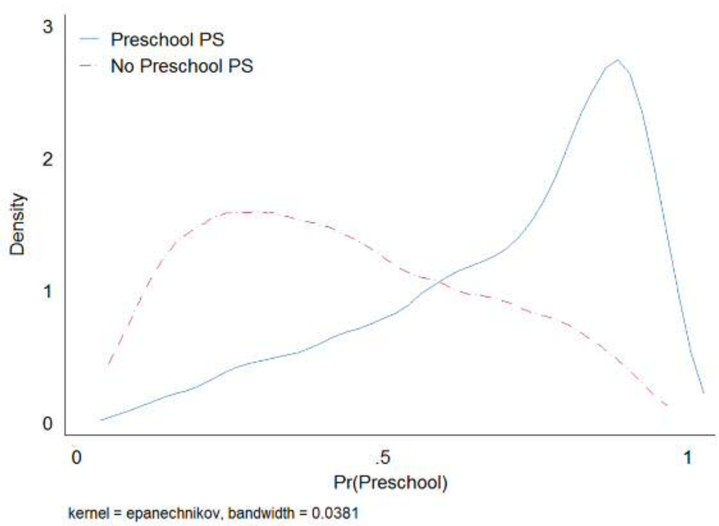
[4] A random assignment of preschool, which would solve the problem in the sense that $\mathbb{E}\left[Y_{0i}|T_i=1\right] = \mathbb{E}\left[Y_{0i}|T_i=0\right]$, is usually not feasible.

[5] In our application, we actually only need the slightly weaker conditional mean independence assumption (CMI), which states that after controlling for X, the treatment does not affect the conditional mean of each potential outcome, whereas the conditional variance might depend on the treatment.

which the respondent lived at age 14, as a proxy for the region in which s/he likely lived before the time of the preschool decision; both of which are likely to affect the selection into preschool attendance because of regional differences in the existence and expansion of the availability of preschool. Further, we use dummy variables for gender and being a second generation migrant.

To illustrate the credibility of our covariates in satisfying the CIA, we estimate a logit equation to obtain the probability of attending preschool conditional on X for all individuals in our sample. Figure 1 shows the resulting distributions of the probability of attending preschool (the propensity score (PS), as in Rosenbaum and Rubin (1983)), based on the covariates in X, for those who actually attended preschool (Preschool PS) and those who did not (No Preschool PS). One can clearly see the high predictive power of the selected covariates X: the people who attended preschool were indeed more likely to have attended, given their covariates, and the people who did not were less likely to have. The probabilities of the two groups are concentrated at the higher or lower levels of the probability distribution, corresponding to their actual attendance. Figure 1 also shows the large overlap, or common support, in the probability of attending preschool for these two groups. This large overlap illustrates that each individual *could* have received treatment or not (or, said differently, for each possible $x \in X$ and each treatment state T_i, $0 < Pr(T_i = i|x) < 1$). It is the background characteristics, captured in X, which make them more or less likely to be assigned treatment.

Figure 1: Propensity score for preschool attendance



Notes: This graph shows shows the distribution of propensity scores for preschool attendance and no preschool attendance based on a logit model using education of the mother, education of the father, age, age squared, second generation migrant, and regional dummies. *Source:* Authors' calculations on EU-SILC 2011.

To further study the credibility of the CIA in our empirical design, we present descriptive statistics of the covariates X used to model treatment assignment in table 2.[6] The table shows the means of the selection covariates in X for those who attended preschool and those who did not. People with and without preschool differ in some of their characteristics quite strongly; these groups differ in particular in their parental education, age, and region. The reweighted columns show that the characteristics of both subgroups balance rather well to the overall population once reweighted. We thus conclude that conditional on X, the treatment probability is almost equalized in the reweighted sample, giving ample support to the credibility of the CIA.

Different techniques to control for selection bias such as matching and regression with controls are valid under the same identifying assumption of conditional independence. In our analyses of the effects of preschool attendance on later socioeconomic outcomes, we study both average effects and effects across the distribution of the outcome. The following paragraphs describe the methods employed to do this.

First and foremost, we use simple observed differences in outcomes for those with and without preschool attendance as a benchmark measure, which we estimate using standard ordinary least squares, regressing the economic outcome of interest on a preschool dummy:

$$Y_i = \alpha + \beta \cdot T_i + \varepsilon_i. \tag{3}$$

We then gradually increase control over selection bias by adding in the demeaned background characteristics $(X_i - \bar{X})$ to the OLS model. Note that demeaning here does not change the coefficients, besides centering the intercept, and therefore also not their interpretation.

$$Y_i = \alpha + \beta \cdot T_i + (X_i - \bar{X})\gamma + \varepsilon_i. \tag{4}$$

Finally, to allow the treatment effect to be heterogenous across different individuals, we increase flexibility by interacting the preschool dummy with all covariates in X. This model allows the preschool effect to be different for individuals with different characteristics. As Imbens and Rubin (2015) propose, we include the covariates in deviations from the sample average, so that the estimated coefficient on the treatment indicator β, can be interpreted as an estimate for the average treatment effect of the treatment in the population. Implicitly this specification allows for separate slope coefficients for treated and control regression functions.

$$Y_i = \alpha + \beta \cdot T_i + (X_i - \bar{X})\gamma + T_i(X_i - \bar{X})\theta + \varepsilon_i \tag{5}$$

In equations (3) through (5), ε_i denotes an error term with mean zero and σ^2 variance.

[6] Note that there is missing information on the education of the father for 247 observations, on the education of the mother for 121 observations, and on the region of residence at age 14 for 41 observations, leaving us (due to some overlap in the missing patterns) a maximum of 5,396 observations for the estimations.

Table 2: Illustration of degree of rebalancing

	Overall	No Preschool	No Preschool reweighted	Preschool	Preschool reweighted
Age	43.1	47.9	44.7	40.0	43.5
	(0.126)	(0.158)	(0.252)	(0.159)	(0.228)
Age squared	1,946.7	2,349.1	2,060.6	1,680.4	1,984.1
	(10.736)	(14.536)	(20.820)	(13.092)	(20.541)
Female	0.51	0.52	0.52	0.51	0.51
	(0.007)	(0.011)	(0.014)	(0.009)	(0.011)
Lower Secondary (Father)	0.45	0.37	0.45	0.51	0.45
	(0.007)	(0.010)	(0.014)	(0.009)	(0.010)
Upper Secondary (Father)	0.11	0.05	0.09	0.14	0.11
	(0.004)	(0.005)	(0.010)	(0.006)	(0.005)
Tertiary (Father)	0.06	0.02	0.08	0.09	0.06
	(0.003)	(0.003)	(0.013)	(0.005)	(0.004)
Lower Secondary (Mother)	0.23	0.14	0.22	0.29	0.22
	(0.006)	(0.007)	(0.013)	(0.008)	(0.007)
Upper Secondary (Mother)	0.16	0.08	0.16	0.22	0.16
	(0.005)	(0.006)	(0.013)	(0.007)	(0.006)
Tertiary (Mother)	0.03	0.01	0.03	0.04	0.03
	(0.002)	(0.002)	(0.010)	(0.004)	(0.002)
Burgenland	0.04	0.03	0.04	0.05	0.04
	(0.003)	(0.004)	(0.006)	(0.004)	(0.003)
Carinthia	0.08	0.11	0.08	0.06	0.07
	(0.004)	(0.007)	(0.006)	(0.004)	(0.007)
Lower Austria	0.20	0.17	0.20	0.22	0.20
	(0.005)	(0.008)	(0.011)	(0.007)	(0.008)
Salzburg	0.07	0.07	0.07	0.07	0.07
	(0.003)	(0.006)	(0.007)	(0.004)	(0.006)
Styria	0.16	0.20	0.16	0.13	0.15
	(0.005)	(0.009)	(0.009)	(0.006)	(0.008)
Tirol	0.09	0.09	0.09	0.09	0.09
	(0.004)	(0.006)	(0.008)	(0.005)	(0.006)
Vorarlberg	0.04	0.02	0.04	0.06	0.04
	(0.003)	(0.003)	(0.008)	(0.004)	(0.003)
Vienna	0.12	0.07	0.14	0.16	0.13
	(0.004)	(0.006)	(0.013)	(0.006)	(0.006)
Second Generation Migrant	0.02	0.01	0.02	0.02	0.02
	(0.002)	(0.003)	(0.004)	(0.002)	(0.003)

Notes: This table shows the means and reweighted means of the main variables used in the sample. Reweights are based on a logit estimation of the preschool attendance dummy on the set of covariates X. Using the propensity score, both subsets are then reweighted to the overall population. Standard errors are given in parentheses. *Source*: Authors' calculations on EU-SILC 2011.

Aside from the preschool effects at the mean, we use two methods to investigate the preschool effects across the full distribution of the economic outcomes $P(Y)$ and all their related measures $\nu(P(Y))$; in this case, the outcome of interest is hourly wages. First, we use the propensity score to balance the covariates of individuals with and without preschool attainment in order to construct counterfactual populations, as proposed in Rosenbaum and Rubin (1983) and DiNardo et al. (1996). As robustness check, we use more flexible re-centered influence function (RIF) regressions to study the preschool effect across the distribution. A re-centered influence function is similar to a standard regression, except that the dependent variable is replaced by the recentered influence function of the statistic of interest (see Fortin et al., 2009). The re-centered influence function approach we specify is as flexible as equation 5, as it also allows for heterogenous treatment effects across all covariates. In Appendix A we provide a short discussion of both methods.

4 Empirical Results

4.1 Effects on educational attainment

We begin by studying the effect of preschool attendance on the later educational attainment of the individuals in our sample. In all specifications, the vector of control variables X comprises variables for mother's educational attainment, father's educational attainment, age, age squared, gender, dummy variables for the Austrian region of residence at age 14, and a dummy for birth in Austria. In table 3 and onwards, "PSA" is an abbreviation for "preschool attendance" and parental education classes are shown as "father/mother educ. 2/3/4", where category 2 is lower secondary, 3 is upper secondary, and 4 is tertiary (the omitted category is maximum primary education). The first two columns in table 3 give the results of the unconditional difference in years of schooling[7] for those who did versus those who did not attend preschool (equation 3), followed by OLS with linear demeaned controls in the middle two columns (equation 4) and a fully interacted linear model on demeaned controls (equation 5) in the last two columns. The raw difference shows that people who attended preschool have an average of 1.17 more years of education. The average treatment effect of preschool attendance on years of schooling is estimated at 0.45 in the model with linear controls, while the one allowing for heterogenous treatment effects – our preferred specification – lies at 0.40 additional years of school. We can decompose the total difference in years of schooling into the causal effect of preschool attendance (0.4 years) – about one-third of the raw difference – and the rest, two-thirds, is selection bias.

The literature discussed in section 2 finds that the benefits of attending preschool differs

[7] Years of schooling is the minimum years of schooling necessary to achieve the level of education reported by the respondent.

across groups. Our results show that the effect of preschool on years of schooling is larger for females (an additional 0.28 years) and migrants (although the latter estimates are economically but not statistically significant at conventional levels), and smaller for those with more highly educated father. The lower returns for children of highly educated parents is not surprising, since these children have more resources at their disposal throughout their lives; kindergarten will thus help them relatively less.

Table 3: Effects of preschool attainment on years of schooling

	Est.	(*s.e.*)	Est.	(*s.e.*)	Est.	(*s.e.*)
Preschool attendance	1.168	(0.068)	0.449	(0.072)	0.402	(0.081)
Intercept	10.939	(0.048)	11.372	(0.051)	11.417	(0.067)
Age			0.123	(0.030)	0.068	(0.062)
Age squared			-0.001	(0.000)	-0.001	(0.001)
Female			0.132	(0.062)	-0.036	(0.087)
Father Educ. 2			0.183	(0.071)	0.115	(0.094)
Father Educ. 3			1.627	(0.140)	1.798	(0.280)
Father Educ. 4			2.574	(0.193)	3.536	(0.439)
Mother Educ. 2			0.530	(0.089)	0.511	(0.153)
Mother Educ. 3			1.442	(0.117)	1.110	(0.217)
Mother Educ. 4			2.226	(0.259)	2.342	(0.608)
2nd gen. migrant			-0.575	(0.222)	-0.883	(0.347)
PSAxAge					0.095	(0.074)
PSAxAge squared					-0.001	(0.001)
PSAxFemale					0.275	(0.122)
PSAxFather ed. 2					0.117	(0.141)
PSAxFather ed. 3					-0.206	(0.327)
PSAxFather ed. 4					-1.125	(0.491)
PSAxMother ed. 2					-0.000	(0.189)
PSAxMother ed. 3					0.400	(0.258)
PSAxMother ed. 4					-0.067	(0.669)
PSAx2nd gen. migrant					0.409	(0.454)
Linear Controls			Yes		Yes	
Heterogenous TE					Yes	
N	5396		5396		5396	

Notes: This table shows the average treatment effect of preschool attainment (PSA) on years of schooling. Demeaned variables are used for all covariates and interactions. Regional dummies and interactions were included as controls (not shown). *Source:* Authors' calculations on EU-SILC 2011.

While the effect of preschool attendance on years of schooling is a quantitatively important .40 years added, table 4 shows that this extra time in school also brings a qualitative improvement to educational attainment. Here we show average marginal effects based on logit models using the same flexible form allowing for heterogenous treatment effects when predicting the probability of completing tertiary education.[8] Attending preschool makes one 4.9 percentage points more likely to complete a degree. This result is highly economically and statistically significant. Moreover, the effect is stronger for women and especially second generation migrants, although these differences are not statistically significant.

Table 4: Effects of preschool attainment on the probability of completing higher education

	Est.	(*s.e.*)	Est.	(*s.e.*)	Est.	(*s.e.*)
Preschool attendance	0.125	(0.011)	0.042	(0.011)	0.049	(0.014)
Intercept	-0.302	(0.008)	-0.238	(0.007)	-0.242	(0.011)
Age			0.016	(0.004)	0.014	(0.013)
Age squared			-0.000	(0.000)	-0.000	(0.000)
Female			0.005	(0.009)	-0.006	(0.018)
Father Educ. 2			0.020	(0.012)	-0.004	(0.021)
Father Educ. 3			0.135	(0.015)	0.167	(0.028)
Father Educ. 4			0.210	(0.018)	0.276	(0.042)
Mother Educ. 2			0.039	(0.013)	0.057	(0.027)
Mother Educ. 3			0.115	(0.013)	0.108	(0.026)
Mother Educ. 4			0.194	(0.025)	0.273	(0.086)
2nd gen. migrant			-0.045	(0.045)	-0.152	(0.139)
PSAxAge					0.007	(0.014)
PSAxAge squared					-0.000	(0.000)
PSAxFemale					0.015	(0.021)
PSAxFather ed. 2					0.030	(0.026)
PSAxFather ed. 3					-0.039	(0.034)
PSAxFather ed. 4					-0.078	(0.048)
PSAxMother ed. 2					-0.030	(0.030)
PSAxMother ed. 3					0.001	(0.030)
PSAxMother ed. 4					-0.090	(0.090)
PSAx2nd gen. migrant					0.126	(0.147)
Linear Controls			Yes		Yes	
Heterogenous TE					Yes	
N	5396		5396		5396	

Notes: This table shows the average treatment effect of preschool attainment (PSA) on the probability of completing tertiary education. Demeaned variables are used for all covariates and interactions. Regional dummies and interactions were included as controls (not shown). *Source:* Authors' calculations on EU-SILC 2011.

In sum, preschool attendance increases both quantitative (years of schooling) and qualitative (probability of completing higher education) educational attainment. These results are in line with, although slightly higher than, the findings in the literature: the increase of years of schooling of .40 years compares to .35 years in the UK Havnes and Mogstad (2011), and the 4.9 percentage point increase in the probability of completing a higher education degree

[8]Tertiary education is defined here as having completed University or *Fachhochschule*.

is higher than the 1.5 percentage point increase found in Goodman and Sianesi (2005). The fact that the preschool effects are stronger in Austria could be explained by the relatively low share of people with a tertiary degree (OECD, 2016) and the earlier tracking age (European Commission, 2015a) compared to Norway and the UK.

4.2 Effects on labor market outcomes

Table 5 shows that the effects of preschool attendance on current labor force participation. Attending preschool increases the likelihood of working full time by 5.3 percentage points. This effect is especially pronounced for women, who are an *additional* 9.4 percentage points more likely to work full time if they attended preschool. The gender gap in the probability of working full time is 39.5 percentage points (see the coefficient on the female dummy variable in the full model); the total preschool effect for women (5.3+9.4=14.7 percentage points) is almost half of that gap. In this sense, preschool attendance is remarkably effective in promoting women's presence in the labor force. As in Goodman and Sianesi (2005), the effect of preschool attendance on the probability of working is stronger for younger people. The negative coefficient on the preschool and age interaction shows that preschool is less important in predicting the probability of working full time for older people.

The next set of empirical exercises calculate the effect of preschool attendance on gross hourly wages. We first calculate Mincerian returns to education for our data. The first two columns in table 6 show that for all employees in our sample, an additional year of schooling increases hourly wages by 6.4%. Adding experience and its square in the next two columns brings this figure closer to eight percent. These findings are in line with other literature on the returns to education in Austria (Fersterer and Winter-Ebmer, 2003). The next two columns add a dummy variable for preschool attendance and show that adding preschool to the model hardly changes the returns to wage to years of schooling, but that the returns to preschool are 6.7%, a rate comparable to an additional year of schooling. The model in the last two columns adds a control for parental education, and shows that despite this addition, the preschool effect is still at 5.7 percent and the wage returns to education are at 7.6 percent.

The relationship between preschool and wages in the last two specifications in table 6 cannot be understood causally, because the models include one's own education, which is itself influenced by preschool attendance (as shown in section 4.1 above). The models are thus misspecified; they suffer from bad control bias. We include them here, though, to show that even when controlling for educational attainment and thus looking at the preschool effect within educational classes, preschool has an economically and statistically significant effect on wages. While the raw difference in wages for people with and without preschool attendance could be understood as an upper bound of the preschool effect on wages (since we know that there is positive selection bias into preschool relative to wages), these specifications controlling

Table 5: Effects of preschool attainment on working full time

	Est.	(*s.e.*)	Est.	(*s.e.*)	Est.	(*s.e.*)
Preschool attendance	0.046	(0.014)	0.031	(0.016)	0.053	(0.018)
Intercept	-0.039	(0.011)	-0.029	(0.011)	-0.050	(0.016)
Age			-0.013	(0.007)	0.032	(0.015)
Age squared			0.000	(0.000)	-0.000	(0.000)
Female			-0.338	(0.009)	-0.395	(0.019)
Father Educ. 2			0.049	(0.016)	0.053	(0.024)
Father Educ. 3			0.030	(0.026)	0.113	(0.055)
Father Educ. 4			0.040	(0.034)	0.085	(0.097)
Mother Educ. 2			-0.004	(0.018)	-0.036	(0.035)
Mother Educ. 3			-0.013	(0.021)	-0.020	(0.042)
Mother Educ. 4			-0.075	(0.049)	-0.118	(0.190)
2nd gen. migrant			-0.078	(0.052)	-0.001	(0.088)
PSAxAge					-0.058	(0.017)
PSAxAge squared					0.001	(0.000)
PSAxFemale					0.094	(0.027)
PSAxFather ed. 2					-0.008	(0.032)
PSAxFather ed. 3					-0.106	(0.063)
PSAxFather ed. 4					-0.054	(0.104)
PSAxMother ed. 2					0.044	(0.041)
PSAxMother ed. 3					0.011	(0.049)
PSAxMother ed. 4					0.055	(0.197)
PSAx2nd gen. migrant					-0.100	(0.108)
Linear Controls			Yes		Yes	
Heterogenous TE					Yes	
N	5068		5068		5068	

Notes: This table shows the average treatment effect of preschool attainment (PSA) on the probability of working full time. Demeaned variables are used for all covariates and interactions. Regional dummies and interactions were included as controls (not shown). People who report being retired are excluded from the sample. *Source:* Authors' calculations on EU-SILC 2011.

for one's own education provide a lower bound. These models eliminate the effect of preschool on wages which is mediated through educational attainment. We discuss this point further in section 4.2.1 below, as well as in Appendix C.

Table 6: Mincerian returns to education and preschool attainment

	Est	(*s.e.*)	Est	(*s.e.*)	Est	(*s.e.*)	Est	(*s.e.*)
Years of schooling	0.064	(0.003)	0.078	(0.003)	0.077	(0.003)	0.076	(0.003)
Experience			0.033	(0.003)	0.034	(0.003)	0.035	(0.003)
Experience squared			-0.001	(0.000)	-0.001	(0.000)	-0.000	(0.000)
Preschool attainment					0.067	(0.015)	0.057	(0.015)
Classical Mincer			Yes		Yes		Yes	
Parental Education							Yes	
N	2712		2712		2712		2712	

Notes: This table shows classical wage regressions (log hourly gross earnings) for all employees, adding preschool attainment as well as parental education. The classical Mincer setting includes controls for gender and regional dummies (not shown). *Source:* Authors' calculations on EU-SILC 2011.

Looking more closely at the preschool effect on hourly wages, we study the impact of preschool attendance on wages for the sample of all employees in the data. In table 7 we observe that attending preschool increases hourly wages by 7.3 percent. The wage effect of preschool is smaller for those with more highly educated parents and stronger for migrants, though these effects are not statistically significant. Note that the coefficient on the female dummy variable (not the interaction with preschool), which gives the gender wage gap, is estimated at roughly 21%, which is similar to other estimates of the gender wage gap in Austria (Böheim et al., 2013). The finding that preschool attendance leads to a 7.3% increase in hourly wages is similar to, though a bit larger than, the findings from the UK (a 3.6% increase at age 33 and a 2.7% increase at age 42 (Goodman and Sianesi, 2005)) and France (a 4.5% increase in hourly wages (Dumas and Lefranc, 2010)). The stronger effects found for Austria may be because of the early tracking age, which makes preschool attendance that much more important in determining later education (track) and wages.

4.2.1 Causal mediation through educational attainment

One may ask to which extent the effect of preschool attendance on earnings is mediated through educational attainment. In other words, what portion of the wage increase from preschool attendance is channeled through the fact that preschool increases schooling, which also increases wages? We use standard approaches from the literature on mediation analysis in, for example, VanderWeele (2015) or Pearl (2009), to answer this question. Details on the methodology can be found in Appendix B. Table 8 shows that the total effect is estimated at about 8%, comparable with our model with linear controls (we use this specification here since

Table 7: Effects of preschool attainment on hourly gross wages

	Est.	(*s.e.*)	Est.	(*s.e.*)	Est.	(*s.e.*)
Preschool attendance	0.078	(0.015)	0.082	(0.017)	0.073	(0.019)
Intercept	2.618	(0.012)	2.616	(0.012)	2.624	(0.016)
Age			0.046	(0.007)	0.030	(0.015)
Age squared			-0.000	(0.000)	-0.000	(0.000)
Female			-0.206	(0.014)	-0.212	(0.022)
Father Educ. 2			0.004	(0.017)	0.004	(0.025)
Father Educ. 3			0.122	(0.026)	0.115	(0.054)
Father Educ. 4			0.107	(0.036)	0.237	(0.105)
Mother Educ. 2			0.084	(0.019)	0.084	(0.034)
Mother Educ. 3			0.171	(0.022)	0.093	(0.052)
Mother Educ. 4			0.155	(0.048)	0.195	(0.207)
2nd gen. migrant			-0.019	(0.058)	-0.058	(0.094)
PSAxAge					0.020	(0.018)
PSAxAge squared					-0.000	(0.000)
PSAxFemale					0.008	(0.028)
PSAxFather ed. 2					0.002	(0.034)
PSAxFather ed. 3					0.010	(0.063)
PSAxFather ed. 4					-0.150	(0.112)
PSAxMother ed. 2					0.001	(0.041)
PSAxMother ed. 3					0.098	(0.058)
PSAxMother ed. 4					-0.025	(0.213)
PSAx2nd gen. migrant					0.050	(0.120)
Linear Controls			Yes		Yes	
Heterogenous TE					Yes	
N	2712		2712		2712	

Notes: This table shows the average treatment effect of preschool attainment (PSA) on gross hourly wages for employees. The bottom and top percentile of wage earners are dropped from the sample. Demeaned variables are used for all covariates and interactions. Regional dummies and interactions were included as controls (not shown). *Source:* Authors' calculations on EU-SILC 2011.

the model does not allow for heterogenous treatment effects). The direct effect of preschool attendance on earnings is estimated at about 6%, which is close to the estimated effect we get from the Mincerian equation controlling for one's later education. The average mediation effect is estimated at about 2%, which means that roughly 27% of the total effect of preschool on earnings is mediated through education. All effects are statistically significant, given the confidence sets which were estimated using 1000 simulations.

Table 8: Mediation of preschool attendance effect on hourly wages by years of schooling

	Est	95% CI	
Average mediation effect	0.022	0.009	0.034
Direct effect	0.061	0.030	0.085
Total effect	0.083	0.047	0.112
% of total effect mediated	0.270	0.200	0.477
N	2712	2712	2712

Notes: This table shows the average causal mediation effect of preschool attendance via years of schooling on log hourly wages for all workers based on 1000 simulations. *Source:* Authors' calculations on EU-SILC 2011.

We now investigate the preschool effects beyond those for the individual, looking at the effect of preschool attendance on the probability that mothers work later in their children's lives.

4.3 Effects on mother's labor force participation

Here we use the same methods as above to predict the effect of a respondent having attended preschool on the probability that their own mother worked when the respondent was 14 years old. We expect positive results, because having a child in preschool may allow the parents – and especially the mother, who is often the primary caregiver – the time and opportunity to participate in the labor force when the child is still young. The additional time at work when the child is young could help her later labor force participation, because the extra time at work enhances her human capital credentials and experience, along with connections in the labor force and opportunity for advancement.

Indeed, table 9 shows that the mothers of children who went to preschool were almost 11 percentage points more likely to be working when the child was 14. This effect is tremendous, especially given the large gender gap in full time workers shown in table 9. The effect seems somewhat higher for more highly educated mothers (see interaction effect), who also have higher labor force participation (see dummy). These findings are logical, given that more highly educated mothers have the highest opportunity costs of not working for pay; they thus benefit the most from having a child in preschool, which freed up the time for them to go to work on the labor market. The results on the effect of preschool on mothers' labor force participation are comparable to findings from studies looking at preschool effects in Canada (7.3 percentage point increase (Lefebvre and Merrigan, 2008)); Israel (7 percentage point increase for Arab mothers (Schlosser, 2005)); the US (a 7.5 percentage point increase for single mothers (Cascio, 2009)); and Argentina (7-14 percentage points (Berlinski and Galiani, 2007)).

Table 9: Effects of preschool attainment on the probability of the mother working at age 14

	Est.	(*s.e.*)	Est.	(*s.e.*)	Est.	(*s.e.*)
Preschool attendance	0.191	(0.018)	0.086	(0.021)	0.108	(0.024)
Intercept	-0.134	(0.015)	-0.066	(0.016)	-0.091	(0.021)
Age			0.010	(0.010)	0.007	(0.021)
Age squared			-0.000	(0.000)	-0.000	(0.000)
Female			0.016	(0.018)	0.057	(0.030)
Father Educ. 2			-0.009	(0.022)	-0.030	(0.034)
Father Educ. 3			-0.059	(0.035)	-0.031	(0.065)
Father Educ. 4			-0.238	(0.048)	-0.593	(0.204)
Mother Educ. 2			0.120	(0.024)	0.127	(0.044)
Mother Educ. 3			0.197	(0.029)	0.163	(0.060)
Mother Educ. 4			0.563	(0.083)	0.313	(0.187)
2nd gen. migrant			0.097	(0.073)	0.042	(0.117)
PSAxAge					0.009	(0.024)
PSAxAge squared					-0.000	(0.000)
PSAxFemale					-0.067	(0.038)
PSAxFather ed. 2					0.041	(0.045)
PSAxFather ed. 3					-0.024	(0.077)
PSAxFather ed. 4					0.391	(0.212)
PSAxMother ed. 2					-0.011	(0.054)
PSAxMother ed. 3					0.050	(0.069)
PSAxMother ed. 4					0.293	(0.211)
PSAx2nd gen. migrant					0.109	(0.153)
Linear Controls			Yes		Yes	
Heterogenous TE					Yes	
N	2690		2690		2690	

Notes: This table shows the average treatment effect of preschool attainment (PSA) on the probability of the mother working when the respondent was 14. Demeaned variables are used for all covariates and interactions. Regional dummies and interactions were included as controls (not shown). People who report being retired are excluded from the sample. *Source:* Authors' calculations on EU-SILC 2011.

4.4 Effects on the distribution of wages

Finally, we turn our analysis to the effect of preschool attendance on the overall distribution of hourly wages. Figure 2 shows the effect of preschool across the wage distribution. The top graph is produced using reweighting with propensity scores, and is closer to a model with linear controls. The bottom graph is produced using re-centered influence function regressions based again on a fully interacted model allowing for heterogenous treatment effects. The patterns are very similar. At the lower end of the distribution of wages, the effect is relatively small. The small effect at the bottom of the distribution could be explained by the existence of minimum wages. Workers at this area of the distribution perhaps *would have* gained from preschool attendance, but the floor on their wages could mask the potential effects. In other words, preschool attendance may have given them a large percent increase in their (very low) wages, but since there is a minimum wage, the wage bump from preschool attendance is not observed. At the upper end, the preschool effect also tends to be somewhat smaller. In between, the effect is rather stable at about 10%. We conclude that the average effects estimated in our models are not driven by a small subset of the population but are rather stable across a large part of the distribution of wages. Across the bulk of the wage distribution, the preschool effect is about 10%.

Furthermore, table 10 shows the effect of preschool attendance on three distributional measures. It shows that the effect on the Gini coefficient is economically and statistically not significant. At the bottom of the distribution, the finding that preschool nudges the ratio of wages at the 10^{th} percentile to those at the 50^{th} percentile downward – meaning that there is more inequality – is also statistically insignificant. As discussed above, this effect could be due to the presence of minimum wages, which guarantee that those without preschool at the lower end of the distribution already earn almost as much as those with preschool. The upper portion of the distribution (measured by the P90/P50 wage ratio), on the other hand, becomes more equal (economically but not statistically significant). Overall, the effects at the top and the bottom of the distribution cancel out, which one can see in the nonexistent effect on the Gini, which measures inequality in the middle of the distribution.

Preschool attendance thus raises wages, in particular for workers in the middle of the wage distribution. To distill inequality at the lower end of the wage distribution, we would need other policy measures in addition to the already existing minimum wages.

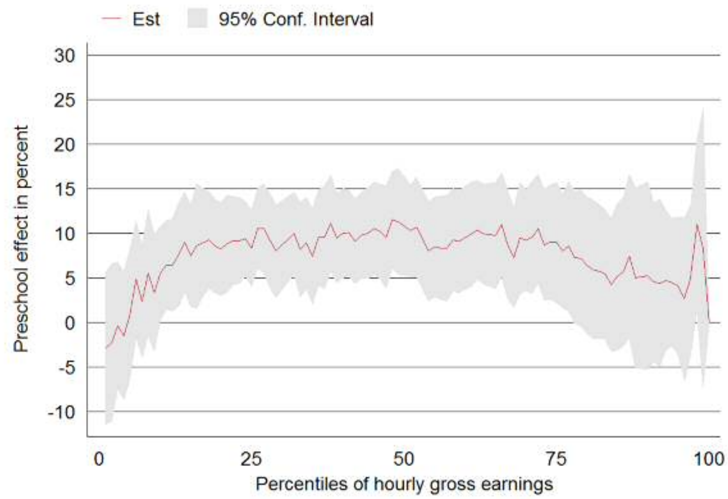
Table 10: Effect of preschool attendance on distributional measures

	Est	$(s.e.)$
Gini diff	-0.0028	(0.0077)
P10/P50 diff	-0.0300	(0.0185)
P90/P50 diff	-0.0899	(0.1092)

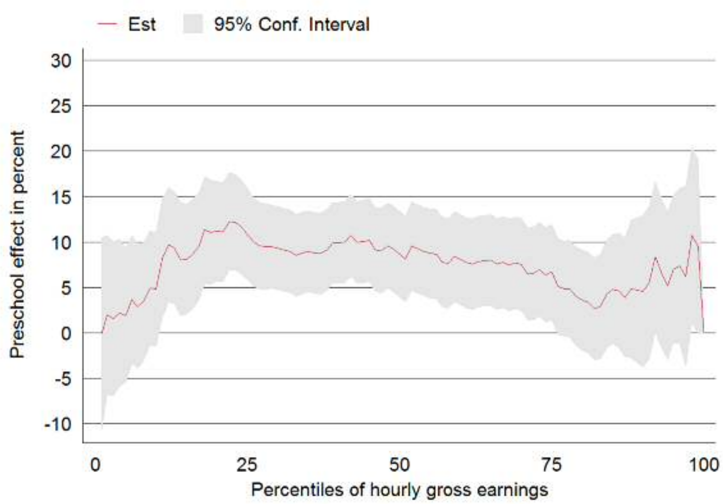
Notes: This table shows the average treatment effect of preschool attendance on distributional measures of the distribution of log hourly wages using reweighting. Standard errors are bootstrapped using 500 replicates.
Source: Authors' calculations on EU-SILC 2011.

Figure 2: Effect of preschool attendance across the gross earnings distribution

(a) Reweighting



(b) RIF regression



Notes: Graph (a) shows the effect of preschool attendance on gross hourly wages across the full wage distribution using reweighting and (conditional) quantile regression. Graph (b) shows the effect of preschool attendance on gross hourly wages across the full wage distribution using recentered influence function regressions. The bottom and top one percentile of wage earners are dropped from the sample. *Source:* Authors' calculations on EU-SILC 2011.

5 Concluding remarks

In this paper, we use a rich data set from Austria to predict the effects of preschool attendance on later socioeconomic outcomes. We are able to control for selection bias into preschool well by using controls for parental education and region of residence. Parental education in particular is a central determinant of whether a child will attend preschool or not. Using regressions with linear controls and allowing for heterogenous treatments effects, along with propensity score re-weighting, recentered influence function regressions, and mediation analysis, we show various ways in which preschool attendance has an important impact on economic life.

At the individual level, preschool leads to about two-fifths of a year more schooling once controlling for background characteristics which influence selection into preschool, with more for women and second-generation migrants (the latter is not statistically significant). It also increases the probability of completing higher education by four to five percentage points, with lower effects for descendants of highly educated parents. The gross hourly wage effects of preschool attendance range from about seven to eight percent, and the effect of the probability of working full time is a positive five percentage points, with much stronger effects for women (an additional nine percentage points). The wage results for the whole population are strongest at the middle of the wage distribution (at about 10%), with a light equalizing effect coming from lower effects for higher earners. Lower earners are also less affected by preschool, perhaps because they are already protected by minimum wages. Finally, we find that mothers whose child attended preschool are eleven percentage points more likely to be working when the child is 14 years old.

Consistent with the literature, the effects of preschool are overwhelmingly positive. Preschool attendance raises wages, educational attainment, and the labor market participation of the preschool attendee and his/her mother. Some states hesitate to implement more preschool programs because of additional costs. However, this analysis shows that preschool raises wages by about seven percent, and it increases labor force participation for the preschool attendees and their mothers. The increased income tax generated from the increased activity on the labor market and the higher wages could be used to help finance preschool programs. Indeed, as discussed by Kleven (2014), the use of taxes to subsidize goods and services which are complementary to labor market participation – such as preschool attendance, as we have seen in this paper – encourage and support active labor supply, which in turn brings money back into the system via income taxes.

It is often difficult to empirically disentangle the effects of preschool on later outcomes from the selection mechanisms which assign some people into preschool. We show how a variety of methods can be employed to deal with this issue. The raw gap in outcomes for those with and without preschool attendance is an upper bound estimate of the effect of preschool, but is ridden with (positive) selection bias. Our data used, from the 2011 Austrian EU-SILC, contain information on the education of the mother and the father, critical determinants of parental circumstances and thus the circumstances which influence the probability of a child being enrolled in preschool. Based on the fact that a large share of descendant's outcomes are determined by parental education (Haveman and Wolfe, 1995), we use measures of parental education as an important determinant of selection into preschool. In these models, we see consistently positive effects of preschool attendance. Going even further and accounting for one's own education to measure the preschool effect within educational classes, which gives a lower bound estimate, shows strong positive wage effects of preschool attendance. We thus conclude that preschool has ubiquitously positive effects on the later economics outcomes studied here.

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Appendix A Methods used to obtain effects beyond the mean

Aside from the preschool effects at the mean, we use two methods to investigate the preschool effects across the full distribution of the economic outcomes $P(Y)$ and all their related measures $\nu(P(Y))$ in section 4.4.

As discussed in section 3.2, we use the propensity score to balance the covariates of individuals with and without preschool attainment in order to construct counterfactual populations, as proposed in Rosenbaum and Rubin (1983) or DiNardo et al. (1996). The counterfactual of interest is $P^{T=0}_{T=1}(Y)$, which is the distribution of the economic outcome for individuals without preschool attainment, with the same characteristics X as individuals with preschool attainment:

$$P^{T=0}_{T=1}(Y) := \int_X P^{T=0}(Y,X)dP^{T=1}(X). \tag{6}$$

The counterfactual distribution in equation 6 can be rewritten as

$$P^{T=0}_{T=1}(Y) := \int_X P^{T=0}(Y,X)\Psi_X(X)dP^{T=0}(X), \tag{7}$$

where the re-weighting function Ψ_X is defined as

$$\Psi_X := \frac{P^{T=1}(X)}{P^{T=0}(X)}. \tag{8}$$

Reweighting requires the estimation of the ratio Ψ_X. We estimate the propensity of each individual to have preschool attainment using a logit model,

$$\hat{P}^{T=1} = Pr(T = 1|X = x_i) = \frac{1}{1 + \mathrm{e}^{-(\beta_0 + X_i'\beta)}}, \tag{9}$$

and then reweight each individual i without preschool attendance by $1/\big(1 - P^{T=1}(X)\big)$ and each individual with preschool attendance by $1/\big(P^{T=1}(X)\big)$ to create counterfactuals for the overall population without and with preschool attendance. The average treatment effect of preschool attainment on any economic outcome of interest ν is then defined as the difference between the reweighted counterfactuals:

$$ATE = \nu(P^{T=1}_{rew}(Y)) - \nu(P^{T=0}_{rew}(Y)). \tag{10}$$

As robustness check, we use more flexible re-centered influence function (RIF) regressions in section 4.4 to study the preschool effect across the distribution. A re-centered influence function is similar to a standard regression, except that the dependent variable is replaced by the recentered influence function of the statistic of interest (see Fortin et al., 2009). Assume that ν can be written as the expectation of a function f of Y, $\nu = E[f(Y)]$. The effect of the treatment on ν can be obtained from

$$\nu^{T=1} - \nu^{T=0} = \int \left(E[f(Y)|X, T = 1] - E[f(Y)|X, T = 0] \right) dP(X). \tag{11}$$

In general, ν will not have this linear form but can be approximated by a linear first order expansion around P^*. This idea underlies the influence function regression approach proposed by Fortin et al. (2009). Thus

$$\nu(P) = \nu(P^*) + \int IF(y; \nu, P^*) d(P - P^*)(y) + R^*, \tag{12}$$

where IF is the influence function of the parameter ν at P^*, and R^* is a second order remainder term. Ignoring the remainder, this representation of ν has the linear form required for the use of the representation given in equation (11). In our case this linear approximation can be stated as

$$\nu(P) \approx \nu(P^{T=0}(Y)) + \int IF(Y; \nu, P^{T=0}(Y)) dP(Y),$$

where $P^{T=0}(Y)$ is the baseline distribution of the economic outcome, which is in our case the distribution given no preschool attainment. Given the CIA and our treatment indicator T_i, we have

$$E[IF(Y)|X] = E[IF(Y)|X, T_i = i],$$

which justifies estimation of the following linear model again including all interactions of the treatment indicator with the covariate vector X, allowing for heterogenous treatment effects (like in equation 5 on page 9):

$$E[IF(Y)|X, T_i] = X \cdot \beta^0 + T_i \cdot X \cdot \beta^1. \tag{13}$$

The average treatment effect of preschool attainment T_i on the population is thus given by

$$ATE = E[X] \cdot \beta^1. \tag{14}$$

In the case of quantiles, the $IF(Y, Q_\tau)$ is given as $(\tau - \mathbb{1}\{Y \leq Q_\tau\}/f_Y(Q_\tau)$, where $\mathbb{1}\{\cdot\}$ is an indicator function; $f_Y(\cdot)$ is the density of the marginal distribution of Y; and Q_τ is the population τ-quantile of the unconditional distribution of Y. The $RIF(Y; Q_\tau)$ is then equal to $Q_\tau + IF(Y, Q_\tau)$, and can be written as

$$
\begin{aligned}
RIF(y;Q_\tau) &= Q_\tau + \frac{\tau - \mathbb{1}\{y \le Q_\tau\}}{f_Y(Q_\tau)} \\
&= \frac{\mathbb{1}\{y > Q_\tau\}}{f_Y(Q_\tau} + Q_\tau - \frac{1-\tau}{f_Y(Q_\tau)} \\
&= c_{1,\tau} \cdot \mathbb{1}\{y > Q_\tau\} + c_{2,\tau} \qquad (15)
\end{aligned}
$$

where $c_{1,\tau} = 1/f_Y(Q_\tau)$ and $c_{2,\tau} = Q_\tau - c_{1,\tau} \cdot (1-\tau)$. As

$$E[\mathbb{1}\{y > Q_\tau\}] = Pr(Y > Q_\tau) = 1 - \tau,$$

it follows that

$$E[RIF(y;Q_\tau)] = c_{1,\tau} Pr(Y > Q_\tau) + c_{2,\tau} = Q_\tau.$$

By the law of iterated expectations, we have

$$E[RIF(y;Q_\tau)] = E_X\{E[RIF(y;Q_\tau)]|X\},$$

and one can run a linear regression of the binary outcome variable $\mathbb{1}\{y > Q_\tau\}$ on X (see Fortin et al. (2011) and Fortin et al. (2009)).

Appendix B Mediation Effects

In section 4.2.1 we introduce mediation effects, which separate the impact of preschool on earnings into (1) the direct effect (preschool → earnings) and (2) the effect which works through additional education (preschool → schooling → earnings). To calculate the mediation effect, one must run three basic regressions.

First, we regress outcome variable Y_i (in this case earnings) on the preschool dummy T_i and covariate vector X_i:

$$Y_i = \alpha + \beta \cdot T_i + X_i\gamma + \varepsilon_i. \qquad (16)$$

Second, we regress the mediator variable M_i, in our case years of schooling, on the preschool dummy T_i and covariate vector X_i:

$$M_i = \alpha + \beta \cdot T_i + X_i\gamma + \varepsilon_i. \qquad (17)$$

Third, we regress the outcome variable Y_i on the preschool dummy T_i, the mediator M_i, and the covariate vector X_i:

$$Y_i = \alpha + \beta \cdot T_i + \tau \cdot M_i + X_i \gamma + \varepsilon_i. \tag{18}$$

Given equations 16, 17, and 18, $\hat{\beta}$ estimated from equation 16 is the total effect, while $\hat{\beta}$ of equation 17 times $\hat{\tau}$ of equation 18 is the mediation effect and the difference between the total effect and the mediated effect is the direct effect.

Appendix C Robustness checks

As a robustness check, we reproduce the top panel of figure 2, showing the effect of preschool on gross wages across the distribution. Here we include the respondent's own education as a control variable, which leads to bad control bias since educational attainment is already an outcome of preschool attendance. However, this exercise illustrates that even inside similar educational groups, preschool attendance has a rather robust effect on earnings. When measuring the effect of preschool on wages while also controlling for one's own education, we produce what could be interpreted as a lower bound of the causal effect of preschool.

Figure 3: Preschool conditional difference across the gross earnings distribution including own education

Notes: This graph shows the effect of preschool attendance on gross hourly wages across the full wage distribution using reweighting. Full time employees only, including own education as an additional control variable. *Source:* Authors' calculations on EU-SILC 2011.