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Intersectional differences in income returns to education

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Bachelorthesis

Bachelor of Sociology

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Abstract

The aim of this study was to test whether there are intersectional differences in the effect of education on income in the Netherlands. In this study we looked at the intersection of gender and migration background. Drawing from Human Capital Theory and Screening theory, theories on discrimination, and Intersectionality theory, we formulated hypotheses on how the income returns to education in income differ between different intersectional groups. By performing a multilevel analysis on data retrieved from the LISSpanel, we showed that there are no intersectional differences in the effect of education on income between the intersectional groups. We did find that women have a lower hourly wage compared to men regardless of their education level, occupational status and age. An ethnic difference in income was not found.

Keywords: Intersectionality, income, education, returns to education, gender, migration background

1. Introduction

Inequality in terms of hourly income is still present on the Dutch labor market to this day. Women on average have a lower hourly income than men (CBS, 2020a), and people with a migration background have a lower hourly income than people without a migration background (In der Maur et al, 2020). Education is seen as an equalizing factor, giving everyone the opportunity to invest in future earnings, regardless of one's identity characteristics. Becker (1994) was one of the first in theorizing a positive relation between educational attainment and income. Indeed it is found that with every year of attained education, a person's individual income increases (Harmon et al, 2000).

However, only some part of the income differences between different groups - particularly between men and women, and people with and without a migration background - can be explained by differences in education (Albrecht, van Vuuren & Vroman, 2004; Huijnk & Andriessen, 2016; Siebers & van Gastel, 2015). Different returns to education also contribute to the pay gaps that are pertinent on the labor market today. For example, women seem to reach top positions less easily than men with a similar educational background (De Hamer & Maas, 2019). In the same regard, people with a migration background have more difficulty finding a job than Dutch people without a migration background with a similar resumé (Arai et al, 2016). In absence of differential treatment and discrimination, we would expect income to be

independent of characteristics such as gender or ethnicity. Moreover, we would expect the same effect of educational attainment on income between groups of different genders and ethnicity. For education to achieve the equalizing effect it was designed to have, equal returns in income are a prerequisite (Blau & Duncan, 1967). However, if returns differ between groups, this can prevent an optimal utilization of the human capital that exists in the Dutch society. Therefore, in studying educational attainment and income, gender and ethnicity are factors that are influential and cannot be overlooked (Brown et al, 2013).

Differences in returns to educational investment are therefore often studied along the lines of different values of a single identity variable, such as gender or ethnicity. However, much less research is done on how combinations of identity attributions impact ones position in society. Consequently, Kimberlé Crenshaw (1989) introduced the ‘intersectionality hypothesis’ into multiracial feminist research, stating that social identities are interconnected and should be understood in relation to each other. In intersectional research, the goal is to move away from analyzing inequality among one single identity variable, and to analyze intersections of multiple identities. Therefore, qualitative methods were used to conduct intersectional research, as these allow for a holistic image of the subjects of study. However, one can account for the internal heterogeneity of the different groups in quantitative methods too, using the right methods (Spierings, 2012). Therefore, the intersectional approach is also increasingly being applied using quantitative methods (Arai et al, 2016; Di Stasio & Larsen, 2020).

Deborah King (1988) added to Crenshaw’s ideas by hypothesizing that members of multiple marginalized groups can experience *multiple jeopardy*. This concept proposes that having a combination of different identity characteristics burdens the subject with a unique societal position, not merely the added disadvantages of the different individual groups to which one belongs. Membership of different privileged groups on the contrary can yield positive experiences, or *multiple advantage* (Settles & Buchanan, 2014). This theory would for instance predict that women with a migration background would have a lower social position compared to men without a migration background than one would expect based on the sum of disadvantages of being female and having a migration background.

The existing intersectional quantitative research on labor market positions in the Netherlands is often focused on hiring procedures (Arai et al, 2016; Di Stasio & Larsen, 2020). In this paper, we study income, which has traditionally been recognized as an informative measure of returns to education (Becker, 1994; Bloch & Smith, 1977; Browne & Misra, 2003; Harmon et al, 2003; Lindsay, 1971). With this research, we therefore add to existing research by applying an intersectional approach to recent empirical data on the respondents’ income and

educational attainment in the Netherlands to answer the following question: *To what extent are there intersectional differences (i.e. sex and ethnic) in the effect of human capital on hourly income?*

To test the differences in effect from educational attainment on hourly income, we used longitudinal data from the LISS panel on households in the Netherlands from 2018 and 2019. As this data is longitudinal, we could ensure we tested for causal effects. Moreover, multiple sampling moments, and additional equipment of respondents without facilities to answer the survey optimized the representativeness of this data. We performed a multilevel regression analysis, as this method allows us to distinguish what proportion of total variance is to be ascribed to intergroup differences and what part can be explained by individual differences. These models provide robust estimations of intersectional differences.

2. Theoretical mechanisms

2.1 Educational Attainment and Income

Educational attainment seems to have a positive effect on income. Many studies have empirically shown that for every year of education an individual attains, their individual income rises (Harmon et al, 2000; Harmon et al, 2003; Ng et al, 2005). In the fields of economics and human resource development, two complementary theories are proposed that explain how this relationship comes about (Dobbs et al, 2008). Human Capital Theory (HCT), introduced by Gary Becker (1994), assumes one's educational attainment would increase the productivity level of the individual, which is in turn rewarded with higher wages (Becker, 1994). In addition to HCT, it is also theorized that education acts as a signal of productivity for employers, leading to higher wages (Spence, 1973; Stiglitz, 1975). This Screening Theory assumes that in processes of hiring, when employers have imperfect information on the functioning and capabilities of the applicant, it benefits the employer to look at an indicator of the capabilities of the applicant, such as a degree (Stiglitz, 1975). Education for instance increases a person's cultural capital and habitus, benefitting someone's productivity levels on the job (Huang, 2019). The education therefore acts as a signal of not only the applicants' capabilities, but also their knowledge of the codes of conduct generally accepted in the workplace.

Both Screening Theory and Human Capital Theory find support in previous literature (Groot & Oosterbeek, 1994; Aina & Pastore, 2020). From these theories we can conduct the following hypothesis:

H1: The more education an individual has attained, the higher their hourly income.

2.2 Gendered differences in income

Although women between 25 and 64 years old have surpassed men in educational attainment in the Netherlands, on average men still earn more than women do (Wennekers et al, 2019; CBS, 2019). It is found that women's starting salary is comparable to men's, but that the wages of women grow slower as their career proceeds (Belley et al, 2012). While there are objective differences in the nature of work and education that women seek (e.g. sectoral differences and part-time contract), these factors cannot fully explain the perceived differences (Kalmijn & Van der Lippe, 1997; Plasman et al, 2008). Indeed, men and women seem to have different returns to their educational attainment (Albrecht, Van Vuuren & Vroman, 2004; Evertsson et al, 2009; Kalmijn & Van der Lippe, 1997; Lyness & Thompson, 1997; De Hamer & Maas, 2019). This indicates that women are treated differently than men, highlighting a source of inequality in the Dutch labor market.

One of the reasons why women earn less than men, is because of the limited opportunity women have to 'rise to the top' (Hultin & Szulkin, 2003). The barrier that prevents women from achieving high positions in companies is often referred to as 'the glass ceiling', as it is transparent but very real in its consequences (Morrison & White, 1987). Oakley (2000) examined different mechanisms through which women have not been able to 'rise to the top', to the same extent as men do. A lack of policies to promote diversity, the different values ascribed to certain characteristics based on a person's gender and gender-based stereotypes could contribute to this 'glass ceiling' (Oakley, 2000). Another possible explanation is the lack of promotion of women into functions that are 'in the line' for positions that are higher up the ladder. One reason for this is that women in the Netherlands disproportionately work in part-time jobs. As a result, they could face certain types of differential treatment preventing them from being considered for promotions (CBS, 2021). For instance, an employer could view working part-time as a sign of having less dedication to their work, as opposed to someone that works full-time (Plasman et al, 2008). Moreover, higher positions might require the employee to work full time. Therefore, part-time employees might not qualify for such positions. In

addition, working part-time also has a direct effect on income, as part-time jobs are overrepresented in occupational sectors that typically yield a lower hourly income (Plasman et al, 2008).

Furthermore, there is evidence for the existence of a so-called ‘fertility discrimination’ mechanism (Becker et al, 2019). This form of discrimination results from hiring processes without perfect information on the productivity of their candidates. Employers view average characteristics of groups to infer a prediction on the individual productivity of members of those groups (Aigner & Cain, 1977; Phelps, 1972). While generalizing, the employer loses eye for the heterogeneity within groups and the capabilities of the applicant come to matter less. As women still take on more tasks in taking care of children than men, they are generally expected to take time off or even quit their jobs when they have children (Treas & Drobnic, 2010). This is costly for an employer, as they have to invest in training a new employee. Not only does having children thus directly impact their career opportunities (Abendroth et al, 2014), employers are also inclined to hire from the group that generally yields less costly employees to start with. Or at least, place women in the positions with the lowest turn-over costs (Bielby & Baron, 1986). This in turn results in another barrier for women to reach higher positions. Consequently, all married women in their fertile age have a significant disadvantage in hiring procedures compared to other groups of women, and men, even when they do not have motherhood plans (Becker et al, 2019).

From the above-mentioned theories, we can conduct the following hypothesis:

H2: Women have a lower hourly income than men, even when controlled for educational attainment.

2.3 Ethnic differences in income

In the hiring of people with a migration background in the Netherland, ethnic discrimination also pertains (Andriessen et al, 2012). Lippens et al. (2020) performed a meta-analysis on the articles testing for either statistical discrimination or taste-based discrimination, and show taste-based discrimination seems to explain ethnic discrimination in the hiring of ethnic minorities better than statistical discrimination does (Guryan and Charles, 2013; Thijssen et al, 2021).

In contrast to statistical discrimination, taste-based discrimination regards attitudes, rather than the maximization of profit. This type of discrimination arises from the aversion or negative attitudes towards a specific group, whether they are implicit or explicit. An attitude is

explicit, when the owner is aware of said attitude. Unlike explicit attitudes, implicit attitudes are much more latent, as the owner is not aware that they are present. They are therefore harder to detect and control. However, it is shown that implicit biases do exist within the selection procedures of the labor market (Blommaert et al, 2012; Rooth, 2010).

Thus, employers' payment decisions might be influenced by pertaining negative stereotypes (Guryan & Charles, 2013). For instance, Swedish evidence showed that the amount of job opportunities for a person of an ethnic minority seemed to correlate with negative attitudes towards this minority group (Carlsson & Rooth, 2012). People without a migration background generally have negative attitudes towards people with a migration background, if there is increasing levels of immigration and growing unemployment, and therefore competition over economic resources and norms and values (Coenders & Scheepers, 1998; Horowitz, 2000; Scheepers et al, 2002). In addition, the tone of news coverage about certain groups impacts the attitudes towards these groups (van Klingeren et al, 2015). As a migration crisis has been prevalent in Europe in the past years (European Committee, 2017), and covered extensively in the news, we expect there to be negative attitudes towards people with a migration background.

We therefore can conduct the following hypothesis:

H3: Individuals with a migration background have a lower hourly income than Dutch natives, even when controlled for educational attainment.

2.4 Intersectional differences

According to intersectionality theory, disadvantages or privileges caused by the membership of a certain identity group can amplify or compensate for those of the membership of other groups (King, 1988; Settles & Buchanan, 2014). People with double disadvantaged identity characteristics would experience a sum of these disadvantages, or an even bigger advantage than one would expect based on adding up the different advantages brought about by membership of different groups (King, 1988). In this literature, social identities like gender and ethnicity are therefore seen as inherently interwoven, and taking the two apart would yield incomplete results (Browne & Misra, 2003). For example, viewing only the differences between women and men would overlook the internal differences of these two groups, making it more difficult to draw accurate conclusions.

Earlier research on job opportunities indeed showed that there are significant differences to be found between the intersectional groups of gender and ethnicity (Arai et al, 2016; Di Stasio & Larsen, 2020). According to this hypothesis, men without a migration background would therefore have on average the best position in society, whereas women with a migration background would have the worst (Browne & Misra, 2003). Having a combination of gender and ethnic characteristics is thus expected to lead to an even bigger disadvantage or privilege to income returns to educational attainment, than one would expect based on the sum of the disadvantages or privileges the combination of gender and ethnic characteristics yields.

Drawing on our previous hypotheses and the intersectionality theory we expect the following results in relation to income:

H4: There are intersectional differences in the effect of human capital on income.

3. Methods

3.1 Data

For the analysis of this thesis, we used data provided by the LISSpanel (*Longitudinal Internet Studies for the Social Sciences*). The panel is drawn by the research institute CentERdata, as part of the project ‘Measurement and Experimentation in the Social Science’. A random probability sample of households was drawn from the Dutch population registers. From these households, all members over the age of 16 were asked to participate. Members that did not have internet access were equipped with computers designed for people that have no experience with computers.

The data is longitudinal, making it possible to test for causal relations in the analysis. The data was collected from 2007 on up until and during this thesis was written. Data on the background variables was collected every month, while data on the core studies of various subjects was collected once every year. Initially, 9.844 households were randomly drawn from the Dutch population registers. 5176 households participated, resulting in 8026 actively participating respondents in 2007 (Scherpenzeel, 2009). In the years 2009, 2011, 2013 and 2016, additional recruitment was done to increase the representativeness of the sample, increasing the external validity (de Vos, 2010).

3.2 Selections and response

The surge of COVID-19 worldwide, starting at the end of 2019, led to an economic crisis in the Netherlands from early March 2020 on (CBS, 2020b). To avoid any COVID-19 related externalities, we decided to use data from before the pandemic started. For this thesis, three individual datasets were used. We used the data on background variables and work and schooling from April 2018 and April 2019. To ensure causality in the tested relations, our dependent variable income and our control variables were derived from the data from 2019. Gender and migration background were both also derived from the data from 2019, to ensure we obtained a large enough sample. As reported, gender and migration background change little over time, we were still able to work with longitudinal data, and ensure causality. Our independent variable measuring educational attainment was derived from the data from 2018.

We select cases using listwise deletion on the variables we used for our analysis. The dataset on work and schooling from 2018 had an initial response of 5831 respondents. The variable measuring educational attainment had 112 missing values after recoding, leaving 5720 valid cases in the dataset. The data on the background variables from 2019 had 9828 cases. After recoding, the variable measuring income had 3055 missing cases. The variable measuring migration background had 2851 missing values. The variables gender, age and employment were also taken from this dataset and had no missing values. 5811 valid cases remained in this dataset. 80,4% of the invited respondents participated in the data on work and schooling (n=5210). The variable on the amount of hours someone worked per week had 2525 missing values after recoding. The variable on the occupational sector had 2266 missing cases. After listwise deleting these missing values, the dataset consisted of 2651 valid cases. After combining all three datasets and listwise deleting all missing values, 2054 valid cases were left in the dataset.

Only respondents who were participating in the labor market were included in the analysis. We therefore only selected respondents who either did paid work, worked in a family business or were self-employed in 2019. In addition, respondents who were younger than 18 or older than 68 were removed from the dataset as they are not participating in the labor market. Outliers and missing values on either of the used variables were listwise deleted, resulting in a sample of 1766 cases.

3.3 Operationalization

Dependent variable

Income was measured as the self-reported monthly income before taxes. We select the gross income of individuals as taxation can differ between different intersectional groups (Kalmijn & van der Lippe, 1997). We used the income variable that CentERdata imputed to compensate for the missing data on the original variable. To normalize the distribution of our dependent variable, we took a logarithm transformation of the income of the respondents, and excluded the respondents who had an income of either 0, or more than 25000 euros.

Independent variables

Gender was measured with two options, which we recoded into the values 0 ‘male’ and 1 ‘female’. To indicate ethnicity, we differentiated two groups: people without a migration background, and people with a migration background. Respectively, these two categories were set up into dummy variables.

Educational attainment was operationalized as the highest level of education with a diploma (De Hamer & Maas, 2019). To ensure a detailed analysis could be done of the returns to education, we used a variable measuring educational attainment with 28 values, covering both current and outdated types of education in the Netherlands. The values were recoded into a continuous variable, using the number of years it typically takes to obtain the degree (Kalmijn & van der Lippe, 1997). This amount was made up of six years of generalized education and the added amount of years it takes to obtain the degree (Kalmijn & van der Lippe, 1997). For categories of education that included different types of education, we took the means of the amount of years it would take to complete either. The values 4 ‘lower and continued special education’ and 28 ‘other’ were computed as missing values, as the amount of years that this education entails varies greatly. A small part of the respondents that did not answer this question, did answer another question in the same dataset measuring educational attainment using six categories. As people with a migration background were disproportionally represented in this group, we added the amount of years this educational category would take on average to the recoded variable for educational attainment for this group of respondents. The respondents that answered 8 ‘other’ to this question, were not included in the analysis¹.

¹ View Appendix A for a translation of the education categories into educational attainment in years.

Control Variables

In our analyses we control for the amount of hours worked per week, and the occupational sector in which the respondent is working, as these factors seem to have a considerable influence on the relation between income and educational attainment (Albrecht, van Vuuren & Vroman, 2004; Kalmijn & van der Lippe, 1997; Plasman et al, 2008; De Ruijter et al, 2003). In this manner, we can control for lurking variables causing objective differences in income.

The respondents filled out how many hours they worked weekly on average. The respondents that reported to work zero hours were also computed as missing, as they were not currently employed. In addition, two outliers were removed from the dataset.

Options to the question in which sector the respondent worked were 1 ‘agriculture, forestry, fishery, hunting’, 2 ‘mining’, 3 ‘utilities production, distribution and/or trade (electricity, natural gas, steam, water)’, 5 ‘construction’, 6 ‘retail trade (including repairs of consumer goods)’, 7 ‘catering’, 8 ‘transport, storage and communication’, 9 ‘financial’, 10 ‘business services (including real estate, rental)’, 11 ‘government services, public administration and mandatory social insurances’, 12 ‘education’, 13 ‘healthcare and welfare’, 14 ‘environmental services, culture, recreation and other services’ and 15 ‘other’. These values were all recoded into dummy variables. There were no respondents who answered 2 ‘mining’. In addition, we controlled for both the linear and the non-linear effect of age, as age has a significant impact on income (Creedy & Hart, 1979; Murphy & Welch, 1990; De Hamer & Maas, 2020).

A one-sample t-test was performed, to test whether there was a significant bias to our selected sample. The test was performed for our dependent variable income, and our independent variables education, gender and ethnicity. T-tests showed that the selection we drew from the sample differed significantly from the original sample regarding the means of income, education and the dummy variable for people with a migration background. More specifically, the means of income ($t=20.791$, $p<.001$) and education ($t=15.307$, $p<.001$) were higher in our selection than in the original dataset. There were less people with a migration background in our selection than in the original dataset ($t=-2.652$, $p=.008$). The proportions of women and men in both datasets did not differ significantly from each other ($t=-.210$, $p=.833$).

Table 1: Descriptive statistics (N=1766).

	Mean	SD	Min	Max
Income ¹	3.435	.264	1.70	4.36
Educational attainment in years	13.600	2.910	0	22
Female	.507	.	0	1
Migration background	.162	.	0	1
Age	46.420	11.917	18	67
Hours worked per week	34.695	10.908	1	80
Occupational sector				
Agriculture	.015	.	0	1
Industrial production	.095	.	0	1
Utilities production/ trade	.011	.	0	1
Construction	.045	.	0	1
Retail trade	.011	.	0	1
Catering	.020	.	0	1
Transport and communication	.052	.	0	1
Financial	.044	.	0	1
Business services	.087	.	0	1
Government services	.096	.	0	1
Education	.097	.	0	1
Healthcare and welfare	.217	.	0	1
Environmental services and recreation	.034	.	0	1
Other	.119	.	0	1

***p<.001

¹The variable income is log-transformed.

3.4 Analytical Strategy

Because we are looking to test for differences in effect of education on income between different intersectional groups, the hypotheses were tested using a multilevel analysis (Wafelaar & Stienstra, 2021). Because the individual respondents are nested within the intersectional groups (or strata), a multilevel analysis fits our data better than an Ordinary Least Squares (OLS) regression model would. Using the multilevel analysis, we can establish what proportion of total variance is to be explained by intergroup differences and what part can be ascribed to individual differences. We therefore can account for intragroup heterogeneity, while testing for intergroup differences. The strata are constructed to represent women with a migration

background, women without a migration background, men with a migration background and men without a migration background. The multilevel models were estimated using Maximum Likelihood Estimation (Hox, 2018). We bootstrapped all estimates, to ensure model stability.

The first model estimates the random intercept of income and the variance between the four strata and individual variance, without any predictors (the null model). This variance decomposition model is estimated according to the following equations (Hox, 2018):

Level 1 equation:

$$Y_{ij} = \beta_{0j} + \varepsilon_{ij}$$

Level 2 equation:

$$\beta_{0j} = \gamma_{00} + u_{0j}$$

Y_{ij} represents the income of respondent i in intersectional group j . This value is predicted by adding the residual deviation of respondent i in stratum j (ε_{ij}) to the average income in stratum j (β_{0j}). β_{0j} is in turn composed by the overall average income γ_{00} and the residual deviation of the average income of stratum j from γ_{00} . The assumption here is that the residual deviations are normally distributed, and have a mean of zero. Integration leads to the following equation:

$$Y_{ij} = \gamma_{00} + u_{0j} + \varepsilon_{ij}$$

The null model also allows us to estimate the intraclass correlation (ICC). The ICC is an estimate of the proportion of the variance that can be explained by intergroup differences, calculated as (Hox, 2018):

$$\rho = \sigma_{u_{0j}}^2 / (\sigma_{u_{0j}}^2 + \sigma_{\varepsilon_{0j}}^2)$$

In this equation, $\sigma_{u_{0j}}^2$ represents the variance in the residual deviation of the mean income of stratum j from the overall mean, and $\sigma_{\varepsilon_{0j}}^2$ represents the variance in residual deviation of respondent i in group j to the average income in stratum j .

Secondly, the control variables were added to the model. Next, we added the dummy variables measuring gender and migration background individually, and in the subsequent model simultaneously. We then included the variable measuring educational attainment into the model. This model can be described as:

$$\begin{aligned} Y_{ij} = & \gamma_{00} + u_{0j} + \beta_1(educ)_{ij} + \beta_2(female)_{ij} + \beta_3(migration\ background)_{ij} \\ & + \beta_4(age)_{ij} + \beta_5(age^2)_{ij} + \beta_6(hours\ worked)_{ij} + \beta_7(agriculture)_{ij} \\ & + [...] + \beta_{19}(other)_{ij} + \varepsilon_{ij} \end{aligned}$$

We finally included a random slope for educational attainment, to test if education affects income differently between strata. Since we already included the fixed effects for gender and migration background, any difference in effect between strata would indicate that there is a bigger difference in effect from education on income between intersectional groups, than the sum of those groups would yield. In this model, the coefficient with which income increases for every increase of education consists of the grand mean of the slope and the random deviation from this average of the different strata.

$$\beta_1(educ)_{ij} = \gamma_{10}(educ)_{ij} + u_{1j}(educ)_{ij}$$

Through substitution, we arrive at the following model:

$$\begin{aligned} Y_{ij} = & \gamma_{00} + u_{0j} + \gamma_{10}(educ)_{ij} + u_{1j}(educ)_{ij} + \beta_2(female)_{ij} \\ & + \beta_3(migration\ background)_{ij} + \beta_4(age)_{ij} + \beta_5(age^2)_{ij} \\ & + \beta_6(hours\ worked)_{ij} + \beta_7(agriculture)_{ij} + [...] + \beta_{19}(other)_{ij} + \varepsilon_{ij} \end{aligned}$$

We calculated how well the models fit the data in comparison to other models using *goodness-of-fit* indicators. We estimated the *-2 Log Likelihood* in terms of Chi-squared for each model. To compare the models with each other, we computed the change in χ^2 (Δ -2LL) and the change in degrees of freedom between two models using the following formulas:

$$\Delta - 2LL = |(-2LL_1) - (-2LL_s)|$$

$$DF_{change} = df_1 - df_s$$

For each DF_{change} we then indicated the critical value of χ^2 , and compared it to the Δ -2LL. If the value for Δ -2LL was higher than the critical value of χ^2 , we concluded the larger model (1) fitted the data significantly better than the smaller model (s). In addition, we estimated the values of Akaike's Information Criterion (AIC) for each model. A decline in AIC-values between models indicates better fitting models.

Lastly, the importance of adding the different predictors is measured with the R-squared, representing the proportion of variance in income that is explained by the predictors in the model. We calculate the R^2 using the following formula, in which M1 represents our null model, and Mk the model which is the object of comparison.

$$R^2 = (\sigma_{M1}^2 - \sigma_{Mk}^2) / \sigma_{M1}^2$$

4. Results

In our null model, the variance in income between strata is $\sigma_{u0j}^2 = .007$ ($p = .001$). The residual variance, or the variance between individuals is $\sigma_{e0j}^2 = .061$ ($p = .001$). The ICC that we calculated from these variances is .104, which means that 10.4% of total variance can be explained by intergroup differences². Traditionally, ICC values of above .05 are regarded as indicating a non-coincidental coherence. Therefore we can conclude a multilevel analysis is relevant to our research.

In model 2, where we added our control variables, the model fit improved according to the reduction in the -2LL and AIC ($\Delta\text{-2LL} = 624.178$)¹. This means the model that included control variables better fits our data than our null model. The variance component is significant, both on the individual level ($p = .001$), and on the strata level ($p = .015$). The R^2 in Model 2 was .296 at the individual level, which means 29.6% of within-strata variance can be explained by our control variables. At the between-strata level, the control variables explain 82.9% of variance.

In Model 3 we added the dummy for people with a migration background. From the AIC and -2LL for Model 3, we can conclude that this model does not fit the data better than Model 2 ($\Delta\text{-2LL} = .015$). Again, the variance is significant on both levels ($p = .001$; $p = .021$). The R^2 shows that, compared to Model 2, Model 3 explains the same percentage of variance at the individual level ($R^2 = .296$). At the strata level, Model 3 explains 83.6% of variance, which is slightly more than Model 2 did ($R^2 = .829$). This would indicate that the variable that was added, migration background, explains a small part of the differences that exist between the intersectional groups.

We included the dummy female and excluded the dummy for people with a migration background in Model 4³. This model has a slightly lower AIC than Models 2 and 3, which indicates this model fits the data better than Models 2 and 3. With the -2LL test, Model 4 was compared with Model 2, as Models 4 and 3 are not nested within each other. The -2LL test suggests Model 4 fits the data better than Model 2 ($\Delta\text{-2LL} = 9.994$). This is consistent with the fact that the gender differences we included in this model explain most of the variance between strata. The variance on the individual level was significant ($p = .001$). The explained variance on the individual level did not differ from that of Models 2 and 3.

² View Appendix B for calculations of model-fit indicators.

³ The converge of the final Hessian matrix is not positive.

Table 2: Results of multilevel analyses on log transformed monthly income before taxes ($N_{strata} = 4$; $N_{individuals} = 1766$)

	Model						
	1	2	3	4	5	6	7
<i>Fixed</i>							
Intercept	3.443** (.008)	2.599** (.086)	2.593** (.080)	2.635** (.088)	2.635** (.086)	2.279** (.080)	2.279** (.082)
<i>Independent variables</i>							
Migration background			.014 (.013)		.013 (.013)	.011 (.012)	.011 (.076)
Female				-.081** (.013)	-.081** (.013)	-.082** (.012)	-.182** (.069)
Educational attainment						.029** (.002)	.029** (.002)
<i>Control variables</i>							
Hours worked per week		.012** (.001)	.012** (.001)	.012** (.001)	.012** (.001)	.011** (.001)	.011** (.001)
Age		.016** (.004)	.016** (.004)	.016** (.004)	.016** (.004)	.015** (.003)	.015** (.003)
Age ²		-.000** (4.211E ⁻⁵)	-.000** (3.993E ⁻⁵)	-.000** (4.166E ⁻⁵)	-.000** (4.198E ⁻⁵)	-.000** (3.765E ⁻⁵)	-.000** (3.882E ⁻⁵)

Occupational sector (ref = other) ¹	No	Yes	Yes	Yes	Yes	Yes	Yes
<hr/>							
Random							
Intercept	.007** (.001)	.001* (.000)	.000 (.000)	.000 (.000)	.000 (.000)	.000 (.000)	
Education							.000 (.000)
<hr/>							
ICC	.104						
R ² ₁		.296	.296	.296	.296	.389	.389
R ² ₂		.829	.836	1.00	1.00	1.00	1.00
<hr/>							
Model fit							
-2LL	87.634	-536.544	-536.694	-546.538	-547.476	-796.391	-796.391
AIC	93.534	-498.544	-496.694	-506.528	-505.476	-752.391	-752.391

*p<.05, **p<.01, ***p<.001 (two-tailed)

Coefficients and s.e. were estimated using stratified bootstrap samples (k=1000).

Standard Errors are in brackets.

ICC = Intraclass Coefficient, R²₁ = explained variance at the individual level, R²₂ = explained variance at the strata level, -2LL = -2 Log Likelihood, AIC = Akaike Information Criterion

¹ The coefficients for the dummies for different occupational sectors per model can be found in Appendix C.

In Model 5⁴, both the dummy measuring gender and the dummy for people with a migration background were added. From the AIC and -2LL for Model 5, we conclude this Model fits the data better than Model 3 (Δ -2LL= 10.782), but is no improvement compared to Model 4 (Δ -2LL= .938)⁵. Again, there was no significant residual variance on the strata level. There was a significant individual level predictor ($p = .001$). Model 5 explained 28.9% of variance at the individual level ($R^2 = .289$), which is similar to the explained variance of Models 2, 3 and 4.

Model 6⁴ shows education has a significant positive effect on income, even when controlled for different control variables ($b = .029$, $p = .001$). These numbers indicate that with every extra year of education, individual income rises with .029 on our log-transformed income scale, which can be translated to 6.90 euros per hour⁶. This outcome confirms our first hypothesis. All control variables loaded in the expected directions. Furthermore, we can conclude that Model 6 fits the data better than all previous models, based on the AIC and -2LL (Δ -2LL= 248.915). Moreover, 38.9% of variance on the individual level can be explained by this model, which is more than any of the previous models. The variance on this level was significant ($p = .001$), while the variance on the strata level was still fully explained by the fixed effects of the variables included in the model.

The last model tested for differences in the slope of education between different strata. Model 7⁴ showed that women have a significantly lower hourly income than men ($b = -.182$, $p = .001$), even when controlled for educational attainment, age and occupational sector. After translating these values of our log-transformed scale of income, it is apparent that women earn on average 34.23 euros less per hour than men². Based on these results, we can accept our second hypothesis. Conversely, no significant difference in income was found between people with and without a migration background ($b = .011$, $p = .745$). We can reject our third hypothesis, stating people with a migration background have a lower hourly income than people without a migration background, regardless of all control variables.

The estimate of the AIC and the -2LL indicates Model 7 fits the data as well as Model 6 (Δ -2LL= .00). The explained variance on the individual level is also equal to that of Model 6 ($R^2 = .389$). As all residual variance between the strata in this model is explained by the fixed effects, we can conclude that there are no significant intersectional differences in the effect of education on income between strata, but that the disadvantage or privilege of a certain groups

⁴ The converge of the final Hessian matrix is not positive.

⁵ The absence of a significant decline in the -2LL and AIC between Models 4 and 5 indicates a decrease of the validity of the results displayed in Model 5.

⁶ $100 \cdot (10^B - 1)$

is just the sum of parts. We can therefore reject the hypothesis that there are intersectional differences in the effect of education on income regarding gender and ethnicity, more than one would expect based on the sum of the effects regarding gender and ethnicity.

5. Discussion

The objective of this study was to test whether there are intersectional differences in the hourly income returns to education in the Netherlands. In this study we looked at the intersection of gender and ethnicity. Based on our results, we can conclude that there are no differences in effect of educational attainment on income between the intersectional groups of people with and without a migration background and men and women, more than one would expect based on the sum of the results of having a certain gender or migration background. Thus, we found no evidence for the existence of a multiple jeopardy mechanism for the intersectional groups in this study. We conclude that education has a significant effect on income, and women had a lower income than men, regardless of their education.

Our data did not show a significant difference in income between people with a migration background and people without a migration background, which was contrary to our expectations. This could partially be due to the fact that our sample of people with a migration background was relatively small, giving us little statistical power to give significant results. Moreover, our selection of cases favored higher educated people in a higher income class, without a migration background. Additional research using a larger dataset would therefore allow for a better estimate of this effect. Furthermore, future research could differentiate between groups of people with a migration background with different countries of origin. This would presumably give a better estimate of the differences between groups in the Netherlands, as there are differences between these groups in positions on the labor market (Jongen et al, 2020).

The variation in income between men and women, regardless of educational attainment, occupational sector and age, can be explained by a multitude of factors. First of all, mechanisms contributing to the so-called ‘glass ceiling’, the overrepresentation of women in part-time jobs, and the persisting traditional household division could influence the income discrepancy between men and women. In addition, discrimination could play a role in multiple ways. The fertility discrimination mechanism could for instance contribute to the pay gap. Moreover, it could also be that discrimination influenced our independent variables. Factors such as the occupational sector could be influenced by discrimination in the school system for example.

However, even if our found differences are to be ascribed to other variables, it still means some groups have a disadvantage compared to others, which doesn't make these differences 'justified'. Therefore, policy makers could invest in breaking down barriers for women to work fulltime and work less in the household if they prefer to, in the form of better policy surrounding child care, and more paid leave for fathers. In addition, employers should be motivated to focus on the capacities of the applicant in the hiring of employees and not their identity characteristics. For instance, this could be done by introducing anonymous application for jobs, or promoting diversity in the workplace.

Some limitations to our research might distort our results. First of all, our operationalization of educational attainment could yield a bias. For people with a migration background, a different variable measuring education was used with less information about the respondents. Thus, variance within educational attainment and therefore within returns to education, could less easily be detected. However, we conducted a robustness check with a variable measuring educational attainment for all respondents using six categories. This check yielded results that were similar to the results that we found. Moreover, measuring educational attainment in years can cause differences in the levels of education to be overlooked. Even though we controlled for occupational sector, and therefore differences in payment between these sectors, analyzing the different types of education separately through including them as dummies, can give additional information about the returns to educational attainment.

Second, the use of education attainment in research in general has some limitations of its own (Marginson, 2017). We estimated our models under the assumption that the relation between education attainment and income is linear of time spent in education. However, in practice this might not be the case, as people in the higher income classes have more benefit from one extra year of education, than people in lower income classes (Becker, 1994; Harmon et al, 2000; Harmon et al, 2003; Park, 1996). Therefore, additional research could benefit from taking into account this non-linear relation.

Third, even though education attainment and work experience are two conceptually different entities, the relevance of experience on the job must not be forgotten. Learning skills and knowledge in a job environment seems to have a similar effect on returns as do more 'formal' forms of education (Becker, 1994). As this factor is an important measure through which employers formulate expectations on the capacities and productivity of their employees, additional intersectional research including this concept is needed. Comparably, social capital is pertinent in research on human capital and wage inequality, and would therefore be a relevant

addition for future research on intersectionality and returns to education (Boxman et al, 1991; Quite et al, 2013; Smith, 2000).

Lastly, although a multilevel method helped us to account for heterogeneity within groups, we cannot ascribe this heterogeneity to specific identity characteristics. The aggregate nature of quantitative research methods can always cause factors and different types of identity characteristics to be overlooked. As intersectionality is such a complex concept, qualitative research on what combinations of identity characteristics yield which results still remains essential to the intersectional research field. Research on intersectionality using quantitative methods can draw from this qualitative research and try to generalize these results, always taking the internal heterogeneity between different groups into account.

Whatever factors might explain the found gap in returns to education between men and women, inequality still seems to persist on the Dutch labor market today. Even though we found no intersectional differences in income returns to education, the intersectional research field still leaves us with many identity characteristics and factors of societal positions to study. In order for society to achieve its optimal potential, barriers based on identity characteristics should be broken down.

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Appendix A: Translation of education category to years of education

Table 3: Operationalization of education in years

Value	Category	Education in years
<i>Highest level of education completed with diploma or certificate</i>		
1	Did not complete any education	0
2	Did not complete primary school	5
3	Primary school	6
4	Lower and continued special education	.
5	VGLO (continued lower education)	8
6	LBO (lower professional education)	10
7	Lower technical school, household school	9
8	MULO, ULO, MAVO (lower/ intermediate secondary education, US: junior high school)	10
9	VMBO vocational training program (preparatory intermediate vocational school)	10
10	VMBO theoretical or combined program (preparatory intermediate vocational school)	10
11	MMS (intermediate girls' school)	11
12	HBS (former pre-university education, US: junior high school)	10
13	HAVO (higher general secondary education, US: junior high school)	11
14	VWO (pre-university education, US: senior high school)	12
15	Gymnasium, atheneum, US: senior high school	12
16	KMBO (short intermediate professional education), VBHO (preparatory higher professional education)	13
17	MBO professional training program (intermediate professional education (BOL))	12
18	MBO professional training program (intermediate professional education (BBL))	12
19	MBO-plus to access HBO, short HBO education (less than two years) (higher professional education)	13
20	HBO (higher professional education, institutes of higher education, new style)	15
21	Teacher training school	14
22	Conservatory and art academy	15
23	Academic education (including technical and economic colleges, former style) bachelor's degree (kandidaats)	15
24	Academic education (including technical and economic colleges, former style) master's degree (doctoraal)	17
25	Academic education, bachelor	15
26	Academic education, master	17

27	Doctor's degree (P.h.D, including doctoral research program to obtain P.h.D.)	22
28	Other	.
<i>Highest level of education completer with diploma or certificate, not attained in the Netherlands</i>		
1	None	0
2	Elementary (comparable to primary education)	6
3	Middle school (comparable to VMBO, VBO, MAVO; intermediate professional education)	10
4	Secondary (comparable to HAVO, VWO, MBO; secondary education)	12
5	Post-secondary, non-tertiary (comparable to post-MBO; continued intermediate professional education)	13
6	Tertiary (comparable to HBO, WO; higher education, university education)	15
7	Post-tertiary (comparable to post-academic, including doctor)	19.5
8	Other	.

Appendix B: Calculations for model-fit

The null model

ICC

The ICC of the null model is $.007098 / (.007098 + .061016) = .104$.

Model 2

Log Likelihood

For the null model, the -2LL is $\chi^2 = 87.634$. The -2LL for Model 2 is $\chi^2 = -536.544$. $\chi^2_{\text{change}} = |-536.544 - 87.634| = 624.178$. The null model contains 3 parameters, and Model 2 contains 19 parameters. For a df_{change} of $19 - 3 = 16$, the critical value for χ^2 is 26.296. As $624.178 > 26.296$, we can conclude Model 2 fits the data better than the null model.

AIC

The AIC of Model 2 (-498.544) is lower than the AIC of our null model (93.534). This indicates Model 2 better fits the data than the null model.

Explained variance

- The explained variance on the individual level is $(.061016 - .042980) / .061016 = .296$.
- The explained variance on the strata level is $(.007098 - .001213) / .007098 = .829$

Model 3

Log Likelihood

The -2LL of Model 3 is $\chi^2 = -536.694$. χ^2_{change} compared to Model 2 is $|-536.694 - (-536.544)| = .15$. For a df_{change} of $20 - 19 = 1$, the critical value of χ^2 is 3.841. As $.15 < 3.841$, we can conclude Model 3 does not fit the data better than Model 2.

AIC

The AIC of Model 3 is -496.694, which is higher than the AIC of Model 2 (-498.544). Model 2 seems to fit our data better than Model 3.

Explained variance

- The explained variance on the individual level is $(.061016 - .042980) / .061016 = .296$
- The explained variance on the strata level is $(.007098 - .001166) / .007098 = .836$

Model 4

Log Likelihood

Model 4 will be compared to Model 2, as Model 3 is not nested in Model 4, but Model 2 is. The -2LL for Model 4 is $\chi^2 = -546.538$. $\chi^2_{\text{change}} = |-546.538 - (-536.544)| = 9.994$. As 9.994 is bigger than the critical value of χ^2 for a df of $20 - 19 = 1$ ($\chi^2 = 3.841$), the -2LL indicates Model 4 fits the data significantly better than Model 2.

AIC

According to the AIC, Model 4 seems to fit the data better than Models 2 and 3. The AIC of Model 4 is -506.528, as opposed to an AIC of -498.544 (Model 2) and -496.694 (Model 3).

Explained variance

- The explained variance on the individual level is $(.061016 - .042966) / .061016 = .296$
- No residual variance on the strata level was found. $(.007098 - .0000) / .007098 = 1.00$

Model 5

Log Likelihood

The -2LL of Model 5 is $\chi^2 = -547.476$. We will compare this model to Models 3 and 4, as both are nested within Model 5. χ^2_{change} compared to Model 3 is $|-547.476 - (-536.694)| = 10.782$. As this is larger than the critical value of χ^2 , 3.841, for $df_{\text{change}} = 21 - 20 = 1$, we can conclude Model 5 fits the data better than Model 3.

χ^2_{change} compared to Model 4 is $|-547.476 - (-546.538)| = .938$. As this is smaller than the critical value of χ^2 , 3.841, for $df_{\text{change}} = 21 - 20 = 1$, we can conclude Model 5 does not fit the data better than Model 3.

AIC

Model 5 shows an AIC of -505.476. This indicates that it fits the data less good than Model 4, but better than Model 3.

Explained variance

- The explained variance on the individual level is $(.061016 - .042943) / .061016 = .296$
- No residual variance on the strata level was found. $(.007098 - .0000) / .007098 = 1.00$

Model 6

Log Likelihood

The -2LL of Model 6 is $\chi^2 = -796.391$. Compared to Model 5, the $\chi^2_{\text{change}} = |-796.391 - (-547.476)| = 248.915$. For a df_{change} of $22 - 21 = 1$, the critical value for χ^2 is 3.841. As $248.915 > 3.841$, we conclude Model 6 fits the data better than Model 5.

AIC

Model 6 has an AIC of -752.391, which indicates it fits the data better than all previous models.

Explained variance

- The explained variance on the individual level is $(.061016 - .037297) / .061016 = .389$
- No residual variance on the strata level was found. $(.007098 - .0000) / .007098 = 1.00$

Model 7

Log Likelihood

As the -2LL of Model 7 is similar to the -2LL of Model 6, we conclude Model 7 fits the data as well Model 6.

AIC

The AIC of Model 7 is -752.391, which is equal to AIC of Model 6. This indicates Model 7 fits the data as well as Model 6.

Explained variance

- The explained variance on the individual level is $(.061016 - .037297) / .061016 = .389$
- No residual variance on the strata level was found. $(.007098 - .0000) / .007098 = 1.00$

Appendix C: Coefficients Occupational sector

Table 4: Results of multilevel analyses of occupational sector dummies on log transformed monthly income before taxes ($N_{strata} = 4$; $N_{individuals} = 1766$)

	Model						
	1	2	3	4	5	6	7
Occupational sector (ref = other)							
Agriculture		-.034 (.056)	-.034 (.059)	-.035 (.058)	-.033 (.060)	-.034 (.053)	-.034 (.054)
Industrial		.058* (.022)	.058** (.022)	.056* (.022)	.057* (.023)	.056* (.021)	.056** (.021)
Trade		.094* (.048)	.093* (.044)	.093* (.045)	.092* (.048)	.085* (.041)	.085* (.039)
Construction		.033 (.024)	.033 (.023)	.031 (.024)	.032 (.025)	.039 (.022)	.039 (.022)
Retail		-.083** (.029)	-.082** (.028)	-.083** (.029)	-.082** (.029)	-.061* (.027)	-.061* (.027)
Catering		-.140** (.041)	-.140** (.040)	-.136** (.040)	-.137** (.042)	-.070 (.040)	-.070 (.038)
Transport		.009 (.027)	.010 (.026)	.008 (.028)	.009 (.027)	.022 (.024)	.022 (.024)
Financial		.127**	.127**	.126**	.127**	.086**	.086**

	(.026)	(.027)	(.029)	(.028)	(.027)	(.025)
Business	.089**	.090**	.087**	.088**	.037	.037
	(.023)	(.023)	(.023)	(.024)	(.022)	(.021)
Government	.148**	.148**	.147**	.148**	.105**	.105**
	(.019)	(.019)	(.020)	(.020)	(.019)	(.019)
Education	.082**	.082**	.080**	.082**	.016	.016
	(.022)	(.021)	(.022)	(.022)	(.021)	(.021)
Healthcare	.063**	.063**	.061**	.063**	.036	.036
	(.020)	(.019)	(.020)	(.020)	(.018)	(.018)
Recreation	.018	.018	.021	.020	-.017	-.017
	(.037)	(.037)	(.037)	(.036)	(.037)	(.037)

*p<.05, **p<.01, ***p<.001 (two-tailed)

Coëfficients and s.e. were estimated using stratified bootstrap samples (k=1000).

Standard Errors are in brackets.
